DIW BERLIN

1207

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2012

Forecasting the Prices and Rents for Flats in Large German Cities

Konstantin A. Kholodilin and Andreas Mense

Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

IMPRESSUM

© DIW Berlin, 2012

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
http://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
http://ideas.repec.org/s/diw/diwwpp.html
http://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html

Forecasting the prices and rents for flats in large German cities

Konstantin A. Kholodilin* Andreas Mense§

April 25, 2012

Abstract

In this paper, we make multi-step forecasts of the monthly growth rates of the prices and rents for flats in 26 largest German cities. Given the small time dimension, the forecasts are done in a panel-data format. In addition, we use panel models that account for spatial dependence between the growth rates of housing prices and rents. Using a quasi out-of-sample forecasting exercise, we find that both pooling and accounting for spatial effects helps to substantially improve the forecast performance compared to the benchmark models estimated for each of the cities separately. In addition, a true out-of-sample forecasting of the growth rates of flats' prices and rents for the next six months is done. It shows that in most cities both prices and rents for flats are going to increase. In some cities, the average monthly growth rate even exceeds 1%, which is a very strong increase compared to the overall price level increase of about 2% per year.

Keywords: Housing prices; housing rents; forecasting; dynamic panel model; spatial autocorrelation; German cities.

JEL classification: C21; C23; C53.

*DIW Berlin, Mohrenstraße 58, 10117 Berlin, Germany, e-mail: kkholodilin@diw.de

§Friedrich-Alexander-Universität Erlangen-Nürnberg, Kochstraße 4, 91054 Erlangen, Germany, e-mail: Andreas.Mense@wiwi.phil.uni-erlangen.de

Contents

1 Introduction **1**

2 Internet-based indices **2**

3 Forecasting models **5**

4 Estimation results **8**

4.1 Flats' prices 8

4.2 Flats' rents 9

5 Forecast accuracy **10**

6 Conclusion **14**

References **15**

Appendix **17**

List of Tables

1 Descriptive statistics of the growth rates of prices and rents for flats, %, 2010:7-2012:4 17

2 Estimation results of the flats' price models, 2010:7-2012:4 18

3 Estimation results of the flats' rent models, 2010:7-2012:4 18

4 Quasi out-of-sample forecast accuracy of flats' price models (RMSFE), 2011:7-2012:4 19

5 Quasi out-of-sample forecast accuracy of flats' rent models (RMSFE), 2011:7-2012:4 19

6 Predicted average growth rates of flats prices and rents, %, 2012:5-2012:10 20

List of Figures

1 Geographical distribution of flats' prices in Germany, April 2012 21

2 Geographical distribution of flats' rents in Germany, April 2012 22

3 Flat price dynamics in 26 large German cities, 2010:6-2012:4 23

4 Flat price dynamics in 26 large German cities, 2010:6-2012:4 (continued) 24

5 Flat rent dynamics in 26 large German cities, 2010:6-2012:4 25

6 Flat rent dynamics in 26 large German cities, 2010:6-2012:4 (continued) 26

7 Monthly growth rates of flat prices in 26 large German cities: actual and predicted, 2010:7-2012:10 27

8 Monthly growth rates of flat prices in 26 large German cities: actual and predicted, 2010:7-2012:10 (continued) 28

9 Monthly growth rates of flat rents in 26 large German cities: actual and predicted, 2010:7-2012:10 29

10 Monthly growth rates of flat rents in 26 large German cities: actual and predicted, 2010:7-2012:10 (continued) 30

1 Introduction

The role of the housing market in the everyday life of society is difficult to overestimate. Home rents and prices directly affect the standard of living of every person. It is well known now that bubbles on real-estate markets are likely to trigger financial crises, which in turn spill over to the real economy. For these reasons alone, it is very important to estimate and forecast home rents and prices. Both problems are especially acute in Germany.

The first problem is a lack of data on real-estate prices in Germany and its regions. Probably due to the fact that the housing prices in Germany had been stagnating for decades, very little attention was paid to constructing the long time series of home price indices at the regional level. In the recent years, the situation started to change, see Kholodilin and Mense (2012).

The second problem is a lack of studies on forecasting the housing prices in Germany is tiny. To the best of our knowledge, there exists only one paper —an de Meulen et al. (2011)— that forecasts German real estate prices for four different market segments (new and existing houses and apartments) using ARDL and VAR as well as forecast combination approaches. Their study is based on monthly data provided by Immobilienscout24 dating back to 2007. The benchmark is a simple AR model. The authors find that ARDL and VAR forecasts single-handedly can hardly improve upon the accuracy of AR forecasts, but find some substantial improvements when weighing the forecasts with the forecast errors of previous periods, especially for the existing houses segment. Clustering, see Aiolfi and Timmermann (2006), proves beneficial in a similar fashion. However, the authors consider only the German market as a whole and do not take into account spatial dependencies.

