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A house prices at risk approach for the German residential real estate market

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Non-technical summary

This paper describes the methodology behind the “prices-at-risk” model for the German residential real estate (RRE) market. The forecast distribution of RRE prices presented in the Deutsche Bundesbank’s 2023 Financial Stability Review is based on this model.

The empirical approach is based on the “growth-at-risk” methodology introduced by Adrian et al. (2019). It estimates the forecast distribution of the German RRE market. In contrast to point forecasts, which focus only on the most likely outcome of future house prices, this model allows for the estimation of downside risks to the German RRE market, i.e. the probability of substantial declines in house prices.

The results from the quantile regression for the German RRE market show that variations in interest rates, housing-market-specific risk premia, and employment predominantly affect the lower quantiles of the forecast distribution. By contrast, past house prices have a more pronounced impact on the median of the forecast. Over the last two years, a large part of the forecast distribution of house prices has shifted into negative territory due to interest rate hikes and the rise in inflation. Across the entire distribution, the model forecasts are lower in 2022Q3 than in 2021Q4. These results hold for both a panel dataset at district level and a Germany-wide aggregate model. Furthermore, the paper highlights the fact that sparsely populated districts have more pronounced downside risks in the RRE market than densely populated ones.

Nichttechnische Zusammenfassung:

In diesem Papier wird die Methodik hinter dem sogenannten Wohnimmobilienpreis-at-Risk-Modell beschrieben. Dieses Modell bildet die Grundlage für die Verteilungsfunktion der im Finanzstabilitätsbericht 2023 der Deutschen Bundesbank prognostizierten Wohnimmobilienpreisentwicklung.

Der empirische Ansatz baut auf dem im Growth-at-Risk-Modell von Adrian et al. (2019) verwendeten Quantilsregressionen auf und wurde mit Daten für Deutschland geschätzt. Im Gegensatz zu Punktprognosen, die nur das wahrscheinlichste Szenario angeben, kann mit dem Wohnimmobilienpreis-at-Risk-Modell die Wahrscheinlichkeit großer Preisrückgänge bestimmt werden.

Die Ergebnisse zeigen, dass das 10%-Perzentil der Wohnungspreisveränderungen stärker auf Zinsänderungen, Risikozuschlägen am Wohnimmobilienmarkt und Änderungen am Arbeitsmarkt reagiert als die Median- und Mittelwertprognose. In den vergangenen zwei Jahren hat sich auf Basis des Modells die Verteilung der Prognose für Wohnimmobilienpreise nach links verschoben. Über die gesamte Verteilung hinweg prognostiziert das Modell zum Beispiel in 2022Q3 geringere Preiswachstumsraten als noch in 2021Q4. Diese Ergebnisse gelten sowohl für die Schätzung mit einem Datensatz auf Kreisebene als auch für das Modell mit einem deutschlandweiten Aggregat. Ferner zeigt sich, dass negative Wachstumsraten in dünn besiedelten Landkreisen wahrscheinlicher sind als in dichter besiedelten Kreisen und Städten.

A house prices at risk approach for the German residential real estate market*

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Abstract

This paper focuses on the downside risks to the German residential real estate market. It applies the "at-risk" methodology to the German housing market. Quantile regressions reveal that different quantiles of the house price forecast distribution are heterogeneously affected by the same exogenous variables. While past house prices have a very pronounced impact on the median, variations in interest rates predominantly affect the lower quantiles of the distribution. Other factors, such as employment, affect different quantiles more equally. The at-risk model shows that, in the recent era of high inflation and rising interest rates, the forecast distribution of house prices has shifted to the left, resulting in lower expected growth rates of real house prices. Additionally, we find that sparsely populated districts have more pronounced downside risks than densely populated ones.

Keywords: residential real estate, housing, growth-at-risk, quantile regression, Germany

JEL-Classification: C32, E37, G01, R31

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1 Introduction

Following a substantial rise in German real residential real estate (RRE) prices over more than a decade, the long upswing phase came to an end in 2022.[1] This highlights the fact that, despite a long upswing in the housing cycle, there is a chance that the boom will end at any given point in time. However, most forecasts for house prices in the German RRE market, such as those produced by the Deutsche Bundesbank in 2022,[2] are point estimates. These point forecasts provide no information on how likely it is that house prices will decline (or rise further). However, macroprudential policymakers and risk managers may be interested in precisely this information. Specifically, based on considerations of financial stability, they may be interested in the likelihood of an adverse scenario. Furthermore, during "normal" times, it might also be worthwhile to assess the probability of (unsustainable) substantial increases in prices. To provide answers to these questions, this paper develops a framework that estimates the entire forecast distribution for German RRE prices.

We expand upon the "at-risk" models introduced by Adrian et al. (2019), which rely on quantile regressions. We add to the literature by estimating such a model using German RRE prices. This is an important extension of the literature, as residential real estate markets are highly heterogeneous and exhibit very different cyclical behaviour. The available models are often estimated using cross-country data. They are therefore not capable of capturing the particularities of the German RRE market. On the downside, the German RRE market, which is less volatile in relative terms, poses more challenges with regard to identification.

In the interest of a robust assessment of developments in German RRE markets, we estimate a univariate model at quarterly frequency and a panel model (consisting of 399 German districts[3]) at annual frequency. For both the univariate and the panel model, our results suggest that, besides the lagged growth of RRE prices, outcomes are driven by interest rate changes, housing market risk premia, and the growth rate of employment, while household debt levels play a relatively smaller role. Interestingly, the contributions of the variables to the forecast of RRE prices vary considerably across different quantiles. While lagged house price growth rates are most important for the median, the developments in lower quantiles are closely linked to changes in interest rates. We observe plausible movements of the forecast distribution over time. In particular, we see that the forecast distribution has shifted to the left since mid-2022, which is consistent with the view that interest rate hikes and rising inflation levels have weighed on the affordability of housing. Moreover, in the univariate model, the distribution has widened somewhat, reflecting comparably high uncertainty about future developments in real house prices.

We find similar results in the panel model. Importantly, by using the rich heterogeneity of 399 German districts, we can show that the forecast distribution is somewhat wider (compared to the univariate model), which qualitatively replicates the findings from the literature that use cross-country variation. The panel model is thus a substitute for those cross-country results. As the panel model allows us to differentiate between districts, we can also show that sparsely populated districts have more pronounced downside risks than densely populated ones. However, this feature seems to be rather invariant over time and is indicative of structurally higher potential for downside risks.

This paper relates to several strands of the literature. Quantile regressions (QRs), as introduced by Koenker and Bassett (1978), have been used extensively in economics and finance. In finance,

[1] Nominal year-on-year house price growth rates were positive from 1994 until 2021; see vdp Research Property Price Index and Kajuth (2021).

[2] see Deutsche Bundesbank (2022).

[3] n this analysis, districts also comprise "district-free" large cities (kreisfreie Städte).

Allen et al. (2009), Baur and Schulze (2005) and Ghysels (2014), amongst others, rely on QRs to generate return distributions. In economics, Girma and Görg (2005) and Chunying (2011) make use of QRs to gauge how foreign direct investment affects economic growth. Fitzenberger et al. (2002), Machado and Mata (2005) and Chernozhukov and Hansen (2004), among others, use QRs to analyse effects on the distribution of income and wealth.

In their seminal paper, Adrian et al. (2019) introduce the "growth-at-risk" (GaR) methodology, in which US real GDP growth is linked to macro and financial variables in a non-linear fashion. Specifically, they show that the lower quantiles of the real GDP forecast distribution vary with the US Federal Reserve's National Financial Conditions Index[4], while the upper quantiles do not. This is consistent with the view that tighter financial conditions could amplify adverse shocks as downside risks grow. By contrast, macroeconomic variables help to predict the median of the growth forecast distribution, but they have no significant impact on the tails of the distribution. Going into greater depth, Adrian et al. (2022) confirm that financial conditions play a key role for the downside risks to growth for a panel of eleven advanced economies, including Germany. However, they identify different behaviour at different time horizons. When financial conditions are loose, downside risks are comparatively low in the near term, but increase over the projection horizon. After eight quarters, the sign of the corresponding coefficient changes.

Lloyd et al. (2023) investigate how foreign financial conditions influence the forecast distribution of domestic GDP growth for a panel of ten advanced economies. Beutel et al. (2022) show that contractionary shocks to monetary policy and financial conditions in the United States increase downside risks to GDP growth in other economies. Galán (2020) focuses on the impact of macroprudential policy measures and finds that they have curbed downside risks to GDP growth. Figueres and Jarociński (2020) and Szendrei and Varga (2023) apply the GaR framework to the euro area and qualitatively confirm the results of Adrian et al. (2019). While Figueres and Jarociński (2020) explain that the relatively broad Composite Indicator of Systemic Stress (CISS) is an important variable for forecasting the GDP growth distribution, Szendrei and Varga (2023) highlight the fact that variables related to banking improve the fit of the model. Building on the GaR methodology, other at-risk models have been developed, such as capital flows at-risk (Gelos et al. (2022) and Goel and Miyajima (2021)), bank capital-at-risk (Lang and Forletta (2020) and Covi et al. (2022)) and house prices at-risk (HPaR).

