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Essays on International Asset Pricing, Cultural Finance, and the Price Effect

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Ulrich Johannes Hammerich

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First examiner:	Prof. Dr. Armin Varmaz
Second examiner:	Prof. Dr. Lars Hornuf
Thesis supervisor:	Prof. Dr. Thorsten Poddig

Universität Bremen

Abstract

This dissertation is not only a pioneer work in the new finance sphere cultural finance, but also a feat of fundamental research in international empirical asset pricing. I present significant evidence that the most basic stock characteristic, the nominal price, is consequential for stock returns (and associated with higher statistical moments) in a comprehensive cross-country dataset comprising 41 countries and a culture-dependent capital market anomaly (as it was already shown e.g. for the momentum effect).

For the case of Germany, I additionally provide an in-depth analysis of the price effect (i.e. a high/low price of an asset goes hand in hand with high/low subsequent returns) as this country offers a unique possibility to investigate the evolution and trigger of this genuinely price-based capital market anomaly due to a rapid and dramatic countrywide dispersion of stock prices in the aftermath of law amendments.

Furthermore, I find the explanatory power of risk factor mimicking hedge portfolios (especially RMRF, HML, and WML, i.e. the beta, value, and momentum factors), which are consistently implemented in empirical asset pricing models (like the FF 3-, 5-, and 6-factor models and the Carhart 4-factor model), as well as their effectiveness as investment styles to vary across cultures.

That is, the spectrum of this dissertation strikes both implications of the weak EMH that time series data (like the price) should have no informational value for future returns and assumptions of theoretical asset pricing models that (only) systematic risk (CAPM), future investment opportunities (ICAPM) or consumption risk (CCAPM) drives asset returns (universally).

Finally, yet importantly, I find evidence that even cultural characteristics in itself (measured via the cultural dimensions of Hofstede and others) have explanatory and predictive power for global, cross-sectional stock returns as well as characteristics-based (hedge) portfolio returns. By virtue of these contributions to pertinent financial research, this dissertation is an empirical primer for possible future fields of research culture-based/culture-neutral asset pricing, asset management, and asset allocation.

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Contents

List of Acronyms

AFFI	French Finance Association
APT	Arbitrage Pricing Theory
AR	Autoregressive
BE	Book Equity
CA	California
CAPM	Capital Asset Pricing Model
CCAPM	Consumption-based Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
cp.	compare
CRSP	Center for Research in Security Prices
DGF	German Finance Association
e.g.	exempli gratia, for example
EMC	Expensive Minus Cheap
EMH	Efficient Market Hypothesis
FF	Fama and French
FMA	Financial Management Association
FOFI	Frontiers of Factor Investing
GB	Gigabyte
GDP	Gross Domestic Product
GLOBE	Global Leadership and Organizational Behavior Effectiveness
GNI	Gross National Income
HML	High Minus Low
HVB	Hypovereinsbank
i.a.	inter alia, amongst others
IBES	Institutional Brokers' Estimate System
IBM	International Business Machines
ICAPM	Intertemporal Capital Asset Pricing Model
i.e.	id est, that is
IMF	International Monetary Fund
IPO	Initial Public Offering
JEL	Journal of Economic Literature
LN	Natural Logarithm
LTO	Long Term Orientation
MAX	Maximum Daily Returns
MHF	Mutual Funds, Hedge Funds and Factor Investing
MOM	Momentum
MV	Market Value
NA	Not Available
NOSH	Number of Shares
OLS	Ordinary Least Squares
PD	Privatdozent
RBFC	Research in Behavioral Finance Conference
RE	Random Effects
RMRF	Return Market (RM) minus return Risk Free (RF) rate
RMW	Robust Minus Weak
SMB	Small Minus Big
SRI	Social Responsible Investing
SSRN	Social Science Research Network
TRD	Thomson Reuters Datastream

UK	United Kingdom
US(A)	United States (of America)
VU	Vrije Universiteit
WML	Winner Minus Loser

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1. Introduction

The objective of this document is to describe the research context in which my cumulative dissertation consisting of three coherent research papers is located. Despite its integrating purpose, this document is also meant to stand for its own.[1] I present an overview of fundamental concepts, theory, and methodology to embed the subsequently described research gaps that I strive to fill, followed by a review of my scope, empirical findings, and contributions of my research papers. I also operate on a superordinate level (that is not feasible within research papers) as I discuss my findings as well as the characteristics and (future) evolution of finance as a scientific discipline in the form of a critical acclaim.[2] Furthermore, I will not spare out delivering some insights into my strategic scientific acting, as I regard this as an integral part of successful academic advancement apart from producing high quality, original research (see Appendix A).

My thesis is located in the highly researched and competitive fields asset pricing and behavioral finance (as well as a very young subfield – cultural finance) on the international stock market. The main background of my research is the plethora of documented capital market anomalies (over 300 published in top academic journals or presented at top conferences plus thousands of working papers and articles in other academic journals; see, e.g., Harvey et al., 2016), which are often based on simple to calculate, readily available firm/stock characteristics (factors) like size, book-to-market, momentum, volatility, and liquidity that were found to be consequential for the (international) cross-section of (expected) stock returns. This situation of empirical finance research is termed as state of "chaos" by Cochrane (2011). Main issues in this context are (1) how these capital market anomalies can be explained respectively reconciled with financial theory (see, e.g., multiple papers of Fama and French, like 1996a, 2016) or alternative concepts and explanations of behavioral finance (e.g., De Bondt and Thaler, 1985; Lakonishok et al., 1994) and (2) implemented as and condensed for investment strategies (e.g., Brandt et al., 2009; Asness et al., 2013) respectively merged at a superordinate level (e.g., Teo and Woo, 2004; Chao et al., 2012; Wahal and Yavuz, 2013; Glas et al., 2017). In a nutshell, I have three prime objectives to fill significant research gaps in this context and advance finance as scientific discipline:

Objective 1: Show that the stock characteristic nominal price is relevant for international investors and a capital market anomaly. The relevance of even this simple characteristic (in fact the most basic information of a stock) would for example question (1) the heart of the neoclassical financial theory, the efficient market hypothesis (EMH) elaborated by Fama (1970, 1991), to a large extent and (2) general, globally consistent risk-based explanations if there is a large international diversity of this effect.

Objective 2: Show that cultural dimensions are consequential for asset pricing tasks and feasible to explain and predict cross-sectional stock returns and (returns on) investment strategies based on anomalies (like price, value, and momentum).

[1] Due to this, I also present abstracts of the papers and their current status in Appendix A, although similar information is additionally (implicitly) presented on the cover page of each research paper. Furthermore, I deliberately present this document in a slightly different formatting to set it apart from the research papers in Appendix C, enhance its handiness, and to comply with page count guidelines of the doctoral degree regulations.

[2] This is mainly done within footnotes to keep the structure of the document consistent and to follow the central theme.

(Implicit) Objective 3: Demonstrate that cultural finance can help closing the gap between risk-based finance and behavioral finance and moderates weaknesses of asset pricing models. In this way, I try to (help) reduce the state of "chaos" (Cochrane, 2011) of the research on the cross-section of stocks and display an effective approach to tame the "factor zoo" (Cochrane, 2009, 2011; Harvey et al., 2016; Feng et al., 2019).

My journey to a cumulative dissertation started in 2015 when I developed three (early stage) conceptual working papers as an independent researcher (Hammerich, 2015a, 2015b, 2015c). The latest of these papers (2015c), "A Bargain Hunter's Dream: High-Priced Stocks", laid the foundations for my first project as a research associate at the University of Bremen, later entitled "Nominal Stock Price Investing" (Paper I, Hammerich et al., 2019), which was initially completed in a first version in fall 2016.[3] This sequence ensured that the empirical results presented in "Nominal Stock Price Investing" (and Hammerich, 2020) suffer not (respectively only marginally) from critical, but widespread biases like data snooping and data mining (e.g., Lo and MacKinley, 1990; Harvey et al., 2016; Linnainmaa and Roberts, 2018), since Hammerich (2015c) laid the fundament for a deductive approach and already developed the main hypothesis (high-priced stocks outperform low-priced stocks) that is tested in Hammerich et al. (2019) for the German stock market. In this sense, the documented price effect in Germany (high-priced stocks *indeed* outperform low-priced stocks in the recent decades) is not another animal in the factor zoo (cp., e.g., Cochrane 2009, 2011; Harvey et al., 2016) that was accidentally sighted in the wilderness, but it was expected to have a habitat in Germany and to show a specific silhouette. In the process of the paper over about three years, not only its silhouette was filled with color and shape, but also its quick, unexpectedly distinct, and rare evolution was documented and traced back. By virtue of these characteristics, the (until then relatively unknown) price effect was an especially interesting specimen to do research on, despite or even more due to its cousinhood with well charted (but nevertheless still puzzling) stock market anomalies like momentum, size, (low) beta, and (low) idiosyncratic volatility (e.g., Banz, 1981; Jegadeesh and Titman, 1993; Ang et al., 2009; Auer and Schuhmacher, 2015) as well as lottery-related anomalies like the MAX effect (Bali et al., 2011; Cheon and Lee, 2017)

The rare international research on the price effect (mainly limited to the US; e.g., Blume and Husic, 1973; Hwang and Lu, 2008; Singal and Tayal, 2018), inconsistent results in the literature (some papers show a high price, some a low price effect), own evidence for a significant low

[3] Hammerich and Frädrich (2017), "Unraveling Momentum", is another research idea that I developed and reflected in winter 2016 with data provided by my co-author in course of my dissertation process. This paper is an early stage conceptual paper that (simply put) traces back the existence, persistence, and magnitude of the momentum effect (and in turn the long-term reversal effect) to the existence and evolution of (other) investment strategies and styles. It initially relies on the intuition provided by Barberis and Shleifer (2003) on the cyclicity of investment styles and the findings of McLean and Pontiff (2016) on a publication effect. However, the developed story is original, somewhat off-the-wall, and (to my knowledge) in uncharted waters. Nevertheless, I could confirm the validity of the main hypotheses in this paper by several prototypical tests based on simulated return data for multiple investment styles in 2018 and (thereby) sharpened the story. However, the topic showed to be complex and proved to be too tricky and sensitive (as it is expected to be highly impactful when performed rigorously) to elaborate further in the course of a cumulative dissertation given a limited time frame and collaboration possibilities. Furthermore, the subject delivered only scarce synergies and overlaps with the other research projects and thus was not (yet) worked out in a comprehensive paper as a part of my cumulative dissertation.

price effect in Asia[4], and findings of my colleagues (Glas et al., 2017) in favor of an European high price effect were the main drivers for a following international safari dedicated to capture the nature of the price effect on international levels that I began in spring/summer 2017. This led to the paper "Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns" (Paper II, Hammerich, 2020), which initially covered 20, and after an extension 41 international stock markets. However, this paper not merely extends the scope to an international investigation of a price effect, but is a pioneer work in the new finance branch "cultural finance" (e.g., Zingales, 2015; Aggarwal et al., 2016; Karolyi, 2016; Nadler and Breuer, 2019). The idea to trace back the apparent regional dependency of the price effect to culture was intuitive and proved to be not too off-wall.[5] In the context of the paper it also became evident that culture measured via cultural dimensions appears to be not only consequential for a price effect, but also for global cross-sectional stock returns in general. This might be one of the most impactful insights of my dissertation.

The third paper (Paper III, Hammerich and Poddig, 2020), entitled "Asset pricing risk factors and cultural dimensions: the hidden steady state variables?" picks up the usefulness of cultural dimensions to explain and predict returns on investment styles and opens another barrel. Here, I and my co-author blaze a trail to culture-based asset pricing, as we manage to link the international efficacy of (some of) the five Fama and French (2015, 2017) risk factor mimicking portfolios as well as Carhart's (1997) momentum factor to cultural dimensions. In sum, I expect this paper to have the strongest impact on future research, as it also strikes the logic and expectations of Merton's (1973) ICAPM and the foundations of commonly accepted (economic) state variables that are proxied by risk factors (Petkova, 2006) applied in asset pricing models. In this sense, the paper operates off the beaten track and offers a novel view on (cultural) variables that predict future investment opportunity sets, despite being (largely) time-invariant. Additionally, it also shows that the international investment styles momentum and value are sensitive to (several) cultural characteristics and thereby expands the path of Chui et al. (2010) and leads – maybe in the future – to culture-based asset allocation.

I structure this document as follows: Section 2 provides some literature that operates in the domain of my research, sketches important theoretical concepts and in this way a brief history of modern finance and thereby motivates the challenges and (expected and needed) forthcoming research in my field. Section 3 briefly introduces the main datasets and specifies methodologies that I frequently use in my papers. In Section 4, I lead over to my specific research field and review and discuss relevant literature of my two intertwined research strands (price effect and the relation of anomalies, risk factors, and cultural dimensions) and pinpoint research gaps. Section 5 summarizes, discusses, and integrates the essence of my research papers (see Appendix C), gives additional insights and empirical findings and displays my contribution. I close by discussing the major implications of my research and future prospects in Section 6. In Appendix A, I provide abstracts and the current status of the papers as well as some strategic considerations regarding publication strategy.

[4] Recently, there are some working papers upcoming that investigate the nominal price effect in specific Asian countries like China and Vietnam (showing also evidence for a low price effect, cp. Hoang, 2018 and Huang et al., 2018).

[5] At the time of this idea, I was not aware of literature like Chui et al. (2010) and other literature on the relation of capital market anomalies and culture (respectively cultural dimensions).

2. Theory and Motivation

The scope of this dissertation is broad. It comprises risk-based finance, behavioral finance, and one of the newest finance branches, namely cultural finance. In doing so, it also tries to help closing the gap between risk-based finance and behavioral finance via cultural finance. The questions covered in this work are manifold and multifaceted, but nevertheless closely linked together. Examples of stroked topics are the crucial questions that are at the center of interest of a large proportion of the financial economics' research community since about the 1970s:

a) Issues regarding capital market anomalies:
  - Under which circumstances do they (a)rise, evolve, disappear or even turn around (Barberis and Shleifer, 2003; Schwert, 2003; Van Dijk, 2011; Avramov et al., 2013; Jacobs, 2015; Keloharju et al., 2016; McLean and Pontiff, 2016; Golez and Koudijs, 2018; Jacobs and Müller, 2020)?
  - Why are they present and existing at all despite known to practitioners and scientists? Are anomalies driven by risk, mispricing (behavioral biases and heuristics), due to limits of arbitrage or are they simply datamining (e.g., Lo and MacKinley, 1990; Fama and French, 1992, 1993; Lakonishok et al., 1994; Shleifer and Vishny, 1997; Grundy and Martin, 2001; Jegadeesh and Titman, 2001; Doukas et al., 2010; Engelberg et al., 2018; Linnainmaa and Roberts, 2018) or due to something different (Novy-Marx, 2014)?
  - How many (and which) are there (Subrahmanyam, 2010; Hou et al., 2011; Harvey et al., 2016; Stambaugh and Yuan, 2016)?
  - Are there rational reasons for their existence (e.g., rational momentum theory; Johnson, 2002)?
  - Are they persistent in the future (Fama, 1998; Harvey, 2017; Linnainmaa and Roberts, 2018)?
  - How important is the method of their measurement (Kothari and Warner, 1997)? How robust are they (Fama 1998; Fama and French, 2008; Green et al., 2017)?
  - Are they internationally uniform (Chui et al., 2010; Fama and French 2012, 2017)?

b) Issues regarding behavioral finance:
  - What drives behavioral biases that are assumed to be a source of mispricing (Daniel et al., 1998; Cronqvist and Siegel, 2014)?
  - Are behavioral biases and associated anomalies universal around the world (Chui et al., 2010)?
  - How are (the sources of) behavioral biases measured, quantified, and operationalized (Oechssler et al., 2009)?
  - Do behavioral biases affect prices (Coval and Shumway, 2005; Bailey et al., 2011)?

c) Issues regarding market efficiency:
  - Are capital markets (empirically) efficient (e.g., Fama, 1970, 1991, 1998)?

- Is the weak form of the EMH (Fama, 1970) wrong, i.e., is time series information like the most basic stock characteristic, the nominal price, informationally consequential for future stock returns (e.g., Blume and Husic, 1973; Birru and Wang, 2016a, 2016b)?

d) Issues regarding empirical asset pricing risk factors:
   - Why perform global risk factors a lot worse than regional ones (e.g., Griffin, 2002; Fama and French, 2012, 2017)? Are markets integrated (Errunza and Losq, 1985; Stulz, 2005)?
   - How are the interdependency structures of risk factors (Fama and French, 2015)?
   - What are the blind spots of risk factors and factor models and how can they be mitigated (Harvey and Siddique, 2000; Easley et al., 2002; Jegadeesh et al., 2019)?
   - How efficient and effective are empirical risk factors for asset pricing (Lewellen et al., 2010; Hou et al., 2015; Daniel et al., 2017)?
   - Is the theoretically assumed connection of risk and return empirically valid (Ang et al., 2006, 2009; Ludvigson and Ng, 2007; Auer and Schuhmacher, 2015)?
   - What determines the cross-section of expected stock returns (Harvey et al., 2016)?

e) Issues regarding state variables:
   - What are relevant state variables that determine future investment opportunities (Merton, 1973)? What are proxies for them (Flannery and Protopapadakis, 2002; Vassalou, 2003; Petkova, 2006)?

f) Issues regarding cultural finance:
   - What is the role of culture in financial decision making (Karolyi, 2016)?
   - How is culture intertwined with macroeconomic variables (Hofstede et al., 2010)?
   - Can culture explain market anomalies (Chui et al., 2010; Cheon and Lee, 2017)?
   - Is cultural finance a paradigm shift (Kuhn, 2012; Aggarwal and Goodell, 2014)?

In the next sections, I start with a motivation of these issues by briefly introducing and discussing the fundamental theory and assumptions behind these crucial questions in a somewhat chronological manner as this embeds the subsequent chapters in a broader context and lays the fundament of the main work of the thesis, the three research papers (see Appendix C). As I sketch a timeline of financial theory and occurring research paradigms, I have to concentrate especially on shortcomings to show why newer theories, research strands, and paradigms like behavioral finance and cultural finance evolved in the first place.

2.1 Asset Pricing Theory and its Limits

The establishment of the capital asset pricing model (CAPM) by Sharpe (1964), Lintner (1965), and Mossin (1966) in the 1960s was one of the most influential research propositions for the modern financial theory (Fama and French, 2004). It (simply put) directly connects (expected) returns of an asset to its inherent, systematic risk and assumes that more risk (in relation to the systematic market risk; i.e. a higher beta) should go hand in hand with higher (expected) returns[6]:

$$E(R_i) = R_f + \left(E(R_m) - R_f\right) * \beta_i \text{ with } \beta_i = \frac{COV(R_m, R_i)}{Var(R_m)} \quad (1)$$

where $E(R_i)$ is the expected return of asset *i*, R_f is the risk free rate and R_m the market return. $E(R_M) - R_f$ gives the market risk premium. The β_i measures the riskiness of asset *i* in relation to the market risk with $\beta_i = 1$ for the market portfolio. Fundamental (but not necessarily realistic) assumptions of the CAPM are e.g. the presence of a market equilibrium and a perfect capital market. Since it is a basic financial model that is routinely taught to students in university courses, I save space and will not discuss it in detail.

Due to its simplicity and theoretical and empirical shortcomings (Fama and French, 2004), in the 1970s more general models respectively enhancements of the CAPM came up in the literature. The basic area of conflict in this context is that more complicated and general models (e.g. arbitrage pricing theory, APT, which leaves the nature and number of return determining factors largely undefined; Ross, 1976) are potentially capable of capturing reality better than simpler, specific and restrictive models (like the CAPM), but are at the same time much more challenging to implement practically (Shanken, 1982).[7] Ross (1976) develops his model under the assumption of an arbitrage-free capital market and shows that (under the condition of a perfect capital market) the expected return of an asset $E(R_j)$ is a result of its loading ($\beta_{n,j}$) on *n* risk premiums

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[6] It is also one of the first feats of what one could call the "mathematicalization" of finance ("Samuelson revolution", Zingales, 2015: 1) that dictates the research paradigm since several decades. Enabled and enforced by rising computational power, more data, better statistical models, and methods, the tornado of quantification and formalization still subordinates a good deal of the financial research community. The same holds for economics as superordinate discipline of finance and the (non-)effectiveness of this approach is similar: *"…most economists make strong efforts to imitate the exact sciences. Economics tends to become a branch of applied mathematics; the majority of all publications in professional journals and books are full of axioms, lemmas and proofs, and they are much concerned with purely formal deductions. Often, when the results are translated into verbal language, or when they are applied empirically, disappointingly little of interest remains."* (Frey, 2013: vii) Furthermore, finance as part of the economic system has never been and never will be a natural science with rigid and time-invariant rules to discover, but a social science (e.g., Frey, 2013) that has to deal with fuzzy, ever-changing man-made systems and objects of investigation (human beings and automated algorithmic trading machines) that to make matters worse can additionally react to external and system-made information and thereby adjust its inherent programming (e.g., Luhmann, 1994, 1997; Hammerich, 2013) that dictates the reaction to certain events.

[7] Furthermore, they are prone to suffer from overfitting problems that are at the latest present when confronting the model with empirical financial markets data that is additionally often flawed. This makes the (sophisticated) model even less effective in real life applications.

λ_i which are assigned to *n* factors φ_i (not displayed) that determine its return R_j. The assumed risk/return relation is (as in the CAPM) linear:

$$E(R_j) = R_f + \beta_{1,j} * \lambda_1 + \beta_{2,j} * \lambda_2 + \beta_{3,j} * \lambda_3 + \cdots + \beta_{n,j} * \lambda_n \quad (2)$$

Established factors that are routinely used in the APT are macroeconomic measures. The results of my thesis however, raise the question if also cultural dimensions are possible return determining factors that would, in the language of the APT, then be connected to risk premiums, although the presence of "cultural risks" sounds not very intuitive.

The CAPM and its prominent later extensions[8], the consumption-based capital asset pricing model (CCAPM; cp. Rubinstein, 1976; Breeden and Litzenberger, 1978 and Breeden, 1979) and the intertemporal capital asset pricing model (ICAPM; Merton, 1973) as its special case are basically rather simple models (since they are analytically and formally describable), but their assumptions are so restrictive (and unrealistic) that they have a hard time to be feasible in quantitative finance.[9] This lack in capturing reality respectively being based on unknown and difficult to identify and measure variables (market portfolio in the CAPM, many possible factors in the APT, consumption risk in the CCAPM, and additionally state variables in the ICAPM) contributed to the development of empirical asset pricing models that I will discuss in the next section. However, these models are also not the answer to everything (MacKinlay, 1995; Barillas and Shanken, 2018).

2.2 Empirical Asset Pricing: Factor Models

With the end of the 1970s and the beginning of the 1980s, an increasing number (Harvey et al., 2016) of so-called anomalies distressed financial markets researchers. The most prominent ones are the size (e.g., Banz, 1981; Reinganum, 1981; Brown et al., 1983; Keim, 1983; Lamoureux and Sanger, 1989; Asness et al., 2018), value (e.g., Stattman, 1980; Rosenberg et al., 1985; Fama and French, 1992, 1993), and momentum effect (e.g., Jegadeesh, 1990; Jegadeesh and Titman, 1993; Carhart, 1997; Rouwenhorst, 1998; Chui et al., 2010).

The existence of these anomalies and their abnormal returns were not explicable by classic financial models like the CAPM. As a consequence, Fama and French (1992, 1993) constructed an empirical asset pricing model that included the size and value anomaly in the shape of so called risk factor mimicking hedge portfolios (Small Minus Big, *SMB* and High Minus Low, *HML*) in addition to the CAPM (using value-weighted market excess returns as explanatory variable; Return Market minus return Risk Free rate, *RMRF*) to capture and explain asset returns better. The basic intuition of this 3-factor model is that all three factors capture distinct

[8] See also the X-CAPM of Barberis et al. (2015).
[9] In Section 2.4, I introduce the main concept of these asset pricing models and discuss how cultural finance can enhance their explanatory power for cross-country analyses.

characteristics of an asset that are (expected to be) associated with (unknown) risks that trigger their abnormal returns. Carhart (1997) extended the Fama/French (FF) 3-factor model to a 4-factor model by including also a momentum factor (Winner Minus Loser, *WML*).[10] One of the latest extensions comes again from Fama and French (2015) who add a profitability (Robust Minus Weak, *RMW*) and investment factor (Conservative Minus Aggressive, *CMA*) (cp. also Fama and French, 2006) to their initial 3-factor model to construct their 5-factor model. Another effective empirical factor model that is less prominent in the literature than the mentioned models is that of Hou et al. (2015). Hou et al. (2018) summarize further recently developed factor models.

It is very common in the newest literature to connect the FF 5-factor model with the Carhart 4-factor model. That is to add the momentum factor to the FF 5-factor model equation to form a 6-factor model (Fama and French, 2018). Equation 3 displays the form of this asset pricing model as an example of state-of-the-art asset pricing methodology to explain returns of an asset or portfolio (r_{it}) by a simple OLS regression on the contemporaneous returns of these six risk factor mimicking hedge portfolios. If the α equals zero then no pricing errors are implied. However, this model is frequently used only in connection with US datasets (due to the high data quality of the commonly used CRSP and Compustat databases) or regarding factors based on world regions like Europe[11]:

$$r_{it} = \alpha_i + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + ro_i RMW_t + c_i CMA_t + w_i WML_t + \varepsilon_{it} \quad (3)$$

Nevertheless, the factor models (apart from the CAPM and other theory based models that I mention in the previous section) were all constructed after the major anomalies size, value, and momentum as well as profitability and investment were detected and cannot defend themselves convincingly to be not (or at least partly) the product of data mining (cp. Harvey et al., 2016). In defense, Fama and French often underline the empirical validity and usefulness of their models that tempers these concerns somewhat (e.g., Fama and French, 2012, 2017). Furthermore, at least regarding *SMB* and *HML* there is indeed some evidence that these risk factors are proxies for assumed state variables (Vassalou, 2003; Petkova, 2006), i.e. they have some connection to financial theory (ICAPM). As a main weakness of these factor models, global ones perform very unsatisfactory when explaining global asset returns. This gives also a hint to the fact that risk factors capture not the same risks worldwide which means that there are international differences in risk perception and risk propensity (cp., e.g., Rieger et al., 2014). In paper III, I show that this shortcoming can be moderated and captured by the inclusion of cultural effects.

With the rise of even more anomalies (Harvey et al., 2016) and the persistence of the already known ones (e.g., Jegadeesh and Titman, 2001), the explanation of these anomalies with risk (and at the same time with the presence of financially rational investors) appeared to be increasingly doubtful. As a reaction, with the middle of the 1990s, a new finance branch “behavioral finance” emerged that explained the existence of those anomalies (and security returns in general) not

[10] I describe the regression equations of these models in more detail in Section 3.2.2.
[11] See Kenneth French’s data library for often used factor returns regarding some world regions: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

(only) by risk but (also) by mispricing due to inherent cognitive, psychological and thus behavioral biases and heuristics of each investor (e.g., Lakonishok et al., 1994; Daniel et al., 1998; 2001; Hong and Stein, 1999; Hirshleifer, 2001).

In later research (in the 2000s and 2010s), the validity of the CAPM lost more and more empirical support (e.g., Fama and French, 1996b, 2004; Frazzini and Pedersen, 2014) as it was found that the assumed risk/return relation (more risk/higher beta is associated with more return and vice versa) does not hold and is in fact often even inversed. This meant an earthquake for the fundamentals of financial theory and resulted, after the eruption of anomalies, (once again) in "chaos" (Cochrane, 2011).

2.3 Behavioral Finance: The Answer?

Behavioral finance is a branch of the finance field that deals with "irrational" preferences and behaviors regarding financial decision making.[12] That is, decision makers not necessarily (purely) maximize their (expected) economic and financial utility in risky setups, but deviate from this paradigm in certain ways coined behavioral biases. It has its origin in the 1970s when, inter alia, Kahneman and Tversky (e.g., 1974; 1979) developed their prospect theory based on experimental studies where they find that risk affinity and aversion deviate in respect of previous wins or losses. Thus, behavioral finance adopts mainly psychological concepts (Daniel et al., 1998) and methods of attaining data (experiments) and transfers them to finance to provide an answer for puzzling phenomena. The rise of behavioral finance in the 1990s (Shiller, 2003) was enforced by the expansion of capital market anomalies that weakened and challenged the explanatory power of classical financial theories (like Markowitz's portfolio theory, Markowitz, 1952 and the EMH, Fama, 1970) and derived models like the CAPM as well as empirical asset pricing risk factor models. In turn, behavioral finance and risk-based finance developed into two suspicious, separate camps that defend their own research paradigm.

A main weak spot of behavioral finance, however, remains the lack of quantifiability, formalization and integration (i.e., a coherent system) of their theories and concepts. The reasons, origins, and interdependencies of the vast amount and several categories of cognitive/psychological and behavioral biases as well as heuristics (e.g., Baker and Nofsinger, 2002; Stracca, 2004) that are shown to translate into divergences in information perception, processing, and evaluation (resulting in "irrational" financial decision making) and the holistic triggering of capital market anomalies often also remain unclear. The deathblow of behavioral

[12] In sociology, there are different concepts of rational acting (not behavior). Acting is a behavior that is subjectively meaningful (and thereby goal oriented). Weber (2006) for example differentiates four general categories of rational acting respectively rationality: instrumental-rational, value-rational, affective, and traditional acting (with the first two as the major ones), whereas most actions are driven by a mixture of these. Only the first category of acting is subsumed by economic and financial utility concepts, but not the second one. Instead of tracing back the "irrational behavior" of certain investors (only) to psychological biases (i.e. affective/emotional acting, which is borderline meaningfully orientated acting for Weber), the much more rational way would be to include *value-rational acting* as a possible origin of capital market anomalies. In cultural finance, one of the newest branches of finance, this is finally the case, despite the continuing huge lack of references to and adoption of sociological research and sociological concepts of the last 100 years like, e.g., Luhmann's (1994, 1997) systems theory and Weber's (1991) theory of action.

finance from methodological view is the common cherry picking of behavioral biases and associated heuristics to explain financial phenomena like the momentum effect (De Bondt et al., 2015). The behavioral biases and behavioral asset pricing models are selected ad hoc from a vast pool of behavioral literature to create a sound story of how the investigated effect comes about, at the same time ignoring contradictory biases and explanations (Shefrin, 2010).[13] Unfortunately, the practice of creating a convincing, (seemingly) consistent story behind research papers is (becoming) standard or even mandatory in finance (and other research fields) for a successful publication. A suspected main driver for this is the publication bias (Sterling, 1959) that favors the publication of "positive" results in scientific journals.[14]

2.4 Cultural Finance: A (the) missing Link and the Bridging?

"It is naive to assume that such [financial] goals are culture-free. (…) The finance function has been the last stronghold in business administration to escape cross-cultural analysis". Hofstede (2001: 385)[15]

Nearly as if it were an immediate reaction to this statement, Grinblatt and Keloharju's (2001) paper was one of the first highly impactful financial research papers that incorporated cultural characteristics when investigating stock holdings and trades. They also explicitly abstain from classifying the influence of culture, distance, and languages as "biases", "which connotes that some form of investor irrationality is behind the influence of these factors" (Grinblatt and Keloharju, 2001: 1072). However, it was not until 2010 when Chui et al. published their paper on the connection of the momentum effect and individualism. Since then, significant (culture-based) research in finance is emerging at a higher rate. Most popular in cultural finance are the cultural

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[13] An associated problem of common research practice is HARKing (Hypothesizing After the Results are Known) (Kerr, 1998).

[14] A partly inconsistent, but realistic theoretical fundament would be a flaw in the context of such a research paradigm. Even papers that are published in the top-tier finance journal like Chui et al. (2010) are not beyond doing this, as their argumentation is (1) based on (biased) results of other researchers and (2) they (have to) limit their behavioral explanations in general to (merely) overconfidence and self-attribution bias (underlining their story) which of course are only a tiny part of heuristics that (potentially) influence financial decision making and thus the (suspected) creation of anomalies like the momentum effect. For example, Moore and Healy (2008) show that 64% of empirical research papers limit their conception of overconfidence to the archetype – overestimation – whereas other manifestations of overconfidence like overprecision and overplacement play only a minor role (31% and 5% of research papers), which exemplifies the scientific bottleneck that hinders objective, unbiased research without other incentives apart from the quest for veracity of scientific evidence. Due to future publication aspirations that make it crucial to develop a sound story and my inherent limited information processing and evaluation capacity, my research papers are not necessarily an exception from this rule.

[15] The pervasiveness of culture goes even so far that it is responsible for errors in measurement, as questionnaires are perceived and understood differently among members of different cultures (Hofstede et al., 2010). That implies not only a local limitation of the evidence of a vast fund of the finance literature to the US, but also a qualitative limitation, since the investigation of other cultures might offer potential research outcomes that are not even considered possible by researchers from a homogenous, mono-cultural background. That is why the importance of international studies executed by international researchers is paramount to capture highly original and impactful evidence (Chui et al., 2010 is an ideal example for this). At the same time, some research results may not be replicable or even inversed in different countries due to the different cultural background.

dimensions of Hofstede (1980, 2001) and Hofstede et al. (2010). Other frequently used cultural dimensions stem from Schwartz (1994) and House et al.'s GLOBE study (2004) (see Table 1).[16]

Table 1 Summary of main datasets on national culture

Datasets	Cultural dimensions	Years of data collection	Countries covered	Survey respondents	Remarks
Hofstede	Four main dimensions: individualism vs. collectivism; power distance; uncertainty avoidance; and masculinity vs. femininity. Later added long-term orientation and indulgence vs. restraint.	Mostly 1967 to 1973	Initially 40 countries; later extended to 50 countries	IBM employees	The most widely cited dataset on national culture. Recently, items from the World Values Survey were used to extend coverage to 93 countries.
Schwartz	Six value types: conservatism; intellectual and affective autonomy; hierarchy; mastery; egalitarian commitment; and harmony.	1990s	Initially 22 countries; later extended to 64 countries	Elementary school teachers and college students	The six value types can be consolidated into two broad dimensions: 1) autonomy vs. conservatism, and 2) hierarchy and mastery vs. egalitarian commitment.
GLOBE	Nine dimensions: assertiveness, institutional collectivism; in-group collectivism; future orientation; gender egalitarianism, humane orientation; performance orientation; power distance; and uncertainty avoidance.	1990s	62 countries	Middle managers	Each cultural dimension is further divided into a value score (i.e., desired practice) and a belief score (i.e., actual practice).
World values Survey	An extensive questionnaire surveying people's values and beliefs toward politics, religion, family, the environment, etc.	Six waves since 1981; 7th wave (2017 to 2018) planned	Nearly 100 countries in recent waves	Sample from general population 18 years and older	No clearly consolidated cultural dimensions. But the survey is conducted every several years to detect the value changes.

Adapted from Aggarwal et al., 2016: p.468.

Newer research often uses these cultural dimensions (instead of less standardized measures and proxies of culture like religion and social norms; e.g., Hong and Kacperczyk, 2009; Kumar et al., 2011; Callen and Fang, 2015), which display cultural differences between nations regarding several aspects (e.g., classifying a country as individualistic or collectivistic), to lay a fundament for the (assumed) presence, prevalence, and extent of biases in investor behavior that is proposed to trigger certain (puzzling) phenomena of financial economics like the momentum effect (Chui et al., 2010), the home and foreign bias (Beugelsdijk and Frijns, 2010; Anderson et al., 2011) and (the extent of) international stock price co-movement (Eun et al., 2015). Basically, cultural finance explains financial behavior by cultural values: "(…) Cultural Finance tries to capture and assess the influence on decisions concerning both the *allocation of funds* and the *procurement of funds* that stems from a decision-maker's cultural background." (Nadler and Breuer, 2019: 193)

Suitably, a recent paper of Tan et al. (2019) for example investigates individual trading behavior of participants of 21 countries and territories and shows that cultural background significantly impacts trade size, frequency, and time frames despite controlling for social and personal characteristics. Thus, culture per se operates not only on aggregate, national level as measured by cultural dimensions (Hofstede et al., 2010), but also on individual level and is consequential for

[16] Virtually all somewhat related papers that also apply quantifiable cultural characteristics for the explanation of stock market anomalies like Chui et al. (2010), Weigert (2015), and Cheon and Lee (2017) use Hofstede's cultural dimensions for their main study and then partly use others like those displayed in Table 1 as robustness check. Thus, I also prefer the cultural dimensions of Hofstede (2001) and Hofstede et al. (2010) to produce comparable results. Furthermore, this is also motivated by the availability of Hofstede's (1980) initial four dimensions since 1980 as my financial datasets also start in this year. In contrast, I cannot legitimately use the dimensions of Schwartz or GLOBE before the 1990s or 2000s (i.e. the dates of measurement/introduction of these dimensions) unless I want to take the risk of introducing some forward-looking bias in my analysis or cut down the sample by at least one decade.

fundamental trading patterns which are the first layer feasible of producing capital market anomalies. Table 2 shows a selection of finance papers that explain such anomalous financial phenomena and investor behavior (at least partly) by cultural differences.

Table 2 Literature on Cultural Finance

Authors (Year)	Title	Journal
Aggarwal, R., Kearney, C., & Lucey, B. (2012)	Gravity and culture in foreign portfolio investment	Journal of Banking & Finance
An, Z., Chen, Z., Li, D., & Xing, L. (2018)	Individualism and stock price crash risk	Journal of International Business Studies
Anderson, C. W., Fedenia, M., Hirschey, M., & Skiba, H. (2011)	Cultural influences on home bias and international diversification by institutional investors	Journal of Banking & Finance
Beracha, E., Fedenia, M., & Skiba, H. (2014)	Culture's impact on institutional investors' trading frequency	International Review of Financial Analysis
Bergsma, K., & Jiang, D. (2016)	Cultural New Year holidays and stock returns around the world	Financial Management
Beugelsdijk, S., & Frijns, B. (2010)	A cultural explanation of the foreign bias in international asset allocation	Journal of Banking & Finance
Breitmayer, B., Hasso, T., & Pelster, M. (2019)	Culture and the disposition effect	Economics Letters
Breuer, W., Riesener, M., & Salzmann, A. J. (2014)	Risk aversion vs. individualism: what drives risk taking in household finance?	The European Journal of Finance
Chang, C. H., & Lin, S. J. (2015)	The effects of national culture and behavioral pitfalls on investors' decision-making: Herding behavior in international stock markets	International Review of Economics & Finance
Chui, A. C., Titman, S., & Wei, K. J. (2010)	Individualism and momentum around the world	The Journal of Finance
Chui, A. C., Kwok, C. C., & Zhou, G. S. (2016)	National culture and the cost of debt	Journal of Banking & Finance
Costa, B. A., Crawford, A., & Jakob, K. (2013)	Does culture influence IPO underpricing?	Journal of Multinational Financial Management
Dang, T. L., Faff, R., Luong, H., & Nguyen, L. (2018)	Individualistic cultures and crash risk	European Financial Management
Darsono, S. N. A. C., Wong, W. K., Ha, N. T. T., Jati, H. F., & Dewanti, D. S. (2021)	Cultural Dimensions and Sustainable Stock Exchanges Returns in the Asian Region	Journal of Accounting and Investment
Eun, C. S., Wang, L., & Xiao, S. C. (2015)	Culture and R 2	Journal of Financial Economics
Grinblatt, M., & Keloharju, M. (2001)	How distance, language, and culture influence stockholdings and trades	The Journal of Finance
Hillert, A., Jacobs, H., & Müller, S. (2014)	Media makes momentum	The Review of Financial Studies
Jiao, W. (2020)	Portfolio manager home-country culture and mutual fund risk-taking	Financial Management
Karolyi, G. A. (2016)	The gravity of culture for finance	Journal of Corporate Finance
Li, K., Griffin, D., Yue, H., & Zhao, L. (2013)	How does culture influence corporate risk-taking?	Journal of Corporate Finance
Lucey, B. M., & Zhang, Q. (2010)	Does cultural distance matter in international stock market comovement? Evidence from emerging economies around the world	Emerging Markets Review
Stulz, R. M., & Williamson, R. (2003)	Culture, openness, and finance	Journal of Financial Economics
Tan, G., Cheong, C., & Zurbruegg, R. (2019)	National Culture and Individual Trading Behavior	Journal of Banking & Finance
Zheng, X., El Ghoul, S., Guedhami, O., & Kwok, C. C. (2012)	National culture and corporate debt maturity	Journal of Banking & Finance

However, culture and measured dimensions are not merely a stirrup holder of behavioral finance that backs behavioral biases and quantifies them (e.g., Wang et al., 2017), but features also connecting factors to classical risk-based finance models like the CCAPM and the ICAPM. The CCAPM (and partly the ICAPM) builds its logic on the variation of savings and consumption and consumption risk that drives market returns. It is an absolute, generic asset pricing model which postulates a positive relation between *the* fundamental risk in economics (i.e., consumption risk) and returns (Mertens, 2017). However, what this asset pricing model does not consider is that cultural characteristics are connected to manifold patterns in consumption (e.g., McCracken, 1990, 2005; De Mooij and Hofstede, 2002; Bao et al., 2003; De Mooij, 2004; Hofstede et al., 2010) which implies that consumption risk is not uniform around the world, but culture dependent (cp. e.g., Chui and Kwok, 2008 on the relation of national culture and life insurance consumption). Additionally, main drivers and characteristics of actions and behavior like risk (Rieger et al., 2014) (and uncertainty) as well as innovation (Herbig and Dunphy, 1998; cp. e.g. Khazanchi et al., 2007 regarding organizational culture) and values like perseverance and thrift are not even perceived and weighted universally among different societies (Hofstede et al., 2010). Guiso et al. (2006) for example show that higher thriftiness is associated with an increase in the national savings rate.

Mertens (2017) provides the essence of the CCAPM which assumes a lifetime utility maximization, zero transaction costs, and no credit constraints for investors[17]: Then, asset prices *p* are expected to be captured by a $p = E[m * x]$ model (with time subscripts written as $p_t = E_t[m_{t+1} * x_{t+1}]$), whereas this model is readily transferable into $1 = E[m * R]$ with $R_{t+1} = x_{t+1}/p_t$ as asset return and x_{t+1} being defined as the absolute profit as sum of future's price and dividend $x_{t+1} = p_{t+1} + d_{t+1}$. Due to the additional presence of a stochastic discount factor *m* which is linked to consumption growth, a possible gateway for culture is present to affect prices and in turn returns of assets: Given $m_{t+1} = \psi * \frac{u'(c_{t+1})}{u'(c_t)}$ with ψ as subjective impatience and the second part of the term defining the marginal utility of present's and future's consumption, there are two possibilities for culture to affect prices and returns:

First, it appears to be plausible that investors with cultural backgrounds deviating on the Long Term Orientation vs. Short Term Orientation sphere[18] (i.e. one of the six cultural dimensions of Hofstede et al., 2010 which was introduced in Hofstede, 2001) have different levels of subjective impatience. Hofstede et al. (2008) for example model trading agents which are extremely short term oriented as being impatient. If one assigns investors from cultures with stronger short term orientation (e.g., US citizens) a higher level of subjective impatience, then short term oriented nations should show, on average, higher asset prices.[19] On the other hand, also Indulgence vs. Restraint[20] (the newest cultural dimension, defined in Hofstede et al., 2010) might come into play

[17] As mentioned in Section 2.1, these are not necessarily realistic assumptions that are additionally likely to vary significantly, e.g. not only between individual and institutional investors, but also within these groups.

[18] "*Long-term orientation* stands for *the fostering of virtues oriented toward future rewards—in particular, perseverance and thrift*. Its opposite pole, *short-term orientation*, stands for *the fostering of virtues related to the past and present—in particular, respect for tradition, preservation of "face," and fulfilling social obligations*." (Hofstede et al., 2010: 239)

[19] The intuitive conjecture that higher prices lead also to higher returns is not necessarily correct as higher prices might lead to an overvaluation of the asset ultimately resulting in lower returns (on a longer term time scale).

[20] In a nutshell, this dimension defines the extent to which people try to control their desires and impulses with people from cultures being restraint typically showing high self-monitoring skills regarding the own behavior: "*Indulgence* stands for *a tendency to allow relatively free gratification of basic and natural human desires related to enjoying life and*

(cp., e.g., Urminsky and Kivetz, 2003). Here, higher indulgence levels are likely associated with a higher degree of subjective impatience leading to higher asset prices. The empirical evidence for these straightforward and thus only one-dimensional hypotheses is mixed. In paper II, operating on a global scale, I find individual stocks from short-term oriented cultures to show on average higher returns and stocks from indulgent cultures to show lower returns.

The second part of the definition of the stochastic discount factor *m* is the marginal utility of consumption. As mentioned above, consumption patterns are empirically very well documented to be culture-dependent and are dependent on or at least associated with manifold cultural characteristics like Individualism vs. Collectivism, Masculinity vs. Femininity, and Uncertainty Avoidance (that is, all other cultural dimensions of Hofstede et al., 2010 except Power Distance). In this way, the multifaceted nature of culture occupies both contact points apart from the absolute profit through which it can (and should) impact the validity and properties of the CCAPM.

The ICAPM also lacks this component of being sensitive to the different local value that its proposed state variables (with wealth being the most fundamental state variable) might have in driving future investment opportunities and thus asset returns. Instead, it is only temporally sensitive to a variation of parameter values of state variables[21] which are assumed to determine the average return of an asset via its exposure to these state variables (Mertens, 2017):

$$E(R_i) = R_f + \beta_i^m * (R_m - R_f) + \sum \beta_i^z * \mu^z \tag{4}$$

with R_f as risk free rate, R_m as market portfolio return, β_i^m as market beta of asset i and β_i^z as the sensitivity of asset i regarding the prices of state variable risk μ^z (where z depicts possibly manifold not further described state variables).[22]

Literature on cultural dimensions, for example Hofstede et al. (2010), finds however that investment opportunity sets given by diverse asset classes (mutual funds, gems, real estate, stocks) are preferred differently between (members of) culturally unlike societies. Especially differences among cultural dimensions Uncertainty Avoidance and Long Term Orientation (LTO) are responsible for these unequal investment preferences. As outlined above for the CCAPM, in the ICAPM national deviations on the LTO sphere should also play a role. I can affirm this conjecture empirically as I find LTO to be the most robust and significant predictor for global cross-sectional stock returns (cp. paper II). Beyond that, LTO qualifies to be a (ICAPM) state

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having fun. Its opposite pole, *restraint*, reflects *a conviction that such gratification needs to be curbed and regulated by strict social norms*." (Hofstede et al., 2010: 281)

21 In fact, on a long time frame (decades), culture can be assumed to be somewhat time-variant (Hofstede et al., 2010 for example proposes however that the *differences* between cultures are quite robust over time). In this way, culture (respectively most likely LTO) could be a (time-varying) ICAPM state variable.

22 This specification of the ICAPM can be lastly derived from the inherent consumer optimization problem regarding current and future consumption and thus shows that the ICAPM is nested in the CCAPM framework (Mertens, 2017).

variable itself as it is the only cultural dimension that forecasts aggregate macroeconomic activity in the form of GNI growth (Hofstede and Minkov, 2010; Hofstede et al., 2010; Minkov and Hofstede, 2012), which is a necessary condition to be fulfilled by a state variable (Cochrane, 2009; Maio and Santa-Clara, 2012; Boons, 2016; Mertens, 2017).

Furthermore, Hofstede et al. (2010) show that especially cultural dimensions Individualism and Power Distance are highly associated with national wealth levels as measured by GNI per capita. Thus, these dimensions are valid proxies for wealth (*the* state variable in the ICAPM and CCAPM that inherently drives consumption capability and investment opportunities due to budget constraints). Due to that, I control for national wealth in my second and third research paper and find that the explanatory/predictive power of these (and other) cultural dimensions stays robust in the presence of GDP per capita. Consequently, cultural characteristics appear to contain information regarding future investment opportunities and/or consumption risk that is *distinct* from the primary state variable wealth and thus qualify as separate state variable(s) that drive asset returns.[23]

In this sense, cultural finance can be a missing link between risk-based and behavioral finance capable of bridging the gap between these two seemingly opposed finance branches. However, cultural finance is not necessarily dependent on the intermediary role of behavioral finance, but in fact has *direct* connecting factors to classical, theoretical financial asset pricing models which are often the starting point for the motivation of empirical studies on the basis of more practically implementable empirical asset pricing models (Section 2.2 and 3.2.2). I investigate this conjecture in more detail in research paper III.

[23] Furthermore, the pervasive, latent, and implicit nature of culture being present everywhere predestines it as being not only *a* state variable, but rather *the* "state variable of state variables". This is due to culture's impact on the economy and financial systems (e.g., Guiso et al., 2006; Kwok and Tadesse, 2006). That is, macroeconomic risks are (partly) "cultural risks".

3. Data and Methodology

In this section, I start introducing the fundamentals of the core of my dissertation – the research papers – by briefly summarizing main data sources and methodological concepts that I frequently use. For a more detailed description, I refer to the papers. The need of highly quantitative data and sound methodology is due to the empirical character of all my research papers. In this way, I can investigate and pursue the imposed research questions and my main objectives (cp., e.g., Section 1) in the most relevant, comprehensive, and reproducible manner for science as well as practice.

3.1 Data

The key data sources for my dissertation are Thomson Reuters Datastream (TRD)[24] and the websites of Hofstede[25], Kenneth French[26], and the IMF[27]. All international data was attained, edited, and handled by myself, as the code, which I wrote in R from scratch. In my papers, I include recommendations of Ince and Porter (2006) when it comes to (financial time series) data editing and adopt procedures from other papers with similar scopes. Examples for these data editing schemes are the exclusion of penny stocks (high data failure density and extreme, result distorting return values) and very small stocks regarding market equity (to restrict the sample to economically meaningful and tradeable firms), winsorizing (that is cutting off exceptionally low or high values due to assumed data failures and replacing these values by predetermined percentile values) and the exclusion of dead/inactive stocks.[28]

The result of my data retrieval is a comprehensive dataset for 43 countries, spanning data from 38 years and including some 40,000 individual stocks in the raw dataset (data for Portugal and Ireland where excluded in my papers due to low stock amount) covering multiple, relevant datatypes for asset pricing and asset management like Total Return Index, Unadjusted Prices, Market Equity, Common Shareholder's Equity, and country-specific risk free rates (e.g., for the implementation of specific, country-level asset pricing models and value-weighted market excess

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[24] Routinely, international studies retrieve data for the US from the Center for Research in Security Prices (CRSP) and Compustat instead of TRD. Unfortunately, I have no access to these and other frequently used sources like Bloomberg and IBES, which also results in a limited possibility to incorporate many various control variables and double-check data and results.
[25] https://www.hofstede-insights.com/product/compare-countries/
[26] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[27] https://www.imf.org/en/data
[28] In general, I am an advocate of editing the raw data rather less than more (as much as necessary, as little as possible), especially when it comes to potentially result distorting procedures which are additionally prone to hindsight bias and data snooping like (sharp) winsorizing of return data. Instead of winsorizing, I prefer to cut off penny stocks, as this procedure eliminates unrealistically high/low returns nearly as well, but is a procedure that is much less prone to hindsight bias.

returns).[29] For the cultural data, I use all six cultural dimensions described in detail in Hofstede et al. (2010).

3.2 Methodology

3.2.1 Non-parametric Procedures

Despite their simplicity, sorts of a given stock universe with regard to certain characteristics of the stocks are (still) the state-of-the-art methodology to test if these characteristics are consequential for (or at least associated with) stock returns. The most straightforward way to measure this non-parametrically is to use single sorts. For this purpose, each given point in time (e.g., each month), all stocks are sorted into equal-sized portfolios (often ten or five) regarding their respective percentile value (e.g., decile or quintile) on the characteristic. The top and bottom portfolios are then used to create a hedge portfolio as a difference between the average (or value-weighted) top and bottom (or bottom and top) portfolio returns. In this way, one can measure the return spread of stocks having in common the most extreme values regarding the sorting criterion (e.g., the spread in the returns of high-priced and low-priced stocks). This sorting procedure is repeated in a specified cycle (for example each month or each six months), defining at the same time the holding time frame for the portfolios.

For some characteristics like momentum and volatility, a time series (and not only the newest, up-to-date value, for example the present nominal price or market equity) is needed to calculate characteristics values. Classically, the momentum of a stock is therefore defined as the (cumulative) return over the time frame t-6 to t-1 (Jegadeesh and Titman, 1993), whereas t is the present month in which the sorting procedure is executed. This time frame, in which the characteristic value is measured, is called the formation period. Both periods, formation and holding period, offer some degrees of freedom for the researcher on how to measure the characteristic in a temporal sense (e.g., Carhart, 1997 uses a formation window of t-12 to t-2, i.e., 11 months and a monthly portfolio reformation/holding period, whereas Chui et al., 2010 use six months for both), but there are also degrees of freedom in qualitative respect. The most basic deviation respectively adjustment of the raw characteristic value is the usage of logarithmic values, e.g. for market equity (Banz, 1981), to account for heteroscedasticity that may distort the significance of the characteristic and violate regression model assumptions. Furthermore, in research paper II, for example, I calculate normalized rank scales to measure price for my panel regressions to create a comparable price measure which is on the one hand independent from currency effects and on the other hand ensures that the price characteristic values are meaningful within each country, as the home bias suggests that investors compare prices of stocks rather within a country (traded in the same currency) than across countries.

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[29] This aggregation of data together with auxiliary material like (hand-collected) international values on cultural dimensions and the coding of all used statistical procedures (apart from using relevant packages like "plm" from the R library of course) is one of the most basic contributions, but certainly not the least important one of my work at University of Bremen.

The other widely used sorting procedures are (independent) double sorts (or triple sorts in the US literature due to the high amount of stocks available). For this methodology, stocks are first sorted with respect to two characteristics independently (as described above); that is for example, four portfolios (using quartile breakpoints) are constructed in a given month regarding size and price. Then, however, 4 times 4 (16) intersection portfolios (or in the US literature often 5 times 5 portfolios; cp., e.g., Fama and French 1993, 2015) are created, meaning that each stock in one of these 16 portfolios has to represent both characteristic specifications (for example being low-priced and at the same time low-sized). In this way, one can for example measure if one characteristic is still consequential for returns in the presence of the other characteristic, respectively if there are absorbing or even additive effects. The main disadvantage of this procedure is that individual portfolios are not equal-sized anymore, as some characteristic combinations are more likely than others (e.g., the combination high size and low price is very unlikely due to the inherent connection of price and size regarding their definitions, see Section 4.1.1). This distorts for example the standard deviations of returns of those portfolios due to a stronger/weaker diversification effect. I suitably adjust this double sorting methodology in research paper two and three with respect to the time-invariant, national values on cultural dimensions used as one sorting criterion and (equally-weighted returns of) extreme portfolios (constituting the hedge portfolios) on cross-country level as second sorting criterion to make it feasible for cross-country level research questions.

3.2.2 Parametric Procedures

The main parametric procedures I use in my dissertation are variations of (multivariate) OLS regressions. These are, once again, methodically quite simple to incorporate, but (nevertheless) represent the state-of-the-art methodology when it comes to asset pricing. The most challenging to calculate and handle regressions were the global pooled OLS (and for robustness test purposes random effect) panel regressions I use in research paper two due to the quite extensive dataset (with millions of data points) and (especially) added (monthly) time dummies to account for time-specific effects.[30] In general, every researcher should like methodically simple models that get along with as less as possible assumptions, constraints, and resources since then it is more likely to get empirically sound results that are still interpretable in a straightforward way and (maybe) most important, last in the future for out-of-sample datasets.[31]

[30] These regressions require a substantial amount of available random-access memory (several hundred GB).

[31] Especially in finance (and asset management/asset pricing, financial forecasting) methodologically sophisticated models that are feasible and successfully incorporated plentiful in other branches of economics and science in general, are not necessarily better than simple models. In fact, I guess a collection of (thorough, free from any bias) theses and dissertations (if they are written to an end at all due to the file drawer problem) that show that simple models are more (or equally) feasible and effective than more complicated models like neural networks (often "fed" with many predictors) for various research questions in finance would fill libraries. Here again, many researchers have fallen for the line of the scientific agents that pushed the "mathematicalization" of finance with little regard to the usefulness of those methods and their ability to capture reality in a social science like finance. Past research of (former) colleagues at University of Bremen and former (private and study-related) data-driven financial markets time series backtesting and forecasting of mine during my university studies are no exception from this rule. Moreover, the crux in financial time series forecasting is not to find models that perform better than others, but to

Specifically, I mainly use the following parametric procedures in my dissertation: asset pricing models (CAPM, 3-factor, and 4-factor model; Fama and French, 1993; Carhart, 1997), Fama-MacBeth (1973) rolling cross-sectional regressions, and pooled OLS panel regressions. In the following, I briefly describe those regression models.

The CAPM (Eq. 5), 3-factor (Eq. 6), and 4-factor model[32] (Eq. 7) are neoclassical asset pricing models (see Section 2.1, 2.2) that regress portfolio returns on risk factors like the value-weighted market excess return (CAPM) and additionally risk factor mimicking portfolios for the size effect and value effect (3-factor model) as well as the momentum effect (4-factor model).

The respective regression equations are:

$$r_{it} = \alpha_i + \beta_i RMRF_t + \varepsilon_{it} \tag{5}$$

$$r_{it} = \alpha_i + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + \varepsilon_{it} \tag{6}$$

$$r_{it} = \alpha_i + \beta_i RMRF_t + s_i SMB_t + h_i HML_t + w_i WML_t + \varepsilon_{it} \tag{7}$$

where r_{it} is the return of portfolio *i* in *t*, α_i is the respective regression constant, $RMRF_t$ is the value-weighted market return (*RM*) in excess of the risk free rate (*RF*) at time *t* and SMB_t, HML_t, and WML_t are the returns on the risk factor mimicking portfolios for the size effect, value effect, and momentum effect (at time *t*) which are calculated in the tradition of Fama and French (1993) and Carhart (1997) (see also the research papers for a detailed methodology). ε_{it} is a time-variant and portfolio specific error term.

The standard procedure using these regression equations is to regress the returns of (e.g., decile/quintile) portfolios (and the hedge portfolio) constructed via sorts with respect to characteristic's values (e.g. nominal price) on these risk factors. If α values in those regressions are significant, then these portfolios yield abnormal returns that cannot be explained by the standard risk factors. Thus, the respective characteristic used for the sorts could be seen as another legitimate capital market anomaly.

Fama and MacBeth (1973) introduced a two-step methodology that is very frequently used in asset pricing and asset management to test the predictive power of certain predictors like stock characteristics for portfolio returns or firm-level stock returns. In the first step, the procedure

find models that are useful at all and exceed naïve forecasts or even random forecasts in their performance and reliability, since only small exploitations can yield dramatic (highly scalable) returns in the longer run.

[32] In paper III, I also use the risk factors of the Fama and French 5-factor model (i.e. the 3-factor model with added profitability and investment factors; see Fama and French, 2015) and the momentum factor of Carhart (1997) (cp. also the new FF 6-factor model; Fama and French, 2018) and investigate their interplay with cultural dimensions. I abstain however from using the 5-/6-factor model in international asset pricing exercises (see paper II) mainly due to data availability issues that would restrict the sample size in some emerging countries even more (or even cancel them out completely due to too low stock count) which would be detrimental for my research setup relying on broad cross-country and thus cross-cultural diversity.

calculates for each available point in time *t* (with T as total number of time periods and T-1 as total number of regressions; lag of (at least) one is needed due to predictive setup, see Eq. 8) a cross-sectional regression. In the second step, all slopes/coefficients of these regressions are tested if they are (on average) different from zero using a t-test.[33] All slopes that are significantly different from zero hint to a relevance of the associated independent variables for predicting the returns of the assets of interest (dependent variable). The regression equations of the first step have the form:

$$r_{it+1} = \alpha_t + \sum_k \beta_{tk} X_{itk} + \varepsilon_{it} \tag{8}$$

where r_{it+1} is the return on asset/portfolio *i* in time *t+1*[34], α_t is the regression intercept for regression *t* and X_{itk} is the value of predictor *k* in time *t* in respect of asset/portfolio *i*. The ε_{it} is the respective error term for each regression.

In research paper II and III, I adjust this framework also regarding the needed research design to capture culture-specific effects. Here, I use also time-invariant cultural dimensions apart from other time-variant predictors like risk factors to predict price (hedge) portfolio returns (Expensive Minus Cheap, EMC). In contrast, in research paper III, I use no lag structure of the regressions (like in the asset pricing models above), since here the explanatory power (and not the predictive power) of risk factors in the presence of cultural variables is in the center of interest. Additionally, I incorporate interaction effects between cultural dimensions and risk factors to measure if the efficacy and explanatory power of these risk factors is dependent from cultural differences. However, the general two-step cross-sectional regression setup is the same.

In my second paper, I also calculate (predictive) pooled OLS (and RE) panel regressions with cross-country firm level returns as dependent variable due to several reasons like robustness test purposes and controlling for temporal (and firm-specific) effects. The basic regression structure, however, is the same as described in equation 8 despite added interaction terms and used time-variant (stock characteristics) and time-invariant (cultural dimensions) predictors. Details on the regression methodologies are described in paper II.

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[33] I follow Cochrane (2009: 223) and calculate AR(1)-adjusted standard errors to be used for the t-test (see also research paper II). Another frequently used estimation method for standard errors in this context that accounts both for heteroscedasticity and autocorrelation are the Newey-West (1987) standard errors. However, since I use logarithmic versions of all variables which are prone to heteroscedasticity (like nominal price) and adjust for the most common and meaningful form of autocorrelation in time series (first-order autocorrelation), I expect my estimators to be consistent as well.

[34] Of course, in reality, the one month ahead return is not known. This notification simply means that the model incorporates a lag structure of values on predictive variables and predicted returns, which is applied on (past) data that is used to calculate the regression parameters in each time step.

4. Literature

In this section, I briefly present relevant literature on the price effect and research on the connection of cultural dimensions and stock returns. The goal is to demonstrate the dire need of more research on these two vital topics that I help filling by my evidence. First, however, I explore the nominal stock price as central characteristic to reveal the contribution and impact of my first two research papers in a more holistic way and from meta-level, which cannot be done in the course of a research paper. Afterwards, I show the importance of cultural characteristics in finance research with a special focus on research gaps. This underlines the contribution of the second and third research paper. Both of these issues were until then major blind spots in the finance literature.

4.1 The Relevance of Nominal Price

"Price is what you pay; value is what you get", Warren Buffett (citing Benjamin Graham)[35]

4.1.1 The Role of Nominal Price in Empirical Financial Research and Market Anomalies

Although a first investigation of a nominal stock price effect (that is, either low-priced stocks outperform high-priced stocks or vice versa) on the US stock market was performed as early as 1973[36] by Blume and Husic, who found indeed evidence for price to be a return determining characteristic, only few papers have done research on a price effect on the US stock market until then and (virtually) no paper investigated price as investment strategy on international levels (see Section 4.1.2).

Completely independent from the existence of a price effect (see Sections 4.1.2 and 5.1 and research papers I and II), price per se plays a central role as intermediary characteristic that is present in multiple definitions of stock market characteristics that were found to trigger abnormal returns (McLean and Pontiff, 2016). For example, price is immediately present in the definitions of the big three of classical market anomalies[37]: size, value, and momentum.

Banz (1981) defines size as the logarithm of market value of equity, *Log(MV)*, which is updated monthly. *MV* in turn is constructed by the number of shares of a stock (*NOSH*) multiplied with the nominal price (*Price*):

[35] https://www.berkshirehathaway.com/letters/2008ltr.pdf

[36] There is an even older paper of Fritzemeier (1936) that investigates the relevance of stock price level for the fluctuation of prices and subsequent price movements. He also finds higher volatility for low-priced stocks and a low price effect in the US like, e.g., Hammerich (2020).

[37] Brennan et al. (1998) for example use LN(1/Price) as measure for liquidity, which is also a prominent anomaly (e.g., Amihud and Mendelson, 1986; Amihud, 2002; Ibbotson et al., 2013; Amihud et al., 2015). Haugen and Baker (1996) use even the (untransformed) market price per share as liquidity factor.

$$Size = Log(MV) \tag{9a}$$

$$MV = NOSH * Price \tag{9b}$$

The consequence is a directly proportional relationship between *Price* and *MV* (under the condition that *NOSH* is constant).

The most common representation of value is the logarithm of the relation of book value of equity (*BE*) and market value of equity (*MV*) that is updated annually as defined by Fama and French (1992):

$$Value = Log(BE/MV) \tag{10a}$$

$$MV = NOSH * Price \tag{10b}$$

This time, price is present in the denominator of the value equation (as driver of *MV*), which results, ceteris paribus, in an inverse relationship of price and value.

For momentum as described by Jegadeesh and Titman (1993) one calculates the buy-and-hold returns of a stock in the time frame *t-6* to *t-1* and updates this value monthly. In empirical data analysis, the returns are usually measured by total return indices that account for all payed dividends and further procedures like stock splits and reverse stock splits that distort the nominal price. The basis of a total return index however, is still the (discrete) return of a stock. Thus, when no price-distorting event occurs, the momentum (*MOM*) of a stock in time *t* would be simply the standardized change in nominal price (*Price*) over the previous six months:

$$MOM_t = \frac{(Price_{t-1}) - (Price_{t-6})}{(Price_{t-6})} \tag{11}$$

Consequently, the major driving force of momentum (and indeed of any return related anomaly) is the change in nominal prices. In principle, if one measures prices monthly, the characteristic price is potentially even more informationally effective than momentum (and precursory, since no lag of one month is applied), which fundamental data is updated only to a degree of 1/6 each month. Furthermore, in many papers on momentum, holding time frames of more than one month are chosen for a momentum strategy. For example, Chui et al. (2010) choose a holding time frame of six months for their momentum portfolios and thus use information on return momentum only every six months to rebalance their portfolios and adjust their investment strategy.

In Table 3, I go beyond these three major characteristics that are closely connected with and dependent on price and show a synopsis of which of the 97 stock market anomalies investigated by McLean and Pontiff (2016) are directly or (to the best of my knowledge) indirectly dependent on price (had a look at any definition). I count 39 out of this (exemplary) sample of 97 anomalies to be intertwined with price[38], whereas the (vast) majority of anomalies classified as "market" and "valuation" are price dependent. Thus, (and with regard to my evidence on an international price effect in papers I and II), price per se is prone to be a material control variable[39] in any paper that investigates these more or less price-dependent anomalies due to their inherent (or indirect) links.

