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Aging and Urban House Prices

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Aging and Urban House Prices

Paper submitted for presentation at the Vfs Annual Conference 2015

Abstract

This paper investigates the long-run relationship between the size and age structure of a city's resident population and the price of local housing. For estimation purposes, we combine city-level demographic information with housing price data for 87 cities in Germany over 1995-2012. Employing a panel error correction framework that accounts for the evolution of city income and housing financing costs, we find that real urban house prices perform stronger in cities that age less rapidly. A combination of the empirical estimates with current population projections suggests that population aging will exert considerable downward pressure on urban house prices in upcoming years.

Keywords: Urban house prices · Demographic change · Germany

JEL classification: G12 · J11 · R31

1 Introduction

Housing is a dominant asset in the household portfolio. At the same time, a considerable part of housing capital in modern economies is concentrated in urban areas.¹ Wealth formation in the private sector is therefore closely tied to the evolution of house prices in the very same locations that lie at the heart of economic activity (Rosenthal and Strange 2004). Since a substantial part of housing capital is debt-financed, unforeseen city house price developments can threaten household net wealth and financial stability (Mian and Sufi 2009). The systemic relevance of urban house prices is further amplified by evidence that real house price changes in cities tend to “ripple” towards geographically adjacent regions (Meen 1999, Lee and Chien 2011).

The aim of this paper is to empirically examine the hypothesis of a long-term equilibrium relationship between urban house prices and the size and age structure of cities. Housing market effects of demographic change have been a vital area of research since the seminal paper of Mankiw and Weil (1989). Eichholtz and Lindenthal (2014) recently provide microeconomic evidence that individual housing demand depends heavily on demography and education. This supports earlier studies like Green and Hendershott (1996) or Ermisch (1996). Recent studies based on macro data also suggest strong empirical links between housing prices and demography at both the national and regional level: Takáts (2012) finds that real house price growth across OECD countries over 1970-2009 was promoted by population growth but depressed by an aging population, *ceteris paribus*.² Saita et al. (2013) confirm these findings based on data for Japanese prefectures and US states over 1976-2010 and 1975-2011, respectively. Their results point towards even stronger house price effects of demography. Especially for Japanese prefectures, the coefficients estimated on the age structure are larger, while those estimated on total population are comparable to those found by Takáts.

Given that housing markets are local by nature, there is a surprising paucity of studies that investigate the long-term housing price effects of demography using city data.³ One of the few exceptions is Maennig and Dust (2008), who study the quantita-

¹ The term “urban area” usually extends to cities, towns as well as larger to conurbations. In this paper, we refer to urban areas as 87 administratively self-standing German cities.

² Takáts’ favorite specification suggests the elasticity of real house prices with respect to total population size to be 1.05, while the elasticity with respect to age structure (old age dependency ratio) is -0.68. According to these findings, the major directional shift to demographic change in the upcoming four decades is expected to decrease real OECD house prices by around 80 basis points per annum on average.

³ Research based on local housing market data has concentrated on the short-run, cyclical behavior of metropolitan housing prices. Some studies focus on transitory metropolitan house price bubbles (Gallin 2008, Goodman and Thibodeau 2008, Glaeser et al. 2008). Others focus on the time series properties of city-level house price data (Capozza et al. 2002, Miller and Peng 2006). Another line of papers has concentrated on heterogeneity with regard to the reactions of city-level house prices to a monetary stimulus or shocks to aggregate macroeconomic variables (Himmelberg et al. 2005, Carlino and DeFina 2008). Yet another strand investigates endogenous contagion and co-cyclicity among metropolitan housing prices (Beenstock and Felsenstein 2010, Kuethe and Pede 2011, Brady 2011, Zhu et al. 2013).

tive relationship between the 1992-2002 percentage change in population and 2002 single-family house prices across 98 German cities. Their analysis suggests no statistically significant relationship between house prices and past population increases, whereas population decline between 1992 and 2002 is associated with significantly lower price levels in 2002. Since their analysis draws on cross-sectional price information only, they could neither assess the long-term effects of gradual changes to population size nor the long-term effects of gradual shifts to a city's age structure on local housing prices.

We add to the existing literature with two main contributions. First, we estimate long-run cointegration relationships between the main variables of interest in a city panel error correction framework. For this purposes, we combine socio-demographic information with housing price data for 87 German cities over 1995-2012. In using German data, we can exploit an exceptionally large variation in demographic developments across local housing markets in order to identify their long-term price effects. Second, based on a combination of our econometric estimates with population forecasts from official sources, we provide probabilistic projections of demography-induced house price effects for each city until the year of 2020. The availability of detailed official demographic projections for each city in the sample is another key advantage of using German data.

Prior to estimating a reasonable econometric model, we argue theoretically that along with changes in the number of households, changes in the age structure of cities can alter the demand for local housing services and housing as a capital good considerably. We point out that the long-term housing price reactions to these demand changes depend on the size of housing supply elasticity, which is reflected in our empirical estimates implicitly. Our econometric results support the hypothesis that the development of a city's size and age structure over time is a fundamental determinant of local long-run house price evolutions. The probabilistic projections of future price trajectories demonstrate that housing equity in many German cities is likely to face considerable headwinds from population aging in upcoming years. We argue that this result is transferable to other countries with similar demographic prospects.

The remainder of this paper is organized as follows. Section 2 reviews theoretical hypotheses regarding the effects of urban demography on house prices. Section 3 introduces the data set, discusses the panel stationarity properties of the data and presents key facts regarding past and expected future demographic developments in Germany. Section 4 considers the econometric framework, presents the econometric results and discusses probabilistic projections of future urban house prices. Section 5 concludes with policy implications.

2 Theory of urban demography and house prices

Economic theory suggests at least three distinct channels by which gradual changes in the total size and age structure of a city's resident population affect local house prices. The first channel is the effect of both demographic variables on the *demand for housing services*. Along with incomes and preferences, the total number of households residing in a city determines the total demand housing services, which in turn determines real house prices in interaction with available housing supply (DiPasquale and Wheaton 1994). The price change due to a shift in total household population can be labelled as size effect. In addition to the size effect, households' demand for housing services underlies a life cycle (Pitkin and Myers 1994, Flavin and Yamashita 2002). Housing services demand is comparatively low during schooling years, increases with labor market entry, peaks at starting and maintaining a family and decreases again in retirement age.⁴ This can be labelled as age effect. Assuming that the long-run city housing supply schedule is finitely elastic, the size effect suggests that if the total number of households in a city increases, so do house prices. The age effect suggests that real house prices decrease if the number of retirement age relative to working age individuals in a city shifts upward.

A second channel refers to the *investment demand for housing* as a durable asset. Young households purchase urban housing capital as a conduit of saving and retirement provision and dissolve (parts of) their housing assets to move to peripheral locations or to rent again in retirement age (Henderson and Ioannides 1983, Kraft and Munk 2011). Analogous to housing services demand, an upward shift in the number of retirement age relative to working age individuals in a city thus implies lower investments demand for urban owner-occupied housing. Again, the long-run price effects of these demand changes depend on the price elasticity of housing supply. Different from housing services demand, the price effects of aging on investment demand are intrinsically self-reinforcing: Forward-looking home buyers anticipate future price declines caused by forthcoming increases in the ratio of sellers to buyers in the market. Since lower expected real house price gains raise housing capital costs, this decreases housing investment demand and prices further today.

A third, more subtle effect concerns the *supply side* of urban housing markets. Local demography is unlikely to affect local construction costs given that construction workers as well as other movable inputs can be hired from elsewhere. However, an essential production factor that may be affected by demography is the amount of land that is made available for new local construction. Anticipating population decline and aging, city planners may opt for tighter zoning to stabilize prices in the stock. Another possi-

⁴ In the presence of borrowing constraints and other frictions, households face obstacles of smoothing housing services consumption over the life cycle and will purchase self-owned housing (which often requires a down payment and high levels of creditworthiness) in later stages in life.

bility is to remove excess housing through demolition. Both options were realized at considerable scale in eastern German cities since reunification (Bernt 2009).

Since we are interested in the long-term price effects of shifts to local demography, our identification strategy relies on the assumption that housing supply is finitely elastic in both directions and can by itself be affected by demography. The partial elasticities of real urban house prices with respect to key demographic variables then reflect the joint effect of these fundamentals on the demand for housing services, the investment demand for housing capital, and the local land market.

Based on the prior theoretical considerations, we define our baseline regression model as follows:

$$P_{it} = \beta_0 + \beta_1 HHPOP_{it} + \beta_2 OADR_{it} + \beta_3 INC_{it} + \beta_4 HCR_{it} + \beta_5 INT_t + \mu_i + \varepsilon_{it} \quad (1)$$

where P_{it} is real house price in city i at time period t , $HHPOP_{it}$ is total household population, $OADR_{it}$ is the number of retirement age to working age residents (the old age dependency ratio) and INC_{it} is real average income per capita. In view of recent empirical evidence that individual education is another key determinant of housing services demand at the household level, we additionally include the number of city workers with college-level education relative to those without any formal education, which we call the city's human capital ratio (HCR_{it}). To account for changes in housing financing costs over time, INT_t indicates the national mortgage interest in year t . The μ_i represent unobserved city-level effects, while ε_{it} is a disturbance term with usual properties. We will evaluate the empirical evidence in favor or against the predictions of theory based on the statistical significance and economic relevance of β_1 and β_2 .

