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Regional Variation in German Real Estate Prices: Socio-Economic and Pandemic Influences

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Abstract

This study examines the real estate market in Germany at the district level, focusing on 401 NUTS 3 regions from 2012 to 2022. Using spatial econometric models, the analysis explores how socio-economic variables and COVID-19-related factors—including infection rates and mobility restrictions—affected regional property prices. Our results indicate that high infection rates and containment measures served as significant housing price drivers, with both direct effects within regions and indirect spillover effects to neighbouring regions. We find that these factors, along with socio-economic variables such as average age and childcare provision, contribute to spatial dynamics in property markets. Robustness checks across regional subgroups and different model specifications support these fin dings. The research contributes to the literature by quantifying the influence of socio-economic and pandemic-related factors on regional real estate price variations and providing evidence of spatial spillover effects. The findings highlight the need for regionally tailored real estate policies to address the diverse impacts of these factors on property markets in Germany, while also offering a framework for analysing similar dynamics in other countries.

Keywords
Regional real estate prices, COVID-19 impact, socio-economic factors, spatial econometrics, NUTS 3 regions, Germany

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Conflict of interest

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1. Introduction

The global real estate market has experienced price increases since the early 2000s, with only an interruption during the 2007-2009 financial crisis. This trend was further complicated by the onset of the COVID-19 pandemic in 2019, which introduced an external shock to the economy. Contrary to initial expectations of a market downturn, property prices in many regions not only remained stable but following a short period of uncertainty. Eurostat data reveals substantial price increases across the EU, with year-on-year growth rates of 8.4% in 2021 and 7.9% in 2022, while Germany experienced even more pronounced increases of 11.6% and 5.3% in the same years, respectively (European Commission 2024).

Beyond these aggregate trends, regional property markets have exhibited increasing heterogeneity. Several factors may contribute to this phenomenon, including historically low financing costs, the growing appeal of urban living spaces in the 2010s, government property policies, and the much-discussed (though often lacking empirical evidence) urban exodus in response to pandemic-related restrictions and the rise of remote work. The impact of these regionally varying policy measures on property prices has dominated public debate, as they impact on individuals' perception of their living environment, from childcare and leisure activities to commuting, and healthcare accessibility.

The COVID-19 pandemic has prompted a rapid shift in consumer preferences, extending beyond well-documented changes in demand for goods and services to include a re-evaluation of individual property situations. For instance, the transition to remote work has spurred increased demand for short-term rentals and second homes in rural areas (Liu & Su, 2021). Colomb & Gallent (2022) note a shift in location preferences towards coastal regions and medium-sized cities. Doling & Arundel (2022) report that 13% of survey respondents from large cities (population over 500k) plan to relocate within the next 12 months, with half citing the pandemic as an influencing factor.

This rapid shift in preferences is particularly intriguing from an economic perspective and carries significant policy implications. Long-standing negative perceptions of lengthy commutes have been challenged by the pandemic-induced shift towards remote work. Moreover, the previously positive valuation of urban agglomerations for work and leisure has been reassessed considering contagion risks, favouring rural locations (Liu & Su 2021; Li & Zhang 2021). Understanding the underlying factors and their quantitative mechanisms is crucial for distinguishing between pandemic-related influences and fundamental changes in the property market, thereby informing targeted property policies.

Property prices are significantly influenced by global financing interest rates, which reached historic lows during the pandemic. These rates must be analysed in conjunction with other purchase-relevant factors to accurately delineate their effects. Understanding these influencing factors has crucial economic policy implications, particularly considering recent economic history. The 2007-2009 global financial crisis, triggered by overvaluations in the US property market, serves as a stark reminder of potential consequences (Jordà et al. 2015). This underscores the importance of rigorous analysis in property market dynamics to inform policy decisions and prevent similar crises.

Despite the importance of these issues, many studies rely on anecdotal evidence rather than rigorous quantitative analysis. There is a particular dearth of regional analyses examining the impact of COVID-19 on the German property market that incorporate fundamental socio-economic factors and regional interdependencies. Our study aims to address these research gaps by analysing the relationship between COVID-19-related factors (such as case numbers and containment measures) and property prices across regions in Germany. Specifically, we investigate:

1. The influence of COVID-19 case numbers on regional property prices, where case numbers represent both a direct indicator of health risk and a proxy for potential state-imposed restrictions.
2. The impact of observed regional-level pandemic containment measures on property prices, such as movement restrictions, as these directly affect housing preferences and mobility patterns.

While the previous hypotheses focus on direct price effects, we extend our analysis to examine potential underlying mechanisms driving these price changes. Following Gupta et al. (2022), we assume that price increases correlate with increased demand, allowing us to indirectly investigate two additional hypotheses:

3. The urban exodus hypothesis: This posits that densely populated areas experience outmigration in response to high COVID-19 case numbers or stringent containment measures, potentially leading to increased demand and prices in less dense areas.
4. The work substitution theory: This suggests a shift from office-based to remote work in areas with strict movement restrictions, potentially altering housing preferences and, consequently, demand patterns.

The anticipated empirical effects for Hypotheses 1 and 2 are ambiguous a priori, as both case numbers and movement restrictions have increased uncertainty while simultaneously strengthening demand for new living spaces with greater individual freedom. Hypotheses 3 and 4 suggest clearer directional effects from an economic perspective. For instance, Liu & Su (2021) found reduced demand in areas with high population density in the US property market, while Brueckner et al. (2023) and Sun & Yuan (2021) discussed the influence of remote work technologies on employee location decisions, noting rising property prices in suburban areas due to COVID-19.

Our study utilizes a panel dataset covering the last 11 years (up to and including 2022) for 401 NUTS-3 regions (districts) in Germany. We employ Spatial Autoregressive (SAR) and Spatial Durbin Models (SDM) to account for unobserved regional heterogeneity and spatial autocorrelations typical of property prices. We pay particular attention to the choice of spatial weighting matrices; an aspect often overlooked in the literature and provide a detailed discussion of the robustness of our results. To enhance the policy relevance and robustness of our findings, we conduct comprehensive subgroup analyses, stratifying districts based on various regional characteristics and employing alternative model specifications. These analyses enable us to assess the consistency of our results across diverse regional contexts and provide insights for targeted, region-specific policy measures.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive literature review on the determinants of property prices and the current state of research regarding COVID-19's impact on the property market. Section 3 delineates our data sources, provides descriptive statistics, and outlines the econometric methodology employed. Section 4 reports our empirical findings, including direct and indirect effects, and presents robustness checks. Section 5 discusses the results within the context of policy implications and addresses the limitations of the study. Section 6 concludes with a synthesis of our findings and their broader implications.

2. Literature

2.1. Spatial dependencies and the real estate market

Spatial dependencies in real estate markets encapsulate the complex interplay of local and regional factors that drive housing price developments. These dependencies show through spatial linkages, where price changes in one region influence neighboring areas, shaped by economic productivity, demographic trends, and infrastructural dynamics. Such interdependencies not only create regional disparities but also highlight the need for robust modeling approaches to capture these dynamics.

The relationship between demand and supply in housing markets forms the foundation for these spatial patterns. Urban centers, characterized by higher wages and superior amenities, typically attract significant demand, while regulatory constraints and limited land availability restrict supply (Hsieh & Moretti 2019; Glaeser & Ward 2009). These imbalances lead to stark regional variations in housing prices and reinforce spatial economic disparities. Externalities, such as neighborhood effects, and spatial autocorrelation further amplify these patterns, creating interlinked price developments across regions.

Pre-COVID studies provide essential insights into spatial dependencies. Hsieh & Moretti (2019) discuss the spatial dispersion of wages and housing costs, demonstrating how these factors influence labor markets in U.S. cities. Similarly, Glaeser & Ward (2009) argue that neighborhood externalities contribute to housing price disparities. In the German context, Otto & Schmid (2018) reveal that real estate prices are spatially autocorrelated, with commuting patterns and local economic factors playing critical roles over time. These studies establish the foundation for understanding regional price dynamics.

At a European level, Cunha & Lobão (2021a) explore price determinants across Portuguese metropolitan areas, highlighting the autoregressive characteristics of housing prices. Their findings provide methodological insights into spatial dependencies in diverse economic contexts. Semerikova et al. (2022) further contribute a German-focused perspective, examining the convergence of housing prices between urban and rural regions. Using spatial econometric models, they demonstrate the significance of regional demand factors, such as unemployment rates and commuter migration, in driving price growth. Advanced econometric techniques have become indispensable for analyzing spatial dependencies. Chica-Olmo et al. (2019) utilize a hedonic regression model corrected for spatial autocorrelation, while Lesage & Pace (2014) and Elhorst (2022) provide theoretical frameworks for applying spatial autoregressive (SAR) and Spatial Durbin Models (SDM). These approaches offer robust tools for capturing spatial and temporal interdependencies in housing markets, forming a critical methodological foundation for studying spatial dynamics during crises.