In this paper, we are trying to solve both problems. First, we construct flats' price and rent indices for 26 large German cities. Second, we suggest a model to simultaneously forecast the prices and rents for flats in these cities.

The rent/price estimates are based on data of the largest German Internet site Immobilienscout24 offering housing for sale and for rent. We collect the data on a monthly basis beginning in June 2010. Hence, the sample is relatively short. We circumvent this problem by pooling the growth rates of housing rents/prices into a panel and correspondingly utilizing panel data models for forecasting. The advantages of such a pooling approach for forecasting have been widely demonstrated in a series of articles for diverse data sets such as Baltagi and Griffin (1997); Baltagi et al. (2003) — for gasoline demand, Baltagi et al. (2000) — for cigarette demand, Baltagi et al.

(2002) — for electricity and natural gas consumption, Baltagi et al. (2004) — for Tobin's q estimation, and Brücker and Siliverstovs (2006) — for international migration, among others.

In addition to pooling, accounting for spatial interdependence between regions may prove beneficial for the purposes of forecasting. Spatial dependence implies that due to spillover effects (e.g., commuter labor and trade flows) neighboring regions may have a similar economic performance and hence location matters. However, the number of studies that illustrate the usefulness of accounting for (possible) spatial dependence effects across cross sections in the forecasting exercise is still limited. For example, Elhorst (2005), Baltagi and Li (2006), and Longhi and Nijkamp (2007), Kholodilin et al. (2008), and Girardin and Kholodilin (2011) demonstrate the forecast superiority of models accounting for spatial dependence across regions using data on demand for cigarettes from states of the USA, demand for liquor in the American states, and German regional labor markets, GDP of German federal states (Bundesländer), and GDP of Chinese provinces, respectively.

The paper has the following structure. Section 2 outlines the construction of our Internet-based flats' price/rent indices for large German cities. Section 3 introduces the forecasting models. In section 4, the estimation results are reported, whereas section 5 compares the quasi out-of-sample forecast accuracy of alternative models and examines the true out-of-sample forecasts. Finally, section 6 concludes.

2 Internet-based indices

This study uses data contained in Internet ads on flats offered for sale and for rent in Germany. The data are downloaded each month starting in June 2010 from the most popular German website Immobilienscout24.de, where real-estate advertisements are published.

There are, of course, other sites, where such ads are placed. However, due to its large market share, Immobilienscout24 is representative enough. For example, at the end of January 2012 the ranking of the different websites that publish the real-estate announcements, according to the number of ads offering flats and houses for rent and sale, was as follows: Immobilienscout24.de (224,400), Quoka.de (155,600), Immowelt.de (142,000), Immonet.de (139,100), Immobilien.de (37,600), and Kalaydo.de (28,600). It should be noticed that about 10% of the Quoka.de ads are from its partner site Immobilienscout24. Given these figures, Immobilienscout24 has a market share of approximately 31%.

Our sample includes 26 large German cities. They were selected based on their population size as well as the number of ads, see Table 1. This is done in order to guarantee the representativeness of data. Too few ads may lead to an overly volatile price or rent index. Table 1 shows that the population of the selected cities attains almost 20 million persons, which is about 25% of the total population of Germany. Over the period 2010:6-2012:4, the number of ads of flats for sale is about 600,000, whereas the number of ads of flats for rent is twice as large. This reflects the dominance of tenant-occupied over owner-occupied housing in Germany. The correlation between the population and the number of ads of flats for sale and for rent is 0.93 and 0.62, respectively. The low correlation in the latter case is due to the overproportionate number of ads in Leipzig, where landlords are having problems in renting out their flats. When Leipzig is excluded, the correlation jumps to 0.88. Overall, the high correlations imply that our data are geographically representative.

Only information on a very reduced set of variables (identification number, city, zip code, area, number of rooms, and area) has been downloaded. This precludes the use of the hedonic regression that would help to adjust the rents/prices for varying quality of flats offered for sale in periods of time[1]. Therefore, only a very basic quality adjustment was conducted. First, the prices per square meter are computed. Second, the more or less homogeneous flats in terms of size were considered by concentrating on the flats with total area falling in the interval between the first and third quartiles. For these "homogenized" data the median of rents/prices for flats were computed.

In addition, the rent/price indices are smoothed in order to get rid of the high volatility of the estimates, which occurs due to an insufficient quality adjustment. For this purpose a back-sided Gaussian kernel with 3-month window is applied:

$$\widetilde{y_t} = \sum_{k=0}^{K} w(t-k) y_{t-k} \tag{1}$$

where y_t is the original value of price/rent index in period t; $k \geq 0$; $K = 2$; $w(t-k)$ is the kernel weight, which is decaying, according to a square root of normal distribution, in $t-k$.