With regard to HPaR, Deghi et al. (2020) introduced a model of 22 advanced economies, including Germany, and a separate model for ten emerging market economies. They find that elevated house price developments in the past, tighter financial conditions, current house price overvaluations, and excessive credit growth lead to greater downside risks to real house prices, while tightening the macroprudential policy stance moves the lower end of the forecast distribution to the right. In addition, real GDP growth rates and monetary policy shocks shift the 5th percentile of the forecast distribution only in advanced economies. They also show that HPaR serves as a leading indicator for financial crises. In parallel, the ECB (2020) developed a model for the euro area with lagged house prices, measures for overvaluation, as well as several spreads and indicators for risk, financial conditions and consumer confidence as explanatory variables. While the models by Deghi et al. (2020) and the ECB (2020) utilise panel data, Galán and Rodríguez-Moreno (2020) establish a model for Spain in which forecasts of real house price growth rates are positively (negatively) linked to lagged values of house price growth and population growth (overvaluation of house prices and credit growth). Alter and Mahoney (2020) rely on more granular city-specific data for the U.S. and Canada. Besides financial conditions and housing supply, household debt, past house prices, and price-to-income ratios mainly cause the left tail of the forecast distribution to shift.

[4] The methodology of the index is described in Brave and Butters (2011). The index is available at https://www.chicagofed.org/research/data/nfci/current-data.

In addition to the literature on quantile regressions and at-risk models, this paper also relates to the literature that explores the determinants of house prices. In general, the literature finds that house prices are driven by (real) interest rates and financial conditions (Agnello and Schuknecht (2011)), capital flows, household income, leverage, and demographics (André (2010) and Cerutti et al. (2017)) as well as the supply of housing (Kajuth et al. (2016)) and lending standards (Duca et al. (2021)).

This paper provides a methodological background to analyses presented in the Deutsche Bundesbank's 2023 Financial Stability Review (see Deutsche Bundesbank (2023)). The paper is structured as follows. Section 2 outlines the at-risk methodology. Section 3 introduces the data and Section 4 presents the results. In these two Sections, we differentiate between a univariate model for the aggregate German RRE market and a panel model at the district level. Finally, Section 5 concludes.

2 Methodology

The at-risk models follow a two-step procedure. In the first step, conditional forecasts are generated for selected quantiles. These forecasts are the fitted results (predicted values) of quantile regressions. In the second step, a density function is estimated by fitting a squared t-distribution to these selected quantiles.

As the name suggests, quantile regressions (QRs) evaluate how a given quantile $\tau \in [0;1]$ of the endogenous variable y_t^τ is linked to exogenous variables X_{t-h}, see Koenker and Bassett (1978). In this paper, we estimate a univariate model using aggregate data for Germany at quarterly frequency and a panel-model using data from 399 German districts at yearly frequency. Equation (1) illustrates this relationship in a univariate framework where α^τ is a constant, β^τ and γ^τ are the corresponding coefficients for X_{t-h} and y_{t-h} and ϵ_t^τ are the error terms at time t. Finally, h captures the forecast horizon. In the univariate analysis, we focus on house price developments over the following year, so that y_t is the year-on-year growth rate of real house prices, and h equals four when applying the univariate model with quarterly data. Equation (2) displays how the QR is applied if a panel is estimated. $y_{i,t}$ and $X_{i,t}$ are the endogenous and exogenous variables of district i at time t. As we focus on annual data for the panel model, we obtain forecasts for the next period when $h = 1$.

$$y_t^\tau = \alpha^\tau + \beta^\tau X_{t-h} + \gamma^\tau y_{t-h} + \epsilon_t^\tau \tag{1}$$

$$y_{i,t}^\tau = \alpha^\tau + \beta^\tau X_{i,t-h} + \gamma^\tau y_{i,t-h} + \epsilon_{i,t}^\tau \tag{2}$$

The regressions in Equations (1) and (2) are similar to an ordinary least squares (OLS) regression. However, while OLS regressions estimate results for the conditional mean, QRs provide an estimation of the conditional quantile. Therefore, unlike an OLS regression which minimises the squared distance between the fitted line and the realisations of the endogenous variable the QR minimises the loss function $L(\epsilon_t, \tau)$ as illustrated in Equation (3).

$$L(\epsilon_t, \tau) = max[\tau\epsilon_t, (\tau - 1)\epsilon_t] \tag{3}$$

In this loss function, observations below (above) the regression line will receive higher weights for small (large) quantiles. For illustrative purposes, Figure (1) displays the contrast between an OLS estimation and QR for the 10th percentile and the median. In this example, the dependent variable is the yearly growth rates of nominal RRE prices in German districts in 2021, while the regressor is the corresponding growth rates in 2020. As expected, the OLS estimates (purple line) and the estimates for the median (red line) are similar, while 40% of the observations are between the 10th percentile (yellow line) and the median.

In both configurations, the regression is carried out separately for $\tau \in \{0.1; 0.25; 0.75; 0.9\}$. De Nicolò and Lucchetta (2017) show that GDP forecasts from quantile regressions are more accurate at the lower end of the distribution than forecasts from traditional VAR and FAVAR models and that the results are more robust to outliers. This is not surprising, as QRs are the best linear unbiased estimator for the conditional quantile.

It should be noted that Equation (2) describes a pooled model in which fixed effects (FEs) are absent. However, unobserved fixed effects cannot be eliminated directly by adding fixed effect dummies to Equation (2), as expectations are not linear in QRs and the fixed effects would instead enter the specification multiplicatively. For this reason, we follow the commonly used procedure from Canay (2011) and assume that the fixed effects do not vary across different quantiles. Specifically, we first estimate Equation (4), which is an OLS version of Equation (2) with fixed effects.

$$y_{i,t} = \alpha_i + \beta X_{i,t-h} + \gamma y_{i,t-h} + \epsilon_{i,t} \tag{4}$$

To "purge" house prices from fixed effects, we estimate Equation (5), where $\widetilde{y_{i,t}} = y_{i,t} - \alpha_i$ with α_i from Equation (4), with the QR estimator introduced above.

$$\widetilde{y_{i,t}^{\tau}} = \alpha^{\tau} + \beta^{\tau} X_{i,t-h} + \gamma^{\tau} \widetilde{y_{i,t-h}} + \epsilon_{i,t}^{\tau} \tag{5}$$

However, for the model based on country data in addition to the model with Canay-FEs we also estimate a pooled model without fixed effects.

In the second step, for both the univariate model and the district-panel model, a skewed t-distribution is fitted to the predicted conditional quantiles of the endogenous variable for each period.[5] Specifically, for the univariate model, we derive a probability density function (pdf) by minimising the squared distance between $\widehat{y_t^{.1}}$, $\widehat{y_t^{.25}}$, $\widehat{y_t^{.75}}$ and $\widehat{y_t^{.9}}$ and the skewed t-distribution by Azzalini and Capitanio (2003). Analogously, the fitted quantiles $\widehat{y_{i,t}^{.1}}$, $\widehat{y_{i,t}^{.25}}$, $\widehat{y_{i,t}^{.75}}$ and $\widehat{y_{i,t}^{.9}}$ determine the pdf for district i in the multivariate case. Following Adrian et al. (2019), we rely on this t-distribution, because it is found to be extremely flexible and is described by only four parameters. Specifically, the t-distribution is characterised by location μ, degree of freedom n, scale σ, and skewness ν. Equation (5) depicts the corresponding distribution, where $t(.)$ and $T(.)$ are the pdf and the cumulative distribution function (cdf), respectively.

$$f(y; \mu, \sigma, \alpha, n) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma}; n\right) T\left(\alpha \frac{y-\mu}{\sigma} \sqrt{\frac{n+1}{n + (\frac{y-\mu}{\sigma})^2}}; n+1\right) \tag{6}$$

Intuitively, the pdf according to Azzalini and Capitanio (2003) is obtained when the pdf of a base t-distribution is multiplied by its corresponding cdf. Thus, when α is low (high), the base pdf (base cdf) has a high weight.

It should be noted that, for fitting the t-distribution, Adrian et al. (2019) rely on $\widehat{y_t^{.05}}$, $\widehat{y_t^{.25}}$, $\widehat{y_t^{.75}}$ and $\widehat{y_t^{.95}}$. In contrast to them, we focus on the 10th and 90th percentiles rather than the 5th and 95th percentiles, because the data set only covers 90 observations in the univariate case. This means that very high and very low percentiles are, to a large extent, driven by just a few observations.[6] As a result, very few observations determine the coefficients at the low and high ends of the distribution.

[5] In other words, our aim is to interpolate between the estimated quantiles.

[6] For the 5th percentile, according to the loss function, only 5% of the observations are given a weight of 0.95 and 95% of the observations do not have strong impact, i.e. they have a weight of 0.05. For the 10th percentile, at least 10% are given a relatively high weight. Additionally, the impact of percentiles with low weights also increases.

While the second step is optional when looking into the development of a particular percentile – because the development of a given percentile is already determined in the first step – the second step has three advantages. First, it can reveal how the entire forecast distribution varies over time. Second, as the pdf is estimated, it also makes it possible to calculate the likelihood of a given rate of growth. For example, the probability of negative house price growth rates could be investigated. Third, the t-distribution enables the generation of smoother results over potentially highly volatile predicted values for the four quantiles. The effects of outliers in a given quantile, say the 10th percentile, are thus curbed to some degree.