3 Data

3.1 Data set

Our econometric analysis relies on a panel data set with 87 German cities on its cross-sectional dimension and 18 years (1995-2012) on its time period dimension. Such data sets are commonly termed *macro panels* or *time series panels* in the literature. Panels characterized by a moderate size of groups and a substantial size of time periods are typically characterized by panel heterogeneity and non-stationarity in the individual time series (Banerjee 1999, Phillips and Moon 2000). Such data sets offer econometric opportunities that differ to a large degree from micro panels. Most notably, they allow dealing with dynamics flexibly and enable the identification of long-term equilibrium relationships (Eberhardt and Teal 2011). . In urban and regional economics, the analysis of non-stationary time series panels with appropriate methods is still scarce⁵: Apergis et al. (2010) investigate the relationship between regional corruption and income.

⁵ The majority of empirical research in the field implements micro panel methods. Time series panel data sets and the respective methods are traditionally more common in international country-level analysis.

Beenstock and Felsenstein (2010) and Holly et al. (2010) are few examples analyzing regional housing prices.

Table 1 reports our variable definitions and data sources. As a representative measure of urban house prices, we use assessed typical resale prices of owner-occupied apartments of medium size, quality and location. The data on house prices is provided by the private consulting firm Bulwien Gesa.⁶ The price information relies on standardized annual surveys among local brokers, appraisers and surveyors. It is used for housing market analysis by the German Bundesbank (Kajuth et al. 2013) and widely respected as a valid indicator of spatially disaggregated house prices.⁷ The real house price in city i at time period t is defined as the average price in EUR per square meter corrected for consumer price inflation in the same period.

Table 1. Variable definitions and sources.

Variable	Definition	Source
Real house price	Real resale apartment price in EUR per sqm	BulwienGesa
Total household population	Number of households in a city	German Federal Institute for Research on Building, Urban Affairs and Spatial Development
Old age dependency ratio	Ratio of retirement age to working age residents	German Regional Statistical Office
Income per capita	Real GDP divided by number of employees	German Federal Statistical Office (GDP) and German Federal Institute for Research on Building, Urban Affairs and Spatial Development (employees)
Human capital ratio	Ratio of high qualified to low qualified workers	German Federal Employment Office
Real mortgage interest rate	Interest rate on building society mortgages minus inflation rate	German Bundesbank

As a measure of the local demand for housing services, we calculate annual city-level household populations combining time series on population obtained from the German Federal Statistical Office with information on average local household size from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (*Bundesinstitut für Bau-, Stadt- und Raumforschung*, BBSR). As a measure of a city's

⁶ Owner-occupied apartments can be considered as a specific type of housing that urban households in Germany are invested in. In comparison to single-family or two-family houses, which are typically prevalent in urban surroundings or more peripheral locations, owner-occupied apartments are typically located in multi-family houses in central urban locations. If defined as the proportion of all residential dwellings that are occupied by their owners, the German home ownership rate is 42.6 per cent (2011 Census). This corresponds to 17.3 million owner-occupied dwellings. 3.5 million, or 20 per cent of all 17.3 million owner-occupied dwellings, are located in city-dominating multi-family buildings.

⁷ The national home price index published by the Federal Statistical Office is derived from disaggregated data reported by public local boards of surveyors (*Lokale Gutachterausschüsse*).

age structure, we compute the old age dependency ratio as the proportion of retirement age (65 years or older) to working age (20-64 years) residents.⁸ As a measure of local purchasing power, we measure annual real city income as total production in city i in year t corrected for CPI inflation in the same period, divided by the total number of employees in the same year. As a measure of urban education, we define the human capital ratio as the proportion of high-qualification jobs (workers with a college degree) to low-qualified jobs (workers without any formal labor market qualification) in the city using information from the German Federal Employment Office. As a measure of the real private housing financing cost at the national level, we use the CPI inflation-corrected effective interest rate on building society mortgages. Interest rate and CPI inflation data are obtained from the German Bundesbank.

Figure 5 illustrates the geographic locations of the 87 cities in the data set. In total, the cities encompass 30.5 per cent of the German population and 33.2 per cent of all households according to the 2011 Census. Table A1 in the Appendix lists mean values and standard deviations of each variable and city over the sample period.

Figure 5. Geographic locations of all 87 cities in the sample.



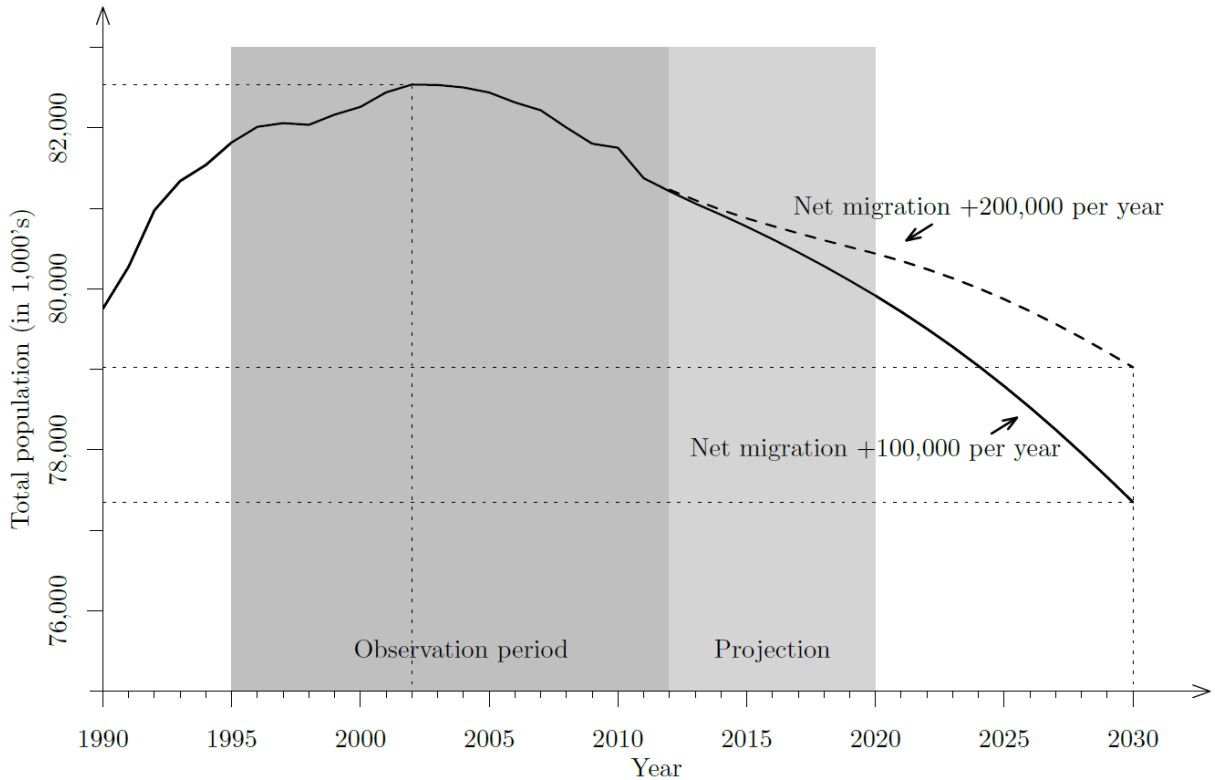
Source: Authors' own visualization using Google Maps.

⁸ Compared to other statistics related to the age distribution of the resident population, such as the median age or skewness measures, the old age dependency ratio is a both economically plausible and compact measure of urban demography. We expect changes in the urban old age dependency ratio over time to capture the underlying economic problem of gradual shifts in the relative proportion of suppliers and demanders in the urban housing market.

3.2 National and city-wide demographic trends in Germany

Like other industrial economies as the US or Japan, Germany will be severely affected by demographic change in upcoming decades. According to the most recent population projection by the German Federal Statistical Office, Germany's total population will decline by 14 to 20 per cent until 2060 based on 81 million in 2012 (Destatis 2009).⁹ The main cause for this shrinkage is Germany's low total fertility rate. Importantly, inward migration may dampen the overall decline in population, but not stop it. Using data from the "medium variant" projection, Figure 1 shows that even under the optimistic assumption of a net migration balance of +200,000 annually, total population will decrease by about two million inhabitants between 2012 (the end year of our sample period) and 2030. For sake of transparency, the projection period for our own house price forecasts is shaded in light grey.