2.2. Impact of COVID-19 on the real estate market

Recent literature highlights the profound impact of the COVID-19 pandemic on real estate markets, with a particular focus on how regional disparities were intensified and housing market dynamics reshaped. Studies emphasize behavioral shifts, such as the increased adoption of remote work, and structural transformations driven by health and mobility restrictions, which collectively influenced migration patterns, transaction volumes, and housing prices.

A key finding in the literature is the increased demand for suburban and rural housing, driven by remote work and changing lifestyle preferences. In the U.S., Whitaker (2021) observed significant urban-to-suburban migration during the pandemic, while Vogiazides & Kawalerowicz (2022) researched on similar trends in Sweden, where residents relocated from urban centers like Stockholm to less dense areas. These shifts were attributed to increased work flexibility and a demand for more distantly related living environments.

In Germany, Dolls & Lay (2023) found that individuals working remotely were significantly more likely to move to suburban or smaller urban areas. Rising housing costs in urban centres intensify this trend, as highlighted by Dolls & Mehles (2021), making suburban living a more attractive financial option. Semerikova et al. (2022) and Stawarz et al. (2022) provide further insights into internal migration patterns in Germany during the pandemic. Semerikova et al. (2022) noted a 5% reduction in inter-county migration intensity in 2020, particularly in urban regions, as movement restrictions limited relocations. Stawarz et al. (2022) observed increased net migration losses in Germany's largest cities, emphasizing the pandemic's role in reshaping regional population dynamics.

COVID-19 also disrupted real estate transaction volumes and market liquidity. Qian et al. (2021) reported a temporary decline in housing transactions in China due to lockdowns and health-related concerns. Similarly, Gascon & Haas (2020) highlighted that stay-at-home orders in the U.S. reduced market activity, even as accommodative monetary policies helped stabilize housing prices. These findings align with those of Francke & Korevaar (2021), and Ambrus et al. (2020), who noted that pandemics historically exert a short-term negative impact on housing markets during periods of heightened uncertainty. Zeng & Yi (2022) conducted a study on the impact of the COVID-19 pandemic on the housing market in Wuhan, China. In their research the authors employed a hedonic price model to construct an index for the prices of used homes in Wuhan and neighbouring capital cities. Subsequently, they applied a Difference-in-Difference (DID) model to conduct a comprehensive analysis of both the new commercial housing and second-hand housing markets. Additionally, they utilized the VAR (Vector Autoregression) model to explore how the housing market responded to the pandemic. The findings from Zeng & Yi (2022) indicate that the pandemic primarily impacted the housing market in terms of transaction volume and area, with minimal effects on housing prices. Notably, reported COVID-19 cases had a short-term adverse impact on the housing market, which diminished within three weeks. This impact was primarily attributed to real estate companies halting housing sales and local governments implementing home quarantine measures, disrupting normal housing transactions.

Housing price dynamics during COVID-19 revealed stark spatial heterogeneity. D'Lima et al. (2022) found that prices in densely populated urban areas decreased, while suburban areas experienced price increases in the U.S. This pattern underscores the importance of spatial modelling to capture regional differences in price adjustments. Li & Kao (2022) further emphasize the spatially nonstationary relationships between housing prices and COVID-19 case rates, offering valuable methodological insights for analysing regional disparities in Germany. Studies applying spatial econometric techniques, such as Spatial Durbin Models (SDM), provide valuable insights into how regional factors influenced price and migration trends during the pandemic (Elhorst (2022; Gupta et al. 2022). These methods were particularly effective in capturing spatial heterogeneity and temporal dynamics in housing markets.

Gupta et al. (2022) extend earlier analyses by exploring long-term trends in housing markets, including how pandemic-induced migration and work-from-home policies reshaped demand for suburban and rural properties. Their findings suggest that while urban housing markets have begun to recover, the shift toward suburban living may represent a structural change with lasting policy implications. Colomb & Gallent (2022) emphasize the need for further research into the long-term effects of pandemic-induced migration trends, particularly in Europe. They argue that policymakers must adapt urban and regional planning to accommodate changing housing preferences, such as the growing demand for suburban infrastructure and connectivity.

3. Data & Method

3.1 Data

Our study analyses the impact of socio-economic factors and the COVID-19 pandemic on housing prices in 401 counties in Germany. The fully balanced panel ranges from 2012 to 2022 and contains 4,411 observations. Each county-year observation includes values for all variables, except interest rates, which are available as national values (i.e. constant across counties) on a yearly basis (Table 1).

The outcome variable is the price per square meter for owner-occupied flats. The data comes from the VALUE Marktdatenbank, which is an established real estate market database in Germany, including prices and rents for houses and further related information.

We measure the effects of the pandemic in terms of incidence rates and the severity of pandemic-related sanctions. The incidence rates express the pandemic’s intensity as the number of confirmed infections per 100,000 inhabitants. The sanctions index quantifies the severity of restrictions imposed by the federal and regional governments regarding mobility and contacts. The set of control variables contains demographic and socioeconomic as well as economic, geographical and infrastructure aspects derived from the literature discussed in Chapter 2.

The demographic structure of a region is captured through the average age and population density as the number of people per square kilometer. The economic situation is addressed via purchasing power per capita and the unemployment rate. The proportion of commuters working outside their home municipality measures the mobility of workers and their access to urban centres with higher concentrations of jobs. To account for the possibility of working remotely, we use the proportion of employees in knowledge-intensive sectors and the proportion of households with access to high-speed broadband connections (DSL50 or higher).

We further measure a region's attractiveness for young families by the proportion of children under age 3 in childcare. Cultural attractiveness is represented by the share of employees in creative sectors. As a region's attractiveness for tourism can drive housing prices, we control for the number of bds available for tourists. Apart from the regional circumstances, the financing costs are a crucial determinant of the housing market. Therefore, we include initial fixed interest rate over 10 years housing loans to private households.

Due to data availability and the fact that a decision for buying a house is a long-term decision, several variables are lagged by one or two years.

Table 1: Literature-based selection of covariates

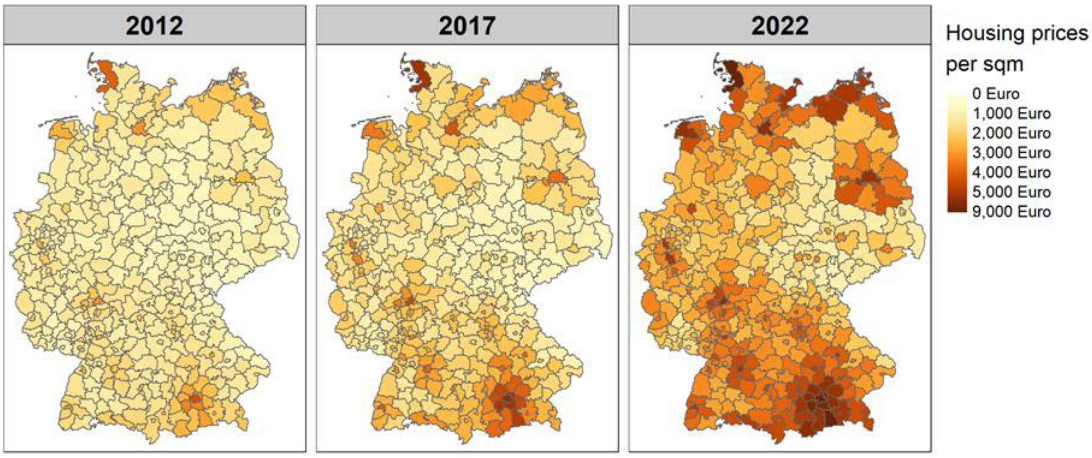
Variable	var	Description	Source	Literature basis et al.
Purchase inventory	dep_Var	Real estate stocks available for sale or acquisition at a given time. Apartments for sale, Euros per square meter, arithmetic mean over the year.	Value AG 2024	Qian et al. (2021)
Purchasing power	PPP	Income impacting occupational and leisure mobility; purchasing power per capita in EUR: Positive impact on the demand	Statistisches Bundesamt 2024	C. T. Hsieh & Moretti (2019), Semerikova et al. (2022)
Unemployment	UE	Share of unemployed persons in the civilian labor force in %: Negative impact on the housing demand	BBSR 2024	Semerikova et al., (2022)
Commuter balance	COM	Commuter balance per 100 employees at the workplace: Positive impact on the demand if mobility possibility is high	BBSR 2024	(Semerikova et al. (2022), Otto & Schmid (2018)
Tourism	LEIS	Number of beds in accommodation establishments per 1.000 inhabitants: Positive influence on the purchasing inventory	BBSR 2024	Cunha & Lobão, (2021b), C. T. Hsieh & Moretti (2019)
Creativitiy and culture	CC	Share of employees at the workplace in creative industries in %: Positive impact on the demand	BBSR 2024	Cunha & Lobão (2021), C. T. Hsieh & Moretti, (2019)