Table 3 Overview of capital market anomalies with nominal price connection

Event	Market	Valuation	Fundamental
Change in Asset Turnover	52-Week High	Advertising/MV	Accruals
Change in Profit Margin	Age-Momentum	Analyst Value	Age
Change in Recommendation	Amihud's Measure	Book-to-Market	Asset Growth
Chg. Forecast + Accrual	Beta	Cash Flow/MV	Asset Turnover
Debt Issuance	Bid/Ask Spread	Dividends	Cash Flow Variance
Dividend Initiation	Coskewness	Earnings-to-Price	Earnings Consistency
Dividend Omission	Idiosyncratic Risk	Enterprise Component of B/P	Forecast Dispersion
Dividends	Industry Momentum	Enterprise Multiple	G Index
Down Forecast	Lagged Momentum	Leverage Component of B/P	Gross Profitability
Exchange Switch	Long-term Reversal	Marketing/MV	G-Score
Growth in Inventory	Max	Org. Capital	G-Score 2
Growth in LTNOA	Momentum	R&D/MV	Herfindahl
IPO	Momentum and Long-term Reversal	Sales/Price	Investment
IPO + Age	Momentum-Ratings	Leverage	
IPO no R&D	Momentum-Reversal	M/B and Accruals	
Mergers	Price	NOA	
Post Earnings Drift	Seasonality	Operating Leverage	
R&D Increases	Short Interest	O-Score	
Ratings Downgrades	Short-term Reversal	Pension Funding	
Repurchases	Size	Percent Operating Accrual	
Revenue Surprises	Volume	Percent Total Accrual	
SEOs	Volume Trend	Profit Margin	
Share Issuance 1-Year	Volume Variance	Profitability	
Share Issuance 5-Year	Volume-Momentum	ROE	
Spinoffs	Volume/MV	Sales Growth	
Sustainable Growth	Tax		
Total External Finance	Z-Score		
Up Forecast			
ΔCapex - ΔIndustry CAPEX			
ΔNoncurrent Op. Assets			
ΔSales - ΔInventory			
ΔSales - ΔSG&A			
ΔWork. Capital			

This table shows a collection of anomalies and their classification (column headers). Anomalies that are directly or indirectly dependent on nominal price are shaded in grey. The table is adapted from the internet appendix of McLean and Pontiff (2016).

Another example for the central role of price in empirical studies is its application as threshold to cut off illiquid, economically irrelevant stocks and in this way also to eliminate defective data, since evidence shows that distorting issues like unrealistically high returns are mainly

38 Naturally, that does not necessarily mean that the bare existence of nominal price in those definitions actually drives the respective anomalies, but rather shows how prevalent price is in financial economics (making it meaningful to test its actual relevance for subsequent returns in isolation).

39 Examples of recent papers controlling for (transformations) of nominal price in regression analyses are e.g. Durand et al. (2013) and Cheon and Lee (2017).

concentrated within low-priced stocks (e.g., Ince and Porter, 2006).[40] Thus, implicitly, researchers are already aware that price is (based on this data failure association) relevant for returns. Beyond that however, it is very important for each careful researcher to know if (and in which direction and magnitude) an inclusion/exclusion of low-priced and penny stocks might have impact on the (country-specific or cross-country) results regardless of the research question as long as returns are measured in the process. Put differently, researchers have to additionally know if either price per se or other effects (apart from data distortions) connected with price generally drive returns of low-priced stocks up or down in their investigated countries. The provision of a kind of world map regarding (possible) country-specific effects of nominal price on returns in general is therefore of paramount, fundamental importance for (sound, sample bias free) statistical inferences and data-driven conclusions for all finance papers applying such stock price cut off procedures. I provide such a world map with my second paper and additionally show the sensitivity of portfolio returns regarding several specific cut offs in my first paper.

Although price as a possible international anomaly (i.e. not explainable by asset pricing factor models) and investment strategy is still disregarded in the literature (see Section 4.1.2), price as stock characteristic and associated effects are not neglected. Table 4 contains several relevant papers that deal with nominal price in the context of various research questions (the far-reaching marketing and management research strand that deals, e.g., with price perception of consumers and price strategies for products is a completely different topic that shows that price outside the stock market sphere is deeply rooted in economic decision making, cp., e.g., Zeithaml, 1988; Lichtenstein et al., 1993). This demonstrates that research is already aware of the importance of price for institutional (e.g., Gompers and Metrick, 2001; Fernando et al., 2012) and individual investors (Kumar, 2009), corporate managers (Fernando et al., 2004; Baker et al., 2009; Amini and Cai, 2018), and financial market mechanisms/patterns (Weld et al., 2009; Bae et al., 2019), but did not yet comprehensively dare (with few exceptions like Kross, 1985; Bhardwaj and Brooks, 1992a, 1992b, and Goff, 1994; Elgers et al., 2002) to see price as fundamental common defining feature and possible driver of many anomalies (like the size and January effect) – not to mention its (explicit) application as investment strategy. A commendable example of financial research that frequently uses share prices (rescaled), is the literature strand on forecasting defaults of public firms. Mertens (2017) presents a brief, but sharp-witted overview of relevant papers in this context.

[40] For example, most of the papers documenting the anomalies investigated by McLean and Pontiff (2016) incorporate price cut-offs of either $5, $2, or $1.

Table 4 Literature on price as stock characteristic and associated financial phenomena

Authors (Year)	Title	Journal
Angel, J. J. (1997)	Tick size, share prices, and stock splits	The Journal of Finance
Bae, K. H., Bhattacharya, U., Kang, J., & Rhee, S. G. (2019)	Nominal stock price anchors: A global phenomenon?	Journal of Financial Markets
Baker, M., Greenwood, R. & Wurgler, J. (2009)	Catering Through Nominal Share Prices	Journal of Finance
Barberis, N. & Huang, M. (2008)	Stocks as lotteries: The implications of Probability Weighting for Security Prices	American Economic Review
Bhardwaj, R. K., & Brooks, L. D. (1992b)	The January anomaly: Effects of low share price, transaction costs, and bid-ask bias	The Journal of Finance
Birru, J., & Wang, B. (2016a)	Nominal price illusion	Journal of Financial Economics
Branch, B. & Chang, K. (1990)	Low price stocks and the January effect	Quarterly Journal of Business and Economics
Brennan, M. J., & Copeland, T. E. (1988)	Stock splits, stock prices, and transaction costs	Journal of Financial Economics
Campbell, J. Y., & Shiller, R. J. (1988)	Stock prices, earnings, and expected dividends	The Journal of Finance
Conroy, R. M. & Harris, R. S. (1999)	Stock splits and information: The role of share price	Financial Management
Dyl, E. & Elliott, W. (2006)	The Share Price Puzzle	Journal of Business
Fernando, C. S., Krishnamurthy, S., & Spindt, P. A. (2004)	Are share price levels informative? Evidence from the ownership, pricing, turnover and performance of IPO firms	Journal of Financial Markets
Fernando, C. S., Gatchev, V. A., & Spindt, P. A. (2012)	Institutional ownership, analyst following, and share prices	Journal of Banking & Finance
Gompers, P. A. & Metrick, A. (2001)	Institutional investors and equity prices	The Quarterly Journal of Economics
Green, T. C. & Hwang, B. (2009)	Price-based return comovement	Journal of Financial Economics
Kross, W. (1985)	The size effect is primarily a price effect	Journal of Financial Research
Kumar, A. (2009)	Who gambles in the stock market?	The Journal of Finance
Weld, W. C., Michaely, R., Thaler, R. H., & Benartzi, S. (2009)	The nominal share price puzzle	Journal of Economic Perspectives

4.1.2 Price Effect

In the finance literature, the existence and direction of a nominal price effect is a quite controversial issue (especially for US data; cp., e.g., the recent paper of Geertsema and Lu, 2019 showing the ongoing debate) that has to be resolved by, on the one hand, (more) broader global evidence (to capture the potential source(s) of a price effect thoroughly) and on the other hand rigorous country-specific investigations using different datasets and methodology. For this purpose, Table 5 shows a compilation and main characteristics of pertinent research on the price effect. The most common measurement of a price effect is the creation of a hedge portfolio of the top decile/quintile of high-priced stocks and the bottom decile/quintile of low-priced stocks regarding the specific stock universe and calculating the return spread of these extreme portfolios (Section 3.2.1). Abnormal returns are routinely calculated by the incorporation of risk factor models like the CAPM and the 3- and 4-factor model (Section 2.2 and 3.2.2) to test if the price effect is likely an outflow of the contemporaneous incidence of major stock market anomalies or a completely new, unexplainable capital market anomaly.

Particularly in the US, researchers find alternately a significant high price effect (especially when controlling for size) (e.g., Seguin and Smoller, 1997; Singal and Tayal, 2018) or a significant low price effect (e.g., Blume and Husic, 1973; Edmister and Greene, 1980; Baytas and Cakici, 1999; Hwang and Lu, 2008; Birru and Wang, 2016b) respectively inconsistent/time-varying results (Geertsema and Lu, 2019) despite using overlapping datasets and time frames (see especially Hwang and Lu, 2008, Birru and Wang, 2016b, and Singal and Tayal, 2018). Other evidence for price being consequential for stock returns, especially in North American markets, is presented by Tseng (1988) and Elfakhani and Wei (2003). I (Hammerich, 2020; second research paper) deliver clear evidence for the existence of an US low price effect and support the US low price camp based on an alternative dataset (Thomson Reuters Datastream, TRD). More details on my evidence, I will present in Section 5 and in research paper II.

In general, the literature strand on a comprehensive international price effect is very scarce, but emerging recently at least regarding country-specific price effects (see for example Zaremba and Żmudziński, 2014; Hoang, 2018; Huang et al., 2018). With respect to the non-existence of a broad international study (apart from a chapter in a book; cp. Zaremba, 2018), I suppose that once again the publication bias (Sterling, 1959; Harvey, 2017) and its preparatory twin, the file drawer problem (Rosenthal, 1979), come into play. As I find no internationally uniform and consistently significant effect, other researchers may very well have abstained from trying to publish these results. However, since I manage to successfully merge cultural effects with the price effect, I present a story that is capable of explaining these (seemingly) contradicting/inconsequential results.

On the other hand, research goes (especially for the US) quite deep into the mechanisms/events that (potentially) generate a price effect (often conditionally and implicitly), like the investigation of stock splits (Brown Jr & Pfeiffer Jr, 2007; Birru and Wang, 2016b; Singal and Tayal, 2018) and information signaling/efficiency of prices (Sloan, 1996; Cohen et al., 2009; Birru and Wang, 2016a; Baruch et al., 2017; Edmans et al., 2017). The theoretical and fundamental prerequisites investigating why one should (rationally) care about nominal price (as an investor and corporate manager) in the first place and why a price effect could be either completely rational or based on legitimate inherent ("irrational") behavior however, are a blind spot. I illuminate these aspects in research paper I. The special delicacy of this research paper is the demonstration of a legitimate, presumably event-based, rapid inversion of a capital market anomaly (the price effect). Such an incidence is (in this distinctness) very rare in the literature and strikes high-impact research on the cyclicity of investment styles (Barberis and Shleifer, 2003), events that end such cycles (McLean and Pontiff, 2016) and ultimately the existence of anomalies at all (Harvey et al., 2016).

Table 5 Key characteristics of literature on the nominal stock price effect

Authors (Year)	Title	Journal	Data	Countries	Time Frame	Price Measure	Methodology (i.a.)	Main Results
Baytas, A., & Cakici, N. (1999)	Do markets overreact: international evidence	Journal of Banking & Finance	Worldscope	USA, Canada, Japan, UK, Germany, France, Italy	1982 to 1991	Unadjusted Price	Bottom 35 firms minus top 35 firms	Significant low price effects in (all) seven industrialized countries
Blume, M. E. & Husic, F. (1973)	Price, beta, and exchange listing	Journal of Finance	Rodney L. White Center for Financial Research	USA	1932 to 1966 (1971)	Unadjusted Price	Cross-sectional regressions, quintile sorts	Monthly returns negatively related to price
Glas, T., Fieberg, C., & Poddig, T. (2017)	Investing with style of styles - and the European evidence	Working Paper	TRD, Kenneth French's Website	Europe (11 countries)	1990 to 2017	Unadjusted Price (logarithmic)	Top price quintile minus bottom price quintile	(Tendency for) high price effect in 9 out of 11 countries
Hammerich, U. J. (2020)	Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns	SSRN Working Paper	TRD, Hofstede, IMF	Worldwide (41 countries)	1980 to 2017	Unadjusted Price (raw/logarithmic/trans-formed)	Top price quintile minus bottom price quintile	(Tendency for) high price effect in 12 out of 15 European countries, (Tendency for) low price effect in 11 out of 13 Asian countries, low price effect for USA
Hammerich, U. J., Fieberg, C., & Poddig, T. (2019)	Nominal Stock Price Investing	SSRN Working Paper	TRD	Germany	1973 to 2017	Unadjusted Price (raw/logarithmic)	Top price decile minus bottom price decile	Low price effect until mid-1990s, high price effect after mid-1990s
Hwang, S., & Lu, C. (2008)	Is Share Price Relevant?	SSRN Working Paper	CRSP, Compustat	USA	1963 (partly 1926) to 2006	Unadjusted Price	Bottom price quintile minus top price quintile	Low price effect (significant in pre-1963 sample)
Seguin, P. J. & Smoller, M. M. (1997)	Share price and mortality: An empirical evaluation of newly listed Nasdaq stocks	Journal of Financial Economics	CRSP	USA	1974 to 1988	Unadjusted Price	Top price decile minus bottom price decile	High price effect after controlling for size
Singal, V., & Tayal, J. (2018)	Stock prices matter	SSRN Working Paper	CRSP, Compustat	USA	1963 to 2015	Unadjusted Price (residual)	Top price decile minus bottom price decile	High price effect after size orthogonalization

4.2 The "Cultural Revolution" in Finance

There already is an emerging strand of literature that summarizes and discusses recent papers on culture-based financial decision making like Aggarwal et al. (2016) and Karolyi (2016), so I abstain from conducting a rigorous literature review here (see Section 4.2.2 for a short review of relevant literature for my scope). Instead, I focus on rather neglected (and at the same time potentially highly impactful) aspects that are expected to impact finance research in the future and thus discuss the (increasing) significance of cultural dimensions which are used to operationalize cultural differences among nations (see also Sections 5.2 and 5.3).

4.2.1 Culture and Finance: State-of-the-art?

To start with, it is not only striking how much (diverse) research is conducted in cultural finance (in recent years), but from whom and where it is published. The special issues of the top-tier journal "Journal of Financial Economics" (see, e.g., Zingales, 2015) and the (borderline) top-tier journal "Journal of Corporate Finance" on cultural finance and applied cultural dimensions (with a prominent role of those proposed by Hofstede) and especially the included review paper of Karolyi (2016) and Aggarwal et al.'s (2016) introduction to cultural finance, showing the openness of some of the most impactful finance researchers for cultural finance issues (however, of course not without a critical acclaim), could be a milestone in the transition of the research paradigm in favor of culture-based financial research. Additionally, I guess, the most (impactful) research on cultural finance in recent years that deals with stock market phenomena is published in the Journal of Banking and Finance (also a very popular borderline top-tier journal) (see Section 2.4, Table 2).

In Hofstede's words one could say, the stronghold of finance is finally (after about 15 years) captured by culture. The donjon however, is still not conquered. I try to help accomplishing this feat by my second and third research paper, where I also use cultural dimensions to explain and predict international cross-sectional stock returns directly as a secondary objective and specifically trace back the explanatory power of state-of-the-art asset pricing models to cultural differences. By this means, I am among the first that dare to investigate (maybe) the supreme discipline of finance, namely the effectiveness and efficiency of international stock market strategies and asset pricing in general, in the light of national culture.

However, further (apart from my initial tests in research paper II) and more rigorous (straight) investigations of cultural dimensions and cross-sectional stock returns (and returns of other asset classes) are yet to perform and to publish. Keeping the publication bias (Sterling, 1959) in mind, one could suspect that this was already tested and the results were not that compelling and thus not considered worthy to follow up this matter and ended up – metaphorically spoken – dumped in a file drawer (Rosenthal, 1979). I can affirm this conjecture, as during my time as a research associate at University of Bremen, we have performed appropriate calculations with lots of different configurations (and controls like financial characteristics and risk factors), but managed to pinpoint only a limited amount of clear effects of particular cultural dimensions that were robust to various liquidity filters. At the same time, these effects were additionally not very straightforward to explain.[41]

Another important question is the immediate risk dependency of assets from different cultural backgrounds. Although there already is a bunch of papers that investigate cultural influence on, for example, the risk perception (Bontempo et al., 1997; Weber and Hsee, 1998), risk preferences (Rieger et al., 2014) and risk aversion of agents (Breuer et al., 2014), international stock return co-movement (Eun et al., 2015), and international diversification (Anderson et al., 2011; Siegel et al., 2011), an explicit establishment of a possible research niche "culture-based/culture-neutral risk management" is virtually untouched. Upcoming exceptions are, e.g., the recent papers of Dang et al. (2018) and An et al. (2018) who find that individualistic cultures are associated with higher future (stock price) crash risk in an international sample covering 36 respectively 42 countries. Weigert (2015) underpins these findings with an earlier study that handles a similar research question with focus on a return premium on crash aversion. In the third research paper (III) I and my co-author tap this cultural risk topic with a focus on cultural dependency of risk factor loadings, but the relation of cultural dimensions and primary and secondary measures of an asset's riskiness like (idiosyncratic) volatility (Ang et al., 2006, 2009), Value-at-Risk, (idiosyncratic) skewness and kurtosis of returns is still largely uncharted. A first step in this direction is presented by Liu (2018) who shows evidence that all of Hofstede et al.'s (2010) cultural dimensions are relevant for implied stock market volatility among 15 countries and by Cheon and Lee (2017) who find that the idiosyncratic volatility puzzle is linked to the MAX premium which in turn is culture-dependent.

4.2.2 Culture and Stock Market Anomalies

Despite the rising research volume on cultural finance issues, literature on cultural dimensions and their connection to cross-sectional stock returns respectively returns on capital market anomalies is comparably rare as research on the price effect. Table 6 illustrates the obvious research gaps as it shows a fraction of (top) papers that would be expected to deal with the impact of culture on stock returns (or less captious, their connection) given the large amount of discovered capital market anomalies (Harvey et al., 2016). Although Chui et al. (2010) is a high impact top-tier journal paper, a good deal of citing literature of this paper refers to the momentum effect or culture affecting corporate finance issues, but does not offer much research on culture as driver for stock returns. In fact, I had (in addition to straightforward searches) a look through all citing literature of Chui et al. (as one should strongly expect that this prominent paper gets cited if a paper deals with the relation of culture and stock returns) and did altogether not find anything immediately relevant for (or related to) my research questions apart from the

[41] This demonstrates also one of the cruxes of the application of cultural dimensions: the establishment of theoretical links of measures of culture and financial decisions that translate into stock price movements and distinguishing indirect and direct effects of culture (Aggarwal et al., 2016). Usually, behavioral finance is adopted to play this intermediary function, however without circumventing the "cherry picking" problematic of behavioral finance explanations in research practice (Section 2.3).

literature presented in Table 6. Especially striking is the fact that a connection of the value effect (maybe the most prominent, legitimate, and widely used capital market anomaly) and individualism was never investigated rigorously although Chui et al. quickly tested this in their paper and reported encouraging results in their last footnote. My co-author and I test this as a side effect in research paper III based on a new and much larger sample than Chui et al. who only use data from Kenneth French's website to tap this research idea.

In general, there are two approaches in the literature to explain and predict the cross-section of stock returns by cultural dimensions (with focus on specific anomalies): (1) direct explanations and (2) indirect explanations. Examples for direct explanations are the application of a double-sort methodology (research papers II and III and e.g., Chui et al., 2010), interaction effects with the return determining characteristic (research paper II and III) and, most straightforward and general, cross-country single-sorts for values on cultural dimensions (research paper III) (see 3.2.1). Indirect explanations typically compound cultural dimensions and other control variables, e.g. via multivariate Fama-McBeth (1973) regressions (research papers II and III and e.g., Chui et al., 2010; Weigert, 2015; Cheon and Lee, 2017) and likely (implicitly) assume that the effect of culture on stock returns and anomalies stems not from culture per se, but from behavioral biases dependent on cultural differences and dimensions, which then are adopted as proxies for these biases (e.g., individualism as proxy for overconfidence which in turn is shown to be connected to the momentum effect in Chui et al., 2010). In my research papers, I implement both of these approaches.

However, I am a clear advocate of a direct influence of culture on anomalies and cross-sectional stock returns (apart from additional indirect effects) due to the high pervasiveness of culture and its nature as an early, readily, and deeply adopted value system pertaining to the full spectrum of (social) actions and thus financial decisions. A simple, associated example for this may be the rise of so-called Islamic Investing (Walkshäusl and Lobe, 2012) and less dogmatic, Social Responsible Investing (SRI; cp., e.g., Galema et al., 2008; Derwall et al., 2011). Here, the vices and virtues (i.e., values) of religion/ethics (a proxy for culture) determine *directly* which stocks (and which financial instruments due to prohibition of interest under Sharia law) are good or evil, respectively moral or immoral, ethical or unethical, without the need of behavioral biases as intermediate. In this cultural frame, the holding of, e.g., alcohol stocks or stocks of firms associated with the arms industry, is a priori not an option throughout all (fellow) believers/social responsible investors, completely independent of which behavioral biases some or most members/fellows may additionally have. The social code "ethical/unethical" is consequently the major determining criterion for which characteristic(s) a stock may have to be potentially purchasable and which one is a real no-no. In the language of the ICAPM, one could say that some investment opportunity sets are no option for some investors (completely independent of their available funds). For instance, Salaber (2013) undermines this example by finding that the strength of the sin anomaly is dependent from which religion (here Protestant or Catholic) is predominant.[42] Recently, Darsono et al. (2021) find evidence that sustainable stock returns are positively associated with individualism levels in the Asian region. Futhermore, they find several additional sustainable market indices return associations with other cultural dimensions like power distance and long term orientation and partly back up (refer to) my findings in research paper II.

[42] One level higher, culture appears to be even responsible for which asset class is preferred (De Mooij, 2004).

Table 6 Key characteristics of literature on the relation of culture/cultural dimensions and stock market anomalies

Authors (Year)	Title	Journal	Data	Countries	Time Frame	Effect	Methodology (i.a.)	Main Results
Bergsma, K., & Jiang, D. (2016)	Cultural New Year holidays and stock returns around the world	Financial Management	TRD, CIA World Factbook	11 countries, mainly Asia	1991 to 2011	Holiday effect	Event study	Abnormal stock returns in month of a cultural New Year
Cheon, Y. H., Lee, K. H. (2017)	Maxing out globally: Individualism, investor attention, and the cross section of expected stock returns	Management Science	TRD, Hofstede	Worldwide (42 countries)	1990 to 2012	MAX effect	Top MAX decile minus bottom MAX decile	MAX premium larger in more individualistic countries
Chui, A. C., Titman, S., & Wei, K. J. (2010)	Individualism and momentum around the world	The Journal of Finance	CRSP, TRD, Hofstede	Worldwide (41 countries)	1980 to 2003	Momentum effect	Top 30% (winners) minus bottom 30% (losers)	Momentum effect connected to national level of individualism
Costa, B. A., Crawford, A., & Jakob, K. (2013)	Does culture influence IPO underpricing?	Journal of Multinational Financial Management	Hofstede; Webpages of Andrei Shleifer and Jay Ritter	Worldwide (39 countries)	NA	IPO underpricing effect	Weighted least squares regression	Degree of IPO underpricing associated with several cultural dimensions
Dou, P., Truong, C., & Veeraraghavan, M. (2016)	Individualism, uncertainty avoidance, and earnings momentum in international markets	Contemporary Accounting Research	CRSP, IBES, TRD, Hofstede	Worldwide (41 countries)	1995 to 2008	Earnings momentum effect	Top minus bottom quintile regarding earnings surprise	Level of individualism positively associated and level of uncertainty avoidance negatively associated with earnings momentum profits
Durand, R. B., Koh, S., & Tan, P. L. (2013)	The price of sin in the Pacific-Basin	Pacific-Basin Finance Journal	TRD, Hofstede	7 Pacific-basin countries	1990 to 2009	Sin effect	Panel regressions; cross-sectional regressions	Underperformance of sin stocks in seven Pacific-basin countries; holding of sin stocks and performance is associated with degree of country's individualism/collectivism
Hammerich, U. J. (2020)	Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns	SSRN Working Paper	TRD, Hofstede, IMF	Worldwide (41 countries)	1980 to 2017	Nominal price effect	Top price quintile minus bottom price quintile	Price effect connected with several cultural dimensions of Hofstede, general link of national, firm-level stock returns and cultural dimensions
Hammerich, U. J., & Poddig, T. (2020)	Asset pricing risk factors and cultural dimensions: the hidden steady state variables?	Working Paper	TRD, Hofstede, IMF, Kenneth French's Website	Worldwide (41 countries)	1980 to 2017	Size, value, momentum, investment, profitability effects	Top 30% minus bottom 30% (or vice versa) regarding each characteristic	Value and momentum effect connected to several cultural dimensions, link of market returns and culture, risk factor efficacy dependent on cultural dimensions
Weigert, F. (2015)	Crash aversion and the cross-section of expected stock returns worldwide	The Review of Asset Pricing Studies	CRSP, Compustat, TRD, Hofstede	Worldwide (40 countries)	1980 to 2014	Crash sensitivity effect	Top lower tail dependence (LTD) quintile minus bottom LTD quintile	LTD premium higher in countries with high individualism values

5. Empirical Results

In this chapter, I will not plainly summarize the main findings of my three research papers separately (since my papers speak most effectively for themselves). Instead, I integrate them with respect to different perspectives and provide additional outcomes, insights, literature connections, and further empirical findings that are not explicitly mentioned in the papers (e.g., to save space and leave the developed story of the papers consistent). This is helpful to determine the reach of the results and further implications (see also Section 6) in the context of the main fields of my research (asset pricing, capital market anomalies, and cultural finance) that I sketched in Section 2. I structure the subsequent three subsections in terms of subject matter (price as an investment strategy, culture and investment styles, culture and asset pricing) and not with regard to the specific research papers to capture the quintessence of my research from a superordinate level. Consequently, Section 5.1 covers research papers I and II, whereas Section 5.2 and 5.3 highlight research papers II and III. In the final chapter (Section 6), I take this up and provide an outlook on future research and a collection of research gaps I see in my scope and close with some prospects of the further evolution of finance as research discipline.

In this section, I start by giving an introductive overview regarding the contribution of my research papers. For this purpose, Table 7 shows the "research density" of my papers regarding numerous categories with a special focus on the classes of anomalies and investment styles I cover and on which characters of these anomalies I call the most attention in my research papers. Additionally, Table 8 gives a summary of key insights for each research paper. Common main issues of my papers are especially the *origin, evolution*, and *interdependence* of anomalies as well as their (efficient) application as risk factors in asset pricing models and as fundamental investment styles for asset management purposes. Due to the long (and especially new) datasets and multiple robustness checks as well as the application of different methodology, the *persistence* and *robustness* of investment strategies and fundamental anomalies is also checked within my papers. The latent, classic question of this broad research spectrum from the view of financial theory is always if financial markets (especially stock markets) are efficient and when, why, and how long this efficiency might be disturbed.

Table 7 Research density of the research papers

Research Paper	I	II	III
Anomalies/Styles (Class)			
Price	XXX	XXX	
Momentum	XX	XX	XXX
Size	XX	XX	XXX
Value	X	XX	XXX
Volatility	XX	XX	
Beta	XX	X	XX
Liquidity	X	X	
Investment			X
Profitability			X
Anomalies (Character)			
Origin	XXX	XXX	XX
Trigger	XXX	X	X
Evolution	XXX	XX	XX
Robustness	XX	XX	XX
Persistence	XX	XX	XX
Interdependence	XX	XX	XXX
Predictive Power	XX	XX	XX
Explanatory Power	XX	XX	XXX
Methodology and Models			
Single Sorts	XXX	XXX	XXX
Double Sorts	XXX	XX	XXX
OLS Regression	XX		
OLS Panel Regression		XXX	
RE Panel Regression		X	
Fama-MacBeth Regression	X	XX	XXX
CAPM	XX		X
FF 3-Factor Model	XX		X
Carhart 4-Factor Model	XXX	XX	X
FF 5-Factor Model			X
FF 6-Factor Model			X
Theoretical Concepts			
Financial Theory	X	X	XX
Behavioral Finance	XX	XX	X
Cultural Finance		XXX	XXX

This table displays the research density of my research papers regarding several categories (row headers). I classify each specific contribution into a (sub-)category and mark the intensity of coverage for each subcategory with an X mark. “X” means lower intensity/focus, “XX” stands for medium emphasis, and “XXX” depicts a core area of the respective paper.

Table 8 Key insights of the research papers

Research Paper I	Sample: Cross-section of German stocks	
	Time frame	
1973 to 2016 (complete)	1994 to 2016 (main)	1973 to 1994 (comparable)
Significantly higher Sharpe ratio and lower volatility; lower beta and lower skewness of returns for high-priced stocks (in relation to low-priced stocks)	(Rational) drivers of a (high) price effect: Bargain hunter deterrence, investment properties (inherent shareholder limitation, liquidity, and tax/money management issues)	Significant low price effect and positive abnormal returns for low price portfolios; negative abnormal returns for high price minus low price hedge portfolios
Returns on high price minus low price hedge portfolio highly significantly (positively) associated with 90% to 10% price quantile ratio	Significant high price effect and positive abnormal returns for high price and low price portfolios; (partly) negative abnormal returns for high price minus low price hedge portfolios; main results are robust for multiple price cut-offs	
Return delta on high price minus low price hedge portfolio highly significantly (negatively) associated with delta of 90% to 10% price quantile ratio	High price portfolios yield higher returns and show throughout highly significantly lower return volatility in multi-investment style setups	
Inversion of price effect at exactly the same time when law amendment on minimum face amount of stocks was introduced: dramatic dispersion of relative price differences as consequence	High price effect is robust vs. return effects on size, skewness, value, momentum, and volatility	

Research Paper II	Sample: Cross-section of stocks for 41 countries	Time frame: 1980 to 2017
	Category	
International price effects	Cultural effects	Further insights
Mainly significantly higher Sharpe ratio (main exception: Asian countries) and lower beta for high price portfolios; worldwide consistently lower volatility and skewness of returns for high-priced stocks (in relation to low-priced stocks)	Long Term Orientation and Indulgence as significant and robust predictors for the global cross-section of stock returns	HML returns significant predictor for EMC returns on country level
Eight countries show significant price effects (either low or high price; Europe and Asia as main clusters); abnormal returns on EMC (expensive minus cheap) hedge portfolio for nine countries	International price effects associated with Individualism and Masculinity; Individualistic countries → high price effect (outlier USA), Masculine countries → low price effect	EMC returns as predictor and explanatory variable of WML returns
Price effects robust vs. size, value, momentum, and volatility effects in seven countries		
General global high price effect in individual stocks when controlled for major characteristics		
Highly significant and robust (abnormal) low price effect in the US from 1980 to 2017 consistent with, e.g., Hwang and Lu (2008)		

Research Paper III	Sample: Cross-section of stocks for 41 countries	Time frame: 1980 to 2017
	Category	
International investment styles	Asset pricing risk factors	Further insights
Returns on country-level value and momentum portfolios significantly (positively) associated with Individualism, but also other cultural dimensions; i.e. results of Chui et al. (2010) last in the future and can be extended to the value effect and further cultural characteristics apart from Individualism	Explanatory power of some of the FF (2018) 6-factor model asset pricing risk factors (especially HML and WML) absorbed/moderated or overlain/enhanced by several cultural dimensions like Individualism and Long Term Orientation	Country-level value-weighted market returns associated with Masculinity

5.1 Price as an Investment Strategy

From a risk management perspective, the number one bottom line of an international price effect would be that high-priced stocks are stocks with low market sensitivity (low beta values) and low volatility, but as a downside show lower levels for skewness of returns than low-priced stocks (i.e. they are more prone to large negative returns). These results appear to be independent from country-specific effects (e.g., cultural differences), since they are virtually present significantly all over the world. At the same time, other (favored) characteristics of high-priced stocks, like being (on average) high momentum stocks and large stocks, are a very robust pattern worldwide.

In addition, the price effect does not suffer from severe return crashes like the momentum effect (Daniel and Moskowitz, 2016), despite the both being closely associated. Although these momentum crashes appear to be manageable (Barroso and Santa-Clara, 2015), an investment in the price effect does not need such a monitoring that was not known a priori. Especially in Germany, however, the price effect is some kind of a grab bag, since on the one hand high-priced stocks are additionally (favored) value stocks. On the other hand, however, a dangerous aspect for a long-term investor is the inversion of the price effect since the mid-1990s. Although I manage to identify a probable and traceable trigger for this (severe top and bottom price decile dispersion due to a stock market law amendment), the future shape of the price effect is less clear than could be expected for the momentum effect. Despite the disappearance (or inversion) of another main anomaly in Germany, the size effect (e.g., research paper I and II; Fieberg et al., 2016), the high speed and magnitude of the inversion of the price effect in Germany is incomparable with any other (country-level) anomaly I came across. In fact, the evolution of the price effect in Germany renders nearly an ideal-typical example for the story of the highly analytical paper of Barberis and Shleifer (2003) that theoretically describes cycles of rapid and severe (news driven) return changes of an investment style (e.g. high price stocks investing) and its twin (low price stocks investing).

As mentioned in Section 4.1.2, (at first sight) the main crux (for an international asset manager as well as a critical researcher) of the price effect is its international inconsistency that may tempt readers of my second paper to the conclusion that the few, significant country-specific effects I find are due to chance (or at least explainable by asset pricing models). At first, if this was the case, this should make – in a bias-free scientific system – no difference for the perception and relevance of the paper, since it is highly legitimate and important to test if price per se is consequential for global stock returns or not (see, e.g., Section 4.1.1 and 4.1.2). Second, despite many insignificant findings on *country-level* (on regional level, this would look more compelling, I guess), I find (1) still too many significant (abnormal) return values (and predictor coefficients) to be just due to chance, (2) strongly amplifying high price effects throughout Europe in the last two decades, (3) no random pattern in the dispersion of significant values, but an obvious concentration of a high price effect in Europe and of a low price effect in Asia and (4) a significantly higher Sharpe ratio (return/risk relation) for high price portfolios vs. low price portfolios in the vast majority of countries outside Asia, the Middle East and the US. This pattern is especially enforced due to the inverse return/risk relation documented by an exceptionally low volatility and market sensitivity of high price portfolios in conjunction with high returns (standing diametrically against standard financial theory like the CAPM that proposes the opposite).

Additionally, I find a broad range of efficacy of country-level asset pricing models (that are expected to be most eligible to explain country-specific anomalies; e.g., Fama and French, 2017) to explain the price effect which gives rise to the assumption that the unlike shapes of the price effect are additionally driven by country-specific (not necessarily culture-dependent) circumstances, which I affirm for Germany in paper I (and could be expected for the US low price effect due to its character as a highly significant and robust outlier).

Nevertheless, the successful investment in a (bare) cross-country price effect is a more challenging and unsecure endeavor (especially if one does not take into account the strengths of culture-based asset allocation, which I discuss in the following section) than (for example) an investment in a globally very consistent momentum effect. However, this weakness also comes along with some strengths that cannot be captured by investing in classical (widely known) investment strategies: (1) the (international) price effect is likely still too unknown (no prominent publications using non-US data) to be under the risk of vanishing in the near future due to the publication effect shown by McLean and Pontiff (2016) for the US.[43] (2) The nominal stock price as sorting criterion appears to be a feasible characteristic to push alphas of other styles and at the same time reduce their risk in terms of return volatility when incorporated in a multi-style strategy. (3) The diametrically opposed price effects in Europe and Asia (as well as the US) enable an investor to profit from both the high price effect and low price effect at the same time (although investing in the same style) and thereby mitigate (or hedge) the main detrimental feature of high-priced stocks, namely their lower skewness of returns.[44] In this way, an investor can (at the same time) profit from both a style and its twin (Barberis and Shleifer, 2003) in a cross-country investment setup. Thus, "intra-style" hedge portfolios of the form $Expensive_{Europe}\ minus\ Expensive_{Asia}$ (EME) or $Cheap_{Asia}\ minus\ Cheap_{Europe}$ (CMC) would be viable.[45] I know of no other characteristic-based investment strategy that offers these (unconventional) opportunities to this extent. For example, I find only two countries (out of 41) that show significantly negative returns on the size effect and none regarding the value and momentum effect (cp. paper III).

5.2 Culture and Investment Styles

In my dissertation, I investigate several investment styles respectively investment strategies in the light of national culture[46]: size, value, momentum, and price. Additionally, I briefly explore a cultural association of investment and profitability. That is, I test all stock characteristics that are the basis of the Fama and French (1993, 2015, 2018) 3-, 5-, and 6-factor model and the Carhart (1997) 4-factor model (paper III) as well as the price anomaly (paper II) on cultural dependence.

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[43] In fact, Jacobs and Müller (2020) show that this documented vanishing of anomalies once they are published is limited to the US and for most countries even inversed, i.e., the anomalies get even stronger after publication (for example in Germany).

[44] For kurtosis values, I find no clear difference between high price and low price portfolios.

[45] One has to keep in mind though that only some countries of these regional clusters show significant price effects.

[46] With respect to (characteristics-based) investment strategies without additional cultural reference, I also investigate a skewness effect in Germany and a worldwide (total) volatility effect.

The most compelling and well explainable links I find for value, momentum, and price regarding Hofstede's (1980, 2001) cultural dimension Individualism vs. Collectivism. However, especially regarding the performed double sorts (and univariate Fama-MacBeth, 1973 regressions) also other cultural dimensions like the newest one, Indulgence vs. Restraint (Hofstede et al., 2010), play a vital role for the magnitude of the return differences of these characteristics when incorporated as international stock market investment strategies. In the multivariate Fama-MacBeth (1973) regressions, though, tested models with all cultural dimensions (even without further control variables) show only limited reliability and consistency regarding the significant links found for the double sorts and univariate regressions. Since Hofstede (1980, 2001) and Hofstede et al. (2010), however, document a (medium) correlation between cross-country values on several (distinct) cultural dimensions (despite the creation of the cultural dimensions via factor analysis that inherently tries to identify and separate clusters of drivers by classifying them as one category; see details in Hofstede, 2001) and thus a certain interdependency of cultural characteristics (not surprisingly due to the pervasive character of culture and the inseparability of its general driving forces values, rituals, heroes, symbols, and practices; see Hofstede et al., 2010), this finding shows that it is meaningful to use cultural dimensions rather holistically than to cherry pick specific dimensions for empirical analysis (as it is predominantly done in the literature).

Consistent with the literature (Chui et al., 2010), I find the most robust connection between Individualism and the momentum effect. I guess this finding alone is a significant contribution that would justify a paper, as I get virtually the same results, despite using a much longer, (real) out-of-sample dataset (ending 2017 instead of 2003 as in Chui et al., 2010). That is, one of the most puzzling anomalies (momentum) is *consistently and constantly* connected to a largely time-invariant determinant of a society (Individualism). Thus, if this is the case for one of the hardest retraceable anomalies, it appears likely that this is also the case for other anomalies found to be linked to cultural dimensions, which shows the exceptionally steady explanatory and predictive power of cultural dimensions for stock market anomalies (and associated investment styles). At the same time, this out-of-sample finding (using similar, but not the same measurement and operationalization, which also shows the robustness of the results of Chui et al., 2010 regarding differences in data configurations) underlines that it is indeed culture that is consequential for the effectiveness and steadiness of investment styles and not e.g. behavioral biases or omitted variables (that are more likely than culture to vary to a certain degree over time and to be caused by cultural differences) that may be correlated with culture and measured dimensions. As additional out-of-style robustness test, I document similar outcomes for the connection of value and Individualism, as here, I find also virtually the same results regarding the double sorts (identical mean return of the hedge portfolio and of course same sign) as Chui et al. (2010) for nearly double the number of countries and once again a much longer sample which results also in clearly significant t-statistics as opposed to Chui et al. (2010) who find only barely significant values.

The price effect is qualitatively a different candidate of a stock market anomaly than value and momentum. The main difference is that it is not consistently present throughout the world. Sharp tongues may say that it is no anomaly simply because of that (but datamining). As I outline in the previous section however, the characteristics of the distribution of significant country-specific price effects make it unlikely for that being the explanation. In paper II, I show that cultural differences are feasible to capture (explain and predict) these (often) diametrically opposed country-specific price effects in a global setting on portfolio level and in the cross-section of firm-specific returns.

I venture to derive a far-reaching hypothesis from this finding (and the evidence of paper III) that impacts the relevance of cultural dimensions beyond the explanation of known, consistent and (internationally) robust anomalies: cultural dimensions are feasible to capture and reveal effects of stock characteristics that are seen as inconsequential for stock returns in the current research paradigm. This means that many unpublished studies on stock characteristics currently lying in file drawers due to inconsistent global results, may yield meaningful results once they would incorporate cultural differences as intermediate variable (e.g., by using interaction effects with cultural dimensions).[47]

5.3 Culture and Asset Pricing

In this section, I have a look at the relation of cultural dimensions and the cross-section of international stock returns. I mainly refer to paper III, but regarding the predictive power of cultural dimensions for global firm-specific stock returns, I also refer to findings of paper II.

In the second paper, I use cultural dimensions (1) for predicting (and explaining) international firm-level returns directly and (2) test the sensitivity of the price characteristic for predicting these stock returns with respect to cultural differences by using interaction effects. In both cases, I find cultural dimensions, especially Long Term Orientation and Indulgence in case (1) and Individualism and Masculinity in case (2), to be immediately feasible to determine the cross-section of stock returns. As mentioned in the introduction, I guess this (1) is the most straightforward and impactful (unique) finding of my dissertation.

In the third paper, I step up to a much more rigorous research question and explicitly investigate if cultural dimensions are useful for maybe the heart of empirical finance – widely applied, state-of-the-art asset pricing models. In doing so, I use all five asset pricing risk factor mimicking hedge portfolios of Fama and French's 5-factor model (2015) as well as Carhart's (1997) momentum factor (cp. also FF, 2018) and explore the dependency of their cross-country explanatory power from cultural differences in an empirical asset pricing context. As methodology, I employ the (slightly adapted, see Section 3.2.2) rolling, cross-sectional regression procedure of Fama and MacBeth (1973) and regress (returns of) each risk factor on the other investigated risk factors (with and without interactions regarding each cultural dimension) to

[47] Consequently, metaphorically spoken, the (as yet) documented anomalies would be only the tip of the iceberg that could be seen from a (land-based) lighthouse (conventional financial theory and asset pricing models) and (in more detail) from a boat (e.g., experiments regarding financial decision making) that swims on the sea of behavioral biases (behavioral finance), but not holistically until having access to a submarine (e.g., measureable cultural dimensions) that goes to the bottom of it (cultural finance). Or put differently, the rabbit hole containing a (concealed) zoo of uncharted (culture-related/culture-dependent) anomalies goes a lot deeper than currently expected (i.e., e.g., if one only determines anomalies with asset pricing factor models). Since even a submarine needs a (land-based) home port, in paper III, I combine the explanatory power of conventional asset pricing risk factors with the discriminating power of cultural dimensions to build an enhanced, culture-based empirical asset pricing model. I depict such a model in the next section.

determine the average cross-country explanatory (and absorbing) power of "culture-knotted" risk factors. The cultural connections of these asset pricing risk factors do not only capture their explanatory power in numerous occasions, but also enhance their efficacy in several regression setups. In this way, I document additive as well as absorbing/moderating effects of several cultural dimensions (virtually all, with the weakest and fewest effects for Masculinity and Uncertainty Avoidance) when interacted with common asset pricing risk factors, which underlines my central hypothesis in paper III. This suggests integrating cultural dimensions as easily to incorporate, virtually time-invariant discriminants or weighting factors for any asset pricing risk factor to boost its explanatory power in international asset pricing exercises (respectively to control the risk factors for well-documented, persistent culture-specific effects). The consequences are basically culture-based (or culture-neutral) empirical asset pricing models that account also for the obvious cultural sensitivity of some characteristics (especially value and momentum) used for the construction of these risk factors (see previous section). These results are highly relevant for both academia and (international) banking and finance practice.

Equation 12 depicts such a general culture-based empirical asset pricing model as it is applied in a similar shape in paper III. Since the values of the cultural dimensions are time-invariant, the form of the estimation method has to deviate somewhat from state-of-the-art risk factor mimicking asset pricing models like the 5-factor model (FF, 2015) with added momentum factor (Carhart, 1997) (i.e., 6-factor model; FF, 2018). Here, rolling Fama-MacBeth (1973) regressions are the most straightforward way to go (with panel regressions as legitimate alternative), instead of contemporaneous OLS regressions over the full sample (applied by the mentioned factor models) which are not statistically feasible due to the zero variance within the country-specific cultural dimension values.

$$\begin{aligned} r_{it} &= \alpha_t + \sum_j \delta_{jt} CULDIM_{ij} \\ &+ \sum_k \beta_{kt} RFACTOR_{ikt} + \sum_j \sum_k \theta_{jkt} CULDIM_{ij} * RFACTOR_{ikt} \\ &+ \sum_l \gamma_{lt} CONTROLS_{il} + \varepsilon_{it} \qquad \forall i,j,k,l,t \end{aligned} \tag{12}$$

r_{it} is the return of a *country-specific* asset or portfolio in time *t* ($t = 1, \ldots, T$) in country *i* ($i = 1, \ldots, N$), where each country *i* has to have a valid cultural value for at least one cultural dimension (*CULDIM*). This return is explained (respectively regressed on) in each *t* by the (time-invariant) values on country-specific cultural dimension *j* ($j = 1, \ldots, J$), (time-varying) returns on *k* ($k = 1, \ldots, K$) country-specific risk factor mimicking hedge portfolios (*RFACTOR*) and the interaction effects on any combination of cultural dimensions and risk factor mimicking hedge portfolios[48] (*CULDIM * RFACTOR*). *CONTROLS* are further *l* ($l = 1, \ldots, L$) (optional) time-

[48] Another option would be to (additionally) integrate characteristics and interact them with cultural dimensions instead of risk factors (only). This would contribute to the long lasting discussion in the literature on whether characteristics or risk factors drive/explain (cross-sectional) asset returns (e.g., Fieberg et al., 2016; Hornuf and

invariant or time-variant control variables like macroeconomic measures (e.g. GDP per capita) that are often used as (proxies for) state variables. ε_{it} is a time-variant error term that captures residual cross-country effects that are not explicitly implemented in the model.

Per definition, this model relies inherently on some variation in cultural dimensions to be viable. Thus, it is only implementable (meaningfully) in a cross-country (and thus cross-culture) research design. Without cultural dimensions one gets a simple "fully globalized/integrated world model" of asset pricing that assumes that neither cultural dimensions (per se) have any explanatory power for country-specific asset or portfolio returns, nor that the efficacy (of the explanatory power) of risk factor mimicking hedge portfolios is culture-dependent. As paper II and III and other papers like Chui et al. (2010) document, this is an unrealistic assumption that leads to a cultural distortion of state-of-the-art asset pricing models like the FF (2015, 2018) 5-/6-factor model and Carhart's (1997) 4-factor model. Instead, with the above-depicted model, I introduce a culture-neutral asset pricing model that accounts for the country-specific as well as the culture-specific nature of risk factors.

As a side effect of my study on culture-based asset pricing in paper III, I also find Masculinity to be a relevant determinant for general (value-weighted) market-level returns, with countries scoring low (i.e. being "feminine") yielding significantly higher market returns in my dataset. This implies some relevance for politics (if this association also possesses some kind of causal link): Shifting a nation's culture toward being more feminine, that is, more consensus-orientated (for example by fostering free speech, unbiased public discourse, and (basic) democratic structures) and respecting life/work balance of the fellow citizens (less working hours and days, unconditional basic income) as well as reduced in-company competition pressure, might be a positive factor for the development of a nation's stock market and (market-wide) stock return growth. On the other hand, this shows that even the return of the market portfolio (being of central interest in empirical and theoretical asset pricing models) appears to be culture-dependent and could be based (partly) on several consumption patterns or other named differences like higher competition tendency that are associated with Masculinity (e.g., Hofstede et al., 2010).

6. Conclusion and Prospects

In essence, the dissertation at hand (further) questions the (universal) empirical validity of central neoclassical theories like the (weak) EMH and theoretical asset pricing models: (1) In investigating and approving the informational value of the nominal price on worldwide levels (for the first time), it successfully tackles the weak EMH (basically hypothesizing the irrelevance of information retrievable from an asset's dataset of prices for investors) in an immediate manner. (2) The large international diversity of the price effect and the cultural dependence of the efficacy of main risk factors (which are also proxies for unknown/difficult to measure state variables deployed in theoretical asset pricing) used in empricial asset pricing, suggests a non-consistency of risk-based explanations and predicitions for international asset returns. To close this gap in

Fieberg, 2020). However, since I explicitly investigate the moderating effect of cultural dimensions for widely used asset pricing risk factors in paper III, I leave this research question for future research.

explanatory and predictive power for international asset returns and capture the spread in magnitude and direction of several capital market anomalies (especially price, momentum, and value), I introduce (in line with seminal, but scarce literature) quantifiable cultural dimensions to shed light on the international zoo of anomalies/factors from a more sociological point of view (potentially integrating the full spectrum of human decision making apart from concentrating (solely) on making profit under risk and additionally assuming an universal, but distorted idea of man like homo economicus).

Despite the emerging role of behavioral finance and cultural finance in closing the explanatory gaps regarding the empirically documented lacks in market efficiency (i.e. the emergence of anomalies), financial theory still serves as a well formalizable and implementable anchor that cannot (and should not) be left out in future asset pricing and asset management research. On the other hand, the strengths of cultural finance and behavioral finance to close financial theory's empirical deficiencies (like the legendary malfunctions of the CAPM which, for example, in case of the price effect, not only does not work, but shows the opposite of what would be expected by financial theory – lower loadings on market sensitivity for high price portfolios despite their outperformance in many markets) are highly visible in mine and other recent research. That said, I suggest the most efficient, smooth, and rational way finance as a discipline could evolve and overcome the empirical shortcomings of their methods and theoretical foundations, would be likely no complete paradigm change, but rather a change in researchers' minds toward incorporating cultural measures as determinants and controls in finance papers in a down-to-earth way, without prejudice and dispassionately like any other macroeconomic variable.[49] This pragmatic attitude to see culture as a vital part of any society and lastly also a logical determinant of financial decision making (Karolyi, 2016), should not exclude referees of conferences and journals (as well as their organizers and editors) since those are the main agents in science that can foster, but also hinder the expansion of new trends, research ideas, and thus innovative branches of a research discipline. This holds more than ever for culture, a (the) genuine part of the human (socio-cultural) evolution per se that led us all the way to the future in which we live in.

I guess the number of future research papers applying cultural dimensions and other standardized measures of cultural differences on asset pricing issues (and maybe even on practical asset management purposes) and especially to decipher the origins of the zoo of anomalies will be exorbitant. On the other hand, even financial theory can learn and be inspired from culture for example due to culture's influence on consumption patterns in a society that could be assumed to be linked to consumption risk, the main driver in the (empirically rarely successfully adopted) CCAPM. Possibly, culture could be the missing piece of a puzzle that gives financial theory an unexpected power of impact and retains their relevance in empirical research in the future.

[49] Chui et al. (2010), Weigert (2015), and Cheon and Lee (2017) are good examples for this.

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Appendices

A. The Papers in a Nutshell and Strategic Considerations

This section contributes additional material regarding a brief summary of the papers, their current status, and strategic insights after I embedded and defined them in detail with the previous sections. This is also due to the goal of this document to serve as a stand-alone script irrespective of knowing my research papers.

In Table A.1, I give a summarizing impression of the papers incorporated in my cumulative dissertation and their (current) status. I rank the papers chronologically (from I to III) in the sense of a time line regarding the sequence of the development of their initial research idea, respectively the initial completion of a first consistent paper version. All papers have already gone through a considerable evolution of versions with paper I being the most matured (see Appendix B for more details). The evolution and current status of the papers reflects also my strategy (see

Section A.2), which is, in a nutshell, targeted on exploiting (social) mechanisms in the scientific system apart from developing (potentially) impactful and original research in the long-term. This process takes a decent time and thus it is not accidental that the papers are not published (yet) in a journal. I am also no friend of publishing for the sake of publishing, but rather try to publish the papers either in journals with high reputation or leave the papers in the state of working papers and conference papers and in this way retain their (future) potential and full copyrights. Suitably, I am also a friend of the open access idea. Consistently, I was not really tempted to give some (more or less sincere) invitations of lower ranked/less known journals a shot that I received especially in the aftermath of conference participations. Additionally, these invitations (naturally) suffer from a selection bias with journals of low reputation (and thus low numbers of submissions) rationally being much more inclined to look for potential papers and send solicitations. With the emergence of so-called predatory journals, publishing in less known journals also contains "buying" some kind of a pig in a poke as well.

A.1 The Papers in a Nutshell

Table A.1 Current status of the research papers[50]

Paper	Title	Authors	Status	Conferences and Seminars
I	Nominal Stock Price Investing	Hammerich, Ulrich J.; Fieberg, Christian; Poddig, Thorsten	Conference Paper, SSRN Working Paper	FMA Annual Meeting, San Diego, 2018; RBFC, Amsterdam, 2018; HVB Seminar, Bochum, 2017
II	Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns	Hammerich, Ulrich J.	Conference Paper, SSRN Working Paper	AFFI, Nantes, 2020 (accepted); DGF Annual Meeting, Essen, 2019; MHF Conference, Lancaster, 2019; HVB Seminar, Hannover, 2019
III	Asset pricing risk factors and cultural dimensions: the hidden steady state variables?	Hammerich, Ulrich J.; Poddig, Thorsten	Working Paper	AFFI, Nantes, 2020 (accepted); FOFI Conference, Lancaster, 2020 (accepted)

To ease locating the specific context of the papers initially and to give a summary of their content for an unfamiliar reader, I present their (extended) abstracts and provide some keywords and JEL codes below:

Paper I:

Abstract: We find that high-priced stocks show significantly higher Sharpe ratios than low-priced stocks. Also, price as an investment style is especially beneficial when applied in a multi-

[50] Newest version of the papers available at https://www.researchgate.net/profile/Ulrich_Hammerich and/or https://ssrn.com/author=2379114 (see also for other publications).

investment style setting, reducing portfolio volatility significantly while adding additional alpha. Implementing robustness tests and factor regressions, the price effect stays alive despite revealing tight connections to investment styles like momentum, low beta, and size. Our framework offers yet ignored explanations why nominal prices are consequential for stock returns. We line our argumentation using an event-based, market-wide dramatic dispersion of stock prices in our sample, turning a strong low price into a strong high price effect.

JEL Classification: G02, G11, G12, G14, G15

Keywords: nominal price effect, behavioral finance, asset pricing, low beta, skewness of returns

Paper II:

Abstract: We document a nominal stock price effect that is (like momentum) associated with (national) culture. Using the full spectrum of cultural dimensions proposed by Hofstede et al. and the cross-section of stock returns of 41 countries, we not only show a robust predictive and explanatory power of price in conjunction with several cultural dimensions, but of cultural differences in general. Although momentum and price are related investment strategies, we find a broad (escalating) European high price effect, but a material low price effect in Asia as well as the most significant and robust low price effect for the US. Most consistent around the world, high-priced stocks show lower return volatility and market betas than low-priced stocks and lower values for skewness of returns. Specifically, we reveal particularly cultural dimensions Individualism and Masculinity to drive the price effect, respectively its opposite poles, and Long Term Orientation and Indulgence to be consequential for the cross-section of expected returns. Additionally, we find the magnitude of country-specific value effects to predict returns on country-level expensive minus cheap (EMC) hedge portfolios. Our findings have far-reaching implications for the validity of financial theory like the EMH, as we report that the most basic stock characteristic, the price, is consequential for stock returns on international level. Even more impactful for future research should be the relevance of cultural differences for the cross-section of expected stock returns in general, as we are the first to explicitly investigate and document this as a groundbreaking side effect of inevitably culture-based financial decision making.

JEL Classification: G02, G11, G12, G14, G15

Keywords: nominal price effect, cultural finance, behavioral finance, asset pricing

Paper III:

Abstract: We find international stock returns on common asset pricing risk factor mimicking hedge portfolios (especially HML and WML) to be connected to several cultural dimensions proposed by Hofstede et al. Using a comprehensive sample of cross-sectional data of 41 countries, we check all factors of the FF five-factor model, RMRF, SMB, HML, RMW, and CMA as well as WML for dependence on national culture. We find substantial evidence for culture as possible omitted, hidden (steady) state variable that impacts the relevance and thus the efficacy of local asset pricing risk factors and in turn the significance of associated investment styles. In line

with related literature, we document a prominent role of Hofstede's Individualism dimension, but also other cultural dimensions like Long Term Orientation and Power Distance that are linked to economic development and growth. We conclude that cultural dimensions are feasible for international asset pricing tasks as they increase goodness-of-fit measures, help integrate risk factors, and partly absorb, moderate or overlay their explanatory power. In contrast to the assumptions of the ICAPM, cultural dimensions likely contain not (only) information on future but on cross-country investment opportunities. That is, cultural dimensions are candidates for state variables in space rather than state variables in time like conventional macroeconomic measures.

JEL Classification: G02, G11, G12, G15

Keywords: asset pricing models, risk factors, cultural finance, state variables, investment styles

A.2 Strategic Considerations

Every cumulative dissertation should contain a section with a (marketing) strategy of the projects, some intuition, and insights into the author's research agenda. Apart from my goal as a researcher to develop original research ideas and/or exploit substantial research niches and subsequently execute these ideas by means of working papers of good quality (with the ultimate goal of publishing in the best possible journal for the specific paper of course), I place special emphasis on strategic acting in the frame of reference – the scientific system. Scientific research is, like economic acting, not limited to dealing with the internal system medium, that is truth in science and money in the economy (e.g., Luhmann, 1994, 1997), but also a multidimensional social act. In the tradition of Weber, a *social* action is an action of an agent with reference to another person/other persons that takes their behavior into account (Weber, 1991). In a very connected world, another form of acting is not very common. Having the role of a researcher, in such a world, one of the most basic tools should be to possess some sensitivity to implications of sociology of science (R. K. Merton, 1973). Since the beginning of my research career in 2015, most of my strategic acting and conceptions were intuitive to me and further sharpened in the process as I gained more experience and insights into the scientific process. Of course this process is not even close to be finished, as lots of experience and knowledge is still missing at the beginning of a research career and I could not yet have learnt from any present and future "mistakes".

Naturally, I can and will not present all of my insights, incentives, intuition, and future plans here and instead focus on the best-documented and most prominent ones that are universally valid for all researchers in finance. Quite early as a research associate, I participated in the HVB Seminar in Münster (in 2016) and from start liked to meet and talk with other young researchers in an intellectually stimulating atmosphere. Right after completion of the first sound version of my first project at University of Bremen in fall 2016, it was a primary goal of mine to present this (and my subsequent papers) at prestigious and high quality international conferences. The benefits of active participation at conferences were obvious to me and of paramount importance in several aspects (networking opportunities, marketing for own research projects, getting a foot into the finance community as a researcher with no formal finance background, enhance presenting abilities, connect travelling and working in a meaningful manner etc.). The importance of *weak* links for subsequent professional success (Granovetter, 1973) is in today's society more important than ever and academic conferences are an ideal vehicle to attain them.

The papers of Reinartz and Urban (2017) and Kerl et al. (2018) on active conference participation and subsequent publishing success in top finance journals finally reassured me that this intuition and my strategy were right.[51] Like me, Kerl et al. (2018) conjecture that some kind of signaling effect regarding the quality of the working paper is (also) responsible for the future publication success and not only the enhanced scientific quality and originality of the paper per se: "Conference participation not only provides opportunities to improve a paper's quality through feedback and discussion, but it also serves as an indicator of quality, increasing both the visibility of one's paper and the reputation of the presenting author and of her co-authors" (Kerl et al., 2018: 26). Editors and referees of journals have both limited time and information processing capacity which makes them prone to rather "soft" decision-making factors like (looking up) past participation of the specific paper in (top) conferences. In this context, the assumption of the effectiveness of the common blind review practice is led to absurdity, since conference papers and their authors are often publicly visible and easily traceable without being a computer expert. Thus, the journal reviewers of the papers are far from being blind in the review process. Consequently, (at least) two factors for the rationality of both editors and referees to give papers that were presented at top conferences positive feedback are obvious: (1) other reputable researchers already had a look at the paper and liked it (thus it is more probable that the paper is indeed worth considering for publication). (2) If they deviate from the opinion of these colleagues, they should have good reason to do so which would increase the time consumption of the review even more (leading to less costs to simply follow the herd).

As a consequence, especially for less reputable researchers (like research associates) it is likely smart to gain this signaling effect of the attendance of (at least) a good conference first and not publish the working paper on a pre-print server like SSRN until then, since also conference reviewers would not be blind in this scenario and could be influenced in their decision making by knowing the author and his/her affiliation. This strategy was especially suited for my second research paper where I am the single author.[52] Nevertheless, it cannot be circumvented that reviewers notice the fact that the paper has not been presented yet at a conference and seemingly was not considered "worth" to be uploaded (yet) on a pre-print server by the author(s), which might be interpreted as negative signal regarding the quality and the status of the paper. In addition, possible prejudice (or reservation[53]) of editors/conference organizers (resulting in an exclusion of the paper before sending it to reviewers) is also a hindrance for attaining some needed initial reputation for each early career researcher from a non-top university.

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[51] In the process of my engagement of strategically sound decision making in the (finance) journal and conference sphere, I considered it as high priority (for my chair and me) to create tables regarding main characteristics of relevant journals and conferences.

[52] Due to my conjecture that more authors of a paper are also a signal for its quality and thus conference participation and journal publication success (average number of authors of top 9 finance papers is about 2.4; Reinartz and Urban, 2017), I wrote my second (single authored) paper in "we" form to be immune to possible prejudice in a blind review.

[53] For some experts in the finance sphere a paper promoting cultural approaches and at the same time (implicitly) questioning financial theory due to the shown relevance of nominal price, may appear to be a potential (long-term) threat in respect of their own research reputation and career. That is, the scientific paradigm (Kuhn, 2012) feels offended and tries to defend itself by rejecting such ideas.

These and other insights affected my assumed ideal typical general paper strategy (as not yet reputable researcher) clearly: (1) Send (as yet unknown) working paper to top (minimum good) conferences (mediocre conferences could possibly lead to a detrimental signal regarding the quality of the paper, since a top paper does not need to be presented there). (2) Revise the paper on the basis of the main criticism of the conference reviewers. (3) Send working paper again to conferences. (4) After acceptation at a good (better top) conference – which can take a decent amount of time (paper is now visible online) maximize marketing of paper (e.g., upload on pre-print server and spread paper in scientific research networks). (5) Try to present at an even better conference and/or seminars.[54] (6) Submit the paper to a journal that is likely (slightly) too high ranked (ensures to sell the paper not below value and to receive quality feedback) for the paper (or first wait until the paper matures – e.g. becomes cited – and gets possibly solicited for publication). (7) After likely rejection, revise the paper again with reference to the main criticism and send it to another journal of similar (or possibly even slightly higher) rank. As main difference, a researcher with high reputation and/or good networks can/should initially upload the paper on a pre-print server (or otherwise reveal that he/she is the author, for example by mentioning the title of the paper on the university website) to get revealable and enhance his/her probability to get accepted at a top conference, since then the reviewer is likely convinced (ab initio) that the paper has to have a good quality. Additionally, if the conference (and later journal) referee has (accidently) a good relationship with the author(s) (and possibly expects (mutual) professional benefits from a positive feedback that increases conference and journal acceptance likelihood) his/her rating of the paper is likely complaisant. As far as I see, the main downsides of this strategy are that it takes a lot of time, dedication, and money (submission fees, conference traveling expenses etc.). However, when having a look at the acknowledgments of top journal papers this is likely the standard procedure: "conference participation seems to be an integral facet of the value chain of the publication process" (Kerl et al., 2018: 26).

B. Collaboration with Peers

My cumulative dissertation consists of three research papers. Two (research papers I and III) are authored together with my supervisor Prof. Dr. Thorsten Poddig and the first paper also with a former colleague, respectively co-supervisor, PD Dr. Christian Fieberg. The second research paper is authored solely by myself. In this appendix, I provide information regarding the extent of this collaboration. I am very grateful for their help, especially regarding the first research paper.

As mentioned in the introduction, the idea, the conceptual framework, and the main hypothesis for the first research paper, "Nominal Stock Price Investing" stems from a previous conceptual working paper ("A Bargain Hunter's Dream: High-Priced Stocks") which I developed in 2015. This paper was chosen by Prof. Dr. Thorsten Poddig and PD Dr. Christian Fieberg to be most appropriate (out of my three conceptual papers written in 2015) to be worked out as an empirical

[54] The average number of conference participations of top 9 finance papers is about 2, whereas only 21% of papers published in one of the top 3 finance journals attended no conference and 16% no seminars (Reinartz and Urban, 2017).

study as my first project at University of Bremen. At the beginning, PD Dr. Fieberg provided some initial financial datasets for Germany, which were later substituted by me to enlarge and update the sample. The story, hypotheses, and especially the code (e.g. for the methodology, data editing, regressions, hypothesis tests, and plots) were also developed and written (solely) by me. The paper has a long history of drafts as it was enhanced multiple times, e.g., by additional methodology and regressions. Once, I also updated the sample completely (especially to attain two substantial subsamples and to present the newest results) and had to calculate everything anew. The multiple drafts were also written entirely by me. Prof. Dr. Poddig and in the first months also PD Dr. Fieberg perused respectively had a look at the manuscript several times and made valuable recommendations especially regarding the methodology and contribution of the paper. PD Dr. Fieberg also double-checked the main results. I presented the paper in the course of the HVB Seminar at University of Bochum, Germany in February 2017, at the 3rd Research in Behavioral Finance Conference (RBFC) at VU Amsterdam, the Netherlands in September 2018 and at the 48th Financial Management Association (FMA) Annual Meeting in San Diego, CA, USA in October 2018.

Although the second research paper is authored by me, it profited (especially at the beginning) substantially from hints of Prof. Dr. Poddig (e.g. regarding the cultural dimensions and the panel regressions) and from some comments of my former colleagues (Tobias Glas and PD Dr. Fieberg). For the second research paper, I attained the vast amount of international datasets that are also the basis of research paper III. I presented this paper at the HVB Seminar at University of Hannover, Germany in May 2019 and at the Mutual Funds, Hedge Funds and Factor Investing (MHF) Conference at Lancaster University Management School, UK in June 2019. Furthermore, I presented it at the 26th Annual Meeting of the German Finance Association (DGF) at University Duisburg-Essen, Germany in September 2019. The paper was also accepted for presentation at the (cancelled) 37th International Conference of the French Finance Association (AFFI) to be held at Audencia Business School in Nantes, France in May 2020.

The third research paper, authored by me and my supervisor Prof. Dr. Poddig is based entirely on my story, hypotheses, code, and datasets. I also solely wrote the manuscript. However, the paper was particularly influenced by the preliminary results of a precursory project which was carried out together with a colleague, Daniel Metko, and Prof. Dr. Poddig. My supervisor also helped substantially in interpreting the results and in discussing the implications of the used methodology. He also made valuable suggestions regarding subsequently performed additional calculations and regressions. I am sure that he would continue to help improve future drafts of this paper. The paper was accepted for presentation at the (cancelled) 37th International Conference of the French Finance Association (AFFI) to be held at Audencia Business School in Nantes, France in May 2020 and at the (postponed) 2nd Frontiers of Factor Investing (FOFI) Conference to be held initially at Lancaster University Management School, UK in spring 2020.