Figure 1. Total population in Germany until 2030



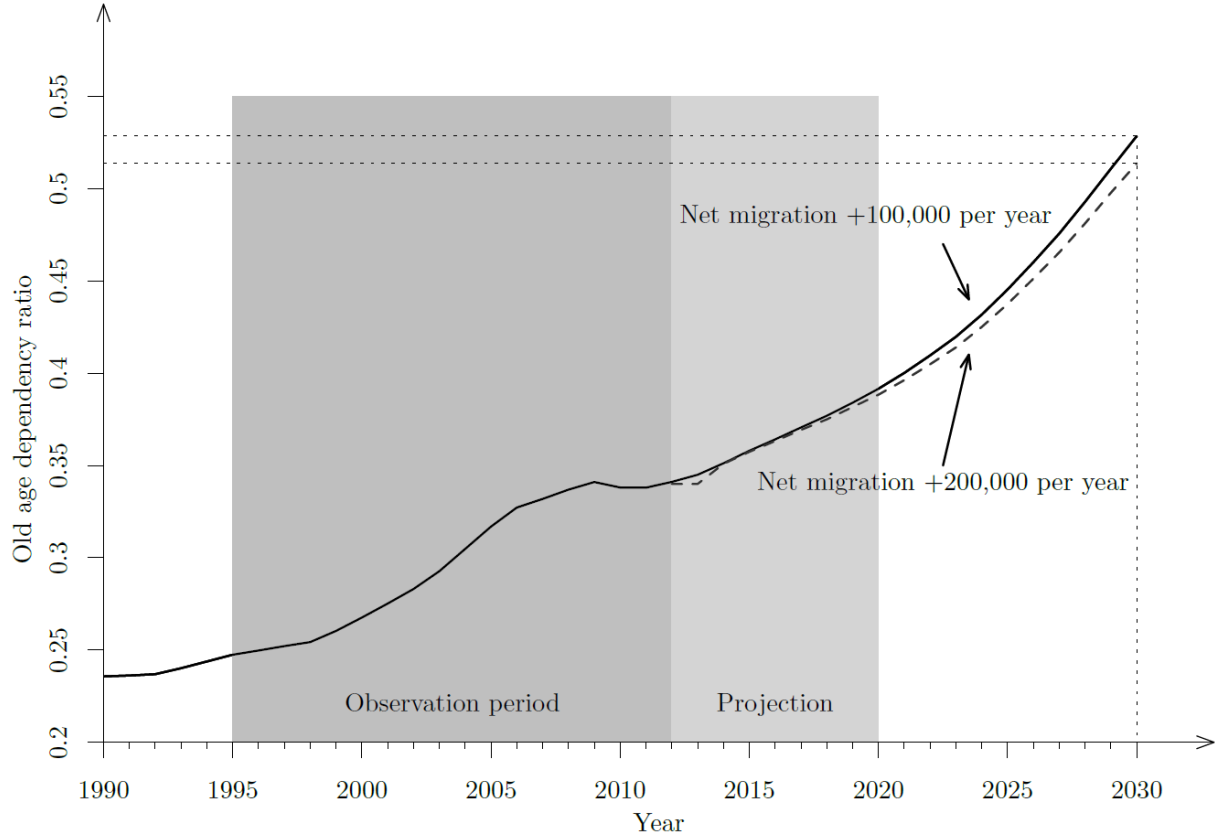
Source: German Federal Statistical Office, 12th Coordinated Population Projection, Var. 1-W1/2

In addition to overall decline, the German population's age profile will undergo substantial change. Due to the low fertility rate and a longer life expectancy, the share of elderly in the population will increase considerably. We illustrate this development in Figure 2 by displaying the past and projected temporal evolution of the nationwide old age dependency ratio, again using information from the medium variant population forecast scenario of the German Federal Statistical Office. According to this forecast

⁹ Since projections on household numbers are not available for the nation, we rely on population figures to illustrate demographic trends at the nation level.

scenario, Germany's nationwide old age dependency ratio will increase from 0.35 in 2012 to more than 0.5 in 2030, showing little sensitivity to net migration. This development is quite noteworthy: compared to the projected decrease in total population of 1.5-3 per cent over the same time horizon, the scenario implies an upward shift in the old age dependency ratio of more than 40 per cent over 2012-2030.

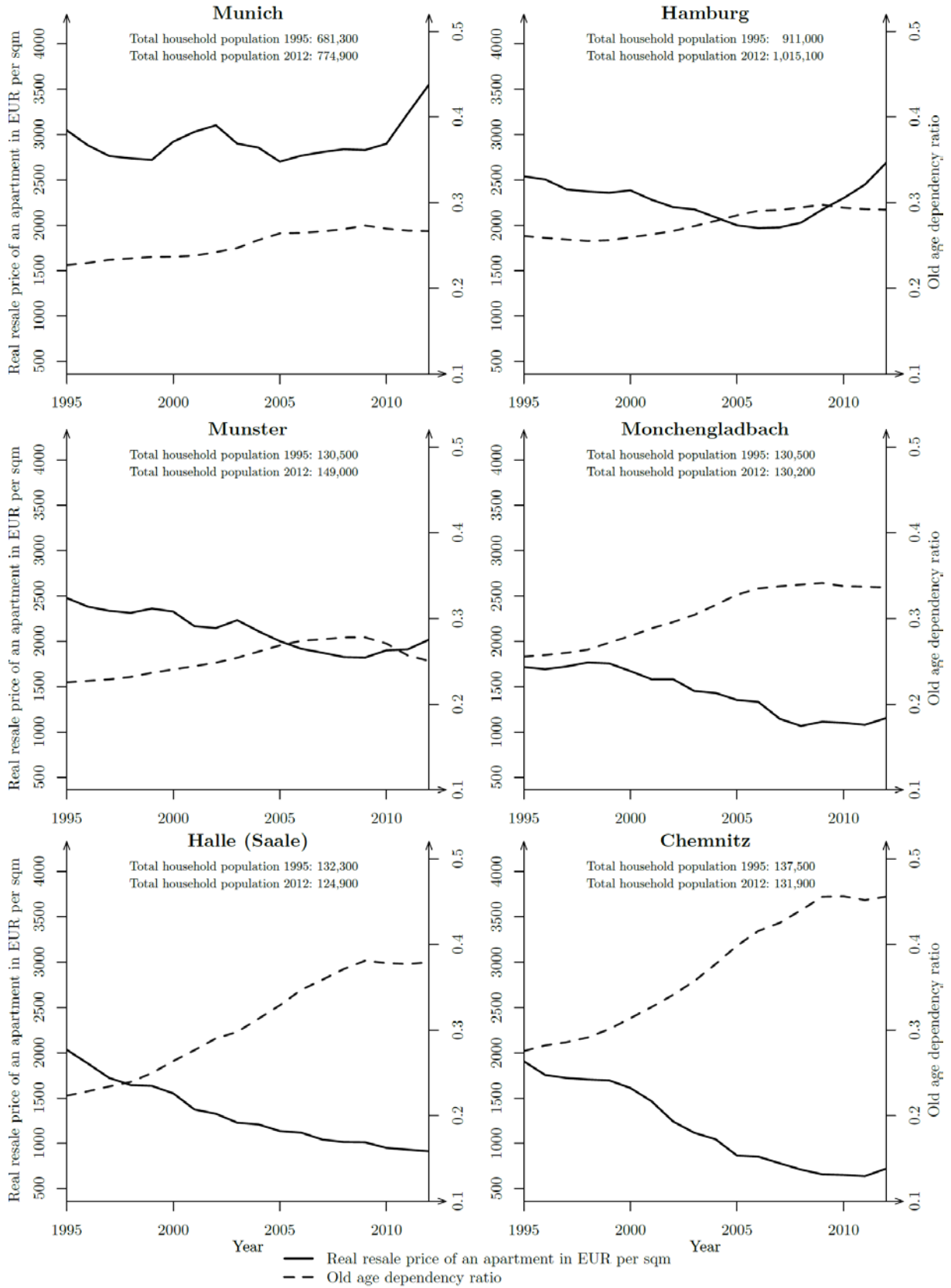
Figure 2. Old age dependency ratio in Germany until 2030.



Source: German Federal Statistical Office, 12th Coordinated Population Projection, Var. 1-W1/2.

A distinct feature of demographic change is its high spatial diversity. Our data reveal that the cross-sectional variation in the temporal development of household population figures and old age dependency ratios across German cities over the sample period 1995-2012 was indeed substantial. Figure 3 displays six different characteristic cases illustrating this variation. Tentatively, more positive demographic developments appear to go along with better performing real urban house prices. For example, in Munich, Bavaria (upper left panel), total household population displayed a continuous increase over 1995-2012, while the old age dependency ratio was low and remained at a constant level. Real house prices in this city displayed a positive trend. The Saxon city of Chemnitz (lower right panel) is an example for exactly contrary developments: Household population declined from 0.138 to 0.132 million over 1995-2012, while the old age dependency ratio increased substantially from 0.28 to 0.45 (a relative increase of 60 per cent). At the same time, real house prices declined by more than 50 per cent. The other four examples display cities that range in between these two extreme cases.

Figure 3. Six examples for city-wide house price, population and old age dependency ratio evolutions, 1995-2012.



Sources: *BulwienGesa*, German Federal Statistical Office, authors' own calculations.

4 Empirical methodology and results

In a first step, we analyze the stationarity properties of our data with established panel stationarity and panel cointegration tests. In a second step, we estimate a panel error correction model (PECM) based on the work of Pesaran and Smith (1995) and Pesaran et al. (1999). The time dimension of our panel data is not large enough to allow reliable inference on the cointegration parameters in each time series separately. However, annual observations of 18 years allow measuring the long-run house price elasticities of our variables of interest based on restrictions on heterogeneity in the cointegration relationships. We exploit the cross-section information of the panel data by group pooling, based on the assumption of strong commonalities across the 87 cities in our sample. Specifically, we assume common long-run cointegration relationships between housing prices and our main explanatory variables among all cities, but allow for heterogeneity across groups in short-run dynamics (Pesaran et al. 1999).

4.1 Panel unit root and cointegration tests

Inference techniques for unit root testing in panel data encompass a substantial body of literature (Harris and Tzavalis 1999, Choi 2001, Levin et al. 2002, Im et al. 2003). Panel unit root tests are based on a first-order autoregressive model allowing for two-way unobserved effects and time trends:

$$\Delta y_{it} = \alpha_i + \theta_t + \delta t + \rho_i y_{i,t-1} + \varepsilon_{it} \quad (2)$$

where y_{it} is the variable of interest, α_i and θ_t represent group and time fixed effects, δt is a deterministic time trend and ε_{it} is a normally distributed error term. Depending on whether the specific test assumes homogeneity or heterogeneity in the autoregressive parameter, the tests involve the null hypothesis that all panels are integrated of order 1 versus the alternative that either all or a fraction of the panels form stationary series.