The smoothed flats' price indices are shown in Figures 3 and 4, while smoothed flats' rent indices are

[1]However, in the future we are planning to download a wider range of flats' characteristics and to use the hedonic approach for construction of the rent/price indices. For the moment, the authors developed such indices for Berlin only, for the period starting in June 2011, see Kholodilin and Mense (2012).

depicted in Figures 5 and 6. The red line is the trajectory of the flat prices/rents in Germany as a whole, which is computed using all the Internet ads. The green line represents the dynamics of the prices/rents in 26 cities. The dark blue line shows the price levels in a corresponding city. The blue areas represent the price continuum between the first and the third quartile.

It can be seen that at the national level both prices and rents demonstrated extremely slow growth, if any. The levels of flats' prices and rents in 26 cities taken together are markedly higher than those in Germany as a whole. They grow somewhat faster than national indices, but still relatively slow.

In eight cities —Berlin, Düsseldorf, Frankfurt am Main, Hamburg, Köln, München, Stuttgart, and Wiesbaden— the prices were above both the national average and the average of 26 cities. The city with the highest flats' prices is München, where the price level is almost triple of the national average. In Berlin, the prices were close to the national average in 2010, but since then diverged substantially from it.

Among the selected 26 cities there are 13 cities (Aachen, Augsburg, Berlin, Bonn, Düsseldorf, Frankfurt, Hamburg, Köln, Mannheim, München, Nürnberg, Stuttgart, and Wiesbaden), where the rents exceed the average German rent. Again, the city with the highest rent is München, where the rents are more than twice as high as the national average. In Berlin, the rents are still not far above the overall German level, but the gap is increasing.

The summary statistics of the growth rate of flats' prices and rents are reported in Table 1. In terms of mean flats' price increases, the "usual suspects" Hamburg, München, and Berlin are at the top of the list in both markets, although rent increases are somewhat lower for München. Here, Nürnberg, Frankfurt, Aachen, Bremen, Düsseldorf, and Bonn experience higher increases.

The mean of flat price changes is negative in nine of the 26 cities of the sample. Strikingly, only one of these cities, Bonn, is not part of the (wider) Ruhrgebiet (Ruhr-Rhine area). Consequently, Düsseldorf is the only city in the Ruhrgebiet that experiences a positive mean trend. The Ruhrgebiet cities also exhibit the lowest mean rent increases for flats. Apart from this group, rents declined on average in Bielefeld and rose only marginally in Leipzig. This picture is consistent with the economic development of the Ruhrgebiet in the past years, reflecting high unemployment and overall economic slowdown. Standard deviations are considerably smaller for rental flats across all cities, which reflects the strong regulations imposed upon landlords by the

German law of tenancy.

The geographical distribution of the flats' prices and rents across Germany is depicted in Figures 1 and 2, respectively. The size of the hexagons is proportional to the flats' price/rent level in April 2012. In Figure 1, three largest hexagons correspond to München, Hamburg, and Frankfurt. The prices for flats in other cities follow after a large interval. Much smaller price levels are observed in East Germany, but also in the Ruhr area. In Figure 2, the ranking of the cities in terms of the rents for flats is similar to that in terms of prices. However, the prices are more unevenly distributed than the rents. This can be explained by the afore mentioned rigidity of German rental market.

3 Forecasting models

In this section, we describe the econometric models that we are using for forecasting the growth rates of flats' prices and rents in 26 large German cities.

We examine a wide range of dynamic panel data (DPD) models starting with individual autoregressive (AR) models, which can be considered as a particular case of DPD models with unrestricted parameters, through fixed-effects models, which impose homogeneity restrictions on the slope parameters, to pooled models, which impose homogeneity restrictions on both intercept and slope parameters. In addition to standard fixed-effects and pooled models, we also consider fixed-effects and pooled models that account for spatial dependence. Two naïve models are also considered: 1) a model, where the this month's value is used as a forecast for the next month, and 2) a model, where the forecast is the average of the growth rates in the past.

As a benchmark model, with which all other models will be compared, we use a linear *individual AR(1)* model (I_{OLS}) and estimate it for each city separately:

$$y_{it} = \alpha_i + \beta_i y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma_i^2) \tag{2}$$

where y_{it} is the monthly growth rate of flats' prices/rents in the i-th city; t is the time index $t = 1, \ldots, T$. In total, since our sample covers the period between June 2010 and April 2012, we have $T = 22$, for the first observation is lost due to differencing.

In addition, given the short time dimension of our data, it should be noted that the OLS estimator of the parameters of individual AR(1) models is biased due to insufficient degrees of freedom as pointed out in Ramanathan (1995).

The next model we consider is the *pooled panel*, P_{OLS}, model:

$$y_{it} = \alpha + \beta y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{3}$$

which imposes the homogeneity restriction on both intercept and slope coefficients across all cities.