3 Data

Univariate Model for the German RRE Market

For the univariate model, our data set covers the period from 1999Q2 to 2022Q3. Our goal is to obtain an estimate of the forecast distribution of real growth rates of house prices. We use house prices from the Association of German Pfandbrief Banks (Verband deutscher Pfandbriefbanken (vdp)), focusing on owner-occupied housing, which we convert into real prices using the national consumer price index (CPI). We extend the series backwards according to the data provided by Kajuth (2021). Figure (2) plots the development of real house prices over time, showing that the real price level initially declined and was at the same level in 2014 as in the early 2000s. From 2014 until 2021Q4, real house prices increased sharply. Afterwards, real house prices first came to a standstill and then have been in decline since 2022Q2.

For the exogenous variables, we rely on the number of employed persons subject to social security contributions, the household debt-to-GDP ratio, the mortgage rate, and a spread between the mortgage rate and the rate on German government bonds (Bunds). The data on the number of employed persons are taken from the German Federal Employment Agency (Bundesagentur für Arbeit) and the data on GDP and household debt are taken directly from the Deutsche Bundesbank. The upper two panels of Figure (3) illustrate the development of the number of employed persons and the household debt-to-GDP ratio. It should be noted that employment fluctuates with (i) the real business cycle, (ii) population growth, and (iii) structural shifts and changes within the population, such as baby boomers entering labour markets or changes in the statutory age of retirement. While the low growth rates in the early 2000s are the result of a recession, the steady increase from 2010 to 2020 can be attributed to all three of these factors. The household debt-to-GDP ratio[7] has tended to decline, but this was interrupted during the coronavirus pandemic. In robustness checks (available upon request), we show that adding other potentially relevant variables does not affect our results. The variables in the robustness checks include growth rates of debt levels, housing investment, changes in debt service ratios, inflation, and credit standards. Adding (implied) volatilities results in a much wider forecast distribution.

For the mortgage rate (with an interest rate fixation period of ten years), we rely on the ECB's MFI statistics. As also argued by the ECB (2020), we use the spread as a measure of risk (appetite) in the housing market. We focus on the interest rate on ten-year German Government "Bunds", which are a proxy for a risk-free interest rate and taken from the Bundesbank, and the mortgage rate with an interest rate fixation period of ten years. However, we observe that the mortgage rate is somewhat sticky and lags behind developments in the risk-free rate. AT the 5% confidence level, we find an AR(1)-process in the month-on-month (mom) differences of the mortgage rate, but no empirical evidence for serial correlation in mom differences of Bunds.[8] If one does not

[7] To obtain the ratio, we sum the GDP of the last four quarters.

[8] The stickiness of the reported mortgage rate may be explained by the time lag between the date on which the contractual terms are fixed and the date on which the contract becomes legally binding and enters the statistics.

control for the different behaviour of the mortgage rate and the Bund rate, the risk component in the spread could be confounded with the structural difference between the two rates. Suppose that the general interest rate level increases affecting both rates identically over the medium-term, i.e. over two months. However, since the mortgage rate is sticky, the increase is somewhat smaller in the month of the shock (and larger in the following month). In this setting, the spread would narrow in the period of the shock, although risks in the housing market would not have increased by assumption. We therefore make the following adjustment to the spread: the spread in a given quarter is defined as the difference between the mortgage rate in the last month of the quarter and the Bunds rate on the last trading day in the second month of that quarter.

The lower panel of Figure (3) highlights the development of the interest rate and the spread. As expected, the mortgage rate was more or less in steady decline until 2019. Since 2021Q4, we can observe a strong increase. The spread fluctuates over time. It trends downwards from 1999 to 2005 and trends upwards until 2019. Since then, no trend can be observed, but it remains volatile.

Table (1) lists all of the variables along with the source. Since we only focus on year-on-year growth rates or differences, we are not faced with issues related to seasonal adjustment.

District-Panel

Although we try to stay as close as possible to the data selected for the univariate model, we have to make adjustments to both the variables and the estimation period for the panel model. At the district level, data are generally only available at annual frequency. Moreover, the beginning of the sample for the vdp price series is 2007. As a consequence, we build our baseline model based on data provided by Bulwiengesa AG, which is available from 2004 until 2022. However, in the online appendix, we show that the results are also robust using the vdp index, which we do not use as a baseline because it covers a shorter period. For this exercise, we construct a time series consisting of the growth rates of the Bulwiengesa dataset for the period from 2005 to 2007 and the growth rates from the vdp index for the period from 2008 to 2022. Again, we obtain a real growth rate by dividing by the national CPI.

Of the exogenous variables, lagged house prices and employment growth are available at the district level, while the mortgage rate, the spread between the mortgage rate and the Bund rate, and the debt-to-GDP ratio are not. While the interest rate and the spread are not expected to vary much between different districts, the debt-to-GDP ratio could be subject to considerable cross-district variation. We therefore decide to drop this variable and keep the mortgage rate and the spread constant over all districts within a given year. The number of employed persons is taken from the Federal Employment Agency and extended backwards using data from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR)).[9] As before, Table (2) lists all of the variables along with their data sources.

4 Results

Univariate Model for the German RRE Market

We begin by analysing the results of the QRs, which is the first stage of the two-stage approach in the at-risk models. As described above, our endogenous variable is the real yoy growth rate of house prices, while the exogenous variables are the yoy differences in the household debt-to-GDP ratio, the mortgage rate, the spread between the mortgage rate and the Bund rate, and the yoy

[9] Interestingly, up until 2019, the annual data from the BBSR are identical to the second-quarter data from the Federal Employment Agency.

growth rate of employment, as well as a lag of the endogenous variable. For the household debt-to-GDP ratio and employment, we rely on lagged values as well, because they are published with a certain delay.

Table (3) documents our findings for the QRs and compares them with OLS results. It should be noted that, although we only use the 10th, 25th, 75th and 90th percentiles to estimate the second stage, we also report the first stage results for the median and the 5th and 95th percentiles as well. We observe that most coefficients from the QRs (except the median) differ substantially from the OLS estimate. This confirms that QRs are the right tool for identifying tail risks, as the impact of the variables changes over the cycle. As expected, the constant is low (and negative) for low quantiles and high (and positive) for higher quantiles. Lagged real house prices play an important role in determining the development of future real house prices, as all coefficients are significant at the 1% level. The coefficients for the 25th, 50th and 75th percentiles are above 0.8, while the coefficients for the 5th, 10th, 90th and 95th percentiles are considerably smaller. The coefficient is particularly small at the lower end of the distribution. This seems intuitive, as the housing cycle in Germany is rather slow and exhibits relatively high persistence. When house prices increase within a given year, there is a high chance that they will also increase in the following year. Conversely, when house prices decrease within a given year, there is a high chance that they will also decrease in the following year. However, there is also a small chance that the respective upswing or downturn in house prices will come to an end, as documented by the 5th percentile.

The mortgage rate has the expected negative sign in six out of seven quantiles and is significant for the 5th and the 10th percentile and the OLS estimation on a ten percent level. The left tail of the distribution is thus more strongly affected by shifts in the mortgage rate than the median or upper quantiles. As a consequence, increases in the mortgage rate also widen the distribution. The spread has similar effects on the forecast distribution. It is (significantly) negative for four (one) of the seven quantiles and also has a more pronounced effect on the left tail of the distribution. While the coefficient for employment growth is positive and significant in all cases, the change in the household debt-to-GDP ratio has a negative impact on the left end and a positive impact on the right end of the distribution. Greater changes in debt ratios thus widen the distribution. This is consistent with the hypothesis that real estate booms go hand in hand with higher indebtedness, and busts with lower indebtedness, as real estate is a leveraged investment. Again, the boom could continue to lead to even higher future debt ratios. By contrast, high household indebtedness and correspondingly high repayments might weigh on the affordability of housing. However, the debt-to-GDP ratio is not significant in any of the eight regressions.

Figure (4) illustrates how the conditional 5th percentile, the conditional 10th percentile and the conditional median of expected house price growth rates have developed according to the estimates of Equation (1). It should be noted that the horizontal axis indicates the ends of each respective forecast period. For example, 2023Q3, is thus the forecast from 2022Q3 to 2023Q3. During the coronavirus pandemic, the 5th percentile and the 10th percentile shifted downwards compared to 2020Q4 as household indebtedness rose and employment growth declined.[10] However, interpretations of the pandemic period are subject to high uncertainty, as other special factors (e.g. changes in households' preferences for living space) may have played important roles. Since 2023Q1, these two lower percentiles declined substantially, mainly due to large interest rate hikes and negative growth rates of real house prices. With regard to the median, we observe that lagged house price growth rates are the primary explanatory factor. Interestingly, the forecast distribution widened during the pandemic. It also declined from 2023Q1 until 2023Q3, but remained above zero.