We employ different types of tests to test the hypothesis of non-stationarity of our panel data. The Levin-Lin-Chu (LLC) test can be viewed as a pooled Augmented Dickey Fuller test because it assumes that all panels have the same autoregressive parameter, $\rho_i = \rho$. In the absence of a deterministic term, the test allows the number of time periods to tend to infinity at a slower rate than the number of cross-sectional units, though T must go to infinity sufficiently fast to secure that $\lim_{N,T \rightarrow \infty} \sqrt{N}/T = 0$. The Harris-Tzavalis (HT) test also assumes homogeneity in the autoregressive parameter. However, different from the LLC test, the number of time periods is fixed (Harris and Tzavalis 1999). The Im-Pesaran-Shin (IPS) test allows each group to have its own autoregressive parameter ρ_i instead of a common ρ (Im et al. 2003). The IPS statistics assume that the number of time periods is fixed while N tends to infinity.

First, we apply each test to the natural logarithms of real city house prices, total household population, old age dependency ratios, income per capita, human capital

ratios, and the real mortgage interest rate in their respective levels. Second, the tests are applied to the first differenced panel series of each variable in logs. For both cases, all tests are performed with and without the inclusion of a deterministic time trend. Appropriate lag lengths are chosen based on the Akaike Information Criterion.

The upper part of Table 2 reports the test results for the non-differenced variables. Except for the LLC test, the null hypothesis of non-stationarity cannot be rejected in most cases, which indicates that at least some variables are I(1). In these cases, a first-difference transformation of the data is needed to generate a stationary time series (Hamilton 1994). The lower part of Table 2 lists the test results after this transformation is taken. Each test rejects the null hypothesis of non-stationarity at common significance levels for each variable except for the old age dependency ratio, where rejection is possible only in two of six cases.

Table 2. Panel unit root tests

Variables	Levin-Lin-Chu		Im-Pesaran-Shin		Harris-Tzavalis	
	$H_0: \varrho_i = \varrho$ for all i $H_a: \varrho < 1$ $T \rightarrow \infty, N \rightarrow \infty$		$H_0: \varrho_i = 1$ for all i $H_a: \varrho_i < 1$ T is fixed, N is fixed		$H_0: \varrho = 1$ $H_a: \varrho < 1$ T is fixed, $N \rightarrow \infty$	
	No trend Test statistic	Trend Test statistic	No trend Test statistic	Trend Test statistic	No trend Test statistic	Trend Test statistic
Levels						
Log real house price	-8.3540 ***	8.7452	-0.3307	12.3455	0.9161	0.8657
Log total household population	-3.3291 ***	-12.7289 ***	5.6639	-4.6835 ***	0.9961	0.7435
Log old age dependency ratio	-15.0019 ***	8.4740	-3.7428 ***	7.6103	0.9504	1.0678
Log income per capita	-3.2574 ***	-8.9903 ***	-1.0221	-4.1044 ***	0.7572 ***	0.4479 ***
Log real mortgage interest rate	13.8687	5.5116	15.3328	-2.7545 ***	1.0092	0.3228 ***
Log human capital ratio	3.9977	-8.2448 ***	15.4250	-1.3790 *	0.9893	0.7537
Differences						
Δ log real house price	-1.3665 *	-5.6437 ***	-3.0969 ***	-1.7243 **	0.2181 ***	0.2751 ***
Δ log total household population	-11.6081 ***	-9.0037 ***	-8.0989 ***	-1.4385 *	0.2296 ***	0.4934 ***
Δ log old age dependency ratio	1.7083	-8.9246 ***	3.0505	3.9729	0.7646 ***	0.8355
Δ log real GDP per employee	-21.6622 ***	-19.0850 ***	-19.9770 ***	-15.2730 ***	-0.1721 ***	-0.1173 ***
Δ log real mortgage interest rate	-5.3395 ***	-5.5048 ***	-8.7086 ***	-3.2233 ***	-0.0667 ***	-0.0667 ***
Δ log human capital ratio	-15.7860 ***	-18.2613 ***	-17.2327 ***	-15.8501 ***	0.0334 ***	0.1328 ***

(* , **, *** denote statistical significance at the 10%-, 5%- and 1%-level, respectively)

If a long-run equilibrium relationship exists between two or more I(1) variables, such that the residuals of a regression of the first variable in levels on a linear combination of the other variables in levels are I(0), then these variables are said to be cointegrated (Engle and Granger 1987). In order to identify cointegration relationships in a panel context, Kao (1999) and Pedroni (1999, 2004) provide residual-based tests. The Kao Augmented Dickey Fuller test (Kao 1999) assumes that the cointegration relationship in each group is homogenous, whereas tests proposed by Pedroni (1999, 2004) allow for heterogeneity in the cointegrating vector. We generate the required residuals based on the theoretically motivated regression relationship presented in Section 2, which explains urban real house prices by means of a linear combination of household numbers,

age structure, income per capita, the human capital ratio and financing costs. In order to account for potential sensitivity of the cointegration tests with respect to different specifications, we apply the tests to different combinations of the explanatory variables (Table 3). The Kao ADF test, the Pedroni panel and Pedroni group tests generally suggest a cointegration relationship between the variables of interest, which is identical among cities in most cases.¹⁰ There is thus supportive evidence that the variables of interest tend towards long-run equilibrium.

Table 3. Panel cointegration tests

Variables	Specification			
	[1]	[2]	[3]	[4]
Log real house price	x	x	x	x
Log total household population	x	x	x	x
Log old age dependency ratio	x	x	x	x
Log income per capita	x	x	x	x
Log human capital ratio			x	x
Log real mortgage interest rate		x		x
Cointegration tests				
Kao ADF-statistic	-4.9407 ***	-3.3990 ***	-3.9364 ***	-4.2792 ***
Pedroni panel v-statistic	1.7056 **	-1.4512	0.9427	-2.2468
Pedroni panel rho-statistic	2.4435	5.2398	5.0082	7.3515
Pedroni panel PP-statistic	-3.6388 ***	-2.7785 ***	-2.1498 **	-3.3356 ***
Pedroni panel ADF-statistic	-4.1325 ***	-1.8974 **	-3.2928 ***	-2.3632 ***
Pedroni group rho-statistic	5.5255	8.3486	7.8563	10.5082
Pedroni group PP-statistic	-6.8314 ***	8.8133 ***	-8.0500 ***	-15.6458 ***
Pedroni group ADF-statistic	-6.4813 ***	-4.3851 ***	-5.4702 ***	-5.4491 ***

(* , ** , *** denote statistical significance at the 10%- , 5%- and 1%-level, respectively)

4.2 Results of panel error correction models

Different techniques are available for the estimation of panel error correction models in which the short-run dynamics are heterogeneous across groups. The mean-group (MG) estimator (Pesaran and Smith 1995) averages the coefficients of N single time-series regressions and allows the intercepts, slope coefficients and error variances to differ across groups. The pooled mean-group (PMG) estimator (Pesaran et al. 1999) relies on a combination of pooling and averaging the coefficients. Like the MG estimator, it allows for heterogeneous short-run dynamics, but constrains the long-run elasticities to be equal across groups. Pooling yields efficient and consistent estimates when the re-

¹⁰ Following Pedroni (1999), the within-dimension statistics (panel) are constructed by summing both the numerator and the denominator terms over the N dimension separately, whereas the between-dimension (group) statistics are constructed by first dividing the numerator and the denominator prior to summing over the N dimension. Because the between dimension do not presume a common first-order autoregressive parameter, it allows to model an additional source of potential heterogeneity across individual cities.

restrictions are valid. Common dynamic fixed-effects estimation (DFE) additionally captures individual unobserved effects on house prices across cities. Like the PMG estimator, it restricts the coefficients of the co-integrating vector to be homogenous across cities. The speed of adjustment coefficient and the short-run coefficients are also assumed as equal.

Building up on the baseline regression model, we define the long-run real house price function as follows:

$$P_{it} = \beta_0 + \beta_{1t}D_{it} + \beta_{2t}E_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

where P_{it} is log real house price, D_{it} is the vector of explanatory demographic variables, E_{it} is the vector of explanatory economic variables, and μ_i is the group-specific unobserved effect. Against the background of panel stationarity and cointegration testing, we assume that the variables in levels follow an I(1) process and are cointegrated. The ARDL(1,1,1) dynamic panel specification of (20) can be stated as:

$$P_{it} = \delta_{10i}D_{it} + \delta_{11i}D_{i,t-1} + \delta_{20i}E_{it} + \delta_{21i}E_{i,t-1} + \lambda_i P_{i,t-1} + \mu_i + \varepsilon_{it} \quad (4)$$

where λ_i are scalars. The error correction representation of (21) is:

$$\Delta P_{it} = \delta_{11t}\Delta D_{it} + \delta_{21t}\Delta E_{it} + \phi_i(P_{i,t-1} - \beta_{0i} - \beta_{1i}D_{it} - \beta_{2i}E_{it}) + \varepsilon_{it} \quad (5)$$

where $\phi_i = -(1 - \lambda_i)$, $\beta_{0i} = \frac{\mu_i}{1-\lambda_i}$, $\beta_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1-\lambda_i}$, and $\beta_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1-\lambda_i}$. The estimated values β_{1i} and β_{2i} are the long-run coefficients of demographic and economic fundamentals and can be readily interpreted as elasticities. The error-correction adjustment parameter ϕ_i is expected to have a negative sign if the variables return to long-run equilibrium after a shock.