An alternative model is the *fixed-effects*, F_{OLS}, model that allows for province-specific intercepts:

$$y_{it} = \alpha_i + \beta y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{4}$$

The fixed-effects model represents an intermediate case between the individual, I_{OLS}, and pooled panel, P_{OLS}, models. It is not as restrictive as the pooled model, which assumes equal average price trends in all cities, and yet allows to take advantage of the panel dimension. From the economic point of view, fixed effects capture differences in price/rent trends between cities related to their heterogeneous economic and demographic structure.

Moreover, we consider the following two types of models that account for spatial correlation that might exist between the cities: the spatial-lag and spatial-error models. One may expect to find the dynamic (stagnating) cities being the neighbors of other dynamic (stagnating) cities due to cross-border spillovers (commuter labor and trade flows).

The spatial dependence is accounted for using an $N \times N$ matrix of spatial weights W which is based on the distance between the cities. We constructed a distance-decay weights matrix with the distance cutoff value corresponding to the median distance between all the cities. The typical element of this matrix, w_{ij}, is defined as:

$$w_{ij} = \frac{1}{d_{ij}^2} \tag{5}$$

where d_{ij} is the great circle distance between the city i and city j.

Moreover, all the elements on the main diagonal of matrix W are equal to zero. The constructed weights matrix is normalized such that all the elements in each row sum up to one.

First, we model the spatial dependence by means of spatial lags of the dependent variable. Typically, it is assumed that the spatial lag model (SLM) accounts for the spillover effects, which are exerted by a region on its neighbors. Such effects result, for example, from the flows commuter labor, interregional trade, technology and entrepreneurship transfers from more developed regions to their less developed neighbors. We examine both pooled and fixed-effects versions of this model. The *pooled spatial lag* model (P_{MLE}^{SLM}) can be written as follows:

$$y_{it} = \alpha + \beta y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{6}$$

The *fixed-effects spatial lag* model (F_{MLE}^{SLM}) is:

$$y_{it} = \alpha_i + \beta y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{7}$$

where ρ is the spatial autoregressive parameter and N is the number of provinces.

The second type of models addresses spatial correlation through a spatial autoregressive error structure, as suggested by Elhorst (2005). Unlike the SLM, the spatial error model (SEM) is thought to reflect the so-called "nuisance" spatial effects, which result, for instance, because the administrative borders do not coincide with the boundaries of the markets. Again, we distinguish between pooled and fixed-effects models. Due to their specific nature, those models are estimated by the Maximum Likelihood method (MLE). The *pooled spatial error* model (P_{MLE}^{SEM}) has the following form:

$$y_{it} = \alpha + \beta y_{it-1} + u_{it} \quad u_{it} = \lambda \textstyle\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{8}$$

The *fixed-effects spatial error* model (F_{MLE}^{SEM}) can be expressed as:

$$y_{it} = \alpha_i + \beta y_{it-1} + u_{it} \quad u_{it} = \lambda \textstyle\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{9}$$

where λ is the coefficient of spatial error autoregression.

We estimate I_{OLS}, P_{OLS}, and F_{OLS} using the OLS method. It is known from the literature that in the context of dynamic panel data models the OLS estimator is subject to a simultaneous equation bias. In order to address this problem it is suggested to use the GMM estimator of Arellano and Bond (1991) to estimate the fixed-effects model without spatial autoregressive lags. Although from the theoretical perspective, the GMM estimators should be preferred to the OLS estimators when applied to dynamic panels with small time dimension, in what follows we use the OLS estimators[2], since in the forecasting context a biased but stable estimator may still deliver a more accurate forecasting performance than an unbiased but unstable one.

The remaining dynamic panel models accounting for spatial effects were estimated using the Maximum Likelihood method as implemented in the Ox codes written by Konstantin A. Kholodilin[3].

4 Estimation results

4.1 Flats' prices

The estimates of the temporal and spatial autoregressive coefficients of all models of flats' prices are presented in Table 2.

First, we report a summary of the estimates of intercept, $\widehat{\alpha_i}$, and the temporal autoregressive coefficient, $\widehat{\beta_i}$, obtained for an autoregressive model estimated for each province separately and reported in columns (1) through (3) of Table 2. Out of 26 intercepts only 7, or 26.9%, are statistically significant at least at the 10% significance level. 11, or 42.3% of, autoregressive coefficients are significant. Using the estimated coefficients we computed the conditional means $(\frac{\alpha_i}{1-\beta_i})$ of sale prices for each of the 26 cities. It reflects the mean expected monthly growth rate of price for flats. The average conditional mean is 0.256. Thus, on average the prices for flats in 26 German cities within the last 2 years have been increasing at a rate of 0.256% a month. In annualized terms, it corresponds to a yearly increase of flats' prices by 3.3%. Indeed, in 16 cities, or in 61.5% of cases, the conditional means exceed 0. The smallest conditional mean is estimated at -0.522% for Essen, whereas the largest one at 1.299% for Hamburg. Aachen, Berlin, and München are three other cities, where the expected growth rates are above 1% per month. Interestingly, Dresden comes very close to this rate with its 0.988% mean

[2]The computations were performed using the DPD package for Ox, see Doornik et al. (2006).
[3]The codes are available upon request. For details about the Ox programming language see Doornik and Ooms (2006).

price increase. The fit of the individual autoregressive models varies considerably, with R^2's between 0.09 and 0.376.