C. Research Papers

C.1 Paper I: Nominal Stock Price Investing

Nominal Stock Price Investing

Ulrich J. Hammerich, Christian Fieberg, and Thorsten Poddig *

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Abstract

We find that high-priced stocks show significantly higher Sharpe ratios than low-priced stocks. Also, price as an investment style is especially beneficial when applied in a multi-investment style setting, reducing portfolio volatility significantly while adding additional alpha. Implementing robustness tests and factor regressions, the price effect stays alive despite revealing tight connections to investment styles like momentum, low beta, and size. Our framework offers yet ignored explanations why nominal prices are consequential for stock returns. We line our argumentation using an event-based, market-wide dramatic dispersion of stock prices in our sample, turning a strong low-price into a strong high-price effect.

JEL Classification: G02, G11, G12, G14, G15

Keywords: nominal price effect, behavioral finance, asset pricing, low beta, skewness of returns

*All authors are from University of Bremen, Department of Finance, Max-von-Laue-Str. 1, 28359 Bremen, Germany.
Corresponding author: Ulrich J. Hammerich (Tel.: +49 421 218 66727).
E-mail addresses: hammerich@uni-bremen.de (U. J. Hammerich), cfieberg@uni-bremen.de (C. Fieberg), poddig@uni-bremen.de (T. Poddig).
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1. Introduction

Since the paper of Sharpe on "Major Investment Styles" (Sharpe, 1978) much research has been conducted on investment strategies and asset pricing models based on sorting criteria. Consequently, five major, legitimate investment styles became evident in the meantime: value/growth (Stattman, 1980; Rosenberg et al., 1985; Fama and French, 1998), size (see, e.g., Banz, 1981; Reinganum, 1981; Brown et al., 1983; Keim, 1983; Lamoureux and Sanger, 1989; Fama and French, 1992; Heston et al., 1999; Rouwenhorst, 1999), momentum (Jegadeesh and Titman, 1993; Carhart, 1997), liquidity (Amihud and Mendelson, 1986; Amihud, 2002; Ibbotson et al., 2013), and volatility (e.g., Ang et al., 2009). Their respective construction is quite simple; nevertheless, they displayed (and for the most part still display, see, for example, Fama and French, 2012) high returns on international markets lasting over decades when applied as investment styles and contribute explanatory power in asset pricing models. Despite their simplicity, considerable debate persists concerning the origins and reasons of their outperformance and explanatory power.

An even simpler sorting criterion, if not the simplest at all, is the nominal price. Perhaps because it looks too simple to be relevant, (nominal) price as an investment style remains quite disregarded in the literature. Seguin and Smoller (1997) document a higher mortality rate for lower-priced stocks than for higher-priced stocks examining a sample of 5,896 NASDAQ stocks between 1974 and 1988 and report that mortality is not related to market capitalization. Furthermore, investors "are not adequately compensated for this additional mortality risk, earning lower risk-adjusted rates of return on portfolios of lower-priced shares than on portfolios of higher-priced shares." (Seguin and Smoller, 1997: p. 333)

Recently, Singal and Tayal (2017) find that (explicitly) controlled for size via orthogonalization, high residual price stocks significantly outperform low residual price stocks by an average raw return of 6.29% per year and by an annualized 4-factor abnormal return of 4.53% on the US stock market from 1963 to 2015. However, regarding raw returns without controlling for size, they find no significant difference. Additionally, they find evidence, that high price stocks have lower beta, lower idiosyncratic volatility, lower idiosyncratic skewness (see also Brandt et al., 2010 and Birru and Wang, 2016), and lower Amihud's (2002) illiquidity (i.e., higher liquidity) than low price stocks.

Providing consistent findings, we empirically investigate the relevance of nominal prices when applied as an investment style on the German stock market and explain price portfolios excess returns (built via price deciles) applying the CAPM, the 3-factor model, and a 4-factor model (Fama and French, 1993; Carhart, 1997).

We choose a German sample for three reasons. First, articles on the price effect regularly concentrate on the US stock market and find ambiguous evidence: recent papers like Singal and Tayal (2017) report findings in favor of high-priced stocks, whereas older papers like Blume and Husic (1973) marked the existence of a low-price effect. We try to resolve this discrepancy by testing the price effect on another internationally prominent stock market, i.e., providing (real) out-of-sample evidence.

Second, and most important, several amendments of the German stock market law in the mid to late 1990s led to a dramatic increase of nominally low-priced stocks on the German stock market amplifying the relative difference of nominal prices of high-priced and low-priced stocks. We can regard these amendments as events to provide further evidence if there is any kind of price effect dependent on nominal price *per se*, as we can expect the effect to get stronger or become evident at all after the middle of the 1990s due to the higher relative price differences of stocks in general. To our knowledge, such law amendments leading to dramatic, countrywide face amount changes and in turn to drastic reductions of nominal stock prices are rare in the international context, especially for prominent stock markets. In the US, for example, mean nominal post-split stock prices quite constantly stay in the $ 30 area since several decades, with an average split ratio of about 2-for-1 (Baker et al., 2009) leading to a very limited (pre-split/post-split) price contrast especially compared to typical nominal price reductions (conversion factor 1:10) due to face amount changes in Germany in the mid-1990s.

Third, in contrast to the US and many other countries like, e.g., Japan, Germany has a permanent low percentage of individual shareholders regarding the total population. Since, on average, individual investors prefer lower priced stocks and institutional investors prefer higher priced stocks (see, e.g., Gompers and Metrick, 2001 and Kumar and Lee, 2006), we expect, *ceteris paribus*, a potential high-price effect (high-priced stocks outperform low-priced stocks) in Germany to be generally weaker than in countries with higher stock market participation of individual investors. Following this argument, a German sample underestimates the demand for low-priced stocks and consequently their prices in comparison to other stock markets. Simultaneously, the returns of low-priced stocks are expected to be relatively high, leading to an underestimation of the magnitude of the (high-)price effect. Hence, a German sample challenges the significance of a potential (high-)price effect to a high degree and renders it a primary choice for testing the robustness of the price effect on a prominent non-US market.

Furthermore, literature still remains at variance *why* nominal prices of stocks should be relevant for investors' decisions in the first place, often referring to a perceived increased upside potential of low-priced stocks (Baker et al., 2009; Green and Hwang, 2009; Kumar, 2009). Also why (individual) investors' perceptions and future expectations concerning skewness and performance differ with nominal price is investigated. Addressing this issue, Birru and Wang (2016) find a systematic investors' overestimation of skewness and performance for low-priced stocks.

Freshening the discussion, we first describe and discuss several as yet neglected potential (multidimensional) explanations, especially concerning price related aspects influencing the desirability of stocks, as well as tax and cash management issues, leading to an expected outperformance and better price stability of high-priced stocks relative to low-priced stocks.

In the second part, the main hypothesis of the paper, that high-priced stocks outperform low-priced stocks on the German stock market is tested empirically. Using all traded German stocks from 1994 to 2016 as initial (raw) dataset (about 2,000 stocks), it is particularly investigated if there is a significant return difference between the cheapest 10% (Portfolio 1, in the following P1) and the most expensive 10% stocks (Portfolio 10, hereafter P10) in the dataset. The findings suggest that there is a statistically significant difference in the returns in favor of high-priced stocks. Moreover, the Sharpe ratios as well as the standard deviations show a very robust significant difference concerning P1 and P10 (P10 has a lower standard deviation of returns than P1 and at the same time higher mean returns, thus a much higher Sharpe ratio). Consequently, if an investor scales up the volatility of P10 (e.g. via leverage) to the same level of P1, the return difference in favor of P10 would be dramatically higher. Or, on the other hand, if an investor scales down the return of P10 to P1 levels, same returns as P1 at an even lower level of volatility could be achieved. Representing a downside of investing in high price stock portfolios, the skewness of the returns of P10 is less favorable as to investors' preferences, being skewed to the left.

Additionally, the CAPM and a Carhart (1997) 4-factor model show that high-priced stocks on average are low beta stocks and have positive, very significant coefficients concerning the Small Minus Big (SMB) and Winner Minus Loser (WML) factor. Low-priced stocks on the other hand are likely high beta stocks and feature a highly significant, comparatively very high, positive factor loading for SMB, but a very significant negative factor loading on WML.

The findings are also subject to several robustness tests based on size, skewness of returns, momentum, and volatility (double) sorts. The price effect (high-priced stocks generally outperform low-priced stocks) stays alive for the most part, revealing interesting links to these sorting criteria: the price effect appears to be steady/especially strong for low, medium, and medium to high sized stocks, for stocks with medium prior 5-year skewness and medium prior 36-month return volatility as well as for prior one-year low to medium momentum stocks, rendering the price investment style a good candidate for generating additional alpha in a multi-investment style portfolio management setting and at the same time reducing return volatility, due to its very robust, low standard deviation of returns. For example, when double sorting for price and momentum, high price/high momentum portfolios yield at least the same returns as high momentum (only) portfolios, at the same time having lower standard deviations of returns.

Besides the evidence for price as an independent investment style (in spite of its strong connections to other styles) and our multidimensional framework depicting possible reasons for its legitimacy, we are able to make another main contribution (due to our German dataset): we document a dramatic change of the price effect from a significant low-price effect between 1973 and 1994 to a significant high-price effect since 1994 and identify the introduction of a law amendment regarding face amount changes in that year as turning point and triggering event.[55] We further underpin our conclusion that price per se is relevant for investors' decisions and consequential for stock returns by conducting price quantile ratio regressions and Fama-MacBeth (1973) cross-sectional regressions.

The following of the paper is structured as follows: Section 2 drafts multidimensional properties (i.e. disadvantages) of high-priced stocks, showing why and how high-priced stocks should be (fundamentally) underpriced relative to low-priced stocks and therefore are prone to outperform the latter. In Section 3, we test the main hypothesis, that high-priced stocks outperform low-priced stocks on the German stock market. Starting with a short description of the used datasets, the methodology and the data preparation is specified. Following, the findings concerning the performance of "price" as an investment style are presented and in Section 4 the outcomes of the asset pricing models explaining price portfolio excess returns are summarized.

[55] International tests of the price effect suggest that there are few country-specific stock markets besides Germany, where similar dramatic inversions of the price effect can be found. Furthermore, apart from the size effect, inversions of, e.g., the value and momentum anomaly are very rare or even non-existent in international stock data. This further underlines the unique characteristics of our dataset for investigating the origin of a (possible) price anomaly (and in turn reasons for inversions of anomalies in general).

Section 5 spotlights the impact of face amount changes on the price effect. Section 6 conducts robustness tests and Section 7 concludes.

2. Characteristics of high-priced stocks

In this section, we outline our multidimensional framework leading to our main hypothesis, that other things being equal, high-priced stocks generally outperform low-priced stocks and show lower volatility. We sketch several aspects, properties, and implications of nominal stock prices, leading to an overvaluation of low-priced stocks relative to high-priced stocks and thus to an outperformance of the latter. The discussed characteristics, however, are not limited to the German market only, but are also expected to generally hold in an international context. We refer to this framework and its implications in the later sections.

2.1 Bargain hunter deterrence

Everyday consumers are trained to identify bargain buys in the (local) store as well as (and even more) on the internet (Grewal et al., 2003). A main buying criterion is the price of a product or a service (Lichtenstein et al., 1993). Although there are cultural differences (see, for example, Lee, 2000), one can assume that a ceteris paribus product/service that is lower in price should always be preferred compared to the same/similar product/service offered at a higher price. When there are price discrepancies, the causes are often quite reasonable, like differences in (perceived) quality, brand name glamour (see, e.g., Aaker, 1996), security standards, performance, reliability, and warranty. Although price seems to have a positive effect on perceived quality, it has at the same time a negative effect on perceived value and willingness to buy (Dodds et al., 1991).

Due to the daily trained bargain hunting, we expect consumers to be unlikely able to (consciously) wipe off their partly in years of consumption and socialization shaped (see, e.g., John, 1999), partly inherent dispositions completely when deciding which stocks to buy.

However, when an investor looks at a list of stocks neither their quality and their properties can be compared at first glance nor can the investor identify bargain buys by means of price differences and sales discounts of similar stocks.[56] First of all, there are no sales discounts at the stock market comparable to store sales discounts (though as a shareholder one can buy new shares at a discounted price during a capital increase, at the same time ones shares dilute). Secondly, the nominal prices of stocks are rather arbitrary (dependent on the ratio of market capitalization and number of shares) and can be adjusted via stock splits and reverse stock splits. The execution of stock splits is often driven by the rationale to increase the interest of potential investors in the stocks and to move the stock into a better trading range (Conroy and Harris, 1999; Dyl and Elliot, 2006), revealing the awareness of stock corporations' managers concerning the "irrational" importance of the nominal prices of their stocks for (potential) investors (see, e.g., Baker et al., 2009).

Singal and Tayal (2017) plastically show the relevance of the price as buying criterion at the stock market comparing pre-split returns and post-split returns. They find consistently lower post-split returns relative to a control group. Further underlining the importance of the nominal price for investors, Birru and Wang (2016) find evidence, that expected skewness increases around the ex-date, but not on the day of the stock split announcement, pointing to the explicit relevance of the price for investors' perceptions and expectations: "The increase of RNSkew around the ex-date instead of the announcement date is consistent with investors reacting only to the change in stock price and inconsistent with an information signaling story." (Birru and Wang,

[56] Potential bargain buys at the stock market are generally very difficult to identify (for example using sophisticated methods of business valuation and analysis). According to the efficient market hypothesis (Fama, 1970), though, there must not exist any identifiable bargain stocks at all using public information or even insider information, since stock prices reflect all available information at any time.

2016: p. 580) This fits very well to the argumentation of this paper, that diverse handicaps (see Section 2; this section) of high-priced stocks cause their outperformance, since these handicaps diminish not until the ex-date, but are still present on the day of the split announcement. Wulff (2001) takes the same line, but uses face amount changes instead of stocks splits on the German stock market (see Section 5) for an event study to investigate ex-date and announcement date returns. He finds (especially for the time frame 1994 to 1996) significantly higher returns on (and around) the ex-date, but not on the announcement date. However, regarding the time frame of 11 to 30 days after the ex-date, (cumulative) abnormal returns of stocks of firms which reduced their face amounts (and in turn their nominal stocks prices) become significantly negative. We find this finding to be consistent with our argumentation in this section, as a *realized* price reduction attracts investors, leading to higher prices and higher returns in the very short-term, but ends up in lower returns due to overvaluation when time frames are increased.

In general product marketing, the reference price (that is, e.g., the price of the same/similar product elsewhere, the former price of a product before a price discount or advertisers' regular price claims) plays a major role in consumers buying intentions (Urbany et al., 1988; Lattin and Bucklin, 1989; Grewal et al., 1998; Mazumdar and Sinha, 2005). Since the properties of different stocks are difficult to compare (see above), consumers could tend to concentrate on easily comparable characteristics like the (difference in) price, subsuming the other, difficult to interpret and classify properties under the common, indifferent general category "stock" or in other words ignoring the other difficult to interpret characteristics as "noise". In this framework, the prices of high-priced stocks would serve as external reference prices (Alford and Biswas, 2002), increasing the perceived value of low-priced stocks and creating the illusion that they are bargain buys. Past prices of stocks would be internal reference prices. Since low-priced stocks generally suffer from a bad/negative (past) momentum (see Table 2), past prices of low-priced stocks tend to be higher than current prices, aggravating the bargain buy illusion. On the other hand, high-priced stocks typically exhibit good/positive (past) momentum, leading to higher present prices in relation to past prices, seemingly rendering high-priced stocks a bad buy.

Based on these aspects, in conjunction constituting the bargain hunter deterrence argument, potential (individual) shareholders should be more likely to take notice of, inform themselves about, talk about and eventually buy nominally cheap(er) stocks rather than nominally expensive ones (see, e.g., Shiller and Pound, 1989 concerning the major influence of talking about stocks with peers on the actual buying decisions of individual investors).

Empirically confirmed, individual investors indeed prefer low price stocks (*why* remains unclear in the literature), which typically are also small size stocks having lottery-like characteristics (Schultz, 2000; Fernando et al., 2004; Dyl and Elliot, 2006; Kumar and Lee, 2006; Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011; Bali and Murray, 2013; Boyer and Vorkink, 2014; Eraker and Ready, 2015). This difference in interest and demand of individual investors due to the nominal prices of stocks is an aspect capable to lead to a fundamental overpricing/underpricing of cheap/expensive stocks, in reality rendering the expensive stocks the cheap ones. Seguin and Smoller (1997) and Singal and Tayal (2017) affirm this conclusion documenting a positive relation of share price and subsequent returns. In addition, this "preference of low price stocks by individual investors might increase the intensity of noise trading and result in increase in volatility of low price stocks." (Singal and Tayal, 2017: p. 14) In Section 3 these findings receive further confirmation, showing the lasting validity of Seguin and Smoller's (1997) evidence two decades later on the German stock market.

However, since institutional investors and mutual funds on the other hand, avoid investing in low price stocks and prefer high price stocks (Falkenstein, 1996; Gompers and Metrick, 2001; Kumar and Lee, 2006; Fernando et al., 2012; Singal and Tayal, 2017), the strength of this argument also depends on the individual to institutional shareholder ratio of stocks, tending to be stronger for stocks from countries with high participation of individual shareholders like the US and weaker in countries with low percentage of individual shareholders like Germany (7% of total population in 2016).[57]

2.2 Tax reduction handicap and cash management

Apart from the behavioral explanations of the first section, in the next point we outline advantages of (nominally) low-priced stocks and therefore disadvantages of (nominally) high-priced stocks when exploiting a tax-free amount/tax-free allowance or reducing taxable capital gains by selling stocks below purchase price.[58] Since an investor gets more shares for the same amount of money when buying a stock with a low (nominal) price compared to a stock with a high (nominal) price, the investor is able to control tax debts more efficiently.[59] This is due to the indivisibility of shares restraining the investor from buying or selling fractions of shares.

Since low-priced stocks are more practical for tax debt reduction purposes they should, at least based on this indivisibility argument, be more likely to be sold at the end of the (fiscal) year and consequently capable to rebound in January (Branch and Chang, 1990). Indeed, Singal and Tayal (2017) find that low-priced stocks perform much better than high-priced stocks on January and that low price loser stocks are likely to rebound in January.

[57] See, e.g., http://www.dai.de/en/what-we-offer/studies-and-statistics/studies.html

[58] In Germany, since 2009, every individual investor has a yearly tax-free amount of € 801 on income upon investments (§ 20 Abs. 9 EStG). Additionally, there is a general tax allowance of € 8,652 (in 2016) on income (§ 32a Abs. 1 EStG). Also since 2009, capital gains from selling stocks can only be applied against losses from selling stocks (§ 20 Abs. 6 EStG). In the UK for example, the personal tax-free allowance for capital gains amounts £11,100 (for 2015/16) and in the USA the personal exemption is $4,050 (in 2016), with reduced taxes on long-term capital gains. As in Germany, in the UK and the USA, (individual) investors can reduce their taxable income by realizing capital losses.

[59] The argument is especially relevant for German individual investors, having a special yearly tax-free amount (see footnote 58). For investors of other countries, naturally the country-specific general tax-free allowances/exemptions or capital gain tax amount deduction possibilities via capital loss realization are more relevant.

The concealed tax advantages of low-priced stocks would justify another price premium and vice versa a rising price discount the higher the price of a stock (resulting in a return premium), since it gets increasingly difficult to exploit tax allowances and tax-free amounts or to manage capital loss compensation and capital gain tax reduction regulations efficiently the higher the stock price.

Furthermore, high-priced stocks are not only less reasonable to sell due to tax issues, but also if one needs a particular amount of cash or if one wants to adjust the portfolio's stock-to-cash ratio. This is based upon the fact that it is easier to exactly get the desired amount when one holds many shares of a company traded at a low price and wants to sell them. On the other hand, of course, a given amount of investment is allocable more efficiently buying low-priced stocks, showing an additional investment advantage of low-priced stocks. Consequently, this argumentation implies less selling interest and selling transactions (and, of course, due to the inherent handicaps also less buying interest and buying transactions) of high-priced stocks, leading to higher stability, less (idiosyncratic) volatility, and less (idiosyncratic) skewness of their share prices (cp., for example, Singal and Tayal, 2017), but (at least based on the forgoing argumentation) also to less liquidity of the shares.

2.3 Investment properties

Some stocks are not only high-priced, but prohibitive for many (individual) investors.[60] First, the trading volume and thus the liquidity of *very* high-priced stocks is typically very low (compared to lower priced stocks).[61] Consequently, *very* high-priced stocks could benefit from an

[60] The prime example is certainly the Berkshire Hathaway Inc. Class A stock (currently traded at a price of about $300,000 per share).

[61] Since *high*-priced stocks are likely also bigger stocks (in respect of size, see Table 2), which in turn are likely highly liquid, the following argument is limited to *very high*-priced stocks.

illiquidity premium (Amihud, 2002), partly explaining their (expected and documented) outperformance. Since then, on the one hand, nominal stock prices would be a major factor for the liquidity of stocks in the extremes, the success of "liquidity as an investment style" (Ibbotson et al., 2013) could be traced back at least partly to a nominal price effect. On the other hand, the opposite is unlikely, as the constitution of returns (and thus share prices) is not explained by liquidity (bid-ask spread) in the presence of the price level.[62] In either case liquidity would be a proxy for share price and vice versa.[63]

However, since *less* high-priced stocks still outperform (see, e.g., P8 in Table 3) and generally have a higher liquidity than low-priced stocks (thus not being able to benefit from an illiquidity premium), illiquidity cannot be the main source of their outperformance.

Relating to size, high-priced stocks are more likely associated with bigger sized companies (see Table 2), not capable of profiting from the size effect (small stocks outperform big stocks), first documented by Banz (1981). But then, especially on the German (and European) stock market, the size effect cannot be empirically confirmed in this paper (see Table 1) and in other recent papers (e.g. Artmann et al., 2012; Fama and French, 2012; Fieberg et al., 2016), anyway.

Another unique characteristic of high-priced stocks is that the number of (potential) shareholders of (very) high-priced stocks is limited,[64] since many (individual) investors simply do

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[62] Actually Brennan and Subrahmanyam (1996: p. 443) find that "*the explanatory power of the bid-ask spread appears largely to be due to the effect of (the reciprocal of) the price level. Indeed, the coefficient of the spread is not significant in the presence of the price level variable and our cost of illiquidity variables.*"

[63] Brennan and Subrahmanyam (1996: p. 443) *"… hypothesize that the spread is proxying for a risk variable associated with price level or firm size that is not captured by the Fama-French three-factor model.*" And, Brennan et al. (1998) for example, use share price as a measure of market liquidity.

[64] Inversely, Singal and Tayal (2017: p. 14) find that "*the number of shareholders is almost seven times higher for low price stocks than for high price stocks …*" potentially increasing the probability of speculative bubbles. This limitation of shareholders is also due to the lower number of shares outstanding for high-priced stocks compared to low-priced stocks (ceteris paribus). For example, a reverse stock split goes hand in hand with a reduction of outstanding shares (and a higher share price), at the same time further limiting the maximum (theoretical) number of shareholders.

not have the required "small money" to merely buy one share. Logically consistent, this is at least part of the reason why individual investors spurn high-priced stocks (cp. Section 2.1). They simply cannot afford to buy them and additionally would be constantly reminded to be too poor, having them on their purchase/wish list nevertheless. To dodge suffering from this mental harm, individual investors could be encouraged to ignore high-priced stocks in the first place. In the less exaggerated cases (e.g., Alphabet Inc. with a current price per share in the high three-digit/low four-digit U.S. dollar region), the (individual) investor could be deterred to buy the stock because of diversification desires and/or savings plans issues. Since diversification plays a major role in reducing portfolio risk (Markowitz, 1952), e.g. measured by standard deviations of returns or value at risk, many individual investors have a rational incentive of investing in lower priced stocks to benefit from the diversification effect.

These "artificial" limitations of the number of (potential) shareholders of high-priced stocks may on the one hand lead to a limited information interest concerning the stocks, less interpersonal communication about the stocks and thus less actual buying decisions and a lower bubble probability.[65] On the other hand the high price likely renders the stocks inappropriate for possible market price manipulations and fraud ultimately harming shareholder value, since high-priced stocks are mostly stocks with a high market capitalization (see Table 2) requiring more capital to significantly "move" the stock price. Furthermore, low-priced stocks could have more upside potential in the perception of individual investors (see, e.g., Green and Hwang, 2009), facilitating fraud and market manipulation success.[66]

Summed up, we state that these aspects decrease the probability that high-priced stocks are fundamentally overpriced at an arbitrary point in time and therefore more likely bargain buys than low-priced stocks.

[65] "*High sentiment – high price stocks strongly outperform high sentiment – low price stocks indicating that sentiment plays a significant role in driving returns and that investors are more likely to bid up the values of low price stocks.*" (Singal and Tayal, 2017: p. 23)

[66] According to Brandt et al. (2010) some firms intentionally preserve high stock prices to deter speculative traders from buying the stocks.

3. Empirical findings

In this part, using data from the German stock market, we spotlight the empirical performance of high-priced stocks and test the general hypotheses (high-priced stocks show high returns and low volatility) derived from our argumentation in Section 2. Descriptive statistics and asset pricing factor models (Section 4) are calculated and applied to get a more profound insight concerning the explanation of the empirically observed investment performance characteristics like (excess) returns and standard deviations of returns. Also, several price cut-offs (see Table A.1 in the appendix) and portfolio sorts (Section 6) are used to test the robustness of the price effect.

3.1 Data

We retrieve the datasets from Thomson Reuters Datastream. The (raw) stock universe contains all German stocks[67] traded between 31.08.1994 and 30.12.2016 (T=269 months, monthly dataset). We set the start date of our (main) sample to August 1994, since an influential stock market law amendment regarding face amount changes is introduced in this month having a dramatic impact on the relative differences of nominal share prices on the German stock market in the subsequent years (see Section 5).[68] Unadjusted Prices time series are downloaded to perform the portfolio sorts and the Total Return Index is used for performance computation of the "price portfolios". Market Value and Common Shareholders' Equity time series of the stocks are downloaded also to calculate the Small Minus Big (SMB) and High Minus Low (HML) factors in the 3-factor and 4-factor model (Fama and French, 1993; Carhart, 1997). After matching of the

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[67] With selection criteria: Primary Quote and Major Security = "Yes" and Exchange = "Deutsche Boerse AG"

[68] Brückner (2013: p. 160) finds a survivorship bias in Datastream's German stock market data before 1990 and an omission bias, that is, back then the coverage for small stocks is a lot less than for large stocks. Also, due to these problems, data before 1990 is excluded in the (main) study.

four mentioned datasets via Datastream IDs and exclusion of finance sector[69] stocks, N=973 stocks are left in the dataset, constituting the final stock universe. The 1-month deposit rate[70] is used as the risk-free interest rate to calculate the excess returns.

3.2 Methodology and data preparation

To avoid major distortions of the findings e.g. due to massive return outliers and erroneous data, for example found in the Total Return Index dataset concerning penny stocks (see Ince and Porter, 2006), several price thresholds/price cut-offs[71] are used (5, 4, 3, 2.5, 2, 1.5, 1, 0.5, and € 0, i.e. non-exclusion) to exclude very low-priced stocks and penny stocks (being likely also very small-sized; see Table 2) from the stock universe before the portfolio sorts are performed and the factors are built. Inactive stocks are also omitted and are defined as stocks having discrete monthly returns of zero four months in a row before t.[72] The stock exclusions

[69] Stocks from Sectors Banks, Financial Services, Life Insurance, Nonlife Insurance, Real Estate Investment and Services, and Real Estate Investment and Trusts are omitted (to facilitate comparability of calculations referring to book-to-market ratios and to stay in line with standard asset pricing literature).

[70] BD EU-Mark 1M Deposit (FT/TR) – Middle Rate

[71] Ince and Porter (2006) exclude any stocks below $1: "*The TDS practice, before decimalization, of rounding prices to the nearest penny can cause nontrivial differences in the calculated returns when prices are small. To avoid this type of error, we drop all observations in both the TDS and CRSP samples when the end-of-previous-month price is less than $1.00.*" (Ince and Porter, 2006: p. 473). The additional advantage of a price cut-off lies in the simultaneous exclusion of extreme return outliers: "*This screen also removes several anomalous observations where a very low priced equity dramatically increases in price and market value, which results in an implausible daily return as large as several thousand percent. Alternative price screens as low as 0.10 or 0.25 work almost as well in mitigating both problems.*" (Ince and Porter, 2006: p. 473, fn. 3) For robustness test purposes of the findings, in this study centered on the relevance of nominal stock prices, the use of several price cut-offs seems to make sound sense.

[72] Datastream's defunct lists for the German stock market are incomplete (Brückner, 2013: p. 154), making it necessary to implement an own effective dead stocks filter. The choice of a four-month time frame is rather

using the price cut-offs and the inactive stocks filter are carried out monthly anew, including filtered stocks again if the conditions are met in the subsequent months, respectively.

After this step, every month t $(t = 1, \ldots, T-1)$, we sort the listed/existing German stocks into price decile portfolios depending on their unadjusted prices, respectively. Following, the discrete monthly returns are calculated for any active stock j $(j = 1, \ldots, J;\ J < N)$ in the ten portfolios via the Total Return Index (RI) of the stocks $(r_{jt} = (RI_{jt}/RI_{jt-1}) - 1)$ for each month t $(t = 2, \ldots, T)$. Arithmetic means of the equal weighted monthly returns of the stocks in each of the ten portfolios finally define the ten price decile portfolio returns on each month in the dataset.

The CAPM, the 3-factor model, and the 4-factor[73] model are designed in the tradition of Fama and French (1993) and Carhart (1997). The value weighted German stocks serve as market proxy. Excess returns (RMRF) are calculated via the difference of the monthly returns of the market proxy (RM) and the monthly yields of the risk free interest rate (RF). r_{it} is the monthly return of price decile portfolio i $(i = 1, \ldots, 10)$ in excess of the one-month deposit rate. The corresponding regression equation of the CAPM therefore is

$$r_{it} = \alpha_i + \beta_i RMRF_t + \varepsilon_{it} \qquad t = 1, 2, \ldots, T \qquad (1)$$

For SMB and HML, we construct six portfolios similar to Fama and French (1993). The six value weighted intersection portfolios (SL, SM, SH, BL, BM, BH) are created via the small stocks portfolio (S) and the big stocks portfolio (B) concerning market capitalization (separated by the median of the market capitalization of all listed/existing German stocks at month t) and

arbitrary, but should represent a good compromise between too long and too short, thus sorting out not too less, but also not too many stocks showing no price movement.

[73] We prefer a traditional 4-factor model including an additional momentum factor to the recently presented 5-factor model (Fama and French, 2015) with added investment and profitability factors (but without momentum factor), since momentum plays an important role in explaining price portfolio's (excess) returns.

the low, medium, and high portfolios built by means of the ratio of Common Shareholder's Equity and Market Value of the stocks (stocks with negative Common Shareholder's Equity are excluded) with a lag of six months (t-6) to ensure that Common Shareholder's Equity of the previous (business) year is known at the time of portfolio construction. The high portfolio contains all stocks with the highest 30% book-to-market equity (value stocks), the low portfolio includes the lowest 30% book-to-market equity stocks (growth stocks), and the medium portfolio holds the 40% stocks that lie between the two extremes. The intersection portfolios are rearranged yearly at the end of June and value weighted portfolio returns are calculated monthly (stocks that become inactive between rearrangements yield zero returns and are excluded after). SMB is the difference, each month, of the average monthly returns of the three "small" portfolios (SL, SM, SH) and the average returns of the three "big" portfolios (BL, BM, BH). HML is the difference, each month, of the average monthly returns of the two "high" portfolios (SH, BH), that is the two portfolios with high book-to-market equity and the average monthly returns of the two "low" portfolios (SL, BL) in respect of book-to-market equity.

The WML factor (PR1YR) is defined like in Carhart (1997): PR1YR is constructed "as the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month." (Carhart, 1997: p. 61, fn. 3) The portfolios are re-formed monthly. r_{it} is the monthly return of price decile portfolio i ($i = 1, \dots, 10$) in excess of the one-month deposit rate, again. The 4-factor model regression equation consequently is (see Carhart, 1997: p. 61):

$$r_{it} = \alpha_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + p_i PR1YR_t + \varepsilon_{it} \qquad t = 1, 2, \dots, T \qquad (2)$$

Table 1 contains performance summary statistics of the constructed factor portfolios to get a first impression of the relevance of the well-established investment styles in the dataset (in the following, for simplicity, the risk-free rate is set zero when calculating Sharpe ratios):

Table 1: Factor portfolios performance, 31.08.1994 to 30.12.2016

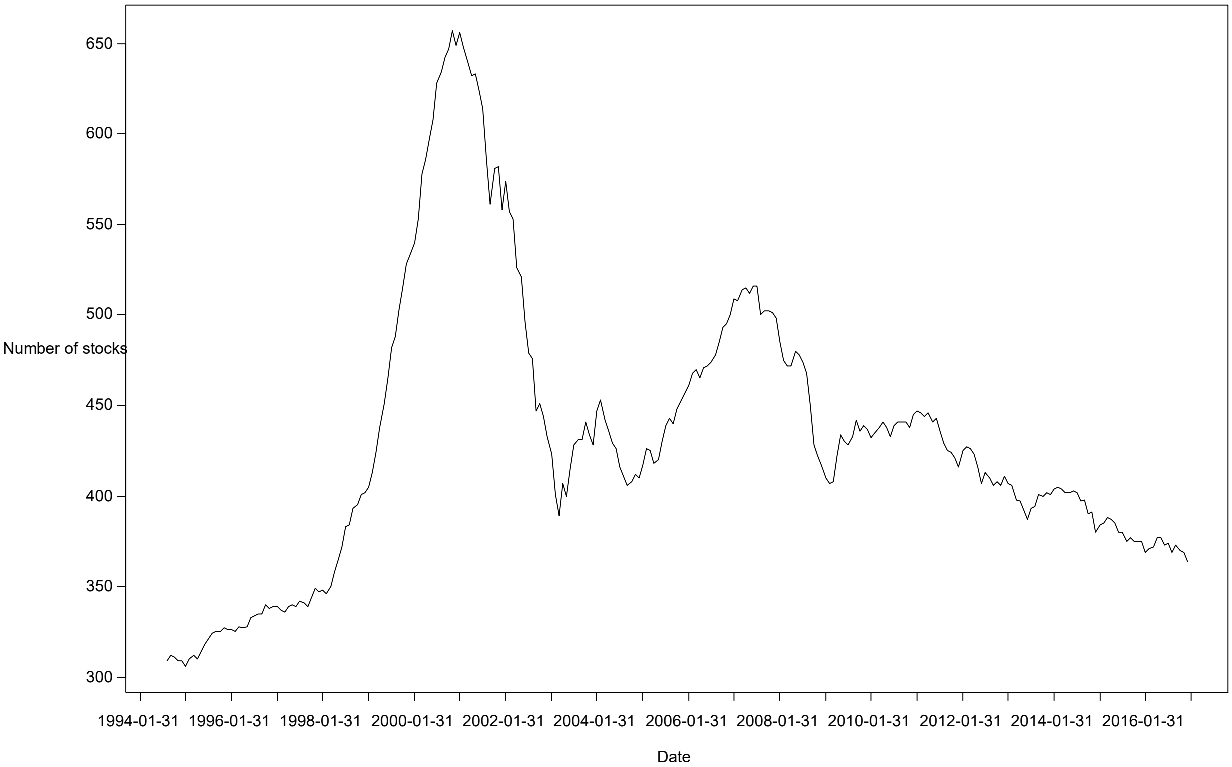
Factor Portfolio	Monthly Return (μ)	Std. Dev. (σ)	Sharpe ratio (S)	p-value μ=0
RM	0.77%	5.24%	0.148	1.61%
SMB	-0.59%	3.67%	-0.160	0.91%
HML	0.66%	3.78%	0.176	0.43%
PR1YR	1.78%	4.41%	0.403	0.00%

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. RM is the market proxy, i.e. the active, value weighted German stocks re-assessed each month. SMB and HML are the factor-mimicking portfolios for size and book-to-market equity as in Fama and French (1993). PR1YR is a factor-mimicking portfolio for one-year return momentum (see Carhart, 1997). The monthly return column displays the mean of the monthly discrete returns of the factor-mimicking portfolios, respectively. Std. Dev. is the standard deviation of the monthly returns; Sharpe ratio is the ratio of the monthly mean returns and the standard deviation of returns. The p-values are derived from a t-test with the null hypothesis that monthly portfolio returns are equal to zero.

The (classical) size effect (SMB) is not only non-existent, but inversed in the used German stocks dataset. The value (HML) and momentum (PR1YR) effects, in contrast, show highly significant, positive monthly returns with a (considerably) above market proxy (RM) mean return (or for value slightly lower) and, like SMB, below market standard deviations of returns. The findings are robust and exhibit low sensitivities regarding the other stock excluding price thresholds.

Figure 1 shows the number of active stocks in the time frame 31.08.1994 to 30.12.2016 with inactive/dead stocks and stocks with nominal prices below € 2 identified and excluded each month, respectively. Beginning with the second lowest number of active stocks (309) and peaking with 657 stocks on 30.11.2000, 364 active stocks are left on 30.12.2016. Considering the minimum number of active stocks, each price decile portfolio contains at least 30 stocks in each month of the dataset.

Figure 1: Number of active German stocks, 31.08.1994 to 30.12.2016



3.3 "Price" investment style performance

In this section, we present the main results of the study concerning the price effect, applying a rolling backtest of price as an investment style. Ten, equal-sized portfolios are built every month based on the active stocks in the dataset (except those lying below the price cut-off/threshold), using the corresponding price deciles as separation factors, respectively. First of all, Table 2 shows the descriptive statistics for mean market value, mean book-to-market equity, and mean prior one year returns (PR1YR) for each of the ten price decile portfolios and each price threshold. As already mentioned in Section 2.3, high-priced stocks are on average also high market value stocks and low-priced stocks are on average stocks with low market value. Hence, with rising stock excluding price thresholds, mean portfolio market values tend to increase as well, since then more and more low market value stocks become excluded (lowest market value stocks are likely to be already excluded at lower price excluding thresholds). P10-stocks have a mean market value of about € 5 billion whereas P1-stocks market value averages stay well below € 0.5 billion for all thresholds and for most thresholds even below € 200 million.

Mean book-to-market ratios show a less linear pattern on first glance with most values below 1, being (clearly) highest for the highest-price portfolio (P10), but second highest for the lowest-price portfolio (P1), constituting a rather U-shaped pattern with a low at P7. Thus, very low-priced stocks and very high-priced stocks tend to be value stocks, whereas medium-priced stocks are rather growth stocks.

The momentum statistics are invariant and clearly positive for the high price portfolios, especially for high stock excluding price thresholds, but drop sharply for low price portfolios and low price thresholds. Likely, a selection mechanism is active due to the (return based) definition of momentum, capable of explaining the (downside) outliers especially displayed in the momentum statistics of P1 and P2 for low stock excluding price thresholds: since P1 and P2 contain the lowest 20% of stocks at time t in respect of price, it is likely that many of these stocks performed badly between t-12 and t-2, thus becoming so cheap at time t to be sorted into P1 and P2 in the first place. Inversely, P9 and P10 show exceptionally high positive momentum statistics, likely containing stocks that performed well between t-12 and t-2. In other words, (past) momentum is an important factor for the (current) nominal price of a stock.

Table 2: Descriptive statistics of the price decile portfolios

Portfolio	Thres-hold (€)	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
	5	229.3	455.5	923.6	1359.1	1258.1	1436.6	1712.3	3483.6	6190.3	4706.5
Mean	4	181.2	373.2	676.8	1054.7	1375.7	1356.9	1577.5	3110.3	5726.4	4920.9
Market	3	154.0	340.5	507.7	725.7	1352.0	1362.4	1469.7	2548.0	5353.6	5104.8
Value	2.5	134.9	308.8	473.5	633.2	1207.3	1329.3	1464.1	2220.7	5224.1	5135.8
(m)	2	120.7	295.6	449.3	532.5	982.2	1332.2	1494.4	1977.2	4993.8	5183.8
	1.5	124.9	278.0	424.7	464.6	779.8	1284.1	1502.5	1779.3	4646.7	5312.5
	1	124.5	265.1	394.7	441.1	630.9	1210.4	1449.3	1694.9	4209.9	5424.4
	0.5	107.5	263.5	382.7	410.8	526.3	1061.5	1458.1	1562.3	3776.3	5529.8
	0	84.1	247.1	362.7	376.3	447.8	651.2	1354.2	1635.4	2988.7	5574.5
	5	0.8073	0.7746	0.7324	0.6903	0.6661	0.6611	0.6076	0.7199	0.7504	1.7742
Mean	4	0.8182	0.8035	0.7512	0.7142	0.6745	0.6709	0.6192	0.7074	0.7331	1.6946
Book-to-	3	0.8587	0.8053	0.7877	0.7473	0.6901	0.6921	0.6258	0.6992	0.7228	1.6025
Market	2.5	0.8771	0.8346	0.7940	0.7590	0.7048	0.6990	0.6326	0.6922	0.7249	1.5513
(Ratio)	2	0.9292	0.8597	0.8018	0.7703	0.7309	0.7026	0.6384	0.6932	0.7189	1.5017
	1.5	0.9904	0.8897	0.8257	0.7836	0.7521	0.7057	0.6448	0.6981	0.7107	1.4561
	1	1.0260	0.9459	0.8533	0.7958	0.7677	0.7258	0.6555	0.6988	0.7047	1.4066
	0.5	1.1477	0.9993	0.8927	0.8157	0.7708	0.7607	0.6595	0.7048	0.7065	1.3499
	0	1.2435	1.3516	0.9865	0.8811	0.8046	0.7898	0.6790	0.7252	0.7070	1.2513
	5	7.98%	10.72%	10.09%	13.12%	15.38%	17.37%	18.31%	18.01%	22.40%	23.13%
Mean	4	6.12%	9.75%	9.60%	12.48%	14.35%	16.36%	18.65%	18.46%	21.96%	23.13%
PR1YR	3	3.25%	8.85%	9.90%	10.94%	13.41%	15.95%	18.41%	18.88%	21.25%	23.26%
(Return)	2.5	2.58%	6.31%	10.00%	9.95%	13.40%	16.20%	18.04%	19.06%	20.85%	23.35%
	2	0.51%	4.83%	9.21%	10.86%	11.59%	16.26%	17.75%	19.21%	20.71%	23.38%
	1.5	-1.57%	4.06%	6.47%	11.29%	11.07%	15.79%	17.37%	18.81%	20.88%	23.42%
	1	-3.45%	2.10%	5.49%	9.86%	10.71%	14.95%	17.38%	18.96%	20.80%	23.53%
	0.5	-7.26%	0.35%	4.07%	7.94%	10.81%	13.78%	17.65%	18.71%	20.52%	23.72%
	0	-13.58%	-8.05%	1.99%	5.91%	9.59%	12.18%	17.44%	18.04%	20.27%	24.06%

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). P1 to P10 are the (equal weighted) price decile portfolios. The three segments of the table show the average market values (in million Euro), book-to-market equity, and prior one year returns for each portfolio and each stock excluding price threshold (€ 5 to € 0), respectively.

In Table 3 we display the findings regarding the performance of the decile portfolios sorted by nominal prices and with < € 2 stocks excluded due to expected data distortions concerning penny stocks (Ince and Porter, 2006). A clear increase of the monthly mean returns from P1 (0.09%) to P10 (1.02%) can be observed. Reversely, the standard deviations of the monthly portfolio returns nearly monotonically fall from P1 (6.25%) to P10 (2.81%), with P4 and P8 as outliers. Accordingly, from P1 to P10, the Sharpe ratios rise even more (with a clear maximum for P10) compared to the mean returns (in relative and absolute numbers), leading to a statistically significant difference of the Sharpe ratios of P1 and P10 (p-value < 0.01%) using the Sharpe ratio equality test of Wright et al. (2014). Fitting in, the monthly mean returns are not significantly different from zero at 10% level of significance with regard to P1 to P6 (except P5), but are significantly different from zero at 1% level of significance concerning P8 to P10. Similar patterns and findings can also be observed when excluding stocks applying the other price cut-offs (see Table A.1 in the appendix).

Furthermore, the null hypothesis that the difference of the monthly mean returns of P10 and P1 (i.e. the monthly mean return of the hedge portfolio) equals zero can be rejected at 1% level of significance for price cut-off € 2 (as well as for € 5), at 5% level of significance for the price cut-offs € 1.5 and € 2.5 and at 10% level of significance for thresholds € 3 and € 4, remaining insignificant for the € 1 price threshold only. Simultaneously, the hedge portfolio (P10-P1) yields an economically large average monthly return of 0.93% (annualized 11.75%). The distribution of returns is left-skewed for P10 and the hedge portfolio (P10-P1), but skewed to the right for P1 (the other price thresholds consistently confirm this finding with threshold € 5 as a minor outlier). That is, (high) negative returns are more probable for high-priced stocks than for low-priced stocks, at least increasing the value of an investment in low-priced stocks somewhat from a risk controlling perspective placing special emphasis on avoiding drawdowns and downside risk. In case of non-exclusion of any stocks by means of a price threshold (see cut-off € 0 in Table A.1), the monthly mean return of P1 makes a big jump to roughly 3.3% (!) and the standard deviation of returns triples to about 18% in relation to the findings reported in Table 3 (as well as in reference to the other price cut-offs; see Table A.1), pointing to the mentioned probable data failures and/or extreme outliers in penny stocks time series (Ince and Porter, 2006). The findings for the other portfolios are similar to those regarding the other price cut-offs.

Table 3: Performance of the decile portfolios sorted by nominal price

Portfolio	Monthly Return (μ)	Std. Dev. (σ)	Sharpe ratio (S)	p-value μ=0	Skewness of Returns
P1	0.09%	6.25%	0.015	80.99%	0.52
P2	0.35%	5.89%	0.059	33.36%	0.01
P3	0.28%	5.32%	0.052	39.10%	-0.10
P4	0.36%	5.45%	0.066	27.76%	-0.30
P5	0.52%	5.07%	0.102	9.68%	-0.38
P6	0.35%	5.04%	0.070	25.20%	-0.26
P7	0.64%	4.53%	0.140	2.22%	-0.77
P8	0.88%	4.60%	0.191	0.20%	0.03
P9	0.80%	4.07%	0.196	0.15%	-0.58
P10	1.02%	2.81%	0.363	0.00%	-0.69
P10-P1	0.93%	5.52%	0.168	0.62%	-1.01
S(P10)=S(P1)			< 0.01%		

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. P1 to P10 are the decile portfolios created via monthly sorting by nominal, unadjusted prices. P1 contains the cheapest 10% stocks; P10 contains the most expensive 10% stocks. The monthly return column displays the mean of the (equal weighted) monthly discrete returns of all stocks in the price decile portfolios, respectively. Std. Dev. is the standard deviation of the monthly returns; Sharpe ratio is the ratio of the monthly mean returns and the standard deviation of returns. The p-values are derived from a t-test with the null hypothesis that monthly portfolio returns are equal to zero. P10-P1 gives the statistics for the hedge portfolio. Skewness of Returns reports the values of the third moment of the monthly returns for each portfolio. S(P10)=S(P1) tests the null if the Sharpe ratios of P10 and P1 are equal (see Wright et al., 2014) and displays the p-value.

4. CAPM, 3-factor, and 4-factor model

Table 4 contains the findings of the CAPM and a 3- and 4-factor model explaining the monthly excess returns of the ten price decile portfolios with < € 2 stocks excluded. The findings are again quite steady in respect of the other stock excluding price thresholds (see Table A.2 in the appendix). The beta coefficient of the CAPM (RMRF) is highly significant throughout the decile portfolios. A bell shaped pattern can be seen in the sequence of beta coefficient values of P1 to P10 with a peak for P6 and a clear low for P10. The t-statistics for beta as well as the adjusted R^2 increase from P1 to P6 and stay on a comparatively high level for P7 to P9, but drop again for P10. Matching the findings regarding the low standard deviation of the monthly (excess) returns of P10, the beta coefficient of P10 is very low (0.38), rendering P10 a low beta portfolio containing low beta stocks on average. Additionally, the positive, significant alpha of P10 (0.63%) is in line with the high (excess) return of this portfolio and cannot be explained by the CAPM. Inversely, the cheap stock portfolios show negative alphas and underperformance regarding monthly (excess) returns. The statistics of the hedge portfolio (P10-P1) confirm these results.

In the 4-factor model these findings remain visible to a large extent, at the same time reflecting the patterns of the descriptive statistics in Table 2. However, especially the SMB factor adds explanatory power to the model, despite the inverse size effect found in the data. Its coefficient starts with a highly significant, positive value for P1 and P2, gradually dropping from P2 to P10. The t-statistics of SMB show a vague bell shaped pattern from P1 to P10, nevertheless remaining positive and highly significant throughout the portfolios. The HML factor indicates (positive) significant coefficients for P1 to P3 only, showing an inconsistent (and insignificant) pattern of coefficients and t-statistics for P4 to P10. The coefficient of the WML factor (PR1YR) monotonically increases from P1 to P10 (with P9 as a minor outlier); starting with a clearly significant negative t-statistic for P1 and being highly significant and positive for P10 (see also hedge portfolio t-statistic). Finally, the adjusted R^2 increases at least moderately in the 4-factor model compared to the CAPM, boosting the goodness of fit measure for the regression concerning the hedge portfolio returns, though.

The 4-factor model cannot sufficiently explain the returns of P10 either, since the alpha is still clearly significantly positive. Also, in the 4-factor model, P1 and P2 now show (marginally) statistically significant positive alpha values. This finding is presumably linked to the strongly negative coefficient of the WML factor for low price portfolios, since in the Fama and French (1993) 3-factor model, the alphas of P1 and P2 become insignificant. On the other hand, in the 3-factor model the alphas of P8 to P10, as well as the alpha of the hedge portfolio (P10-P1), are significant at 1% level of significance (see t-statistics in Table 4), showing whopping 3-factor abnormal returns for the hedge portfolio (P10-P1) and P10 of 0.85% and 0.67% (with t-statistics of 3.01 and 5.45). We report though, that the 4-factor abnormal returns for the hedge portfolio become insignificant for the € 2 cut-off and the € 5 cut-off (Table A.2, Panel A), but show a significantly negative alpha value in case of choosing a € 1 cut-off (Table A.2, Panel B). Consequently, the inclusion of the WML factor is quite influential when explaining price portfolios (excess) returns, but also very sample-sensitive.

Table 4: Price decile portfolios statistics concerning CAPM and factor models

Performance			CAPM			3-factor model					4-factor model					
Port-folio	Excess Return	Std. Dev.	Alpha	RMRF	Adj. R-sq	Alpha	RMRF	SMB	HML	Adj. R-sq	Alpha	RMRF	SMB	HML	PR1YR	Adj. R-sq
P1	-0.05%	6.37%	-0.49%	0.71	0.345	-0.17%	1.11	1.16	0.15	0.664	0.51%	0.94	0.94	0.16	-0.40	0.720
			-1.52	*11.65*		*-0.74*	*21.01*	*14.93*	*2.20*		*2.15*	*17.46*	*12.09*	*2.59*	*-7.15*	
P2	0.21%	6.03%	-0.25%	0.74	0.421	0.07%	1.13	1.15	0.13	0.776	0.49%	1.03	1.01	0.14	-0.25	0.799
			-0.87	*13.68*		*0.40*	*27.82*	*19.12*	*2.55*		*2.61*	*23.91*	*16.29*	*2.83*	*-5.50*	
P3	0.15%	5.43%	-0.33%	0.75	0.534	-0.09%	1.06	0.89	0.13	0.792	0.18%	0.99	0.80	0.13	-0.16	0.803
			-1.41	*17.17*		*-0.58*	*29.91*	*17.09*	*2.78*		*1.04*	*25.84*	*14.51*	*2.96*	*-3.94*	
P4	0.24%	5.57%	-0.25%	0.77	0.538	0.05%	1.04	0.82	0.00	0.771	0.20%	1.01	0.77	0.00	-0.09	0.774
			-1.05	*17.28*		*0.31*	*27.38*	*14.62*	*-0.05*		*1.08*	*23.82*	*12.68*	*0.00*	*-1.96*	
P5	0.38%	5.18%	-0.10%	0.75	0.592	0.20%	0.98	0.72	-0.04	0.810	0.17%	0.99	0.73	-0.04	0.02	0.809
			-0.46	*19.29*		*1.36*	*30.53*	*15.08*	*-0.97*		*1.06*	*27.53*	*13.98*	*-0.98*	*0.46*	
P6	0.23%	5.16%	-0.27%	0.79	0.655	-0.03%	0.98	0.58	-0.04	0.801	-0.12%	1.00	0.61	-0.04	0.05	0.802
			-1.40	*22.07*		*-0.17*	*29.67*	*12.00*	*-0.89*		*-0.74*	*27.29*	*11.59*	*-0.93*	*1.44*	
P7	0.50%	4.63%	0.05%	0.70	0.650	0.25%	0.88	0.53	0.00	0.792	0.13%	0.91	0.57	0.00	0.07	0.795
			0.31	*21.83*		*1.85*	*29.20*	*11.99*	*-0.03*		*0.87*	*27.25*	*11.87*	*-0.08*	*2.05*	
P8	0.76%	4.71%	0.33%	0.69	0.604	0.54%	0.84	0.48	-0.05	0.727	0.29%	0.90	0.56	-0.06	0.15	0.740
			1.76	*19.78*		*3.44*	*23.94*	*9.17*	*-1.21*		*1.74*	*23.61*	*10.08*	*-1.33*	*3.67*	
P9	0.67%	4.16%	0.26%	0.65	0.687	0.39%	0.74	0.30	-0.02	0.745	0.16%	0.80	0.37	-0.03	0.13	0.759
			1.81	*23.73*		*2.91*	*24.83*	*6.67*	*-0.64*		*1.14*	*24.66*	*7.89*	*-0.76*	*3.98*	
P10	0.87%	2.82%	0.63%	0.38	0.501	0.67%	0.44	0.19	0.04	0.537	0.35%	0.52	0.29	0.04	0.19	0.599
			5.05	*16.05*		*5.45*	*16.15*	*4.59*	*1.16*		*2.79*	*18.39*	*7.08*	*1.08*	*6.37*	
P10-P1	0.92%	5.61%	1.13%	-0.33	0.094	0.85%	-0.66	-0.97	-0.11	0.386	-0.16%	-0.41	-0.65	-0.12	0.59	0.542
			3.36	*-5.25*		*3.01*	*-10.58*	*-10.53*	*-1.34*		*-0.59*	*-6.85*	*-7.41*	*-1.79*	*9.36*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months; effective time frame is 257 months due to the calculation of the WML factor). < € 2 stocks are excluded every month anew. The excess return column displays the mean of the (equal weighted) monthly discrete returns of all stocks in the price decile portfolios in excess of the one-month deposit rate, respectively. Std. Dev. is the standard deviation of the monthly excess returns. RMRF is the market proxy excess return: monthly return of the value weighted German stocks minus the one-month deposit rate. SMB and HML are the factor-mimicking portfolios for size and book-to-market equity as in Fama and French (1993). PR1YR is a factor-mimicking portfolio for one-year return momentum (see Carhart, 1997). See equation (1) for the corresponding regression equation of the CAPM, (2) for the corresponding regression equation of the 4-factor model and (2) without WML factor (PR1YR) for the regression equation of the 3-factor model. The t-statistics are written in italics.

5. Impact of face amount changes

5.1 Pre mid-1990s "price" performance

When we ignore the potential data distortions and have a look at the time frame 31.01.1973 to 29.07.1994 for the purpose of comparison, the picture differs (see Table 5): the mean return of the (high price) hedge portfolio (P10-P1) is now highly significantly negative (p-value of t-test with H0: $\mu=0$ is below 1%). Inversely, the mean return of a P1-P10 (low price) hedge portfolio is highly significantly positive, adding up to a monthly mean return of 0.69%. P1 generates a monthly mean return of 1.22% which is much higher than the 0.09% for the post mid-1990s dataset. Also P1's standard deviation of returns (5.16%) is only marginally higher than P10's standard deviation of returns (4.10%) as opposed to the findings for the last two decades where we find a clearly lower value for high price portfolios. This also contributes to a significant difference of the Sharpe ratios of P1 and P10 in favor of P1 (p-value 1.68%).[74] Skewness of returns also show a less consistent and robust pattern than in the newer dataset, tending to confirm the recent evidence, though (cp. Table 3).

[74] In the complete sample (1973 to 2016), the Sharpe ratio difference in favor of high-priced stocks (P10) stays alive, though (at 1 % level of significance).

Table 5: Pre mid-1990s price decile portfolios performance statistics

Portfolio	Monthly Return (μ)	Std. Dev. (σ)	Sharpe ratio (S)	p-value μ=0	Skewness of Returns
P1	1.22%	5.16%	0.237	0.02%	0.23
P2	1.00%	4.73%	0.211	0.08%	0.03
P3	1.07%	4.61%	0.233	0.02%	-0.32
P4	0.72%	4.24%	0.169	0.71%	-0.09
P5	0.86%	4.18%	0.206	0.10%	0.11
P6	0.73%	4.25%	0.171	0.62%	-0.08
P7	0.81%	3.96%	0.205	0.11%	-0.31
P8	0.48%	4.13%	0.117	6.08%	0.07
P9	0.59%	4.04%	0.145	2.04%	-0.82
P10	0.53%	4.10%	0.130	3.71%	-0.30
P10-P1	-0.69%	3.45%	-0.199	0.15%	-0.20
S(P10)=S(P1)			1.68%		

German stocks (31.01.1973 to 29.07.1994) represent the stock universe (T=259 months). < € 2 stocks are excluded every month anew. P1 to P10 are the decile portfolios created via monthly sorting by nominal, unadjusted prices. P1 contains the cheapest 10% stocks; P10 contains the most expensive 10% stocks. The monthly return column displays the mean of the (equal weighted) monthly discrete returns of all stocks in the price decile portfolios, respectively. Std. Dev. is the standard deviation of the monthly returns; Sharpe ratio is the ratio of the monthly mean returns and the standard deviation of returns. The p-values are derived from a t-test with the null hypothesis that monthly portfolio returns are equal to zero. P10-P1 gives the statistics for the hedge portfolio. Skewness of Returns reports the values of the third moment of the monthly returns for each portfolio. S(P10)=S(P1) tests the null if the Sharpe ratios of P10 and P1 are equal (see Wright et al., 2014) and displays the p-value.

5.2 Face amount changes and relative price difference

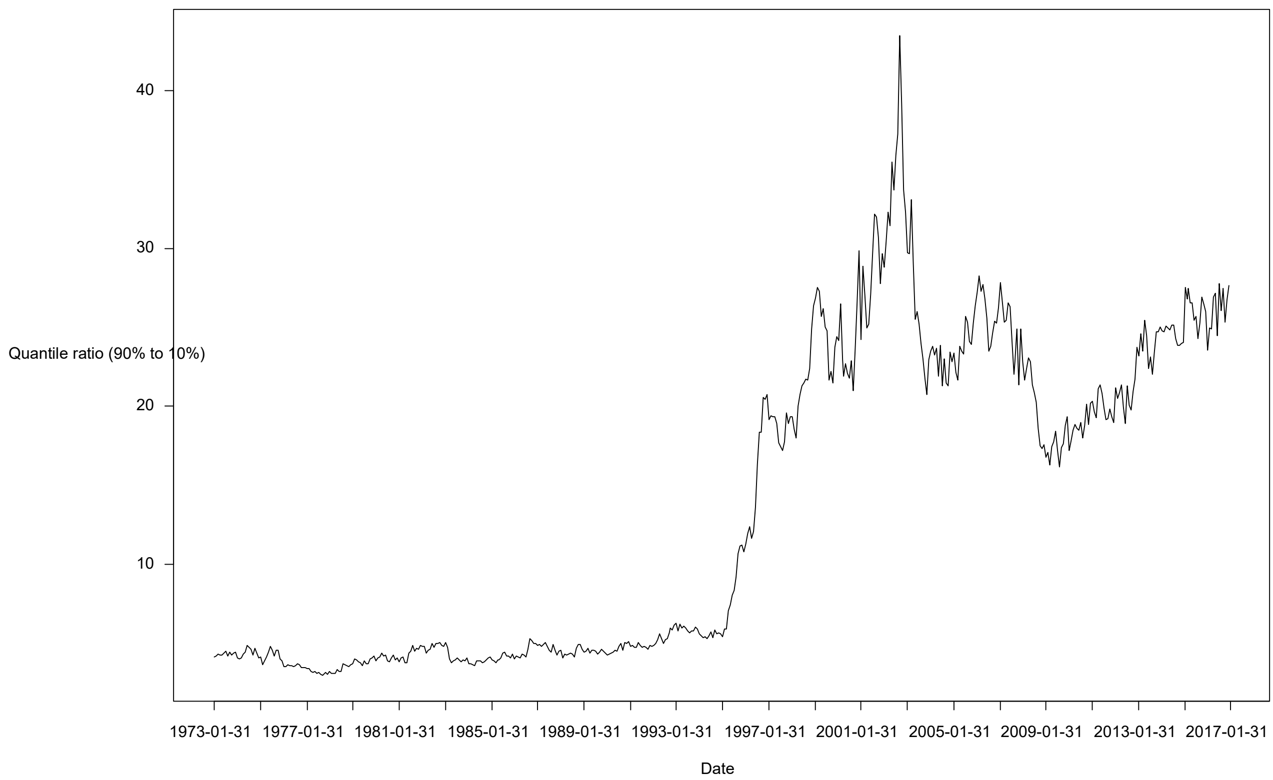
At least partly, this dramatic change in the returns of the hedge portfolios, turning a strong low-price effect into a high-price effect, could be due to several amendments of the German stock market law especially in the 1990s to increase the interest of individual investors in the stock market.[75] At that time, the minimum required face amount of a stock was reduced from 50 DM to 5 DM (equivalent to a stock price conversion factor of 1:10), resulting in face amount changes of the stocks of 95 companies from 01.08.1994 to 31.12.1996, in turn leading to a dramatic reduction of nominal stock prices throughout the German stock market with a second wave in the late 1990s in the course of the "New Market", when minimum required face amounts where further reduced to € 1 on 01.01.1999 (Wulff, 2001). Since these amendments led to the advent of many penny stocks and low-priced stocks on the German stock market for the first time, amplifying the relative difference of nominal prices of high-priced and low-priced stocks (cp. Figure 2),[76] it makes perfectly sense why high-priced stocks outperform low-priced stocks since the mid-1990s, but not in the prior decades (cp. Tables 3, 5 and 6). We base this argumentation on the increasing relevance of the described stock characteristics in respect of price for investors (see Section 2), when market-wide stock price discrepancies are higher. Furthermore, as outlined in Section 2, individual investors prefer low-priced stocks, which are

[75] See especially the "2. Finanzmarktfoerderungsgesetz" from 26.07.1994 (e.g., Wulff, 2001). This goal of these law amendments was accomplished outstandingly, as the clear increase in the number of shareholders in Germany (peaking in 2000/2001) since the mid-1990s shows (e.g., boosting the number of shareholders by over 50% from 1997 to 2000) (see https://www.dai.de/en/what-we-offer/studies-and-statistics/statistics.html).

[76] For example, in January 1973, the 10%-quantile regarding stock prices amounts to € 68.26 and the 90%-quantile is € 284.28 (90% to 10% quantile ratio of about 4.2). As of July 1999, 10%-quantiles always stay below € 10 (average of 3.38 until Dec. 2016) and remain around € 3 since summer 2001. The mean 90%-quantile adds up to € 80.99, generating an average 90% to 10% quantile ratio of about 24 between July 1999 and December 2016.

available abundantly not before the mid-1990s (for the first time), contributing to a higher demand, overvaluation, and underperformance of these in the subsequent years.

Figure 2: 90% to 10% price quantile ratio, 31.01.1973 to 30.12.2016



5.3 Sub-samples "price" performance

In Table 6, we report summary performance statistics of the hedge portfolio (P10-P1) for several sub-periods. It stands out that on average, high-priced stocks still underperformed low-priced stocks by a considerable (though statistically insignificant) 0.47% per month from May 1990 to August 1994 (on the eve of the first wave of face amount changes). In the prior period (January 1986 to April 1990) low price portfolios even generated a statistically significant and economically very large mean return of 1.37% per month in excess of high price portfolios. Four out of five sub-periods from January 1973 to August 1994 show higher mean returns in favor of low price stock portfolios (see Table 6, Panel A).

In contrast, past mid-1990s, four out of five sub-samples show consistently higher returns (partly significant and economically very large) in favor of the 10% most expensive stocks (see Table 6, Panel B).[77] In conjunction with the findings of the previous section, this strongly supports our hypothesis that nominal price per se, respectively the relative differences of share prices of stocks, is a direct driver of the price effect (cp. Section 2), consistent with the findings of, for example, Baker et al. (2009), Birru and Wang (2016), and Singal and Tayal (2017) regarding stock splits and Wulff (2001) in respect of face amount changes.

[77] As Table 6 shows, the (high) price investment style does, unlike momentum based strategies, not suffer from a severe performance crash in times of high general market distress, for example between 2009 and 2013 during financial crisis (cp. Daniel and Moskowitz 2016).

Table 6: Price decile hedge portfolio (P10-P1) performance regarding sub-samples

Panel A: "Price" performance prior to first wave of face amount changes

Sub-period time frame	Jan. 1973 - April 1977	May 1977 - Aug. 1981	Sept. 1981 - Dec. 1985	Jan. 1986 - April 1990	May 1990 - Aug. 1994
Monthly Return (μ)	**-1.04%	0.51%	*-1.02%	***-1.37%	-0.47%
Std. Dev. (σ)	3.54%	3.17%	3.73%	3.57%	2.99%
Sharpe ratio (S)	-0.293	0.160	-0.274	-0.384	-0.156

Panel B: "Price" performance during/after face amount change wave(s)

Sub-period time frame	Sept. 1994 - Dec. 1998	Jan. 1999 - April 2003	May 2003 - Aug. 2007	Sept. 2007 - Dec. 2011	Jan. 2012 - Dec. 2016
Monthly Return (μ)	*0.94%	*2.52%	-0.02%	0.44%	**0.76%
Std. Dev. (σ)	3.40%	9.89%	4.88%	3.66%	2.86%
Sharpe ratio (S)	0.276	0.255	-0.003	0.121	0.264

German stocks (31.01.1973 to 30.12.2016) represent the stock universe (T=528 months). Sub-sample time frames cover 52 months for the first nine periods, respectively and 60 months for the last period. < € 2 stocks are excluded every month anew. The monthly return row reports the mean of the (equal weighted) monthly discrete returns of the hedge portfolio (P10-P1) in the specified time frames, respectively. Std. Dev. is the standard deviation of the monthly returns; Sharpe ratio is the ratio of the monthly mean returns and the standard deviation of returns. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer to p-values derived from a t-test (H0: μ=0).

5.4 Price quantile ratio regressions

In Table 7 (Panel A), we underline this conclusion as we show a highly statistically significant coefficient (t-statistic of 3.97) for the (90% to 10%) quantile ratio (QR) when explaining (P10-P1) hedge portfolio's returns (equation 3) regarding the complete sample (1973 to 2016).

$$\mathrm{P10_t} - \mathrm{P1_t} = \alpha + \mathrm{qQR_t} + \varepsilon_\mathrm{t} \qquad\qquad \mathrm{t} = 1, \ldots, \mathrm{T} \tag{3}$$

Also consistent, QR has no explanatory power within our comparative/main subsample, since then QR values permanently stay on consistently low/high levels (see upper segment of Table 7, Panel B and Panel C, left column, respectively; cp. also Figure 2). In addition, we suppose in line with our argumentation in Section 2 that if the relative difference between high-priced and low-priced stocks is (too) small as in the time frame 1973 to 1994 (i.e., the high to low price quantile ratio level is low), investors are possibly largely indifferent in respect to price as stock characteristic and trading criterion, contributing to a non-activation/deactivation of the high-price effect.