Our baseline regression specification explains the evolution of real urban house prices with the temporal evolutions of the total number of resident households, old age dependency ratios and the real city incomes per capita. The additional price determinants are subsequently combined with this baseline specification. From theory, we expect the elasticities of real house prices with respect to the number of households, real income and the human capital ratio to be positive. Negative long-run elasticities of house prices are meanwhile expected with respect to the old age dependency ratio and the national real mortgage interest rate.

The results of estimating each different specification with the MG, PMG and DFE estimators are reported in Table 4. Since the MG and PMG estimators are inconsistent if the true data generating process includes unobserved city heterogeneity, we employ the common Hausman specification test to each specification. The Hausman test indicates the presence of unobserved city fixed-effects, such that the discussion of our re-

sults focuses on the DFE-estimation results. As the favorite specification, we identify DFE Specification [2], which includes only significant explanatory variables.¹¹

Table 4. Results of different panel error correction model specifications

	Specification			
	[1]	[2]	[3]	[4]
Pooled mean-group estimation				
Log total household population	1.5415 ***	1.0677 ***	1.2196 ***	0.7268 ***
Log old age dependency ratio	-1.1603 ***	-1.3009 ***	-1.4495 ***	-1.2551 ***
Log income per capita	0.1891 ***	0.3517 ***	0.1630 ***	0.3001 ***
Log human capital ratio			0.1377 ***	-0.1455 ***
Log real mortgage interest rate		-0.0776 ***		-0.1379 ***
Error correction term	-0.3029 ***	-0.2730 ***	-0.3022 ***	-0.3072 ***
Mean-group estimation				
Log total household population	1.6801 *	2.4003 **	4.7370	1.7768
Log old age dependency ratio	-1.5237 ***	-2.2503 ***	-2.9243 ***	-1.1854 **
Log income per capita	0.4342	0.8999	-1.8570	-0.0645
Log human capital ratio			0.2710	0.0583
Log real mortgage interest rate		-0.0537 *		-0.1378 **
Error correction term	-0.6227 ***	-0.6698 ***	-0.7380 ***	-0.8450 ***
Dynamic fixed-effects estimation				
Log total household population	1.6581 ***	1.3847 ***	1.5043 ***	1.3519 ***
Log old age dependency ratio	-1.2634 ***	-1.8283 ***	-1.4991 ***	-1.8682 ***
Log income per capita	0.3020 **	0.3589 **	0.3493 **	0.3677 ***
Log human capital ratio			0.2106 ***	0.0322
Log real mortgage interest rate		-0.2763 ***		-0.2698 ***
Error correction term	-0.1635 ***	-0.1318 ***	-0.1437 ***	-0.1306 ***

(* , ** , *** denote statistical significance at the 10%-, 5%- and 1%-level, respectively)

The signs estimated for the coefficients of the long-run cointegration relationship between real urban house prices and their demographic and economic fundamentals generally meet with the theoretical expectations. We find that a city's total household population is an important driver of real local house prices: a one per cent increase in the number of resident households is associated with a 1.38 per cent average increase in prices in the long run. In addition to city size, the results also support our key hypothesis that population aging goes along with decreasing house prices. The coefficient estimated on the old age dependency ratio carries the expected negative sign and is significantly different from zero. An increase in the old age dependency ratio by one per cent implies 1.83 per cent lower real house prices in the long run on average. This is an economically meaningful effect.

Regarding the controlling covariates, an increase in real city income per capita by one per cent is associated with a 0.36 per cent long-run increase in real house prices.

¹¹ The Hausman test favors the DFE model prior to PMG model and lastly the MG model.

The human capital ratio is statistically insignificant in the DFE estimation if national mortgage interest rates are included. Upward shifts to housing financing costs by one per cent at the nation level shift urban home prices downward by 0.28 per cent on average. This estimate implies that long-run urban house prices in Germany decrease by close to 30 per cent on average if the national mortgage interest rate doubles. A coefficient of this size suggests that the European Central Bank's low interest rate policy in response to the financial crisis plays an important role in explaining the substantial increase in real housing prices in many German cities since 2009.

Regarding the error correction behavior of house prices, the coefficient estimated for the speed of adjustment of error correction is negative and significant. This is in line with theoretical expectations that real urban house prices return to their long-run equilibrium values after demographic or economic shocks. The estimated size of the speed of adjustment parameter albeit indicates that prices can stay away from their equilibrium values for prolonged periods of time.

Table 5 compares our findings with the results of the two recent relevant studies by Takáts (2012) and Saita et al. (2013). Albeit a direct comparison is limited by differences in specification and data, the table illustrates a striking similarity of the results. The coefficient we find for the elasticity of real house prices with respect to total population (+1.38) lies slightly below the respective coefficients that Saita et al. measure in their most comparable specification for regions in Japan (+2.02) and the US (+1.81), whereas it is larger than the respective elasticity Takáts finds for OECD countries (+1.05). Some of these differences might also reflect that our population measure is less noisy, though our results appear to be largely insensitive to the use of households versus individual population.¹²

In absolute terms, the real house price elasticity we find with respect to the old age dependency ratio (-1.83) ranges above the respective elasticities that Saita et al. find for US states (-0.54) and Japanese prefectures (-1.73). It is also more than one percentage point larger than the one Takáts finds for OECD countries (-0.68).

The empirical relationship between real house prices and real per capita incomes is quite comparable among the three studies. Importantly, all studies find the respective elasticity to be positive and less than one. Our elasticity measure of +0.36 lies in between the one Saita et al. find for Japanese prefectures (+0.23) and for US states (+0.45). In OECD countries, the real income elasticity of house prices appears to be considerably higher (+0.88). Such large elasticity estimates may, however, reflect measurement error due to aggregation problems in national data.

In summary, our econometric results yield additional evidence supporting the theoretical claim that local demographic developments act as a strong driver of capital gains in housing markets in the long run. Concerning the old age dependency ratio,

¹² If we use population instead of household figures, we find the following elasticities in our DFE estimation: log total population: 1.6799, log old age dependency ratio: -1.1698, log income per capita: 0.3631. Further results are provided in the Appendix.

against the background of all three studies there is now conclusive evidence for an economically meaningful negative effect of aging on house prices at the local, the regional and the national level.

Table 5. Comparison of estimated elasticities in different studies¹³

Results		Saita et al. (2013)			Takáts (2012)	
Variables	Germany	Variables	Japan	U.S.	Variables	Nation
Panel units (N)	87 cities	Panel units (N)	47 prefectures	50 states	Panel units (N)	22 countries
Time periods (T)	18 years	Time periods (T)	34 years	36 years	Time periods (T)	40 years
Log real resale apartment price		Log real land / housing price			Log real house price	
Log total household population	1.3847	Log total population	2.0220	1.8079	Log total population	1.0547
Log old age dependency ratio	-1.8283	Log old age dependency ratio	-1.7280	-0.5363	Log old age dependency ratio	-0.6818
Log income per capita	0.3589	Log GDP per capita	0.2302	0.4525	Log GDP per capita	0.8842
Error correction term	-0.1635	Error correction term	-0.1056	-0.1199	Error correction term	N/A

4.3 Probabilistic forecasts of demography-related house price effects

We now use the DFE estimation results of the panel error correction model for probabilistic forecasts of expected demography-related house price effects until the year of 2020. To this end, we first multiply the annual expected percentage change of total household population and the old age dependency ratio in each city¹⁴ with their respective real house price elasticities estimated in our favorite specification. We then compute the mean annual expected real house price change. Based on the standard errors of the two respective elasticity estimates, we also provide a 90 per cent confidence interval for the annual price effect. In Table 6, the 87 cities in the sample are ranked according to the total size of the mean expected annual demography-induced price effect.

In almost the entire sample, local demographic change will most likely lead to lower real house prices until 2020, *ceteris paribus*. The strongest negative demography-induced price effects have to be expected for cities in eastern Germany. Most of these cities already experienced past severe price declines. The expected annual demography-induced price effect is positive only for one city (Dusseldorf). In order to interpret these projections appropriately, it is important to remember that they assume all other relevant price-explaining factors to remain constant. In each city, negative demography-induced price effects could be (over-)compensated by gains to productivity, lower real housing financing costs, or unobserved city-level effects. Since the exact size of the regression coefficients is sensitive to the specification (Table 4), the quantitative values should also not be overstated relative to the projections' qualitative implications.

For a deeper understanding of expected demography-related house price effects, in Figure 6 we split up graphically the combined impact of demography into the specific

¹³ The results of Saita et al. (2013) refer to their baseline specification of a panel error correction model including regional fixed effects. The results of Takáts refer to a pooled OLS model in first differences including time fixed effects. We provide pooled OLS regression results in first differences with our data in the Appendix.

¹⁴ Data on household and population age structure projections is provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR 2009).