Interest	INT	loans to private households, initial fixed interest rate over 10 years: Positive/Negative impact depending on the level of interest rate.	EZB 2024	Jordà et al. (2015), Hiller & Gröbel (2016)
Childcare	CC	Share of children under age 3 in childcare: Positive impact on the demand of housing in remote areas	BBSR 2024	C. T. Hsieh & Moretti, (2019)
Broadband supply	BS	Percentage of households with broadband coverage with at least 50 Mbit/s.': Positive impact as remote office opportunities increase	BBSR 2024	Gupta et al. (2021)
Cases incidence	CI	Confirmed COVID-19 infections per 100,000 inhabitants	RKI 2024	Zeng & Yi (2022), Dolls & Mehles (2021)
Sanctions index	SI	Bundle of measures, contact restrictions, mobility reduction: Negative impact on the demand	RKI 2024	Zeng & Yi (2022), Dolls & Mehles, (2021)

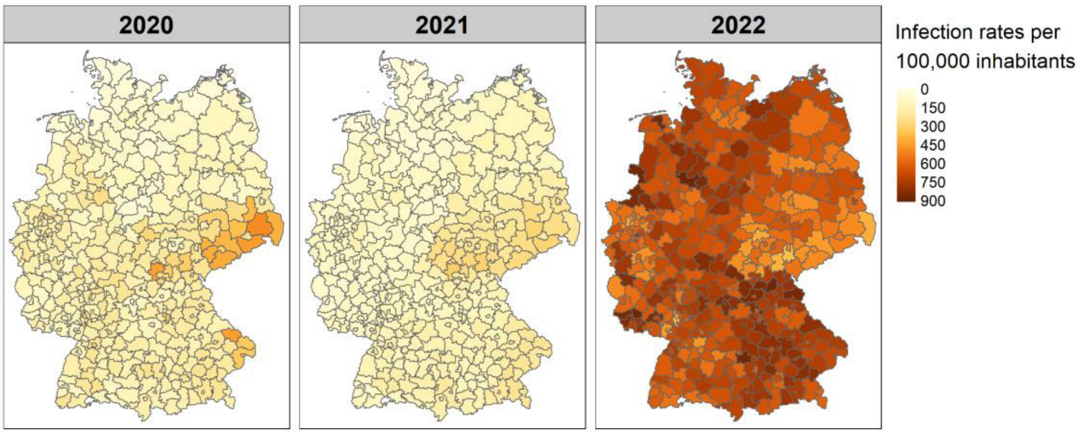
3.2 Descriptive statistics

Between 2012 and 2022, housing prices in Germany increased in almost all regions. Especially major cities and surrounding metropolitan areas experienced strong increases of more than 10% per year, whereas in rural and less economically successful regions, price growth was more modest. The COVID-19 pandemic only briefly paused the general strong upward trend (see Figure 1).

In federal states like Bavaria and Baden-Württemberg, with their strong industry, housing prices were high, whereas levels in Eastern states like Saxony, Thuringia, and Saxony-Anhalt were much lower, reflecting their economic conditions with higher unemployment and lower income levels as well as their unfavourable population development. North Rhine-Westphalia and Hesse experienced high housing demand and prices due to population increases and the high degree of urbanization.



Panel a)



Panel b)

Figure 1: Panel a) describes the development of housing prices per square meter (sqm) for the years 2012, 2017, and 2022. A sharp increase in housing prices can be observed, especially in the North and South of Germany. Panel b) shows the distribution of COVID-19 case rates per 100,000 inhabitants in Germany for the years 2020, 2021, and 2022. The case rates started in the North of Bavaria and Saxony-Anhalt. By the year 2022, the cases were equally distributed across Germany. Source: Value AG 2024, RKI 2024

In regions with a high density of tourist's accommodation, which are included in our measure of housing prices, like around the North and Baltic Sea and near the Alps, price levels are higher. The regional development of the COVID-19 pandemic in Germany between 2020 and 2022 varied significantly across different states and periods. The first major outbreaks in Germany started in February 2020 with initial cases in Bavaria and North Rhine- Westphalia. As a reaction to the rising number of cases, first nationwide lockdown measures were taken in March 2020, including the closure of certain non-essential businesses, schools, and further public institutions. First vaccination campaign slowly started in December 2020, during spring and summer 2021, vaccinations became available to the broad public.

Throughout the year, Germany still experienced infection waves with strong regional variation. Especially eastern regions with low vaccination rates showed high incidence rates at the end of 2021. The emergence of the Omicron variant led to another strong nationwide infection wave. However, due to higher vaccination rates, widespread vaccine availability, and the virus's endemic spread, sanction measures and restrictions were applied at the regional level.

3.3 Model and Identification Strategy

Our research utilizes a unique spatial panel dataset that comprises price information for N=401 German districts from 2012 to 2022, and covariates from 2010 to 2022, as outlined in Section 3.1. This dataset extends beyond conventional panel structures by incorporating comprehensive geographical information derived from shapefiles (available at https://daten.gdz.bkg.bund.de/produkte/vg/). For econometric analysis, this geographical data is translated into a symmetric $N \times N$ spatial weight matrix W, which captures distances or neighbourhood relationships.

Our analytical framework is grounded in Tobler's first law of geography (Tobler, 1979), which posits that closer entities demonstrate stronger relationships than those further apart. This concept is particularly salient in spatial real estate datasets, where price dependencies between neighbouring regions are well-documented due to various theoretical and empirical factors (Can (1992); Osland (2010); Stamou et al. (2017); Wilhelmsson (2002)).

It is crucial to emphasize that these spatial dependencies extend beyond mere similarities in covariates, such as economic, geographical, or socio-economic aspects of the regions. To comprehend price spillover effects, we directly model prices of neighbouring regions as weighted influencing factors on a region's prices, thereby explicitly operationalizing Tobler's law. This approach is empirically substantiated in Section 4.1 through spatial autocorrelation measures such as Moran's I statistic.

A key argument in favour of including spatial relationships in econometric models is to reduce potential bias and improve estimation efficiency. LeSage and Pace (2009) demonstrate (for data sets with strictly positive values - as in the case of our property prices) that ordinary least squares (OLS) systematically overestimate the coefficients compared to models that take spatial spillover effects into account. When confronted with elevated prices in neighbouring regions that are the result of spatial spillovers, OLS erroneously ascribes these increases to the existing explanatory variables, rather than to the unmodeled spillover effects (cf. LeSage and Pace, 2009, p. 19).

The application of spatial econometric models allows us to explicitly consider these spillover effects in the following. From the multitude of spatial models available (for a current overview, see LeSage & Pace (2021); Elhorst (2022)), we select two models for our analysis that can reflect spatial price spillover effects and are therefore particularly suitable for the real estate market.

The Spatial Autoregressive (SAR) model represents a simple and widely used approach, defined as:

$$y = \rho Wy + X\beta + \alpha + \varepsilon \quad (1)$$

where α represents unobserved region-specific effects and the remaining notation follows standard conventions (see e.g. Stata, 2019). In the SAR model, the spatial weight matrix W is responsible for assigning higher weights to closer regions than to more distant ones. This formulation in (1) clearly shows that the dependent variable y is influenced not only by the explanatory variables X, but also by the spatially weighted values of y itself in neighbouring regions. A classic application of the SAR model in the property context is presented by Wilhelmsson (2002), who demonstrates the effectiveness of the model in capturing spatial dependencies in housing markets.

The literature often employs neighbourhood matrices as models for W, assigning specific weights to adjacent regions (and/or their second/third order neighbours, etc.) without considering actual distances. Alternatively, various functions of linear distances between regional centres are used, often using logarithmic transformations. We consider the latter approach to be more appropriate for modelling property prices, as location quality is often (though not always) perceived through proximity to specific regions. To address potential criticisms of this approach, we conduct robustness tests of our results in Section 4.2, where we analyse different specifications.

A frequently applied extension of the SAR model is the Spatial Durbin Model (SDM), which additionally incorporates spatially lagged independent variables (although there are numerous other models that encompass the SAR, cf. Elhorst, 2022). Formally, the SDM can be expressed as an extension of equation (1):

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \quad (2)$$

where WX represents the spatially lagged independent variables, and θ is the corresponding parameter vector. The SDM enables the estimation of both direct and indirect (spillover) effects, which are essential for understanding the complex dynamics of spatial dependencies in real estate markets. The direct effects arise from the influence of explanatory variables within the same region, whereas the indirect effects capture the impact of an explanatory variable in a neighbouring region on the dependent variable in the focal region. Specifically, global spillover effects are generated by the spatial lag of the dependent variable (ρWy), which allows feedback effects across the entire system of regions. Local spillover effects, on the other hand, stem from the inclusion of spatially lagged independent variables ($WX\theta$), permitting explanatory variables to exert influence beyond their immediate region. This dual structure enables a nuanced understanding of how property prices are affected not only by local factors but also by conditions in neighboring areas, an essential aspect given the interconnectedness of real estate markets (Brasington, 2004).