The columns (4) and (5) of Table 2 contain the estimation results obtained for the pooled model (equation (3)) and for the fixed-effects model (equation (4)) using OLS. All the intercept estimates are positive and significant. The estimates of temporal autoregressive parameters for these models are significant and positive and very close to the median autoregressive parameter estimate of the individual models. As a result, the conditional mean of the pooled model is similar to the average conditional mean of individual autoregressive models. Given the large heterogeneity of the growth rates of prices, the pooled model can hardly be a good option for the forecasting exercise, since it imposes too much homogeneity. The goodness-of-fit of the panel models without spatial effects is very close to that of the median of individual autoregressive models: in case of the pooled model, $R^2 = 0.227$, while the determination coefficient of the fixed-effects model is $R^2 = 0.143$.

The columns (6) through (9) of Table 2 report the parameter estimates of the panel models accounting for spatial dependence. Again, the estimates of the temporal autoregressive coefficients are positive and significant. The estimated spatial autoregressive coefficients are positive, but not significant. However, this does not automatically imply that spatial effects are useless when forecasting prices, as will be seen in section 5. The R^2's of the spatial lag models are again in the same range as those of the models without spatial effects, whereas the spatial error models perform somewhat worse.

4.2 Flats' rents

The estimation results of the models of flats' rents are reported in Table 3. Here, the picture is considerably brighter especially for the spatial effects models.

The OLS estimates of the simple AR(1) models are closer together and almost always positive for both the intercept term and the autoregressive coefficient. As in case of prices for flats, only 7 intercepts are statistically significant at the 10% level. Exactly half of all the autoregressive coefficients are statistically significant. Unlike the prices for flats, where about 40% of the cities displayed negative conditional mean growth rates, only in 1 city the rents for flats have been decreasing. The average conditional mean monthly growth rate of rents among the 26 cities is 0.339% , which is substantially higher than the mean monthly growth rate of rents. The

corresponding annualized growth rate is 4.2%. The minimum conditional mean is -0.003% in case of Krefeld, whereas the largest conditional mean of 1.068% is observed in Berlin, which corresponds to an annualized growth rate of 13.6%. Thus, the growth rates of rents for flats are much less heterogeneous than those of the prices. They are almost all positive and much less spread out. The R^2 is now in the wider range of 0 to 0.723.

The pooled and fixed-effects models produce autoregressive coefficients that are significant and very close to each other. However, the R^2 is in the range of 0.16 to 0.23, which is similar to the flats' prices estimations. The biggest difference between rents and prices lies in the importance of spatial dependence that the spatial-lag and spatial-error models suggest for rental flats: The spatial-lag models in columns (6) and (7) produce highly significant estimates for ρ. The spatial-error models have somewhat less precise estimates for λ, where the fixed-effects model estimate is significant at the 5% level and the pooled estimate at 10%. Given the small number of observations in the time dimension and the fact that the estimates lie close together, these estimates nevertheless suggest that forecasting precision improves when accounting for spatial dependence.

To summarize, on the basis of our estimation results we conclude the following. First, in most cases, the temporal autoregression is statistically significant and thus past prices and rents appear to play an important role in explaining their future values. Second, the spatial dependence is statistically significant for flats' rents, which implies that there is a relatively high degree of dependence between the housing markets in the neighboring cities. In line with our estimates, we suggest that this dependence plays a greater role in the rental flats market, where people first search for a dwelling when moving close to a new job. This might be of importance when some regions boom economically, which also drives up prices in the cities nearby. This spatial dependence does not seem to play a role for the market of flats for sale. Third, the estimates for the autoregressive coefficients appear to be relatively stable for all panel models and both markets. They range from 0.275 to 0.485 and are all statistically significant.

5 Forecast accuracy

For each model we forecast the h-month growth rates of prices/rents for flats, $\Delta^h y_{i,t+h} = y_{i,t+h} - y_{it}$, where $h = 1, 2, \ldots, 6$ for all 26 cities. The forecasting period is 2011:8-2012:4. The forecasts are made in a recursive manner. First, the models are estimated over the period 2010:7-2011:7. Next, forecasts are made for 2011:8,

2011:9, ..., 2012:1. Second, the estimation period is extended to the period 2010:7-2011:8 and the forecasts for 2011:9, 2011:10, ..., 2012:2 are made. This procedure gives us $(9-(h-1)) \times N$ quasi out-of-sample forecasts for the h-month growth rate.