Figure (5) highlights how the forecast distribution developed from 2020Q4 to 2023Q3. Before the

[10]Employment growth turned negative in the period from 2021Q3 to 2022Q2.

pandemic, i.e. in 2020Q4[11] the median forecast of real house price growth was 5.4%, while the probability of a negative real house price growth was 0.8%. The pandemic shifted the forecast distribution to the right, as visualised by the distribution for 2022Q4. The median of the forecast distribution increased by 1.6 percentage points (pp) from 2020Q4 to 2022Q4. This is consistent with the view that the pandemic may have fuelled households' housing preferences, as they spent more time at home and may have expected to work more from home after the end of the pandemic (Battistini et al. (2021)). Households might also be willing to invest more in housing, as forced savings increased their liquidity buffers. The recent episode of high inflation and interest rate rises has caused the entire forecast distribution to shift to the left. In 2023Q3, the one-year forecasts for the median and the 10th percentile are 0.9% and -2.6%, respectively. The latter indicates that price declines are not unlikely. The probability of a negative growth rate over the next year is 31.6%.

To evaluate the model, we compare its historical performance with actual historical house price developments. The Whisker Boxplots in Figure (6) show the out-of-sample sample forecast. We rely on a rolling-window approach for the out-of-sample forecast. Specifically, for the conditional forecast of the growth rate from 2015Q4 to 2016Q4, we rely on data from the beginning of our sample, i.e. 1999Q2, to 2015Q4. With this data, the QRs are estimated and the corresponding predicted house price growth rates are fitted to the skewed t-distribution. Finally, the percentiles displayed in Figure (6) stem from this t-distribution. We subsequently add a period and repeat the exercise for the forecast of further periods. More precisely, for the forecast starting as of 2016Q1, we use data up until 2016Q1, and so on.

While the model performs well on average, two limitations stand out. First, up until the recent era of high inflation, the model had a tendency to produce estimates that were too low (median vs. realisation). [12] Whilst it would be preferable if the model's forecasts matched the observed distribution, from a risk management perspective, it seems to be preferable to overemphasise rather than underestimate downside risks. Overemphasising downside risks could be considered a type II error in statistical hypothesis testing. Awareness of this shortcoming aids the understanding and use of the model's results in that looking at changes in certain percentiles may be more reliable than focusing on their corresponding levels. Second, due to its design, the model is not capable of detecting turning points. Although it is a well-established fact that turning points are difficult to forecast (see Quigley (1999)), two main factors are behind the unsuccessful forecasting of turning points of our model. First, the model is backward-looking. It does not contain variables that are forward-looking, such as forward rates, because these variables would add uncertainty to the estimation of the QRs. Furthermore, such variables have not been demonstrated to improve the model's performance. The conclusion is that house prices do not seem to react to forward-looking variables, but rather to the realisation of contemporary variables. However, the estimated parameters also show that there is high persistence. Second, real house prices in Germany were not subject to a major and sudden turning point until 2022Q4, as documented by Figure (2). There is thus little historical evidence that the model could build upon. However, the recent turnaround is generating more realised values at the lower end of the growth distribution, which is likely to improve the model's performance going forward.

It is important to note that cross-district models use the variation from districts with more volatile housing markets and are thus capable of generating larger swings and larger declines (in the tails)

[11] As before 2020Q4 refers to the period from 2019Q4 to 2020Q4. It is thus based on data that were available in 2019Q4

[12] 12If the law of large numbers applied, it would be expected that 5%of the observations would each be below and above the plots, 20% would be on each side in the black dashed area, and 50% would be in the blue area, split equally above and below the red line. By contrast, we observe an excessive number of actual values above the median of the forecast distribution.

in growth rates. While these models may be better at "forecasting" large declines at the current juncture, their identification is carried out based on data from districts with completely different real estate cycles.

District-Panel

We start by verifying that the results from the univariate model also hold under the district panel. Afterwards, we dive deeper into the panel dimension and differentiate between various district characteristics. More precisely, we differentiate between densely and sparsely populated districts.

Again, we first present the results from the QRs. While Table (4) shows the results when Canay FEs are included, Table (5) shows the outcomes from the pooled model. We observe that both approaches lead to almost the same results. All variables, in fact, have the same sign. Only the constant differs somewhat between the two models, which is a result of the design of the fixed effects. The results are also qualitatively similar to the univariate model, as shown in Table (3). However, we observe three quantitatively important differences. First, the constant is much lower at the left end of the distribution and much higher at the right end, highlighting that, within the panel, a higher number of extreme positive and extreme negative growth rates are observed than on an aggregate nationwide basis. Second, lagged house prices have a much smaller impact across all quantiles as well as in the OLS estimation. Both of these results make sense intuitively, as higher numbers of extreme values at the district level, which show up in the results, become washed out in the aggregate series. The smaller coefficients could be the result of inter-district substitution of housing demand.[13] Moreover, unlike the univariate model, the panel does not include the period from 1999 to 2003, during which house prices remained relatively stable. However, as in the univariate model, the impact of the AR term is smaller at the left tail of the distribution. Third, the mortgage rate and spread have a negative impact not only on the left tail of the distribution, but also on the right tail. Still, an increase in the rate or the spread widens the distribution, as the coefficient at lower quantiles is higher in absolute terms.

Figures (7) and (8) show the forecast distributions for Germany when the Canay-FE and pooled models are applied, respectively. Again, the year on the axis refers to the respective period of each forecast. We obtain a forecast for Germany by weighting each observation of a district by its population size relative to the overall population of Germany. As the coefficients for both models are very similar, as shown in Tables (5) and (3), and the weighted realisations are identical, the two forecast distributions are very similar as well. However, in comparison to the univariate model, we obtain a much wider distribution, which reflects the relatively large differences between the constants at lower and higher quantiles. For example, there is a ten percent chance that house prices in 2023 will fall by more than -9.0% (-8.7%) when applying the Canay-FE model (pooled model). Furthermore, in contrast to the univariate model, the forecast distribution has shifted to the left from 2020 to 2022. More importantly, the leftward shift in the recent period of high interest rates is found in both the univariate model and the panel model.

The panel data allows distinctions to be made between districts according to characteristics that are important for developments in the housing market. An appropriate supplementary analysis would be to investigate whether there are differences among districts with different population densities.[14] We only provide evidence from the pooled model. However, as before the results are very similar when Canay FEs are included.

[13] Inter-district substitution of housing demand could be explained by the following example. Supposing that house prices grew disproportionally in a given district in a given period, households would then reduce their demand in that particular district and increase their demand in other (neighbouring) districts with lower past rates of house price growth.

[14] First, we collect the median population density of each district for the period from 2004 to 2020. We then identify the median across all districts. Here, a district is not allowed to switch between the two groups over time.

Tables (6) and (7) present the corresponding results for the QRs. Interestingly, for relatively sparsely populated districts, the constant is comparably smaller at the 5th, 10th and 25th percentiles and higher at the 75th, 90th and 95th percentiles. This is in line with the fact that house price developments are more volatile for districts with a low population densities. The impact of past house prices is less pronounced in sparsely populated districts throughout all quantiles, possibly reflecting the fact that real house price growth rates from 2004 to 2022 were higher for densely populated districts.[15] However, as before, in both samples, the AR term at the left tail of the distribution is smaller than the median. On average, the mortgage rate has similar effects in both samples. Interestingly, the spread, which is a measure of risk appetite, has a more or less constant negative effect for different quantiles in densely populated districts and no significant effect on the right tail of the distribution in sparsely populated districts. Increasing risk premia thus do not seem to affect the right tail of the distribution in sparsely populated districts.

Building on these coefficients, Figures (9) and (10) show the development of the forecast distribution. The conditional forecast for 2020, which is based on pre-pandemic data, suggests a higher probability of high growth rates in densely populated districts. For instance, the median (the 10th percentile) is 5.8% (1.8%) in densely populated districts in comparison to sparsely populated districts with a median of 5.2% (10th percentile of -1.1%). However, the leftward shift from 2019 to 2022 is of a similar magnitude for both samples. Specifically, the median of the forecast distribution for densely populated districts declines by 3.4 pp in comparison to 4 pp for sparsely populated districts. For 2023, the median and the tenth percentile of the forecast distribution are again smaller for sparsely populated districts, at -5.2% and -9.5%, respectively, in comparison to -4.8% and -7.8%, respectively, for densely populated districts.

Building on this evidence, we split our sample into two groups of districts. One group consists of large cities (kreisfreie Städte, "district-free cities") and the other group of all other district types, based on the classification of district types ("Siedlungsstrukturelle Kreistypen") provided by the BBSR.[16]. Tables (8) and (9) present the results, which are qualitatively similar, although the main differences between rural and urban areas are less pronounced. In other words, for cities, the constant is larger at the 5th and 10th percentiles, the AR terms are generally larger, and the spread is smaller at the 90th and 95th percentiles. As a result, the fitted density functions, as displayed in Figures (11) and (12), also look very similar to those in Figures (9) and (10).

5 Conclusion

The recent downturn in the German RRE market has made researchers, policymakers, and other market participants rethink the role of inherent downside risks in the market. This paper adds to this discussion by providing a tool for analysing (i) the variables that move (different parts of) the forecast distribution of real house price growth rates, (ii) how this distribution varies over time, and (iii) which districts are predominately exposed to these downside risks. For this purpose, we build upon Adrian et al. (2019) and apply their at-risk methodology to the German RRE market. We rely on QRs to show that macroeconomic and financial variables affect different quantiles of the house price forecast distribution to different degrees. We find that, in particular, the middle of the forecast distribution is affected by past rates of house price growth, whilst interest rate changes move the left tail of the distribution to a greater degree. Other macroeconomic variables, such as employment, have a more or less equal impact across the various quantiles. We then

[15] The unweighted mean of districts' growth rates in the period from 2004 to 2022 is 90% for districts with high population densities and 69% for districts with low population densities.