Given the multitude of spatial econometric models available, it is not definitively clear that our "bottom-up" approach (OLS => SAR => SDM), which follows Elhorst (2010), is the only correct path for model selection (cf. LR tests in Table 2). Misspecification remains a risk, and studies have demonstrated that spatial autocorrelation is easily detected in LM tests (e.g., Brunsdon et al. 2002)), although the underlying cause could be other forms of model misspecification.

Nevertheless, the SDM offers a degree of robustness against model misspecifications. It can be shown that the results remain unbiased even if spatially autocorrelated errors (as in the SEM model) are present but not explicitly formulated in equation (2) (LeSage (2014)).

Our decision to employ SAR or SDM models is primarily based on the theoretical consideration that global spillover effects are an inherent characteristic of the real estate market and should therefore be captured by econometric models. This perspective aligns with similar approaches found in the literature, as demonstrated by studies conducted by Li & Kao (2022), Cellmer et al. (2020), Cellmer et al. (2021) and Lee & Huang (2022).

Alternative methods for modelling spatial panel data in real estate research include Geographically Weighted Regression (GWR). GWR shifts the analytical focus from global spatial spillovers to the heterogeneity of relationships across different regions, thereby enabling locally varying parameter estimates (Fotheringham et al., 2002). Recent literature has explored hybrid approaches, such as SAR-GWR combinations (Lee & Huang, 2022), which integrate global spatial dependence with local coefficient variation. Additionally, advanced techniques like the Kernel-based Geographically and Temporally Weighted Autoregressive (KBGTWAR) model have been developed (Shim & Hwang, 2018).

Nonetheless, our study is primarily oriented towards exploring global spatial relationships, as articulated in our research hypotheses in Section 1. Regional heterogeneity is addressed through the diverse manifestations of our explanatory variables, which negates the necessity for the GWR model that might lead to overfitting.

Theoretical discussions regarding price spillovers in real estate markets further justify our selection of the Spatial Durbin Model (SDM), which comply with our research objectives. Moreover, the SDM offers robustness against certain forms of model misspecification, maintaining unbiased results even in the presence of spatially autocorrelated errors not explicitly modelled (LeSage, 2009).

Our methodological choices are verified by recent empirical studies in real estate economics, including work by Li and Kao (2022), Cellmer et al. (2020), and Cellmer et al. (2021), which employ similar spatial modelling approaches. This growing body of literature highlights the relevance and efficacy of spatial econometric modelling in capturing the complex dynamics of real estate markets.

4. Empirical results

4.1 Coefficient estimates

The statistical analysis was conducted using the spxtregress family of commands in Stata 18 MP2. Table 1 presents the estimated coefficients for three models: Ordinary Least Squares (OLS) with fixed effects, Spatial Autoregressive (SAR), and Spatial Durbin Model (SDM), as discussed in Section 3.3 and based on Equations (1) and (2).

Our presentation in Table 1 follows a bottom-up approach as suggested by Elhorst (2010), beginning with an OLS panel model that incorporates spatial fixed effects but excludes spatial lags. The Hausman test yields a chi-square statistic of 167.73 (df = 13), supporting the use of a fixed-effects estimator. However, Moran's I statistic (z-values ≥ 29 for all years) indicates significant spatial autocorrelation in the OLS model residuals. Consequently, we present the SAR specification (Equation 1) with fixed effects in the second column of Table 1. It is important to note that for both the SAR (column 2) and SDM (column 3) models, which are non-linear, Table 2 presents coefficient estimates rather than marginal effects typically associated with linear regression (LeSage & Pace, 2021). A more nuanced interpretation of the parameters, accounting for spatial spillover effects, is provided in Table 3 and discussed in the subsequent section.

In the SAR model, the spatial autoregressive parameter (rho) is statistically significant ($p < 0.01$), as corroborated by the likelihood ratio (LR) test (test statistic = 111.92, df = 1). This finding, coupled with the Moran's I results, underscores the superiority of the SAR model over OLS in this context.

Table 2 also introduces interaction effects between COVID-19 case numbers and government containment measures, as well as interest and unemployment rates. Interaction effects allow us to examine how the relationship between one variable (e.g., property prices) changes depending on the level of another variable (e.g., COVID-19 case numbers). The first interaction examines the potential interplay between health risks (represented by COVID-19 case numbers) and policy responses (government containment measures) in shaping real estate prices. This interaction allows for a more nuanced economic interpretation of how heightened health risks could influence property demand, particularly in regions with strict containment policies. The second interaction incorporates regional interest rates as a proxy since financing rates are not available at the regional level. By integrating unemployment rates into this interaction, we effectively create a form of risk-adjusted interest rates that reflect the economic realities faced by potential buyers. This approach recognizes that higher unemployment can lead to increased risk premiums on loans, thereby affecting housing affordability and demand.

The SDM incorporates both global and local spillover effects, as elaborated in Section 3.3. An LR test comparing the SDM to the SAR model (test statistic = 768.54, df = 13) rejects the null hypothesis, indicating that the SDM provides a better fit to the data. Table 2 presents the SDM coefficient estimates separately for the X-vector and its spatial lags. While the estimated X coefficients in the SDM are comparable to those in the SAR model in terms of significance and magnitude, with a few exceptions, a more substantive interpretation requires examination of the results in Table 3, which we discuss in the following section.

Table 2: Coefficient estimates

	OLS FE X	SAR FE (direct) X	SDM FE X	WX
Population density	0.000279 ***	0.000189 *	0.0000272	0.000886
	(0.0000751)	(0.0000744)	(0.0000705)	(0.000491)
Purchasing power pc	0.000101 ***	0.0000804 ***	0.0000342 ***	0.0000183
	(0.00000298)	(0.00000349)	(0.00000435)	(0.0000176)
Unemployment rate	-0.0291 ***	-0.0315 ***	-0.0227 ***	-0.0459 **
	(0.00369)	(0.00364)	(0.00420)	(0.0170)
Average age	-0.0650 ***	-0.0565 ***	-0.0672 ***	-0.0999 *
	(0.00624)	(0.00619)	(0.00596)	(0.0447)
Interest mortgage (10y)	-0.0816 ***	-0.0695 ***	-0.276 ***	0.198 ***
	(0.00719)	(0.00717)	(0.0150)	(0.0263)
Interest x Unemployment	0.00686 ***	0.00674 ***	0.00714 ***	0.00577
	(0.000693)	(0.000682)	(0.000873)	(0.00365)
Incidence rate (COVID-19)	0.000435 ***	0.000382 ***	0.000519 ***	-0.000466 *
	(0.0000328)	(0.0000327)	(0.0000548)	(0.000214)
Measures index (COVID-19)	0.00442 ***	0.00353 ***	0.00550 ***	-0.00586 ***
	(0.000197)	(0.000211)	(0.000502)	(0.00109)
Incidence x Measures	-0.0000190 ***	-0.0000173 ***	-0.0000171 ***	0.0000163
	(0.00000193)	(0.00000190)	(0.00000252)	(0.0000113)
Commuter flow	0.0446 ***	0.0350 ***	0.0238 ***	-0.0167
	(0.00335)	(0.00342)	(0.00352)	(0.0183)
Overnight stays (tourist)	0.00156	0.00218	-0.000204	0.0150
	(0.00155)	(0.00152)	(0.00141)	(0.0174)
Employees in creative sectors	-0.00807 **	-0.00676 *	-0.00526 *	0.0236
	(0.00294)	(0.00290)	(0.00265)	(0.0393)
Share kindergarten	0.00219 ***	0.00218 ***	-0.000268	0.0182 ***
	(0.000636)	(0.000626)	(0.000653)	(0.00324)
Broadband supply	0.000640 ***	0.000500 ***	0.000469 ***	-0.00336 ***
	(0.000107)	(0.000106)	(0.000106)	(0.000707)
Employees knowledge-intensive	0.000106	-0.0000493	0.00168	0.0190
	(0.00159)	(0.00156)	(0.00143)	(0.0111)

Constant	7.618 (0.301)	***				
lambda			0.223	***	0.752	***
			(0.0209)		(0.0541)	
sigma_e			0.0802	***	0.0727	***
			(0.000896)		(0.000813)	
LR Hausman(df)	167.73(13)	***	111.92(1) vs. OLS	***	768.54(13) vs. SAR	***

Standard errors are reported in parentheses. Significance levels are denoted as: ***p<0.01p < 0.01p<0.01, **p<0.05p < 0.05p<0.05, *p<0.1p < 0.1p<0.1.

4.2 Direct and indirect effects

Table 3 presents summary measures for the direct, indirect, and total effects, as the conventional interpretation of coefficients as marginal effects is not applicable due to the non-linearity of the models. Following LeSage (2009), we employ a procedure based on average values to compute these summary measures.