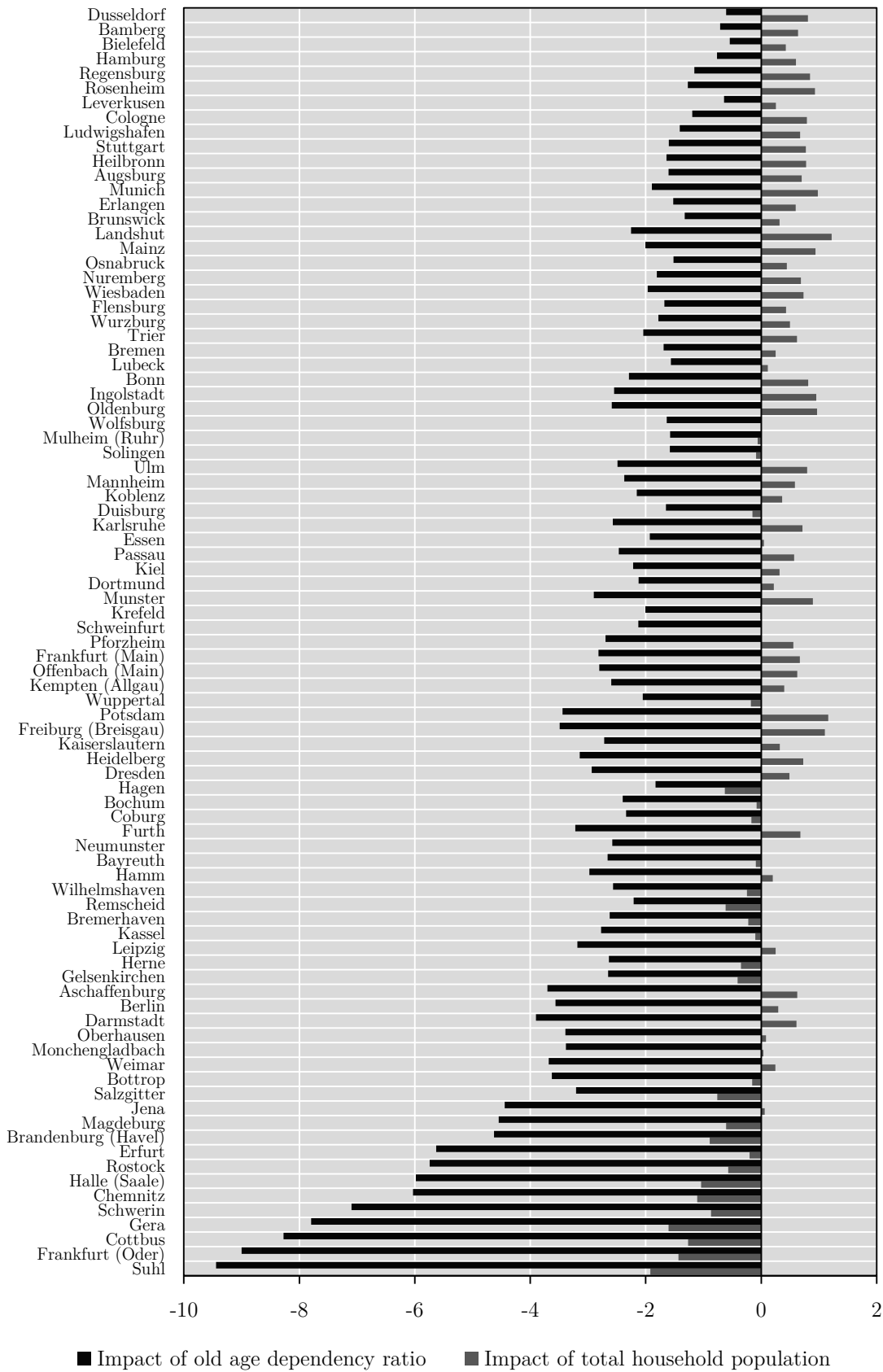
contributions of household population growth and aging. The graph illustrates that until 2020, the major part of the expected adverse demography-induced house price effects in German cities will be a consequence of gradual increases in the old age dependency ratio. Increased housing services demand due to growing household numbers will by itself dampen annual average house price decline in many cities. In some cities, the positive partial price impact of household growth is likely to compensate the negative partial price impact of aging to a meaningful extent.

Table 6. Annual demography-induced real house price change in per cent, 2012-2020

Rank	City	90% confidence interval			Rank	City	90% confidence interval		
		maximum	mean	minimum			maximum	mean	minimum
1	Dusseldorf	0.58	0.20	-0.17	45	Frankfurt (Main)	-1.52	-2.15	-2.78
2	Bamberg	0.25	-0.07	-0.40	46	Offenbach (Main)	-1.57	-2.18	-2.79
3	Bielefeld	0.11	-0.12	-0.34	47	Kempton (Allgau)	-1.70	-2.20	-2.69
4	Hamburg	0.16	-0.16	-0.49	48	Wuppertal	-2.01	-2.23	-2.44
5	Regensburg	0.15	-0.31	-0.77	49	Potsdam	-1.39	-2.28	-3.17
6	Rosenheim	0.17	-0.34	-0.85	50	Freiburg (Breisgau)	-1.51	-2.39	-3.26
7	Leverkusen	-0.21	-0.39	-0.57	51	Kaiserslautern	-1.91	-2.40	-2.88
8	Cologne	0.04	-0.40	-0.85	52	Heidelberg	-1.72	-2.41	-3.10
9	Ludwigshafen	-0.30	-0.74	-1.17	53	Dresden	-1.87	-2.45	-3.02
10	Stuttgart	-0.33	-0.82	-1.32	54	Hagen	-2.43	-2.46	-2.48
11	Heilbronn	-0.36	-0.86	-1.36	55	Bochum	-2.18	-2.48	-2.77
12	Augsburg	-0.43	-0.90	-1.37	56	Coburg	-2.25	-2.51	-2.77
13	Munich	-0.30	-0.92	-1.53	57	Furth	-1.86	-2.54	-3.23
14	Erlangen	-0.50	-0.93	-1.35	58	Neumunster	-2.23	-2.58	-2.93
15	Brunswick	-0.71	-1.01	-1.30	59	Bayreuth	-2.42	-2.75	-3.08
16	Landshut	-0.29	-1.03	-1.78	60	Hamm	-2.30	-2.78	-3.26
17	Mainz	-0.45	-1.06	-1.68	61	Wilhelmshaven	-2.55	-2.81	-3.07
18	Osnabruck	-0.70	-1.07	-1.44	62	Remscheid	-2.74	-2.82	-2.90
19	Nuremberg	-0.63	-1.12	-1.62	63	Bremerhaven	-2.57	-2.85	-3.13
20	Wiesbaden	-0.70	-1.23	-1.76	64	Kassel	-2.53	-2.87	-3.22
21	Flensburg	-0.86	-1.25	-1.63	65	Leipzig	-2.41	-2.93	-3.46
22	Wurzburg	-0.86	-1.28	-1.70	66	Herne	-2.75	-2.99	-3.22
23	Trier	-0.92	-1.42	-1.93	67	Gelsenkirchen	-2.84	-3.06	-3.27
24	Bremen	-1.12	-1.44	-1.76	68	Aschaffenburg	-2.35	-3.08	-3.81
25	Lubeck	-1.20	-1.45	-1.71	69	Berlin	-2.67	-3.27	-3.86
26	Bonn	-0.87	-1.48	-2.08	70	Darmstadt	-2.54	-3.29	-4.04
27	Ingolstadt	-0.90	-1.59	-2.28	71	Oberhausen	-2.82	-3.31	-3.80
28	Oldenburg	-0.92	-1.62	-2.32	72	Monchengladbach	-2.87	-3.34	-3.82
29	Wolfsburg	-1.41	-1.64	-1.86	73	Weimar	-2.84	-3.44	-4.03
30	Mulheim (Ruhr)	-1.44	-1.64	-1.83	74	Bottrop	-3.34	-3.78	-4.22
31	Solingen	-1.48	-1.67	-1.85	75	Salzgitter	-3.80	-3.97	-4.13
32	Ulm	-1.07	-1.69	-2.32	76	Jena	-3.76	-4.38	-5.01
33	Mannheim	-1.25	-1.79	-2.32	77	Magdeburg	-4.75	-5.15	-5.56
34	Koblenz	-1.37	-1.79	-2.22	78	Brandenburg (Havel)	-5.21	-5.52	-5.83
35	Duisburg	-1.63	-1.80	-1.97	79	Erfurt	-5.13	-5.83	-6.53
36	Karlsruhe	-1.25	-1.86	-2.46	80	Rostock	-5.74	-6.32	-6.90
37	Essen	-1.60	-1.88	-2.16	81	Halle (Saale)	-6.58	-7.02	-7.47
38	Passau	-1.36	-1.90	-2.44	82	Chemnitz	-6.71	-7.14	-7.56
39	Kiel	-1.48	-1.90	-2.32	83	Schwerin	-7.31	-7.96	-8.62
40	Dortmund	-1.54	-1.91	-2.28	84	Gera	-8.91	-9.40	-9.89
41	Munster	-1.29	-2.00	-2.72	85	Cottbus	-8.87	-9.54	-10.22
42	Krefeld	-1.75	-2.02	-2.29	86	Frankfurt (Oder)	-9.72	-10.43	-11.15
43	Schweinfurt	-1.84	-2.13	-2.42	87	Suhl	-10.76	-11.36	-11.96
44	Pforzheim	-1.57	-2.14	-2.71					

Source: Authors' own calculations.

Figure 5. Annual partial impacts of age structure and the number of households on real urban house prices in per cent, 2012-2020



Source: Authors' own calculations.

5 Conclusions

How urban house prices are affected by demographic change in industrialized countries in the long run is of critical relevance for home owners, investors and policy makers alike. Using German data, the results of this paper provide empirical evidence that the effects of aging and population shrinkage on city-level house prices are negative and economically meaningful. This adds to related recent findings by other researchers based on national and regional housing market data. Extrapolating the empirical relationships that we identify with historical data to the future of urban house prices, we demonstrate that demographic change is likely to contribute to lower real home price growth in almost any German urban area until the year of 2020. This means an amplification of the already existing headwind effects that demographic development unfolded on German home prices in recent years.