[16] The types differ mainly by population density, ranging from large cities to rural areas with low population densities (see https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/kreise/siedlungsstrukturelle-kreistypen/kreistypen.html).

show that the recent period of high inflation and rising interest rates has resulted in a leftward shift of the entire forecast distribution. These findings hold under both a univariate model with quarterly Germany-wide data and a disaggregated panel version of the model with annual data for 399 German districts. The district panel reveals different dynamics across different district characteristics. Most importantly, we find that the forecast distribution in sparsely populated districts is shifted to the left in comparison to their densely populated counterparts.

The findings of the paper highlight the fact that it is not useful to focus solely on the mean or median forecasts, as there are meaningful changes throughout the entire forecast distribution across the cycle. Furthermore, the results from the panel estimation suggest that looking at the German aggregate (mean) may also underestimate tail risks, as the potential downside risks at the district level may be even more pronounced. Hence, the changes in the forecast distribution may be more informative, especially for applications that focus on unusually high or unusually low actual values. Moreover, because the uncertainty surrounding forecasts varies over time, policymakers could use the information from this class of model as a communication tool to make market participants aware of the higher uncertainty surrounding a central forecast.

This paper focuses on the forecast distribution over the next year, mainly because developments in RRE markets in Germany have proven to be rather persistent and the reliability of modelling year-on-year changes is, in our view, more important than potentially noisy quarter-on-quarter developments. However, this focus on year-on-year growth rates comes at the cost of the model having difficulties in predicting turning points in house price growth rates. An appropriate extension would be to develop a model at quarterly frequency that is better suited for these turning points.

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Appendix

Table 1: Data sources - univariate model

Variable	Data Source
House Prices	vdp Research
CPI	Deutsche Bundesbank
Employment	Bundesagentur für Arbeit
Household Debt	Deutsche Bundesbank
GDP	Deutsche Bundesbank
Mortgage Rate	ECB
Bunds Rate	Deutsche Bundesbank

Table 2: Data sources - panel model

Variable	Data Source
House Prices	Bulwiengesa & vdp Research
CPI	Deutsche Bundesbank
Employment	Bundesagentur für Arbeit & BBSR
Mortgage Rate	ECB
Bunds Rate	Deutsche Bundesbank

Table 3: Quantile regression results - baseline model

Quantile	5	10	25	50	75	90	95	OLS
Constant	-2.1***	-1.8***	-0.72*	0.3	1.0***	1.9***	2.9***	0.021
Lagged House Pr.	0.37***	0.69***	0.81***	0.89***	0.89***	0.73***	0.64***	0.83***
Mortgage Rate	-1.8***	-1.4**	-0.60	-0.13	-0.32	-0.35	0.26	-0.82*
Spread	-1.7*	-1.4	-0.78	-0.81	0.21	0.59	2.2	-0.89
Employment	0.59**	0.45**	0.20*	0.40**	0.37**	0.40*	0.45*	0.32**
Debt-to-GDP	-0.078	-0.065	-0.081	0.015	0.18	0.26	0.57	0.003

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap.

Table 4: Quantile regression results - panel model with Canay-FEs

Quantile	5	10	25	50	75	90	95	OLS
Constant	-5.7***	-4.2***	-2.0***	0.15*	2.6***	5.3***	7.2***	0.79**
Lagged House Pr.	0.29***	0.34***	0.43***	0.51***	0.51***	0.49***	0.47***	0.46***
Mortgage Rate	-3.5***	-4.1***	-3.7***	-3.3***	-3.0***	-2.6***	-2.5***	-3.8***
Spread	-2.1***	-1.4***	-1.3***	-0.94***	-0.96***	-0.24	-0.52	-1.2***
Employment	0.65***	0.58***	0.59***	0.71***	0.73***	0.63***	0.61***	0.77***

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The fixed effects are generated following Canay (2011). The corresponding levels are constructed via bootstrap. As outlined in Eguren Martin et al. (2021), we have to follow Adrian et al. (2019) and bootstrap solely along the time dimension. Given that the pooled model produces similar results, the bias can be assumed to be marginal.

Table 5: Quantile regression results - pooled panel model

Quantile	5	10	25	50	75	90	95	OLS
Constant	-6.2***	-4.9***	-2.7***	0.68***	1.7***	4.5***	6.1***	0.79**
Lagged House Pr.	0.31***	0.34***	0.44***	0.52***	0.52***	0.51***	0.50***	0.47***
Mortgage Rate	-3.3***	-4.0***	-3.8***	-3.4***	-3.1***	-2.4***	-2.4***	-3.8***
Spread	-1.8***	-1.2***	-1.4***	-1.1***	-1.0***	-0.12	-0.03	-1.2***
Employment	0.52***	0.53***	0.57***	0.71***	0.77***	0.61***	0.68***	0.78***

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap.

Table 6: Quantile regression results - low population density

Quantile	5	10	25	50	75	90	95	OLS
Constant	-6.9***	-5.2***	-2.9***	0.18***	2.0***	4.9***	6.9***	0.84**
Lagged House Pr.	0.29***	0.28***	0.38***	0.46***	0.48***	0.48***	0.48***	0.43***
Mortgage Rate	-2.4***	-3.2***	-3.8***	-3.6***	-3.3***	-2.6***	-2.7***	-3.9***
Spread	-1.6*	-1.1*	-1.5***	-0.67	-0.35	0.56	1.3	-0.82*
Employment	0.40***	0.37***	0.48***	0.69***	0.81***	0.76***	0.66***	0.80***

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap. Estimates stem from a pooled model.

Table 7: Quantile regression results - high population density

Quantile	5	10	25	50	75	90	95	OLS
Constant	-5.5***	-4.4***	-2.4***	0.56***	1.4***	3.8***	5.3***	0.73**
Lagged House Pr.	0.37***	0.41***	0.49***	0.59***	0.57***	0.54***	0.52***	0.52***
Mortgage Rate	-4.5***	-4.5***	-3.5***	-3.0***	-2.9***	-2.8***	-2.6***	-3.7***
Spread	-0.88*	-0.96*	-1.0***	-1.4***	-1.6***	-1.1***	-1.0***	-1.4***
Employment	0.47***	0.51***	0.57***	0.68***	0.74***	0.65***	0.65***	0.71***

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap. Estimates stem from a pooled model.

Table 8: Quantile regression results - rural areas

Quantile	5	10	25	50	75	90	95	OLS
Constant	-6.5***	-5.0***	-2.9***	0.78***	1.7***	4.7***	6.1***	0.84**
Lagged House Pr.	0.29***	0.31***	0.41***	0.49***	0.52***	0.50***	0.51***	0.45***
Mortgage Rate	-3.1***	-3.4***	-3.7***	-3.4***	-3.2***	-2.5***	-2.1***	-3.6***
Spread	-1.8***	-1.1***	-1.6***	-0.95***	-1.1**	-0.09	0.41	-1.1***
Employment	0.50***	0.45***	0.59***	0.77***	0.89***	0.72***	0.68***	0.86***

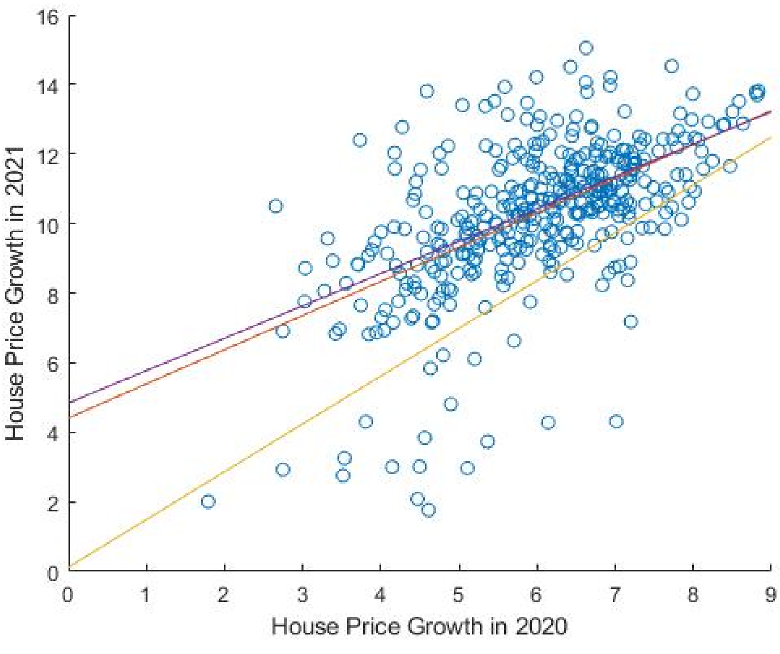
Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap. Estimates stem from a pooled model.