Furthermore, the comparatively weak high-price effect between May 2003 and December 2011 particularly with regard to the (mainstream) downside trend in Figure 2 (observable in the same time frame), suggests that not only the level of the high to low price quantile ratio determines, respectively indicates the (expected) strength of the (high-)price effect, but also the rate of change of the high to low price quantile ratio. Downside trends in high to low price quantile ratios dampen the relative differences in price between high price and low price stocks and cut down the relevance and strength of the arguments in Section 2, whereas upside trends amplify the (return compensated) disadvantages of high-priced stocks, strengthening or even triggering a high-price effect (cp. strong upside trend in Figure 2 and high P10-P1 returns between September 1994 and April 2003, as well as since January 2012). To test this hypothesis, the bottom segment of Table 7 shows the regression outcomes with delta (first differences of) QR (ΔQR) as explanatory variable (equation 4). We find this connection to hold for the comparative sample (1973 to 1994), only. In this time frame, the coefficient of ΔQR is positive and statistically significant at the 5 % level (t-statistic of 1.98).

$$P10_t - P1_t = \alpha + q\Delta QR_t + \varepsilon_t \qquad t = 2, \dots, T \qquad (4)$$

Table 7: Price quantile ratio and delta quantile ratio regressions

	Panel A: Complete dataset		Panel B: Pre mid-1990s		Panel C: Post mid-1990s	
Dependent var.	P10-P1	ΔP10-P1	P10-P1	ΔP10-P1	P10-P1	ΔP10-P1
Constant	-0.0096	0.0025	0.0142	0.0204	-0.0008	0.0212
	-2.81	*0.52*	1.03	1.11	-0.06	1.11
QR	0.0008	-0.0002	-0.0048	-0.0046	0.0005	-0.0010
	3.97	*-0.67*	*-1.55*	*-1.12*	*0.79*	*-1.16*
Adj. R-sq	0.0273	-0.0010	0.0054	0.0010	-0.0014	0.0013
Constant	0.0014	0.0006	-0.0071	0.0004	0.0095	0.0011
	0.70	*0.23*	*-3.30*	*0.13*	*2.80*	*0.24*
ΔQR	-0.0021	-0.0162	0.0192	-0.0330	-0.0027	-0.0159
	-1.13	*-6.71*	*1.98*	*-2.59*	*-1.26*	*-5.41*
Adj. R-sq	0.0005	0.0772	0.0112	0.0217	0.0022	0.0958

German stocks (31.01.1973 to 30.12.2016) represent the stock universe (T=528 months). < € 2 stocks are excluded every month anew. Panel A shows regression results for the complete sample, Panel B reports outcomes for the comparative pre mid-1990s dataset (31.01.1973 to 29.07.1994) and Panel C contains findings for our main dataset (31.08.1994 to 30.12.2016). In the upper segment, we regress (delta) P10-P1 returns in t (t=1(2),…,T) on the 90% to 10% price quantile ratio (QR) in t (and a constant). In the bottom segment, we regress (delta) P10-P1 returns in t (t=2,…,T) on the 90% to 10% delta price quantile ratio (ΔQR) in t (and a constant). All "delta" variables are calculated by the (first) differences of the respective values from t-1 to t. The t-statistics of the respective coefficients are written below in italics. The row "Adj. R-sq" reports the values of the adjusted R^2's for each regression.

For further insights and completeness, Table 7 also reports the respective regressions with delta (first differences of) P10-P1 returns (ΔP10-P1) as dependent variable (equations 5 and 6; see right columns in each Panel of Table 7).

$$\Delta(\mathrm{P10_t} - \mathrm{P1_t}) = \alpha + \mathrm{qQR_t} + \varepsilon_\mathrm{t} \qquad \mathrm{t} = 2, \dots, \mathrm{T} \tag{5}$$

$$\Delta(\mathrm{P10_t} - \mathrm{P1_t}) = \alpha + \mathrm{q}\Delta\mathrm{QR_t} + \varepsilon_\mathrm{t} \qquad \mathrm{t} = 2, \dots, \mathrm{T} \tag{6}$$

The most striking (but also puzzling) finding of this configuration is the very highly significant, negative coefficient of ΔQR when regressing ΔP10-P1 on ΔQR (t-statistic of -6.71 for the complete sample). At first glance, this appears to contradict the hypotheses derivable from our framework (Section 2) and the previous findings, since an increasing discrepancy between high- and low-priced stocks from t-1 to t is associated with a decreasing return for the high minus low price (P10-P1) hedge portfolio from t-1 to t and thus with a weaker high-price effect.

However, a closer look reveals a consistent explanation: the narrower/wider the (90% to 10%) quantile ratio gets from t-1 to t, the less beneficial it is for an investor to hold low-priced/high-priced stocks (in relation to the complete stock universe) in the sense of the aspects specified in Section 2. A (temporary) reduction of the quantile ratio leads to more (simultaneous) selling actions of low-priced stocks and thus to lower prices and lower returns of these stocks in relation to higher priced stocks (in the short term). This rationale is based upon our argumentation that low-priced stocks become less advantageous (relative to other, i.e., on average higher priced stocks), e.g. in tax controlling and portfolio managing aspects, when (market-wide) price discrepancies are lower. As a result, in the short term, (temporarily) lower price differences result in (temporarily) inferior returns of low-priced stocks, in the long term however, in superior returns due to undervaluation (cp. strong low-price effect until the mid-1990s, when price discrepancies were low). The opposite holds for high-priced stocks. Also consistent, lagged values of ΔQR have no (respectively inversed) predictive/explanatory power (i.e., mainly positive, partly significant coefficients) for ΔP10-P1 returns, whereas lagged values of QR are still significant when explaining/predicting P10-P1 returns (consistently significant, positive coefficients for QR), underlining the relevance of time scale (see also Wulff, 2001) for these seemingly contradicting effects.

5.5 Asset pricing models' evidence for pre mid-1990s dataset

On its own, the relative price difference argument of the previous sections cannot explain why a strong low-price effect can be observed pre mid-1990s. For this purpose, in Table 8, we show 4-factor and 3-factor model outcomes for the time frame June 1980[78] to July 1994. Even the asset pricing models have a hard time explaining P1 and P10-P1[79] returns primarily, reflected in significant alpha values.[80] As in Section 4, the SMB factor contributes much explanatory power to the models, especially when compared to the CAPM. Its coefficient shows a high and positive value for P1, again. In this comparative dataset, though, as opposed to the main dataset used in Section 3 and 4, a marginal (positive) size effect is detectable (monthly mean return of 0.3% compared to -0.59% in the main dataset; cp. Table 1). Since in this comparative dataset low-priced stocks are also generally low-sized stocks (cp. Table 2) the observed low-price effect presumably benefits from the (yet) active size effect. The opposite is even more likely to hold (see also Kross, 1985), since the low-price effect is of much higher magnitude than the size effect (P1-P10 return of 0.91%). Also HML and WML monthly mean returns are (much) lower (0.53% and 0.61%, respectively) and show less explanatory power in the factor models than in the main dataset. Notably, the clearly weaker momentum effect is also linked to the inversion of the price effect in this earlier sample (especially results of other European markets confirm this finding).

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[78] Due to data availability reasons regarding Common Shareholders' Equity time series, we cannot begin our analysis prior to 1980.

[79] We report P10-P1 statistics and not P1-P10 statistics to facilitate comparability with Section 4 results.

[80] Note also the significant alpha value of P10-P1 in the 4-factor model as opposed to the results in Table 4.

Table 8: Price decile portfolios statistics concerning CAPM and factor models for comparative pre mid-1990s dataset

	Performance		CAPM			3-factor model					4-factor model					
Port-folio	Excess Return	Std. Dev.	Alpha	RMRF	Adj. R-sq	Alpha	RMRF	SMB	HML	Adj. R-sq	Alpha	RMRF	SMB	HML	PR1YR	Adj. R-sq
P1	1.25%	5.24%	0.87%	0.85	0.584	0.49%	1.01	0.78	0.07	0.742	0.66%	1.00	0.75	0.13	-0.32	0.767
			3.22	*14.87*		*2.21*	*20.89*	*9.85*	*0.98*		*3.09*	*21.75*	*9.93*	*1.78*	*-4.20*	
P2	0.89%	4.90%	0.50%	0.89	0.733	0.28%	1.01	0.54	-0.03	0.823	0.36%	1.01	0.52	-0.01	-0.14	0.828
			2.46	*20.79*		*1.65*	*26.97*	*8.74*	*-0.51*		*2.07*	*27.17*	*8.60*	*-0.11*	*-2.23*	
P3	0.83%	4.97%	0.45%	0.87	0.679	0.13%	0.98	0.56	0.13	0.767	0.14%	0.98	0.56	0.13	-0.02	0.766
			1.98	*18.25*		*0.64*	*22.38*	*7.82*	*1.89*		*0.67*	*22.27*	*7.74*	*1.89*	*-0.21*	
P4	0.45%	4.36%	0.08%	0.83	0.795	-0.16%	0.90	0.42	0.11	0.860	-0.15%	0.90	0.42	0.11	-0.02	0.859
			0.51	*24.66*		*-1.19*	*30.40*	*8.59*	*2.26*		*-1.11*	*30.26*	*8.50*	*2.28*	*-0.32*	
P5	0.57%	4.25%	0.21%	0.80	0.776	0.07%	0.89	0.40	-0.05	0.847	0.10%	0.89	0.40	-0.04	-0.06	0.847
			1.34	*23.37*		*0.51*	*29.35*	*8.11*	*-1.12*		*0.73*	*29.30*	*7.98*	*-0.88*	*-1.21*	
P6	0.53%	4.18%	0.19%	0.78	0.772	0.02%	0.87	0.42	-0.02	0.848	0.03%	0.87	0.42	-0.02	-0.02	0.847
			1.17	*23.07*		*0.14*	*29.44*	*8.64*	*-0.53*		*0.21*	*29.31*	*8.54*	*-0.45*	*-0.38*	
P7	0.42%	4.12%	0.09%	0.74	0.711	-0.09%	0.83	0.43	-0.01	0.792	-0.12%	0.83	0.44	-0.01	0.05	0.791
			0.50	*19.68*		*-0.61*	*24.34*	*7.72*	*-0.13*		*-0.75*	*24.32*	*7.76*	*-0.27*	*0.81*	
P8	0.29%	4.48%	-0.06%	0.80	0.709	-0.12%	0.91	0.39	-0.20	0.791	-0.14%	0.91	0.39	-0.20	0.04	0.791
			-0.32	*19.60*		*-0.69*	*24.42*	*6.40*	*-3.38*		*-0.80*	*24.38*	*6.42*	*-3.44*	*0.66*	
P9	0.37%	4.46%	0.00%	0.83	0.761	-0.11%	0.91	0.34	-0.07	0.809	-0.12%	0.91	0.34	-0.07	0.02	0.808
			0.02	*22.41*		*-0.66*	*25.62*	*5.90*	*-1.20*		*-0.72*	*25.54*	*5.90*	*-1.25*	*0.41*	
P10	0.34%	4.22%	-0.01%	0.79	0.775	0.00%	0.87	0.26	-0.22	0.834	-0.05%	0.88	0.27	-0.24	0.11	0.838
			-0.06	*23.26*		*0.03*	*27.85*	*5.09*	*-4.52*		*-0.38*	*28.24*	*5.33*	*-4.88*	*2.12*	
P10-P1	-0.91%	3.45%	-0.88%	-0.06	0.001	-0.48%	-0.14	-0.52	-0.30	0.182	-0.72%	-0.13	-0.48	-0.37	0.42	0.288
			-3.20	*-1.06*		*-1.87*	*-2.45*	*-5.60*	*-3.33*		*-2.91*	*-2.38*	*-5.51*	*-4.40*	*4.89*	

German stocks (30.06.1980 to 29.07.1994) represent the stock universe (T=170 months; effective time frame is 158 months due to the calculation of the WML factor). < € 2 stocks are excluded every month anew. The excess return column displays the mean of the (equal weighted) monthly discrete returns of all stocks in the price decile portfolios in excess of the one-month deposit rate, respectively. Std. Dev. is the standard deviation of the monthly excess returns. RMRF is the market proxy excess return: monthly return of the value weighted German stocks minus the one-month deposit rate. SMB and HML are the factor-mimicking portfolios for size and book-to-market equity as in Fama and French (1993). PR1YR is a factor-mimicking portfolio for one-year return momentum (see Carhart, 1997). See equation (1) for the corresponding regression equation of the CAPM, (2) for the corresponding regression equation of the 4-factor model and (2) without WML factor (PR1YR) for the regression equation of the 3-factor model. The t-statistics are written in italics.

6. Robustness analysis

In addition to the price cut-offs in Section 3.3, in the next sections, we conduct several robustness tests of the (high-)price effect based on price, size, skewness of returns, momentum, and volatility double sorts for our main dataset. At last, we implement Fama-MacBeth (1973) rolling cross-sectional regressions to test the robustness of the price effect when predicting (firm-specific) stock market returns.

6.1 Size and price

Table 2 showed a strong positive correlation of size and nominal price. To investigate the interrelation of size and price in respect of portfolio performance and the robustness of the price effect when controlling for size, we construct 16 (4x4) independently double-sorted quartile portfolios on size and price. Table 9 reports the main performance statistics of these portfolios and the respective hedge portfolios (high minus low; 4-1). Although the difference is only barely significant, high price portfolios still show consistently higher returns and significantly different/lower standard deviations of returns than low price portfolios (cp. Table 3 and A.1). These findings are largely invariant and independent of the other sorting criterion, size (see two right columns of Table 9). On the other hand, consistent with the evidence reported in Table 1, the size effect stays non-existent (or rather inversed) when controlling for price, reflected in insignificant, inconsistent (partly negative) mean returns of the hedge portfolios (see bottom rows of Table 9). The high standard deviation of returns of the high size/low price portfolio is for the most part due to the generally low number of stocks constituting this portfolio, since the characteristics combination high size/low price is rare in the dataset and in some months not even fulfilled by any stocks, leading to a limited diversification effect.

When we conduct (conditional) double sorts explicitly controlling for size[81], the findings remain consistent to a large extent, likewise revealing a weaker price effect for high-sized stocks only (cp. bottom row segments of Table 9). This evidence is also approved when creating price decile portfolios with value weighted returns of the portfolios' constituting stocks (Table 10) as opposed to equally weighted returns (see Table 3).

Table 9: Performance of 16 (4x4) independently double-sorted quartile portfolios on size and price

		Price				
	Portfolio	1 (low)	2	3	4 (high)	high-low (4-1)
	1 (low)	0.43%	0.46%	*0.56%	***1.10%	0.66%
		5.57%	*4.60%*	*4.88%*	*5.03%*	*/6.67%*
	2	-0.01%	0.34%	*0.52%	***0.64%	0.66%
		6.80%	*5.94%*	*4.79%*	*3.96%*	****/6.60%*
Size	3	0.16%	0.25%	0.44%	***0.88%	*0.72%
		7.45%	*5.70%*	*5.73%*	*3.40%*	****/6.22%*
	4 (high)	0.47%	**1.01%	**0.81%	***0.92%	0.55%
		12.35%	*6.75%*	*5.31%*	*4.35%*	****/10.84%*
	high-low	0.04%	0.54%	0.25%	-0.17%	
	(4-1)	****/11.10%*	****/5.64%*	*5.85%*	***/6.15%*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. Stocks are independently categorized into 16 (4x4) portfolios based on the quartile breakpoints concerning size and price. The first row in the specific table segments displays the mean of the (equal weighted) monthly discrete returns (μ) of all stocks in the double-sorted quartile portfolios, respectively. The associated standard deviations of portfolio (and hedge portfolio) returns are written below in italics. The right column and the two rows at the bottom give the statistics for the hedge portfolios (high-low; 4-1). ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer either to p-values derived from a t-test (H0: μ=0) – see indications preceding the respective mean returns – or (for the hedge portfolios, only) to p-values derived from an F-test with the null that the ratio of variances of the two portfolios constituting the respective hedge portfolio (high-low; 4-1) equals 1 (see indications preceding the standard deviations of the hedge portfolios).

[81] Outcomes of conditional/dependent double sorts regarding price, size, skewness of returns, and momentum are available on request.

The price effect becomes less robust and marginally significant (see p-value of the hedge portfolio) and also the relative and absolute difference in the standard deviations of returns between P10 and P1 is lower, resulting in a less clear, though still significant difference of the Sharpe ratios of P10 and P1.

Table 10: Performance of the decile portfolios sorted by nominal price with value weighted returns

Portfolio	Monthly Return (μ)	Std. Dev. (σ)	Sharpe ratio (S)	p-value μ=0	Skewness of Returns
P1	0.13%	7.42%	0.017	77.85%	0.08
P2	0.28%	7.67%	0.036	55.59%	-0.11
P3	0.91%	8.76%	0.104	8.89%	1.65
P4	0.80%	7.15%	0.112	6.70%	-0.28
P5	0.59%	7.33%	0.081	18.43%	-0.04
P6	0.33%	6.06%	0.055	36.66%	-0.26
P7	0.28%	6.30%	0.044	47.05%	-1.00
P8	0.78%	5.98%	0.130	3.42%	-0.33
P9	1.14%	5.99%	0.190	0.20%	0.37
P10	0.84%	5.73%	0.146	1.73%	-0.62
P10-P1	0.71%	6.77%	0.105	8.71%	-0.21
S(P10)=S(P1)			3.87%		

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. P1 to P10 are the decile portfolios created via monthly sorting by nominal, unadjusted prices. P1 contains the cheapest 10% stocks; P10 contains the most expensive 10% stocks. The monthly return column displays the mean of the value weighted monthly discrete returns of all stocks in the price decile portfolios, respectively. Std. Dev. is the standard deviation of the monthly returns; Sharpe ratio is the ratio of the monthly mean returns and the standard deviation of returns. The p-values are derived from a t-test with the null hypothesis that monthly portfolio returns are equal to zero. P10-P1 gives the statistics for the hedge portfolio. Skewness of Returns reports the values of the third moment of the monthly returns for each portfolio. S(P10)=S(P1) tests the null if the Sharpe ratios of P10 and P1 are equal (see Wright et al., 2014) and displays the p-value.

6.2 Skewness and price

Since the price effect appears to be negatively related to the skewness of returns (see Tables 3, A.1 and 10), the price effect could simply be a compensation/premium for the negative skewness of the high-price portfolios. Table 11 highlights this hypothesis, as we report main performance statistics of 16 (4x4) independently double-sorted quartile portfolios on prior 60-month skewness of returns and price. Not confirming the compensation hypothesis, the price effect (see two right columns of Table 11) is strongest for prior 5-year medium-skewness stocks (cp. middle row segments of Table 11) reflected in (highly) significant monthly mean returns of the associated hedge portfolios (0.68% and 0.97%). However, the findings show some inconsistency due to the near zero mean returns of the hedge portfolios when sorting for low skewness of returns (-0.03%) and high skewness of returns (0.01%). On the one hand, conditional sorts for low-skewness stocks confirm this outcome of the independent double sort, showing also a near zero monthly mean return for the hedge portfolio. On the other hand, after explicitly controlling for high-skewness stocks, (clearly) positive monthly mean returns for the price hedge portfolios are displayed. Additionally, the skewness of returns statistics of high price portfolios indicate positive values for skewness when explicitly controlled for high prior 5-year skewness. Thus, when we select a portfolio of prior 5-year high skewness, high-priced stocks, the disadvantage of expensive stocks, namely their negative skewness of returns is diminishing, at the same time revealing some general autocorrelation concerning the skewness of portfolio returns.

As for size, the standard deviations of returns in respect of high price portfolios are clearly significantly different/lower compared to low price portfolios throughout all sorting configurations (performing an F-test comparing the variances).

Table 11: Performance of 16 (4x4) independently double-sorted quartile portfolios on skewness of returns and price

		Price				
	Portfolio	1 (low)	2	3	4 (high)	high-low (4-1)
	1 (low)	**1.03%	**0.88%	***0.97%	***1.00%	-0.03%
		6.37%	*5.46%*	*5.22%*	*3.85%*	****/5.32%*
	2	0.20%	***0.86%	***0.88%	***0.87%	**0.68%
		5.58%	*4.44%*	*4.25%*	*3.22%*	****/4.63%*
Skewness of Returns	3	0.30%	***0.97%	***0.89%	***1.27%	***0.97%
		5.45%	*4.25%*	*3.74%*	*3.01%*	****/4.87%*
	4 (high)	*0.87%	*0.70%	0.26%	***0.75%	0.01%
		6.45%	*5.26%*	*4.45%*	*3.93%*	****/6.85%*
	high-low	-0.16%	-0.19%	*-0.71%	-0.23%	
	(4-1)	*7.53%*	*5.32%*	***/5.36%*	*4.58%*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. Stocks are independently categorized into 16 (4x4) portfolios based on the quartile breakpoints concerning prior 60-month skewness of returns (reducing the effective time frame to 209 months) and price. The first row in the specific table segments displays the mean of the (equal weighted) monthly discrete returns (μ) of all stocks in the double-sorted quartile portfolios, respectively. The associated standard deviations of portfolio (and hedge portfolio) returns are written below in italics. The right column and the two rows at the bottom give the statistics for the hedge portfolios (high-low; 4-1). ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer either to p-values derived from a t-test (H0: μ=0) – see indications preceding the respective mean returns – or (for the hedge portfolios, only) to p-values derived from an F-test with the null that the ratio of variances of the two portfolios constituting the respective hedge portfolio (high-low; 4-1) equals 1 (see indications preceding the standard deviations of the hedge portfolios).

6.3 Momentum and price

The 4-factor model revealed the importance of momentum when explaining price decile portfolios excess returns. Due to the strong mutual link of price and momentum, it is necessary to eliminate the possibility that the price effect is just a proxy for the momentum effect. Since asset pricing models are not capable of exploring this issue profoundly, Table 12 reports monthly mean returns and standard deviations of returns for 16 (4x4) independently double-sorted portfolios on price and momentum. For this purpose, like in the previous sections, we use quartile breakpoints to construct the portfolios along with the respective hedge portfolios. The findings reflect the importance of the WML factor (see Section 4) when explaining the price effect, lowering the return difference of high price minus low price (4-1) portfolios considerably when controlling for momentum, except for low to medium momentum portfolios. Nevertheless, the returns of the hedge portfolios stay positive, documenting a persisting (but weaker) price effect after (explicitly) controlling for momentum. As for skewness and size, the differences in standard deviations of high price and low price portfolios stay very robust and highly significant.

Due to the strength of the momentum effect in the dataset, high-momentum stocks generally generate much higher returns than low-momentum stocks throughout the double-sorted portfolios (see bottom rows of Table 12). However, when we control for high price, the momentum effect weakens to some degree, reflected in the lowest monthly mean return of the momentum hedge portfolios (1.29%). Also, the momentum hedge portfolios generally show higher standard deviations of returns than the price hedge portfolios.

Especially interesting for investors applying multi-investment style strategies, the standard deviations of returns for high price and (medium to) high momentum portfolios (2.87% and 3.94%) are lower than for low price and (medium to) high momentum portfolios (4.72% and 5.31%), yielding slightly higher mean returns. Thus, the combination of (high) price and (high) momentum results less in generating additional alpha compared to a (high) momentum only strategy, but in a decreasing portfolio risk, measured by the standard deviation of returns, while yielding the same (or slightly higher) returns.

Table 12: Performance of 16 (4x4) independently double-sorted quartile portfolios on momentum and price

		Price				
	Portfolio	1 (low)	2	3	4 (high)	high-low (4-1)
	1 (low)	-0.26%	**-0.90%	-0.53%	0.09%	0.50%
		7.67%	*6.73%*	*7.78%*	*6.47%*	****/6.83%*
	2	-0.13%	0.01%	0.02%	**0.73%	**0.86%
		5.96%	*5.34%*	*5.71%*	*4.59%*	****/5.03%*
Momentum	3	*0.54%	*0.50%	**0.53%	***0.76%	0.21%
		4.72%	*4.02%*	*3.85%*	*2.87%*	****/4.02%*
	4 (high)	***1.24%	***1.36%	***1.24%	***1.39%	0.15%
		5.31%	*4.48%*	*4.16%*	*3.94%*	****/4.62%*
	high-low	***1.50%	***2.26%	***1.77%	***1.29%	
	(4-1)	****/6.30%*	****/5.21%*	****/6.62%*	****/6.09%*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. Stocks are independently categorized into 16 (4x4) portfolios based on the quartile breakpoints concerning prior one-year return momentum (reducing the effective time frame to 257 months) and price. The first row in the specific table segments displays the mean of the (equal weighted) monthly discrete returns (μ) of all stocks in the double-sorted quartile portfolios, respectively. The associated standard deviations of portfolio (and hedge portfolio) returns are written below in italics. The right column and the two rows at the bottom give the statistics for the hedge portfolios (high-low; 4-1). ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer either to p-values derived from a t-test (H0: μ=0) – see indications preceding the respective mean returns – or (for the hedge portfolios, only) to p-values derived from an F-test with the null that the ratio of variances of the two portfolios constituting the respective hedge portfolio (high-low; 4-1) equals 1 (see indications preceding the standard deviations of the hedge portfolios).

6.4 Volatility and price

At last, we check if the (high) price effect is driven by the (low) volatility effect which we find to be concurrently existent in our German sample (not reported; see also e.g., Blitz and van Vliet, 2007), as we find a clear association between our price portfolios and associated volatility levels. As volatility measure of each stock, we use prior 36-month standard deviations of returns and use quartile breakpoints to assign each active stock to its respective volatility portfolio. After the construction of 16 (4x4) independently double-sorted portfolios on volatility and price (Table

13), we find the price effect to stay alive especially for medium volatility portfolios (see average monthly returns of the price hedge portfolios of 0.63% and 0.74%, which are nearly significant at 1% level). Expensive portfolios show (lasting) higher returns than cheap portfolios throughout all combinations and lower levels of standard deviations of returns, even for the low volatility portfolios (climaxing in an extraordinary low monthly return volatility of 2.35% for the high price, low volatility intersection portfolio). These findings make it very unlikely that the price effect is the volatility effect in disguise, no matter how volatility is measured, since Ang et al. (2009) show a very high correlation of total volatility (which we use) and idiosyncratic volatility.

Table 13: Performance of 16 (4x4) independently double-sorted quartile portfolios on volatility and price

		Price				
	Portfolio	1 (low)	2	3	4 (high)	high-low (4-1)
	1 (low)	**0.60% *4.43%*	***0.89% *3.04%*	***0.87% *2.97%*	***0.86% *2.35%*	0.26% ****/4.20%*
	2	**0.64% *4.80%*	***0.83% *4.45%*	***1.00% *4.57%*	***1.27% *3.98%*	**0.63% ****/3.76%*
Volatility	3	0.39% *5.74%*	*0.63% *5.39%*	**0.84% *5.03%*	***1.13% *4.90%*	**0.74% ***/4.60%*
	4 (high)	0.07% *7.29%*	0.43% *7.14%*	-0.45% *10.02%*	0.54% *11.87%*	0.71% ****/11.70%*
	high-low (4-1)	-0.49% ****/7.08%*	-0.46% ****/6.39%*	**-1.32% ****/9.65%*	-0.30% ****/11.26%*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). < € 2 stocks are excluded every month anew. Stocks are independently categorized into 16 (4x4) portfolios based on the quartile breakpoints concerning prior 36-month volatility (standard deviation) of returns (reducing the effective time frame to 233 months) and price. The first row in the specific table segments displays the mean of the (equal weighted) monthly discrete returns (μ) of all stocks in the double-sorted quartile portfolios, respectively. The associated standard deviations of portfolio (and hedge portfolio) returns are written below in italics. The right column and the two rows at the bottom give the statistics for the hedge portfolios (high-low; 4-1). ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer either to p-values derived from a t-test (H0: μ=0) – see indications preceding the respective mean returns – or (for the hedge portfolios, only) to p-values derived from an F-test with the null that the ratio of variances of the two portfolios constituting the respective hedge portfolio (high-low; 4-1) equals 1 (see indications preceding the standard deviations of the hedge portfolios).

6.5 Rolling cross-sectional regressions

Finally, we examine the robustness of the price effect using rolling, cross-sectional Fama-MacBeth (1973) regressions (Table 14). Equation 7 specifies the implemented regression model with control variables:

$$r_{it+1} = \alpha_t + p_t LN(Price)_{it} + s_t LN(Size)_{it} + b_t BTM_{it} + m_t PR1YR_{it} + v_t VOL_{it} + \varepsilon_t \qquad (7)$$

r_{it+1} is the next-month return for firm $i\ (i = 1, \ldots, N)$ and LN(Price) and LN(Size) are the natural logarithm of the unadjusted, nominal price and market capitalization, respectively. BTM and PR1YR depict the six months lagged book-to-market ratio and prior one-year return momentum variables. VOL is the prior 36-month standard deviation of returns (volatility). ε_t is the error term for each rolling regression at time $t\ (t = 1, \ldots, T - 1)$. We split our dataset into two parts to take account of the dramatic change of the price effect documented in Section 5: Panel B (main dataset) and Panel A (comparative pre mid-1990s dataset). For both samples we run rolling cross-sectional regressions with LN(Price) as lone predictor first, before we include the specified, characteristics-based control variables (as shown above in equation 7), to test the robustness of the price effect when predicting next-month returns.

The results in Panel A reflect the found low-price effect in Germany for our pre mid-1990s dataset showing negative coefficients for LN(Price). However, when we include the defined control variables (model specifications II and III), the (AR(1)-adjusted) t-statistic falls (clearly) below significant levels. The high-price effect evident in our main sample (Panel B) is more robust. Here, t-statistics always stay around (or above) 2 for all model configurations. LN(Size) plays a very marginal role for predicting cross-sectional returns when controlled for the other variables. The importance of momentum (PR1YR) as return-predicting characteristic on the other hand increases even more over time, but is at the same time not capable of cutting down the predictive power of LN(Price) in our main dataset significantly (similar to VOL).

Table 14: Fama-MacBeth (1973) cross-sectional regressions results

	Panel A: Pre mid-1990s			Panel B: Post mid-1990s		
	I	II	III	IV	V	VI
Constant	0.0248	0.0217	0.0179	-0.0009	-0.0002	0.0070
	3.43	*2.63*	*2.58*	*-0.21*	*-0.04*	*2.47*
	[2.62]	*[2.03]*	*[2.30]*	*[-0.15]*	*[-0.03]*	*[2.40]*
LN(Price)	-0.0027	-0.0024	-0.0016	0.0020	0.0015	0.0011
	-2.38	*-1.60*	*-1.24*	*2.87*	*2.23*	*1.92*
	[-1.81]	*[-1.19]*	*[-0.94]*	*[2.55]*	*[2.10]*	*[1.92]*
LN(Size)		-0.0002	-0.0002		-0.0000	-0.0003
		-0.31	*-0.34*		*-0.09*	*-0.57*
		[-0.29]	*[-0.32]*		*[-0.10]*	*[-0.65]*
BTM		0.0003	0.0005		0.0004	-0.0000
		0.94	*1.38*		*1.98*	*-0.05*
		[1.01]	*[1.44]*		*[1.72]*	*[-0.05]*
PR1YR		0.0154	0.0154		0.0118	0.0079
		3.23	*3.73*		*5.28*	*3.62*
		[3.01]	*[3.49]*		*[4.62]*	*[3.18]*
VOL			-0.0111			-0.0223
			-0.30			*-1.33*
			[-0.30]			*[-1.19]*
Adj. R-sq	0.009	0.047	0.057	0.008	0.027	0.034

German stocks (30.06.1980 to 30.12.2016) represent the stock universe (T=439 months). < € 2 stocks are excluded every month anew. Panel A shows regression results for the comparative pre mid-1990s dataset (30.06.1980 to 29.07.1994) and Panel B for our main dataset (31.08.1994 to 30.12.2016). We regress next-month firm returns on a constant; LN(Price), that is the current natural logarithm of nominal price of each firm; LN(Size), i.e. the log market capitalization of each firm at the present month; BTM (six months lagged book-to-market ratio of each firm, updated in June each year), PR1YR, which is the prior one-year return (return of each firm measured from t-12 to t-2) and VOL (prior 36-month return volatility). Columns I and IV report outcomes of these rolling Fama-MacBeth (1973) cross-sectional regressions with LN(Price) as independent variable only, whereas models used in columns II, and V include LN(Size), BTM and PR1YR as control variables. Models III and VI additionally add VOL (see equation 7). The t-statistics of the respective coefficients are written below in italics and the AR(1)-adjusted t-statistics are reported in square brackets. The row “Adj. R-sq” gives the values of the average cross-sectional adjusted R^2’s.

7. Conclusion

Investing in high-priced stocks is a promising candidate to be another legitimate investment style. Relying on German stock market data, we first assess the (recent) performance of high-priced stocks in comparison to low-priced stocks over the course of the last 22 years based on monthly data. Comparing monthly returns, standard deviations, and skewness of returns, as well as Sharpe ratios of low-price decile portfolios to high-price decile portfolios, we find consistently higher returns, lower standard deviations, higher Sharpe ratios, and negative values for skewness regarding the high-price decile portfolios. After conducting independent (and conditional) double sorts on price, size, skewness of returns, momentum, and volatility via quartile breakpoints, the findings especially stay valid for all but high-sized stocks, prior medium-skewness, and -volatility stocks as well as for prior low to medium momentum stocks.

Outlining behavioral finance/economics, tax, and investment related aspects in the first part (Section 2), the paper offers diverse, but nevertheless often linked arguments why these empirical findings also make sense from a theoretical view. Starting with behavioral aspects of consumers concerning product, service, and stock prices, we discuss how low-priced stocks offer tax debt reduction and cash management benefits for the shareholder, justifying a price premium for low-priced stocks and conversely a price discount for high-priced stocks. Additionally, at the end of the first part, we outline several investment-related aspects, including limitation of shareholders, diversification issues, and liquidity and show the relevance of nominal stock prices for investors and in turn also for corporate managers, being responsible for encouraging investments and increasing shareholder value.

In the empirical part, implementing and applying a CAPM and a 4-factor model, price decile portfolio excess returns are explained especially well by market proxy excess returns and the SMB factor, having highly significant t-statistics. Generally low t-statistics can be found for HML. Contributing additional important explanatory power, especially when compared to the 3-

factor Fama and French (1993) model, the WML factor is particularly relevant for explaining returns of the highest-price (significant positive coefficients) and the lowest-price (significant negative coefficients) portfolios. Due to its mutual, direct relation to price, this adds up very well.

Overall, the asset pricing models show that excess returns of high-price portfolios are associated with highly statistically significant low betas and highly statistically significant positive factor loadings for SMB[82] and WML. In contrast, excess returns of low-price portfolios are associated with highly statistically significant high betas and highly statistically significant, positive coefficients with high factor loadings for SMB and statistically significant negative factor loadings for WML. Additionally, the 4-factor model and the 3-factor model are not capable of fully explaining the excess returns of the price portfolios (reflected in significant alphas especially for P1, P10, and partly P10-P1), leaving the investment in high-priced stocks an abnormally profitable and at the same time very low-volatile investment style over the course of 22 years on the German stock market.

Furthermore, with this paper, we are, to our knowledge, the first to present striking evidence for the (direct) relevance of nominal share price levels and relative price differences on a complete country-specific stock universe for the significance, steadiness, and evolution of an investment style by comparing price portfolios' returns pre and post far-reaching face amount changes on an internationally prominent stock market.

Since the price effect (high-priced stocks generally outperform low-priced stocks), respectively the relevance of the nominal stock price for investors' future expectations concerning stock (performance) characteristics and investment behavior is empirically confirmed for the US stock market (Seguin and Smoller, 1997; Birru and Wang, 2016; Singal and Tayal, 2017) and for the recent decades also for the German stock market, further investigations on the relevance of price as an investment style on international markets appear to be a fruitful endeavor.

[82] Note though, that the size effect is non-existent or rather inversed in our sample.

However, of course, not only the bare existence of a global price effect itself should be spotlighted, but also the more robust findings, like the comparatively very low return volatility of high price stock portfolios. In turn, following this approach, the (expected) drivers of the price effect and its associated effects, like the (change in) magnitude of relative differences of share prices, could be scrutinized more profoundly (e.g. via comparative event history analysis using country-specific stock market law amendments and their subsequent influence on the price effect), potentially adding further (causal) explanatory power answering the question why and how such a simple characteristic like the nominal price should be relevant to investors.

Another approach could focus more on the mutual links of price to already existing, well documented investment styles and puzzling stock market anomalies like the momentum, liquidity, and volatility effect, potentially finally revealing why these anomalies are existing at all and remain robust, despite being widely known to investors. At last, implementing and testing a nominal price strategy in a realistic, sophisticated (multi-investment style) portfolio management setting (see, e.g., Asness et al., 2015) and especially exploiting the associated low-volatility effect in the process, could demonstrate the practical power of price as an investment style in a vivid way.

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Appendix

Table A.1: Price decile portfolios performance statistics for several price cut-offs

Portfolio	Cut-off (€)	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Monthly Return (µ)	5	0.23%	0.33%	0.50%	0.50%	0.34%	**0.62%	***0.75%	***0.80%	***0.87%	***0.99%	***0.76%
	4	0.45%	0.21%	0.31%	*0.61%	0.34%	*0.58%	**0.67%	***0.88%	***0.84%	***0.98%	*0.53%
	3	0.39%	0.21%	0.31%	0.48%	0.46%	0.43%	**0.68%	***0.92%	***0.79%	***1.00%	*0.61%
	2.5	0.21%	0.25%	0.26%	0.44%	*0.51%	0.36%	**0.68%	***0.89%	***0.79%	***1.01%	**0.80%
	1.5	0.30%	0.06%	0.40%	0.47%	0.34%	0.35%	**0.66%	***0.88%	***0.77%	***1.02%	**0.72%
	1	0.57%	0.10%	0.37%	0.43%	0.38%	0.44%	*0.53%	***0.81%	***0.83%	***1.02%	0.45%
	0.5	0.28%	0.27%	0.38%	0.45%	0.22%	0.46%	*0.47%	***0.83%	***0.86%	***1.00%	*0.72%
	0	***3.28%	0.36%	0.33%	0.51%	0.31%	0.34%	*0.47%	***0.77%	***0.83%	***1.03%	**-2.24%
Std. Dev. (σ)	5	5.35%	5.42%	5.37%	5.05%	5.14%	4.82%	4.42%	4.72%	3.81%	2.70%	4.38%
	4	5.97%	5.37%	5.28%	5.39%	4.99%	4.87%	4.57%	4.68%	3.81%	2.74%	5.19%
	3	6.11%	5.53%	5.36%	5.29%	5.02%	5.05%	4.48%	4.63%	3.94%	2.76%	5.33%
	2.5	5.90%	5.90%	5.29%	5.37%	5.10%	4.97%	4.41%	4.69%	4.04%	2.78%	5.13%
	1.5	6.48%	5.79%	5.60%	5.52%	4.98%	5.03%	4.60%	4.65%	4.07%	2.84%	5.67%
	1	7.09%	5.99%	5.48%	5.55%	5.10%	4.99%	4.70%	4.62%	4.11%	2.86%	6.21%
	0.5	7.43%	6.42%	5.69%	5.60%	5.15%	5.02%	4.68%	4.72%	4.08%	2.91%	6.55%
	0	17.96%	7.31%	6.02%	5.63%	5.34%	5.05%	4.61%	4.80%	4.11%	2.96%	17.68%
Sharpe Ratio (S)	5	0.043	0.062	0.093	0.099	0.067	0.128	0.169	0.169	0.229	0.367	***0.174
	4	0.076	0.039	0.060	0.113	0.068	0.119	0.148	0.188	0.221	0.359	***0.102
	3	0.064	0.037	0.058	0.091	0.092	0.086	0.151	0.199	0.200	0.361	***0.113
	2.5	0.036	0.043	0.050	0.082	0.101	0.072	0.153	0.190	0.197	0.364	***0.156
	1.5	0.046	0.011	0.071	0.084	0.068	0.069	0.143	0.188	0.190	0.358	***0.127
	1	0.080	0.017	0.068	0.077	0.074	0.087	0.112	0.176	0.202	0.356	***0.072
	0.5	0.038	0.042	0.067	0.081	0.042	0.092	0.101	0.176	0.210	0.344	***0.110
	0	0.182	0.049	0.055	0.090	0.058	0.068	0.102	0.160	0.202	0.349	**-0.127
Skew-ness of Returns	5	-0.39	-0.30	-0.43	-0.26	-0.12	-0.60	-0.95	0.30	-0.70	-0.38	0.05
	4	0.23	-0.31	-0.43	-0.24	-0.12	-0.72	-0.81	0.04	-0.57	-0.59	-0.62
	3	0.60	-0.15	-0.33	-0.42	-0.11	-0.37	-0.80	-0.01	-0.65	-0.60	-0.93
	2.5	0.69	-0.04	-0.18	-0.36	-0.31	-0.35	-0.76	0.05	-0.58	-0.74	-1.23
	1.5	0.34	0.12	0.03	-0.07	-0.52	-0.17	-0.78	-0.03	-0.57	-0.77	-0.65
	1	0.58	0.14	-0.08	0.10	-0.53	-0.17	-0.72	-0.12	-0.53	-0.79	-0.90
	0.5	0.77	0.33	-0.07	0.05	-0.21	-0.24	-0.81	0.00	-0.58	-0.84	-1.13
	0	4.33	0.57	-0.03	0.37	-0.17	-0.22	-0.60	-0.08	-0.78	-0.75	-4.63

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months). Performance statistics are reported for the price decile portfolios along with the hedge portfolio for several additional price thresholds/cut-offs (cp. Table 3). ***, **, and * indicate significance at 1%, 5%, and 10%, respectively and refer to p-values derived from a t-test with the null hypothesis that monthly portfolio returns are equal to zero (see monthly return panel) and to p-values derived from a Wright et al. (2014) Sharpe ratio equality test (H0: S(P10)=S(P1)) for the Sharpe ratio panel.

Table A.2: Price decile portfolios statistics concerning CAPM and 4-factor model for additional price cut-offs

Panel A: < € 5 stocks excluded

	Monthly		CAPM			4-factor model					
Portfolio	Excess Return	Std. Dev.	Alpha	RMRF	Adj. R-sq	Alpha	RMRF	SMB	HML	PR1YR	Adj. R-sq
P1	0.10%	5.44%	-0.33%	0.68	0.431	0.15%	1.00	0.96	0.14	-0.20	0.759
			-1.27	*13.97*		*0.77*	*23.30*	*15.60*	*3.00*	*-4.39*	
P2	0.20%	5.54%	-0.25%	0.71	0.462	0.27%	1.00	0.90	0.06	-0.19	0.751
			-0.98	*14.86*		*1.38*	*22.60*	*14.01*	*1.22*	*-4.06*	
P3	0.37%	5.49%	-0.11%	0.77	0.556	0.30%	1.06	0.84	0.15	-0.19	0.801
			-0.49	*17.93*		*1.74*	*26.86*	*14.82*	*3.55*	*-4.59*	
P4	0.38%	5.15%	-0.10%	0.76	0.614	0.16%	0.99	0.66	-0.01	-0.05	0.782
			-0.50	*20.22*		*0.96*	*25.67*	*11.94*	*-0.20*	*-1.19*	
P5	0.20%	5.25%	-0.29%	0.77	0.595	-0.06%	1.01	0.70	-0.07	0.01	0.776
			-1.36	*19.43*		*-0.35*	*25.33*	*12.13*	*-1.57*	*0.20*	
P6	0.51%	4.93%	0.04%	0.74	0.639	-0.04%	1.02	0.69	0.03	0.12	0.797
			0.20	*21.33*		*-0.26*	*28.74*	*13.45*	*0.85*	*3.16*	
P7	0.61%	4.52%	0.19%	0.67	0.618	0.20%	0.92	0.63	0.02	0.07	0.778
			1.09	*20.36*		*1.34*	*26.80*	*12.77*	*0.66*	*1.85*	
P8	0.68%	4.83%	0.22%	0.73	0.639	0.23%	0.92	0.50	-0.01	0.07	0.729
			1.20	*21.29*		*1.27*	*22.88*	*8.57*	*-0.27*	*1.66*	
P9	0.75%	3.89%	0.39%	0.58	0.627	0.16%	0.76	0.39	0.02	0.16	0.708
			2.59	*20.75*		*1.08*	*22.52*	*7.97*	*0.53*	*4.64*	
P10	0.84%	2.71%	0.63%	0.34	0.442	0.27%	0.51	0.33	0.08	0.20	0.581
			4.93	*14.26*		*2.20*	*18.25*	*8.24*	*2.51*	*6.63*	
P10-P1	0.74%	4.43%	0.95%	-0.33	0.157	0.13%	-0.49	-0.63	-0.06	0.40	0.542
			3.74	*-6.97*		*0.60*	*-10.07*	*-9.07*	*-1.20*	*7.79*	

Table A.2, continued

Panel B: < € 1 stocks excluded

Portfolio	Monthly Excess Return	Std. Dev.	CAPM Alpha	CAPM RMRF	CAPM Adj. R-sq	4-factor model Alpha	RMRF	SMB	HML	PR1YR	Adj. R-sq
P1	0.45%	7.23%	-0.06%	0.81	0.35	1.02%	1.07	1.12	0.21	-0.45	0.798
			-0.16	*11.86*		*4.53*	*20.96*	*15.56*	*3.44*	*-8.96*	
P2	-0.04%	6.13%	-0.51%	0.74	0.412	0.31%	0.95	0.90	0.09	-0.31	0.784
			-1.72	*13.43*		*1.59*	*21.40*	*14.24*	*1.65*	*-7.02*	
P3	0.24%	5.59%	-0.22%	0.74	0.486	0.25%	0.98	0.85	0.20	-0.17	0.792
			-0.87	*15.58*		*1.44*	*24.50*	*15.00*	*4.14*	*-4.41*	
P4	0.30%	5.67%	-0.20%	0.80	0.556	0.26%	1.01	0.77	0.03	-0.12	0.797
			-0.83	*17.92*		*1.48*	*25.32*	*13.50*	*0.60*	*-3.01*	
P5	0.23%	5.21%	-0.24%	0.75	0.578	0.06%	0.96	0.71	-0.02	-0.03	0.794
			-1.12	*18.74*		*0.39*	*26.06*	*13.50*	*-0.48*	*-0.74*	
P6	0.32%	5.11%	-0.16%	0.76	0.629	-0.05%	0.98	0.64	-0.01	0.05	0.783
			-0.83	*20.85*		*-0.29*	*26.40*	*12.08*	*-0.15*	*1.46*	
P7	0.38%	4.81%	-0.08%	0.74	0.658	-0.01%	0.92	0.54	0.08	0.03	0.776
			-0.44	*22.23*		*-0.08*	*25.99*	*10.72*	*1.88*	*0.91*	
P8	0.70%	4.74%	0.26%	0.70	0.612	0.28%	0.89	0.52	-0.05	0.10	0.729
			1.39	*20.10*		*1.62*	*23.05*	*9.56*	*-1.06*	*2.62*	
P9	0.71%	4.20%	0.29%	0.66	0.690	0.18%	0.80	0.34	0.06	0.10	0.740
			2.00	*23.88*		*1.22*	*23.87*	*7.17*	*1.59*	*2.92*	
P10	0.87%	2.88%	0.62%	0.40	0.533	0.34%	0.54	0.27	0.10	0.16	0.616
			5.01	*17.12*		*2.79*	*19.24*	*6.84*	*2.89*	*5.76*	
P10-P1	0.42%	6.32%	0.68%	-0.42	0.118	-0.68%	-0.53	-0.85	-0.11	0.61	0.663
			1.82	*-5.94*		*-2.66*	*-9.22*	*-10.47*	*-1.64*	*10.74*	

German stocks (31.08.1994 to 30.12.2016) represent the stock universe (T=269 months, effective time frame is 257 months due to the calculation of the WML factor). Panel A reports statistics with < € 5 stocks excluded every month anew and Panel B excludes stocks below € 1. RMRF is the market proxy excess return: monthly return of the value weighted German stocks minus the one-month deposit rate. SMB and HML are the factor-mimicking portfolios for size and book-to-market equity as in Fama and French (1993). PR1YR is a factor-mimicking portfolio for one-year return momentum (see Carhart, 1997). See equation (1) for the corresponding regression equation of the CAPM and (2) for the corresponding regression equation of the 4-factor model. The t-statistics are written in italics.

C.2 Paper II: Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns

Price, Cultural Dimensions, and the Cross-Section of Expected Stock Returns

Ulrich J. Hammerich *

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Abstract

We document a nominal stock price effect that is (like momentum) associated with (national) culture. Using the full spectrum of cultural dimensions proposed by Hofstede et al. and the cross-section of stock returns of 41 countries, we not only show a robust predictive and explanatory power of price in conjunction with several cultural dimensions, but of cultural differences in general. Although momentum and price are related investment strategies, we find a broad (escalating) European high-price effect, but a material low-price effect in Asia as well as the most significant and robust low-price effect for the US. Most consistent around the world, high-priced stocks show lower return volatility and market betas than low-priced stocks and lower values for skewness of returns.

JEL Classification: G11, G12, G14, G15, G41

Keywords: nominal price effect, cultural finance, behavioral finance, asset pricing, market anomalies

* University of Bremen, Department of Finance, Max-von-Laue-Str. 1, 28359 Bremen, Germany.

Contact: *Tel.*: +49 421 218 66727; *E-mail address*: hammerich@uni-bremen.de

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1. Introduction

Major stock characteristics like size and book-to-market equity are (among others) directly dependent on the nominal share price of a stock.[83] Despite the enormous impact of these and many other stock characteristics on finance research in the last decades (e.g., Harvey et al., 2015; Linnainmaa and Roberts, 2018) and their identification and implementation as international asset pricing risk factors (e.g., Fama and French, 1993, 2012, 2015, 2017; Carhart, 1997) and investment strategies (e.g., Asness et al., 2013, 2018; Jacobs and Mueller, 2019), research on an international price effect (i.e., price per se is consequential for future returns of an asset) is virtually non-existent in the finance literature. This is even more astonishing as a very early study of Blume and Husic (1973) already documents an outperformance of low-priced stocks in the US, which was confirmed by later evidence of Hwang and Lu (2008) and Birru and Wang (2016b). The conclusion of Kross (1985) that the size effect is mainly a price effect and the evidence of Bhardwaj and Brooks (1992) for a dependency of the January effect on a contemporaneous low-price effect are early examples for the relevance of an overdue study on the character of an international price effect as the (potential) origin or explanatory source of manifold "animals" (anomalies) of the "zoo" (Cochrane, 2011). Later literature for example links (low) nominal price to studies on lottery-type stocks (Kumar, 2009; Birru and Wang, 2016a) and uses it (in a logarithmic version) as robust explanatory variable for the MAX effect (Cheon and Lee, 2017). At the same time, Birru and Wang (2016b) find clear evidence that the nominal price premium in the US is independent from premiums on lottery-type stock characteristics like extreme returns, idiosyncratic volatility, and expected idiosyncratic skewness and robust regarding measures of limits of arbitrage like liquidity.

[83] The size or market equity of a firm is defined as its nominal share price times the number of outstanding shares. Book-to-market equity is (usually) calculated as common shareholder's equity divided by market equity (which is, again, dependent on price).

Furthermore, a possible international price effect would challenge the weak form of the efficient market hypothesis (EMH) (Fama, 1970) to an extraordinary extent, as price is the embodiment of (publicly accessible) past information contained in time series and data sheets of securities. Although recently emerging research suggests that there is a (high) price effect (high-priced stocks outperform low-priced stocks) in many Western/European countries and nominal stock prices are consequential for subsequent returns (e.g., Glas et al., 2017; Singal and Tayal, 2017; Hammerich et al., 2018), a comprehensive international sample that particularly includes Asian countries is still missing. Like momentum (e.g., Jegadeesh and Titman, 1993; Carhart, 1997; Chui et al., 2010) for example, price is a very simple investment style (and thus it is even more puzzling that it appears to be an abnormally profitable and at the same time low-risk investment strategy) that invests in nominally high-priced stocks (top price decile/quintile) and sells low-priced stocks (bottom price decile/quintile) at a given portfolio formation date, whereas holding time frames usually span one month, before the price hedge portfolio is readjusted.[84]

Our findings suggest diverse country-specific price effects (in several countries) that are not consistently explained by standard finance asset pricing models[85] and (e.g.) a tendency toward a general high-price effect in Europe (see also Glas et al., 2017) as opposed to a low-price effect in Asia, i.e. regional price effect clusters. This proves our intuition to be more than reasonable as we conjecture that cultural differences might drive (some) variety throughout national price effects which is in line with previous related evidence on other anomalies (cp., e.g., Chui et al., 2010, who already managed to link momentum to culture). We discuss this in detail in Section 3.

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[84] Price as an investment strategy does inherently not suffer materially from frequent portfolio turnovers pushing up transaction costs, as it is (especially in the extremes; like for US stocks quoting above several hundred U.S. dollars or being penny stocks) a rather steady stock characteristic (as opposed to momentum for example). A very cheap (expensive) stock usually remains cheap (expensive) for a decent amount of time, if there is no surprising (disturbing) (external) event.

[85] This also means that some (unknown) priced risk that may be associated with investing in nominal price is not only not evenly distributed throughout the world, but (in fact) apparently operates diametrically in specific countries.

In addition, articles on the connection of cultural effects (commonly measured by cultural dimensions), capital market anomalies (and derived investment styles) as well as (and even more) stock returns in general still rarely exist (see, e.g., Karolyi, 2016 for a brief overview of studies exploring the impact of culture for financial decision making and employed cultural datasets, and Nadler and Breuer, 2019 for a structured overview of cultural finance as a research field), although this approach could (like the investigation of the price effect) reveal new connecting factors, especially regarding the (still puzzling) existence and persistence of the "zoo of new factors" (Cochrane, 2011; Harvey et al., 2015) and (forthcoming) capital market anomalies. Chui et al. (2010) laid a cornerstone for a new finance branch "cultural finance" (e.g., Zingales, 2015; Nadler and Breuer, 2019) as they managed to link evidence on international momentum returns to culture, or more specifically to the extent of individualism prevailing in a country. Doing so, they implicitly tested behavioral finance theories on overconfidence and self-attribution bias as these behavioral patterns are positively associated with individualism.

Since momentum shows similar return patterns (low to negative returns in Asian countries, high returns in Western/European countries, cp. e.g., Chui et al., 2010)[86] and price and momentum are clearly overlapping investment styles (almost per definition, since ceteris paribus, intermediate-term winner stocks have to show higher prices than past loser stocks on average, and vice versa, which is also confirmed in unreported descriptive statistics for the vast majority of countries), we also test if two related styles are both driven by (or at least connected to) culture. In this way, we not only execute a successful "out-of-style" robustness test of the explanatory and predictive power of cultural dimensions for stock market investment styles, but also show that cultural characteristics on their own are consequential for global cross-sectional stock returns in general and remain robust even after controlling for major stock return predictors.

With this paper we make several contributions to the emerging field of cultural finance as well as to the mainstream finance literature debating and exploring the existence, connections and

[86] The difference to momentum however is that price is not only non-existent in Asia, but clearly negative.

origins of international capital market anomalies: First, we test price in each of the 41 countries in our dataset individually and compare it to the country-specific performance of established investment styles (size, value, and momentum). In the process, we implement and execute standard asset pricing tests and cross-sectional regressions, to see if price can be explained by financial risk factors and if it is a robust predictor of stock returns on country level. In a second step, we use Hofstede's (1980, 2001) cultural dimensions[87] to test our main hypothesis that price is, like momentum (cp. Chui et al., 2010), connected to cultural aspects defining a society and the behavioral patterns of its inhabitants in a long-term, largely time-invariant and general manner.[88] The universal strength of cultural dimensions lies in their stability and quantifiability that behavioral finance is in dire need of to validate their theories. Hofstede and others provide us with such a tool that puts (rather fuzzy) behavioral finance on a comparably firm footing and at the same time remind us that behavioral finance theories and implications (that are often the product of Western minds) should not naively be transferred and applied to all cultural backgrounds (cp., e.g., Hofstede et al., 2010).

The rest of the paper is organized as follows. In the next section, we briefly introduce the concept of nominal stock price and sketch its interdependence with other major stock characteristics, showing its relevance for finance research. Thereafter, we define the six cultural dimensions proposed by Hofstede et al. (2010) and in this way reveal the paramount importance of culture for behavioral finance issues in general. In Section 3, we briefly review literature regarding the price effect and the connection of culture and finance and develop our hypotheses. Following, we introduce our financial and cultural datasets and report basic characteristics and statistics of our country-specific samples. In Section 5, we test the price effect on an international

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87 Hofstede (2001) proposes five distinct cultural dimensions: Power Distance, Individualism, Masculinity, Uncertainty Avoidance, and Long Term Orientation (a sixth dimension called Indulgence was added later in Hofstede et al., 2010) that together characterize national cultures (see Section 2.2).

88 "National Culture cannot be changed, but you should understand and respect it." (Geert Hofstede; https://www.hofstede-insights.com/models/national-culture/)

level, report main performance characteristics and compare price portfolio results with established risk factor mimicking portfolios. In Section 6, we move on to standard asset pricing tests and robustness checks of price. Section 7 tests our culture-related sub hypotheses and main hypothesis that price is linked to culture, interprets the results and provides further implications. Section 8 concludes the paper.

2. Theoretical Foundations

2.1 Nominal Stock Price

The nominal price of a stock (that is, a stocks' actual market price) should not matter at all in fully efficient markets (cp., e.g., Fama, 1970) as it is (as public information) readily obtainable for any investor and therefore should be priced in especially rapidly in case of containing some relevant information for the market. In addition, it is specifically arbitrary (like, e.g., a firm name) as it can be altered easily via stock splits and reverse stock splits[89] (in this way increasing or reducing the number of outstanding shares). Apart from its inherent arbitrariness, the nominal price is (either per definition, correlation or due to market mechanisms) connected to various stock characteristics that have been shown to be eligible for predicting and explaining international stock returns. As an example for how common price really is in the "zoo" of anomalies, we have a look at the definitions of the 97 anomalies that are investigated in the study of McLean and Pontiff (2016). We manage to identify 39 of these 97 anomalies to be directly or indirectly connected with nominal price. Most obviously, virtually all anomalies incorporating returns have to be based more or less on price, since *ceteris paribus* the price of a security is *the* key variable for calculating its returns. The prevalence of price does also not exclude some major

[89] Another, but less common option for firm managers to manipulate nominal stock prices are face amount changes (e.g., Hammerich et al., 2018).

anomalies used as risk factors in asset pricing models and as investment styles which is outlined in the following.

Per definition, stock characteristics size (market capitalization of a firm) and value (often measured as book-to-market equity) are directly dependent on price – or more specifically – on the movement of the stock price. The higher the stock price, the higher the firm's market capitalization, as size is calculated as price times number of outstanding shares which leads to a perfectly proportional relationship between price and size. In the case of value, the relation is less straightforward, since price is present in the denominator (consisting of market capitalization or market equity). Thus, in general, high prices make it more likely to classify a stock as growth stock (having a low book-to-market equity ratio), since then, the value of the denominator increases. The momentum of a stock (past return performance) and price are mutually dependent: an increase in price leads to a higher momentum and a higher momentum leads to a higher price. However, the classification of a stock via price is, especially in the extremes, less volatile than via its (short to intermediate term) momentum, since, e.g., a very high-priced stock stays still very high-priced (in relation to the complete stock universe) even after a 50% price drop, whereas at the same time its momentum would be abysmal. This also cuts back transaction costs to some degree when incorporating a price based investment strategy instead of (or in addition to) a momentum strategy, since portfolio turnover is lower.

In the case of the liquidity of a stock, price is also an influencing factor.[90] This is due to a general market mechanism, namely the indivisibility of shares, leading *ceteris paribus* to a higher stock market turnover for low-priced stocks and a lower turnover for high-priced stocks (cp., e.g., Singal and Tayal, 2017). In turn, a lower liquidity of a stock is also automatically linked to a lower (very) short-term volatility of its nominal price. Birru and Wang (2016b) however

[90] Price can also be used as a liquidity proxy, e.g. LN(1/Price) (Brennan and Subrahmanyam, 1996; Brennan et al., 1998).

document for US stocks that the price premium is not the illiquidity effect (Amihud, 2002) or the volatility effect (Ang et al., 2009) in disguise.

Beyond that, many papers point to the relevance of nominal stock prices for investors' decisions (e.g., Gompers and Metrick, 2001; Fernando et al., 2004; Kumar 2009; Fernando et al., 2012; Birru and Wang, 2016a, 2016b; Hammerich et al., 2018). This is also well justifiable in the light of classical heuristics and biases like availability and anchoring (Tversky and Kahneman, 1974) where easy to access and remember characteristics (like the stock price) have a higher retrievability and are thus more likely to influence judgment and decision making. The higher appearance of institutional investors on high-priced stocks shareholder's lists – whereas low-priced stocks are teeming with private investors and noise traders[91] (see, e.g., Kumar, 2009; Fernando et al., 2012) – also suggests to witness lower volatility and lower market sensitivity of high-priced stocks returns as opposed to low-priced stocks returns. We will see these hypotheses confirmed not only on the US market (Singal and Tayal, 2017) and in Europe (Glas et al., 2017; Hammerich et al., 2018), but worldwide in Section 5.

Furthermore, firm managers are aware of the relevance of stock prices to investors (e.g., Conroy and Harris 1999; Baker et al., 2009). In the US case for example, nominal stock prices remain at about $35 since the Great Depression (Weld et al., 2009), which led to the catering theory of Baker et al. (2009), where managers lower stock prices when they witness investors to overestimate the value of low-priced stocks. Weld et al. (2009) themselves ascribe this constant share price practice to customs and norms as they find neither signaling theories nor optimal trading ranges to account for this issue.

[91] For example, Singal and Tayal (2017) report (for the US market) that low-priced stocks have seven times as many shareholders as high-priced stocks.

2.2 Cultural Dimensions

Hofstede et al. (2010: 6) define culture as „the collective programming of the mind that distinguishes the members of one group or category of people from others." In a temporal context it resembles "the unwritten book with rules of the social game that is passed on to newcomers [of a society] by its members, nesting itself in their minds." (Hofstede et al., 2010: 26) Unlike the basic layer of human nature which is universal to all humans and inherited, culture is learned. It is a collective phenomenon based on the social environment in which a distinctive group or category of people is raised and socialized. Due to its social nature it is also separate from the top layer, "personality" (whereas culture is the middle layer) which is specific to an individual. Although "personality" is also learned, it is at the same time also partly inherited like the human nature. The core of distinctive cultures is constituted by (largely time-invariant) values, which are emotionally based, general tendencies regarding the preference of certain state of affairs over others, like e.g. the (perceived) morality or immorality of an action. In this way, values determine how people in a country generally think, feel, and act (Hofstede et al., 2010).[92]

In his model of national cultures, Hofstede (2001) initially proposes four distinctive cultural dimensions (Power Distance, Individualism, Masculinity, and Uncertainty Avoidance) based on a value score database of international IBM employees that was created via extensive surveys for example on work goals between 1967 and 1973. The values of these four dimensions (identified using factor analysis) where initially determined for 40 countries in Hofstede (1980). Based on extensions described in Hofstede (2001) and Hofstede et al. (2010) designed to mimic

[92] Due to the pervasive nature of culture that nests itself in human minds very early in their lifetime, possible endogeneity issues regarding causal influences on economic decision making appear not very likely as it is documented in various examples of human history (cp., e.g., Guiso et al., 2006). As another example, to check for endogeneity, Breuer et al. (2014) use an instrumental variable for Individualism when explaining equity participation ratios of households and virtually report the same results when using Hofstede's (1980) Individualism dimension itself.

the initial methodology and to enlarge the covered countries in a consistent manner, data for 76 countries is now available. Later, two additional cultural dimensions (Long Term Orientation and Indulgence), each available for 93 countries, were added based on World Values Survey data. Several replication studies showed the (primary) dimensions to be still valid and to be insensitive to the used methods and datasets (Hofstede et al., 2010). The now six cultural dimensions together (but at the same time also each dimension independently) define the basic nature of distinctive national cultures – or more specifically – the relative differences of countries (rather than individuals) regarding preferences for one state of affairs over another (i.e., e.g., aspects of behavior associated with the distinction individualism versus collectivism). Thus, the values/scores of the dimensions (see Section 4.2) should not be understand as absolute, but rather as relative (to other cultures), since each dimension value is determined in relative terms regarding all of Hofstede's (initially) included countries (Hofstede, 2001).[93]

Power Distance is a dimension dedicated to capture the way a society handles inequalities among people. Scores on this dimension inform about the degree of dependence of subordinates regarding relationships with their bosses. Hofstede et al. (2010: 61) put it that way: "Power distance can (…) be defined as *the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally*. *Institutions* are the basic elements of society, such as the family, the school, and the community; *organizations* are the places where people work." High Power Distance scores of a society show that people generally accept a hierarchical order. On the other side of the scale are societies in which people strive to equalize the distribution of power and – if inequalities of power are (still) present – require justification for this state of affairs.[94]

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[93] For more details on, e.g., the construction and calculation of the culture indices (values), the underlying factors/factor analysis, the used survey questions, and further implications and correlations, see Hofstede (2001) and Hofstede et al. (2010).

[94] See also Hofstede's website for (the) short summaries of the cultural dimensions: https://www.hofstede-insights.com/models/national-culture/

One of the most impactful and universal dimensions is Individualism (versus Collectivism). It proposes two poles in which members of a society are either clustered in groups (collectivism) or loosely connected (individualism). The two poles of this dimension are defined as follows: "*Individualism* pertains to *societies in which the ties between individuals are loose: everyone is expected to look after him- or herself and his or her immediate family*. *Collectivism* as its opposite pertains to *societies in which people from birth onward are integrated into strong, cohesive in-groups, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty*." (Hofstede et al., 2010: 92) One striking example of the general differences between collectivistic and individualistic societies is that in individualistic societies, members are expected to have and to share their own (diverse) opinions whereas in collectivistic societies members are expected to conform with and stand in for the majority opinion of their (often situation-dependent) (in-)group to which they (feel to) belong.[95] Also, joint-stock companies are regularly in the hands of individual investors in individualistic societies as opposed to collectivistic societies where families, collectives or the government are more likely in charge (Hofstede et al., 2010). Furthermore, there are many meaningful correlations of the degree of Individualism (and even more with Masculinity and Uncertainty Avoidance) and consumer behavior data (Hofstede 2001; De Mooij & Hofstede, 2002; De Mooij, 2004, 2010; Hofstede et al., 2010).