As any projection of the future, the results of our probabilistic forecasts of city house prices have to be treated with the appropriate care. The causal mechanisms underlying the empirical links between house prices and demography can and do change with changes in household preferences, housing finance institutions and the design of pension systems. Urban demographic developments may also not be fully exogenous to urban house prices, given that rational households chose locations based inter alia on intercity house price differences. Another factor determining the price effect of demographic shifts at the urban level is housing supply. Our results indicate that over the sample period of 1995-2012, housing supply has been finitely elastic, because otherwise such large price effects are not possible. Lerbs (2014) provides econometric evidence at the German district level that housing supply in Germany is indeed inelastic, finding a long-run elasticity estimate of 0.33 for single-family homes. Future increases in the elasticity of housing supply can theoretically deplete the real price effects of forthcoming shifts to housing demand. However, given the durability-related downward stickiness of housing supply, we see strong signs that aging and shrinking cities in Germany and elsewhere will face tough times in combating future demography-induced losses to housing wealth within the relevant time horizons.

Future research could take our findings as a starting point to stronger think about the potential endogeneity of aging and house prices. Do price declines due to an aging society provoke young people to move in or move out of a city? As adverse price effects of aging make urban owner-occupied housing more affordable, this might render young households to invest in an aging city. To disentangle these dynamic second-round effects, it may be crucial to account for the distribution and evolution of urban amenities (Hiller and Lerbs 2015).

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Appendix

Table A1. Summary statistics (mean, std. dev. in parentheses), 1995-2012

No.	City	Real house price (EUR)	Total household population	Old age dependency ratio	Income per capita (EUR)	Human capital ratio
1	Flensburg	1160 (192)	45033 (2014)	0.3 (0.01)	71386 (5311)	0.4 (0.12)
2	Kiel	1541 (276)	132783 (1987)	0.26 (0.02)	72652 (2074)	0.78 (0.16)
3	Lubeck	1515 (210)	119650 (1518)	0.35 (0.03)	64019 (1912)	0.48 (0.11)
4	Neumunster	1361 (256)	38683 (285)	0.33 (0.04)	64862 (1747)	0.35 (0.07)
5	Hamburg	2272 (204)	949633 (35913)	0.28 (0.02)	100218 (3005)	0.92 (0.24)
6	Brunswick	1335 (245)	135472 (3196)	0.32 (0.02)	71605 (1251)	0.84 (0.24)
7	Salzgitter	1203 (210)	55661 (1208)	0.35 (0.05)	75299 (7313)	0.38 (0.12)
8	Wolfsburg	1294 (229)	61961 (1044)	0.35 (0.05)	170174 (28571)	0.87 (0.62)
9	Oldenburg	1362 (239)	83522 (3562)	0.27 (0.02)	70793 (1812)	0.67 (0.21)
10	Osnabruck	1469 (217)	85389 (1526)	0.29 (0.02)	80770 (2349)	0.53 (0.13)
11	Wilhelmshaven	1003 (244)	43550 (825)	0.36 (0.05)	74714 (5288)	0.43 (0.09)
12	Bremen	1438 (181)	292789 (8812)	0.31 (0.03)	85741 (3230)	0.82 (0.19)
13	Bremerhaven	1005 (192)	63667 (1582)	0.34 (0.03)	65378 (3780)	0.38 (0.12)
14	Dusseldorf	2254 (250)	303200 (7250)	0.29 (0.02)	136138 (3480)	1 (0.28)
15	Duisburg	1466 (230)	247511 (3309)	0.33 (0.03)	65360 (3703)	0.43 (0.11)
16	Essen	1699 (331)	295250 (2028)	0.34 (0.03)	79446 (3986)	0.81 (0.19)
17	Krefeld	1464 (221)	118517 (1542)	0.31 (0.04)	70439 (3434)	0.5 (0.11)
18	Monchengladbach	1427 (258)	130117 (799)	0.3 (0.03)	55727 (1777)	0.36 (0.11)
19	Mulheim (Ruhr)	1835 (181)	84317 (502)	0.37 (0.04)	76761 (4399)	0.51 (0.13)
20	Oberhausen	1396 (153)	104628 (780)	0.32 (0.03)	50224 (1561)	0.45 (0.08)
21	Remscheid	1479 (181)	56700 (1491)	0.33 (0.04)	67650 (2711)	0.33 (0.06)
22	Solingen	1540 (224)	80356 (426)	0.33 (0.04)	51789 (1911)	0.22 (0.07)
23	Wuppertal	1393 (225)	181672 (3796)	0.32 (0.03)	61988 (1670)	0.43 (0.09)
24	Bonn	1813 (105)	160389 (5796)	0.28 (0.01)	114905 (5732)	1.16 (0.3)
25	Cologne	2024 (159)	520811 (14559)	0.26 (0.02)	94952 (4405)	0.85 (0.2)
26	Leverkusen	1784 (270)	79300 (1002)	0.33 (0.05)	92572 (8437)	0.75 (0.23)
27	Bottrop	1479 (181)	57239 (618)	0.32 (0.03)	41547 (2465)	0.25 (0.05)
28	Gelsenkirchen	1260 (275)	134928 (4599)	0.34 (0.02)	59025 (2957)	0.43 (0.14)
29	Munster	2117 (210)	139594 (5541)	0.25 (0.02)	99945 (3771)	0.9 (0.15)
30	Bielefeld	1464 (204)	166311 (2037)	0.32 (0.02)	64844 (1372)	0.52 (0.12)
31	Bochum	1568 (217)	198422 (865)	0.32 (0.02)	55816 (2814)	0.55 (0.11)
32	Dortmund	1502 (225)	289133 (3130)	0.32 (0.03)	63441 (2041)	0.71 (0.15)
33	Hagen	1469 (184)	98783 (2255)	0.35 (0.04)	65778 (2278)	0.35 (0.09)
34	Hamm	1271 (198)	85078 (1537)	0.3 (0.03)	50986 (2513)	0.33 (0.08)
35	Herne	1395 (273)	86783 (1102)	0.33 (0.02)	40390 (1996)	0.39 (0.09)
36	Darmstadt	2067 (198)	74672 (1922)	0.28 (0.01)	106630 (4469)	1.26 (0.22)
37	Frankfurt (Main)	2675 (90)	355583 (9948)	0.25 (0.01)	154661 (5726)	1.2 (0.23)
38	Offenbach (Main)	1761 (172)	60839 (1125)	0.26 (0.02)	69673 (5026)	0.78 (0.21)
39	Wiesbaden	2320 (330)	141972 (3640)	0.29 (0.02)	103827 (3586)	0.89 (0.24)
40	Kassel	1217 (285)	101694 (900)	0.31 (0.01)	89178 (2163)	0.74 (0.15)
41	Koblenz	1543 (194)	56161 (588)	0.34 (0.03)	116652 (3076)	0.47 (0.1)
42	Trier	1616 (203)	56244 (2582)	0.29 (0.01)	76775 (4489)	0.58 (0.12)
43	Kaiserslautern	1286 (211)	52378 (645)	0.3 (0.02)	73635 (3346)	0.46 (0.11)
44	Ludwigshafen (Rhein)	1553 (247)	81744 (959)	0.3 (0.03)	130199 (5828)	0.62 (0.14)
45	Mainz	1702 (162)	100072 (4669)	0.25 (0.02)	92748 (6677)	0.99 (0.17)

Table A1. (Continued)