Table 9: Quantile regression results - cities

Quantile	5	10	25	50	75	90	95	OLS
Constant	-5.2***	-4.2***	-2.1***	-0.33***	0.14***	3.6***	6.1***	0.72**
Lagged House Pr.	0.42***	0.44***	0.52***	0.59***	0.57***	0.51***	0.51***	0.52***
Mortgage Rate	-5.4***	-4.8***	-3.6***	-3.0***	-2.9***	-2.7***	-2.1***	-4.3***
Spread	-1.5***	-0.41	-0.32	-1.4***	-1.1***	-0.65	-0.89*	-1.2***
Employment	0.44***	0.47***	0.44***	0.55***	0.63***	0.62***	0.53***	0.6***

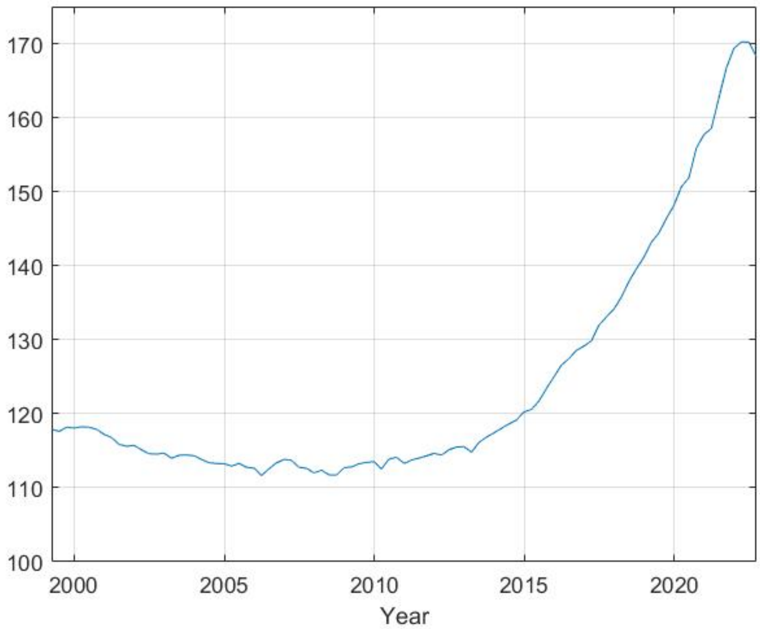
Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The corresponding levels are constructed via bootstrap. Estimates stem from a pooled model.

Figure 1: Quantile regressions scatter plot



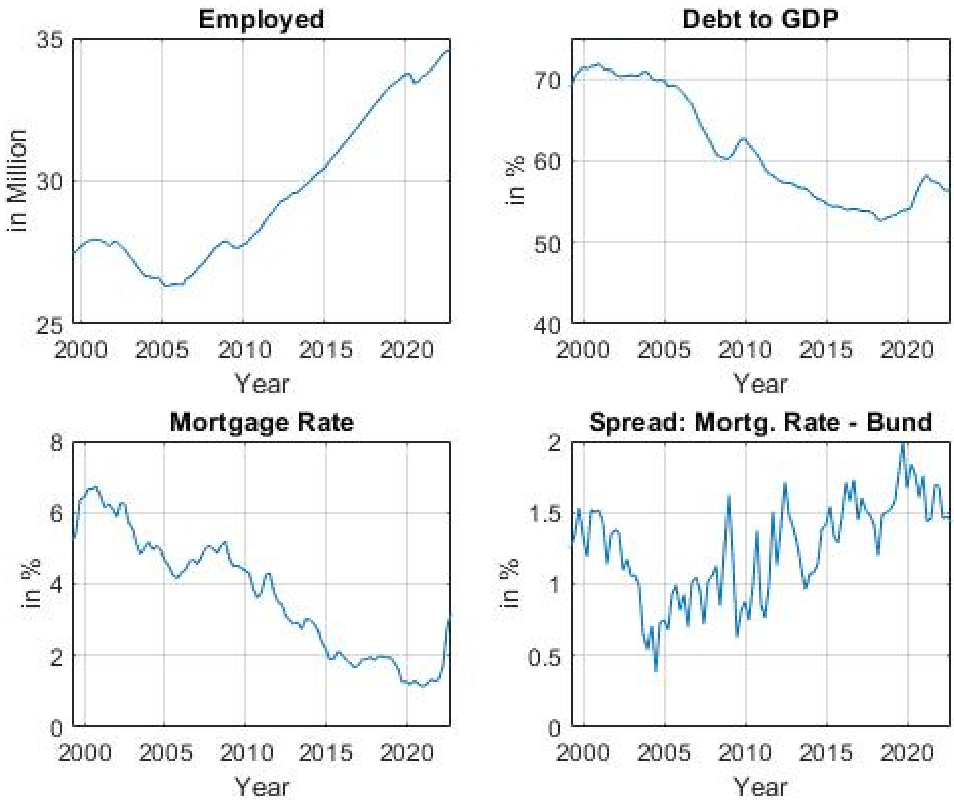
Notes: The purple line shows the OLS estimates, while the yellow and red lines show the QR results for the 10th percentile and the median, respectively.

Figure 2: Development of real house prices



Notes: Nominal house prices for owner-occupied housing are taken from the Verband deutscher Pfandbriefbanken (vdp) and extended backwards according to data provided by Kajuth (2021). The CPI has been applied to calculate real prices.

Figure 3: Development of exogenous variables



Notes: Top-left: Number of employed persons subject to social security contributions (Bundesagentur für Arbeit); Top-right: Household debt to GDP ratio (Deutsche Bundesbank) Bottom-left: Mortgage rate (ECB); Bottom-right: Spread between mortgage rate and rate on German government bonds (ECB; Bundesbank).

Figure 4: Factors contributing to the historical development of forecast quantiles

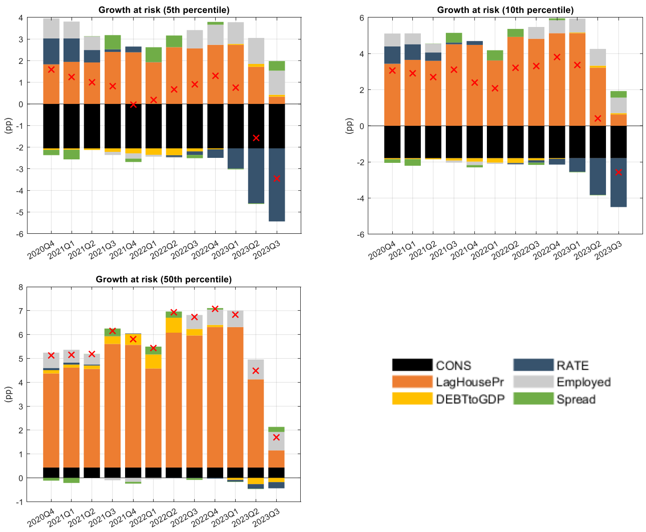
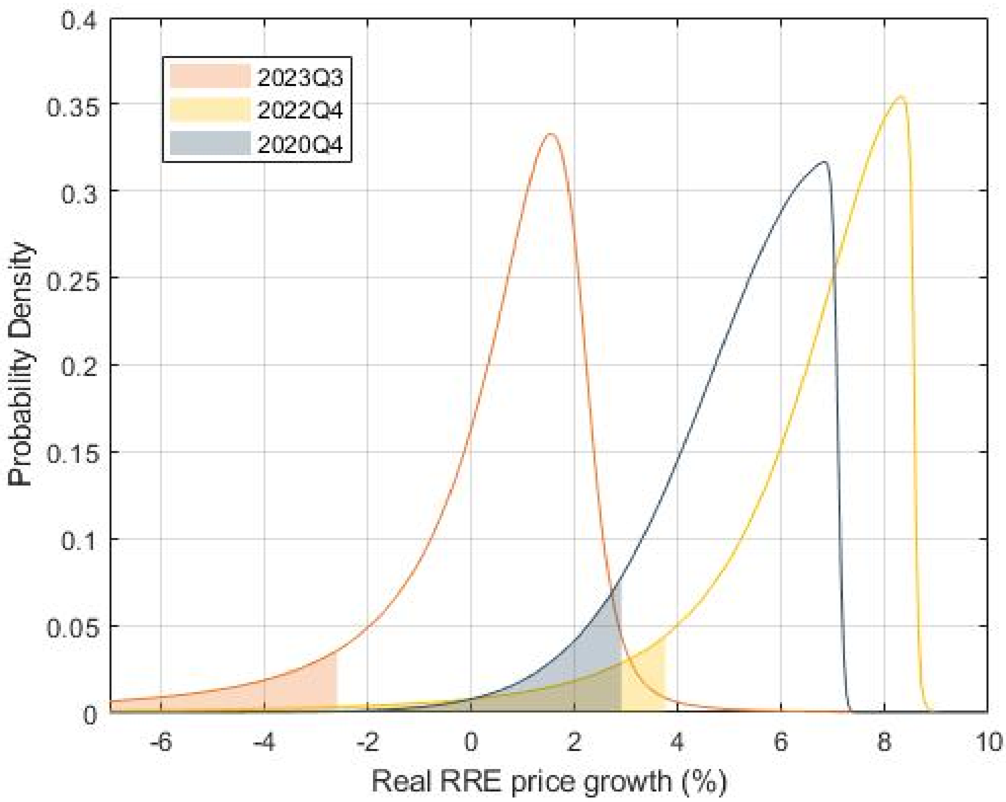
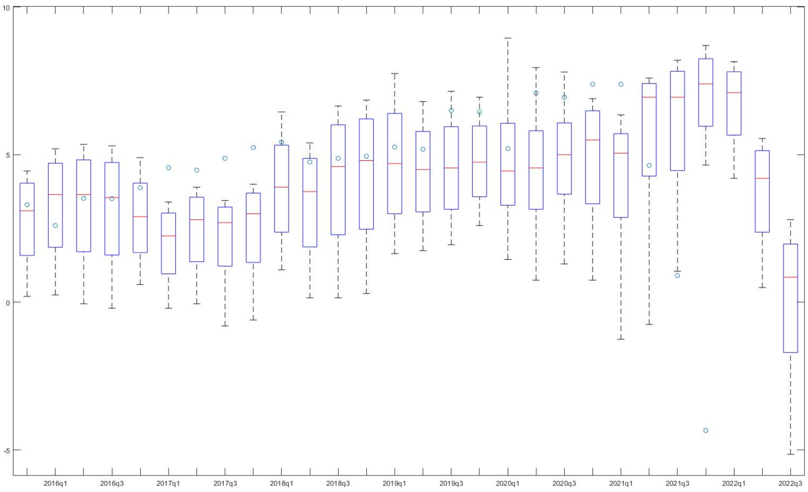