1. Direct effects: These measure the impact of a change in an explanatory variable in a specific region on the dependent variable in the same region. This includes both the immediate effect and feedback effects that occur as the impact passes through neighbouring regions and back to the original region.
2. Indirect effects (or spillover effects): These capture the impact of a change in an explanatory variable in a specific region on the dependent variable in all other regions. In the SDM, these effects can be decomposed into local and global spillovers.
3. Total effects: These are the sum of direct and indirect effects, representing the overall impact of a change in an explanatory variable across all regions.

It is important to note that in spatial models, these effects can vary across observations. Therefore, following LeSage and Pace (2009), we report average effects as summary measures in Table 3. Note also that Table 3 no longer outputs separate beta and theta coefficients. The 'impact' command in Stata fully integrates spatial interactions, producing a single estimated coefficient per variable.

Comparing the direct and indirect effects between the SAR and SDM models reveals notable similarities in magnitude and significance for purchasing power, unemployment rate, age, and interest rate. However, the influence of population density appears insignificant in the SDM model. (We address potential endogeneity issues related to population density separately in Section 4.3.) Of particular interest are the coefficients for COVID-19 incidence and related measures:

1. Direct effects: Both models show positively significant direct effects of incidences and measures on a region's real estate prices, with a negative interaction term. This suggests that the positive demand influence due to COVID-19-related mobility restrictions outweighs potential negative effects (e.g., uncertainty, job losses, or reduced accessibility). We elaborate on this interpretation in Section 5.
2. Indirect effects: While the SAR model indicates significant indirect effects of incidences and measures on surrounding regions' property prices, these effects (along with the total effect) become insignificant in the SDM

model. This discrepancy may be attributed to the SAR model erroneously identifying an influence on surrounding regions' property prices due to omitted variables, which becomes insignificant when local spillover effects are included in the SDM.

To elucidate this difference, we consider the composition of indirect effects from local and global spillovers. The SAR model only incorporates global spillovers, which are not confined to neighbouring regions defined by the W matrix. In contrast, the SDM includes both global and local spillovers, with the latter limited to neighbouring regions with non-zero weights in the spatial weight matrix (SWM) (see Elhorst, 2014 for a technical exposition). The absence of local spillovers in the SAR model may have led to an overestimation of global effects. These findings underscore the importance of model selection in spatial econometrics and highlight the nuanced interpretation required when analysing spatial spillover effects in the context of COVID-19's impact on real estate markets.

Nevertheless, thirdly, we theorized that being located in a cluster reduces the diverging effect of AI. To assess this hypothesis, we further split our dataset into cluster firms and non-cluster firms to calculate a model only with cluster firms (see Model 4). Similar to Model 1, we can observe that AI also has a direct significant positive influence on the labour productivity of firms located within clusters. However, in contrast to the previous Model 3, the interaction term between AI knowledge and firm type is highly significant and negative, meaning that within clusters particularly laggard firms profit from AI knowledge. Similar to Model 3, we also graphically plot the corresponding average marginal effects of AI on the labour productivity within clusters. Contrary to the full sample, Figure 2 shows that within clusters particularly laggard firms benefit from AI knowledge within their knowledge base, while in the case of frontier firms we even find evidence for a negative influence of AI knowledge. Therefore, we can accept hypothesis H3, that the diverging effect of AI knowledge on firms’ productivity gap is reduced by being located in a cluster.

Table 3: Direct and indirect effects

	SAR FE			SDM FE		
	direct	indirect	total	direct	indirect	total
Population density	0.000279 ***	0.0000512 *	0.0002407 *	0.0000387	0.0034103	0.003449
	(0.0000751)	(0.0000203)	(0.000094)	(0.0000706)	(0.0019986)	(0.0020042)
Purchasing power pc	0.000101 ***	0.0000217 ***	0.0001022 ***	0.0000347 ***	0.0001656 **	0.0002003 ***
	(0.00000298)	(0.00000224)	(0.00000373)	(0.00000432)	(0.0000529)	(0.0000526)
Unemployment rate	-0.0291 ***	-0.008518 ***	-0.0400723 ***	-0.0235209 ***	-0.2370843 **	-0.2606052 ***
	(0.00369)	(0.0014628)	(0.0047959)	(0.0041497)	(0.0721602)	(0.0714937)
Average age	-0.065 ***	-0.0152596 ***	-0.0717879 ***	-0.0690748 ***	-0.5659389 **	-0.6350137 ***
	(0.00624)	(0.0023174)	(0.0078422)	(0.0059619)	(0.1812476)	(0.1816649)
Interest mortgage (10y)	-0.0816 ***	-0.0187625 ***	-0.0882673 ***	-0.2760431 ***	-0.0365645	-0.3126076 ***
	(0.00719)	(0.0027282)	(0.0090314)	(0.0148916)	(0.0904481)	(0.088567)
Interest x Unemployment	0.00686 ***	0.0018213 ***	0.0085681 ***	0.0072811 ***	0.0419122 **	0.0491933 ***
	(0.000693)	(0.0002838)	(0.0008909)	(0.0008566)	(0.0140358)	(0.0137769)
Incidence rate (COVID-19)	0.000435 ***	0.0001031 ***	0.0004852 ***	0.0005176 ***	-0.0002871	0.0002305
	(0.0000328)	(0.0000141)	(0.0000415)	(0.0000539)	(0.000722)	(0.0007049)
Measures index (COVID-19)	0.00442 ***	0.0009529 ***	0.0044828 ***	0.0054814 ***	-0.0064884	-0.001007
	(0.000197)	(0.0001058)	(0.0002464)	(0.0004985)	(0.0035301)	(0.0034135)
Incidence x Measures	-0.000019 ***	-0.00000468 ***	-0.000022 ***	-0.0000171 ***	0.000013	-0.00000409
	(0.00000193)	(0.00000073)	(0.00000243)	(0.00000246)	(0.0000385)	(0.0000374)
Commuter flow	0.0446 ***	0.0094534 ***	0.0444731 ***	0.023782 ***	0.0045394	0.0283214
	(0.00335)	(0.0012599)	(0.0041867)	(0.0034834)	(0.0667381)	(0.0663265)
Overnight stays (tourist)	0.00156	0.000588	0.0027663	-0.0000155	0.0559851	0.0559695
	(0.00155)	(0.0004199)	(0.0019387)	(0.0014089)	(0.0652972)	(0.0653844)
Employees in creative sectors	-0.00807 **	-0.0018251 *	-0.0085862 *	-0.0050117	0.0739449	0.0689332
	(0.00294)	(0.0008031)	(0.0036758)	(0.0027757)	(0.1514163)	(0.1523682)
Share kindergarten	0.00219 ***	0.0005891 ***	0.0027713 **	-0.0000399	0.0677063 ***	0.0676664 ***
	(0.000636)	(0.0001831)	(0.0007981)	(0.000648)	(0.0162675)	(0.0162514)
Broadband supply	0.00064 ***	0.0001352 ***	0.0006358 ***	0.0004307 ***	-0.0113334 **	-0.0109027 **
	(0.000107)	(0.0000311)	(0.0001333)	(0.0001047)	(0.003467)	(0.0034657)
Employees knowledge-intensive	0.000106	-0.0000133	-0.0000626	0.0019359	0.0761075	0.0780434
	(0.00159)	(0.0004222)	(0.0019861)	(0.0014509)	(0.0440619)	(0.0443525)

Standard errors are reported in parentheses. Significance levels are denoted as: ***p<0.01p < 0.01p<0.01, **p<0.05p < 0.05p<0.05, *p<0.1p < 0.1p<0.1.

4.3 Robustness Checks

To assess the stability and generalizability of our findings presented in Sections 4.1 and 4.2, we conducted a comprehensive set of robustness checks and sensitivity analyses based on our preferred Spatial Durbin Model (SDM). Due to space constraints, we focus on four key variables in presenting these results: purchasing power and unemployment rate, widely accepted determinants of real estate prices, and the COVID-19-specific variables of incidence and measures index (Table 4).

The results in Table 4 demonstrate that the magnitude and significance levels of the coefficient estimates from Sections 4.1 and 4.2 are robust to various model specifications. Notably, this robustness extends to regional variations (northern, western, southern, and eastern districts), an important finding given the pronounced north-south and west-east disparities in the German real estate market (Brausewetter et al. 2022). The substitution of rental prices for purchase prices as the outcome variable preserves the sign and significance of our main results, supporting the generalizability of our findings across Germany's diverse real estate markets, which are subject to varying degrees of government regulation (Mense et al. 2019).

To address potential endogeneity concerns related to population density, we estimated a reduced model excluding this variable (row “Model without pop dens.”, Table 4). The robustness of our results to this exclusion, coupled with the inclusion of purchasing power and commuter balance as potential instrumental variables, mitigates endogeneity concerns.

We further validated our model selection by comparing our results to those obtained from Spatial Error Model (SEM) and Spatial Autoregressive Combined (SAC) specifications. The SEM, which does not account for spillover effects in covariates, and the SAC, which nests both SAR and SEM (LeSage, 2009), yield comparable results for the coefficients of interest. Lastly, we tested the sensitivity of our results to alternative spatial weighting matrices, including neighbourhood and neighbour-neighbour specifications, finding no substantial changes in the sign or significance of our main results.