No.	City	Real house price (EUR)	Total household population	Old age dependency ratio	Income per capita (EUR)	Human capital ratio
46	Stuttgart	2190 (137)	307156 (8540)	0.27 (0.02)	118480 (5842)	1.18 (0.28)
47	Heilbronn	1791 (199)	57906 (1665)	0.3 (0.03)	89443 (8596)	0.37 (0.06)
48	Karlsruhe	1832 (178)	153872 (4044)	0.29 (0.01)	97370 (3363)	0.76 (0.18)
49	Heidelberg	2463 (193)	79428 (2261)	0.23 (0.01)	88009 (4317)	1.12 (0.23)
50	Mannheim	1811 (302)	160139 (2931)	0.28 (0.02)	99744 (4866)	0.69 (0.17)
51	Pforzheim	1709 (156)	60028 (2071)	0.32 (0.03)	69865 (2102)	0.35 (0.09)
52	Freiburg (Breisgau)	2225 (214)	114456 (5879)	0.23 (0.01)	72404 (3118)	0.85 (0.19)
53	Ulm	1819 (184)	59211 (2707)	0.27 (0.02)	107404 (2758)	0.73 (0.17)
54	Ingolstadt	1856 (179)	55950 (3887)	0.28 (0.02)	130488 (23233)	0.61 (0.27)
55	Munich	2923 (206)	707367 (37403)	0.25 (0.02)	108409 (4169)	1.28 (0.3)
56	Rosenheim	2165 (250)	28433 (1379)	0.29 (0.03)	75575 (3612)	0.44 (0.11)
57	Landshut	1747 (291)	28717 (1748)	0.34 (0.02)	86823 (4555)	0.35 (0.07)
58	Passau	1450 (160)	26006 (481)	0.32 (0.02)	93914 (8839)	0.45 (0.13)
59	Regensburg	2105 (211)	74233 (5268)	0.28 (0.01)	122807 (7327)	0.78 (0.23)
60	Bamberg	1701 (206)	36150 (1045)	0.34 (0.01)	98090 (2418)	0.45 (0.11)
61	Bayreuth	1332 (188)	37944 (553)	0.3 (0.02)	87989 (3174)	0.47 (0.11)
62	Coburg	1446 (231)	20450 (263)	0.37 (0.02)	102684 (16515)	0.54 (0.14)
63	Erlangen	2025 (195)	54383 (1662)	0.28 (0.02)	112169 (9893)	1.48 (0.21)
64	Furth	1531 (146)	57428 (1795)	0.28 (0.02)	62095 (3527)	0.46 (0.11)
65	Nuremberg	1723 (239)	258833 (6768)	0.31 (0.02)	82661 (1760)	0.6 (0.15)
66	Aschaffenburg	1709 (210)	30961 (1274)	0.31 (0.02)	105174 (9469)	0.33 (0.06)
67	Schweinfurt	1159 (67)	25250 (599)	0.39 (0.02)	147194 (14123)	0.42 (0.09)
68	Wurzburg	1868 (163)	73467 (3935)	0.28 (0.01)	85976 (5246)	0.64 (0.14)
69	Augsburg	1571 (181)	135033 (4721)	0.32 (0.01)	83724 (2521)	0.55 (0.14)
70	Kempton (Allgau)	1589 (190)	31933 (1747)	0.35 (0.03)	83667 (4976)	0.39 (0.08)
71	Berlin	2065 (297)	1904589 (70324)	0.25 (0.03)	52946 (1697)	1.03 (0.24)
72	Brandenburg (Havel)	1134 (247)	36356 (668)	0.34 (0.08)	42518 (4080)	0.98 (0.07)
73	Cottbus	1293 (159)	57611 (1594)	0.28 (0.06)	49587 (3239)	1.44 (0.23)
74	Frankfurt (Oder)	1313 (277)	31261 (1480)	0.27 (0.07)	52875 (5240)	1.06 (0.29)
75	Potsdam	1985 (158)	74272 (6758)	0.26 (0.04)	59446 (2466)	1.64 (0.38)
76	Rostock	1459 (241)	108411 (4718)	0.29 (0.07)	50919 (3322)	1.39 (0.25)
77	Schwerin	1442 (255)	51000 (763)	0.3 (0.07)	54460 (2818)	1.05 (0.2)
78	Chemnitz	1174 (449)	133206 (1973)	0.37 (0.07)	53137 (3639)	1.78 (0.16)
79	Dresden	1847 (230)	265872 (22771)	0.31 (0.04)	55514 (4355)	2.03 (0.34)
80	Leipzig	1610 (431)	274144 (20262)	0.31 (0.04)	48844 (2037)	1.7 (0.26)
81	Halle (Saale)	1317 (338)	127439 (2031)	0.31 (0.06)	48192 (2396)	1.26 (0.17)
82	Magdeburg	1198 (389)	121644 (3211)	0.32 (0.05)	52788 (2667)	1.19 (0.16)
83	Erfurt	1654 (402)	105128 (5604)	0.28 (0.04)	55097 (1001)	1.49 (0.15)
84	Gera	1182 (415)	55094 (1075)	0.34 (0.07)	40445 (2417)	1.12 (0.18)
85	Jena	1713 (268)	52811 (3829)	0.26 (0.04)	51300 (6458)	2.65 (0.53)
86	Suhl	1319 (332)	20894 (1148)	0.31 (0.09)	42601 (3863)	1.52 (0.11)
87	Weimar	1422 (270)	31806 (2476)	0.29 (0.03)	41556 (1809)	2.04 (0.33)

Table A2. Panel unit root tests (with total population)¹⁵

Variables	Levin-Lin-Chu		Im-Pesaran-Shin		Harris-Tzavalis	
	H ₀ : $\varrho_i = \varrho$ for all i H _a : $\varrho < 1$ T $\rightarrow \infty$, N $\rightarrow \infty$		H ₀ : $\varrho_i = 1$ for all i H _a : $\varrho_i < 1$ T is fixed, N is fixed		H ₀ : $\varrho = 1$ H _a : $\varrho < 1$ T is fixed, N $\rightarrow \infty$	
	No trend Test statistic	Trend Test statistic	No trend Test statistic	Trend Test statistic	No trend Test statistic	Trend Test statistic
Levels						
Log total population	-4.9696 ***	-16.6893 ***	3.0758	-8.1085 ***	0.9521	0.7495
Differences						
Δ log total population	-14.3234 ***	-8.8736 ***	-9.9758 ***	-2.9017 ***	0.4475 ***	0.7419 ***

(* , ** , *** denote statistical significance at the 10%- , 5%- and 1%-level, respectively)

Table A3. Panel cointegration tests (with total population)

Variables	Specification			
	[1]	[2]	[3]	[4]
Log real house price	x	x	x	x
Log total population	x	x	x	x
Log old age dependency ratio	x	x	x	x
Log income per capita	x	x	x	x
Log human capital ratio			x	x
Log real mortgage interest rate		x		x
Cointegration tests				
Kao ADF-statistic	-5.0648 ***	-3.4578 ***	-4.1662 ***	-4.1743 ***
Pedroni panel v-statistic	1.6879 **	-1.8163	0.4713	-2.9768
Pedroni panel rho-statistic	2.7446	5.4385	5.0553	7.2363
Pedroni panel PP-statistik	-1.9993 **	-1.7544 **	-1.3428 *	-2.8197 ***
Pedroni panel ADF-statistic	-1.5103 *	-0.1682	-0.7108	-0.0828
Pedroni group rho-statistic	5.9360	8.5958	8.3828	10.5682
Pedroni group PP-statistic	-3.6233 ***	-4.7883 ***	-5.3198 ***	-11.2893 ***
Pedroni group ADF-statistic	-3.3459 ***	-2.2755 **	-3.3221 ***	-3.1787 ***

(* , ** , *** denote statistical significance at the 10%- , 5%- and 1%-level, respectively)

¹⁵ Data source of total population: German Federal Statistical Office.

Table A4. Panel error correction models (with total population)

	Specification			
	[1]	[2]	[3]	[4]
Pooled mean-group estimation				
Log total population	0.6739 ***	-0.0034	0.2217	0.2172
Log old age dependency ratio	-0.9299 ***	-1.3148 ***	-1.4178 ***	-1.7757 ***
Log income per capita	0.2515 ***	0.1530 ***	0.0718	0.1321 **
Log human capital ratio			0.2157 ***	0.1101 ***
Log real mortgage interest rate		-0.1077 ***		-0.1431 ***
Error correction term	-0.3355 ***	-0.3075 ***	-0.3206 ***	-0.2845 ***
Mean-group estimation				
Log total population	-7.9397	0.2125	2.6389	6.4633
Log old age dependency ratio	-1.0608	-1.5215 ***	-0.7348	-2.2524 ***
Log income per capita	-2.3644	3.8148	-0.3953	1.3166
Log human capital ratio			-0.3741	-0.1770
Log real mortgage interest rate		-0.0296		0.0876
Error correction term	-0.6431 ***	-0.6675 ***	-0.7309 ***	-0.8367 ***
Dynamic fixed-effects estimation				
Log total population	1.6799 ***	1.4248 ***	1.5531 ***	1.4055 ***
Log old age dependency ratio	-1.1698 ***	-1.6619 ***	-1.3565 ***	-1.6883 ***
Log income per capita	0.3631 ***	0.4172 ***	0.3992 **	0.4200 ***
Log human capital ratio			0.1559 ***	-0.0085 **
Log real mortgage interest rate		-0.2370 ***		-0.2444 ***
Error correction term	-0.1616 ***	-0.1339 ***	-0.1470 ***	-0.1345 ***

(* , ** , *** denote statistical significance at the 10%- , 5%- and 1%-level, respectively)

Table A5. Pooled OLS regression with all variables in first differences

Pooled OLS regression	Specification			
	[1]	[2]	[3]	[4]
Δ Log total household population	0.0379	0.0622	0.0377	0.0618
Δ Log old age dependency ratio	-0.8495 ***	-0.7978 ***	-0.8481 ***	-0.7940 ***
Δ Log income per capita	0.0401	0.0235	0.0405	0.0245
Δ Log human capital ratio			0.0036	0.0089
Δ Log real mortgage interest rate		-0.0158 ***		-0.0160 ***
<i>Regression diagnostics</i>				
R ²	0.1127	0.1183	0.1128	0.1184
Adj. R ²	0.1109	0.1159	0.1103	0.1154
AIC (BIC)	-4,970 (-4,949)	-4,968 (-4,941)	-4,968 (-4,941)	-4,975 (-4,943)
Δ Log total population	-0.2635	-0.2195	-0.2706 *	-0.2297
Δ Log old age dependency ratio	-0.8926 ***	-0.8379 ***	-0.8905 ***	-0.8341 ***
Δ Log income per capita	0.3180	0.0168	0.0327	0.0180
Δ Log human capital ratio			0.0084	0.0128
Δ Log real mortgage interest rate		-0.0150 ***		-0.0152 ***
<i>Regression diagnostics</i>				
R ²	0.1143	0.1193	0.1143	0.1195
Adj. R ²	0.1125	0.1169	0.1119	0.1165
AIC (BIC)	-4973 (-4952)	-4979 (-4952)	-4971 (-4944)	-4977 (-4946)

(*, **, *** denote statistical significance at the 10%-, 5%- and 1%-level, respectively)