Figure 5: Forecast distribution for the univariate model



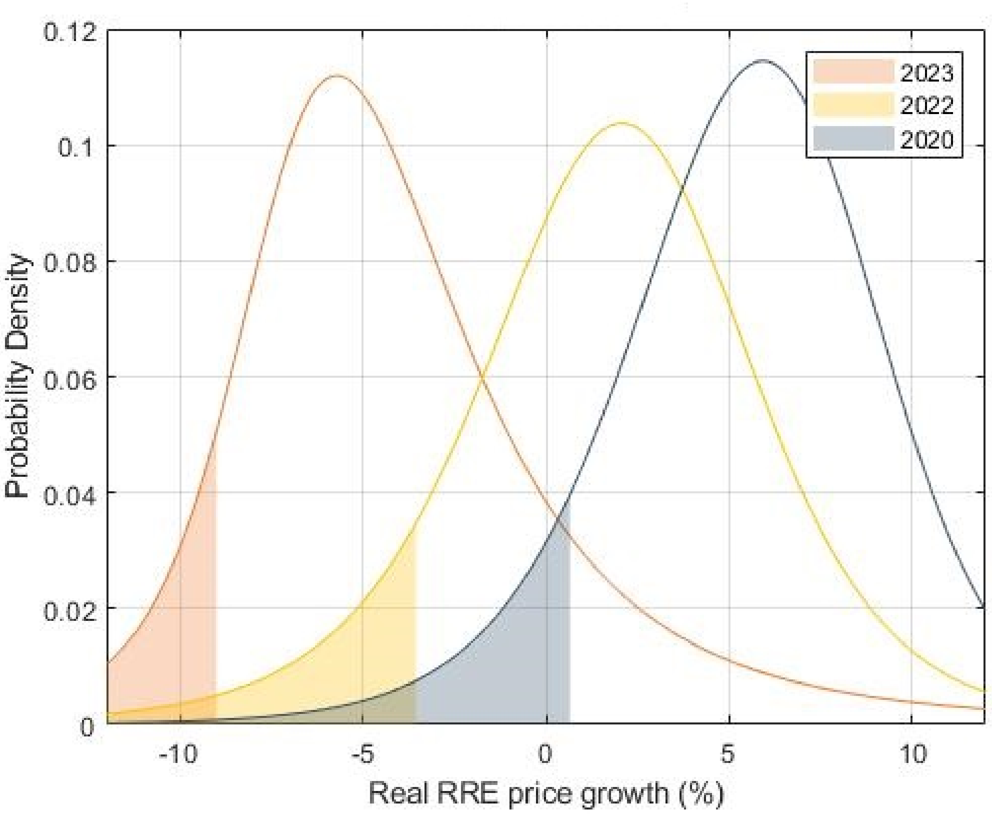
Notes: The periods in the legend refer to the ends of the respective forecast horizons. For example, 2023Q3 is the forecast from 2022Q3 to 2023Q3. The shaded areas depict the 10th percentiles.

Figure 6: Out of sample forecast



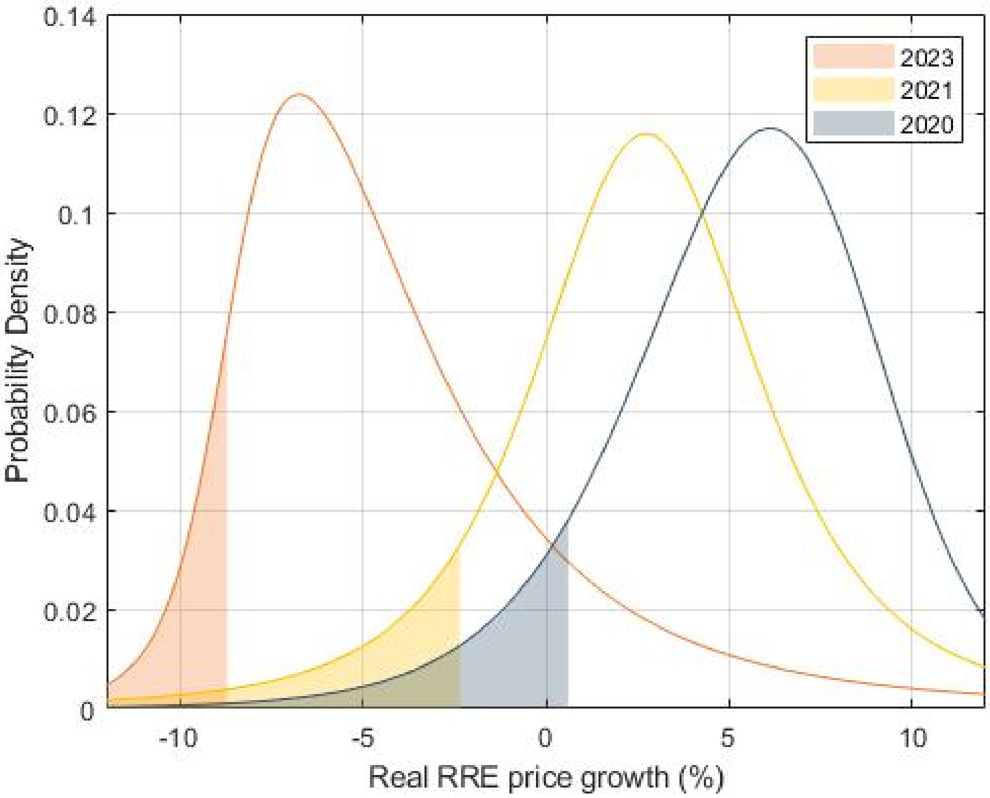
Notes: The periods in the legend refer to the ends of the respective forecast horizons. For example, 2023Q3 is the forecast from 2022Q3 to 2023Q3. The red lines of the Whisker Boxplots indicate the median, while the upper (lower) blue lines mark the upper (lower) quartiles and the black lines mark the 5th and 95th percentile, respectively. The blue dots represent the actual real house price growth rates.

Figure 7: Forecast distribution for the FE-panel model



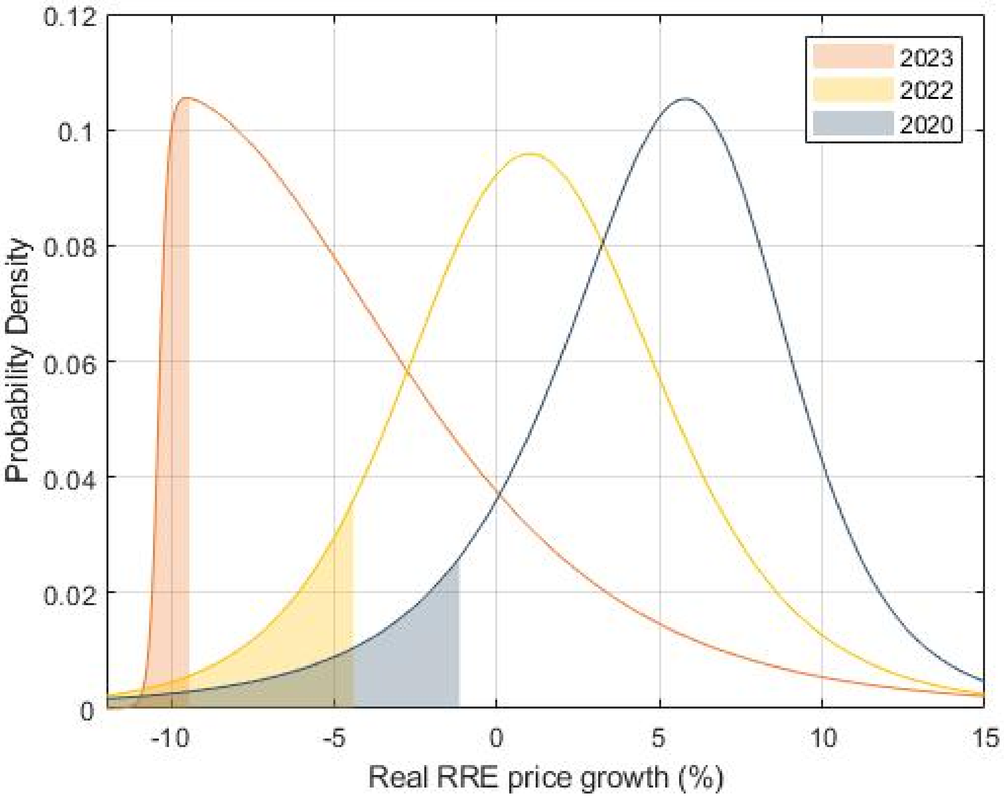
Notes: The periods in the legend refer to the ends of the respective forecast horizons. The fixed effects are generated following Canay (2011). The shaded areas depict the 10th percentiles. Districts are weighted by their populations.