Beyond the variations presented in Table 4, we conducted additional analyses to assess the influence of panel length and regional composition. Figures 2 and 3 display coefficient estimates for purchasing power and the measures index, respectively, based on 100 random draws of 90% of German districts. These results corroborate the robustness of our estimates to regional variations, as they are all within the 95% confidence interval of our full-sample estimation, and underscore that our conclusions are not driven by the inclusion or exclusion of specific regions.

Table 5 presents the results of our analysis using truncated panels with varying start dates between 2012 (our original specification) and 2020. Most variables maintain their sign and significance across these different times, with exceptions primarily limited to very short panels beginning in 2019 or 2020. For instance, purchasing power (from 2018), unemployment (only from 2020), and the measures index (from 2018) lose significance in these truncated panels. However, the marked stability of results for panels starting between 2012 and 2018 supports our choice of an 11-year period, which excludes the distortions of the 2008-2011 global financial crisis (Mian & Sufi 2009) while providing sufficient pre-pandemic data to avoid overfitting to COVID-19-era trends.

In conclusion, our extensive robustness checks and sensitivity analyses strongly support the validity and generalizability of our main findings. The results demonstrate resilience to variations in model specification, regional composition, and time, enhancing confidence in the reliability of our estimates and the broader implications of our study for understanding the impact of COVID-19 on real estate markets.

Table 4: Sensitivity analyses for selected variants of the SDM used in section 4.2 (parameter estimates and standard errors)

	Purchasing Power		Unemployment rate		Incidence		Measures		N
Original SDM FE	0.0000342	***	-0.0227	***	0.000519	***	0.0055	***	4411
	(0.00000435)		(0.0042)		(0.0000548)		(0.000502)		
North	0.0000267	**	-0.0543	***	0.000475	**	0.00598	***	693
	(0.00001)		(0.00966)		(0.000163)		(0.00131)		
West	0.0000374	***	-0.0245	***	0.000292	**	0.00506	***	1331
	(0.00000668)		(0.00618)		(0.0000978)		(0.000695)		
South	0.0000323	***			0.0005148	***	0.0056581	***	1540
	(0.00000585)		(0.0104518)		(0.0000869)		(0.0007402)		
East	0.0000627	***	-0.0314566	**	0.0008561	***	0.0056457	***	847
	(0.0000164)		(0.0115915)		(0.0001653)		(0.0015331)		
Rent vs. purchase prices	0.00000878	***	-0.00361	*	0.000256	***	0.00144	***	4411
	(0.00000154)		(0.00149)		(0.0000193)		(0.000177)		
Model without pop dens.	0.0000336	***	-0.023	***	0.000528	***	0.00552	***	4411
	(0.00000434)		(0.00417)		(0.0000546)		(0.000502)		
Reduced set of covariates*	0.0000309	***	-0.0208	***	0.000581	***	0.00609	***	4411
	(0.00000431)		(0.00419)		(0.0000536)		(0.000478)		
SEM	0.0000346	***	-0.024	***	0.000564	***	0.00582	***	4411
	(0.00000429)		(0.00394)		(0.0000513)		(0.000461)		
SAC	0.0000282	***	-0.0215	***	0.000488	***	0.00505	***	4411
	(0.00000427)		(0.0039)		(0.0000518)		(0.000475)		
SWM: CONT vs. DIST	0.0000335	***	-0.0149	***	0.00042	***	0.00451	***	4411
	(0.00000433)		(0.00419)		(0.0000543)		(0.000498)		
SWM: CONT 2nd neighb.	0.0000339	***	-0.0146	***	0.00042	***	0.0046	***	4411
	(0.00000431)		(0.00418)		(0.0000541)		(0.000496)		

* Model without commuter flow, overnight stays (tourist), employees in creative sectors, share kindergarten, broadband supply, employees knowledge-intensive. Standard errors are reported in parentheses. Significance levels are denoted as: ***p<0.01p < 0.01p<0.01, **p<0.05p < 0.05p<0.05, *p<0.1p < 0.1p<0.1.

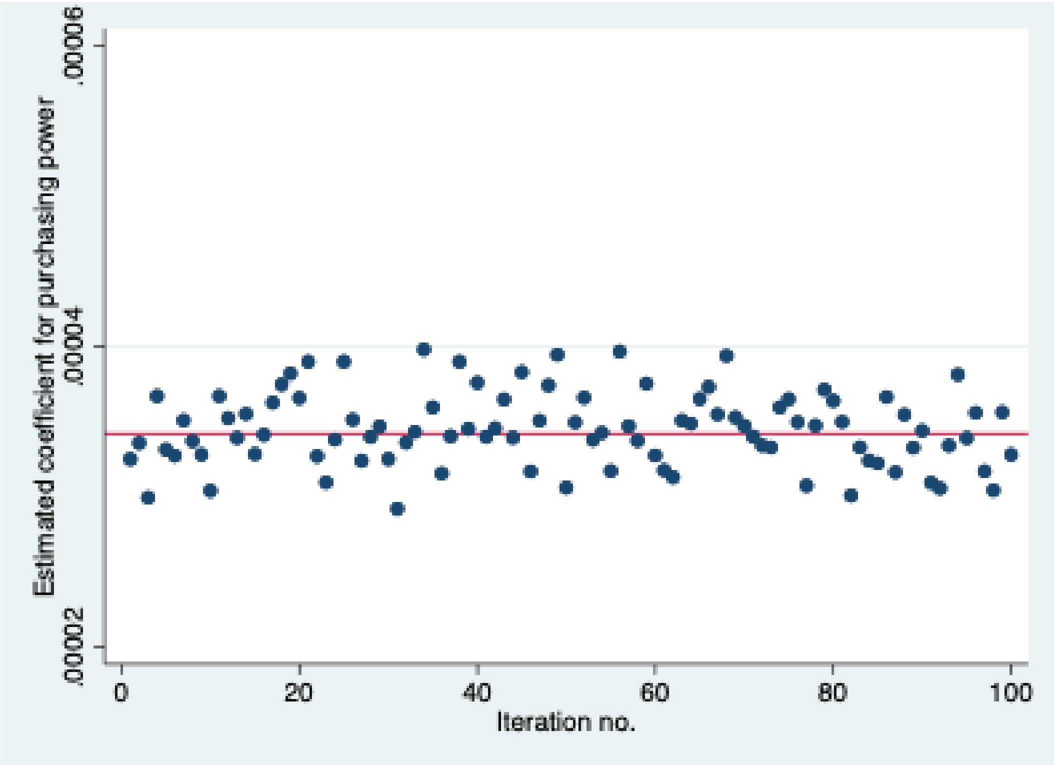


Figure 2: Estimates of the parameter purchasing power for 100 random draws of 90%

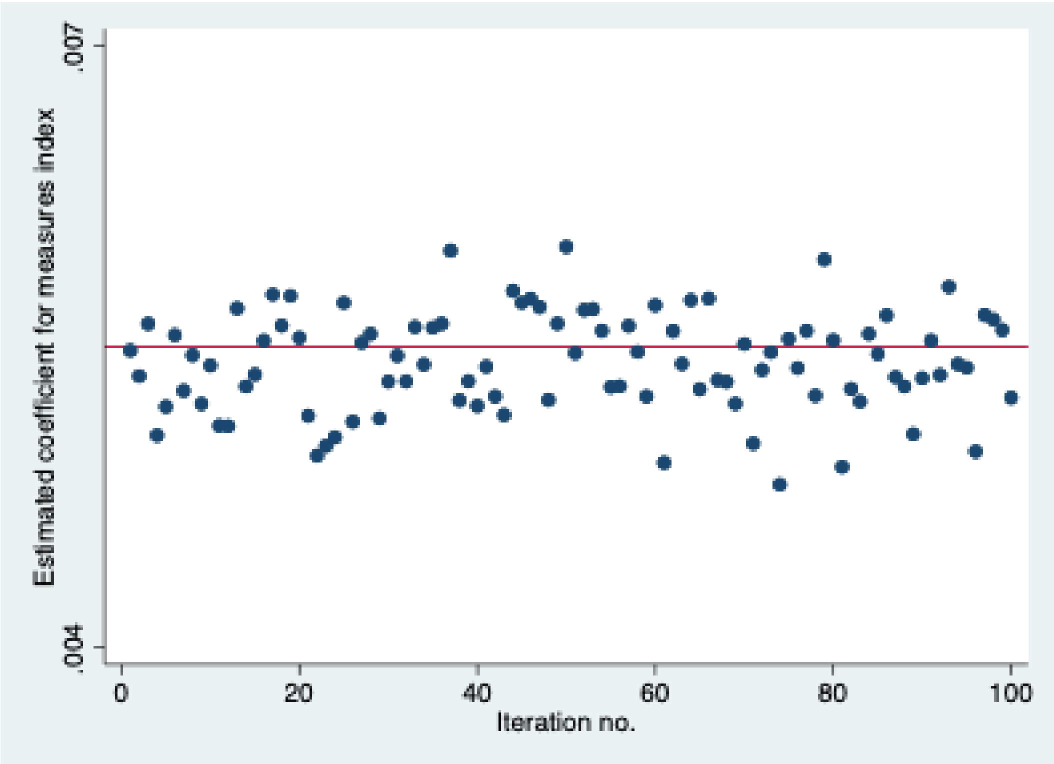


Figure 3: Estimates of the parameter measures index for 100 random draws of 90% of the districts.