For all models, except for the spatial-lag models, the forecasts are made in a standard way. The forecasts based on the spatial-lag models are conducted using a two-step procedure. In order to illustrate this procedure, it is worthwhile re-writing the spatial-lag models (6) and (7) in the following matrix form for the pooled model:

$$\mathbf{y} = \alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1} + \rho \mathbf{W}\mathbf{y} + \boldsymbol{\varepsilon} \tag{10}$$

and for the fixed-effects model:

$$\mathbf{y} = (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y}_{\mathbf{-1}} + \rho \mathbf{W}\mathbf{y} + \boldsymbol{\varepsilon} \tag{11}$$

where $\mathbf{y}$ is a $NT \times 1$ vector of the y_{it} stacked by month and city such that the first N observations refer to the first year, etc. Correspondingly, $\mathbf{y}_{\mathbf{-1}}$ is a $NT \times 1$ vector of the $y_{i,t-1}$ stacked by year and province. $\mathbf{I}_N$, $\mathbf{I}_T$, and $\mathbf{I}_{NT}$ are the unit matrices with dimensions $N \times N$, $T \times T$, and $NT \times NT$, respectively. The $NT \times NT$ matrix $\mathbf{W} = \mathbf{I}_T \otimes W$ is the block-diagonal matrix with the $N \times N$ matrix W of spatial weights on its main diagonal, where $\otimes$ is the Kronecker product. $\boldsymbol{\imath}_{NT}$ and $\boldsymbol{\imath}_T$ are the NT and T unit vectors, respectively, such that α and $\boldsymbol{\alpha}$ are correspondingly a common intercept and a $N \times 1$ vector of cross-section specific intercepts in the pooled and the fixed-effects spatial-lag models.

Models (10) and (11) can be re-written in the following reduced form:

$$\begin{aligned} (\mathbf{I_{NT}} - \rho \mathbf{W})\mathbf{y} &= \alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1} + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}[\alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1}] + (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{12}$$

$$\begin{aligned} (\mathbf{I_{NT}} - \rho \mathbf{W})\mathbf{y} &= (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y}_{\mathbf{-1}} + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}[(\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y}_{\mathbf{-1}}] + (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{13}$$

where only the past values of $\mathbf{y}$ appear on the right-hand side of the equations.

The multi-step ahead forecasts from the spatial-lag models can now be obtained as follows: First, we estimate the parameters of the models (10) and (11), as outlined above. Secondly, we use the reduced form equations (12) and (13) for the models with identical spatial dependence in order to generate the forecasts.

The accuracy of forecasting the flats' prices is reported in Table 4, whereas the forecasting performance of the flat rents models is shown in Table 5. The forecasting performance is measured by the root mean square forecast error (RMSFE) calculated for all months and over all cities for each forecasting horizon, $h = 1, 2, \ldots, 6$. Each table consists of two panels: The upper panel reports RMSFE, while the lower panel represents the relative RMSFE, that is, RMSFE of each model divided by the corresponding RMSFE of the benchmark (individual autoregressive) model.

Firstly, the panel models are compared to the naïve models. Naïve model 1, which uses the previous period value as a forecast, is almost always worse than all other models, regardless of forecasting horizon. The forecast accuracy of the naïve model 2, whose forecasts are just the averages of the growth rates in the past, is substantially better than that of the naïve model 1 and comparable to that of the individual autoregressive models.

Secondly, the individual autoregressive models, I_{OLS}, are compared to the panel models. The results of our forecasting exercise further strengthen the evidence previously reported in a number of studies such as Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), Kholodilin et al. (2008), and Girardin and Kholodilin (2011) among others, that pooling helps to improve forecast accuracy. The individual AR model is less accurate than all the panel models at the one-period forecast horizons. The only exception is P_{OLS}. The fixed-effects model without spatial effects also dominates the AR(1) process for both markets and all but two horizons: Only for $h \geq 5$ does the AR(1) model have a lower $RMSFE$ in the flats for rent market.

Thirdly, and most importantly, the fixed-effects models with spatial dependence dominate all other models *in both market segments*, albeit the fixed-effects model FE_{OLS} comes very close in the market of flats for sale, which reflects the insignificance of the estimates for the spatial coefficients in this case. In the case of flats for rent, both fixed-effects models with spatial dependence outperform all other models.

Thus, in line with our expectations, the application of panel models accounting for spatial effects as a rule

results in a better forecast accuracy compared to the corresponding non-spatial models. The panel-data models accounting for spatial effects always produce more accurate forecasts than their non-spatial counterparts. To summarize, pooling and accounting for spatial effects contribute to the improvement in forecast accuracy.