Figure 8: Forecast distribution for the pooled panel model



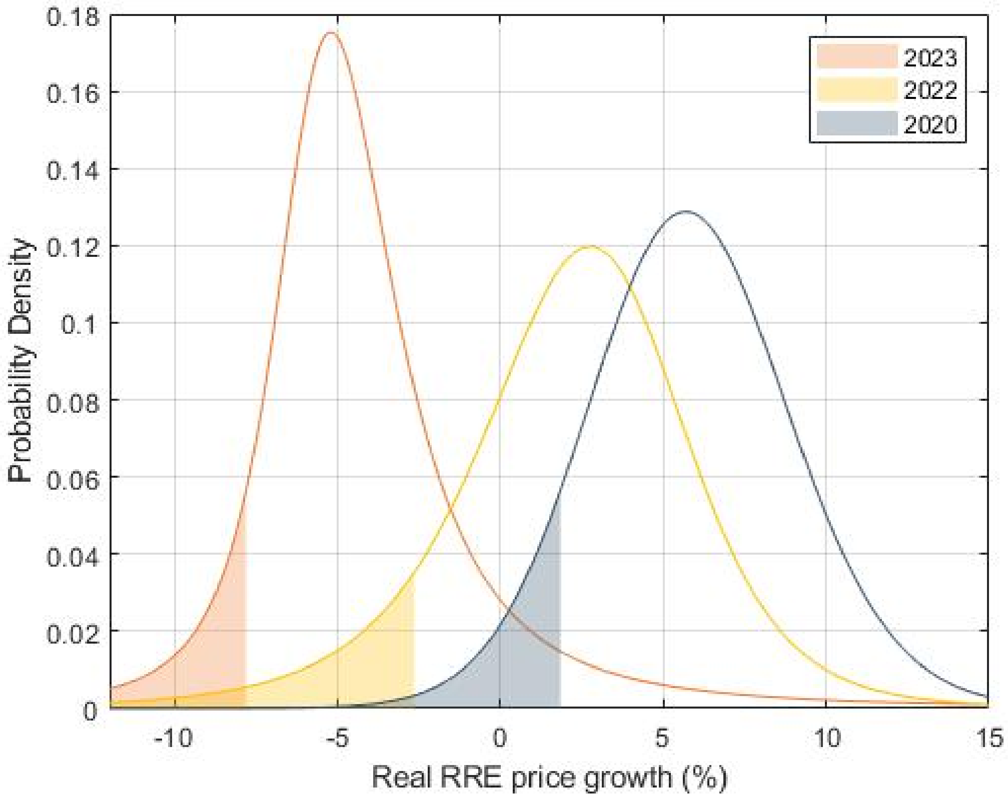
Notes: The periods in the legend refer to the ends of the respective forecast horizons. The shaded areas depict the 10th percentiles. Districts are weighted by their populations.

Figure 9: Forecast distribution for the low population density model



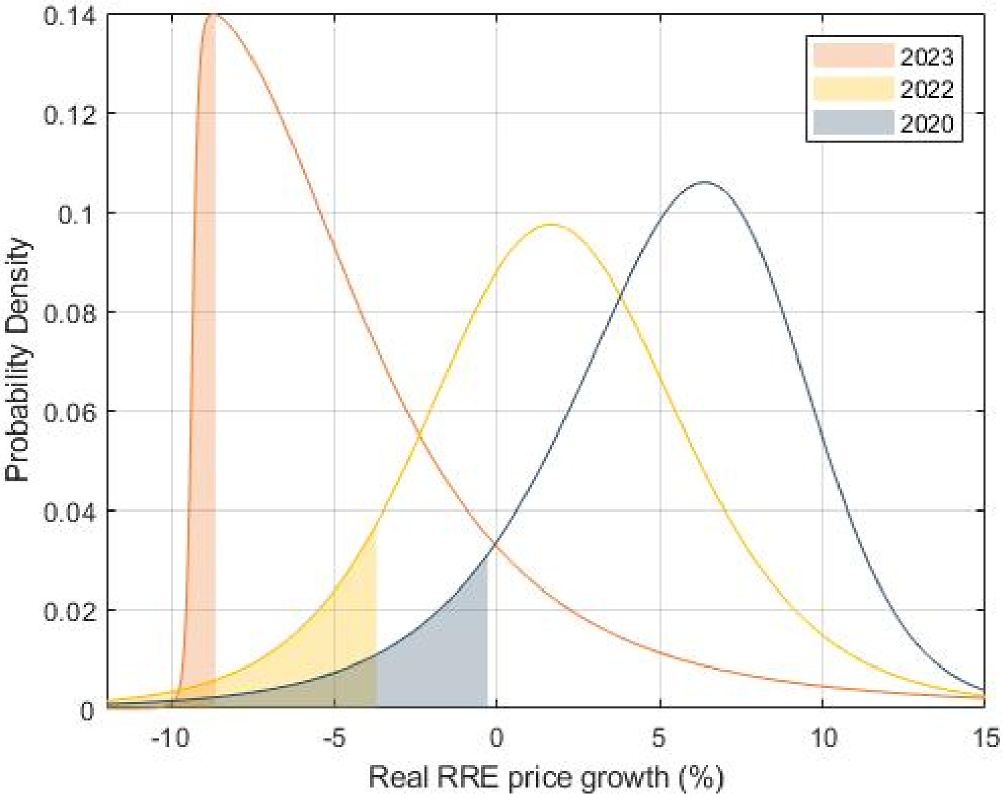
Notes: The periods in the legend refer to the ends of the respective forecast horizons. The shaded areas depict the 10th percentiles. Districts are weighted by their populations.

Figure 10: Forecast distribution for the high population density model



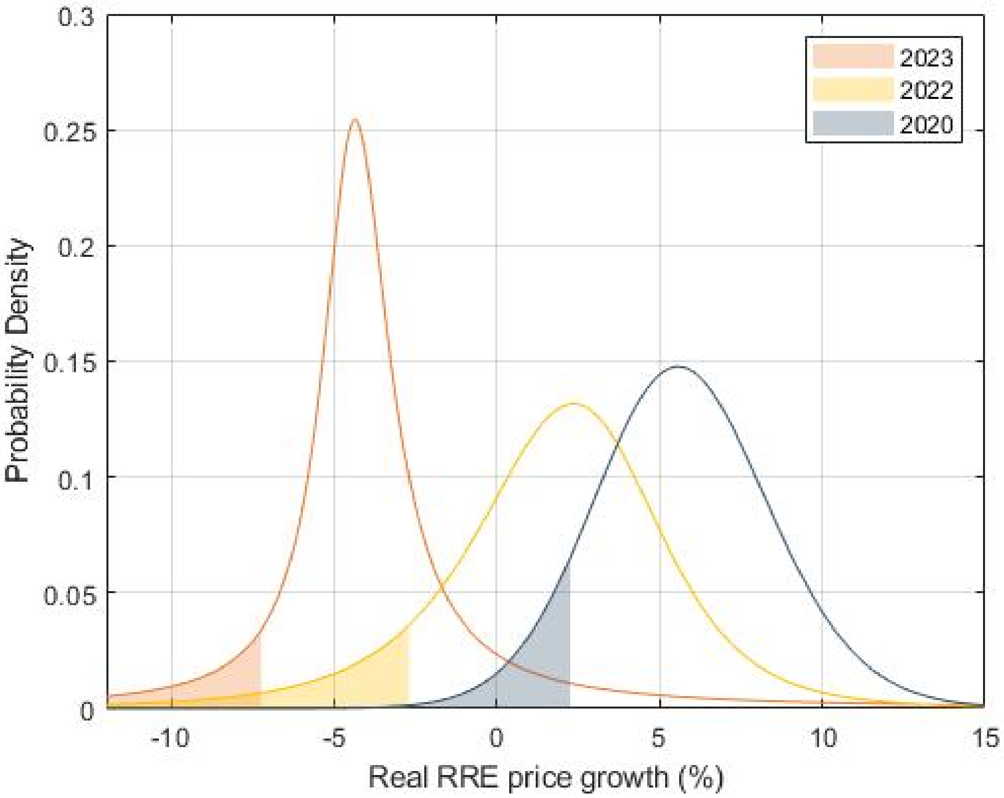
Notes: The periods in the legend refer to the ends of the respective forecast horizons. The shaded areas depict the 10th percentiles. Districts are weighted by their populations.

Figure 11: Forecast distribution for the rural area model



Notes: The periods in the legend refer to the ends of the respective forecast horizons. The shaded areas depict the 10th percentiles. Districts are weighted by their populations.

Figure 12: Forecast distribution for the city model



Notes: The periods in the legend refer to the ends of the respective forecast horizons. The shaded areas depict the 10th percentiles. Districts are weighted by their populations.