A third traditional culture dimension, labeled Masculinity versus Femininity (as it is the only dimension that showed consistently different scores among male and female IBM employees), is (like Individualism) also based on work goal items from the original IBM study of Hofstede (1980, 2001). "*A society is called* masculine *when emotional gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life*." On the other hand, a "*society is called* feminine *when emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the*

[95] This could, e.g., contribute to higher market efficiency and lower herding behavior in individualistic societies (see, for example, Chang and Lin, 2015; Eun et al., 2015).

quality of life." (Hofstede et al., 2010: 140) Masculine societies foster competitiveness and strive for career and success that is supposed to be shown by its members (performance society). Feminine societies prefer cooperation and are consensus-orientated (welfare society). The own (good) performance is generally underrated and concealed in those societies, for instance (Hofstede et al., 2010).

Uncertainty Avoidance as the last remaining initial IBM study dimension, deals with a societies' anxiety level due to ambiguous or unknown situations and the extent of an avoidance of these. Uncertainty and anxiety are both diffuse feelings which have no certain probability for an event or an object attached to it (as opposed to risk and fear). Therefore, the higher the Uncertainty Avoidance level of a society is, the more rigid codes of behavior and belief exist and approaches and ideas that are innovative and off-the-wall are regarded with suspicion[96] (e.g., resulting in less new trademarks and higher constraints due to rules for "intrapreneurs" in such societies). However, what these societies lose in invention and (basic) innovation, they make up leeway in implementation of new ideas and processes and developing new products and services (especially due to their higher need for precision and formalization). In the investment sphere, this difference in anxiety tolerance also expresses in, other things being equal, a preference for precious metals and gems in strong uncertainty-avoidant societies, whereas uncertainty-accepting countries tend to invest more in stocks (De Mooij, 2004; Hofstede et al., 2010).

The first new cultural sphere, Long Term versus Short Term Orientation, deals with the attitudes of a society toward their own past while handling current and coming challenges: "*long-term orientation* stands for *the fostering of virtues oriented toward future rewards—in particular, perseverance and thrift*. Its opposite pole, *short-term orientation*, stands for *the fostering of virtues related to the past and present—in particular, respect for tradition, preservation of "face," and fulfilling social obligations*." (Hofstede et al., 2010: 239) An interesting example for economic implications connected with this dimension is that (as the name suggests) in long-term orientated cultures, long-term profits (10

[96] Short-term orientated societies are additionally wary of societal change.

years in the future) are rated more important than short-term (this year's) profits and vice versa[97] (Hofstede et al., 2010). De Mooij (2004) additionally shows that investing in real estate (i.e., a long-term commitment) is more common in long-term orientated countries, whereas in short-term orientated countries investments in mutual funds are much in demand.

The last and latest culture dimension, first proposed in Hofstede et al. (2010), Indulgence versus Restraint, is highly associated with (expressions of) happiness and optimism in a society and resembles to a certain degree the distinction between a loose and tight society. "*Indulgence* stands for *a tendency to allow relatively free gratification of basic and natural human desires related to enjoying life and having fun*. Its opposite pole, *restraint*, reflects *a conviction that such gratification needs to be curbed and regulated by strict social norms*." (Hofstede et al., 2010: 281)

3. Literature Review and Hypotheses Development

3.1 Price Effect

Blume and Husic (1973) are the first to investigate a price effect (in the following that is, nominally high-priced stocks outperform low-priced stocks or vice versa) on the NYSE and at the same time drawing connections of stock price to beta, documenting evidence of an inverse relationship of price and returns and a positive (though insignificant) relation of beta and returns in the time frame 1932 to 1966. Contradicting this early US evidence, Seguin and Smoller (1997) report lower risk-adjusted rates of return for portfolios containing low-priced stocks than for portfolios of high-priced stocks for a sample of NASDAQ stocks between 1974 and 1988. By trend, Singal and Tayal (2017) affirm this newer finding (using US stock market data from 1963 to 2015) as they report an outperformance of high-priced stocks when explicitly controlled for

[97] The US is a prime example for a short-term orientated culture that turns special attention to short-term profits and fast spending of money (reflected in a low savings rate) (Hofstede et al., 2010). This finding gets further underlined due to the common quarterly dividend payout on the US stock market.

size (but no return differences when not controlled for size) and empirically document a negative impact of stock splits (resulting in price deterioration) on subsequent returns. However, Hwang and Lu (2008) and Birru and Wang (2016b)[98] find a robust low-price effect (low-priced stocks outperform high-priced stocks) for the US using a similar time frame (1963 to 2006 and 1968 to 2013) and the same data sources (CRSP and Compustat) as Singal and Tayal (2017). Besides the US evidence, we find recent papers of Glas et al. (2017) and Hammerich et al. (2018) to report a high-price effect (measured by a high-price minus low-price or expensive minus cheap hedge portfolio) in 9 out of 11 European countries and for Germany since the 1990s. One exception regarding the investigation of an international price effect is Baytas and Cakici (1999) who document a consistent low-price effect for seven industrialized countries (USA, Canada, Japan, UK, Germany, France, Italy), but using only a limited time frame (1983 to 1991).

On a more thorough and diverse international basis (and of course, using a larger time frame and recent data), results on a possible stock price effect have been, to our knowledge, not yet published, although price is (directly) connected to – or could be partly seen as proxy for – several established stock characteristics used as investment styles and for the construction of common financial risk factors (see Section 2.1) and thus has the potential to shed, e.g., further light on the existence and origin of the internationally robust (with the exception of some Asian countries), but still puzzling momentum effect.

Especially referring to the most consistent empirical findings of the recent papers (Glas et al., 2017; Singal and Tayal, 2017, and Hammerich et al., 2018) which find portfolios consisting of high-priced (expensive) stocks to outperform portfolios of low-priced (cheap) stocks, at the same time showing a clearly lower return volatility, higher risk-adjusted returns, lower market sensitivity and lower, respectively negative values for skewness of returns for expensive

[98] However, Birru and Wang (2016b) find no effect regarding raw nominal price and use a fitted price variable instead. See also the recent paper of Geertsema and Lu (2019) showing the ongoing debate regarding the nature of an US price effect.

portfolios, we derive four sub hypotheses H1a to H1d (all in relation to low-priced portfolios) and one main hypothesis (H1) for our international test of the price effect (see Sections 5 and 6):

H1. Expensive portfolios outperform cheap portfolios.

H1a. Expensive portfolios show lower return volatility.

H1b. Expensive portfolios yield higher risk-adjusted returns.

H1c. Expensive portfolios exhibit lower market sensitivity.

H1d. Expensive portfolios have lower/negative values for skewness of returns.

In the next section, we draw possible cultural prerequisites that are connected with the extent of the fulfillment of H1. Furthermore, we sketch conditions of national cultures that make the contrary hypothesis (cheap portfolios outperform expensive portfolios) more likely.

3.2 Culture-based Market Anomalies: Is Price one of them?

In the finance domain, research on the impact of culture, respectively cultural dimensions of Hofstede (2001) and others (e.g., Schwartz, 1994 and House et al., 2004) on financial decision making is on the rise. Especially investment biases, like the home and foreign bias (e.g. Grinblatt and Keloharju, 2001; Beugelsdijk and Frijns, 2010; Anderson et al., 2011; Aggarwal et al., 2012; Beracha et al., 2014) and behavioral pitfalls like herding (Chang and Lin, 2015) are in the focus of research, mainly from a global perspective. Another strand of literature focuses on the linkage of stock price comovement and culture (Lucey and Zhang, 2010; Eun et al., 2015). Other recent papers applying cultural dimensions in the corporate finance sphere are for example Zheng et al. (2012), Li et al. (2013), and Chui et al. (2016).

The only prominent paper[99] that connects culture and stock returns (or more specifically, the momentum effect) directly is Chui et al. (2010).[100] They manage to link the strength of the international momentum effect (past winner stocks outperform past loser stocks in an intermediate 3 to 12 month time frame) to one of Hofstede's cultural dimensions (Individualism), in particular and find that the higher the tendency of a society to promote a loosely-knit social framework (i.e. individualism), the stronger is, on average, the momentum effect. As the price and the momentum of a stock are related, we expect a possible international price effect to be especially linked to Individualism. However, since there is no profound theoretical framework depicting which cultural dimensions are connected to (or even consequential for) stock returns (and stock investment styles based on anomalies like momentum), we include all six cultural dimensions of Hofstede and others (Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long Term Orientation, and Indulgence; Hofstede et al., 2010) in this study. This holistic incorporation of cultural characteristics also appears more proper for any empirical study (than a concentration on only some or even one) since these dimensions are somewhat correlated with each other as well as related to alternative cultural measures from other studies (Schwartz, 1994; Hofstede, 2001; House et al., 2004; Hofstede et al., 2010) and thus likely moderate themselves in regressions. Our initial main hypothesis regarding the connection of culture and the price effect therefore is:

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[99] Another (less prominent) paper is Durand et al. (2013): They manage to link culture (i.e., the individualism index of Hofstede (2001)) to the performance of sin stocks and the ratios of substantial/governmental shareholders investing in those stocks. Investors in more collectivistic countries are not deterred from investing in sin stocks (or even inclined to invest) contrary to more individualistic countries, leading to an underperformance of sin stocks in seven Pacific-Basin markets as opposed to a clear outperformance in, e.g., the US. Weigert (2015) and Cheon and Lee (2017) on the other hand, manage to link the presence of the MAX premium and of a crash sensitivity effect (measured by lower tail dependence) to more individualistic countries.

[100] However, Chui et al. (2010) completely concentrate on the momentum effect without investigating the predictive power of cultural dimensions for international (firm-specific) stock returns in general.

H2: Cultural characteristics are consequential for a nominal stock price effect.

In the following, we refine this general hypothesis regarding the impact of specific cultural dimensions. Our argumentation basically relies on behavioral patterns and investment preferences (which are traced back to cultural characteristics) of (different) stock investors that determine the demand (function) of either high-priced stocks or low-priced stocks. In doing so, we also refer to papers that propose and show that culture has an impact on (country-level) stock ownership structures[101] like Grinblatt and Keloharju (2001), de Jong and Semenov (2006), Caramelli and Briole (2007), Breuer et al. (2014), and Holderness (2017). Specifically, Breuer et al. (2014) provide evidence that all four initial dimensions of Hofstede (1980) are significant explanatory variables for the stock participation puzzle of households with, e.g., higher Individualism levels being associated with higher stockholding participation and additionally more risk propensity.

Since momentum and price are related investment styles, the cultural explanations of momentum of Chui et al. (2010), especially regarding the (behavior-based) links of individualism and momentum are also (partly) transferable to price. Birru and Wang (2016a), show that investors overestimate the skewness of returns of low-priced stocks and therefore their future performance relative to high-priced stocks. Since people in individualistic cultures are more overoptimistic about their abilities, tend to overestimate the precision of their predictions (cp. Heine et al., 1999; Van den Steen, 2004; Grinblatt and Keloharju, 2009) and are more willing to take financial risks (Breuer et al., 2014), it is likely that low-priced (lottery-type) (Kumar, 2009) stocks appear to be more attractive to investors in individualistic cultures (leading to an overvaluation and lower returns of low-priced stocks relative to high-priced stocks). In addition,

[101] Data on time series of country-level or even firm-specific shareholder structures are not readily attainable for broad global studies like ours and are routinely applied only in studies based on US data (e.g., Asquith et al., 2005). However, in line with the results of Breuer et al. (2014), we regard Hofstede's (1980) dimensions as proxies (and causal drivers) (cp. also Guiso et al., 2006) for the stockholding participation of individual investors.

people in collectivistic countries tend to have high self-monitoring which helps to reduce cognitive biases caused by overconfidence (Biais et al., 2005) and overoptimism (Church et al., 2006). This connection (of collectivism) to a high self-monitoring ability is also reflected in the Indulgence dimension (defining the extent to which people try to control their desires and impulses) with low scores (depicting restrained people) in (collectivistic) Asian countries, especially.

It seems also reasonable that self-indulgent (presumably sensation-seeking and rather extrovert[102]) investors prefer low-priced stocks that often have lottery-like characteristics (see, e.g., Grinblatt and Keloharju, 2009; Kumar, 2009) resulting in an overvaluation. George (2002) shows for example that buying compulsiveness in respect of lottery tickets and scratch cards is positively associated with the extraversion dimension of personality. In line with this, Hofstede and McCrae (2004) document a significant positive correlation between Individualism (0.64) and Long Term Orientation (0.56) as well as a negative correlation of Power Distance (-0.57) with the extraversion factor of personality. Masculinity is found to be an additional inverse predictor of extraversion levels. Indulgence as the newest dimension was not yet incorporated as a cultural dimension at the time of the study (2004), but it appears to be an educated guess that this dimension is likely to be also connected to extraversion. These associations with extraversion are consistent with our hypotheses (see below) where we expect Individualism (Collectivism) and Long Term Orientation (Short Term Orientation) to be positively related to a high (low) price effect and Masculinity (Femininity) to be linked to a low (high) price effect.

Another point is the differing ownership structure of joint-stock companies in individualistic vs. collectivistic countries (cp. Hofstede et al., 2010; Breuer et al., 2014) as sketched above (more individual shareholders of joint-stock companies vs. more institutional type shareholders). Since individual investors prefer low-priced stocks and institutional investors

[102] Social transmission (Han et al., 2018) might also come into play here and could drive up the utility of strongly socializing investors/speculators to hold low-priced stocks even more.

rather demand high-priced stocks (Kumar, 2009; Fernando et al., 2012), we expect this to contribute also to an undervaluation and outperformance of low-priced stocks (vs. high-priced stocks) in collectivistic nations (and the opposite in individualistic countries). Thus, we expect individualistic/self-indulgent (collectivistic/restrained) cultures to trigger a high-price effect (low-price effect):[103]

H2a: *High* (low) values of Individualism are connected to a *high*- (low-)price effect.

H2b: *High* (low) values of Indulgence are linked to a *high*- (low-)price effect.

A possible factor for the prevalence of a low-price effect in "masculine", i.e. competition-orientated cultures could be based upon the existence of more sophisticated (institutional) investors due to higher competitive pressure in masculine countries. Anderson et al. (2011) underline this assumption, as they find (institutional) portfolios (of investors) from countries with higher Masculinity levels to display lower levels of home bias and additionally to be more diversified abroad (i.e. indicating more sophisticated investors that are less prone to biases). They also find that investor behavior is impacted directly by culture and not merely indirectly through channels like regulatory and legal framework. Consistently, Breuer et al. (2014) show that higher Masculinity levels are negatively associated with household's equity participation ratios. Since it is known that institutional investors (who are more sophisticated than (most) private investors) prefer high-priced stocks as opposed to private investors who prefer low-priced stocks (e.g., Kumar, 2009; Fernando et al., 2012), in masculine countries, high-priced stocks tend, under our

[103] In the following, we construct each hypothesis in a two-way form. In doing so, we refer to Barberis and Shleifer (2003) who (theoretically) propose that naturally, the investment (of a sophisticated investor) in an investment style (e.g. investing in high-priced stocks) is primarily financed by withdrawing funds from the respective twin style (low-priced stocks). In this way, the attractiveness (and therefore the performance) of an investment style has an (indirect) impact on (the performance of) its twin style. However, we mark the expected main effects with italics.

assumption, to be overbought and yield lower returns relative to more feminine (cooperation-orientated) countries.

H2c: *High* (low) values of Masculinity are related to a *low*- (high-)price effect.

With regard to a possible influence of Long Term Orientation (LTO) and Uncertainty Avoidance (UA) on the price effect, we assume that the observed strong association of price and size (cp. Table 4) could be consequential. IPOs for example, are mainly performed by smaller firms with future-orientated business models, offering their stocks at low to moderate share prices (Fernando et al., 2004). In countries with high scores of LTO, i.e. future-orientated cultures, and low scores of UA, that is cultures which are open for new, unorthodox ideas, we expect these young, small, innovative, and rather low-priced firms to be more attractive to (IPO) investors when compared to more traditional/rigid cultures (countries scoring low on LTO/high on UA). This goes hand in hand with higher demand, an overvaluation and thus lower returns of low-sized, low-priced stocks, contributing to an expected high-price effect in countries with high (low) LTO (UA) and a low-price effect in low-LTO (high-UA) countries. Underlining this argumentation, Costa et al. (2013) document higher (initial) IPO underpricing (i.e., a larger price increase due to high demand when the stock is traded on the secondary market for the first time) for high-LTO, low-UA, and high-PD[104] (that is, power is accepted and excepted to be distributed unequally by the less powerful members of society) countries.

[104] We develop no dedicated hypothesis regarding PD, since we are not able to draw sufficiently meaningful connections between PD and a price effect. In tendency, we expect higher (lower) PD levels to be rather associated with low (high) price effects due to the negative correlation of PD with extraversion (Hofstede and McCrae, 2004) and the positive connection of PD with household's stock participation ratio (Breuer et al., 2014).

Furthermore, as de Mooij (2004) documents that low-LTO countries (e.g., the US) are associated with higher demand for mutual funds,[105] we conjecture that this increases (in turn) the demand for high-priced stocks (and thus their likelihood for overvaluation), since these are favored by institutional investors (e.g. mutual funds) (Fernando et al., 2012), whereas mutual funds show a strong aversion to low-priced stocks (Falkenstein, 1996). Regarding high-UA countries it also appears to be reasonable to expect that (individual) investors in those countries rather spurn securities with lottery-like characteristics like low-priced stocks (Kumar, 2009) when compared to low-UA societies. Their low levels of anxiety tolerance deter them from speculating in this kind of stocks or even stocks in general (cp. Hofstede, 2001; de Mooij, 2004; Hofstede et al., 2010). Since (ceteris paribus) this affects the country-wide stocks' ownership structure in favor of institutional investors, the result is an excess demand for high-priced stocks (relative to low-priced stocks) leading to an underperformance of these. Based on these arguments, we state our last two sub hypotheses as follows:

H2d: *High* (low) values of LTO are connected to a *high*- (low-)price effect.

H2e: *Low* (high) values of UA are linked to a *high*- (low-)price effect.

In ascribing the international price effect(s) to cultural characteristics, we have to rely on a certain degree of home bias to be present around the world which is documented by papers like Anderson et al. (2011) for institutional investors. In this way, national investors can drive the price effect in their home country by preferring either low-priced or high-priced stocks, whereas the specific preference is expected to be (lastly) (co-)determined by their culture (cp. hypotheses construction above). Consequently, the degree of home bias in a country is likely also an indirect determinant/indicator for the prominence of a respective country-specific price effect. However,

[105] For example, in 2018 about 44% of US households owned mutual funds, which is equivalent to about 100 million individual mutual fund shareholders. (cp. https://www.ici.org/research/investors/ownership)

since the home bias itself is culture-dependent (Anderson et al., 2011), we regard it as sufficient to use cultural dimensions as (fundamental) proxy variables for the prevalence of home bias. As Anderson et al. (2011) find Individualism, Masculinity, Uncertainty Avoidance, and Long Term Orientation (Power Distance and Indulgence are not included in their study) to be significant determinants for the extent of home bias in (institutional) portfolios and funds, we expect these cultural dimensions to be especially consequential for the magnitude and direction of possible price effects in an international sample.

Apart from these rather behavior-based arguments which are backed by cultural drivers, we conjecture that cultural mechanisms have also an effect on model implications of financial theory. The Markowitz model of portfolio theory implies that the choice between riskless and risky assets is determined by the risk aversion parameter of an investor (Markowitz, 1952). However, as Breuer et al. (2014) empirically show, Individualism is the main explanatory variable of risk propensity of households whereas variables explicitly dedicated to capture risk aversion and loss aversion are insignificant in the performed regression while absorbing Individualism's explanatory power not at all. Thus, especially Individualism might influence investor's decision making not only on the more behavior-based track resulting in mispricing, but also via risk-based contact points. In turn, a possible price anomaly is likely to be triggered via both channels, since individualistic (collectivistic) investors not only prefer (volatile) low-priced (higher priced/non-lottery) stocks due to their "irrational" biases and traits like overconfidence/extraversion (self-monitoring/introversion), but also rationally due to their higher (lower) risk propensity.

4. Data

In the following, we introduce the used datasets (and the applied data editing methodology) to perform our tests of an international price effect and its expected connection to national culture.

4.1 Financial Time Series

We retrieve the financial data of our international sample from Thomson Reuters Datastream (TRD) and the IMF (for gross domestic product (GDP) per capita data[106]). We select 41 countries to be included in our study (Table 1).[107] The sample starts – for many, especially developed countries – in June 1980 and ends for all countries in April 2017. All stocks listed at the countries' major stock exchange in the respective time frames are included in the (raw) sample.[108] We end up with a total of 31,807 stocks and a maximum sample length of 442 months (stocks from financial sectors are excluded to facilitate comparability of calculations referring to book-to-market ratios especially as this is common practice in asset pricing). For each of these stocks, we download data on TRD data types Total Return Index, Unadjusted Price, Market Value, and Common Shareholder's Equity. We require each country to have at least 30 active stocks in each consecutive month of the sample to attain a sufficient number of stocks for our price portfolios (and risk factors).[109] To mitigate data quality and illiquidity problems (see, e.g., Ince and Porter, 2006), we exclude values in the specific month if the market capitalization of a

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[106] http://www.imf.org/external/pubs/ft/weo/2017/01/weodata/index.aspx

[107] Ang et al. (2009) and Fama and French (2012), for example, limit their international sample to (23) developed countries only (with 16 European countries), but include only three Asian countries (Japan, Hong Kong, Singapore). Since our research question relies on cultural diversity in our sample, we choose a more heterogeneous and (regionally) balanced sample which also includes unique and large national cultures like China and India.

[108] We restrict the sample to primary listings traded in local currencies at their home stock exchange. We include both dead and active stocks in the raw data and implement our own inactive stocks filter (we do so also due to Datastream's incomplete dead stocks lists).

[109] We cut off (i.e. set "not available") all months which do not fulfill this prerequisite until the month when at least 30 stocks are continuously available through April 2017. Due to this filter, we have to dismiss Ireland and Portugal completely. Apart from these two countries, we cover all countries of Chui et al. (2010) and additionally include Russia and Saudi Arabia.

stock is below the first decile[110] of all stocks in its associated country (every month anew). Second, to account for extreme values due to Datastream's rounding policy for very low-priced stocks, we set, in each month, stock data missing if a stock's unadjusted price is below 1 currency units. Third, we test if a stock is still actively traded/tradable and exclude a stock in a specific month, if it showed monthly returns of zero in the previous four months, respectively. These filters help us to focus more on liquid stocks (without cutting down the sample size too much) and especially ensure that results are not driven by small-sized penny stocks which typically exhibit most data failures (e.g. return outliers).

4.2 Hofstede's Cultural Indices

The cultural data spans the six cultural dimensions proposed by Geert Hofstede and others (Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long Term Orientation, and Indulgence; see Hofstede et al., 2010). We get the data of the six cultural dimensions for each of the 41 countries in our sample (Table 2) directly from Hofstede's website.[111] Each dimension is labelled in the way that high scores indicate strong fulfillment of that label in a country. For example, a high score (e.g., 80) for Masculinity and Individualism marks a "masculine", individualistic society (as opposed to a feminine, collectivistic society scoring low on these dimensions), whereas a low score (e.g., 20) for Long Term Orientation depicts a normative society that prefers to maintain time-honored traditions as opposed to more pragmatic, future-orientated societies scoring high on this dimension. The dimensions were

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[110] Asness et al. (2013), for example, use a much more rigorous liquidity filter as they only include the very biggest stocks that cumulatively account for 90% of the total market capitalization which results, for the US case, in an inclusion of only the top 17% of all US firms on average. However, since Asness et al. (2013) concentrate on implementable investment strategies and not, like us, on asset pricing, we decide to exclude only the very smallest stocks in each country-specific stock universe (comparably to Chui et al., 2010 who use a 5% cut-off).

[111] https://www.hofstede-insights.com/product/compare-countries/; cp. also Hofstede et al. (2010)

initially defined in the way that they are restricted to a value between 0 and 100 (only countries that were added in the extensions after 1980 partly exhibit values above 100; cp., e.g., Hofstede et al., 2010). Furthermore, as outlined in Section 2.2, the values should not be understood as absolute, but rather as relative values, since each value is determined in relative terms regarding all of Hofstede's included countries (initially 40) for each dimension, respectively (Hofstede, 2001). In our sample, the culture dimension values reach from a lowest value of 0 to a maximum of 100 representing a high diversity across national cultures as could be expected for an international sample.

Table 1: Summary statistics of international financial data

Our (financial) sample consists of individual stock data from 41 international markets. All data is received from Thomson Reuters Datastream. We include only primary class (common) stocks that are listed in local currency on the major stock exchange in their home country. We exclude stocks from financial sectors, stocks below the first decile of market capitalization in each month within each country, stocks below 1 currency unit and inactive stocks showing zero returns over the prior four months. The table reports the included countries in alphabetical order, the starting year of the respective country-specific samples (earliest date is June 1980), total number of months for each country, the average and total number of stocks in each sample and the average of the monthly median nominal stock prices for each country in local currency. The end date for each country-specific sample is April 2017.

Market	Starting year	Number of months	Number of firms (average)	Number of firms (total)	Nominal price (median)
Argentina	2002	178	51	92	5.1
Australia	1980	442	224	2431	2.7
Austria	1987	358	55	130	66.6
Bangladesh	2008	106	49	73	254.7
Belgium	1985	382	75	178	68.2
Brazil	1998	226	90	206	17.0
Canada	1980	442	454	1630	9.0
Chile	1990	322	110	205	405.4
China	1993	286	567	1157	9.8
Denmark	1987	358	107	228	311.0
Finland	1990	322	83	207	11.6
France	1980	442	440	1373	65.7
Germany	1980	442	353	973	79.3
Greece	1988	346	132	337	4.7
Hong Kong	1983	406	256	1524	2.8
India	1990	322	850	1514	84.4

Table 1: continued.

Market	Starting year	Number of months	Number of firms (average)	Number of firms (total)	Nominal price (median)
Indonesia	1991	310	205	426	1172.8
Israel	1992	298	219	388	10.8
Italy	1983	406	116	403	6.2
Japan	1980	442	1769	3258	730.5
Malaysia	1985	382	293	902	2.9
Mexico	1991	310	79	168	19.4
Netherlands	1980	442	106	244	28.3
New Zealand	1992	298	55	188	2.8
Norway	1982	418	107	408	67.6
Pakistan	1993	286	132	193	51.5
Philippines	1992	298	79	190	6.7
Poland	1995	262	198	535	14.1
Russia	2004	154	118	251	78.5
Saudi Arabia	2005	142	79	118	38.9
Singapore	1982	418	67	647	2.3
South Africa	1980	442	156	596	13.6
South Korea	1985	382	545	896	12816.4
Spain	1987	358	89	229	12.5
Sweden	1986	370	201	791	69.5
Switzerland	1980	442	131	274	746.1
Taiwan	1989	334	498	940	27.7
Thailand	1989	334	293	665	27.6
Turkey	1988	346	163	319	6.4
UK	1980	442	1087	3452	118.1
US	1980	442	1240	3068	25.9

Table 2: Statistics of cultural indices

This table reports the values of Hofstede et al.'s cultural dimensions for each country in our dataset in alphabetical order. Culture dimension scores are standardized in the way that they lay within the interval [0, 100]. We receive the data directly from Hofstede's website. The value on the Indulgence dimension is not available (NA) for Israel.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Argentina	49	46	56	86	20	62
Australia	36	90	61	51	21	71
Austria	11	55	79	70	60	63
Bangladesh	80	20	55	60	47	20
Belgium	65	75	54	94	82	57
Brazil	69	38	49	76	44	59
Canada	39	80	52	48	36	68
Chile	63	23	28	86	31	68
China	80	20	66	30	87	24
Denmark	18	74	16	23	35	70
Finland	33	63	26	59	38	57
France	68	71	43	86	63	48
Germany	35	67	66	65	83	40
Greece	60	35	57	100	45	50
Hong Kong	68	25	57	29	61	17
India	77	48	56	40	51	26
Indonesia	78	14	46	48	62	38
Israel	13	54	47	81	38	NA
Italy	50	76	70	75	61	30
Japan	54	46	95	92	88	42
Malaysia	100	26	50	36	41	57
Mexico	81	30	69	82	24	97
Netherlands	38	80	14	53	67	68
New Zealand	22	79	58	49	33	75
Norway	31	69	8	50	35	55
Pakistan	55	14	50	70	50	0
Philippines	94	32	64	44	27	42
Poland	68	60	64	93	38	29
Russia	93	39	36	95	81	20
Saudi Arabia	95	25	60	80	36	52
Singapore	74	20	48	8	72	46
South Africa	49	65	63	49	34	63
South Korea	60	18	39	85	100	29
Spain	57	51	42	86	48	44
Sweden	31	71	5	29	53	78
Switzerland	34	68	70	58	74	66
Taiwan	58	17	45	69	93	49
Thailand	64	20	34	64	32	45
Turkey	66	37	45	85	46	49
UK	35	89	66	35	51	69
US	40	91	62	46	26	68

5. International Performance of Price Portfolios

In this section, we test our hypotheses regarding an international price effect (see Section 3.1). We report main performance statistics of international price portfolios – Expensive Minus Cheap (EMC) – for each country and show returns of three common risk factor mimicking portfolios, Small Minus Big (SMB), High Minus Low (HML), and Winner Minus Loser (WML) for comparison (we construct these portfolios following Fama and French, 1993 and Carhart, 1997).[112] In each month and for each country, we sort stocks by unadjusted price and assign the top 20% stocks to the Expensive (E) portfolio and the bottom 20% to the Cheap (C) portfolio. The two portfolios are equal weighted and rebalanced each month to form the EMC hedge portfolio. We use quintile breakpoints instead of, for example, decile breakpoints to ensure a sufficient number of stocks in each portfolio, especially in those countries with lower numbers of stocks and at the beginning of the sample. The returns are measured in local currencies to keep the assumed link of nominal stock prices and subsequent returns engaged.[113]

[112] We define SMB and HML in the tradition of Fama and French (1993): we form six value-weighted intersection portfolios (present month's median market capitalization is used to get the small and big portfolio, S and B). Top 30%, middle 40%, and bottom 30% of stocks ranked by book-to-market ratio (common shareholder's equity divided by market value, with values lagged six months and negative values excluded) are used to get a high (H), middle (M), and low (L) portfolio. The intersection portfolios are (initially) formed and rearranged (once) each year in June (i.e., using previous year's book-to-market ratios), whereas returns are calculated monthly. SMB is built via the difference of the average monthly returns of the three small portfolios (SL, SM, SH) and the three big portfolios (BL, BM, BH); HML incorporates the difference of the average monthly returns of the two high portfolios (SH, BH) and the two low portfolios (SL, BL). WML is the equal-weighted winner-minus-loser portfolio. Following Carhart (1997), each month t, stocks are ranked by cumulative returns from month t-12 to month t-2. Stocks in the top 30% build the winner portfolio (W) and stocks in the bottom 30% the loser portfolio (L). WML is the difference of average monthly returns of these portfolios, rearranged monthly.

[113] Anyway, other studies on international stock returns show virtually identical results for returns measured in local currencies and U.S. dollars (e.g., Ang et al., 2009; Chui et al., 2010).

Several first conclusions concerning the international price effect can be derived from Table 3:[114] First, it is not an internationally uniform investment style like value (see HML column) as EMC portfolios show (drastically) differing returns in many countries (this holds also for size; see SMB column). The momentum mimicking portfolio WML also shows, like HML, consistent positive returns, except in some Asian/Eastern countries. Examining the raw returns, we find a consistent low-price effect in Asian/Middle East countries (where at the same time, the momentum effect is remarkably weaker compared to nearly the rest of the world or even non-existent/insignificant with a few exceptions like India, Bangladesh,[115] and Israel, showing the linkage of momentum and price) and a tendency toward a high-price effect for Europe (cp. also Glas et al., 2017), although the results are mainly not significant. Also striking, we find (with a t-statistic of -3.56) the most robust (low-)price effect (see also Table 4 and 5) in the US (that is getting even stronger in the newer half of our sample), which is not corresponding to the evidence of Singal and Tayal (2017),[116] but confirming the older US evidence of Blume and Husic (1973), Baytas and Cakici (1999), Hwang and Lu (2008), and Birru and Wang (2016b).

On the other hand, regarding return volatilities, our international sample shows significantly lower values for the expensive (E) portfolios compared to cheap (C) portfolios (see F-test column showing the p-values) in all countries (except Italy, Israel, and South Africa),

[114] When we use a 5% market capitalization cut-off (like e.g. Ang et al., 2009 and Chui et al., 2010) instead of a 10% cut-off, performance statistics do not change in the big picture.

[115] The positive outlier for momentum in India is also documented by Ansari and Khan (2012) and Chui et al. (2010) who also document a strong momentum effect for Bangladesh and Hong Kong.

[116] Note however, that there are several differences in the research design and the used data regarding our study and Singal and Tayal (2017). For example, Singal and Tayal (2017) control for size via orthogonalization (i.e. they use residual prices) when calculating returns of price (decile) portfolios. When they do not control for size, returns of high-price and low-price portfolios are nearly identical (similar to Birru and Wang, 2016b). Also, their time frame spans the years 1963 to 2015 and includes the entire US stock universe, whereas we concentrate on NYSE stocks only. Nevertheless, Hwang and Lu (2008) confirm our results (also regarding raw returns) using the same data sources and nearly the same time frame (1963 to 2006) as Singal and Tayal (2017).

providing strong support of H1a. Connected to that, the Sharpe ratio equality test of Wright et al. (2014) indicates higher Sharpe ratios (in the following, we use this common term defining risk/return ratios) for the E-portfolio in most countries outside of Asia and the Middle East (column SR-test). Skewness of return values of the EMC portfolios are again quite consistent and show negative values for all but three countries and a few clear (negative) outliers. More specifically, only three countries (Norway, Bangladesh, and South Africa) show higher values for skewness of returns for E-portfolios than for C-portfolios (not reported), confirming H1d.

The Euro conversion in several European countries in 1999 (except Denmark, Norway, Poland, Sweden, Switzerland, and the UK) does not seem to have a (systematic) impact on the price effect: In France, Greece, and Italy a price effect stays virtually non-existent in both periods (before and after 1999) and in the Netherlands the observed high-price effect remains unchanged. On the other hand, in Austria and Spain the effect reverses from a low-price to a high-price effect. Germany experiences an especially rapid inversion toward a high-price effect with a turning point around the mid-1990s, i.e. before the Euro conversion (here Hammerich et al., 2018 argue that this inversion could be amplified or even triggered due to law amendments regarding face amounts of shares in the 1990s). In Belgium, the returns of high-price portfolios increase over time (high-price effect strengthens) and Finland shows no price effect before 1999 and a clear (statistically significant) high-price effect after.

However, in Switzerland (no Euro), the respective high-price effect appears not before 1999 and is statistically significant since then (like in Finland), whereas Denmark also shows a clear inversion from a low-price to a (highly statistically significant) high-price effect, despite not being affected by a currency conversion. Poland shows a weak high-price effect in both periods and in Norway it stays unchanged (or gets slightly stronger), but insignificant. For Sweden and the UK our data indicates an intensification of the high-price effect toward statistically significant levels like in Belgium. An obvious main factor for these inversions from a low-price to a high-price effect or step-ups of the latter is the amplification of the momentum effect (and to a lower degree the inversion of the size effect) which can be witnessed especially in several European markets of our dataset in the course of the last decades that drives up the high-price effect due to its inherent linkage. However, there are also some countries (especially in Asia and the US) that contradict or attenuate this correlation and deter from concluding that price is a simple outflow or by-product of the momentum effect. We examine this in the next section.

Table 3: Performance statistics of EMC hedge portfolios and risk factor portfolios

Within each country and for each month, we rank all stocks by nominal, unadjusted price. Stocks in the top 20% are assigned to the expensive (E) portfolio and those in the bottom 20% to the cheap (C) portfolio. The portfolios are equal-weighted and (re)formed at the end of each month. The zero-cost "price" portfolio expensive-minus-cheap (EMC) is the hedge portfolio. EMC returns are calculated at the end of each month as the difference of monthly returns of the E and C portfolio, formed at the end of the prior month, respectively. Column "Return" reports the average monthly returns of the EMC hedge portfolio for each country in each (region-specific) panel. Countries in Panel F are assigned to category miscellaneous (Misc.). The other columns report t-statistics of a t-test with the null hypothesis that monthly mean returns are equal to zero (T-stat.), standard deviations of monthly returns (SD), p-values of an one-sided F-test with the null that the ratio of variances is equal to 1 (small p-values indicate that variances of C portfolios are larger than variances of E portfolios), the ratio of Return and SD (Sharpe) with negative values not reported (n/a), p-values of a Wright et al. (2014) Sharpe ratio equality test (small p-values indicate that Sharpe ratios of E portfolios are larger than Sharpe ratios of C portfolios) and skewness of returns of the EMC portfolios (Skew). The three columns on the right give average monthly returns of common risk factor portfolios mimicking the size (SMB), value (HML), and momentum (WML) effect for the purpose of comparison (see fn. 112). The longest time frame of a country-specific dataset is June 1980 to April 2017 (442 months, cp. Table 1).

	EMC							SMB	HML	WML
	Return	T-stat.	SD	F-Test	Sharpe	SR-Test	Skew		Return	
Panel A: The Americas										
North										
Canada	-0.05%	-0.22	4.99%	0.00	n/a	0.00	-0.26	0.45%	0.16%	1.42%
US	-0.78%	-3.56	4.55%	0.00	n/a	0.61	-2.22	0.35%	0.19%	0.26%
Middle & South										
Argentina	0.22%	0.42	6.71%	0.00	0.03	0.00	-2.06	0.68%	1.24%	0.34%
Brazil	0.16%	0.29	8.26%	0.00	0.02	0.00	-1.77	0.34%	0.86%	1.27%
Chile	-1.30%	-1.70	13.47%	0.00	n/a	0.00	-14.27	-0.38%	1.68%	0.46%
Mexico	-0.06%	-0.20	5.35%	0.04	n/a	0.37	-0.82	-0.31%	0.55%	1.24%
Panel B: Europe										
Austria	0.32%	0.98	6.07%	0.00	0.05	0.05	-1.36	-0.02%	1.19%	1.10%
Belgium	0.70%	2.92	4.63%	0.00	0.15	0.00	-0.60	-0.21%	0.41%	1.37%
Denmark	0.44%	1.82	4.50%	0.00	0.10	0.00	-0.33	-0.51%	0.43%	1.21%
Finland	0.50%	1.60	5.52%	0.00	0.09	0.00	-0.89	-0.03%	0.60%	1.02%
France	-0.05%	-0.27	4.12%	0.00	n/a	0.00	-0.75	0.00%	0.36%	1.23%
Germany	0.20%	0.98	4.34%	0.00	0.05	0.00	-0.91	-0.31%	0.70%	1.33%
Greece	-0.08%	-0.19	7.51%	0.00	n/a	0.12	-1.25	0.34%	0.36%	0.69%
Italy	-0.01%	-0.06	3.93%	0.08	0.00	0.41	0.14	-0.50%	0.59%	0.95%
Netherlands	0.57%	2.41	4.94%	0.00	0.12	0.00	-0.77	-0.08%	0.34%	1.31%
Norway	0.38%	1.18	6.47%	0.00	0.06	0.00	-0.58	-0.04%	0.25%	1.29%
Poland	0.16%	0.47	5.38%	0.00	0.03	0.14	-0.55	0.76%	0.57%	1.54%
Spain	0.06%	0.22	5.23%	0.00	0.01	0.06	-0.38	-0.18%	0.64%	0.95%
Sweden	0.77%	2.34	6.21%	0.00	0.12	0.00	-0.92	-0.13%	0.05%	1.24%
Switzerland	0.31%	1.66	3.92%	0.00	0.08	0.00	-0.49	-0.24%	0.32%	1.17%
UK	0.56%	2.85	4.05%	0.00	0.14	0.00	-1.02	0.14%	0.45%	1.54%

Table 3: continued.

	EMC							SMB	HML	WML
	Return	T-stat.	SD	F-Test	Sharpe	SR-Test	Skew		Return	
Panel C: Asia										
Bangladesh	0.84%	0.83	9.82%	0.00	0.09	0.06	-0.17	0.96%	-0.16%	1.39%
China	-1.21%	-2.71	7.39%	0.00	n/a	0.97	-1.20	0.61%	0.17%	0.00%
Hong Kong	0.37%	1.41	5.19%	0.00	0.07	0.00	-0.39	-0.45%	1.03%	0.78%
India	-0.61%	-1.28	8.39%	0.00	n/a	0.11	-0.95	0.70%	0.53%	1.64%
Indonesia	-1.08%	-1.52	12.32%	0.00	n/a	0.01	-4.32	0.43%	1.05%	-0.04%
Japan	-0.83%	-2.93	5.91%	0.00	n/a	0.98	-0.56	0.17%	0.59%	0.15%
Malaysia	-0.26%	-0.80	6.33%	0.00	n/a	0.11	-1.73	0.26%	0.39%	0.80%
Pakistan	-0.27%	-0.47	9.42%	0.00	n/a	0.00	-1.68	0.10%	1.00%	0.73%
Philippines	-1.27%	-2.49	8.65%	0.00	n/a	0.84	-1.45	0.19%	0.43%	0.49%
Singapore	-0.11%	-0.42	5.24%	0.00	n/a	0.26	-0.81	-0.01%	0.84%	0.74%
South Korea	-1.07%	-1.93	10.67%	0.00	n/a	0.73	-1.93	0.26%	1.35%	0.23%
Taiwan	-0.24%	-0.55	8.01%	0.01	n/a	0.60	-0.46	-0.08%	-0.05%	0.26%
Thailand	-0.77%	-1.45	9.58%	0.00	n/a	0.15	-3.47	0.22%	0.73%	0.41%
Panel D: Middle East										
Israel	-0.36%	-1.38	4.42%	0.19	n/a	0.89	-1.46	-0.06%	1.70%	1.58%
Saudi Arabia	-0.17%	-0.35	5.48%	0.00	n/a	0.62	-1.41	-0.32%	0.50%	0.07%
Turkey	-0.43%	-0.50	15.67%	0.00	n/a	0.00	-8.30	-0.69%	1.02%	-0.43%
Panel E: Oceania										
Australia	0.19%	1.18	3.40%	0.00	0.06	0.04	0.28	-0.05%	0.44%	1.36%
New Zealand	0.12%	0.50	4.17%	0.00	0.03	0.09	-0.07	-0.16%	0.96%	1.37%
Panel F: Misc.										
Russia	0.51%	0.94	6.41%	0.00	0.08	0.03	-0.91	-0.19%	1.00%	0.54%
South Africa	0.06%	0.25	5.09%	0.90	0.01	0.57	0.25	-0.12%	0.56%	1.47%

6. Asset Pricing Models and Robustness Checks

6.1 4-Factor Model

To investigate if common financial risk factors can explain EMC portfolio returns on country level and to test H1c, we implement a Carhart (1997) 4-factor[117] model. Table 4 shows the regression results: we regress EMC returns (for each country $j = 1, 2, \ldots, 41$) on a market proxy MKT, i.e. monthly value-weighted excess returns (using short term deposit rates in local currency if available), and corresponding hedge portfolios mimicking the size (SMB), value (HML), and momentum (WML) effect:

$$rEMC_{jt} = \alpha_j + b_j MKT_{jt} + s_j SMB_{jt} + h_j HML_{jt} + w_j WML_{jt} + \varepsilon_{jt} \quad t = 1, 2, \ldots, T \tag{1}$$

We (still) find significant (mainly negative) alpha values in nine countries (US, Argentina, Mexico, France, Germany, China, the Philippines, South Korea, and New Zealand) and a barely significant value in the UK. The (absolute) peak value is reported for the US, which shows a whopping 4-factor alpha t-statistic of -4.12 (with an abnormal mean return of about 5% p.a. for a cheap minus expensive hedge portfolio) and thus even more significant abnormal returns than raw returns. For Asia and the Middle East, we report mainly negative alpha values. The market beta values (coefficients of MKT) are virtually worldwide negative and show mainly significant t-

[117] A traditional 4-factor model enables us to explicitly investigate the (presumed) relevance of momentum when explaining price hedge portfolio returns as opposed to, e.g., the 5-factor model of Fama and French (2015) that leaves out the momentum factor in exchange for added investment and profitability factors. In this way, we also circumvent likely data availability and quality issues especially regarding economically less developed countries that we would face, if we constructed RMW and CMA on local (country) level (like our other factors).

statistics, which clearly confirms H1c[118] (that expensive portfolios show lower market sensitivity than cheap portfolios) and is also in line with the evidence in Table 3 that expensive (E) portfolios exhibit lower return volatility than cheap (C) portfolios. The mainly significantly negative coefficients for SMB and HML (and more precisely, unreported descriptive statistics) also indicate that around the world, on average,[119] expensive stocks are bigger stocks with lower book-to-market ratios (i.e. growth stocks) than cheap stocks. We find average momentum values however, measured by prior one year returns, to be clearly higher for expensive portfolios relative to cheap portfolios on most international markets. Hence, on the one hand, EMC portfolios (and expensive portfolios) generally exhibit a strong connection to a low market beta and the momentum effect (positive WML factors), whereas on the other hand, EMC portfolios (and expensive portfolios) are inversely linked to the size effect (negative SMB factors) and the value effect (negative HML factors). The opposite holds for cheap portfolios (on average). Effectively, this means that nearly worldwide, EMC portfolios offer solid hedge potential against systemic (market) risk and common size and value (risk) factors.

However, though common risk factors cannot thoroughly explain EMC returns and thus the price effect on specific international stock markets, EMC returns can be explained by a 4-factor model in most countries (but not nearly as much as would be expected, if the price effect was no anomaly), confirming the obvious (construction-inherent) mutual links of price with common characteristics (a follow-up study for example shows international EMC returns to explain WML returns; t-statistic >13). Then again, values for adjusted R^2 drastically differ between countries with a highest value for Chile (0.93) and a lowest value for Russia (0.04), showing a limited international efficacy of common financial risk factors when explaining EMC portfolio returns (also reflected in partly positive, but partly negatively significant alphas).

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[118] Negative loadings of the country-specific EMC hedge portfolios on the market beta factor consistently go hand in hand with high(er) betas for cheap portfolios and with low(er) betas for expensive portfolios (not reported).

[119] For example, it is possible that specific low-priced, small-sized stocks also load negatively on SMB.

Table 4: 4-factor regression outcomes with EMC hedge portfolio returns as dependent variable

This table shows Carhart (1997) 4-factor regression results. We regress monthly country-specific EMC portfolio returns on four known asset-pricing risk factors. Each panel depicts a different world region (except Panel F that includes miscellaneous countries that do not fit the other categories) to facilitate comparability of the outcomes and show assumed regional dependency. MKT is the market proxy, that is, monthly value-weighted excess returns, calculated, as every other factor of the performed 4-factor regressions, for each country-specific stock universe. We use, when available, local short-term deposit rates (1M to 3M) in local currency as risk free rates (or if not available – respectively when covering only short time frames – local short-term treasury bills and equivalents) to calculate excess returns. The three columns in the middle of the table report the factor loadings/coefficients of common risk factor portfolios mimicking the size (SMB), value (HML), and momentum (WML) effect (see fn. 112). "Alpha" labels the coefficients of the regression constant. Adj. R^2 gives the value of the adjusted R^2 for each regression and T displays the available number of months for each regression with maximum (country-dependent) time frame coverage from June 1981 to April 2017 (430 months; we need an extra 12 months to calculate WML returns which reduces the effective time frame by one year). The t-statistics of each regression coefficient are reported on the right of each coefficient in italics and parentheses.

	Alpha		MKT		SMB		HML		WML		Adj. R^2	T
Panel A: The Americas												
North												
Canada	0.16%	*(0.85)*	-0.42	*(-9.97)*	-0.87	*(-14.79)*	-0.14	*(-2.96)*	0.25	*(6.32)*	0.44	430
US	-0.41%	*(-4.12)*	-0.20	*(-8.05)*	-0.92	*(-23.93)*	-0.41	*(-8.75)*	0.54	*(20.31)*	0.81	430
Middle & South												
Argentina	1.10%	*(2.39)*	-0.24	*(-4.41)*	-0.61	*(-6.92)*	-0.22	*(-3.37)*	0.25	*(2.77)*	0.30	166
Brazil	0.06%	*(0.14)*	-0.19	*(-2.01)*	-0.44	*(-3.40)*	-0.27	*(-3.27)*	0.42	*(4.21)*	0.41	114
Chile	0.40%	*(1.19)*	-0.36	*(-4.03)*	-0.32	*(-3.41)*	-0.93	*(-14.45)*	0.54	*(8.41)*	0.93	210
Mexico	-0.70%	*(-2.74)*	0.07	*(1.42)*	-0.61	*(-8.52)*	-0.31	*(-6.07)*	0.38	*(7.55)*	0.41	270
Panel B: Europe												
Austria	-0.02%	*(-0.05)*	-0.03	*(-0.39)*	-0.14	*(-1.67)*	-0.19	*(-2.79)*	0.44	*(7.18)*	0.14	310
Belgium	0.24%	*(0.94)*	-0.26	*(-4.29)*	-0.42	*(-5.73)*	-0.19	*(-3.17)*	0.42	*(7.09)*	0.27	315
Denmark	-0.19%	*(-0.88)*	-0.20	*(-3.97)*	-0.34	*(-5.61)*	-0.02	*(-0.40)*	0.50	*(9.24)*	0.29	346
Finland	0.41%	*(1.37)*	-0.25	*(-5.19)*	-0.43	*(-5.64)*	-0.09	*(-1.75)*	0.35	*(5.81)*	0.21	310
France	-0.37%	*(-2.24)*	-0.25	*(-7.68)*	-0.45	*(-9.09)*	-0.24	*(-5.66)*	0.45	*(11.56)*	0.42	430
Germany	-0.36%	*(-2.37)*	-0.31	*(-9.52)*	-0.60	*(-11.99)*	-0.15	*(-3.69)*	0.50	*(13.30)*	0.57	430
Greece	0.05%	*(0.18)*	-0.20	*(-5.59)*	-0.67	*(-15.35)*	-0.25	*(-5.36)*	0.23	*(5.40)*	0.48	334
Italy	0.10%	*(0.56)*	-0.04	*(-1.12)*	-0.22	*(-3.85)*	-0.41	*(-10.14)*	0.04	*(1.11)*	0.22	394
Netherlands	0.08%	*(0.35)*	-0.11	*(-2.41)*	-0.31	*(-6.28)*	-0.03	*(-0.79)*	0.43	*(8.27)*	0.25	430
Norway	0.03%	*(0.11)*	-0.43	*(-9.92)*	-0.69	*(-11.89)*	-0.22	*(-4.50)*	0.35	*(7.79)*	0.45	375
Poland	0.07%	*(0.22)*	-0.05	*(-1.28)*	-0.40	*(-7.09)*	-0.23	*(-4.50)*	0.36	*(6.45)*	0.30	250
Spain	-0.02%	*(-0.06)*	-0.22	*(-4.48)*	-0.69	*(-10.84)*	-0.23	*(-3.75)*	0.29	*(5.32)*	0.39	300
Sweden	0.23%	*(0.95)*	-0.12	*(-2.89)*	-0.82	*(-14.41)*	-0.03	*(-0.71)*	0.45	*(10.56)*	0.56	336
Switzerland	-0.06%	*(-0.34)*	-0.22	*(-5.54)*	-0.45	*(-8.14)*	-0.06	*(-1.21)*	0.39	*(9.18)*	0.30	430
UK	0.28%	*(1.94)*	-0.16	*(-5.35)*	-0.61	*(-18.24)*	-0.37	*(-7.07)*	0.40	*(10.91)*	0.59	430

Table 4: continued.

	Alpha		MKT		SMB		HML		WML		Adj. R^2	T
Panel C: Asia												
Bangladesh	0.27%	*(0.46)*	-0.35	*(-4.71)*	-0.16	*(-1.41)*	-0.80	*(-8.51)*	0.37	*(3.82)*	0.70	88
China	-0.95%	*(-2.85)*	-0.23	*(-7.00)*	0.08	*(1.29)*	-0.16	*(-2.90)*	1.03	*(12.50)*	0.47	274
Hong Kong	0.22%	*(1.09)*	-0.08	*(-2.99)*	-0.59	*(-15.76)*	-0.23	*(-6.08)*	-0.04	*(-1.00)*	0.41	376
India	0.04%	*(0.12)*	-0.02	*(-0.31)*	-0.74	*(-13.60)*	-0.66	*(-13.91)*	0.55	*(8.24)*	0.70	202
Indonesia	-0.33%	*(-0.79)*	-0.45	*(-7.40)*	-0.55	*(-10.40)*	-0.12	*(-2.64)*	0.89	*(15.46)*	0.74	262
Japan	-0.31%	*(-1.41)*	-0.24	*(-5.56)*	-0.59	*(-9.34)*	-0.69	*(-8.51)*	0.52	*(9.06)*	0.42	430
Malaysia	-0.06%	*(-0.27)*	-0.33	*(-9.20)*	-0.28	*(-6.00)*	-0.46	*(-8.18)*	0.33	*(7.14)*	0.51	370
Pakistan	0.64%	*(1.36)*	-0.46	*(-6.05)*	-0.43	*(-4.46)*	-0.45	*(-5.60)*	0.66	*(8.13)*	0.51	175
Philippines	-1.08%	*(-2.25)*	-0.28	*(-3.52)*	-0.41	*(-5.04)*	-0.17	*(-2.69)*	0.20	*(3.51)*	0.14	286
Singapore	0.21%	*(0.81)*	-0.19	*(-3.83)*	-0.47	*(-6.41)*	-0.15	*(-2.70)*	-0.03	*(-0.68)*	0.18	267
South Korea	-0.85%	*(-2.36)*	-0.15	*(-3.26)*	-0.57	*(-9.85)*	0.11	*(1.78)*	0.91	*(16.77)*	0.64	303
Taiwan	-0.40%	*(-1.54)*	0.09	*(2.43)*	-0.12	*(-2.18)*	-0.87	*(-20.00)*	0.47	*(9.45)*	0.66	322
Thailand	0.22%	*(0.59)*	-0.84	*(-12.83)*	-1.07	*(-12.06)*	-0.57	*(-8.63)*	0.57	*(8.47)*	0.67	248
Panel D: Middle East												
Israel	-0.46%	*(-1.83)*	0.11	*(2.06)*	-0.17	*(-3.72)*	0.04	*(1.11)*	0.02	*(0.65)*	0.12	269
Saudi Arabia	-0.05%	*(-0.16)*	-0.15	*(-3.28)*	-0.30	*(-4.66)*	-0.52	*(-5.89)*	0.58	*(7.90)*	0.51	130
Turkey	-0.06%	*(-0.14)*	-0.05	*(-1.42)*	-0.29	*(-3.97)*	-0.20	*(-3.13)*	1.15	*(30.48)*	0.80	256
Panel E: Oceania												
Australia	0.33%	*(1.72)*	-0.18	*(-4.25)*	-0.60	*(-10.04)*	-0.07	*(-1.34)*	0.10	*(2.28)*	0.33	241
New Zealand	-0.54%	*(-2.16)*	0.06	*(0.95)*	-0.29	*(-4.37)*	0.05	*(1.04)*	0.39	*(5.98)*	0.18	286
Panel F: Misc.												
Russia	0.65%	*(1.20)*	-0.03	*(-0.42)*	-0.21	*(-2.21)*	-0.18	*(-1.53)*	0.09	*(1.38)*	0.04	142
South Africa	-0.01%	*(-0.03)*	0.18	*(4.69)*	-0.47	*(-9.67)*	-0.21	*(-4.92)*	0.01	*(0.28)*	0.28	430

6.2 Fama-MacBeth Cross-Sectional Regressions

As robustness check of price's (country-specific) predictive power, Table 5 shows Fama-MacBeth (1973) rolling cross-sectional regressions results for all 41 countries. We regress next-month country-specific firm-level stock returns (r_{it+1}) on a constant, the natural logarithm of price (LN(Price)), size (LN(Size)), book-to-market ratio (LN(BTM)), prior one year return momentum (MOM), and prior three year standard deviation of returns (VOL):

$$r_{it+1} = \alpha_t + p_t LN(Price)_{it} + s_t LN(Size)_{it} + b_t LN(BTM)_{it} + m_t MOM_{it} + v_t VOL_{it} + \varepsilon_t \qquad (2)$$

where ε_t is a time-variant error term.

Although robust t-statistics (see used AR(1)-adjusted standard errors $\sigma(\bar{x})$ with ρ as first-order autocorrelation and $\sigma(x)$ as standard deviation of the respective regression coefficient x with $x \in \{\alpha, p, s, b, m, v\}$ and T as the number of months in Eq.(3) and e.g., Cochrane, 2009: 223) of our price variable are mainly insignificant, we still find significant values (at 5% confidence level) for seven countries (Australia, Belgium, Brazil, Israel, Poland, Switzerland, and the most significant value for the US).[120]

[120] Note however that even an internationally very robust and consistent investment style like volatility (see, e.g., Ang et al., 2009) shows only four significant t-statistics in our regression setup. We choose total volatility instead of e.g., idiosyncratic volatility as predictor in our regressions, since these two volatility measures are very highly correlated (Ang et al., 2009). In addition, total volatility is interpretable and implementable in a more straightforward way since it is not dependent on (and sensitive to) the choice of an underlying asset pricing factor model (generating the residuals) and enables us to directly control for the low (total) volatility levels consistently found for expensive portfolios around the world (see Table 3).

$$\sigma(\bar{x}) = \frac{\sigma(x)}{\sqrt{T}} \sqrt{\frac{1+\rho}{1-\rho}} \tag{3}$$

If these results were due to chance, on average only two significant values could be expected. Without VOL as predictor, we find t-statistics for Argentina, Hong Kong, and Spain to increase above 2 (and for China to decrease below -2) whereas values for Australia and Belgium reach nearly 4, which makes these country-specific price effects very likely not a coincidence. On a regional basis our results reveal a tendency for positive values in Europe (also present if we leave out VOL) and regarding the economically most important Asian countries (China and Japan), a slight tendency for negative values in Asia. Most striking however, is once again the price effect for our US sample, as here we report the highest (absolute) t-statistic of -2.71 for our logarithmic price variable which is consistent with the findings of the preceding sections.

Table 5: Fama-MacBeth cross-sectional regressions results

This table reports outcomes of rolling cross-sectional regressions: Following Eq.(2), in each month and within each country, we regress next-month firm returns (countries are clustered in regions in the table, except Panel F) on a constant; LN(Price), that is the current natural logarithm of nominal price of each firm (in country-specific major currency unit; with the prominent exception of the UK); LN(Size), that is the log market capitalization (in millions of country-specific major currency unit) of each firm at the present month; LN(BTM) (logarithm of six months lagged book-to-market ratio of each firm, updated in June each year); MOM, which is the one-year return momentum (return of each firm measured from t-12 to t-2) and VOL (prior three-year firm-specific return standard deviation). The AR(1)-adjusted t-statistics (derived from a t-test with the null that the mean of the coefficients equals zero with an additional term when calculating standard errors that accounts for common first-order serial correlation of the coefficients, see, e.g., Cochrane, 2009 and Eq.(3)) of the respective coefficients are written on the right in italics and in parentheses. "Adj. R^2" reports the values of the average cross-sectional adjusted R^2's. The maximum effective time frame coverage of our country-specific regressions is July 1983 to April 2017 (405 months; we need an extra 36 months to calculate return volatility which reduces the effective time frame by three years and skip another month due to the prior calculation of our lagged predictors).

	Constant		LN(Price)		LN(Size)		LN(BTM)		MOM		VOL		Adj. R^2
Panel A: The Americas													
North													
Canada	0.0173	*(4.24)*	-0.0006	*(-0.56)*	-0.0008	*(-1.55)*	0.0014	*(1.68)*	0.0067	*(2.85)*	-0.0158	*(-0.97)*	0.051
US	0.0257	*(6.59)*	-0.0022	*(-2.71)*	-0.0008	*(-2.97)*	0.0005	*(1.20)*	0.0031	*(1.50)*	-0.0191	*(-1.03)*	0.048
Middle & South													
Argentina	0.0447	*(3.55)*	0.0028	*(1.58)*	-0.0024	*(-1.71)*	0.0056	*(1.78)*	-0.0064	*(-0.94)*	-0.0441	*(-1.36)*	0.059
Brazil	0.0303	*(3.32)*	0.0023	*(2.04)*	-0.0017	*(-1.99)*	0.0045	*(2.62)*	0.0039	*(0.77)*	-0.0595	*(-2.72)*	0.047
Chile	0.0237	*(2.08)*	-0.0012	*(-1.23)*	0.0002	*(0.18)*	0.0051	*(2.68)*	0.0006	*(0.10)*	-0.0337	*(-0.99)*	0.064
Mexico	0.0067	*(0.91)*	0.0006	*(0.35)*	0.0006	*(0.65)*	0.0058	*(3.61)*	0.0021	*(0.42)*	-0.0060	*(-0.15)*	0.069
Panel B: Europe													
Austria	0.0055	*(0.89)*	0.0007	*(0.54)*	0.0007	*(0.86)*	0.0029	*(2.28)*	0.0140	*(2.77)*	-0.0415	*(-1.41)*	0.088
Belgium	0.0054	*(1.40)*	0.0013	*(2.28)*	-0.0000	*(-0.05)*	0.0030	*(3.34)*	0.0136	*(3.77)*	-0.0366	*(-1.35)*	0.065
Denmark	0.0053	*(0.87)*	-0.0002	*(-0.38)*	0.0008	*(1.28)*	0.0028	*(1.97)*	0.0117	*(3.65)*	-0.0245	*(-1.11)*	0.050
Finland	0.0116	*(1.69)*	0.0013	*(1.17)*	-0.0007	*(-0.81)*	0.0002	*(0.18)*	0.0119	*(2.96)*	-0.0125	*(-0.35)*	0.086
France	0.0144	*(3.41)*	0.0005	*(0.90)*	-0.0006	*(-1.05)*	0.0016	*(1.84)*	0.0094	*(4.04)*	-0.0150	*(-1.11)*	0.047
Germany	0.0113	*(2.86)*	-0.0001	*(-0.11)*	0.0000	*(0.02)*	0.0011	*(1.55)*	0.0102	*(4.28)*	-0.0202	*(-1.03)*	0.049
Greece	0.0209	*(1.85)*	0.0013	*(0.82)*	-0.0014	*(-0.97)*	0.0028	*(1.90)*	0.0035	*(0.69)*	-0.0590	*(-2.48)*	0.088
Italy	0.0064	*(1.43)*	-0.0004	*(-0.54)*	0.0006	*(1.20)*	0.0015	*(1.60)*	0.0078	*(1.75)*	-0.0381	*(-1.31)*	0.063
Netherlands	0.0094	*(2.04)*	0.0009	*(1.11)*	-0.0002	*(-0.37)*	0.0022	*(2.30)*	0.0122	*(3.64)*	-0.0236	*(-0.65)*	0.077
Norway	0.0129	*(1.76)*	0.0005	*(0.40)*	-0.0006	*(-0.64)*	0.0040	*(2.06)*	0.0069	*(1.85)*	0.0159	*(0.71)*	0.068
Poland	0.0093	*(0.81)*	0.0029	*(2.05)*	-0.0037	*(-3.43)*	0.0022	*(1.24)*	0.0041	*(0.80)*	0.0763	*(1.55)*	0.052
Spain	0.0103	*(1.95)*	0.0011	*(1.27)*	0.0000	*(0.01)*	0.0015	*(1.63)*	0.0096	*(1.77)*	-0.0471	*(-1.65)*	0.094
Sweden	0.0070	*(0.87)*	0.0020	*(1.63)*	-0.0007	*(-1.11)*	-0.0001	*(-0.12)*	0.0087	*(2.32)*	-0.0106	*(-0.39)*	0.068
Switzerland	0.0013	*(0.32)*	0.0008	*(2.09)*	0.0002	*(0.59)*	0.0020	*(2.74)*	0.0130	*(4.35)*	-0.0105	*(-0.29)*	0.061
UK	0.0140	*(3.23)*	-0.0002	*(-0.37)*	-0.0004	*(-0.85)*	0.0021	*(3.14)*	0.0097	*(5.73)*	-0.0091	*(-0.76)*	0.033

Table 5: continued.

	Constant		LN(Price)		LN(Size)		LN(BTM)		MOM		VOL		Adj. R^2
Panel C: Asia													
Bangladesh	0.0076	*(0.18)*	0.0029	*(0.65)*	-0.0004	*(-0.17)*	-0.0008	*(-0.21)*	0.0068	*(0.80)*	-0.0955	*(-1.13)*	0.171
China	0.0668	*(3.64)*	-0.0060	*(-1.63)*	-0.0050	*(-3.27)*	-0.0034	*(-1.25)*	0.0058	*(1.27)*	-0.0178	*(-0.94)*	0.074
Hong Kong	0.0258	*(2.68)*	0.0005	*(0.41)*	-0.0007	*(-0.67)*	0.0049	*(3.64)*	0.0041	*(1.32)*	-0.0469	*(-2.08)*	0.064
India	0.0328	*(2.77)*	0.0011	*(1.08)*	-0.0025	*(-2.77)*	0.0016	*(1.06)*	0.0083	*(2.95)*	0.0190	*(1.18)*	0.062
Indonesia	0.0436	*(1.41)*	0.0026	*(0.95)*	-0.0030	*(-1.99)*	0.0040	*(1.82)*	-0.0043	*(-1.25)*	-0.0057	*(-0.37)*	0.046
Japan	0.0256	*(2.75)*	-0.0017	*(-1.37)*	-0.0005	*(-0.82)*	0.0027	*(4.18)*	-0.0009	*(-0.37)*	-0.0061	*(-0.37)*	0.080
Malaysia	0.0245	*(2.80)*	0.0013	*(0.64)*	-0.0020	*(-1.70)*	0.0034	*(2.63)*	0.0079	*(2.20)*	-0.0251	*(-1.18)*	0.078
Pakistan	0.0287	*(2.50)*	0.0014	*(0.73)*	-0.0013	*(-1.16)*	0.0044	*(2.20)*	0.0058	*(1.74)*	-0.0057	*(-0.24)*	0.083
Philippines	0.0324	*(2.31)*	0.0016	*(1.30)*	-0.0027	*(-1.56)*	0.0009	*(0.46)*	-0.0018	*(-0.25)*	0.0083	*(0.32)*	0.045
Singapore	0.0189	*(2.19)*	-0.0005	*(-0.29)*	-0.0007	*(-0.57)*	0.0011	*(0.81)*	0.0150	*(3.39)*	-0.0712	*(-1.77)*	0.087
South Korea	0.0375	*(1.28)*	0.0001	*(0.05)*	-0.0019	*(-1.54)*	0.0039	*(2.66)*	-0.0022	*(-0.92)*	-0.0327	*(-1.70)*	0.094
Taiwan	0.0154	*(1.06)*	-0.0025	*(-0.66)*	-0.0002	*(-0.21)*	-0.0012	*(-0.43)*	0.0050	*(1.09)*	-0.0190	*(-0.64)*	0.102
Thailand	0.0129	*(1.19)*	0.0002	*(0.08)*	0.0001	*(0.06)*	0.0055	*(3.08)*	-0.0009	*(-0.27)*	-0.0102	*(-0.43)*	0.067
Panel D: Middle East													
Israel	0.0136	*(0.93)*	-0.0025	*(-2.15)*	-0.0001	*(-0.07)*	0.0094	*(1.68)*	0.0137	*(2.00)*	0.0364	*(0.46)*	0.060
Saudi Arabia	0.0158	*(0.93)*	0.0029	*(0.95)*	-0.0008	*(-0.61)*	0.0071	*(2.21)*	-0.0013	*(-0.17)*	-0.1485	*(-2.05)*	0.130
Turkey	0.0488	*(3.32)*	-0.0038	*(-0.85)*	-0.0032	*(-2.06)*	0.0025	*(0.70)*	-0.0026	*(-0.55)*	0.0245	*(0.69)*	0.045
Panel E: Oceania													
Australia	0.0193	*(4.54)*	0.0021	*(2.41)*	-0.0011	*(-2.04)*	0.0026	*(2.41)*	0.0100	*(4.07)*	-0.0538	*(-1.60)*	0.070
New Zealand	0.0112	*(1.84)*	0.0004	*(0.27)*	0.0001	*(0.19)*	0.0039	*(2.48)*	0.0172	*(3.84)*	-0.0250	*(-0.44)*	0.061
Panel F: Misc.													
Russia	0.0120	*(0.79)*	0.0010	*(0.95)*	-0.0013	*(-1.04)*	-0.0010	*(-0.40)*	-0.0070	*(-1.05)*	0.0005	*(0.01)*	0.036
South Africa	0.0165	*(2.22)*	-0.0007	*(-0.92)*	0.0004	*(0.52)*	0.0027	*(2.75)*	0.0074	*(2.07)*	-0.0225	*(-0.65)*	0.080

7. Culture, Price, and Stock Returns

The previous sections point to a large diversity of the existence, magnitude, direction, and robustness of the price effect across the tested countries that is not consistently explained by standard finance models. In this section, we test our main hypothesis H2 (and our respective culture dimension related sub hypotheses from Section 3.2), that price is connected with culture, since cultural characteristics and differences are known to be comparably stable over time and are also major macro-social drivers that influence attitudes, values, beliefs, behaviors, practices, and actions of a whole population (e.g., Hofstede et al., 2010) having a permanent impact on investment decisions and the efficacy of associated investment styles (see, e.g., Chui et al., 2010).