It would be also interesting to see not only the quasi out-of-sample forecasts of prices and rents for the past periods, but also to really predict them into the future. Therefore, we estimated the models for the whole period, for which the data are available, that is, 2010:7-2012:4, and made the true out-of-sample forecasts. The forecasts of flats' prices for the period 2012:5-2012:10 are depicted in Figures 7 and 8, whereas the forecasts of flats' rents are shown in Figures 9 and 10. For the sake of visibility only three models are shown in the figures: individual autoregressive model, I_{OLS}; fixed-effects model without spatial effects, FE_{OLS}; and fixed-effects spatial-lag model, FE^{SLM}_{MLE}. These are the best models in terms of forecast accuracy.

The first thing to notice is that in majority of the cases the forecasts produced using different models are similar. For flats' prices, the forecasts differ in case of Bochum, Dresden, Düsseldorf, Leipzig, and München. For flats' rents, the differences between the forecasts are observed in case of Berlin, Dortmund, Essen, Frankfurt, and Nürnberg. Normally, the difference is the largest in the beginning of forecasting period and then it diminishes, since the forecasts converge to the conditional mean of the model. In case of Berlin rents, however, the difference is even increasing over time. Moreover, the forecast differences are larger for rents than for prices, given the higher model uncertainty of the former.

The flats prices are predicted to increase over 2012:5-2012:10 in 16-17 cities, see Table 6. For a number of cities, we predict a relatively strong monthly flat price increase exceeding 1% per month. These "boom" cities include München, Frankfurt, Hamburg, and Berlin, but also Augsburg and Aachen. Interestingly, Dresden's flat prices picked up considerably in 2011 and are expected to increase by close to 1% per month over the forecast horizon. This is in contrast to Leipzig, the second city from the former GDR in the sample, where the flats' prices are expected to stagnate in the near future. On the other hand, our forecasts suggest that prices will be relatively constant in the cities of the Ruhrgebiet during the next six months. Here, Essen, Bochum, and Krefeld perform especially bad, whereas we expect a slight improvement for Gelsenkirchen, Duisburg, and Mönchengladbach. In Wiesbaden, prices increased considerably during the first months of 2012 and are predicted to do so in the near future as well.

The rents for flats are expected to go up in 25 cities. On average, the flats' prices and rents should grow at the same rate. However, in 16 cities the flats' rents are projected to grow stronger than the prices for flats. In several cities —Berlin, Bielefeld, Dresden, Frankfurt, Hamburg, Köln, München, and Wiesbaden— just the opposite is expected: here, the prices will grow much faster than the rents. The largest absolute differences between the growth rates of prices and those of rents are to be observed in Frankfurt (1.1 percentage points), Dresden (0.75), and Berlin (0.67). In Hamburg (0.59 percentage points) and München (0.35), this development is less pronounced. Price increases in these cities do not seem to be driven by proportional increases in rents, but by the expectations of future price increases. This can be regarded as a sign of strong speculation in these regional markets, when the prices drift apart from the levels that are supported by the fundamental factors. However, in order to be able to talk about ensuing speculative bubbles in certain German cities one needs to examine in more detail the trends of the real-estate market.

6 Conclusion

In this paper, we made two contributions. First, we computed the Internet-based flats' price and rent indices for 26 German cities over the period 2010:6-2012:4. Second, we undertook the quasi out-of-sample forecasting of 1- through 6-month growth rates of these indices over the period 2010:8-2012:4 using several dynamic panel data models with and without spatial effects.

Our main finding is that fixed-effects panel models accounting for spatial dependence produce the best forecast accuracy —as measured by the Root Mean Squared Forecast Error— compared to any other model examined in this paper. This finding remains robust across all forecasting horizons. Compared to the individual autoregressive models, these models lead to a decrease in the RMSFE by 7-8% for both flats for sale and for rent.

In addition, a true out-of-sample exercise was undertaken to predict the growth rates of prices and rents for flats within the nearest 6 months, i.e., 2012:5-2012:10. It shows that in less than a half of all cities the flats' prices are expected to increase at a fairly strong rate. In contrast, the rents are expected to increase in the vast majority of the cities. However, in several cities the prices are projected to grow much faster than the rents, which might be explained by the speculative tendencies. In case of Berlin probably a catching up might be

also at work, which means that the current prices for flats are undervalued but are gradually adjusting to their fundamental value.

References

Aiolfi, M. and A. Timmermann (2006). Persistence in forecasting performance and conditional combination strategies. *Journal of Econometrics 135*(1-2), 31–53.

an de Meulen, P., M. Micheli, and T. Schmidt (2011). Forecasting house prices in Germany. Ruhr Economic Papers 0294, Rheinisch-Westflisches Institut für Wirtschaftsforschung, Ruhr-Universität Bochum, Universität Dortmund, Universität Duisburg-Essen.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies 58*(2), 277-297.