Table 5: Coefficient estimator (only for the vector X, the vector WX was omitted) of the SDM model from Section 4.2 for truncated panels with the specified start date

	2012-2022	2013-2022	2014-2022	2015-2022	2016-2022	2017-2022	2018-2022	2019-2022	2020-2022
Population density	0.00002721	0.00001009	-0.00007245	-0.00010829	-0.00016545	-0.00035688	-0.00058811*	-0.00029467	-0.00019825
Purchasing power pc	0.00003418***	0.00003067***	0.00003102***	0.00003337***	0.00003454***	0.00006958***	0.0000408**	0.00001104	0.000009801
Unemployment rate	-0.02272259***	-0.02195099***	-0.0167043**	-0.01000503	-0.01780362*	-0.01525001	-0.03381761***	-0.03146295**	-0.01546875
Average age	-0.06716932***	-0.05830327***	-0.04472258***	-0.03947198***	-0.03008632*	-0.04644109**	-0.07093821***	-0.02103514	0.02690753
Interest mortgage (10y)	-0.27592003***	-0.33975795***	-0.32136801***	-0.32455429***	-0.42941255***	-0.29035971***	-0.46199201***	-0.51120305***	-0.59019575***
Interest x Unemployment	0.00713995***	0.0060304***	0.00360779*	0.00264756	0.00498481	0.00226586	0.00550585	0.00679964*	-0.00301178
Incidence rate (COVID-19)	0.00051853***	0.00044722***	0.00044049***	0.00040799***	0.0003534***	0.00032139***	0.00020047**	0.00014723*	0.0001467*
Measures index (COVID-19)	0.00550323***	0.00413787***	0.00398513***	0.00382253***	0.00212255**	0.0025865**	-0.00002962	-0.00172485	-0.00128618
Incidence x Measures	-0.00001711***	-0.00001478***	-0.00001452***	-0.00001362***	-0.00001307***	-0.00001181***	-0.000007396**	-0.000005484*	-0.000005571
Commuter flow	0.02376674***	0.02149662***	0.02336325***	0.02463432***	0.02571507***	0.01943014**	0.01421674	0.0168247	0.01967105
Overnight stays (tourist)	-0.00020402	-0.00033244	-0.0004105	-0.00113014	-0.00082917	-0.00174359	-0.00227361	-0.00202567	-0.00166824
Employees in creative sectors	-0.00526071*	-0.00658449*	-0.00759678*	-0.00783971	-0.00414355	-0.00013983	0.00081283	-0.0031555	-0.01560572
Share kindergarten	-0.00026784	-0.00033777	-0.00062589	-0.00059046	0.00025845	0.00166502	0.00160812	-0.00004701	0.00019748

Broadband supply	0.00046885***	0.00043834***	0.00048814**	0.00046389*	0.0006124**	0.00093119***	0.00110126**	0.00129793*	0.00208985**
Employees knowledge-intensive	0.00167966	0.00069441	-0.00031102	-0.00129638	-0.00301842	-0.00358559	-0.00630522	-0.00534482	0.00141116

Significance levels are denoted as: ***p<0.01p < 0.01p<0.01, **p<0.05p < 0.05p<0.05, *p<0.1p < 0.1p<0.1.

5. Discussion

A key challenge in interpreting the econometric results presented in Section 4 lies in distinguishing between the coefficient estimates in Table 2 and the direct and indirect effects reported in Table 3. Note that the coefficient estimates in our spatial model provide insights into the fundamental relationships between independent variables and property prices, serving as the foundation for deriving both direct (within-region) and indirect (spillover) effects.

Focusing on the results from the SDM to address Hypotheses 1 and 2, we observe that the estimated beta coefficients for both COVID-19 case numbers and containment measures are positively significant, while their corresponding theta coefficients are negatively significant. This pattern suggests that heightened pandemic pressure within a region, whether from increased case numbers or stringent containment measures, is associated with rising property prices in that area. This counterintuitive finding may be attributed to an increased demand for private living spaces during the pandemic. This association may be explained by an increased demand for residential properties as individuals seek more stable living environments during uncertain times, even if this necessitates paying higher prices (see Table 2).

From a spatial perspective, an intriguing observation emerges regarding the localized nature of these effects. The negative theta coefficient suggests that rising case numbers in one region may lead to declining property prices in neighbouring areas. This spatial spillover effect could be attributed to reduced mobility during the pandemic, as individuals tend to remain in familiar environments for organizational and safety reasons, potentially decreasing their propensity to invest in real estate in adjacent regions with high infection rates.

While our study does not provide direct statistical evidence for the following interpretations, they offer plausible economic explanations for the observed spatial dynamics. Stringent containment measures in one region may impact economic activity and purchasing power in neighbouring areas, particularly in highly interconnected regions. This could result in diminished demand for real estate in these adjacent areas, especially if economic pressures become palpable there as well. Furthermore, strict measures in one region may reduce the attractiveness of surrounding areas for commuters or potential new residents, as mobility and economic interconnectedness across the entire area may decrease.

Further examination of the significantly negative interaction effect (see Table 2) reveals that the combination of high case numbers and stringent containment measures tends to depress property prices within a region. This suggests a compounding effect where the deterrent impacts of both factors (case numbers and measures) are amplified when occurring simultaneously. A plausible interpretation is that the concurrent presence of high infection rates and strict containment policies may more severely impair regional economic activity and employment opportunities compared to the isolated occurrence of either factor, thereby reducing demand for real estate in the affected area. Note that such interaction effects are common in empirical economics and have been observed in various contexts, such as the interplay between monetary and fiscal policies on economic growth (Blanchard & Perotti 2002).

The significantly positive spillover effect (theta coefficient) aligns with this interpretation: When both high case numbers and stringent measures coincide in one region, neighbouring areas appear to benefit. This dynamic contrasts with the previously described effect of regional loyalty observed when considering only one factor in isolation. The simultaneous presence of both factors (case numbers and measures) alters the spatial dynamics of the real estate market.

In summary, this interaction demonstrates that the concurrent presence of high case numbers and strict containment measures in a region exerts downward pressure on local property prices, due to perceptions of reduced liveability or economic stability. Simultaneously, this combination leads to increased demand and rising prices in adjacent regions, suggesting a potential "displacement" effect. The interplay of these factors may thus trigger a more pronounced "push-and-pull" dynamic between affected and neighbouring regions, resulting in a spatial redistribution of property values.

Further examination of the direct, indirect, and total effects in Table 3 aligns consistently with the previously outlined narrative: The direct effects of both case numbers and containment measures are significantly positive, indicating that they lead to higher property prices within a region. This supports the earlier arguments regarding increased demand for private living spaces during the pandemic. Conversely, the indirect effects are negative, albeit not reaching statistical significance. The direct effect of the interaction term remains significantly negative, corroborating the notion of "displacement movements" to neighbouring regions as discussed earlier. It is important to note, however, that while the positive indirect effect of the interaction term aligns with our interpretation, it does not achieve statistical significance.

To address Hypotheses 3 and 4 presented in the introduction, we extended our models by incorporating additional interaction terms: population density × incidence, and broadband availability × containment measures (not shown in Tables 2 & 3). The primary results remain largely consistent with our initial findings. In the Spatial Durbin Model (SDM), the population density × incidence interaction yields a significant beta-coefficient of -5.31e-08 (SE = 1.08e-08, $p < 0.001$) and a non-significant theta-coefficient of 8.52e-08 (SE = 6.58e-08). The interaction between density and containment measures produces a significant beta coefficient of -4.55e-07 (SE = 1.29e-07, $p<0.001$) and a significant theta coefficient of 1.97e-06 (SE= 8.20e-07, $p<0.05$). For the broadband availability × containment measures interaction, we observe a non-significant beta-coefficient of 1.54e-05 (SE = 1.04e-05) and a significant theta-coefficient of 2.36e-04 (SE = 6.57e-05, $p < 0.001$) in the SDM.

These findings lend support to Hypothesis 3, which posits that densely populated areas experience outmigration in response to high case numbers or stringent containment measures. The significant negative interaction between population density and incidence suggests that in highly populated areas, increased case numbers indeed lead to a decline in property prices. This could indicate that in densely populated regions, individuals are more likely to relocate or reduce their property search activities due to heightened health risks associated with high infection rates. Moreover, the positive and significant theta-coefficient for the density × measures interaction implies that this outmigration from densely populated, high-incidence areas contributes to increased real estate demand in neighbouring regions. This spatial spillover effect suggests that people are not only avoiding these high-density areas but are also relocating to adjacent, less densely populated, or less affected regions. These findings provide empirical support for the urban exodus hypothesis.