7.1 World Regions and Common Cultural Characteristics

At first, Table 6 presents the values of Hofstede et al.'s six cultural dimensions for all countries in our dataset sorted by world region.[121] We calculate the means and standard deviations of the six cultural dimensions for each world region (except for those countries sorted in the category miscellaneous) to give a quick impression of the main differences and commonalities among the regions, as this helps to interpret our main results regarding the culture dimensions and the connection to the price effect (Sections 7.2 to 7.4). Most striking is the difference in the dimension Individualism between Asian and Western developed countries. High values on this scale depict individualistic countries, whereas countries ranked low on this index are collectivistic. Other remarkable patterns are that many Asian, respectively less developed countries show high Power Distance values as opposed to developed countries (e.g., all English-

[121] For example, what (all) American countries have in common is that they experienced substantial immigration especially from European countries. On the other hand, the American cultures where influenced far longer by natives than the European cultures. Maybe this is reflected by the very similar, consistently low values for Long Term Orientation (indicating more traditional societies) as opposed to the clearly higher LTO values found in Europe.

speaking countries) and that Asian cultures are generally going hand in hand with restrained societies (see, e.g., Hofstede et al., 2010).

Table 6: Culture indices and commonalities among world regions

In this table, we structure Hofstede et al.'s culture dimension values (presented in Table 2) for each country by region-specific clusters (Panel A to E; Panel F contains miscellaneous countries). We report average values (row "Mean") for each world region alongside standard deviations (row "Standard Dev.") in italics to facilitate comparability between regional clusters.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Panel A: The Americas						
North						
Canada	39	80	52	48	36	68
US	40	91	62	46	26	68
Mean	*39.5*	*85.5*	*57.0*	*47.0*	*31.0*	*68.0*
Standard Dev.	*0.7*	*7.8*	*7.1*	*1.4*	*7.1*	*0.0*
Middle & South						
Argentina	49	46	56	86	20	62
Brazil	69	38	49	76	44	59
Chile	63	23	28	86	31	68
Mexico	81	30	69	82	24	97
Mean	*65.5*	*34.3*	*50.5*	*82.5*	*29.8*	*71.5*
Standard Dev.	*13.3*	*9.9*	*17.1*	*4.7*	*10.5*	*17.4*
Panel B: Europe						
Austria	11	55	79	70	60	63
Belgium	65	75	54	94	82	57
Denmark	18	74	16	23	35	70
Finland	33	63	26	59	38	57
France	68	71	43	86	63	48
Germany	35	67	66	65	83	40
Greece	60	35	57	100	45	50
Italy	50	76	70	75	61	30
Netherlands	38	80	14	53	67	68
Norway	31	69	8	50	35	55
Poland	68	60	64	93	38	29
Spain	57	51	42	86	48	44
Sweden	31	71	5	29	53	78
Switzerland	34	68	70	58	74	66
UK	35	89	66	35	51	69
Mean	*42.3*	*66.9*	*45.3*	*65.1*	*55.5*	*54.9*
Standard Dev.	*18.0*	*13.0*	*25.4*	*24.3*	*16.2*	*14.7*

Table 6: continued.

Market	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	Long Term Orientation	Indulgence
Panel C: Asia						
Bangladesh	80	20	55	60	47	20
China	80	20	66	30	87	24
Hong Kong	68	25	57	29	61	17
India	77	48	56	40	51	26
Indonesia	78	14	46	48	62	38
Japan	54	46	95	92	88	42
Malaysia	100	26	50	36	41	57
Pakistan	55	14	50	70	50	0
Philippines	94	32	64	44	27	42
Singapore	74	20	48	8	72	46
South Korea	60	18	39	85	100	29
Taiwan	58	17	45	69	93	49
Thailand	64	20	34	64	32	45
Mean	*72.5*	*24.6*	*54.2*	*51.9*	*62.4*	*33.5*
Standard Dev.	*14.4*	*11.1*	*15.2*	*24.0*	*23.9*	*15.8*
Panel D: Middle East						
Israel	13	54	47	81	38	NA
Saudi Arabia	95	25	60	80	36	52
Turkey	66	37	45	85	46	49
Mean	*58.0*	*38.7*	*50.7*	*82.0*	*40.0*	*50.5*
Standard Dev.	*41.6*	*14.6*	*8.1*	*2.6*	*5.3*	*2.1*
Panel E: Oceania						
Australia	36	90	61	51	21	71
New Zealand	22	79	58	49	33	75
Mean	*29.0*	*84.5*	*59.5*	*50.0*	*27.0*	*73.0*
Standard Dev.	*9.9*	*7.8*	*2.1*	*1.4*	*8.5*	*2.8*
Panel F: Misc.						
Russia	93	39	36	95	81	20
South Africa	49	65	63	49	34	63

7.2 Two-way Sorts on Cultural Dimensions and Price

As a first straightforward, nonparametric test of our hypotheses regarding the connection of the price effect and the proposed cultural dimensions (cp. Section 3.2), we perform two-way portfolio sorts (see Table 7). We use our country-specific price quintile portfolios (E and C) of Section 5 and generate equal-weighted returns of these portfolios in each month across all active (that is yielding non-NA returns) countries that at the same time have to be constituents of one of our three portfolios given each cultural dimension (we add results on the Power Distance dimension for the sake of completeness): Every country is either sorted in the Low (bottom 30%), High (top 30%) or Middle (neither top, nor bottom; i.e. middle 40%) category with respect to its value on any of the six cultural dimensions, respectively. Given these portfolios, we form 3 x 2 (6) intersection portfolios regarding each cultural dimension (Panels A to F in Table 7). We additionally construct hedge portfolios based on every portfolio sorted into the Expensive and Cheap category (E minus C) and High and Low category (portfolios with high value on cultural dimension minus portfolios with low value on cultural dimension), respectively. At last we add – also to check if our results are consistent – the hedge portfolio (or simply put the return spread) of the hedge portfolios (see bottom right corner in each panel of Table 7).

Not surprisingly, we find the most consistent results regarding our hypothesis of the link of Individualism and price (H2a). Panel B of Table 7 shows that E-portfolios from collectivistic countries (low Individualism score) significantly underperform C-Portfolios from those countries (low-price effect). The respective (E minus C) hedge portfolio shows a significantly negative average return of -0.44% per month with a t-statistic of -2.54. On the other hand, E-portfolios from individualistic countries (high Individualism score) outperform C-portfolios (average monthly return of 0.22%, t-statistic 1.93) which results in an average monthly return spread of 0.69% (t-statistic of 3.73), showing clear evidence for a high-price effect in (more) individualistic countries and thereby underlining the results of Chui et al. (2010) regarding a concurrent momentum effect associated with an (increasingly) individualistic culture. In respect of Uncertainty Avoidance (Panel D) and Indulgence (Panel F), we find (only) one side of our hypotheses (H2e and H2b) confirmed: C-portfolios perform better than E-portfolios (low-price effect) in countries with high scores on Uncertainty Avoidance and low values for Indulgence. However, the displayed t-statistics are highly significant with (absolute) values around 3 and the hedge portfolio return spread in Panel F shows like for Individualism a highly significant value (average monthly return of 0.58% with a t-statistic of 3.73). Panel C additionally underpins hypothesis H2c as we find that masculine cultures tend to result in a low-price effect. For H2d (connection of Long Term Orientation and price), we find mixed, respectively all in all no evidence, since results on the one hand confirm our hypothesis, but on the other hand contradict it (however both on insignificant levels, see Panel E). Interestingly, for Power Distance (Panel A) we find some significant evidence that low values are connected to a high-price effect and high values correlate with a low-price effect. Possible explanations for this finding are difficult and would be ad hoc, since we initially abstained from hypothesizing due to the lack of a well-founded relationship between the properties of this cultural dimension and a possible price effect (apart from, e.g., the negative correlation of Power Distance with extraversion; Hofstede and McCrae, 2004, cp. fn. 22). However, as we show in the next sections, when controlled for the other cultural dimensions and additional control variables, the connection between Power Distance and price turns out to be not robust.

In general, we find high-price (E) portfolios to have (clearly) higher t-statistics than low-price portfolios despite several cases in which C-portfolios yield significantly higher mean returns. This is once again due to one of our main findings in Section 5 that E-portfolios' returns are less volatile than C-portfolios' returns.

A brief look at the other sorting direction (see hedge portfolio returns at the bottom of each panel) also reveals a clear sensitivity regarding returns of different cultural classes within top (E) and bottom (C) price portfolios. For example, feminine nations show on average 0.58 (0.46) percentage points higher monthly returns (t-statistics of 4.20 and 2.65) for expensive (cheap) portfolios when compared to masculine nations. However, this sorting direction does not control for (like the other sorting direction where we compare returns of price portfolios within the same countries), e.g., different inflation rates across nations driving up the returns. Thus, these results should be interpreted only as a rough hint that cultural classes itself are linked to different general return levels.[122]

7.3 Fama-MacBeth EMC Hedge Portfolio Regressions

In this section we step up and examine possible international determinants of the price effect by performing Fama-MacBeth (1973) regressions. We choose a lag structure for our regression equation (Eq. 4), that is, we regress one-month ahead Expensive minus Cheap (EMC) hedge portfolio returns of our j ($j = 1, 2, \ldots, 41$) countries ($rEMC_{jt+1}$) on the six cultural dimensions of Hofstede et al. (2010), common financial risk factors, and a national wealth proxy. This enables us to additionally test the predictive power (and not only the explanatory power, since we already investigated this in Section 6) of SMB, HML, and WML in a meaningful way:

$$rEMC_{jt+1} = \alpha + DIM_j d + RISKCON_{jt} c + gGDPpc_j + \varepsilon_{jt} \tag{4}$$

where α is the regression constant, DIM_j is a vector of the six (time-invariant) cultural dimensions Power Distance (PD), Individualism (INDIV), Masculinity (MASC), Uncertainty Avoidance (UA), Long Term Orientation (LTO), and Indulgence (INDUL) and $RISKCON_{jt}$ is a vector of three (time-varying) financial risk factor control variables, that is the factor-mimicking

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122 A follow-up study shows that country-level market returns are indeed significantly associated with Masculinity levels (more masculine countries showing lower value-weighted returns) and that higher Power Distance is (barely) significantly connected with higher market returns.

portfolios for the size (SMB), value (HML), and momentum effect (WML). $GDPpc_j$ is the value of the GDP per capita (in U.S. dollars) for each country j in 1980[123] and ε_{jt} is a time-varying error term. We calculate the t-statistics using the same procedure as depicted in Section 6.2 and Eq. (3) (first-order autocorrelation robust t-statistics).

Table 8 reports the results of these EMC Fama-MacBeth regressions. We find Panel A (Model 1 to 6) to show consistent evidence regarding our sorts (Table 7) on cultural dimensions and price portfolios and confirm all our hypotheses (H2a, H2b, H2c, H2e) apart from H2d regarding the connection of LTO and a price effect. All cultural dimensions apart from LTO can predict (and explain) EMC returns on their own on significant levels (with the clearly strongest single predictor being INDIV, which once again underlines the evidence of Chui et al., 2010). MASC proves to be the most robust cultural predictor of EMC returns, since it stays significant in virtually all performed regressions. The factor-mimicking portfolio for the value effect (HML)

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[123] We use the (time-invariant) GDP per capita value of 1980 instead of a time series of yearly GDP per capita data due to three reasons: First, we would have a nonstationarity problem in our regressions when using time series data, since GDP per capita values are clearly increasing worldwide over time. Second, we do not want to mitigate this problem via a stationary GDP per capita growth variable since this would only be a second-rank proxy of national wealth that is reliably connected to the values of Long Term Orientation, only (Hofstede et al., 2010). Third, Hofstede et al. (2010) also apply comparable data as national wealth proxy since they find many correlations between their cultural dimensions and national wealth being strongest when using GNI per capita values at the time of the IBM study, i.e. around 1970 (and thus the same time the data for the construction of the initial four cultural dimensions was collected). For example, Hofstede et al. (2010) find that GNI per capita explains 71% of the differences in Individualism scores for the initial fifty countries of the IBM study and that the GNI per capita of 1970 is an important predictor for Power Distance values (poorer countries are associated with higher PD values and vice versa). We use the country-specific GDP per capita values of 1980 since this is the earliest date in our dataset received from the IMF website (http://www.imf.org/external/pubs/ft/weo/2017/01/weodata/index.aspx) and our main datasets also start in 1980. Additionally, the first book of Hofstede on his four initial cultural dimensions was also published in that year (Hofstede, 1980), so we limit the possibility of some kind of forward looking bias. We get data for all 41 countries except for Russia.

is another strong predictor of one-month ahead EMC returns in our global sample and is significant throughout all regression configurations: the stronger the value effect, that is, the higher the HML return in the preceding month, the lower (on average) are subsequent EMC returns (i.e., weaker high-price effect and stronger low-price effect). SMB returns affect EMC returns in the same direction (weak size effect associated with strong high-price effect in the next month and vice versa) and WML returns in the opposite direction (strong momentum effect leads to strong high-price effect and vice versa). However, for SMB and WML the effects are not significant[124] (see Panel B). These results are consistent with our evidence in Section 6.1 where we find EMC returns to load negatively on SMB and HML, but positively on WML and coherent with the inherent connections of price, size, value, and momentum outlined in Section 2.1.

However, also the GDP per capita of 1980 is capable of predicting the magnitude of EMC returns on significant levels alone (Panel C) and is an important control variable when it comes to our cultural dimensions,[125] since it affects the coefficients of our cultural variables (and to a lesser extent that of the risk factor controls), leaving the cultural connections of the price effect engaged though when looking at our most comprehensive models (Panel D in Table 8).

We find the documented cultural connections of the price effect to hold also – or being even clearer pronounced – on global firm-specific levels, where the "cultural price effect" is very robust and persistent in presence of financial control variables and GDP per capita. In the next, final section, we investigate this important remaining issue profoundly and also show a direct connection of global stock returns and cultural dimensions irrespective of a price effect.

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[124] When we regress one-month ahead WML returns on EMC returns though, we get a significant t-statistic (2.12). Consequently, EMC returns are a significant predictor of WML returns on cross-country level, but not vice versa.

[125] See, e.g., Rieger et al. (2014) who also use GDP per capita as control variable in their study on risk preferences around the world.

Table 7: Price profits and cultural dimensions

In this table, we present outcomes of two-way sorts on (country-level) top and bottom quintile price portfolios (see columns Expensive and Cheap) and three categories regarding the (country-specific) values on any cultural dimension (bottom 30%: Low, middle 40%: Medium, and top 30%: High), respectively. We display the respective results for each cultural dimension and structure them by using panels (Panel A to F). Country-average monthly returns of the intersection portfolios across all (active) countries in our sample (test period is from June 1981 to April 2017) are presented in the upper line of each segment alongside t-statistics (below in italics and parentheses). In the right column and the bottom row of every panel, we report the statistics for the hedge portfolios (E minus C; High minus Low). In the bottom right segment, we give statistics for the hedge portfolio return spread.

Panel A: Power Distance and Price	Price Portfolios		
Index on Power Distance	Expensive (E)	Cheap (C)	E minus C
Low	1.19%	0.90%	0.29%
	(6.87)	*(3.99)*	*(2.53)*
Medium	1.55%	1.92%	-0.37%
	(8.37)	*(7.98)*	*(-2.71)*
High	1.56%	1.82%	-0.26%
	(6.93)	*(6.12)*	*(-1.82)*
High minus Low	0.37%	0.92%	-0.55%
	(2.41)	*(4.05)*	*(-3.39)*

Panel B: Individualism and Price	Price Portfolios		
Index on Individualism	Expensive (E)	Cheap (C)	E minus C
Low	1.26%	1.70%	-0.44%
	(5.66)	*(5.38)*	*(-2.54)*
Medium	1.65%	1.88%	-0.22%
	(8.02)	*(7.75)*	*(-1.69)*
High	1.20%	0.99%	0.22%
	(7.08)	*(4.28)*	*(1.93)*
High minus Low	-0.07%	-0.77%	0.69%
	(-0.43)	*(-2.94)*	*(3.73)*

Panel C: Masculinity and Price	Price Portfolios		
Index on Masculinity	Expensive (E)	Cheap (C)	E minus C
Low	1.72%	1.76%	-0.04%
	(8.59)	*(6.57)*	*(-0.28)*
Medium	1.39%	1.39%	0.00%
	(6.97)	*(4.95)*	*(0.01)*
High	1.14%	1.30%	-0.16%
	(6.49)	*(6.20)*	*(-1.72)*
High minus Low	-0.58%	-0.46%	-0.12%
	(-4.20)	*(-2.65)*	*(-0.85)*

Panel D: Uncertainty Avoidance and Price	Price Portfolios		
Index on Uncertainty Avoidance	Expensive (E)	Cheap (C)	E minus C
Low	1.40%	1.50%	-0.10%
	(7.34)	*(6.00)*	*(-0.91)*
Medium	1.23%	1.12%	0.11%
	(6.78)	*(4.84)*	*(0.97)*
High	1.63%	2.04%	-0.41%
	(8.28)	*(7.95)*	*(-2.73)*
High minus Low	0.23%	0.54%	-0.31%
	(1.49)	*(2.49)*	*(-1.92)*

Panel E: Long Term Orientation and Price	Price Portfolios		
Index on Long Term Orientation	Expensive (E)	Cheap (C)	E minus C
Low	1.35%	1.48%	-0.13%
	(7.95)	*(6.62)*	*(-1.05)*
Medium	1.81%	1.81%	-0.01%
	(8.37)	*(6.48)*	*(-0.05)*
High	1.16%	1.31%	-0.15%
	(6.16)	*(5.37)*	*(-1.37)*
High minus Low	-0.19%	-0.17%	-0.02%
	(-1.59)	*(-1.00)*	*(-0.15)*

Panel F: Indulgence and Price	Price Portfolios		
Index on Indulgence	Expensive (E)	Cheap (C)	E minus C
Low	1.33%	1.80%	-0.47%
	(6.88)	*(7.07)*	*(-3.40)*
Medium	1.65%	1.68%	-0.03%
	(7.77)	*(6.06)*	*(-0.20)*
High	1.26%	1.15%	0.11%
	(7.71)	*(5.38)*	*(0.99)*
High minus Low	-0.07%	-0.65%	0.58%
	(-0.60)	*(-3.43)*	*(3.73)*

Table 8: Determinants and predictors of cross-country EMC returns: Fama-MacBeth regressions results

We regress, each month, one-month ahead country-specific EMC (Expensive minus Cheap) hedge portfolio returns on a constant, the six cultural dimensions of Hofstede et al., the (previous month) returns of three (country-level) factor-mimicking portfolios for the size (SMB), value (HML), and momentum effect (WML) and a national wealth proxy (GDP per capita of 1980: GDPpc). The regressions start in June 1981 and end in April 2017. We divide the results in four panels (Panel A to D) and up to seven tested models, depending on the included determinants and predictors. Panel D incorporates all variables. The top line of each row gives mean values of the coefficients across all performed regressions, the bottom line reports first-order autocorrelation robust t-statistics (in italics and parentheses; cp. Sect. 6.2 and Eq. (3)). Right down at the bottom, we display average values for adjusted R^2's.

	Panel A: Cultural Dimensions							*Panel B: Common Risk Factors*				*Panel C: Develop-ment*	*Panel D: Comprehen-sive*		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)		(1)	(2)	(3)
Constant	0.00445	-0.00715	0.00316	0.00217	0.00153	-0.00683	0.00531	-0.00075	-0.00013	-0.00113	-0.00033	-0.00477	0.00986	0.00198	0.00409
	(2.35)	*(-2.89)*	*(1.47)*	*(1.17)*	*(0.74)*	*(-2.78)*	*(0.63)*	*(-0.66)*	*(-0.12)*	*(-0.97)*	*(-0.29)*	*(-2.44)*	*(1.15)*	*(0.20)*	*(0.52)*
PD	-0.00010						-0.00001						-0.00007	-0.00001	0.00001
	(-3.02)						*(-0.28)*						*(-0.99)*	*(-0.13)*	*(0.15)*
INDIV		0.00012					0.00007						0.00006	0.00004	0.00012
		(3.36)					*(1.00)*						*(0.78)*	*(0.68)*	*(1.92)*
MASC			-0.00008				-0.00007						-0.00008	-0.00005	-0.00008
			(-2.61)				*(-2.34)*						*(-2.12)*	*(-1.64)*	*(-2.19)*
UA				-0.00006			-0.00006						-0.00002	-0.00004	-0.00006
				(-2.15)			*(-1.39)*						*(-0.56)*	*(-0.69)*	*(-1.37)*
LTO					-0.00004		0.00001						-0.00004	-0.00001	-0.00002
					(-1.37)		*(0.21)*						*(-0.93)*	*(-0.18)*	*(-0.37)*
INDUL						0.00011	-0.00002						-0.00003	-0.00002	-0.00009
						(2.90)	*(-0.39)*						*(-0.44)*	*(-0.23)*	*(-1.20)*
SMB								-0.02372			-0.01218		-0.03562		-0.04670
								(-1.44)			*(-0.66)*		*(-1.60)*		*(-1.83)*
HML									-0.03970		-0.03796		-0.05753		-0.06597
									(-2.09)		*(-1.98)*		*(-2.69)*		*(-2.87)*
WML										0.01853	0.02014		0.03184		0.02126
										(0.95)	*(0.98)*		*(1.21)*		*(0.67)*
GDPpc												0.00000		0.00000	0.00000
												(3.13)		*(1.11)*	*(0.85)*
Adj. R^2	0.0082	0.0153	0.0063	0.0007	0.0015	0.0029	0.0324	0.0207	0.0252	0.0242	0.0640	0.0238	0.1019	0.0346	0.1115

7.4 Global Panel Regressions

Table 9 reports results of pooled OLS panel regressions[126] of global firm-specific returns (r_{it+1}) as dependent variable and various lagged predictors (lag-1 respectively), including $Price$, financial control variables $FINCON_k$ (Size, LN(BTM), and MOM; $k = 1, \dots, K; K = 3$), our development/national wealth proxy GDP per capita (in U.S. dollars) of 1980 ($GDPpc$), the six ($l = 1, \dots, L; L = 6$) time-invariant[127] cultural dimensions of Hofstede et al. (DIM_l) and price interaction effects ($Price * DIM_l$)

$$r_{it+1} = \alpha + pPrice_{it} + FINCON'_{it}c + DIM'_{i}d + (Price_{it} * DIM'_{i})x + gGDPpc_i + u_{it} \quad (5)$$

where α is the intercept, c is a K-dimensional column vector of parameters, d and x are L-dimensional column vectors of parameters and $FINCON'_{it}$ and DIM'_{i} is a K-dimensional row vector of time-varying financial controls and a L-dimensional row vector of time-invariant cultural dimensions, respectively. $Price_{it}$ is our rank-scaled[128] price variable (with parameter p), $GDPpc_i$ is the used national wealth proxy (parameter g) and u_{it} is an idiosyncratic error term.

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[126] We choose this model, since the fulfillment of one of the unrelatedness assumptions *specific to* the random effects model (firm-specific effects uncorrelated with explanatory variables, i.e. a random variable) is questionable in our datasets and the appliance of this model is common in related literature (see, e.g. Chui et al., 2010). In general, panel regressions enable us to investigate one important remaining research question relating to the connection of price, culture, and global firm-specific stock returns in an ideal way. Since standard finance asset pricing literature mainly uses basic OLS regressions, we initially follow the established methodology in Section 6 and 7. These panel regressions also serve as robustness tests for our (preceding) results of the previous sections.

[127] The fixed effects model is not an option here, since it cancels all time-invariant regressors.

[128] We apply (for each country) a normalized ranking scale (values between 0 and 1) on country-specific (i.e., currency-dependent) values of price and size to get values that are both currency-independent (important for global comparability of price and size values) and restricted to a common scale: We separately rank each stock in each

One of the six cultural variables Power Distance (PD), Individualism (INDIV), Masculinity (MASC), Uncertainty Avoidance (UA), Long Term Orientation (LTO), and Indulgence (INDUL) – LTO – shows significant coefficients (measured by cluster-robust t-statistics with the time-specific identifier as cluster and with time (month) dummies; respective results for firm clusters and time clusters without time dummies, respectively[129] are reported in Appendix A) in all regressions.[130] Reflecting our diverse and often diametrically opposed results in the previous sections, a general, global price effect is not detectable in the majority of the performed panel regressions (see row "Price"), even when not including financial and cultural control variables as well as price and culture dimensions interaction effects (see Model 1 in Table 9).[131] On the other hand, the low variation in the coefficients and (constantly significant) t-statistics of the three financial control variables (see Model 2 and 4 to 6 in Table 9) regardless of the added cultural dimensions and interaction effects shows that cultural dimensions and financial variables unlikely capture the same return predicting/asset pricing (risk) factors (at least

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country by price and size (bottom-up) and divide this rank by the total number of active stocks in each month. This standardized scaling also ensures that our results (regarding size) are not driven by country samples with many internationally prominent high-cap stocks like in the US.

129 Note that time clusters (by month) generally reduce the significance of the t-statistics in our panel regressions clearly (cp. results of Table A.1 and A.2 in Appendix A). Regarding the connection of price and culture dimensions, when using firm clusters, we get significant values for the interaction effects of price with four cultural dimensions and for all cultural dimensions in the culture variables only model (Model 3). The results with time clusters but without time dummies (Table A.1) however are very similar to the outcomes in Table 9. T-statistics for LTO and Price x INDIV and Price x MASC interaction effects prove to be very robust throughout all regression configurations.

130 An implementation of an alternative random effects model (with time/firm clusters; with or w/o time dummies), a look at standard t-statistics, using unwinsorized data and non-lagged independent variables as robustness tests does not change the results concerning the price effect, the impact of cultural variables, and our conclusions materially.

131 The significance of "Price" is particularly determined by the inclusion of financial control variables, getting insignificant again when including price and culture dimensions interaction effects.

in the global cross-section). Only the momentum characteristic shows some sensitivity when including the cultural dimensions, reflected in a (slightly) lower t-statistic and value of the coefficient.

We derive two main conclusions regarding our main hypothesis H2 (culture and price are linked), our sub hypotheses and the connection of stock returns and culture in general: First, two cultural dimensions (LTO and INDUL) show some robust predictive power for global firm-level returns (although the values of the cultural dimensions are time-invariant) in our culture dimensions only model (and after controlling for the mentioned investment styles). Second, in conjunction with price, two other dimensions show additional predictive power (see significant t-statistics of the interaction terms and lasting robust coefficients and t-statistics of Price x INDIV and Price x MASC after controlling for GDPpc). In these regression setups (Model 5 and 6) also LTO is a marginally significant predictor when interacting with price. Specifically, in this panel regression setup, three of our sub hypotheses (H2a, H2c, and less clearly H2d) are confirmed: high individualism values foster the strength of the (high-) price effect in a global context (see robust t-statistics above 2.80 for Price x INDIV for Models 5 and 6 in Table 9), clearly supporting H2a and the assumed link of the common cultural origin of the (high-)price and momentum effect, which is also stronger in highly individualistic (Western) countries and weaker in collectivistic (Asian) countries (Chui et al., 2010). We additionally identify the cultural dimension Masculinity to be especially strongly connected with price, showing similar absolute values of robust t-statistics as Individualism (below -3.11) when multiplied with our ranking-scaled price variable. LTO displays to be a marginally important predictor (t-statistics around 1.70) in conjunction with price as well. Thus, on a global cross-sectional level, high values of Masculinity weaken a (high-)price effect, whereas high levels of LTO strengthen it (and vice versa),[132] confirming H2c and H2d.[133] Also striking is that price becomes completely insignificant

[132] A good example of a country fulfilling all these characteristics in an "ideal typical" way is the Netherlands, showing high values on INDIV and LTO, but low levels on MASC, resulting in a high-price effect. Inversely, the

(t-statistic falls from 2.03 to virtually zero) when including the price and culture dimensions interaction effects (cp. Models 4 to 6). That is, a general global high-price effect evident in Model 4 is completely attributable to (absorbed by) cultural effects. With respect to the connection of UA and INDUL to price, our hypothesis H2e is also underpinned (correct sign), but on a clearly insignificant level, whereas we find no support for H2b in our panel regressions (wrong sign and insignificant). PD also shows a marginal predictive power when connected to price, as opposed to the weak, inconsistent effect of PD on its own (Table 7 and 8 however show contradictory results). Thus, when predicting firm-specific returns, the general acceptance of hierarchical structures in the population could possibly also foster a high-price effect to some degree (whereas a society that strives for equality is in tendency linked to a low-price effect). As additional significant control variable, GDP per capita predicts lower stock returns for stocks from countries with higher national wealth and vice versa (t-statistic of -2.44) and absorbs the predictive power of some cultural dimensions like LTO to a certain degree (cp. fn. 123) at the same time nearly not at all impacting the t-statistics of the price and culture dimensions interaction effects (Model 6).

Philippines, for example, shows low levels of INDIV and LTO and (moderately) high levels of MASC which is connected to a low-price effect.

[133] In an earlier version of this paper we use the top 20 countries ranked by yearly GDP in U.S. dollars (projected data for 2017, received from the IMF website) which cover about 80% of global yearly GDP and perform nearly the same panel regressions. We find similar results regarding our price and culture dimensions interaction effects: Price x INDIV, Price x MASC, and Price x LTO are all clearly significant (respective t-statistics of 3.27, -2.41, and 2.85). Also the main conclusions regarding our other hypotheses remain unchanged in this alternative dataset, showing that the robustness of our findings is not sample-dependent and in fact hold even (more) for the economically most relevant countries.

8. Conclusion

With this paper, we contribute to the emerging field of cultural finance trying to explain (puzzling) financial phenomena with cultural effects. Investigating the international price effect (to our knowledge for the first time based on a comprehensive, internationally diverse sample covering several decades), we manage to link another stock market investment strategy to culture (or more specifically, to the cultural dimensions of Hofstede et al.) as was already successfully demonstrated for momentum by Chui et al. (2010) apart from other studies like Weigert (2015) and Cheon and Lee (2017) that (also) link less prominent anomalies to Individualism. However, the distinct feature separating the price effect from other (mainly internationally more homogenous) anomalies is particularly its large (diametrical) spread in effect direction and magnitude when comparing country-level price effects. Although, or even more due to its regional/country-specific dependency, the price effect is a quite ideal specimen of a capital market anomaly for cultural finance issues, as it is, in contrast to momentum, not only connected to Individualism, but to other cultural dimensions (especially Masculinity and partly Long Term Orientation as well as Uncertainty Avoidance, Indulgence, and Power Distance; i.e. showing sensitivity regarding all six investigated dimensions) when predicting international stock returns.

Beyond that, by using international panel data, we make a further step toward generalization and additionally show that cultural differences on their own are capable of predicting and explaining individual stock returns around the world (we know no other paper that investigated this before).

Furthermore, the two regional price effect clusters (Europe and Asia) that we document, are not only interesting for culture-based asset pricing, but also in the context of international investment styles. As we find, the (main) drawback of investing in high-priced stocks in Europe is the associated negative skewness of returns as opposed to low-priced stocks which generally (worldwide) show higher/positive values for skewness of returns. By investing in high-priced

European stocks and low-priced Asian (and US) stocks, this weakness can be mitigated and an investor is enabled to profit from both price effect worlds. However, the (future) robustness of these price effect clusters has to be witnessed with open eyes and with caution as our (diverse) findings regarding standard-finance asset pricing and robustness tests on country level suggest.[134] On the other hand, the consistently escalating high-price effect in Europe over the course of the last two decades creates a cheerful sentiment for the profitableness of price as legitimate, culture-based investment strategy.

To conclude, a collection of influencing and stimulating findings for future research are: (1) the price effect is by far the most robust in the US (unexpectedly turning out to be a low-price effect), showing for example a very highly significant 4-factor model alpha t-statistic below -4. This outcome is also one of the most puzzling (additionally challenges the weak EMH of Fama, 1970 to a high extent as it implies that the most basic and readily attainable stock characteristic, the price, has informational value for investors on the most intensely investigated stock market in the world) and needs more detailed country-specific investigation, as in general individualistic countries show a high-price effect, the US, though, as very individualistic country shows the opposite. However, Individualism is only one of our incorporated six cultural dimensions and thus only partly determines cultural differences between nations. (2) Expensive portfolios are virtually worldwide also portfolios with low volatility. At the same time, our evidence indicates that the price effect is not the volatility effect in disguise. Merging these effects together with low beta (e.g., in a multi-style strategy) which is also associated with (high-)price portfolios could reveal interesting opportunities from a risk management perspective. (3) We find that HML returns can predict EMC returns. Furthermore, EMC returns can *predict* WML returns on a cross-

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[134] Given the evidence of Jacobs and Mueller (2019) on a non-existent (or even inverse) international publication effect (publications of papers on country-specific anomalies lead *not* to deteriorating returns of associated investment strategies, but for most countries even to an amplification) apart from the US (McLean and Pontiff, 2016), our results should not (with the exception of the US low-price effect) be affected “negatively” by a publication of this study (or other papers on the price effect and associated anomalies).

country level, but not vice versa. On the other hand, both EMC returns and WML returns can *explain* each other on country level. The question that arises here is the nature of the causal structure between these factor-mimicking hedge portfolios. (4) We find culture to be a vital variable in predicting and explaining stock returns in a global dataset.[135] This is certainly the most far-reaching indication of our paper, which is however at the same time a very difficult to interpret and challenging to isolate effect (e.g., due to the inherently pervasive, contemporaneous, and steady nature of culture that for example deters from executing event studies regarding cultural change). We hope these aspects can stimulate further potentially eye-opening research on the price effect and especially on culture-based asset pricing, asset management, and asset allocation.

[135] We feel confident in drawing the conclusion that it is indeed culture per se having an effect on stock returns. First, Chui et al. (2010) show that even the inclusion of numerous control variables varying between countries (like culture) and over time (unlike culture) cannot destroy the link of individualism and the momentum effect. Since Chui et al. (2010) also have, as opposed to us (due to the limited research on (the origin of) the price effect and even more on culture-based asset pricing), a vast fund of literature regarding expected determinants of momentum to rely on, we focused (as a pioneer of culture-based asset pricing) on exploring the impact of the full spectrum of culture (six cultural dimensions instead of one) instead. Second, what cultural dimensions respectively cultural differences separates from, e.g., macroeconomic measures is that they are accepted and expected to be time-invariant (see, e.g., Hofstede et al., 2010). That is, from the time of their measurement on (around 1970 for the initial four dimensions), cultural differences between nations are the steadiest "variable", whereas all other candidates to predict and explain international stock returns are fluctuating. There are virtually no (man-made) factors that impact and pervade the broad cultural heritage (see, e.g., Inglehart and Baker, 2000) – culture however is capable of affecting all of them (including economic decision making, e.g., Guiso et al., 2006).

Table 9: Global panel regressions results with price and culture indices interaction effects

This table presents the results of pooled OLS panel regressions (see Eq.(5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM), and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (time-specific) error term and with time (month) dummies are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM), and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation), and INDUL (Indulgence) are the six culture dimensions proposed by Hofstede et al. Each stock gets its (time-invariant) country-specific value for these six variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R^2 reports the adjusted R^2 for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM), and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01198	0.01304	0.02708	0.02622	0.02871	0.02577
	[18.71]	*[16.47]*	*[5.96]*	*[6.29]*	*[4.51]*	*[4.23]*
Price	-0.00046	0.00357		0.00342	-0.00072	-0.00003
	[-0.36]	*[2.11]*		*[2.03]*	*[-0.12]*	*[-0.01]*
Size		-0.00242		-0.00243	-0.00269	-0.00279
		[-1.90]		*[-1.90]*	*[-2.07]*	*[-2.15]*
LN(BTM)		0.00389		0.00415	0.00411	0.00406
		[6.94]		*[7.43]*	*[7.39]*	*[7.30]*
MOM		0.00362		0.00322	0.00321	0.00318
		[3.59]		*[3.20]*	*[3.19]*	*[3.14]*
PD			0.00003	0.00003	-0.00001	-0.00003
			[0.73]	*[0.81]*	*[-0.19]*	*[-0.47]*
INDIV			-0.00004	0.00000	-0.00007	-0.00001
			[-0.93]	*[0.01]*	*[-1.30]*	*[-0.10]*
MASC			-0.00005	-0.00004	0.00004	0.00003
			[-1.40]	*[-1.12]*	*[0.71]*	*[0.58]*

Table 9: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00003	-0.00002	-0.00000
			[-0.18]	*[-0.76]*	*[-0.43]*	*[-0.03]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-3.37]	*[-2.88]*	*[-2.72]*	*[-2.10]*
INDUL			-0.00012	-0.00011	-0.00010	-0.00007
			[-2.27]	*[-2.34]*	*[-1.34]*	*[-0.94]*
Price x PD					0.00008	0.00008
					[1.49]	*[1.40]*
Price x INDIV					0.00014	0.00014
					[2.94]	*[2.80]*
Price x MASC					-0.00015	-0.00016
					[-3.11]	*[-3.20]*
Price x UA					-0.00001	-0.00001
					[-0.27]	*[-0.35]*
Price x LTO					0.00007	0.00007
					[1.63]	*[1.70]*
Price x INDUL					-0.00003	-0.00003
					[-0.53]	*[-0.55]*
GDPpc						-0.00000
						[-2.44]
n	29,333	27,221	29,235	26,871	26,871	26,679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.085463	0.098490	0.084766	0.099238	0.099290	0.099407

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Appendix A. Alternative panel regression configurations

Table A.1: Global panel regressions results with time clusters (without time dummies)

This table presents the results of pooled OLS panel regressions (see Eq.(5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM), and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (time-specific) error term are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM), and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation), and INDUL (Indulgence) are the dimensions proposed by Hofstede et al. Each stock gets its (time-invariant) country-specific value for these variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R^2 reports the adjusted R^2 for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM) and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01060	0.01053	0.02496	0.02414	0.02709	0.02388
	[4.30]	*[4.03]*	*[4.56]*	*[3.96]*	*[3.24]*	*[3.04]*
Price	-0.00060	0.00448		0.00426	-0.00081	-0.00017
	[-0.47]	*[2.77]*		*[2.65]*	*[-0.13]*	*[-0.03]*
Size		-0.00148		-0.00135	-0.00158	-0.00167
		[-1.14]		*[-1.03]*	*[-1.19]*	*[-1.26]*
LN(BTM)		0.00485		0.00513	0.00510	0.00505
		[5.92]		*[6.18]*	*[6.14]*	*[6.07]*
MOM		0.00168		0.00129	0.00128	0.00127
		[0.87]		*[0.66]*	*[0.65]*	*[0.65]*
PD			0.00003	0.00003	-0.00002	-0.00003
			[0.65]	*[0.84]*	*[-0.27]*	*[-0.55]*
INDIV			-0.00003	0.00001	-0.00006	0.00000
			[-0.64]	*[0.25]*	*[-1.14]*	*[0.05]*
MASC			-0.00004	-0.00003	0.00004	0.00004
			[-0.97]	*[-0.76]*	*[0.76]*	*[0.64]*

Table A.1: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00004	-0.00003	-0.00001
			[-0.28]	*[-0.93]*	*[-0.52]*	*[-0.13]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-3.20]	*[-2.94]*	*[-2.72]*	*[-2.17]*
INDUL			-0.00011	-0.00012	-0.00010	-0.00007
			[-1.92]	*[-2.05]*	*[-1.19]*	*[-0.86]*
Price x PD					0.00009	0.00009
					[1.66]	*[1.59]*
Price x INDIV					0.00014	0.00013
					[2.89]	*[2.77]*
Price x MASC					-0.00014	-0.00015
					[-2.87]	*[-2.98]*
Price x UA					-0.00001	-0.00002
					[-0.34]	*[-0.41]*
Price x LTO					0.00007	0.00007
					[1.56]	*[1.62]*
Price x INDUL					-0.00003	-0.00004
					[-0.55]	*[-0.58]*
GDPpc						-0.00000
						[-2.21]
n	29,333	27,221	29,235	26,871	26,871	26,679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.000001	0.001317	0.000435	0.001792	0.001836	0.001914

Table A.2: Global panel regressions results with firm clusters (without time dummies)

This table presents the results of pooled OLS panel regressions (see Eq.(5)) of monthly global firm-specific stock returns on price, culture variables, culture and price interactions, as well as size, logarithm of book-to-market (LN(BTM)), one-year return momentum (MOM), and GDP per capita (GDPpc) as control variables. All independent variables are lag-1 predictors (apart from the time-invariant variables). We test six different regression configurations marked in the first row as Model (1) to (6). The coefficients of the respective predictors are given in the first line; cluster-robust (Huber/White) t-statistics (clustered by time/month) allowing for heteroscedasticity and serial correlation of the (firm-specific) error term are reported below in italics and square brackets. Price and Size are normalized, rank-scaled variables with a 0 to 1 scale. Low values depict low-priced and low-sized stocks; high values assign high-priced and high-sized stocks. Values for Price, Size, LN(BTM), and MOM, are measured within a country-specific stock market. PD (Power Distance), INDIV (Individualism), MASC (Masculinity), UA (Uncertainty Avoidance), LTO (Long Term Orientation), and INDUL (Indulgence) are the dimensions proposed by Hofstede et al. Each stock gets its (time-invariant) country-specific value for these variables, depending on in which home country it is listed in our dataset (the same holds for our development proxy GDPpc). Predictors linked with a cross ("x") mark interaction effects between the named predictors. "n" and "N" show the number of stocks and the total number of observations available for each panel regression, respectively. Adj. R² reports the adjusted R² for each regression. To ensure that results are not driven by any remaining extreme values, we additionally winsorize values of returns, LN(BTM) and MOM by replacing each value above the 99.9%- and below the 0.1%-quantile by this quantile value. The panel regressions comprise the time frame June 1981 to April 2017 (430 months; we need the 12 months prior to June 1981 to calculate initial momentum returns which reduces the effective time frame by one year).

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01060	0.01053	0.02496	0.02414	0.02709	0.02388
	[67.66]	*[54.23]*	*[30.94]*	*[25.45]*	*[12.54]*	*[10.99]*
Price	-0.00060	0.00448		0.00426	-0.00081	-0.00017
	[-2.42]	*[14.26]*		*[13.59]*	*[-0.24]*	*[-0.05]*
Size		-0.00148		-0.00135	-0.00158	-0.00167
		[-4.65]		*[-4.37]*	*[-5.06]*	*[-5.35]*
LN(BTM)		0.00485		0.00513	0.00510	0.00505
		[44.73]		*[46.43]*	*[46.41]*	*[46.17]*
MOM		0.00168		0.00129	0.00128	0.00127
		[10.44]		*[7.94]*	*[7.88]*	*[7.78]*
PD			0.00003	0.00003	-0.00002	-0.00003
			[4.32]	*[4.49]*	*[-0.96]*	*[-1.95]*
INDIV			-0.00003	0.00001	-0.00006	0.00000
			[-4.97]	*[1.64]*	*[-4.89]*	*[0.23]*
MASC			-0.00004	-0.00003	0.00004	0.00004
			[-10.06]	*[-7.44]*	*[4.73]*	*[4.05]*

Table A.2: continued.

Model	(1)	(2)	(3)	(4)	(5)	(6)
UA			-0.00001	-0.00004	-0.00003	-0.00001
			[-2.66]	*[-8.78]*	*[-3.11]*	*[-0.75]*
LTO			-0.00011	-0.00009	-0.00013	-0.00010
			[-23.01]	*[-19.19]*	*[-11.36]*	*[-8.98]*
INDUL			-0.00011	-0.00012	-0.00010	-0.00007
			[-16.89]	*[-15.28]*	*[-5.75]*	*[-3.86]*
Price x PD					0.00009	0.00009
					[3.49]	*[3.39]*
Price x INDIV					0.00014	0.00013
					[6.63]	*[6.46]*
Price x MASC					-0.00014	-0.00015
					[-9.74]	*[-10.01]*
Price x UA					-0.00001	-0.00002
					[-0.98]	*[-1.19]*
Price x LTO					0.00007	0.00007
					[3.71]	*[3.88]*
Price x INDUL					-0.00003	-0.00004
					[-1.25]	*[-1.32]*
GDPpc						-0.00000
						[-14.78]
n	29,333	27,221	29,235	26,871	26,871	26,679
N	4365718	3555905	4375762	3522306	3522306	3509103
Adj. R^2	0.000001	0.001317	0.000435	0.001792	0.001836	0.001914

C.3 Paper III: Asset pricing risk factors and cultural dimensions: the hidden steady state variables?

Asset pricing risk factors and cultural dimensions: the hidden steady state variables?

Ulrich J. Hammerich and Thorsten Poddig *

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Abstract

We find international stock returns on common asset pricing risk factor mimicking hedge portfolios (especially HML and WML) to be connected to several cultural dimensions proposed by Hofstede et al. Using a comprehensive sample of cross-sectional data of 41 countries, we check all factors of the FF five-factor model, RMRF, SMB, HML, RMW, and CMA as well as WML for dependence on national culture. We find substantial evidence for culture as possible omitted, hidden (steady) state variable that impacts the relevance and thus the efficacy of local asset pricing risk factors and in turn the significance of associated investment styles.

JEL Classification: G02, G11, G12, G15

Keywords: asset pricing models, risk factors, cultural finance, state variables, investment styles

*All authors are from University of Bremen, Chair of Finance, Max-von-Laue-Str. 1, 28359 Bremen, Germany.

Corresponding author: Ulrich J. Hammerich (Tel.: +49 421 218 66727).

E-mail addresses: hammerich@uni-bremen.de (U. J. Hammerich), poddig@uni-bremen.de (T. Poddig).

1. Introduction

The seminal paper of Chui et al. (2010) documents that the momentum effect on international stock markets is connected to individualism as measured by one of Hofstede's (1980, 2001) cultural dimensions. In their future prospects, Chui et al. (2010) quickly test the connection of the value effect (book-to-market) and individualism. Despite the promising preliminary results, this link as well as possible cultural connections of other major risk factors like size, profitability, and investment (e.g., Fama and French, 2012; Novy-Marx, 2013; Titman et al., 2013; Watanbe et al., 2013) were not yet explored (thoroughly) in a paper.[136] Chui et al. (2010) also lack to (explicitly) investigate the implications of culture regarding the efficacy of risk factor mimicking portfolios used in asset pricing models. In this paper, we pick up this research gap and take advantage of far-reaching implications like the legitimacy of culture-based respectively culture-neutral asset pricing that come along with this topic.

A series of papers show regional or even country-specific risk factors to explain returns better than global factors (e.g., Griffin, 2002; Fama and French, 2012, 2017), which suggests that markets are not (yet) fully integrated (Fama and French, 2012, 2017). Furthermore, several papers show general weaknesses of common risk factor approaches used in asset pricing models (e.g., Kan and Zhang 1999; Lewellen et al., 2010) which is also reflected in the necessity to update and enhance them to capture returns of internationally persisting and newly discovered anomalies better (Fama and French, 2015, 2016, 2017). The local limitedness of asset pricing models makes us curious and is at the same time suspicious to us. We guess the most far-reaching and

[136] As yet, the financial literature comprises only few papers that incorporate cultural dimensions and link them to stock returns, especially when investigating stock market anomalies. Examples for this very new strand of literature are Durand et al. (2013), Weigert (2015), and Cheon and Lee (2017) who link the strength of the sin, lower tail dependence, and MAX premium to individualism as well as Costa et al. (2013) and Hammerich (2019) who manage to connect initial IPO underpricing, the nominal stock price effect and (individual) cross-sectional stock returns to several cultural dimensions of Hofstede (1980, 2001) and Hofstede et al. (2010).

fundamental reason for this might be differences in culture, known to impact general and financial development, (financial) institutions, and (financial) structures of nations (e.g., Hofstede and Bond, 1988; Husted, 1999; De Jong and Semenov, 2002, 2006; Kwok and Tadesse, 2006; Guiso et al., 2006; Aggarwal and Goodell, 2009) as well as openness of financial markets (Stulz and Williamson, 2003). The following obvious question (which is however going beyond the scope of our paper) would be if the lasting situation of not yet fully integrated markets is actually due to culture (per se). Beugelsdijk and Frijns (2010) and Anderson et al. (2011) deliver reasons to suppose that, as they show the home and foreign bias in international investments to be dependent on cultural differences. Eun et al. (2015) additionally find that country-specific stock price co-movement is associated with cultural characteristics.

We investigate this financial markets integration (deficiency) issue from another starting point, as we are (to our knowledge) the first to explore if (cross-country) returns on all common asset pricing risk factor mimicking portfolios proposed by Fama and French (in the following FF) and Carhart, namely the value-weighted market excess return (RMRF), small minus big (SMB), high minus low (HML), winner minus loser (WML), robust minus weak (RMW), and conservative minus aggressive (CMA) (FF 1993, 2015, 2018; Carhart, 1997) are dependent on culture.[137] In doing so, we go a step further than Chui et al. (2010) by not only extending the cultural links beyond momentum (WML) to other investment styles, but also show that cultural differences impact the efficacy of risk factors when explaining (other) risk factor’s portfolio returns. Specifically, we test in this paper whether cultural differences absorb or at least moderate

[137] Due to the longer tradition of the FF (1993) 3-factor model and the Carhart (1997) 4-factor model, we concentrate on the cultural sensitivity of the factors of these models and present results regarding the new factors of the FF (2015) 5-factor model in the appendix (Appendix B). We do so also due to data availability issues, as for RMW and CMA we rely on data of Kenneth French that is only available for some world regions and not on country level. Furthermore, a country-specific construction of these new factors would cut down the sample size of covered stocks especially of smaller (emerging) markets even more and likely result in a complete drop out of more countries (cp. minimum of 30 stocks threshold in Section 3.1).

respectively enhance the explanatory power of risk factors when explaining other risk factors. In this way, we explore if culture as an all-pervading (value) system can (help) integrate risk factors and act as binding material between them. As this is the case, common risk factors are to some degree proxies for cultural dimensions, rendering culture a kind of state variable.

With Merton's (1973) ICAPM a quest for the existence and nature of state variables and potential proxies began (e.g., Chen et al., 1986; Fama, 1998; Petkova, 2006; Maio and Santa-Clara, 2012; Boons 2016). We tap this topic as we show that factor-mimicking risk factor portfolios meant to proxy for these state variables (e.g., FF 1993, 2012, 2017) are sensitive to cultural differences regarding their cross-country explanatory power. The evidence suggests that culture and measurable cultural dimensions are very likely to be connected with or even causal for these unknown state variables, if culture is not one of these itself. Several papers already show a connection of commonly accepted state variables and culture: Fidrmuc and Jacob (2010) and Bae et al. (2012) link the global dividend yields to several dimensions of Hofstede (1980, 2001) and Shao et al. (2013) to Schwartz's (1994) cultural dimensions. Other papers show a link of cultural dimensions of Hofstede and Schwartz to corporate debt ratios (Chui et al., 2002) and debt maturity choice (Zheng et al., 2012), corporate risk taking (Li et al., 2013), and cost of debt and bankruptcy risk (Chui et al., 2016) which are likely linked to the default spread, whereas the FF factors also explain a large part of this state variable (Elton et al., 2001). The big difference is however, that cultural dimensions are not classical state variables in the sense of Merton, since they experience no (or only very slow) innovations, but nevertheless forecast future investment opportunities. They are no state variables (in time), but rather hidden (that is difficult to measure, grasp and quantify as well as highly pervasive) and largely time-invariant steady state variables (in space) that capture not intertemporal but rather interregional and/or intercultural differences in future investment opportunities as it is legitimate in a globalized, but not yet fully integrated world.

Summed up, our main contribution to the literature and our goal is threefold: (1) We test and document the cultural dependency of further significant investment styles, (2) show explanatory and predictive power of steady state variables (i.e. the six cultural dimensions of Hofstede et al., 2010) for stock returns (in particular risk factor mimicking portfolios), and (3) introduce culture as vital (background) variable and ingredient for efficient, global asset pricing by showing a link between values on cultural dimensions and the efficacy of asset pricing risk factors.

The rest of the paper is structured as follows. In Section 2, we develop our main hypothesis. Section 3 introduces the used datasets and defines the variables. In Section 4, we investigate the relationship between major asset pricing risk factors and cultural dimensions. Section 5 concludes the paper.

2. Hypothesis development

Liew and Vassalou (2000) show that SMB and HML are assisting factors for predicting future rates of economic growth. Vassalou (2003) in turn suggests that SMB and HML may be proxies for news about future GDP growth and also shows that accounting for macroeconomic risk reduces the information content of both FF factors. Petkova (2006: 582) draws a deduction from this: "*The relation between the FF factors and GDP growth is consistent with an ICAPM explanation behind the three-factor model. According to this explanation, changes in the investment opportunity set are summarized by changes in future GDP growth.*"

We see a missing chain link in this relationship, since cultural dimensions of Hofstede (1980, 2001) – especially Long Term Orientation (LTO) – are able to predict future economic growth (in particular for poor countries), measured by an increase in GNI per capita (Hofstede et al., 2010) and GNI per capita in turn can explain variations in Individualism scores and predict Power Distance values. Gorodnichenko and Roland (2011) also find that Individualism has a robust effect on long-run growth. That is, if FF risk factors proxy for future GDP growth and are also capable of predicting future growth rates, it is likely that these risk factors also proxy for cultural characteristics. Furthermore, if changes in the investment opportunity set are summarized by changes in future GDP growth (Petkova, 2006) and these changes in growth are related to cultural differences, then culture itself would be a state variable in the sense of Merton's (1973) ICAPM that is proxied by the FF risk factors.[138]

In this paper, we investigate if this is the case as we check if common risk factors are sensitive to cultural differences and if their explanatory power remains robust in the presence of the national cultural dimensions proposed by Hofstede et al. (2010). Our main hypothesis is therefore formulated as follows.

Hypothesis: The explanatory power of local (country-specific/regional) asset pricing risk factor mimicking portfolios is absorbed respectively moderated by differences in national culture.

The effectiveness and validity of this conjectured mechanism relies also on a certain dependency of the return premia of common asset pricing risk factors on cultural characteristics. Especially for WML, this relationship of culture and the extent of the momentum effect prevailing in a country is shown and founded very well by Chui et al. (2010). They argue that the well-documented return premium on momentum is likely triggered indirectly by culture via the positive association of overconfidence and self-attribution bias (which are suspected drivers of

[138] We assume however that cultural differences are not only connected to macroeconomic risk and economic growth, which in turn are captured by FF risk factors, but contain informational value that goes beyond this dimension. Petkova (2006: 582) states for example that "*changes in financial investment opportunities are not necessarily exclusively related to news about future GDP growth*." Furthermore, Boons (2016) even suggests that the factors SMB and HML do not capture the macroeconomic risk in state variables, but rather the characteristics like size which drives out the default spread risk premium. We leave this controversial topic for future research and focus on the sensitivity of widely applied risk factors to cultural differences, instead of e.g., the cross-sectional sensitivity of characteristics in the light of culture or vice versa.

momentum in the literature, see, e.g., Daniel et al., 1998) with Individualism levels (as measured by Hofstede, 1980, 2001). Thus, they assume a mispricing mechanism that originally relies on cultural differences that produces the momentum effect (abnormal returns on WML) in a differing extent throughout the world. As this cultural connection of momentum is only the most prominent example of a factor that predicts and explains the cross-section of (expected) stock returns in the emerging strand of literature on cultural finance, we expect that similar links between behavioral biases, heuristics, and cultural differences are also present for other common risk factors.[139] We check the plausibility of this assumption empirically and review the evidence on momentum as we investigate the relation of returns on common asset pricing risk factors and all six cultural dimensions of Hofstede et al. (2010) before we tackle our main hypothesis.

3. Data and performance of factor portfolios

3.1 Data

In this section we briefly discuss and introduce the data and the major variables used in this study. In Appendix A we define the variables in more detail. As cultural proxies, we adopt the six cultural dimensions of Hofstede et al. (2010). We retrieve the national index values for each of the cultural dimensions Power Distance (*PDI*), Individualism (*IDV*), Masculinity (*MAS*),

[139] For example, the association of analytic vs. holistic thinking styles and individualistic vs. collectivistic cultures (Choi and Nisbett, 2000; Nisbett et al., 2001) may be consequential for the value effect (see Section 4.3.2). Furthermore, the vast number of literature, e.g., on cultural effects regarding financial structures, institutions, and development as well as investment preferences, corporate decision making, and corporate culture (cp. named literature in Section 1 as a small sample) also suggests to see some differences in national market (excess) returns and thus the efficacy and relevance of the market factor across cultures. In respect of the size effect it appears plausible to expect larger (on average more globalized) firms to be less influenced by national culture, for instance (i.e. differences in cultural sensitivity across the components of the SMB factor).

Uncertainty Avoidance (*UAI*), Long Term Orientation (*LTO*), and Indulgence versus Restraint (*IVR*) directly from Hofstede's website.[140] We get data for all our 41 covered countries for each cultural dimension except the *IVR* value for Israel which is not available. Each cultural dimension is defined in a way that the values lay between 0 and 100 (see, e.g., Hofstede, 2001 for a detailed description of the methodology). The cultural scores for each country in our dataset are listed in Table 1.

The cultural dimensions are time-invariant values constructed in a way to capture differences in central cultural characteristics (that is especially values defining preferences for one state of affairs over others) among nations rather than representing absolute cultural measures. As absolute measures of culture in a country may differ over time, differences between countries are more likely to hold at least over several decades (Hofstede et al., 2010). The initial four dimensions of Hofstede (1980) *PDI*, *IDV*, *MAS*, and *UAI* stem from a global study designed to capture value scores of about 88,000 international IBM employees located in 72 countries, which was performed between 1967 and 1973. In Hofstede (2001) *LTO* and in Hofstede et al. (2010) *IVR* are added as additional cultural dimensions that measure aspects of culture not contained in the original dimensions.

To control for the connections of several cultural dimensions to national economic development and growth (see Section 2 and for example Hofstede et al., 2010), we add the national *GPDpc* (GPD per capita in U.S. dollars) values as explanatory variable in our forthcoming regressions.[141] However, since the cultural dimensions are time-invariant, we set *GDPpc* to be also time-invariant and displaying GPD per capita values of 1980, only.[142] We do so,

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[140] https://www.hofstede-insights.com/product/compare-countries/; see also Hofstede et al. (2010)

[141] The data is received from the IMF website for all of our 41 countries except Russia: http://www.imf.org/external/pubs/ft/weo/2017/01/weodata/index.aspx

[142] We also use the yearly time series of GDP per capita (1980 to 2017) as robustness check and find the results for the regressions in Section 4.2 and 4.3 to not change materially when substituting the time-invariant GDP per capita variable by the time-variant one.

as we want to isolate the informational value of the complete set of cultural dimensions in our regressions (Sections 4.2 and 4.3) only so far as it is guaranteed that *GDPpc* cannot anticipate (absorb) the predictive power (or association) of certain cultural dimensions regarding economic development (especially *PDI* and *IDV*) and growth (*LTO*) (cp. Section 2). That is, *GDPpc* and cultural dimensions have more comparable properties (time-invariant) and *GDPpc* does not have an "unfair" advantage due to containing information that would otherwise be measured by (unavailable) time-*variant* cultural dimensions. Furthermore, the usage of *GDPpc* time series would add a nonstationarity problem due to increasing *GDPpc* levels over time. As Hofstede published the results on the initial cultural dimensions in 1980, we choose this year to represent our economic development benchmark.

The financial datasets are retrieved from Thomson Reuters Datastream. To enable us to compare our results to Chui et al. (2010) and to update their results regarding the cultural connections of momentum in a consistent manner, we cover all countries of their dataset apart from Ireland and Portugal for which our threshold of at least 30 consecutively active stocks for each month of the country-specific time frame is not fulfilled (this is to ensure a sufficient and statistically meaningful number of stocks to construct our country-specific risk factor mimicking portfolios). For enhanced cultural diversity and to compensate this drop out, we add Russia and Saudi Arabia to be included in our study.

Our cross-country raw stock universe covers well over 30,000 stocks (common stocks in local currency only) listed at the respective main home stock exchange (primary listing) of each of our 41 countries. As it is common practice in asset pricing studies to exclude financial stocks, we adopt this procedure and exclude all stocks assigned by Datastream to be primarily financial sector stocks. The maximum time frame coverage is from June 1980 to April 2017 which is fulfilled especially by large, developed countries. The shortest time frame coverages are usually displayed by (financially) less developed countries, however with a minimum of still about 9 years for Bangladesh. Table 1 summarizes key characteristics of the covered countries regarding their time frame and stock count coverage. Since the results of our study are relevant for an international research community and to respect the unique cultural heritage of each nation, we measure stock returns in country-specific currencies. However, as Chui et al. (2010) for example show, their results are virtually identical whether returns are measured in U.S. dollars or in country-specific currency.

We edit the raw datasets as follows to account for data errors and to cut out the most illiquid and smallest stocks: in each month and within each country-specific dataset, we set not available (1) all stocks with a market equity below the 10th percentile of all active stocks in that month, (2) stocks displaying an unadjusted price below 1 currency units, and (3) stocks showing zero returns in each of the preceding four months. This ensures to omit the most illiquid and economically meaningless stocks, as well as those which typically exhibit most data failures (penny stocks).

Given the financial datasets,[143] we construct our left-hand side (LHS) portfolios for the upcoming regressions. However, in Section 4.3 these portfolios also appear on the right-hand side (RHS) of the regressions as we explain risk factors with other risk factors (also in conjunction with cultural dimensions). The following portfolios are the country-specific risk factor mimicking hedge portfolios *RMRF*, *SMB*, *HML*, and *WML* which we build in the tradition of FF (1993) and Carhart (1997).[144] For *RMW* and *CMA* (FF, 2015, 2018) we use Kenneth French's database[145] and download return time series for all available four regions (North America, Europe, Japan, Asia Pacific ex Japan). We assign these regional returns to the respective countries in our dataset covered by this world region. In this way, we get return time series of

[143] We download in particular the Total Return Index, Market Value, Common Shareholder's Equity time series, and time series of country-specific risk free rates (that is local short-term deposit rates, 1M to 3M, respectively returns of short-term treasury bills or equivalents in local currency) for each country-specific stock universe.

[144] See Appendix A for a detailed definition.

[145] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

RMW and *CMA* for 21 countries.[146] Values for *RMW* and *CMA* of countries not covered by Kenneth French's regions are set not available.

RMRF is the value-weighted market return (*RM*) in excess of the risk free rate (*RF*). *SMB* and *HML* are the risk factor mimicking hedge portfolios for the size and value effect (FF, 1993), and *WML* is the risk factor mimicking hedge portfolio for the momentum effect (Carhart, 1997). *RMW* and *CMA* mimic risk factors for profitability and investment (FF, 2015, 2018).

[146] Specifically, our datasets of *RMW* and *CMA* cover the following countries: Canada and the US (region North America), Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Italy, Netherlands, Norway, Spain, Sweden, Switzerland (Europe), Australia, Hong Kong, New Zealand, Singapore (Asia Pacific), and Japan.

Table 1
Summary statistics.

Country	Period	No. of firms (av.)	No. of firms (total)	*PDI*	*IDV*	*MAS*	*UAI*	*LTO*	*IVR*
Argentina	2002-2017	51	92	49	46	56	86	20	62
Australia	1980-2017	224	2431	36	90	61	51	21	71
Austria	1987-2017	55	130	11	55	79	70	60	63
Bangladesh	2008-2017	49	73	80	20	55	60	47	20
Belgium	1985-2017	75	178	65	75	54	94	82	57
Brazil	1998-2017	90	206	69	38	49	76	44	59
Canada	1980-2017	454	1630	39	80	52	48	36	68
Chile	1990-2017	110	205	63	23	28	86	31	68
China	1993-2017	567	1157	80	20	66	30	87	24
Denmark	1987-2017	107	228	18	74	16	23	35	70
Finland	1990-2017	83	207	33	63	26	59	38	57
France	1980-2017	440	1373	68	71	43	86	63	48
Germany	1980-2017	353	973	35	67	66	65	83	40
Greece	1988-2017	132	337	60	35	57	100	45	50
Hong Kong	1983-2017	256	1524	68	25	57	29	61	17
India	1990-2017	850	1514	77	48	56	40	51	26
Indonesia	1991-2017	205	426	78	14	46	48	62	38
Israel	1992-2017	219	388	13	54	47	81	38	NA
Italy	1983-2017	116	403	50	76	70	75	61	30
Japan	1980-2017	1769	3258	54	46	95	92	88	42
Netherlands	1980-2017	106	244	38	80	14	53	67	68
Malaysia	1985-2017	293	902	100	26	50	36	41	57
Mexico	1991-2017	79	168	81	30	69	82	24	97
New Zealand	1992-2017	55	188	22	79	58	49	33	75
Norway	1982-2017	107	408	31	69	8	50	35	55
Pakistan	1993-2017	132	193	55	14	50	70	50	0
Philippines	1992-2017	79	190	94	32	64	44	27	42
Poland	1995-2017	198	535	68	60	64	93	38	29
Saudi Arabia	2005-2017	79	118	95	25	60	80	36	52
Singapore	1982-2017	67	647	74	20	48	8	72	46
South Africa	1980-2017	156	596	49	65	63	49	34	63
South Korea	1985-2017	545	896	60	18	39	85	100	29
Spain	1987-2017	89	229	57	51	42	86	48	44
Sweden	1986-2017	201	791	31	71	5	29	53	78
Switzerland	1980-2017	131	274	34	68	70	58	74	66
Russia	2004-2017	118	251	93	39	36	95	81	20
Taiwan	1989-2017	498	940	58	17	45	69	93	49
Thailand	1989-2017	293	665	64	20	34	64	32	45
Turkey	1988-2017	163	319	66	37	45	85	46	49
UK	1980-2017	1087	3452	35	89	66	35	51	69
US	1980-2017	1240	3068	40	91	62	46	26	68

This table shows the available time frame (starting month is always June of the respective year; all datasets end in April 2017), average and total number of stocks as well as the index values on the cultural dimensions of Hofstede et al. (2010) for each country in our dataset.

3.2 Performance of risk factor portfolios

In this section, we test the performance of our main risk factor mimicking portfolios *RMRF*, *SMB*, *HML*, and *WML* and report the results in Table 2 to get a first impression of the international significance of these portfolios.

We find our results for *WML* to be in line with Chui et al. (2010) in the big picture, despite our slightly different methodology regarding how the momentum effect is measured. We calculate cumulative returns from past 12 to past 2 months and rebalance the winner (W) and loser (L) portfolios monthly as in Carhart (1997), whereas Chui et al. (2010) use formation and holding time frames of 6 months respectively. In general, the momentum effect slightly increased since the end of Chui et al.'s (2010) time frame (2003), as we find a monthly mean *WML* return of 0.89% throughout all countries, whereas Chui et al. (2010) report an average *WML* return of only 0.68%. We also report a clear minority of countries (3 out of 41) to show negative *WML* returns that are like in Chui et al. (2010) always not statistically significant (they find 4 countries to show negative returns). The lowest returns are in general displayed by Asian/Middle East countries like China, Japan, Indonesia, Saudi Arabia, and Turkey. That already hints to the lasting validity of Chui et al.'s (2010) findings regarding the cultural connection of the momentum effect. We show clear confirmation of this preliminary evidence in the next sections.

The value effect (*HML*) is also positively significant in the majority of our countries, whereas maximum t-statistics (about 4) are still well below the maximum t-statistics of the momentum effect (exceeding 8). The size effect (*SMB*) shows to be an internationally inconsistent effect, as it shows every now and then both significantly negative and positive t-statistics. Returns on *RMRF* are internationally positive (with the exception of Brazil) and to a good deal statistically significant.

Table 2
Market, size, value, and momentum profits by country.

Country	*RMRF*		*SMB*		*HML*		*WML*	
Argentina	0.96%	(1.57)	0.68%	(1.57)	1.24%	(2.43)	0.34%	(0.83)
Australia	0.39%	(1.52)	-0.05%	(-0.29)	0.44%	(2.69)	1.36%	(7.42)
Austria	0.36%	(1.26)	-0.02%	(-0.08)	1.19%	(4.19)	1.10%	(3.68)
Bangladesh	1.48%	(1.86)	0.96%	(1.69)	-0.16%	(-0.21)	1.39%	(1.81)
Belgium	0.76%	(2.85)	-0.21%	(-1.07)	0.41%	(1.71)	1.37%	(6.26)
Brazil	-0.29%	(-0.59)	0.34%	(0.86)	0.86%	(1.87)	1.27%	(2.70)
Canada	0.39%	(1.79)	0.45%	(2.96)	0.16%	(0.78)	1.42%	(6.37)
Chile	0.95%	(3.50)	-0.38%	(-0.77)	1.68%	(2.52)	0.46%	(0.84)
China	1.11%	(1.52)	0.61%	(1.63)	0.17%	(0.39)	0.00%	(-0.01)
Denmark	0.71%	(2.76)	-0.51%	(-2.31)	0.43%	(1.74)	1.21%	(5.69)
Finland	0.64%	(1.48)	-0.03%	(-0.10)	0.60%	(1.78)	1.02%	(3.65)
France	0.68%	(2.75)	0.00%	(-0.00)	0.36%	(1.71)	1.23%	(6.22)
Germany	0.55%	(2.24)	-0.31%	(-1.89)	0.70%	(4.02)	1.33%	(6.56)
Greece	0.10%	(0.20)	0.34%	(0.90)	0.36%	(1.01)	0.69%	(1.84)
Hong Kong	0.96%	(2.53)	-0.45%	(-1.64)	1.03%	(3.78)	0.78%	(2.95)
India	0.86%	(1.70)	0.70%	(1.81)	0.53%	(1.20)	1.64%	(5.05)
Indonesia	0.55%	(1.13)	0.43%	(0.83)	1.05%	(1.87)	-0.04%	(-0.09)
Israel	0.53%	(1.63)	-0.06%	(-0.13)	1.70%	(2.86)	1.58%	(2.45)
Italy	0.59%	(1.93)	-0.50%	(-2.61)	0.59%	(2.54)	0.95%	(3.90)
Japan	0.31%	(1.22)	0.17%	(0.99)	0.59%	(4.45)	0.15%	(0.78)
Malaysia	0.58%	(1.66)	0.26%	(0.93)	0.39%	(1.80)	0.80%	(2.77)
Mexico	0.39%	(1.10)	-0.31%	(-1.26)	0.55%	(1.81)	1.24%	(3.97)
Netherlands	0.73%	(3.11)	-0.08%	(-0.38)	0.34%	(1.41)	1.31%	(6.39)
New Zealand	0.39%	(1.66)	-0.16%	(-0.75)	0.96%	(3.67)	1.37%	(6.49)
Norway	0.54%	(1.69)	-0.04%	(-0.16)	0.25%	(1.02)	1.29%	(4.49)
Pakistan	1.52%	(2.96)	0.10%	(0.26)	1.00%	(2.37)	0.73%	(1.80)
Philippines	0.47%	(1.22)	0.19%	(0.50)	0.43%	(0.90)	0.49%	(0.95)
Poland	0.09%	(0.18)	0.76%	(2.29)	0.57%	(1.62)	1.54%	(4.60)
Russia	0.94%	(1.65)	-0.19%	(-0.37)	1.00%	(2.52)	0.54%	(0.93)
Saudi Arabia	0.82%	(1.16)	-0.32%	(-0.70)	0.50%	(1.47)	0.07%	(0.18)
Singapore	0.40%	(1.19)	-0.01%	(-0.03)	0.84%	(3.11)	0.74%	(2.66)
South Africa	0.65%	(2.26)	-0.12%	(-0.50)	0.56%	(2.17)	1.47%	(6.00)
South Korea	0.47%	(1.00)	0.26%	(0.75)	1.35%	(4.11)	0.23%	(0.67)
Spain	0.47%	(1.58)	-0.18%	(-0.91)	0.64%	(2.86)	0.95%	(3.41)
Sweden	0.77%	(2.15)	-0.13%	(-0.55)	0.05%	(0.18)	1.24%	(4.07)
Switzerland	0.76%	(3.85)	-0.24%	(-1.61)	0.32%	(2.02)	1.17%	(6.26)
Taiwan	0.47%	(1.07)	-0.08%	(-0.28)	-0.05%	(-0.16)	0.26%	(0.87)
Thailand	0.69%	(1.40)	0.22%	(0.68)	0.73%	(2.11)	0.41%	(1.25)
Turkey	0.83%	(1.11)	-0.69%	(-1.33)	1.02%	(1.77)	-0.43%	(-0.68)
UK	0.54%	(2.63)	0.14%	(0.69)	0.45%	(3.46)	1.54%	(8.61)
US	0.61%	(3.17)	0.35%	(2.78)	0.19%	(1.82)	0.26%	(1.36)

We present average monthly returns on our four main risk factor mimicking portfolios RMRF, SMB, HML, and WML alongside respective t-statistics (in parentheses) for each country over the country-specific maximum time frame (see Table 1). Detailed definitions of these risk factors are given in the appendix (Appendix A).

4. Asset pricing risk factors and cultural dimensions

4.1 Portfolios on cultural dimensions and top and bottom risk factor components

In this section, we investigate the relation between the six cultural dimensions of Hofstede et al. (2010) and the profitability of size, value, and momentum strategies. At first, all countries are classified into three groups with respect to each cultural dimension. Low values depict the bottom 30%, medium values assign the middle 40%, and high values define the top 30% regarding each cultural dimension across all countries. In the next step, we construct (country-specific) size, value, and momentum portfolios (bottom 30% and top 30% respectively, which are equivalent to the extreme portfolios that define our risk factor mimicking hedge portfolios) and sort these portfolios by the defined cultural classes. In Table 3, 4, and 5 we report the average monthly returns of these (two-way) sorted portfolios (first defining cultural classes and then calculating average portfolio returns within these classes; i.e. a dependent sort).[147]

Confirming the results of Chui et al. (2010), we find very similar values for the momentum portfolios sorted by *IDV* (Table 5), despite their considerably older (covering the years 1984 to 2003) and shorter sample (19 years vs. 36 years). Chui et al. report an average monthly return spread of the momentum hedge portfolios of 0.65% with a t-statistic of 4.30 which is virtually identical to our finding (0.66% average monthly return with a t-statistic of 4.41). As we extend the connections of momentum beyond *IDV*, we also find significant hedge portfolio return spreads for sorts by *PDI* and *IVR* (returns of -0.37% and 0.55% with respective t-statistics of -2.67 and 4.41). Furthermore, we find a clear, highly significant momentum effect

[147] We abstain from conducting sorts with country-specific *RMRF* values, since a construction of a high *RMRF* minus low *RMRF* hedge portfolio (or vice versa) is not part of the asset pricing risk factors and is neither feasible nor conventional as a characteristics-based country-specific portfolio (cp. however the results of the sorts regarding RM and cultural dimensions in Appendix C).

irrespective of cultural classes, reflecting our strong evidence regarding an international momentum effect in Table 2.

In Table 4 we also confirm the preliminary results of Chui et al. (2010) regarding the connection of the value effect and *IDV*. Here, we obtain an identical value for the outperformance of low-*IDV* value hedge portfolios compared to high-*IDV* value hedge portfolios of 0.43% with a clearly significant t-statistic of 2.84 as opposed to the barely significant t-statistic of 1.87 reported by Chui et al. (however, in their quick follow-up study only 22 countries were included and data from the Kenneth French website was used). Furthermore, we report a significant dependency of the value effect from *UAI* and *IVR* levels (returns of 0.33% and -0.28% with respective t-statistics of 2.34 and -2.28).

Looking at a possible connection of the size effect to cultural dimensions (Table 3), we find little evidence for that to be the case (no significant effects), at least in case of an application of a sorting methodology that cannot account for interdependency effects of cultural dimensions.

As we find returns of high-*PDI* and low-*MAS* countries to be consistently higher throughout all sorts (apart from minor exceptions), we also check if levels of cultural dimensions are directly connected to cross-country value-weighted market returns. We report the results on these sorts in Table C.1 in Appendix C. We indeed find a significant connection of low-*MAS* values and higher market returns (average outperformance of 0.38%, t-statistic 2.88) and a barely significant relation of high-*PDI* values and higher market returns (mean outperformance of 0.29%, t-statistic 1.74). An intuitive explanation for the dependency of market returns on *MAS* would be that the higher competitiveness inherent in firm- and organizational cultures in those societies (Hofstede et al., 2010) results in friction losses inside firms (e.g. dense networks of intrigues) and/or between firms (e.g. higher marketing expenses and pricing pressure due to stronger competition) located in this country that are detrimental for the firm performance and thus its returns. This conjecture is also in line with economic theory which describes that higher ("ruinous") competition results in less corporate profits (cp., e.g., Clark, 1940). However, related literature shows little empirical evidence for this and rather supports the contrary (e.g., Deshpandé and Farley, 2004; Hou and Robinson 2006). Since this issue is not the main concern of this study, we leave this puzzle for future research.

Table 3
Size profits and cultural dimensions.

Panel A: Power Distance and Size

PDI	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.08%	1.11%	-0.03%
	(5.74)	*(5.44)*	*(-0.31)*
Medium	1.44%	1.46%	-0.02%
	(7.83)	*(6.96)*	*(-0.22)*
High	1.54%	1.45%	0.09%
	(6.18)	*(5.63)*	*(0.73)*
High minus low	0.47%	0.35%	0.12%
	(2.51)	*(2.01)*	*(0.89)*

Panel B: Individualism and Size

IDV	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.32%	1.28%	0.04%
	(5.68)	*(4.85)*	*(0.29)*
Medium	1.53%	1.48%	0.05%
	(7.61)	*(6.70)*	*(0.51)*
High	1.07%	1.10%	-0.04%
	(5.68)	*(5.58)*	*(-0.44)*
High minus low	-0.32%	-0.22%	-0.10%
	(-1.70)	*(-1.14)*	*(-0.72)*

Panel C: Masculinity and Size

MAS	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.43%	1.56%	-0.13%
	(6.93)	*(6.58)*	*(-1.10)*
Medium	1.42%	1.25%	0.17%
	(6.28)	*(5.32)*	*(1.50)*
High	1.15%	1.12%	0.04%
	(6.42)	*(5.85)*	*(0.46)*
High minus low	-0.28%	-0.44%	0.17%
	(-2.07)	*(-3.37)*	*(1.48)*

Panel D: Uncertainty Avoidance and Size

UAI	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.44%	1.28%	0.15%
	(6.64)	*(5.95)*	*(1.74)*
Medium	1.07%	1.16%	-0.09%
	(5.92)	*(5.38)*	*(-0.91)*
High	1.54%	1.53%	0.01%
	(7.67)	*(6.88)*	*(0.11)*
High minus low	0.11%	0.25%	-0.14%
	(0.63)	*(1.55)*	*(-1.08)*

Panel E: Long Term Orientation and Size

LTO	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.28%	1.25%	0.02%
	(7.22)	*(6.10)*	*(0.26)*
Medium	1.97%	1.59%	0.38%
	(8.47)	*(6.56)*	*(2.79)*
High	1.09%	1.15%	-0.06%
	(5.43)	*(5.40)*	*(-0.67)*
High minus low	-0.18%	-0.10%	-0.08%
	(-1.42)	*(-0.81)*	*(-0.81)*

Panel F: Indulgence and Size

IVR	Small (S)	Big (B)	S minus B
	Size Portfolios		
Low	1.37%	1.29%	0.08%
	(6.61)	*(5.85)*	*(0.75)*
Medium	1.41%	1.45%	-0.03%
	(6.81)	*(5.95)*	*(-0.29)*
High	1.18%	1.20%	-0.02%
	(6.59)	*(6.33)*	*(-0.25)*
High minus low	-0.20%	-0.10%	-0.10%
	(-1.36)	*(-0.69)*	*(-0.84)*

This table reports average monthly size profits for country-average portfolios classified by all six cultural dimensions of Hofstede et al. (2010), respectively. All size returns are equally weighted across all country-specific size portfolios. We allocate all countries in our sample to three classes – low (bottom 30%), medium (middle 40%), and high (top 30%) – based on their scores on each cultural dimension. We cover the period June 1980 to April 2017. The corresponding t-statistics are written in italics and are in parentheses. Detailed definitions of the size portfolios and the cultural dimensions are given in the appendix.

Table 4
Value profits and cultural dimensions.

Panel A: Power Distance and Value	Value Portfolios		
PDI	High (H)	Low (L)	H minus L
Low	1.35%	0.82%	0.53%
	(6.86)	*(4.15)*	*(5.79)*
Medium	1.82%	1.11%	0.71%
	(8.66)	*(5.79)*	*(6.76)*
High	1.76%	1.15%	0.61%
	(6.44)	*(4.91)*	*(4.61)*
High minus low	0.41%	0.33%	0.08%
	(2.14)	*(1.93)*	*(0.57)*

Panel B: Individualism and Value	Value Portfolios		
IDV	High (H)	Low (L)	H minus L
Low	1.66%	0.87%	0.80%
	(6.07)	*(3.88)*	*(5.73)*
Medium	1.89%	1.15%	0.74%
	(8.67)	*(5.42)*	*(6.49)*
High	1.27%	0.89%	0.37%
	(6.40)	*(4.63)*	*(4.23)*
High minus low	-0.44%	-0.01%	-0.43%
	(-2.07)	*(-0.07)*	*(-2.84)*

Panel C: Masculinity and Value	Value Portfolios		
MAS	High (H)	Low (L)	H minus L
Low	1.82%	1.17%	0.65%
	(7.93)	*(5.29)*	*(5.36)*
Medium	1.64%	1.00%	0.64%
	(6.51)	*(4.60)*	*(4.85)*
High	1.38%	0.86%	0.52%
	(7.34)	*(4.73)*	*(6.44)*
High minus low	-0.44%	-0.31%	-0.13%
	(-3.19)	*(-2.11)*	*(-1.02)*

Panel D: Uncertainty Avoidance and Value	Value Portfolios		
UAI	High (H)	Low (L)	H minus L
Low	1.58%	1.09%	0.48%
	(7.09)	*(5.12)*	*(4.83)*
Medium	1.38%	0.81%	0.57%
	(6.65)	*(4.23)*	*(6.18)*
High	1.96%	1.15%	0.81%
	(8.70)	*(5.60)*	*(6.85)*
High minus low	0.38%	0.05%	0.33%
	(2.24)	*(0.31)*	*(2.34)*

Panel E: Long Term Orientation and Value	Value Portfolios		
LTO	High (H)	Low (L)	H minus L
Low	1.57%	1.02%	0.55%
	(7.90)	*(5.22)*	*(5.56)*
Medium	1.96%	1.38%	0.58%
	(8.07)	*(6.19)*	*(4.74)*
High	1.41%	0.80%	0.62%
	(6.46)	*(4.03)*	*(6.39)*
High minus low	-0.15%	-0.22%	0.07%
	(-1.15)	*(-1.67)*	*(0.58)*

Panel F: Indulgence and Value	Value Portfolios		
IVR	High (H)	Low (L)	H minus L
Low	1.69%	0.91%	0.78%
	(7.42)	*(4.50)*	*(7.14)*
Medium	1.74%	1.14%	0.60%
	(7.12)	*(5.38)*	*(5.04)*
High	1.44%	0.94%	0.50%
	(7.64)	*(5.07)*	*(5.57)*
High minus low	-0.26%	0.03%	-0.28%
	(-1.65)	*(0.18)*	*(-2.28)*

This table reports average monthly value profits for country-average portfolios classified by all six cultural dimensions of Hofstede et al. (2010), respectively. All value returns are equally weighted across all country-specific value portfolios. We allocate all countries in our sample to three classes – low (bottom 30%), medium (middle 40%), and high (top 30%) – based on their scores on each cultural dimension. We cover the period June 1980 to April 2017. The corresponding t-statistics are written in italics and are in parentheses. Detailed definitions of the value portfolios and the cultural dimensions are given in the appendix.

Table 5
Momentum profits and cultural dimensions.

Panel A: Power Distance and Momentum	Momentum Portfolios		
PDI	Winner (L)	Loser (L)	W minus L
Low	1.71%	0.44%	1.27%
	(8.80)	*(1.96)*	*(10.55)*
Medium	1.90%	1.34%	0.57%
	(9.82)	*(5.87)*	*(4.81)*
High	2.04%	1.14%	0.90%
	(8.09)	*(4.01)*	*(5.89)*
High minus low	0.33%	0.70%	-0.37%
	(1.84)	*(3.37)*	*(-2.67)*

Panel B: Individualism and Momentum	Momentum Portfolios		
IDV	Winner (L)	Loser (L)	W minus L
Low	1.62%	1.07%	0.55%
	(6.47)	*(3.75)*	*(3.70)*
Medium	2.10%	1.26%	0.84%
	(9.90)	*(5.25)*	*(6.14)*
High	1.70%	0.49%	1.21%
	(8.92)	*(2.13)*	*(9.84)*
High minus low	0.04%	-0.62%	0.66%
	(0.23)	*(-2.66)*	*(4.41)*

Panel C: Masculinity and Momentum	Momentum Portfolios		
MAS	Winner (L)	Loser (L)	W minus L
Low	2.11%	1.25%	0.86%
	(9.82)	*(4.85)*	*(6.44)*
Medium	1.83%	0.84%	0.99%
	(8.07)	*(3.20)*	*(7.44)*
High	1.64%	0.69%	0.95%
	(8.90)	*(3.25)*	*(8.60)*
High minus low	-0.47%	-0.56%	0.09%
	(-3.43)	*(-3.49)*	*(0.79)*

Panel D: Uncertainty Avoidance and Momentum	Momentum Portfolios		
UAI	Winner (L)	Loser (L)	W minus L
Low	1.85%	0.88%	0.96%
	(8.62)	*(3.62)*	*(7.83)*
Medium	1.66%	0.70%	0.96%
	(8.55)	*(3.09)*	*(8.38)*
High	2.12%	1.35%	0.77%
	(10.14)	*(5.50)*	*(5.70)*
High minus low	0.27%	0.46%	-0.19%
	(1.62)	*(2.40)*	*(-1.35)*

Panel E: Long Term Orientation and Momentum	Momentum Portfolios		
LTO	Winner (L)	Loser (L)	W minus L
Low	1.80%	0.87%	0.93%
	(9.52)	*(3.99)*	*(7.70)*
Medium	2.34%	1.22%	1.12%
	(10.00)	*(4.69)*	*(8.65)*
High	1.56%	0.78%	0.78%
	(7.70)	*(3.27)*	*(6.55)*
High minus low	-0.23%	-0.08%	-0.15%
	(-1.80)	*(-0.55)*	*(-1.35)*

Panel F: Indulgence and Momentum	Momentum Portfolios		
IVR	Winner (L)	Loser (L)	W minus L
Low	1.77%	1.15%	0.62%
	(8.51)	*(4.71)*	*(4.70)*
Medium	2.02%	1.14%	0.88%
	(8.74)	*(4.34)*	*(6.43)*
High	1.78%	0.61%	1.17%
	(9.85)	*(2.89)*	*(10.22)*
High minus low	0.00%	-0.55%	0.55%
	(0.03)	*(-3.31)*	*(4.41)*

This table reports average monthly momentum profits for country-average portfolios classified by all six cultural dimensions of Hofstede et al. (2010), respectively. All momentum returns are equally weighted across all country-specific momentum portfolios. We allocate all countries in our sample to three classes – low (bottom 30%), medium (middle 40%), and high (top 30%) – based on their scores on each cultural dimension. We cover the period June 1980 to April 2017. The corresponding t-statistics are written in italics and are in parentheses. Detailed definitions of the momentum portfolios and the cultural dimensions are given in the appendix.

4.2 Cultural dimensions and returns on risk factors: the direct relationship

In this section, we explore if cultural dimensions are capable of explaining risk factor mimicking portfolio returns in a two-step Fama-MacBeth (1973) regression setting.[148] This serves on the one hand as a robustness test of the results of the previous section and on the other hand as plausibility checks for the results of the following sections. First, we perform rolling, cross-sectional monthly regressions regarding the following regression model (Eq. 1) for our i ($i = 1, 2, \dots, 41$) countries:

$$RFP_{it} = \alpha_t + CUL_i\delta_t + \gamma_t GDPpc_i + \varepsilon_{it} \tag{1}$$

where *RFP* stands for one of our six tested risk factor portfolios (*RMRF*, *SMB*, *HML*, *WML*, *RMW*, and *CMA*), α is the regression constant, *CUL* is a vector of our six cultural dimensions (*PDI*, *IDV*, *MAS*, *UAI*, *LTO*, *IVR*) – respectively in the univariate models *CUL* is a place holder for one cultural dimension – and *GDPpc* is our national development proxy that controls for time-invariant effects of economic development and culture (GDP per capita of 1980). The ε_{it} is an error term. Following Cochrane (2009), in the second step, we calculate AR(1) robust t-statistics of the attained time series of coefficients.

Tables 6 and 7 present the results for our four main risk factor portfolios. Results with *RMW* and *CMA* on the LHS of Eq. (1) are presented in the appendix (Appendix B), since these results have only limited validity and informational value due to the underlying regional return time series. Table 6 reports no reliable direct explanatory power of cultural dimensions for *RMRF*

[148] We deviate from the classical Fama-MacBeth approach as we regress risk factor returns in *t* on predictor values measured also in *t* (instead of regressing values in *t+1* on values in *t*). We do so as we want to investigate the sensitivity regarding the *explanatory* power of risk factors (and not their predictive power) as it is done in common asset pricing models (Carhart, 1997; FF 1993, 2015) (where portfolio returns in *t* are also regressed on returns of risk factor mimicking portfolios in *t*). Additionally, we (also) use time-*invariant* variables on the RHS.

(apart from *MAS*) and *SMB*. Only for Model 7 (8) in Panel B which comprises all cultural dimensions, we find a significant (barely significant) value for *UAI* and barely significant values for *PDI* when explaining *SMB*. This is no surprise as the insignificant findings for the size and culture sorts in the previous section are consistent with that. Furthermore, we note that cultural dimensions have also only limited potential in directly explaining value-weighted market excess returns (*RMRF*), with only *MAS* as a barely significant factor (cp. consistent results in Table C.1).

For *HML* and especially *WML*, we find more promising indication that these risk factor mimicking portfolios are directly explainable by cultural dimensions (see Table 7). Two (three) single cultural dimensions, *UAI* and *IVR* (*IDV*) are (barely) significant explanatory variables for cross-country *HML* returns. In the more comprehensive regression models (7 and 8), we find *PDI* to become a clearly significant factor. For *WML*, we report even four cultural dimensions to be (very) significant in the univariate regressions, with *IDV* being the outstanding explanatory factor (t-statistic of 4.65[149]) that stays also very significant (t-statistic above 2.7) in the comprehensive culture (and *GDPpc*) model, whereas all other cultural dimensions become insignificant. Essentially, this means that especially *HML* and *WML* are immediate proxy variables for different levels of national culture regarding several (specific) cultural dimensions, whereas (in presence of these dimensions) the connection to *GDPpc* is rather inconsequential (with the exception of *HML*; cp. also Table 10). Furthermore, a rather holistic setting (including all cultural dimensions) is best suited to explain returns on risk factor mimicking hedge portfolios (especially in case of *RMRF*) most effectively (yielding highest adjusted R^2's).

Regarding *RMW* and *CMA* we find vague indication that these risk factors are also somewhat explainable by time-invariant cultural dimensions (e.g., *MAS* as factor for *RMW* returns). Due to the limited validity of the dataset regarding these factors however, we abstain from drawing overhasty conclusions and leave this for future research to investigate in more detail.

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[149] Chui et al. (2010) report once again a very similar t-statistic of 4.84 for IDV in the same regression.

Table 6
Fama-MacBeth regressions with RMRF and SMB on cultural dimensions.

	Panel A: RMRF								*Panel B: SMB*							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00473	0.00774	0.00844	0.00799	0.00523	0.00846	0.01183	0.01031	-0.00028	-0.00000	-0.00140	0.00166	0.00060	0.00001	-0.00255	-0.00542
	(1.74)	*(2.20)*	*(2.80)*	*(2.77)*	*(1.88)*	*(2.53)*	*(1.13)*	*(0.82)*	*(-0.20)*	*(-0.00)*	*(-0.85)*	*(1.15)*	*(0.45)*	*(0.00)*	*(-0.49)*	*(-0.89)*
PDI	0.00003						0.00008	0.00006	0.00001						0.00009	0.00008
	(0.89)						*(1.03)*	*(0.70)*	*(0.30)*						*(1.91)*	*(1.87)*
IDV		-0.00003					-0.00002	-0.00002		-0.00000					0.00003	0.00005
		(-0.72)					*(-0.22)*	*(-0.20)*		*(-0.07)*					*(0.62)*	*(1.10)*
MAS			-0.00004				-0.00004	-0.00003			0.00003				0.00004	0.00003
			(-1.86)				*(-1.66)*	*(-1.16)*			*(1.27)*				*(1.31)*	*(1.10)*
UAI				-0.00003			-0.00009	-0.00008				-0.00002			-0.00009	-0.00007
				(-0.96)			*(-1.39)*	*(-0.91)*				*(-1.09)*			*(-2.11)*	*(-1.77)*
LTO					0.00002		0.00005	0.00004					-0.00001		0.00002	0.00003
					(0.61)		*(1.05)*	*(0.84)*					*(-0.28)*		*(0.65)*	*(0.85)*
IVR						-0.00004	-0.00005	-0.00004						0.00000	-0.00002	-0.00000
						(-1.18)	*(-1.04)*	*(-0.57)*						*(0.06)*	*(-0.42)*	*(-0.03)*
GDPpc								0.00000								-0.00000
								(0.22)								*(-0.55)*
Adj. R-sq	0.0190	0.0324	-0.0024	0.0177	0.0102	0.0077	0.1100	0.1375	0.0055	0.0117	0.0031	0.0048	0.0012	0.0051	0.0343	0.0433

We regress, each month, country-specific returns on risk factor mimicking portfolios RMRF (Panel A) or SMB (Panel B) on a constant, the six cultural dimensions of Hofstede et al. (2010) and our economic development proxy GDPpc. The regressions cover the time frame June 1980 to April 2017 and comprise 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). Following Cochrane (2009), we calculate AR(1) robust t-statistics and report them below the average coefficients of each explanatory variable in italics and parentheses. Mean values on adjusted R^2s are given at the bottom of each regression configuration. Detailed definitions of the used variables are given in the appendix.

Table 7
Fama-MacBeth regressions with HML and WML on cultural dimensions.

	Panel A: HML								*Panel B: WML*							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00669	0.00897	0.00588	0.00310	0.00546	0.00997	0.01580	0.01487	0.01365	0.00129	0.01110	0.01149	0.01207	0.00271	-0.00430	-0.00235
	(4.18)	*(4.32)*	*(3.63)*	*(1.72)*	*(3.59)*	*(4.61)*	*(2.18)*	*(2.12)*	*(6.55)*	*(0.56)*	*(5.79)*	*(5.30)*	*(6.77)*	*(1.16)*	*(-0.64)*	*(-0.34)*
PDI	-0.00001						-0.00012	-0.00014	-0.00008						0.00006	0.00008
	(-0.47)						*(-2.40)*	*(-2.92)*	*(-2.50)*						*(1.29)*	*(1.54)*
IDV		-0.00006					-0.00007	-0.00003		0.00014					0.00016	0.00016
		(-1.94)					*(-1.36)*	*(-0.64)*		*(4.65)*					*(2.77)*	*(2.73)*
MAS			0.00001				0.00002	0.00001			-0.00004				-0.00001	-0.00002
			(0.26)				*(0.61)*	*(0.23)*			*(-1.64)*				*(-0.51)*	*(-0.85)*
UAI				0.00005			0.00006	0.00006				-0.00004			-0.00003	-0.00004
				(2.07)			*(1.45)*	*(1.58)*				*(-1.69)*			*(-0.74)*	*(-1.03)*
LTO					0.00001		-0.00003	-0.00001					-0.00006		0.00001	0.00001
					(0.42)		*(-0.80)*	*(-0.18)*					*(-2.52)*		*(0.49)*	*(0.31)*
IVR						-0.00008	-0.00006	-0.00004						0.00012	0.00005	0.00003
						(-2.13)	*(-1.17)*	*(-0.63)*						*(3.63)*	*(1.13)*	*(0.58)*
GDPpc								-0.00000								0.00000
								(-1.72)								*(0.19)*
Adj. R-sq	0.0036	0.0058	-0.0047	-0.0019	-0.0055	0.0044	0.0406	0.0308	0.0059	0.0194	0.0004	0.0108	0.0131	0.0108	0.0650	0.0780

We regress, each month, country-specific returns on risk factor mimicking portfolios HML (Panel A) or WML (Panel B) on a constant, the six cultural dimensions of Hofstede et al. (2010) and our economic development proxy GDPpc. The regressions cover the time frame June 1980 to April 2017 and comprise 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). Following Cochrane (2009), we calculate AR(1) robust t-statistics and report them below the average coefficients of each explanatory variable in italics and parentheses. Mean values on adjusted R^2s are given at the bottom of each regression configuration. Detailed definitions of the used variables are given in the appendix.

4.3 Culture as moderating effect of risk factor's efficacy

The previous section showed that cultural dimensions have *direct* explanatory power for some (especially *HML* and *WML*), but not all risk factor mimicking portfolios. In the following sections, we investigate in more detail if culture acts as a *moderating* factor for the efficacy of risk factors when explaining cross-country portfolio returns, as this is expected to be much more likely (see Section 1, 2, and our developed hypothesis).

4.3.1 The baseline model

To test this, we need a benchmark model to compare if cultural dimensions have this moderating or even absorbing effect. For this purpose, we enhance our regression model of Section 4.2 (Eq. 1) by incorporating the main risk factor mimicking portfolios (*RMRF*, *SMB*, *HML*, *WML*), that is the risk factors of the Carhart (1997) 4-factor model. Results for an equivalent model with the FF5 risk factors (*RMRF*, *SMB*, *HML*, *RMW*, and *CMA*) are attached to the appendix (Appendix B). One risk factor always serves as LHS variable and the remaining risk factors are assigned to the RHS of the regression equation (Eq. 2). The methodology (two-step Fama-MacBeth regressions) is the same as in Section 4.2:

$$RFP_{it} = \alpha_t + CUL_i\delta_t + RFPo_{it}\theta_t + \gamma_t GDPpc_i + \varepsilon_{it} \qquad (2)$$

where *RFP* stands for one of our four explained risk factor portfolios (*RMRF*, *SMB*, *HML*, *WML*; results for *RMW* and *CMA* are in the appendix), α is the regression constant, *CUL* is a vector of our complete set of six cultural dimensions (*PDI*, *IDV*, *MAS*, *UAI*, *LTO*, *IVR*) and *RFPo* is vector of our other risk factor portfolios (that is three out of four incorporated risk factors with the risk factor on the LHS naturally omitted). *GDPpc* and ε_{it} are the development proxy and an error term as described in Section 4.2. We once again calculate AR(1) adjusted t-statistics. The results on our baseline model are presented in Panel A of Table 8 to 11, respectively and in Appendix B (Tables B.2 to B.4).

We use risk factors as dependent variable and not for example Size-B/M portfolios as FF (1993, 2015) as LHS variables to explore how the dependency structures of risk factors themselves are and if we can integrate them by incorporating cultural effects (see next section).

The baseline model outcomes confirm the direct relevance of some cultural dimensions (*PDI* and *IDV*) when explaining *HML* and *WML* returns, specifically (see Panel A in Tables 10 and 11), but also reports importance of *LTO* when explaining *SMB* (Table 9) and shows a high robustness of these cultural dimensions in presence of major risk factors (t-statistics of -2.12, -2.77, and 4.30 for *LTO*, *PDI*, and *IDV* in Table 9, 10, and 11; cp. also confirmatory results regarding the non-randomness of the coefficients in Table C.2 in Appendix C). The risk factors, however, are more important explanatory variables throughout all regressions, since they show consistently (very) significant regression slopes and boost adjusted R^2 values clearly.[150] Interestingly, in an international context, all (except *RMW* and *CMA*) risk factor mimicking portfolios load significantly negative on each other which shows clear, multiple interdependencies between risk factors (cp., e.g., FF, 2017). In the next section, we show that these interdependency structures are overlain by cultural effects.

4.3.2 Cultural dimensions and risk factor interactions

To test our hypothesis of Section 2, we now introduce interaction effects for the risk factors (RHS) and the cultural dimensions. We perform varying regressions for each combination of risk factor *RFPo* and cultural dimension *CUL* (where *CUL* is a place holder for one of the six

[150] This is also due to their nature as time-varying variables, which renders their (potential) explanatory power (a priori) higher than that of time-invariant variables.

cultural dimensions) first (see Panels B, C, D in Tables 8 to 11) and test a comprehensive model with all interaction effects as a last step (Panel E). The regression model consequently is:

$$RFP_{it} = \alpha_t + CUL_i\delta_t + RFPo_{it}\theta_t + \gamma_t GDPpc_i + (CUL_i * RFPo_{it})\eta_t + \varepsilon_{it} \qquad (3)$$

where *CUL*RFPo* is the added cultural dimension and risk factor portfolio interaction term. All remaining components of the regression equation (Eq. 3) are equivalent to Eq. 2 (described in the previous section).

In general, the main results of these regressions are as follows. The coefficients of *RMRF* and especially *SMB* prove to stay significant more often than the coefficients of the other risk factor mimicking portfolios when including the respective interaction effects. This reflects the results of the previous sections where we find no single cultural dimension to significantly explain these risk factors (apart from *MAS* being a barely significant variable when explaining *RMRF*).

However, there are still several interaction effects that push down the t-statistics of *RMRF* below significant levels (seven times) and change their coefficients considerably. *RMRF* is most consistently absorbed by the inclusion of *RMRF*IDV* interactions, resulting always in an insignificant t-statistic. In two of three regressions also *IVR* has significant impact. Additionally, there are numerous interaction effects with *RMRF* that on themselves display (very) significant t-statistics (also shifting coefficients of *RMRF* clearly, see Table 9 and 10) and additive effects of *RMRF* in conjunction with *PDI*, *MAS*, and *IVR* (i.e., the significance of *RMRF* rises in the presence of these interaction effects;[151] see Table 10). This means that cultural differentiation in asset pricing models also helps to significantly improve the efficacy of *RMRF* (and that of other risk factors, see below) when explaining (other) risk factor portfolio returns apart from capturing material explanatory power of "bare" risk factors.

[151] The interaction of *RMRF* and *PDI* stays also very robust in Monte Carlo simulations (Table C.2 in Appendix C).

The explanatory power of *SMB* drops only once below significant levels when including a *SMB*LTO* interaction term in Table 11. Nevertheless, various *SMB*CUL* interaction effects cut down the significance of *SMB* considerably, despite the central role of *SMB* as explanatory variable (reflected in, on average, the highest t-statistics of all risk factors in the baseline regressions). On the other hand, we find significant interaction effects of *SMB* with several cultural dimensions, especially when explaining *RMRF* returns (where we also report an additive effect of *SMB* and *PDI* that also stays robust in the comprehensive model; cp. Table 8, 9, and C.2).

HML and *WML* show the strongest sensitivity regarding the included interaction effects (i.e. nine times insignificant coefficients, respectively). The explanatory power of *HML* is (like *RMRF*) most often and most severely absorbed by *IDV*-interactions (and also by interaction terms with *IVR*; furthermore, *HML* is a proxy candidate for these dimensions, cp. Section 4.2), resulting in constantly insignificant t-statistics of *HML* in this regression configuration and negative coefficients of this interaction term. This finding is also consistent with our evidence presented in Table 4, Panel B and Table 7, Panel A, where we find an inverse (significant) connection of individualism and the value effect. A straightforward interpretation of this finding would be the link of individualism and analytic thinking styles found for members of individualistic cultures (Choi and Nisbett, 2000; Nisbett et al., 2001). The focus on individual attributes of the analyzed object to explain and predict its behavior is a blueprint of value investing and its associated fundamental analysis. In contrast, people from collectivistic cultures are rather holistic thinkers, which implies that they are possibly more likely to recognize stocks as a system and abstain from analyzing stocks individually. Consequently, value strategies are more intensely employed and exploited in individualistic cultures, which results in an overvaluation and lower returns for value stocks compared to similar stocks in collectivistic societies. In turn, the value anomaly is weaker and therefore the explanatory power of a factor mimicking portfolio for the value effect (*HML*) is less relevant when explaining stock returns.

In presence of *HML*CUL* interaction effects, the coefficients of *HML* fluctuate clearly when explaining *RMRF* and *SMB* returns (Table 8 and 9), whereas 4 out of 6 interaction effects show significant t-statistics as well as two additive effects for *PDI* and *MAS* with *RMRF* as dependent variable. Furthermore, we find *HML* to be most steadily (but also only slightly) moderated (by several cultural interactions) when explaining *WML* returns (Table 11).

WML has the strongest sensitivity with regard to a *WML*LTO* interaction effect (that has at the same time the highest effect for a culture-based enhancement of *WML*, i.e. absolute t-statistics up to -3 for the interaction effects), cutting down the explanatory power of *WML* to nearly zero (maximum absolute t-statistic of -0.65). *WML*IDV* and *WML*PDI* are the runner-up interaction effects when it comes to t-statistics and impact on the variation of *WML*'s coefficient. However, also all other cultural dimensions reduce the significance of *WML* when included as interaction terms throughout all regressions.

When we have a look at the comprehensive model (Panel E in Table 8 to 11), which incorporates all culture and risk factor interactions, these outcomes remain robust. *HML* and *WML* are most heavily absorbed by these interactions as they show insignificant t-statistics throughout all regressions in Panel E. *RMRF* and *SMB* stay significant in one out of three regressions (where they represent RHS variables), respectively. The importance of compound cultural interaction effects in asset pricing models is also displayed by the higher adjusted R^2 in comparison with the baseline model and the models with only one interaction effect. However, this is also going along with detrimental general statistical effects due to the higher number of (interaction) variables which in turn increase the vulnerability to multi-collinearity (reflected in very high VIF values). Thus, the outcomes of the comprehensive model should only be interpreted as a rough tendency. Nevertheless, as our Monte Carlo simulations show (see Table C.2 in Appendix C), (far too) many coefficients of the cultural dimensions, their interaction effects as well as the risk factor mimicking hedge portfolios in the comprehensive models lay significantly outside of intervals of coefficients that would be expected if values on cultural dimensions were just random numbers that inherently cannot contain any explanatory power.

With respect to the validity of our initial hypothesis (cultural interactions can moderate or even absorb the explanatory power of risk factors), we receive sound confirmation that not only all risk factors are likely to be moderated by culture, but some are potentially even absorbed by cultural effects. This holds also for our (rough) results regarding the FF5 risk factors *RMW* and *CMA* (see Appendix B), where we find the strongest sensitivity for *CMA* when including a *LTO*-interaction effect. The evidence of *SMB*, *HML*, *WML*, and *CMA* to be (respectively) absorbed by (or to proxy for) *LTO* as well as *IDV* (for *RMRF*, *HML*, *WML*) and the additive effects for *RMRF*, *SMB*, *HML* in case of *PDI* supports the fundament and validity of our hypothesis construction in Section 2, where we refer to Vassalou's (2003) hypothesis that *SMB* and *HML* proxy for news about future GDP growth. As *LTO*, *IDV*, and *PDI* are the only cultural dimensions of Hofstede et al. (2010) that have predictive power for future GNI growth/long-run growth or are associated with GNI per capita (Hofstede et al., 2010; Gorodnichenko and Roland, 2011), we provide compelling consistent evidence that these dimensions drive significant information content of several risk factors likely using economic development as intermediary variable. In turn, this suggests that culture is a background variable of at least one common macroeconomic state variable, i.e. a hidden steady state variable (of a state variable).

Summed up, we believe that the incorporation of cultural dimensions in asset pricing studies can serve as a handy tool to account (1) for the (as yet) limited international integration of financial markets that is reflected in a poor explanatory power of global asset pricing models (e.g., FF 2012, 2017) and (2) to easily and reliably boost the explanatory power of those models (and their factors) in international asset pricing exercises. In doing so, cultural dimensions could be integrated (for example in global asset pricing models) as some kind of weighting factors in respect of risk factors. Upcoming research could readily pick up these connecting factors and hypotheses that are now well-founded due to our insights regarding country-specific and local asset pricing models.

Another point is that we manage to somewhat integrate common risk factors and indicate that they proxy for a common, universal omitted (steady) state variable – national culture measured in the form of cultural dimensions. We leave this interesting and potentially far-reaching, but also challenging to isolate subject for additional (more specific) future research.

Table 8
Fama-MacBeth regressions with RMRF on common risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model			*Panel B:*	*SMBx CUL*					*Panel C:*	*HMLx CUL*					*Panel D:*	*WMLx CUL*			*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
Constant	0.00602	0.00532	0.00348	0.00469	0.00174	0.00551	0.00273	0.00593	0.00394	0.00572	0.00573	0.00743	0.00030	0.00547	0.00592	0.00678	0.00171	0.00791	0.00489	0.00969
	(1.03)	*(0.96)*	*(0.58)*	*(0.81)*	*(0.30)*	*(0.95)*	*(0.45)*	*(0.95)*	*(0.70)*	*(0.98)*	*(1.00)*	*(1.23)*	*(0.05)*	*(0.93)*	*(1.03)*	*(1.07)*	*(0.28)*	*(1.30)*	*(0.86)*	*(0.52)*
PDI	0.00001	0.00001	0.00001	0.00001	0.00002	0.00001	-0.00001	-0.00001	0.00000	0.00001	0.00001	0.00000	0.00002	0.00002	0.00002	0.00000	0.00001	0.00000	0.00001	-0.00000
	(0.17)	*(0.20)*	*(0.15)*	*(0.14)*	*(0.41)*	*(0.17)*	*(-0.22)*	*(-0.33)*	*(0.14)*	*(0.40)*	*(0.27)*	*(0.04)*	*(0.66)*	*(0.43)*	*(0.50)*	*(0.10)*	*(0.35)*	*(0.13)*	*(0.26)*	*(-0.02)*
IDV	0.00003	0.00002	0.00004	0.00001	0.00004	0.00004	0.00002	0.00003	0.00003	0.00003	0.00005	0.00004	0.00005	0.00004	0.00003	0.00002	0.00006	0.00003	0.00004	-0.00006
	(0.69)	*(0.55)*	*(0.95)*	*(0.36)*	*(1.09)*	*(1.10)*	*(0.51)*	*(0.78)*	*(1.03)*	*(0.72)*	*(1.20)*	*(1.15)*	*(1.28)*	*(0.88)*	*(0.76)*	*(0.44)*	*(1.63)*	*(0.71)*	*(1.09)*	*(-0.50)*
MAS	-0.00000	-0.00001	-0.00000	0.00001	-0.00001	-0.00001	-0.00001	0.00001	0.00000	-0.00002	-0.00001	-0.00001	-0.00001	-0.00000	0.00001	-0.00001	0.00001	-0.00000	0.00000	-0.00008
	(-0.03)	*(-0.27)*	*(-0.04)*	*(0.26)*	*(-0.24)*	*(-0.19)*	*(-0.40)*	*(0.18)*	*(0.16)*	*(-0.59)*	*(-0.40)*	*(-0.29)*	*(-0.28)*	*(-0.02)*	*(0.28)*	*(-0.34)*	*(0.23)*	*(-0.15)*	*(0.07)*	*(-0.85)*
UAI	-0.00004	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003	-0.00001	-0.00003	-0.00004	-0.00004	-0.00004	-0.00005	-0.00004	-0.00004	-0.00005	-0.00005	-0.00003	-0.00006	-0.00004	0.00007
	(-1.37)	*(-0.81)*	*(-1.03)*	*(-0.93)*	*(-0.74)*	*(-1.04)*	*(-0.42)*	*(-1.04)*	*(-1.15)*	*(-1.34)*	*(-1.06)*	*(-1.65)*	*(-1.22)*	*(-1.18)*	*(-1.70)*	*(-1.45)*	*(-0.76)*	*(-1.94)*	*(-1.10)*	*(0.78)*
LTO	-0.00001	-0.00002	-0.00001	-0.00001	-0.00000	-0.00002	-0.00000	-0.00001	-0.00000	-0.00001	-0.00000	-0.00001	0.00001	-0.00002	-0.00002	-0.00000	0.00001	-0.00001	-0.00001	-0.00013
	(-0.16)	*(-0.54)*	*(-0.39)*	*(-0.34)*	*(-0.13)*	*(-0.52)*	*(-0.05)*	*(-0.39)*	*(-0.05)*	*(-0.19)*	*(-0.12)*	*(-0.22)*	*(0.43)*	*(-0.56)*	*(-0.47)*	*(-0.06)*	*(0.20)*	*(-0.34)*	*(-0.17)*	*(-1.16)*
IVR	-0.00003	-0.00003	-0.00002	-0.00003	-0.00001	-0.00005	0.00001	-0.00003	-0.00003	-0.00004	-0.00006	-0.00005	0.00001	-0.00004	-0.00003	-0.00003	-0.00003	-0.00004	-0.00003	-0.00004
	(-0.87)	*(-0.67)*	*(-0.54)*	*(-0.70)*	*(-0.18)*	*(-1.15)*	*(0.32)*	*(-0.69)*	*(-0.66)*	*(-0.87)*	*(-1.40)*	*(-1.17)*	*(0.31)*	*(-0.98)*	*(-0.86)*	*(-0.72)*	*(-0.60)*	*(-1.06)*	*(-0.69)*	*(-0.32)*
SMB	-0.30222	-0.59621	-0.17729	-0.41219	-0.16248	-0.45914	-0.14729	-0.30532	-0.31014	-0.28968	-0.30303	-0.31369	-0.31305	-0.30651	-0.31352	-0.29752	-0.30049	-0.31371	-0.30216	-1.33553
	(-13.45)	*(-15.01)*	*(-3.30)*	*(-8.65)*	*(-2.81)*	*(-9.41)*	*(-2.40)*	*(-13.53)*	*(-13.47)*	*(-13.15)*	*(-12.93)*	*(-13.44)*	*(-14.04)*	*(-13.74)*	*(-14.03)*	*(-13.51)*	*(-13.25)*	*(-13.72)*	*(-13.73)*	*(-2.90)*
HML	-0.06171	-0.06099	-0.06534	-0.05763	-0.06581	-0.07132	-0.06357	-0.20407	-0.00771	-0.13261	-0.10804	-0.07042	0.17247	-0.06268	-0.06890	-0.06499	-0.05594	-0.06646	-0.05973	-0.70547
	(-2.95)	*(-2.88)*	*(-3.13)*	*(-2.72)*	*(-3.03)*	*(-3.51)*	*(-3.06)*	*(-4.58)*	*(-0.16)*	*(-3.37)*	*(-2.21)*	*(-1.18)*	*(2.85)*	*(-2.82)*	*(-3.14)*	*(-3.03)*	*(-2.80)*	*(-3.23)*	*(-2.78)*	*(-1.53)*
WML	-0.11133	-0.11160	-0.10707	-0.11012	-0.11605	-0.10685	-0.11523	-0.11162	-0.11299	-0.10931	-0.11299	-0.11067	-0.11711	-0.09506	-0.13719	-0.05732	-0.07767	-0.03136	-0.12216	-0.01490
	(-4.11)	*(-4.00)*	*(-3.80)*	*(-4.00)*	*(-4.21)*	*(-3.61)*	*(-4.19)*	*(-4.10)*	*(-4.17)*	*(-3.98)*	*(-4.11)*	*(-4.15)*	*(-4.35)*	*(-1.88)*	*(-2.38)*	*(-1.23)*	*(-1.45)*	*(-0.64)*	*(-1.75)*	*(-0.02)*
GDPpc	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(1.16)	*(1.40)*	*(1.52)*	*(1.70)*	*(1.30)*	*(1.26)*	*(1.06)*	*(1.24)*	*(1.32)*	*(1.32)*	*(1.21)*	*(0.84)*	*(1.18)*	*(1.29)*	*(1.33)*	*(1.26)*	*(0.96)*	*(1.20)*	*(0.92)*	*(2.02)*
SMBxPDI		0.00494																		0.00957
		(6.70)																		*(2.75)*
SMBxIDV			-0.00288																	0.00565
			(-3.69)																	*(1.70)*
SMBxMAS				0.00205																-0.00008
				(2.31)																*(-0.02)*
SMBxUAI					-0.00245															0.00056
					(-2.60)															*(0.20)*
SMBxLTO						0.00276														0.00508
						(2.89)														*(1.84)*

Table 8
Continued.

Model	*Panel A: Baseline model*	*Panel B: SMBx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel C: HMLx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel D: WMLx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel E: Compre-hensive*
SMBxIVR							-0.00350													0.00060
							(-3.39)													*(0.20)*
HMLxPDI								0.00241												0.00561
								(2.75)												*(1.67)*
HMLxIDV									-0.00143											-0.00050
									(-2.00)											*(-0.20)*
HMLxMAS										0.00154										0.00475
										(2.01)										*(2.04)*
HMLxUAI											0.00076									0.00018
											(0.98)									*(0.08)*
HMLxLTO												0.00000								-0.00023
												(0.00)								*(-0.09)*
HMLxIVR													-0.00483							0.00223
													(-4.57)							*(0.72)*
WMLxPDI														-0.00036						0.00265
														(-0.39)						*(0.47)*
WMLxIDV															0.00040					0.00300
															(0.46)					*(0.48)*
WMLxMAS																-0.00104				-0.00200
																(-1.31)				*(-1.10)*
WMLxUAI																	-0.00061			0.00096
																	(-0.73)			*(0.24)*
WMLxLTO																		-0.00154		-0.00309
																		(-1.90)		*(-1.23)*
WMLxIVR																			-0.00002	-0.00466
																			(-0.02)	*(-1.05)*
Adj. R-sq	0.2721	0.2859	0.2896	0.2810	0.2976	0.3004	0.2936	0.2854	0.2813	0.2713	0.2875	0.2964	0.2957	0.2792	0.2857	0.2692	0.2820	0.2880	0.2852	0.4271
VIF mean	2.36	6.33	4.17	5.97	5.42	5.31	6.27	7.23	5.13	6.25	5.80	5.28	6.85	6.98	4.79	6.07	6.30	5.21	7.00	417.96
VIF max.	3.88	23.64	11.73	21.46	18.10	17.59	22.72	28.65	17.23	23.47	20.28	17.73	26.50	27.13	14.71	21.75	22.77	17.03	27.00	2541.01

We present outcomes of Fama-MacBeth regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding each RHS risk factor mimicking portfolio (here SMB, HML and WML) and each cultural dimension of Hofstede et al. (2010) (Panels B to D; cp. Eq. 3) as well as a comprehensive model with compound interaction effects (Panel E; cp. Eq. 3) as explanatory variables. The dependent variable is RMRF. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom lines display mean values for adjusted R²s as well as mean and max. variance inflation factors (VIF) regarding each rolling regression. We cover the time frame June 1990 to April 2017 and comprise data of 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). See the appendix for a detailed definition of all used variables.

Table 9

Fama-MacBeth regressions with SMB on common risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model			*Panel B:*	*RMRFx CUL*					*Panel C:*	*HMLx CUL*					*Panel D:*	*WMLx CUL*			*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
Constant	0.00619	0.01344	0.00707	0.01142	0.00639	0.00571	0.00309	0.00815	0.00773	0.00330	0.00734	0.00583	0.00718	0.00560	0.00796	0.00879	0.00256	0.00467	0.00868	0.05220
	(1.59)	*(3.27)*	*(1.82)*	*(2.44)*	*(1.54)*	*(1.37)*	*(0.57)*	*(1.99)*	*(1.89)*	*(0.77)*	*(1.63)*	*(1.43)*	*(1.67)*	*(1.32)*	*(1.94)*	*(2.25)*	*(0.61)*	*(1.19)*	*(2.24)*	*(1.62)*
PDI	0.00003	-0.00008	0.00003	0.00002	0.00002	0.00003	0.00004	-0.00000	0.00002	0.00004	0.00002	0.00003	0.00002	0.00003	0.00002	0.00002	0.00002	0.00004	0.00001	-0.00037
	(0.77)	*(-1.58)*	*(0.83)*	*(0.63)*	*(0.59)*	*(0.94)*	*(1.01)*	*(-0.13)*	*(0.74)*	*(1.23)*	*(0.62)*	*(0.77)*	*(0.59)*	*(0.80)*	*(0.70)*	*(0.46)*	*(0.48)*	*(1.16)*	*(0.17)*	*(-1.49)*
IDV	0.00004	0.00002	0.00002	0.00004	0.00004	0.00004	0.00005	0.00002	0.00003	0.00005	0.00003	0.00003	0.00003	0.00003	0.00001	0.00003	0.00005	0.00004	0.00004	-0.00025
	(0.97)	*(0.44)*	*(0.55)*	*(1.19)*	*(1.10)*	*(1.17)*	*(1.47)*	*(0.65)*	*(0.79)*	*(1.48)*	*(0.80)*	*(0.78)*	*(0.68)*	*(0.76)*	*(0.19)*	*(0.87)*	*(1.42)*	*(1.06)*	*(0.94)*	*(-1.64)*
MAS	0.00001	0.00002	0.00001	-0.00008	0.00001	0.00001	0.00001	0.00002	0.00001	0.00000	0.00001	0.00002	0.00002	0.00002	0.00002	-0.00002	0.00001	0.00000	0.00002	0.00019
	(0.46)	*(0.64)*	*(0.36)*	*(-1.96)*	*(0.36)*	*(0.39)*	*(0.44)*	*(0.78)*	*(0.50)*	*(0.08)*	*(0.42)*	*(0.65)*	*(0.65)*	*(0.91)*	*(0.95)*	*(-0.67)*	*(0.38)*	*(0.01)*	*(0.62)*	*(1.37)*
UAI	-0.00001	-0.00000	-0.00001	0.00000	0.00001	-0.00002	-0.00001	0.00000	-0.00002	-0.00003	-0.00001	-0.00001	-0.00000	-0.00001	-0.00003	-0.00001	0.00002	-0.00001	-0.00001	-0.00002
	(-0.25)	*(-0.14)*	*(-0.59)*	*(0.07)*	*(0.30)*	*(-0.74)*	*(-0.54)*	*(0.10)*	*(-0.91)*	*(-1.11)*	*(-0.54)*	*(-0.24)*	*(-0.19)*	*(-0.22)*	*(-1.09)*	*(-0.31)*	*(0.70)*	*(-0.53)*	*(-0.32)*	*(-0.23)*
LTO	-0.00007	-0.00008	-0.00006	-0.00008	-0.00008	-0.00007	-0.00005	-0.00007	-0.00007	-0.00004	-0.00007	-0.00008	-0.00008	-0.00007	-0.00006	-0.00007	-0.00006	-0.00004	-0.00007	-0.00024
	(-2.12)	*(-2.45)*	*(-1.78)*	*(-2.23)*	*(-2.42)*	*(-1.79)*	*(-1.68)*	*(-2.18)*	*(-2.03)*	*(-1.26)*	*(-2.05)*	*(-2.46)*	*(-2.39)*	*(-2.21)*	*(-1.94)*	*(-2.16)*	*(-2.03)*	*(-1.08)*	*(-2.35)*	*(-1.68)*
IVR	-0.00002	-0.00003	-0.00002	-0.00003	-0.00003	-0.00002	-0.00000	-0.00004	-0.00005	-0.00000	-0.00003	-0.00001	-0.00004	-0.00002	-0.00002	-0.00002	0.00001	-0.00003	-0.00005	-0.00028
	(-0.65)	*(-0.68)*	*(-0.52)*	*(-0.91)*	*(-0.68)*	*(-0.60)*	*(-0.07)*	*(-0.95)*	*(-1.06)*	*(-0.02)*	*(-0.85)*	*(-0.18)*	*(-0.70)*	*(-0.54)*	*(-0.53)*	*(-0.50)*	*(0.18)*	*(-0.68)*	*(-1.11)*	*(-1.29)*
RMRF	-0.26999	-0.70482	-0.03917	-0.39659	-0.25796	-0.39295	0.01415	-0.27075	-0.26595	-0.26066	-0.26617	-0.28149	-0.27563	-0.27370	-0.27682	-0.26657	-0.26846	-0.27385	-0.27111	-1.35723
	(-15.45)	*(-14.04)*	*(-0.83)*	*(-7.82)*	*(-5.27)*	*(-9.99)*	*(0.23)*	*(-15.39)*	*(-15.63)*	*(-15.53)*	*(-15.93)*	*(-15.35)*	*(-16.53)*	*(-15.46)*	*(-16.16)*	*(-14.92)*	*(-15.41)*	*(-16.07)*	*(-15.36)*	*(-3.78)*
HML	-0.16425	-0.17538	-0.17445	-0.16737	-0.16927	-0.17613	-0.17825	-0.21391	-0.09342	-0.12348	-0.23504	-0.13862	-0.04630	-0.16494	-0.17603	-0.16277	-0.16216	-0.17669	-0.16880	0.07932
	(-10.97)	*(-11.12)*	*(-11.28)*	*(-10.82)*	*(-11.09)*	*(-11.29)*	*(-10.78)*	*(-4.75)*	*(-1.64)*	*(-3.24)*	*(-5.77)*	*(-3.02)*	*(-0.81)*	*(-10.44)*	*(-11.47)*	*(-10.85)*	*(-10.68)*	*(-11.75)*	*(-11.42)*	*(0.21)*
WML	-0.13949	-0.13892	-0.14368	-0.12936	-0.14772	-0.14064	-0.14650	-0.14336	-0.13666	-0.14938	-0.13697	-0.13012	-0.14127	-0.10518	-0.20986	-0.18065	-0.11947	0.00439	-0.12145	0.27825
	(-6.57)	*(-6.55)*	*(-6.71)*	*(-6.01)*	*(-6.82)*	*(-6.37)*	*(-7.05)*	*(-6.59)*	*(-6.69)*	*(-7.06)*	*(-6.34)*	*(-6.29)*	*(-6.67)*	*(-2.21)*	*(-3.50)*	*(-4.59)*	*(-2.52)*	*(0.09)*	*(-2.18)*	*(0.77)*
GDPpc	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	0.00000
	(-0.95)	*(-0.64)*	*(-1.04)*	*(-1.00)*	*(-1.00)*	*(-0.93)*	*(-0.88)*	*(-0.62)*	*(-0.57)*	*(-1.30)*	*(-0.76)*	*(-0.98)*	*(-0.65)*	*(-0.87)*	*(-1.06)*	*(-1.13)*	*(-1.21)*	*(-0.98)*	*(-1.07)*	*(1.17)*
RMRFxPDI		0.00732																		0.01065
		(7.88)																		*(3.80)*
RMRFxIDV			-0.00534																	0.00058
			(-6.94)																	*(0.25)*
RMRFxMAS				0.00262																-0.00100
				(2.82)																*(-0.31)*
RMRFxUAI					-0.00036															0.00169
					(-0.51)															*(1.18)*
RMRFxLTO						0.00232														0.00357
						(3.18)														*(1.78)*

Table 9
Continued.

	Panel A: Baseline model			*Panel B:*	*RMRFx CUL*					*Panel C:*	*HMLx CUL*					*Panel D:*	*WMLx CUL*			*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
RMRFxIVR							-0.00600													0.00245
							(-5.13)													*(0.96)*
HMLxPDI								0.00113												-0.00084
								(1.32)												*(-0.27)*
HMLxIDV									-0.00149											-0.00251
									(-1.73)											*(-0.93)*
HMLxMAS										-0.00067										-0.00279
										(-0.93)										*(-1.44)*
HMLxUAI											0.00118									0.00332
											(1.79)									*(0.91)*
HMLxLTO												-0.00059								0.00145
												(-0.72)								*(0.53)*
HMLxIVR													-0.00222							-0.00549
													(-2.18)							*(-1.81)*
WMLxPDI														-0.00047						-0.00335
														(-0.53)						*(-1.07)*
WMLxIDV															0.00144					-0.00301
															(1.44)					*(-0.93)*
WMLxMAS																0.00070				0.00024
																(1.00)				*(0.09)*
WMLxUAI																	-0.00037			-0.00125
																	(-0.51)			*(-0.79)*
WMLxLTO																		-0.00273		0.00245
																		(-2.99)		*(0.76)*
WMLxIVR																			-0.00028	-0.00285
																			(-0.29)	*(-1.00)*
Adj. R-sq	0.2288	0.2620	0.2592	0.2444	0.2478	0.2532	0.2604	0.2496	0.2525	0.2348	0.2491	0.2453	0.2554	0.2417	0.2538	0.2275	0.2406	0.2583	0.2457	0.4223
VIF mean	2.38	7.33	4.41	6.82	5.90	5.53	6.34	7.24	4.86	6.07	5.74	5.33	6.71	6.94	4.83	6.17	6.31	5.19	7.23	428.39
VIF max.	3.91	28.98	11.88	25.35	20.24	18.72	22.75	28.47	15.62	21.62	19.82	17.53	24.89	26.94	15.08	22.25	22.88	16.88	27.81	2846.64

We present outcomes of Fama-MacBeth regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding each RHS risk factor mimicking portfolio (here RMRF, HML and WML) and each cultural dimension of Hofstede et al. (2010) (Panels B to D; cp. Eq. 3) as well as a comprehensive model with compound interaction effects (Panel E; cp. Eq. 3) as explanatory variables. The dependent variable is SMB. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom lines display mean values for adjusted R²s as well as mean and max. variance inflation factors (VIF) regarding each rolling regression. We cover the time frame June 1990 to April 2017 and comprise data of 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). See the appendix for a detailed definition of all used variables.

Table 10

Fama-MacBeth regressions with HML on common risk factors, cultural dimensions, and interaction terms.