Regarding Hypothesis 4, which posits a shift from office-based to remote work in areas with strict movement restrictions, our findings offer insights. The significantly positive beta coefficient for broadband availability indicates that improved broadband access in a region tends to increase property prices within that region. This supports the work substitution theory, as broadband access is a crucial factor in a region's attractiveness for remote work. Conversely, the negative and significant theta coefficient suggests that good broadband coverage in one region could lead to a decrease in property prices in neighbouring regions. This may indicate that well-connected regions attract potential property buyers from adjacent areas, potentially reducing demand in neighbouring regions.

Examining the interaction effects, the non-significant beta coefficient for the interaction between strict measures and broadband availability suggests that this combination does not have a strong effect on property prices within the region itself. However, the significantly positive theta coefficient for this interaction indicates that stringent measures combined with good broadband availability in one region positively influence property prices in neighbouring regions. This could be interpreted as strict restrictions combined with good broadband access in one region making surrounding areas more attractive, possibly because people seek to settle in nearby areas with less stringent restrictions but still offering good broadband connectivity.

These findings on the influence of broadband availability on real estate markets also have potential economic policy implications. The significant positive direct coefficient for broadband (Table 3) should not be interpreted as suggesting that increased broadband coverage is negative due to its association with rising property prices. Rather, it enhances a region's attractiveness as a "direct effect." However, this highlights the limitations of our analysis, as we cannot distinguish between price and attractiveness, or numerical demand based on the available data.

A significant economic policy implication of our study is the evidence that pandemics such as COVID-19 can function as price drivers in the real estate market, potentially increasing the risk of price bubble formation. This finding has important policy implications:

Firstly, policymakers should consider the potential risks of excessive price increases in the real estate sector during global health crises. The combination of low interest rates and government support measures can boost demand for real estate, thereby driving up prices. This phenomenon has been extensively discussed in the literature, for instance by Balemi et al. (2021).

Our results, which show significant positive effects of case numbers and government measures on property prices, suggest that pandemics dynamically influence real estate markets through specific demand shifts. Particularly during crisis periods such as the COVID-19 pandemic, high case numbers and stringent measures function as price drivers by promoting increased demand for living space and security in privately used properties. This carries the risk of demand rapidly transitioning into price bubbles, especially when population mobility and consumption behaviour are severely restricted.

This finding underscores the necessity for regulatory authorities to implement risk mitigation mechanisms to prevent speculative excesses in the real estate market. One potential approach could involve tightening credit lending guidelines that specifically target and counteract market overheating during such demand booms. These targeted measures could help maintain market stability without unduly restricting overall economic growth.

Our results, demonstrating significant positive effects of case numbers and government measures on property prices, prove robust across various specifications and regional subgroups. Notably, these effects were observed not only for property prices but also for rental rates. This suggests that pandemic-induced demand shifts affect both purchase and rental markets, indicating a comprehensive structural impact on the real estate sector. Such widespread effects highlight the need for policymakers to consider both homeownership and rental markets when formulating responses to crisis-induced market dynamics.

Further robustness analyses reinforce the stability of these findings. Our results remain consistent when estimating the model with various specifications, alternative weighting matrices, and accounting for potential endogeneity issues. This consistency demonstrates that the observed effects are largely independent of methodological and structural assumptions, lending credibility to our interpretation.

In conclusion, our discussion briefly addresses the influence of socioeconomic variables on property prices and their economic policy implications. Our findings are supported by existing literature, which reinforces confidence in our results. Population density is consistently described in the literature as a positively significant variable in relation to property prices (although not significant in our SDM and, as described in Chapter 4, carries a certain endogeneity risk). Examples from the literature include Ou et al. (2023) and Cellmer et al. (2020). The influence of unemployment rate can also be described as uniform in the literature. Examples supporting our results include Tomal (2019) and Cohen & Karpavičiūtė (2017).

While economic policy control options are limited for the above variables, they are more evident for variables such as average age (significantly negative, see e.g., Breidenbach et al. (2024) or kindergarten provision (significantly positive, scarcely studied in the literature, but see Koekkoek (2022). These findings suggest that an aging population may impair a region's economic dynamism, negatively affecting property demand and prices. To economically strengthen these regions, policy measures could aim to increase their attractiveness specifically for younger demographics. This is emphatically underlined by the significantly positive kindergarten coefficient. Investments in modern educational, leisure, and health facilities tailored to the needs of younger households can increase the appeal for young families and career starters. Targeted incentives, such as subsidies or tax relief for businesses, could create new jobs, particularly in innovative sectors attractive to younger workers.

While these insights are not novel from an economic policy perspective, the value of our analysis lies in substantiating them with quantitative empirical evidence.

Our study has several limitations that warrant acknowledgment and provide avenues for future research. A key limitation is the unavailability of interest rate data at the regional level. This constrains our ability to account for regional variations in interest rates that might differentially influence housing price changes across regions. However, we have mitigated this limitation by incorporating a reliable proxy variable through the interaction of unemployment rate and interest rates. This interaction captures the primary risk factor in property financing, as described in Chapter 4. Further, distinguishing between fundamental, long-term price increases and temporary effects due to COVID-19 remains challenging. The complex interplay of pandemic-related factors and underlying market dynamics makes it difficult to isolate persistent trends from transient shocks. Finally, the potential time lag in real estate markets should be discussed. Our dataset concludes in 2022, which may not fully capture the COVID-19 pandemic effect on the real estate market due to the protracted nature of property transactions. The full impact of the pandemic on housing markets may become more evident in subsequent years, suggesting the need for continued longitudinal studies.

6. Conclusion

This study contributes to the understanding of the regional dynamics within the German real estate market during the COVID-19 pandemic. By analysing 401 NUTS-3 regions from 2012 to 2022, we provide novel insights into how socio-economic variables, infection rates and government containment measures are associated with property prices. This research is the first to incorporate government COVID-19 measures as an explanatory variable in a spatial analysis of real estate prices, which adds a novel perspective to the existing literature. We employ advanced spatial econometric models to capture both direct effects within regions and indirect spillover effects to neighbouring areas, revealing intricate spatial dynamics often overlooked in previous studies. Our comprehensive approach, combining pandemic-specific data with traditional socio-economic variables, allows us to control for aspects of regional heterogeneity that might otherwise preclude the identification of COVID-19-related factors.

Our findings have important implications for both real estate market theory and regional economic policy. Specifically, our analysis revealed that regions with higher infection rates experienced increased property prices within the affected areas, while more restrictive mobility measures also tended to drive prices up. However, the interaction between these factors showed a negative effect, indicating that the price-increasing impact of infection rates was mitigated in areas with stricter containment measures. These results challenge conventional understanding of crisis impacts on property markets and reveal the multifaceted nature of pandemic-induced changes in housing demand and regional attractiveness.

We observed negative spillover effects to neighbouring districts, indicating a complex spatial dynamic in the real estate market during the pandemic. The pandemic has not only accelerated existing trends but also introduced new patterns in housing demand, particularly with the rise of remote work, highlighting the need for improved digital infrastructure to support these shifts. These findings suggest a interplay between health risks, government interventions, and housing demand across regions. From a theoretical perspective, this highlights the need to incorporate crisis-induced behavioural changes, policy responses, and spatial interdependencies into models of real estate market dynamics. For policymakers, our results underscore the importance of considering both direct and indirect consequences of public health measures on housing markets across different spatial scales. They also point to the necessity of developing regionally tailored approaches to housing policy that account for the diverse and sometimes contrasting impacts of large-scale crises like pandemics on local and neighbouring property markets.

Our findings highlight the need for differentiated regional real estate policies that account for the varying impacts of socio-economic and pandemic-related factors. Specifically, policymakers should recognize that regions with high infection rates may require targeted interventions to stabilize property markets, while areas experiencing negative spillover effects from neighbouring districts might need support to mitigate declining property values. Additionally, integrating social infrastructure considerations, such as childcare availability and digital connectivity, as well as addressing demographic trends through initiatives aimed at attracting younger populations, is crucial for enhancing the vitality of aging regions and stabilizing property markets. These tailored approaches can enhance resilience in local property markets and address the complex dynamics revealed by our study, fostering more sustainable urban and regional development.

Looking ahead, our findings open several avenues for future research. Long-term studies tracking the persistent effects of the pandemic on property markets and migration patterns would be particularly valuable. Additionally, investigating how the interplay between remote work trends and regional attractiveness evolves over time could offer further insights into post-pandemic urban development. However, a potential shortcoming of our study is its focus on Germany, which may limit the generalizability of our findings to other contexts. This study contributes to a deeper understanding of real estate market dynamics during crises, highlighting the complex interactions between health risks, policy interventions, and socio-economic factors that shape property markets.

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