Model	*Panel A: Baseline model*	*Panel B: RMRFx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel C: SMBx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel D: WMLx CUL* (1)	(2)	(3)	(4)	(5)	(6)	*Panel E: Compre-hensive*
Constant	0.01297	0.01284	0.01097	0.01401	0.01497	0.01016	0.00596	0.01237	0.01333	0.01434	0.01207	0.01203	0.01036	0.01006	0.01731	0.01308	0.01269	0.01330	0.01226	-0.01966
	(2.76)	*(2.36)*	*(2.26)*	*(2.86)*	*(2.91)*	*(1.94)*	*(1.03)*	*(2.66)*	*(2.67)*	*(3.05)*	*(2.48)*	*(2.54)*	*(2.04)*	*(2.02)*	*(3.39)*	*(3.00)*	*(2.28)*	*(2.88)*	*(2.51)*	*(-1.10)*
PDI	-0.00009	-0.00009	-0.00009	-0.00008	-0.00009	-0.00007	-0.00008	-0.00008	-0.00008	-0.00008	-0.00009	-0.00008	-0.00008	-0.00004	-0.00010	-0.00009	-0.00008	-0.00008	-0.00009	0.00000
	(-2.77)	*(-1.81)*	*(-2.51)*	*(-2.37)*	*(-2.87)*	*(-2.38)*	*(-2.30)*	*(-2.36)*	*(-2.37)*	*(-2.35)*	*(-2.59)*	*(-2.55)*	*(-2.48)*	*(-1.00)*	*(-2.82)*	*(-2.97)*	*(-2.43)*	*(-2.62)*	*(-2.65)*	*(0.03)*
IDV	0.00000	-0.00001	0.00006	0.00000	-0.00000	0.00002	0.00002	-0.00001	-0.00002	-0.00000	0.00001	0.00000	0.00000	0.00001	-0.00003	-0.00000	0.00001	-0.00000	0.00000	0.00012
	(0.08)	*(-0.29)*	*(1.44)*	*(0.00)*	*(-0.08)*	*(0.66)*	*(0.50)*	*(-0.28)*	*(-0.57)*	*(-0.04)*	*(0.35)*	*(0.08)*	*(0.05)*	*(0.20)*	*(-0.87)*	*(-0.08)*	*(0.26)*	*(-0.00)*	*(0.11)*	*(0.87)*
MAS	-0.00000	0.00001	-0.00000	-0.00003	-0.00001	-0.00000	0.00000	-0.00001	-0.00001	-0.00002	-0.00001	0.00000	-0.00001	-0.00000	0.00000	-0.00001	-0.00000	-0.00000	0.00001	-0.00036
	(-0.17)	*(0.57)*	*(-0.14)*	*(-0.79)*	*(-0.23)*	*(-0.11)*	*(0.06)*	*(-0.44)*	*(-0.29)*	*(-0.78)*	*(-0.24)*	*(0.01)*	*(-0.23)*	*(-0.18)*	*(0.15)*	*(-0.28)*	*(-0.16)*	*(-0.21)*	*(0.30)*	*(-1.77)*
UAI	0.00001	0.00001	-0.00001	0.00001	-0.00002	0.00000	0.00000	0.00000	0.00000	0.00001	0.00002	0.00002	-0.00000	-0.00000	-0.00000	0.00000	0.00001	0.00000	0.00001	0.00001
	(0.36)	*(0.18)*	*(-0.51)*	*(0.41)*	*(-0.65)*	*(0.16)*	*(0.15)*	*(0.00)*	*(0.13)*	*(0.47)*	*(0.53)*	*(0.73)*	*(-0.11)*	*(-0.09)*	*(-0.04)*	*(0.12)*	*(0.25)*	*(0.21)*	*(0.36)*	*(0.17)*
LTO	0.00000	-0.00001	0.00004	-0.00001	0.00000	0.00001	0.00001	0.00001	0.00001	-0.00001	0.00001	-0.00001	0.00002	0.00000	-0.00001	0.00000	0.00001	-0.00000	-0.00000	0.00021
	(0.13)	*(-0.17)*	*(1.09)*	*(-0.26)*	*(0.09)*	*(0.21)*	*(0.42)*	*(0.31)*	*(0.18)*	*(-0.27)*	*(0.26)*	*(-0.33)*	*(0.67)*	*(0.13)*	*(-0.18)*	*(0.13)*	*(0.27)*	*(-0.03)*	*(-0.12)*	*(1.49)*
IVR	0.00001	0.00001	0.00000	0.00002	0.00002	0.00003	0.00009	0.00003	0.00001	-0.00001	0.00001	0.00001	0.00003	0.00001	-0.00002	0.00001	-0.00000	0.00001	0.00000	0.00053
	(0.22)	*(0.27)*	*(0.07)*	*(0.40)*	*(0.52)*	*(0.78)*	*(1.61)*	*(0.77)*	*(0.31)*	*(-0.14)*	*(0.17)*	*(0.15)*	*(0.74)*	*(0.18)*	*(-0.42)*	*(0.30)*	*(-0.01)*	*(0.23)*	*(0.02)*	*(3.13)*
RMRF	-0.04612	-0.28882	0.05198	-0.15192	-0.04487	-0.06066	0.19488	-0.04268	-0.04892	-0.04822	-0.05326	-0.05193	-0.05302	-0.04259	-0.05711	-0.05090	-0.04282	-0.05739	-0.04651	-0.78255
	(-2.35)	*(-4.82)*	*(0.91)*	*(-3.62)*	*(-0.83)*	*(-1.10)*	*(3.57)*	*(-2.19)*	*(-2.42)*	*(-2.25)*	*(-2.60)*	*(-2.53)*	*(-2.61)*	*(-2.11)*	*(-2.85)*	*(-2.56)*	*(-2.15)*	*(-2.75)*	*(-2.28)*	*(-1.85)*
SMB	-0.19905	-0.21126	-0.21872	-0.20204	-0.20956	-0.21753	-0.21762	-0.23346	-0.10998	-0.16988	-0.29002	-0.26555	-0.14184	-0.19657	-0.20914	-0.19860	-0.19421	-0.22137	-0.20260	-0.53968
	(-9.08)	*(-9.61)*	*(-9.55)*	*(-8.75)*	*(-9.34)*	*(-9.41)*	*(-9.54)*	*(-4.00)*	*(-2.26)*	*(-3.15)*	*(-5.39)*	*(-4.59)*	*(-2.35)*	*(-9.08)*	*(-9.65)*	*(-9.17)*	*(-8.54)*	*(-10.19)*	*(-9.55)*	*(-1.16)*
WML	-0.08659	-0.09079	-0.09364	-0.08283	-0.09186	-0.08647	-0.08949	-0.08082	-0.08441	-0.09394	-0.09005	-0.07887	-0.08291	0.01838	-0.17513	-0.14393	-0.08034	-0.03200	-0.14349	0.83529
	(-3.69)	*(-3.92)*	*(-4.06)*	*(-3.57)*	*(-3.77)*	*(-3.68)*	*(-3.70)*	*(-3.44)*	*(-3.45)*	*(-3.79)*	*(-3.89)*	*(-3.38)*	*(-3.53)*	*(0.30)*	*(-3.18)*	*(-2.81)*	*(-1.30)*	*(-0.65)*	*(-2.20)*	*(1.13)*
GDPpc	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(-3.70)	*(-3.00)*	*(-3.89)*	*(-3.58)*	*(-3.64)*	*(-3.98)*	*(-3.10)*	*(-3.18)*	*(-3.01)*	*(-3.46)*	*(-4.03)*	*(-3.37)*	*(-3.22)*	*(-3.19)*	*(-3.79)*	*(-3.25)*	*(-3.71)*	*(-3.74)*	*(-3.36)*	*(-1.67)*
RMRFxPDI		0.00379																		0.00848
		(3.84)																		*(2.25)*
RMRFxIDV			-0.00264																	0.00331
			(-2.64)																	*(1.13)*
RMRFxMAS				0.00222																0.00226
				(2.99)																*(0.78)*
RMRFxUAI					-0.00002															0.00092
					(-0.02)															*(0.63)*
RMRFxLTO						0.00028														0.00239
						(0.30)														*(0.87)*

Table 10
Continued.

	Panel A: Baseline model	*Panel B: RMRFx CUL*						*Panel C: SMBx CUL*						*Panel D: WMLx CUL*						*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
RMRFxIVR							-0.00533													-0.00364
							(-4.96)													*(-1.24)*
SMBxPDI								0.00081												0.00570
								(0.77)												*(1.55)*
SMBxIDV									-0.00205											0.00637
									(-2.42)											*(2.07)*
SMBxMAS										-0.00057										-0.00098
										(-0.60)										*(-0.28)*
SMBxUAI											0.00149									0.00254
											(1.86)									*(1.63)*
SMBxLTO												0.00088								-0.00109
												(0.91)								*(-0.40)*
SMBxIVR													-0.00133							-0.00807
													(-1.25)							*(-2.44)*
WMLxPDI														-0.00212						-0.00067
														(-2.04)						*(-0.17)*
WMLxIDV															0.00179					0.00220
															(1.98)					*(0.86)*
WMLxMAS																0.00106				-0.00182
																(1.24)				*(-0.79)*
WMLxUAI																	-0.00011			-0.00190
																	(-0.12)			*(-1.13)*
WMLxLTO																		-0.00112		-0.00130
																		(-1.28)		*(-0.35)*
WMLxIVR																			0.00126	-0.01237
																			(1.11)	*(-1.98)*
Adj. R-sq	0.1456	0.1762	0.1700	0.1609	0.1605	0.1683	0.1743	0.1695	0.1596	0.1583	0.1726	0.1610	0.1761	0.1717	0.1758	0.1506	0.1604	0.1549	0.1695	0.3952
VIF mean	2.40	7.28	4.46	6.86	5.97	5.64	6.40	6.29	4.24	5.95	5.39	5.41	6.23	6.79	4.70	5.97	6.08	5.42	6.99	808.79
VIF max.	3.95	28.43	12.06	25.49	20.52	19.30	23.07	22.94	12.00	21.06	17.99	17.78	22.34	26.04	14.15	20.92	21.58	17.76	26.40	8104.89

We present outcomes of Fama-MacBeth regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding each RHS risk factor mimicking portfolio (here RMRF, SMB and WML) and each cultural dimension of Hofstede et al. (2010) (Panels B to D; cp. Eq. 3) as well as a comprehensive model with compound interaction effects (Panel E; cp. Eq. 3) as explanatory variables. The dependent variable is HML. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom lines display mean values for adjusted R^2s as well as mean and max. variance inflation factors (VIF) regarding each rolling regression. We cover the time frame June 1990 to April 2017 and comprise data of 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). See the appendix for a detailed definition of all used variables.

Table 11
Fama-MacBeth regressions with WML on common risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model	*Panel B: RMRFx CUL*						*Panel C: SMBx CUL*						*Panel D: HMLx CUL*						*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
Constant	0.00570	0.00609	0.00640	0.00409	0.00551	0.00672	0.00776	0.00476	0.00467	0.00757	0.00844	0.00651	0.00406	0.00610	0.00513	0.00670	0.00521	0.00865	0.00583	-0.01195
	(1.22)	*(1.25)*	*(1.24)*	*(0.79)*	*(1.15)*	*(1.46)*	*(1.31)*	*(1.03)*	*(0.94)*	*(1.57)*	*(1.90)*	*(1.50)*	*(0.81)*	*(1.24)*	*(1.05)*	*(1.36)*	*(1.07)*	*(1.77)*	*(1.20)*	*(-0.72)*
PDI	0.00002	-0.00001	-0.00000	0.00002	0.00003	0.00001	-0.00000	0.00006	0.00004	0.00001	-0.00000	0.00002	0.00003	-0.00001	0.00000	0.00000	0.00002	-0.00000	0.00002	0.00001
	(0.40)	*(-0.20)*	*(-0.06)*	*(0.58)*	*(0.65)*	*(0.22)*	*(-0.07)*	*(1.53)*	*(0.95)*	*(0.29)*	*(-0.07)*	*(0.42)*	*(0.70)*	*(-0.18)*	*(0.06)*	*(0.12)*	*(0.38)*	*(-0.11)*	*(0.38)*	*(0.04)*
IDV	0.00016	0.00015	0.00012	0.00015	0.00016	0.00015	0.00016	0.00015	0.00015	0.00016	0.00015	0.00017	0.00017	0.00015	0.00014	0.00016	0.00017	0.00016	0.00017	-0.00016
	(4.30)	*(4.15)*	*(2.17)*	*(4.10)*	*(4.30)*	*(4.00)*	*(3.97)*	*(4.35)*	*(4.07)*	*(4.16)*	*(4.04)*	*(4.86)*	*(4.33)*	*(3.95)*	*(3.89)*	*(4.46)*	*(4.85)*	*(4.47)*	*(4.74)*	*(-1.00)*
MAS	0.00000	0.00001	0.00000	0.00002	0.00002	0.00000	-0.00000	0.00001	0.00000	-0.00001	-0.00000	-0.00001	0.00000	0.00002	0.00001	0.00001	0.00000	-0.00000	-0.00000	-0.00001
	(0.19)	*(0.47)*	*(0.20)*	*(0.55)*	*(0.65)*	*(0.07)*	*(-0.12)*	*(0.28)*	*(0.08)*	*(-0.49)*	*(-0.04)*	*(-0.25)*	*(0.18)*	*(0.71)*	*(0.22)*	*(0.50)*	*(0.16)*	*(-0.14)*	*(-0.03)*	*(-0.15)*
UAI	-0.00003	-0.00004	-0.00001	-0.00004	-0.00007	-0.00005	-0.00003	-0.00005	-0.00004	-0.00005	-0.00004	-0.00004	-0.00004	-0.00001	-0.00003	-0.00004	-0.00003	-0.00004	-0.00005	-0.00004
	(-1.13)	*(-1.10)*	*(-0.41)*	*(-1.19)*	*(-1.76)*	*(-1.82)*	*(-1.04)*	*(-1.79)*	*(-1.26)*	*(-1.87)*	*(-1.38)*	*(-1.58)*	*(-1.23)*	*(-0.52)*	*(-0.82)*	*(-1.31)*	*(-0.90)*	*(-1.33)*	*(-1.44)*	*(-0.49)*
LTO	-0.00003	-0.00001	-0.00000	-0.00002	-0.00001	-0.00001	-0.00000	-0.00002	-0.00002	-0.00001	-0.00003	-0.00001	-0.00002	-0.00004	-0.00001	-0.00003	-0.00002	-0.00002	-0.00002	0.00019
	(-0.80)	*(-0.31)*	*(-0.13)*	*(-0.61)*	*(-0.37)*	*(-0.24)*	*(-0.09)*	*(-0.76)*	*(-0.49)*	*(-0.33)*	*(-0.85)*	*(-0.24)*	*(-0.58)*	*(-1.11)*	*(-0.35)*	*(-0.69)*	*(-0.54)*	*(-0.52)*	*(-0.44)*	*(1.92)*
IVR	0.00001	0.00002	0.00002	0.00001	0.00001	0.00001	-0.00002	0.00001	0.00001	-0.00001	-0.00000	-0.00000	0.00001	0.00001	0.00003	-0.00001	-0.00000	-0.00002	-0.00001	0.00064
	(0.19)	*(0.42)*	*(0.45)*	*(0.20)*	*(0.26)*	*(0.18)*	*(-0.32)*	*(0.11)*	*(0.25)*	*(-0.13)*	*(-0.01)*	*(-0.03)*	*(0.24)*	*(0.12)*	*(0.72)*	*(-0.13)*	*(-0.10)*	*(-0.40)*	*(-0.18)*	*(3.28)*
RMRF	-0.11456	-0.19802	-0.04435	-0.16752	-0.13770	-0.19184	-0.04804	-0.12124	-0.11289	-0.11784	-0.11839	-0.11046	-0.12376	-0.11631	-0.10809	-0.10973	-0.11193	-0.11089	-0.11454	1.13497
	(-4.58)	*(-3.49)*	*(-0.91)*	*(-3.55)*	*(-2.64)*	*(-3.91)*	*(-1.01)*	*(-4.87)*	*(-4.41)*	*(-4.83)*	*(-4.76)*	*(-4.11)*	*(-4.76)*	*(-4.77)*	*(-4.53)*	*(-4.46)*	*(-4.74)*	*(-4.31)*	*(-4.56)*	*(1.76)*
SMB	-0.15568	-0.16766	-0.16733	-0.15140	-0.16805	-0.16346	-0.16829	-0.15030	-0.15433	-0.21080	-0.10051	-0.00370	-0.14106	-0.16174	-0.15468	-0.15926	-0.14907	-0.15049	-0.15326	1.05278
	(-6.94)	*(-7.51)*	*(-7.32)*	*(-6.60)*	*(-6.99)*	*(-7.25)*	*(-7.60)*	*(-2.90)*	*(-3.18)*	*(-3.77)*	*(-2.00)*	*(-0.07)*	*(-2.44)*	*(-7.09)*	*(-7.08)*	*(-6.96)*	*(-6.25)*	*(-6.32)*	*(-6.31)*	*(1.41)*
HML	-0.07584	-0.07564	-0.08096	-0.07153	-0.07804	-0.07282	-0.07792	-0.07541	-0.06972	-0.08036	-0.08493	-0.07118	-0.07276	-0.09209	-0.03836	-0.08395	-0.07546	-0.09005	-0.09089	0.22735
	(-3.64)	*(-3.37)*	*(-3.85)*	*(-3.30)*	*(-3.58)*	*(-3.28)*	*(-3.71)*	*(-3.61)*	*(-3.28)*	*(-3.77)*	*(-4.16)*	*(-3.53)*	*(-3.43)*	*(-2.03)*	*(-0.76)*	*(-1.61)*	*(-1.60)*	*(-1.94)*	*(-1.59)*	*(0.32)*
GDPpc	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(-0.59)	*(-0.84)*	*(-1.06)*	*(-0.29)*	*(-0.53)*	*(-0.86)*	*(-0.63)*	*(-0.51)*	*(-0.74)*	*(-0.37)*	*(-0.73)*	*(-0.95)*	*(-0.57)*	*(-0.56)*	*(-0.84)*	*(-0.78)*	*(-0.75)*	*(-0.86)*	*(-0.60)*	*(-1.39)*
RMRFxPDI		0.00131																		-0.00253
		(1.52)																		*(-0.70)*
RMRFxIDV			-0.00123																	-0.00426
			(-1.36)																	*(-0.94)*
RMRFxMAS				0.00102																0.00124
				(1.34)																*(0.50)*
RMRFxUAI					0.00020															-0.00643
					(0.29)															*(-3.04)*
RMRFxLTO						0.00144														-0.00089
						(2.11)														*(-0.32)*

Table 11
Continued.

	Panel A: Baseline model			*Panel B: RMRFx CUL*						*Panel C: SMBx CUL*						*Panel D: HMLx CUL*				*Panel E: Compre-hensive*
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	
RMRFxIVR							-0.00146													-0.00922
							(-1.51)													*(-1.66)*
SMBxPDI								0.00003												-0.00672
								(0.04)												*(-1.37)*
SMBxIDV									0.00014											-0.00445
									(0.15)											*(-1.29)*
SMBxMAS										0.00105										0.00686
										(1.07)										*(1.90)*
SMBxUAI											-0.00107									-0.00749
											(-1.27)									*(-2.05)*
SMBxLTO												-0.00275								-0.00293
												(-3.10)								*(-0.98)*
SMBxIVR													-0.00030							-0.00760
													(-0.28)							*(-1.14)*
HMLxPDI														0.00020						0.00274
														(0.25)						*(0.64)*
HMLxIDV															-0.00045					0.00321
															(-0.58)					*(1.08)*
HMLxMAS																0.00008				-0.00138
																(0.08)				*(-0.59)*
HMLxUAI																	-0.00002			-0.00242
																	(-0.02)			*(-1.16)*
HMLxLTO																		0.00015		-0.00176
																		(0.18)		*(-0.53)*
HMLxIVR																			0.00048	-0.00524
																			(0.48)	*(-0.82)*
Adj. R-sq	0.2126	0.2221	0.2276	0.2174	0.2255	0.2254	0.2299	0.2268	0.2345	0.2232	0.2292	0.2381	0.2241	0.2234	0.2262	0.2331	0.2274	0.2282	0.2320	0.3536
VIF mean	2.35	7.49	4.44	6.87	5.89	5.52	6.28	6.24	4.17	5.96	5.45	5.30	6.27	7.11	4.90	5.78	5.74	5.42	6.81	456.30
VIF max.	3.86	29.78	12.15	25.74	20.44	19.10	22.60	23.14	12.09	21.54	18.36	17.67	22.67	28.05	15.65	20.16	19.85	18.37	25.56	2691.90

We present outcomes of Fama-MacBeth regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding each RHS risk factor mimicking portfolio (here RMRF, SMB and HML) and each cultural dimension of Hofstede et al. (2010) (Panels B to D; cp. Eq. 3) as well as a comprehensive model with compound interaction effects (Panel E; cp. Eq. 3) as explanatory variables. The dependent variable is WML. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom lines display mean values for adjusted R^2s as well as mean and max. variance inflation factors (VIF) regarding each rolling regression. We cover the time frame June 1990 to April 2017 and comprise data of 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). See the appendix for a detailed definition of all used variables.

5. Conclusion

With this paper we not only pioneer to extend the compelling evidence of Chui et al. (2010) regarding a connection of momentum and individualism to other internationally prominent investment styles and further cultural dimensions, but investigate if cultural dimensions are feasible in international asset pricing exercises.

At first, we specifically manage to link the magnitude of the international momentum and value effect directly to culture, whereas Hofstede's (1980, 2001) Individualism vs. Collectivism dimension plays an outstanding role. Hereby, we strongly confirm the lasting validity of the results of Chui et al. (2010) based on a much newer dataset. However, in a holistic, compound cultural model also other cultural dimensions like Power Distance, Uncertainty Avoidance, Long Term Orientation, and Indulgence vs. Restraint come into play. Masculinity on the other hand shows predictive power for global market returns.

Second, we test if the extent of (and variation in) explanatory power and efficacy of country-specific (and local) asset pricing factor models can be traced back to the sensitivity of common risk factors regarding values on cultural dimensions. As this is the case, we lead the way to culture-based asset pricing and show that the inclusion of handy, time-invariant cultural dimensions can on the one hand moderate and absorb the relevance and significance of risk factors and on the other hand boost the explanatory power of those risk factors when interacting them with cultural dimensions. Additionally, cultural dimensions help vitally to integrate distinct risk factors on cross-country level, as we explain (returns on) risk factors with other risk factors in conjunction with cultural dimensions.

Third, with this paper we tap the discussion on state variables that started ever since the introduction of Merton's (1973) ICAPM. We see some indirect overlap of our findings with previous research (e.g., Vassalou, 2003; Hahn and Lee, 2006; Petkova 2006; Boons 2016) that discusses the nature of asset pricing risk factors like *SMB* and *HML* as proxies for state variables like GPD per capita, term spread, default spread, and dividend yield. In our paper, we find that asset pricing risk factors serve also as a proxy for cultural differences in an international asset pricing context. Specifically, we find (all in all) the clearest indication for *WML* and *HML* to proxy for (and to be absorbed by) *IDV* (as well as *IV*R and *PDI*) and additionally for *SMB* and *WML* (and *CMA*) to be absorbed by *LTO*. *RMRF* is moderated (or even absorbed) by several cultural dimensions and shows the strongest sensitivity for an inclusion of interaction effects with *IDV* and *IV*R as well as an additive effect with *PDI* (like *SMB* and *HML*). The consistent evidence of several risk factors to be moderated/absorbed by (respectively to proxy for) *LTO*, *IDV*, and (partly be enhanced by) *PDI* seems to provide sound evidence that GDP (growth) only serves as an intermediary state variable, whereas risk factors more likely proxy cultural dimensions (directly) rather than its economic counterpart that is predictable by *LTO* (cp. Hofstede et al., 2010). Furthermore, we find cultural dimensions that are associated with economic development (*PDI* and *IDV*; see e.g., Hofstede et al., 2010 and Gorodnichenko and Roland, 2011) to be especially important for the explanation of risk factors' returns and their enhancement/moderation when used as explanatory (RHS) variables.

A primary subject for future research would be to integrate risk factors (and their characteristics), macroeconomic (established) state variables and cultural dimensions. In this way one could explore if common state variables (1) retain their relevance as (distinct) state variables or (2) if culture is more likely a state variable of these state variables that manages to explain (or moderate/absorb) a large degree of their predictive power for (profitable) future investment opportunity sets. As we already include GPD per capita in this study and show that cultural dimensions keep their power for an estimation of future cross-country investment profits regarding major investment styles (whereas *GDPpc* only plays a secondary role in most regression set-ups in the presence of cultural dimensions),[152] we predict that cultural dimensions will likely keep a good deal of this capability in the presence of other common state variables. If this is

[152] Since values on cultural dimensions are time-invariant, the results for predictive and explanatory models are virtually the same.

further confirmed to be the case, then Merton's ICAPM that states that *innovations* in state variables are responsible for the variation in returns, is prone to a necessary review that also state variables experiencing no or only very slow innovations (culture in the shape of measurable cultural dimensions) have impact on returns and the future profitability of investment opportunity sets. In an alternative or enhanced model, cultural dimensions could serve as cross-sectional rather than intertemporal state variables (state variables in space vs. in time) that capture disparities in cross-cultural and cross-national investment opportunity sets (varying in space) that are reflected in differences in stock market anomalies (especially momentum and value) and even market-wide stock returns.

Referring to Karolyi (2016), we see much potential for national culture in understanding (and breaking away) the limits of asset pricing models and look forward to further explore the possibilities of cultural dimensions – especially in the pioneering task of culture-based asset pricing.

Appendix A. Description of variables

Variable	Definition
I. Cultural dimensions	
Power Distance (*PDI*)	"PDI scores inform (...) about dependence relationships in a country. In small-power-distance countries, there is limited dependence of subordinates on bosses, and there is a preference for consultation (...) In large-power-distance countries, there is considerable dependence of subordinates on bosses. (...) subordinates are unlikely to approach and contradict their bosses directly. (…) Power distance can therefore be defined as *the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally. Institutions* are the basic elements of society, such as the family, the school, and the community; *organizations* are the places where people work." (Hofstede et al., 2010: 61) A higher score indicates a higher degree of power distance.
Individualism (*IDV*)	"*Individualism* pertains to *societies in which the ties between individuals are loose: everyone is expected to look after him- or herself and his or her immediate family. Collectivism* as its opposite pertains to *societies in which people from birth onward are integrated into strong, cohesive in-groups, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty*." (Hofstede et al., 2010: 92) A higher score indicates a higher degree of individualism. For instance, individualistic cultures are associated with higher stock market participation rates of individual investors.
Masculinity (*MAS*)	"*A society is called* masculine *when emotional gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success, whereas women are supposed to be more modest, tender, and concerned with the quality of life*." On the other hand, a "*society is called* feminine *when emotional gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the quality of life*." (Hofstede et al., 2010: 140) A higher score indicates a higher degree of masculinity. For example, masculine nations foster competitiveness whereas feminine societies are rather consensus- and cooperation-orientated.
Uncertainty Avoidance (*UAI*)	"*Uncertainty avoidance* can (…) be defined as *the extent to which the members of a culture feel threatened by ambiguous or unknown situations*. This feeling is, among other manifestations, expressed through nervous stress and in a need for predictability: a need for written and unwritten rules." (Hofstede et al., 2010: 191) A higher score indicates a higher degree of uncertainty avoidance. Regarding investment preferences uncertainty-avoidant (-accepting) nations have a preference for precious metals (stocks).
Long Term Orientation (*LTO*)	"*Long-term orientation* stands for *the fostering of virtues oriented toward future rewards—in particular, perseverance and thrift*. Its opposite pole, *short-term orientation*, stands for *the fostering of virtues related to the past and present—in particular, respect for tradition, preservation of "face," and fulfilling social obligations*." (Hofstede et al., 2010: 239) A higher score indicates a higher degree of long term orientation. For example, high (low) LTO countries show rather fast (slow) economic growth (in poor countries), a large (small) savings quote and invest in real estate (mutual funds). (cp. Hofstede et al., 2010: 275)
Indulgence versus Restraint (*IVR*)	"*Indulgence* stands for *a tendency to allow relatively free gratification of basic and natural human desires related to enjoying life and having fun*. Its opposite pole, *restraint*, reflects *a conviction that such gratification needs to be curbed and regulated by strict social norms*." (Hofstede et al., 2010: 281) A higher score indicates a higher degree of indulgence.
II. Financial variables	
Market return (*RM*)	RM_{it} is the value weighted market return in month t for country i.
Excess market return (*RMRF*)	$RMRF_{it}$ stands for the value weighted market return in month t for country i (RM_{it}) in excess of the country-specific risk free rate (RF_{it}). Risk free rates are short-term deposit rates (1M to 3M) or (especially if the covered time frame is larger) country-specific short-term treasury bills or equivalents in local currency.
Small minus big (*SMB*) High minus low (*HML*)	SMB_{it} is the return on the small minus big hedge portfolio and HML_{it} is the return on the high minus low hedge portfolio in month t for country i mimicking the size effect and the value effect. As in FF (1993), we build six value-weighted intersection portfolios (present month's median market capitalization is used to get the small and big portfolio, *S* and *B*). Top 30%, middle 40% and bottom 30% of stocks ranked by book-to-market ratio (common shareholder's equity divided by market value, with values lagged six months and negative values excluded) are used to get a high (*H*), middle (*M*) and low (*L*) portfolio. The intersection portfolios are (initially) formed and rearranged (once) each year in June (i.e., using previous year's book-to-market ratios), whereas returns are calculated monthly. *SMB* is

	the difference of the average monthly returns of the three small portfolios (*SL*, *SM*, *SH*) and the three big portfolios (*BL*, *BM*, *BH*); *HML* is the difference of the average monthly returns of the two high portfolios (*SH*, *BH*) and the two low portfolios (*SL*, *BL*).
Winner minus loser (*WML*)	WML_{it} is the return on an equal-weighted winner minus loser portfolio in month *t* for country *i*. Following Carhart (1997), each month *t*, stocks are ranked by cumulative returns from month *t-12* to month *t-2*. Stocks in the top 30% build the winner portfolio (*W*) and stocks in the bottom 30% the loser portfolio (*L*). *WML* is the difference of average monthly returns of these portfolios, rearranged monthly.
Robust minus weak (*RMW*)	"RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios, *RMW =1/2 (Small Robust + Big Robust) - 1/2 (Small Weak + Big Weak).*" (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html). See more details on Kenneth French's website where we also downloaded the datasets.
Conservative minus aggressive (*CMA*)	"CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, *CMA =1/2 (Small Conservative + Big Conservative) - 1/2 (Small Aggressive + Big Aggressive).*" (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html). See more details on Kenneth French's website where we also downloaded the datasets.
GPD per capita (*GDPpc*)	$GDPpc_i$ is the GDP per capita value of 1980 in U.S. dollars for country *i*. The data is received from the IMF website (http://www.imf.org/external/pubs/ft/weo/2017/01/weodata/index.aspx).

Appendix B. Further tests with profitability (RMW) and investment (CMA) factors

Table B.1
Fama-MacBeth regressions with RMW and CMA on cultural dimensions.

	Panel A: RMW								*Panel B: CMA*							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.00410	0.00248	0.00434	0.00304	0.00356	0.00284	0.00372	0.00360	0.00226	0.00268	0.00249	0.00345	0.00337	0.00237	0.00336	0.00352
	(4.24)	*(2.27)*	*(4.11)*	*(2.31)*	*(2.72)*	*(3.05)*	*(2.64)*	*(2.37)*	*(1.56)*	*(2.25)*	*(1.75)*	*(2.71)*	*(2.42)*	*(2.05)*	*(2.55)*	*(2.56)*
PDI	-0.00001						-0.00002	-0.00002	0.00000						0.00002	0.00002
	(-1.62)						*(-0.85)*	*(-0.81)*	*(0.54)*						*(1.20)*	*(1.13)*
IDV		0.00002					0.00001	0.00001		-0.00000					-0.00000	0.00000
		(1.42)					*(1.41)*	*(1.69)*		*(-0.27)*					*(-0.23)*	*(0.43)*
MAS			-0.00002				-0.00002	-0.00002			-0.00000				0.00001	0.00001
			(-2.06)				*(-1.41)*	*(-1.43)*			*(-0.06)*				*(0.75)*	*(0.60)*
UAI				0.00001			0.00002	0.00002				-0.00002			-0.00002	-0.00002
				(0.54)			*(0.85)*	*(0.85)*				*(-1.45)*			*(-1.26)*	*(-1.26)*
LTO					-0.00000		0.00001	0.00001					-0.00002		-0.00002	-0.00002
					(-0.08)		*(0.55)*	*(0.40)*					*(-1.47)*		*(-1.38)*	*(-1.20)*
IVR						0.00001	-0.00001	-0.00001						0.00000	0.00000	0.00001
						(1.40)	*(-1.50)*	*(-1.47)*						*(0.20)*	*(0.43)*	*(0.72)*
GDPpc								0.00000								-0.00000
								(0.71)								*(-1.00)*
Adj. R-sq	-0.0209	0.0295	0.0144	0.0857	0.0409	-0.0203	0.2114	0.1966	-0.0190	0.0368	0.0172	0.0774	0.0417	-0.0165	0.2049	0.1883

We regress, each month, country-specific returns on risk factor mimicking portfolios RMW (Panel A) or CMA (Panel B) on a constant, the six cultural dimensions of Hofstede et al. (2010) and our economic development proxy GDPpc. The regressions cover the time frame July 1990 to April 2017 and comprise 39 countries (Israel and Russia are omitted due to missing values for IVR and GDPpc). Following Cochrane (2009), we calculate AR(1) robust t-statistics and report them below the average coefficients of each explanatory variable in italics and parentheses. Mean values on adjusted R^2s are given at the bottom. Cp. appendix for variables' definitions.

Table B.2

Fama-MacBeth regressions with RMRF on FF5 risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model	*Panel B: RMWxCUL*						*Panel C: CMAxCUL*					
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.00200	-0.04719	-0.00701	-0.00931	-0.03210	-0.00694	0.11289	-0.02719	0.00599	-0.02094	-0.03011	0.02062	0.06590
	(0.24)	*(-1.10)*	*(-0.60)*	*(-0.60)*	*(-1.14)*	*(-0.56)*	*(1.06)*	*(-0.75)*	*(0.47)*	*(-0.99)*	*(-0.93)*	*(1.50)*	*(1.34)*
PDI	-0.00006	0.00061	-0.00012	-0.00011	-0.00019	-0.00011	-0.00014	0.00044	-0.00006	-0.00009	-0.00013	-0.00010	-0.00015
	(-1.28)	*(0.96)*	*(-2.18)*	*(-2.11)*	*(-2.38)*	*(-1.73)*	*(-1.82)*	*(0.61)*	*(-1.18)*	*(-1.58)*	*(-1.61)*	*(-1.58)*	*(-1.91)*
IDV	0.00007	0.00013	0.00017	0.00011	0.00017	0.00010	0.00015	0.00012	0.00005	0.00009	0.00010	0.00007	0.00015
	(1.50)	*(1.77)*	*(1.37)*	*(2.16)*	*(2.43)*	*(1.56)*	*(2.02)*	*(1.81)*	*(0.27)*	*(1.57)*	*(1.43)*	*(1.14)*	*(2.23)*
MAS	-0.00004	-0.00004	-0.00004	0.00012	-0.00005	-0.00003	-0.00004	-0.00004	-0.00004	0.00027	-0.00005	-0.00006	-0.00004
	(-1.61)	*(-1.29)*	*(-1.29)*	*(0.80)*	*(-1.81)*	*(-1.18)*	*(-1.20)*	*(-1.41)*	*(-1.47)*	*(1.39)*	*(-1.85)*	*(-1.90)*	*(-1.42)*
UAI	-0.00002	0.00006	0.00006	0.00003	0.00031	0.00005	0.00007	0.00006	-0.00003	0.00002	0.00030	0.00001	0.00008
	(-0.65)	*(0.79)*	*(1.11)*	*(0.74)*	*(1.66)*	*(0.73)*	*(0.77)*	*(0.85)*	*(-0.46)*	*(0.42)*	*(1.24)*	*(0.14)*	*(0.96)*
LTO	0.00007	0.00004	0.00002	0.00004	0.00004	0.00004	0.00005	0.00004	0.00006	0.00005	0.00007	-0.00023	0.00006
	(1.62)	*(0.96)*	*(0.37)*	*(1.06)*	*(0.86)*	*(0.30)*	*(1.13)*	*(0.98)*	*(1.48)*	*(1.20)*	*(1.81)*	*(-1.29)*	*(1.51)*
IVR	-0.00009	-0.00004	-0.00005	-0.00008	-0.00001	-0.00005	-0.00047	-0.00007	-0.00010	-0.00007	-0.00002	-0.00008	-0.00016
	(-1.39)	*(-0.67)*	*(-0.82)*	*(-1.30)*	*(-0.17)*	*(-0.81)*	*(-1.00)*	*(-1.11)*	*(-1.67)*	*(-1.12)*	*(-0.26)*	*(-1.23)*	*(-0.27)*
SMB	-0.36688	-0.37539	-0.38313	-0.39045	-0.37682	-0.38099	-0.36361	-0.36634	-0.38039	-0.37880	-0.37977	-0.38108	-0.35165
	(-15.89)	*(-16.01)*	*(-16.82)*	*(-15.83)*	*(-15.61)*	*(-15.42)*	*(-14.89)*	*(-15.10)*	*(-15.71)*	*(-15.17)*	*(-15.52)*	*(-16.01)*	*(-14.60)*
HML	-0.14868	-0.15720	-0.15345	-0.15255	-0.14035	-0.14450	-0.15463	-0.14822	-0.15369	-0.15046	-0.14266	-0.14420	-0.15019
	(-6.96)	*(-6.83)*	*(-6.69)*	*(-5.00)*	*(-5.77)*	*(-6.13)*	*(-6.41)*	*(-6.35)*	*(-7.07)*	*(-6.72)*	*(-6.35)*	*(-6.57)*	*(-6.44)*
RMW	-0.23585	-5.23563	0.69020	-0.57439	-0.17676	-0.37117	9.40657	0.03417	0.66823	-1.06063	-1.32643	0.10402	5.21205
	(-0.58)	*(-1.25)*	*(0.85)*	*(-0.40)*	*(-0.08)*	*(-0.31)*	*(1.04)*	*(0.09)*	*(1.39)*	*(-1.24)*	*(-0.89)*	*(0.25)*	*(1.00)*
CMA	0.73527	0.67049	0.61474	0.41771	0.51002	0.28648	-3.77864	2.78947	0.41965	-0.52462	-0.38955	-0.22562	-2.97895
	(1.97)	*(0.76)*	*(1.51)*	*(0.68)*	*(0.43)*	*(0.71)*	*(-0.75)*	*(1.52)*	*(0.54)*	*(-0.41)*	*(-0.28)*	*(-0.26)*	*(-1.24)*
GDPpc	0.00000	-0.00000	0.00000	0.00000	0.00000	0.00000	-0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00000
	(0.53)	*(-0.16)*	*(0.64)*	*(0.84)*	*(0.04)*	*(0.70)*	*(-0.59)*	*(0.26)*	*(0.91)*	*(0.74)*	*(0.05)*	*(0.42)*	*(-0.40)*
RMWxPDI		0.07830											
		(1.21)											
RMWxIDV			-0.00498										
			(-0.38)										
RMWxMAS				-0.01174									
				(-0.72)									
RMWxUAI					-0.02210								
					(-0.81)								
RMWxLTO						0.00157							
						(0.10)							
RMWxIVR							-0.04733						
							(-0.69)						
CMAxPDI								-0.03611					
								(-1.02)					
CMAxIDV									0.00534				
									(0.45)				
CMAxMAS										0.01277			
										(0.84)			
CMAxUAI											0.02112		
											(1.29)		
CMAxLTO												0.01041	
												(0.77)	
CMAxIVR													0.01965
													(0.66)
Adj. R-sq	0.3496	0.3501	0.3489	0.3568	0.3625	0.3463	0.3579	0.3466	0.3518	0.3563	0.3640	0.3517	0.3527

We present outcomes of regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding the new FF5 risk factor mimicking portfolios (RMW and CMA) and each cultural dimension of Hofstede et al. (2010) (Panels B and C; cp. Eq. 3) as explanatory variables. A comprehensive model with compound interaction effects is omitted due to singularities (only 21 countries available due to limitations of used Kenneth French's datasets and thus less degrees of freedom). The dependent variable is RMRF. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom line displays mean values of adjusted R^2s. We cover the time frame July 1990 to April 2017. See the appendix for a detailed definition of all used variables.

Table B.3

Fama-MacBeth regressions with SMB on FF5 risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model	*Panel B: RMWxCUL*						*Panel C: CMAxCUL*					
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.00006	-0.02173	-0.02889	0.00327	0.02540	0.01093	-0.11794	-0.03599	-0.00433	-0.02020	0.00350	0.00142	-0.01738
	(0.01)	*(-0.59)*	*(-1.91)*	*(0.20)*	*(1.22)*	*(0.61)*	*(-1.04)*	*(-0.80)*	*(-0.34)*	*(-0.89)*	*(0.14)*	*(0.10)*	*(-0.31)*
PDI	0.00001	-0.00011	-0.00007	0.00000	0.00001	0.00005	0.00005	0.00042	-0.00005	-0.00003	0.00002	0.00001	0.00003
	(0.14)	*(-0.18)*	*(-1.01)*	*(0.04)*	*(0.14)*	*(0.69)*	*(0.56)*	*(0.58)*	*(-0.96)*	*(-0.51)*	*(0.22)*	*(0.13)*	*(0.40)*
IDV	0.00001	0.00008	0.00046	0.00005	0.00003	0.00001	0.00002	0.00004	0.00012	0.00005	0.00001	0.00005	0.00002
	(0.27)	*(1.04)*	*(1.87)*	*(0.83)*	*(0.38)*	*(0.15)*	*(0.32)*	*(0.70)*	*(0.63)*	*(1.06)*	*(0.14)*	*(0.88)*	*(0.32)*
MAS	-0.00001	-0.00002	-0.00001	-0.00005	-0.00001	-0.00000	-0.00000	-0.00003	-0.00001	0.00023	-0.00003	-0.00002	-0.00001
	(-0.22)	*(-0.70)*	*(-0.16)*	*(-0.32)*	*(-0.35)*	*(-0.11)*	*(-0.15)*	*(-0.96)*	*(-0.41)*	*(0.93)*	*(-0.88)*	*(-0.65)*	*(-0.34)*
UAI	0.00004	0.00009	0.00012	0.00003	0.00002	-0.00002	-0.00002	0.00005	0.00011	0.00006	0.00028	0.00002	-0.00001
	(0.98)	*(1.19)*	*(1.63)*	*(0.58)*	*(0.11)*	*(-0.29)*	*(-0.26)*	*(0.94)*	*(2.08)*	*(1.43)*	*(1.14)*	*(0.24)*	*(-0.13)*
LTO	-0.00004	-0.00002	-0.00005	-0.00005	-0.00002	-0.00010	-0.00002	-0.00001	-0.00006	-0.00003	0.00001	0.00009	-0.00000
	(-1.13)	*(-0.62)*	*(-1.23)*	*(-1.22)*	*(-0.60)*	*(-0.55)*	*(-0.45)*	*(-0.30)*	*(-1.44)*	*(-0.71)*	*(0.18)*	*(0.54)*	*(-0.08)*
IVR	0.00000	0.00000	0.00004	-0.00001	-0.00004	-0.00004	0.00023	-0.00000	0.00003	-0.00001	-0.00005	-0.00003	-0.00089
	(0.03)	*(0.06)*	*(0.57)*	*(-0.08)*	*(-0.56)*	*(-0.53)*	*(0.57)*	*(-0.01)*	*(0.47)*	*(-0.12)*	*(-0.62)*	*(-0.45)*	*(-1.52)*
RMRF	-0.43090	-0.43753	-0.44921	-0.45842	-0.44328	-0.43736	-0.42198	-0.42944	-0.43952	-0.44247	-0.43777	-0.44295	-0.41504
	(-17.87)	*(-16.48)*	*(-15.52)*	*(-16.39)*	*(-16.22)*	*(-15.14)*	*(-14.64)*	*(-17.52)*	*(-17.11)*	*(-16.77)*	*(-16.34)*	*(-16.24)*	*(-14.68)*
HML	-0.21719	-0.23036	-0.22354	-0.21499	-0.21460	-0.22136	-0.21007	-0.23328	-0.23062	-0.22846	-0.22200	-0.22877	-0.21076
	(-10.30)	*(-9.21)*	*(-8.67)*	*(-7.45)*	*(-8.12)*	*(-9.50)*	*(-7.54)*	*(-9.84)*	*(-10.68)*	*(-9.18)*	*(-9.46)*	*(-10.01)*	*(-7.87)*
RMW	0.02495	-5.46755	3.17288	-1.55769	0.15203	-2.15710	-9.15928	-1.82788	0.40552	-0.77573	0.48456	0.04052	-6.52851
	(0.07)	*(-1.71)*	*(2.11)*	*(-0.95)*	*(0.10)*	*(-1.19)*	*(-0.88)*	*(-1.05)*	*(0.96)*	*(-0.93)*	*(0.42)*	*(0.08)*	*(-1.11)*
CMA	0.93453	1.44046	0.56745	0.71226	-0.91810	-0.17451	6.00496	3.00334	1.04811	0.74082	-1.56174	-1.75202	4.59110
	(2.67)	*(1.00)*	*(1.49)*	*(1.23)*	*(-0.94)*	*(-0.33)*	*(1.12)*	*(1.21)*	*(1.33)*	*(0.48)*	*(-1.08)*	*(-1.97)*	*(1.48)*
GDPpc	0.00000	-0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(1.00)	*(-0.14)*	*(0.73)*	*(0.43)*	*(0.92)*	*(1.14)*	*(0.46)*	*(0.16)*	*(1.10)*	*(0.76)*	*(0.90)*	*(1.34)*	*(0.69)*
RMWxPDI		0.07926											
		(1.25)											
RMWxIDV			-0.05853										
			(-1.89)										
RMWxMAS				0.00660									
				(0.38)									
RMWxUAI					0.00438								
					(0.22)								
RMWxLTO						0.03049							
						(1.35)							
RMWxIVR							0.03668						
							(0.50)						
CMAxPDI								-0.02619					
								(-0.66)					
CMAxIDV									-0.00660				
									(-0.50)				
CMAxMAS										-0.00582			
										(-0.31)			
CMAxUAI											0.00078		
											(0.05)		
CMAxLTO												0.02728	
												(2.20)	
CMAxIVR													-0.00227
													(-0.05)
Adj. R-sq	0.2936	0.2977	0.2956	0.2955	0.3069	0.3032	0.3277	0.2982	0.2759	0.2978	0.3062	0.2884	0.3185

We present outcomes of regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding the new FF5 risk factor mimicking portfolios (RMW and CMA) and each cultural dimension of Hofstede et al. (2010) (Panels B and C; cp. Eq. 3) as explanatory variables. A comprehensive model with compound interaction effects is omitted due to singularities (only 21 countries available due to limitations of used Kenneth French's datasets and thus less degrees of freedom). The dependent variable is SMB. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom line displays mean values of adjusted R^2s. We cover the time frame July 1990 to April 2017. See the appendix for a detailed definition of all used variables.

Table B.4

Fama-MacBeth regressions with HML on FF5 risk factors, cultural dimensions, and interaction terms.

	Panel A: Baseline model	*Panel B:*	*RMWxCUL*					*Panel C:*	*CMAxCUL*				
Model		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01314	-0.02541	0.00413	0.01216	0.04262	0.02066	-0.16300	-0.04613	0.01260	-0.00175	0.01979	-0.00191	-0.06176
	(1.78)	*(-0.83)*	*(0.24)*	*(0.75)*	*(1.21)*	*(1.05)*	*(-0.92)*	*(-1.12)*	*(0.82)*	*(-0.09)*	*(0.64)*	*(-0.10)*	*(-0.75)*
PDI	-0.00006	0.00004	-0.00012	-0.00013	-0.00005	-0.00006	-0.00000	0.00057	-0.00011	-0.00010	-0.00003	-0.00009	-0.00002
	(-1.06)	*(0.06)*	*(-1.30)*	*(-2.11)*	*(-0.56)*	*(-0.58)*	*(-0.03)*	*(1.00)*	*(-1.33)*	*(-1.78)*	*(-0.29)*	*(-1.05)*	*(-0.18)*
IDV	-0.00009	-0.00004	-0.00010	0.00002	-0.00006	-0.00007	-0.00013	-0.00002	-0.00015	-0.00005	-0.00006	-0.00002	-0.00012
	(-1.32)	*(-0.51)*	*(-0.49)*	*(0.30)*	*(-0.58)*	*(-0.68)*	*(-1.30)*	*(-0.22)*	*(-0.99)*	*(-0.89)*	*(-0.73)*	*(-0.23)*	*(-1.22)*
MAS	0.00001	0.00002	0.00002	-0.00015	0.00002	0.00003	0.00002	0.00000	0.00003	0.00019	-0.00000	0.00002	0.00000
	(0.44)	*(0.67)*	*(0.48)*	*(-0.52)*	*(0.51)*	*(0.78)*	*(0.47)*	*(0.11)*	*(0.73)*	*(0.84)*	*(-0.11)*	*(0.67)*	*(0.10)*
UAI	-0.00003	-0.00001	0.00006	0.00013	-0.00016	-0.00002	-0.00008	-0.00002	0.00005	0.00004	0.00021	0.00003	-0.00008
	(-0.45)	*(-0.12)*	*(0.51)*	*(1.43)*	*(-0.58)*	*(-0.15)*	*(-0.66)*	*(-0.24)*	*(0.45)*	*(0.85)*	*(0.95)*	*(0.29)*	*(-0.64)*
LTO	0.00004	0.00003	-0.00003	0.00001	0.00001	-0.00024	0.00003	0.00006	-0.00003	0.00004	0.00008	0.00030	0.00006
	(0.77)	*(0.57)*	*(-0.47)*	*(0.23)*	*(0.15)*	*(-2.01)*	*(0.65)*	*(1.27)*	*(-0.39)*	*(0.81)*	*(1.68)*	*(1.79)*	*(1.14)*
IVR	-0.00000	-0.00003	0.00002	0.00005	-0.00005	-0.00004	0.00027	-0.00008	0.00003	0.00000	-0.00009	-0.00001	-0.00074
	(-0.07)	*(-0.50)*	*(0.31)*	*(0.63)*	*(-0.68)*	*(-0.50)*	*(0.54)*	*(-0.98)*	*(0.40)*	*(0.04)*	*(-0.88)*	*(-0.10)*	*(-1.11)*
RMRF	-0.19773	-0.20657	-0.22192	-0.24935	-0.18718	-0.20306	-0.21435	-0.21756	-0.21293	-0.22928	-0.22388	-0.20728	-0.20741
	(-5.22)	*(-5.50)*	*(-5.34)*	*(-4.94)*	*(-4.33)*	*(-4.59)*	*(-5.40)*	*(-5.71)*	*(-5.17)*	*(-6.20)*	*(-5.90)*	*(-5.15)*	*(-5.21)*
SMB	-0.27329	-0.29835	-0.28772	-0.31626	-0.27335	-0.28138	-0.29487	-0.33082	-0.28161	-0.30344	-0.32172	-0.28609	-0.29025
	(-8.79)	*(-10.04)*	*(-9.21)*	*(-7.48)*	*(-8.14)*	*(-8.47)*	*(-9.17)*	*(-7.76)*	*(-8.62)*	*(-10.62)*	*(-8.33)*	*(-8.96)*	*(-9.17)*
RMW	0.70653	0.14828	0.27789	-2.45052	3.50515	1.33708	-14.7770	-2.23131	1.64544	-0.11968	1.96548	1.79527	-8.62980
	(1.23)	*(0.04)*	*(0.21)*	*(-0.76)*	*(1.98)*	*(1.06)*	*(-0.90)*	*(-0.81)*	*(2.05)*	*(-0.27)*	*(0.99)*	*(1.83)*	*(-0.92)*
CMA	0.10509	1.21314	0.46272	-0.13812	-0.47813	0.09463	7.66244	5.27190	0.59675	0.64414	-0.47588	-0.17039	-0.14631
	(0.31)	*(0.52)*	*(0.73)*	*(-0.27)*	*(-0.37)*	*(0.11)*	*(0.91)*	*(1.27)*	*(0.68)*	*(0.36)*	*(-0.20)*	*(-0.14)*	*(-0.04)*
GDPpc	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(-1.25)	*(-0.57)*	*(-0.37)*	*(-0.93)*	*(-0.12)*	*(-0.14)*	*(-0.45)*	*(-0.35)*	*(-0.41)*	*(-0.61)*	*(-0.13)*	*(-0.07)*	*(-0.35)*
RMWxPDI		-0.03671											
		(-0.39)											
RMWxIDV			0.02481										
			(1.14)										
RMWxMAS				0.02680									
				(0.69)									
RMWxUAI					-0.00068								
					(-0.03)								
RMWxLTO						0.00957							
						(0.62)							
RMWxIVR							0.05882						
							(0.53)						
CMAxPDI								-0.08398					
								(-1.52)					
CMAxIDV									0.00071				
									(0.06)				
CMAxMAS										-0.00864			
										(-0.41)			
CMAxUAI											-0.00509		
											(-0.24)		
CMAxLTO												0.00607	
												(0.51)	
CMAxIVR													0.08812
													(1.92)
Adj. R-sq	0.1470	0.1509	0.1364	0.1292	0.1455	0.1402	0.1627	0.1563	0.1218	0.1283	0.1384	0.1256	0.1575

We present outcomes of regressions regarding our baseline model (Panel A; cp. Eq. 2); with added stepwise variations in individual interaction effects (marked with an "x") regarding the new FF5 risk factor mimicking portfolios (RMW and CMA) and each cultural dimension of Hofstede et al. (2010) (Panels B and C; cp. Eq. 3) as explanatory variables. A comprehensive model with compound interaction effects is omitted due to singularities (only 21 countries available due to limitations of used Kenneth French's datasets and thus less degrees of freedom). The dependent variable is HML. AR(1) robust t-statistics as described in Cochrane (2009) are written below the corresponding coefficients in italics and parentheses. The bottom line displays mean values of adjusted R^2s. We cover the time frame July 1990 to April 2017. See the appendix for a detailed definition of all used variables.

Appendix C. One-way sorts and Monte Carlo simulations

Table C.1
Market returns and cultural dimensions.

Cultural Dimension	*PDI*	*IDV*	*MAS*	*UAI*	*LTO*	*IVR*
Low	1.05%	1.14%	1.43%	1.22%	1.14%	1.19%
	(5.34)	*(4.58)*	*(6.21)*	*(5.93)*	*(5.75)*	*(5.61)*
Medium	1.32%	1.36%	1.14%	1.09%	1.52%	1.32%
	(6.51)	*(6.15)*	*(5.18)*	*(5.25)*	*(6.39)*	*(5.68)*
High	1.34%	1.07%	1.05%	1.37%	1.07%	1.12%
	(5.51)	*(5.69)*	*(5.69)*	*(6.39)*	*(5.27)*	*(6.17)*
High minus low	0.29%	-0.09%	-0.38%	0.15%	-0.07%	-0.08%
	(1.74)	*(-0.52)*	*(-2.88)*	*(0.95)*	*(-0.58)*	*(-0.57)*

This table reports average monthly value weighted market (RM) profits for country-average portfolios classified by all six cultural dimensions of Hofstede et al. (2010), respectively. All RM returns are equally weighted across all country-specific portfolios. We allocate all countries in our sample to three classes – low (bottom 30%), medium (middle 40%) and high (top 30%) – based on their scores on each cultural dimension. We cover the period June 1980 to April 2017. The corresponding t-statistics are written in italics and are in parentheses.

As robustness check of our main results in Section 4.3 regarding the moderating character of cultural dimensions, we perform Monte Carlo simulations (cp. results in Table C.2). This is also meaningful due to very high VIF values for the comprehensive models that suggest that coefficients and associated standard errors as well as t-statistics are (likely) unstable and invalid in these regressions. The purpose of Monte Carlo simulations in this context is to investigate how severe these distortions really are for insights derivable from these comprehensive models. For comparison and for additional evidence, we also include the baseline regression models.

Our procedure is as follows: First, we assign arbitrary values for each cultural dimension (drawn from an equal distribution of numbers/integers ranging from 0 to 100, i.e. sampling with replacement) to any of our 41 countries in our dataset. Based on these random values, we rerun the baseline and comprehensive regressions as described in Section 4.3 and save outcomes of the coefficients for any explanatory variable (as well as adjusted R^2 values). We repeat this procedure 10,000 times to obtain an empirical distribution of coefficient values that could be expected if cultural dimensions are random, that is cannot contain (by construction) any informational value meaningful to explain returns of risk factor mimicking hedge portfolios. In the last step, we investigate if (real) empirical coefficient values (obtained in Section 4.3) lay outside of 95% confidence intervals that are calculated based on the sample of 10,000 "random" coefficients.

Overall, this procedure shows that (far) too many real empirical coefficients of the cultural dimensions and the interaction effects lay outside of these confidence intervals (we mark the real empirical coefficients in bold if this is the case; cp. Table C.2), as would be expected if the results were due to chance (cp. especially the outcomes when explaining *WML* returns; Panel D). Furthermore, the coefficients of RHS risk factors (and *GDPpc*) lay also outside of these intervals most of the time which means that also RHS risk factor (and *GDPpc*) coefficients are significantly different if real cultural dimension values are used. The (second) most robust cultural dimension in these Monte Carlo simulations is (*IDV*, *IVR*) *LTO* with (three) five coefficient values lying outside 95% confidence intervals (out of eight regressions). Regarding the interaction effects, we find most non-random coefficient values for RHS risk factors when connected with *IVR*, *PDI*, and *IDV*. Hereby, interactions with *SMB* show the most coefficients (11) to be located outside of the confidence intervals. Regarding the adjusted R^2's, we find two (four) of eight values to be (barely) non-random and all adjusted R^2's to show values at least in the upper half of the confidence intervals.

Consequently, cultural dimensions not only help increase goodness-of-fit measures of regression models when explaining risk factor mimicking hedge portfolio returns and show non-random explanatory power when used as "bare" variables, but are even viable in comprehensive models including extensive interaction effects with risk factors (despite present severe multicollinearity in this set-up).

Table C.2
Monte Carlo simulations.

Panel A: RMRF	*Baseline model*	*Comprehensive*
Constant	0.00602 *[-0.00273,0.00776]*	0.00969 *[-0.01338,0.01532]*
PDI	0.00001 *[-0.00004,0.00004]*	0.00000 *[-0.00011,0.00011]*
IDV	0.00003 *[-0.00004,0.00004]*	-0.00006 *[-0.00011,0.00011]*
MAS	0.00000 *[-0.00004,0.00004]*	-0.00008 *[-0.00011,0.00011]*
UAI	**-0.00004** *[-0.00004,0.00004]*	0.00007 *[-0.00011,0.00011]*
LTO	-0.00001 *[-0.00004,0.00004]*	**-0.00013** *[-0.00011,0.00011]*
IVR	-0.00003 *[-0.00004,0.00004]*	-0.00004 *[-0.00011,0.00011]*
SMB	-0.30222 *[-0.32503,-0.29341]*	**-1.33553** *[-0.85198,0.19322]*
HML	-0.06171 *[-0.06415,-0.03493]*	**-0.70547** *[-0.58517,0.38615]*
WML	**-0.11133** *[-0.10367,-0.07286]*	-0.01490 *[-0.50062,0.31478]*
GDPpc	0.00000 *[0.00000, 0.00000]*	0.00000 *[0.00000, 0.00000]*
SMBxPDI		**0.00957** *[-0.00413,0.00414]*
SMBxIDV		**0.00565** *[-0.00426,0.00417]*
SMBxMAS		-0.00008 *[-0.00425,0.00413]*
SMBxUAI		0.00056 *[-0.00416,0.00428]*
SMBxLTO		**0.00508** *[-0.00425,0.00415]*
SMBxIVR		0.00060 *[-0.00434,0.00426]*

Panel B: SMB	*Baseline model*	*Comprehensive*
Constant	0.00619 *[-0.00208,0.00971]*	**0.05220** *[-0.0105,0.02048]*
PDI	0.00003 *[-0.00005,0.00005]*	**-0.00037** *[-0.00012,0.00012]*
IDV	0.00004 *[-0.00005,0.00005]*	**-0.00025** *[-0.00012,0.00012]*
MAS	0.00001 *[-0.00005,0.00005]*	**0.00019** *[-0.00012,0.00012]*
UAI	-0.00001 *[-0.00004,0.00004]*	-0.00002 *[-0.00012,0.00012]*
LTO	**-0.00007** *[-0.00005,0.00005]*	**-0.00024** *[-0.00012,0.00012]*
IVR	-0.00002 *[-0.00005,0.00005]*	**-0.00028** *[-0.00012,0.00012]*
RMRF	-0.26999 *[-0.28562,-0.2568]*	**-1.35723** *[-0.85321,0.22375]*
HML	**-0.16425** *[-0.14284,-0.11659]*	0.07932 *[-0.61841,0.26404]*
WML	**-0.13949** *[-0.13032,-0.10267]*	**0.27825** *[-0.51609,0.25683]*
GDPpc	0.00000 *[0.00000, 0.00000]*	**0.00000** *[0.00000, 0.00000]*
RMRFxPDI		**0.01065** *[-0.00444,0.00432]*
RMRFxIDV		0.00058 *[-0.00429,0.00432]*
RMRFxMAS		-0.00100 *[-0.00417,0.00427]*
RMRFxUAI		0.00169 *[-0.00425,0.0043]*
RMRFxLTO		0.00357 *[-0.00432,0.00435]*
RMRFxIVR		0.00245 *[-0.00423,0.00431]*

Panel C: HML	*Baseline model*	*Comprehensive*
Constant	0.01297 *[0.00094,0.0134]*	**-0.01966** *[-0.01263,0.02297]*
PDI	**-0.00009** *[-0.00005,0.00005]*	0.00000 *[-0.00014,0.00014]*
IDV	0.00000 *[-0.00005,0.00005]*	0.00012 *[-0.00014,0.00014]*
MAS	0.00000 *[-0.00005,0.00005]*	**-0.00036** *[-0.00014,0.00014]*
UAI	0.00001 *[-0.00005,0.00005]*	0.00001 *[-0.00014,0.00014]*
LTO	0.00000 *[-0.00005,0.00005]*	**0.00021** *[-0.00014,0.00014]*
IVR	0.00001 *[-0.00005,0.00005]*	**0.00053** *[-0.00014,0.00014]*
RMRF	-0.04612 *[-0.05961,-0.02601]*	**-0.78255** *[-0.61668,0.41953]*
SMB	**-0.19905** *[-0.1736,-0.14072]*	-0.53968 *[-0.80592,0.33434]*
WML	**-0.08659** *[-0.08089,-0.05163]*	**0.83529** *[-0.47231,0.32807]*
GDPpc	**0.00000** *[0.00000, 0.00000]*	**0.00000** *[0.00000, 0.00000]*
RMRFxPDI		**0.00848** *[-0.00421,0.00414]*
RMRFxIDV		0.00331 *[-0.00422,0.00423]*
RMRFxMAS		0.00226 *[-0.00417,0.00416]*
RMRFxUAI		0.00092 *[-0.00422,0.00425]*
RMRFxLTO		0.00239 *[-0.00416,0.00408]*
RMRFxIVR		-0.00364 *[-0.0042,0.00425]*

Panel D: WML	*Baseline model*	*Comprehensive*
Constant	0.00570 *[0.0005,0.01672]*	**-0.01195** *[-0.00604,0.02749]*
PDI	0.00002 *[-0.00007,0.00006]*	0.00001 *[-0.00013,0.00013]*
IDV	**0.00016** *[-0.00007,0.00006]*	**-0.00016** *[-0.00013,0.00013]*
MAS	0.00000 *[-0.00006,0.00007]*	-0.00001 *[-0.00013,0.00013]*
UAI	-0.00003 *[-0.00006,0.00007]*	-0.00004 *[-0.00013,0.00013]*
LTO	-0.00003 *[-0.00006,0.00006]*	**0.00019** *[-0.00013,0.00013]*
IVR	0.00001 *[-0.00006,0.00006]*	**0.00064** *[-0.00013,0.00013]*
RMRF	**-0.11456** *[-0.11056,-0.08318]*	**1.13497** *[-0.49632,0.26241]*
SMB	**-0.15568** *[-0.13959,-0.10942]*	**1.05278** *[-0.61299,0.27985]*
HML	**-0.07584** *[-0.07443,-0.04696]*	0.22735 *[-0.47743,0.29966]*
GDPpc	**0.00000** *[0.00000, 0.00000]*	**0.00000** *[0.00000, 0.00000]*
RMRFxPDI		-0.00253 *[-0.00295,0.00304]*
RMRFxIDV		**-0.00426** *[-0.00297,0.00303]*
RMRFxMAS		0.00124 *[-0.00296,0.003]*
RMRFxUAI		**-0.00643** *[-0.00299,0.00305]*
RMRFxLTO		-0.00089 *[-0.00307,0.00296]*
RMRFxIVR		**-0.00922** *[-0.00304,0.00299]*

Table C.2

Continued.

	Panel A: RMRF Baseline model	Comprehensive		*Panel B: SMB* Baseline model	Comprehensive		*Panel C: HML* Baseline model	Comprehensive		*Panel D: WML* Baseline model	Comprehensive
HMLxPDI		**0.00561**	HMLxPDI		-0.00084	SMBxPDI		**0.00570**	SMBxPDI		**-0.00672**
		[-0.00379,0.00384]			*[-0.00346,0.00344]*			*[-0.00454,0.00465]*			*[-0.0036,0.00356]*
HMLxIDV		-0.00050	HMLxIDV		-0.00251	SMBxIDV		**0.00637**	SMBxIDV		**-0.00445**
		[-0.00384,0.00399]			*[-0.00354,0.00355]*			*[-0.00453,0.00458]*			*[-0.00363,0.00358]*
HMLxMAS		**0.00475**	HMLxMAS		-0.00279	SMBxMAS		-0.00098	SMBxMAS		**0.00686**
		[-0.00391,0.00387]			*[-0.00349,0.00342]*			*[-0.00446,0.00448]*			*[-0.00347,0.00361]*
HMLxUAI		0.00018	HMLxUAI		0.00332	SMBxUAI		0.00254	SMBxUAI		**-0.00749**
		[-0.00381,0.00395]			*[-0.00342,0.00351]*			*[-0.00455,0.00456]*			*[-0.00354,0.0036]*
HMLxLTO		-0.00023	HMLxLTO		0.00145	SMBxLTO		-0.00109	SMBxLTO		-0.00293
		[-0.0039,0.00385]			*[-0.00347,0.0035]*			*[-0.00459,0.0047]*			*[-0.00359,0.00365]*
HMLxIVR		0.00223	HMLxIVR		**-0.00549**	SMBxIVR		**-0.00807**	SMBxIVR		**-0.00760**
		[-0.0039,0.00394]			*[-0.0035,0.00339]*			*[-0.00447,0.00452]*			*[-0.00358,0.0036]*
WMLxPDI		0.00265	WMLxPDI		**-0.00335**	WMLxPDI		-0.00067	HMLxPDI		0.00274
		[-0.00329,0.00334]			*[-0.00311,0.00311]*			*[-0.00319,0.00316]*			*[-0.00304,0.00312]*
WMLxIDV		0.00300	WMLxIDV		-0.00301	WMLxIDV		0.00220	HMLxIDV		**0.00321**
		[-0.00317,0.00329]			*[-0.00309,0.00311]*			*[-0.0032,0.0031]*			*[-0.00304,0.00314]*
WMLxMAS		-0.00200	WMLxMAS		0.00024	WMLxMAS		-0.00182	HMLxMAS		-0.00138
		[-0.00316,0.00324]			*[-0.00315,0.00304]*			*[-0.00329,0.00314]*			*[-0.00301,0.00311]*
WMLxUAI		0.00096	WMLxUAI		-0.00125	WMLxUAI		-0.00190	HMLxUAI		-0.00242
		[-0.00325,0.00324]			*[-0.00324,0.00315]*			*[-0.00319,0.00311]*			*[-0.00305,0.00309]*
WMLxLTO		-0.00309	WMLxLTO		0.00245	WMLxLTO		-0.00130	HMLxLTO		-0.00176
		[-0.00325,0.00324]			*[-0.00313,0.00313]*			*[-0.00323,0.00319]*			*[-0.00303,0.00313]*
WMLxIVR		**-0.00466**	WMLxIVR		-0.00285	WMLxIVR		**-0.01237**	HMLxIVR		**-0.00524**
		[-0.00322,0.00337]			*[-0.00309,0.00311]*			*[-0.00324,0.00313]*			*[-0.00314,0.00306]*
Adj. R-sq	**0.2721**	0.4271	Adj. R-sq	0.2288	0.4223	Adj. R-sq	0.1456	0.3952	Adj. R-sq	**0.2126**	0.3536
	[0.1967,0.2418]	*[0.3254,0.4518]*		*[0.1894,0.2296]*	*[0.3537,0.4528]*		*[0.1195,0.1619]*	*[0.2891,0.3964]*		*[0.151,0.1903]*	*[0.2835,0.3772]*

This table reports outcomes of Monte Carlo simulations that test the robustness of the empirical coefficients (upper line of each segment) and adjusted R^2s (at the bottom) regarding the baseline and comprehensive models (cp. Tables 8 to 11; Panels A to D refer to these tables respectively). Each rolling Fama-MacBeth (1973) regression model in each column is run and calculated 10,000 times, whereas national values of every cultural dimension are randomly drawn from an equal distribution (sampling with replacement with numbers between 0 and 100) in each cycle. We calculate 95% confidence intervals based on the empirical distribution (attained from the simulations) for any coefficient and the adjusted R^2s (see below in brackets). If (real) empirical values lay outside the interval, we mark the respective coefficient/adjusted R^2 in bold. Qualitatively similar results are found for a resampling approach, where the (real) empirical values within each cultural dimension are arbitrarily assigned to the 41 countries.

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