Baltagi, B. H., G. Bresson, J. M. Griffin, and A. Pirotte (2003). Homogeneous, heterogeneous or shrinkage estimators? Some empirical evidence from French regional gasoline consumption. *Empirical Economics 28*(4), 795-811.

Baltagi, B. H., G. Bresson, and A. Pirotte (2002). Comparison of forecast performance for homogeneous, heterogeneous and shrinkage estimators: Some empirical evidence from US electricity and natural gas. *Economics Letters 76*(3), 375-382.

Baltagi, B. H., G. Bresson, and A. Pirotte (2004). Tobin q: Forecast performance for hierarchical Bayes, shrinkage, heterogeneous and homogeneous panel data estimators. *Empirical Economics 29*(1), 107-113.

Baltagi, B. H. and J. M. Griffin (1997). Pooled estimators vs. their heterogeneous counterparts in the context of dynamic demand for gasoline. *Journal of Econometrics 77*(2), 303-327.

Baltagi, B. H., J. M. Griffin, and W. Xiong (2000). To pool or not to pool: Homogeneous versus hetergeneous estimations applied to cigarette demand. *The Review of Economics and Statistics 82*(1), 117-126.

Baltagi, B. H. and D. Li (2006). Prediction in the panel data model with spatial correlation. *Spatial Economic Analysis 1*, 175-185.

Brücker, H. and B. Siliverstovs (2006). On the estimation and forecasting of international migration: How relevant is heterogeneity across countries? *Empirical Economics 31*(3), 735-754.

Doornik, J. A., M. Arellano, and S. Bond (2006). Panel data estimation using DPD for Ox. Mimeo.

Doornik, J. A. and M. Ooms (2006). *Introduction to Ox*. London: Timberlake Consultants Press.

Elhorst, J. P. (2005). Unconditional maximum likelihood estimation of linear and log-linear dynamic models for spatial panels. *Geographical Analysis 37*, 85-106.

Girardin, E. and K. A. Kholodilin (2011). How helpful are spatial effects in forecasting the growth of Chinese provinces? *Journal of Forecasting 30*, 622–643.

Kholodilin, K. A. and A. Mense (2012). Internet-based hedonic indices of rents and prices for flats. Example of Berlin. DIW Berlin Discussion Paper 1191.

Kholodilin, K. A., B. Siliverstovs, and S. Kooths (2008). A dynamic panel data approach to the forecasting of the GDP of German Länder. *Spatial Economic Analysis 3*(2), 195-207.

Longhi, S. and P. Nijkamp (2007). Forecasting regional labor market developments under spatial heterogeneity and spatial correlation. *International Regional Science Review 30*, 100-119.

Ramanathan, R. (1995). *Introductory Econometrics*. Dryden Press/Harcourt Brace.

Appendix

Table 1: Descriptive statistics of the growth rates of prices and rents for flats, %, 2010:7-2012:4

Town	Population 1000 persons 2009	Flats for sale					Flats for rent				
		Number of ads	Min	Mean	Max	SD deviation	Number of ads	Min	Mean	Max	SD deviation
Aachen	258	3,708	-4.43	0.97	4.61	1.91	8,519	-2.75	0.53	2.68	1.28
Augsburg	263	15,614	-0.79	0.55	2.56	0.87	11,942	-0.54	0.33	1.59	0.61
Berlin	3435	148,640	-0.88	1.00	2.84	0.90	226,787	0.00	0.70	1.71	0.52
Bielefeld	323	9,419	-2.89	0.35	3.27	1.64	13,154	-1.71	-0.04	1.29	0.87
Bochum	377	9,528	-1.90	-0.44	1.38	0.98	19,524	-1.42	0.17	1.03	0.62
Bonn	319	10,955	-3.03	-0.14	2.87	1.55	17,010	-0.98	0.40	1.66	0.67
Bremen	547	10,846	-1.55	0.48	2.59	1.07	15,102	-2.70	0.53	2.14	1.30
Dortmund	582	17,325	-1.36	-0.11	1.18	0.60	36,714	-0.65	0.22	1.32	0.55
Dresden	513	28,575	-0.85	0.80	2.69	1.04	56,139	-0.35	0.26	0.69	0.29
Düsseldorf	585	20,404	-1.03	0.36	2.45	0.97	51,680	-0.32	0.44	1.12	0.36
Duisburg	493	13,236	-1.60	-0.21	2.61	1.07	39,586	-0.58	0.08	0.87	0.38
Essen	578	21,846	-1.88	-0.33	1.79	1.09	62,672	-0.54	0.01	0.73	0.33
Frankfurt-am-Main	668	22,064	-1.73	0.85	3.39	1.33	43,038	-0.75	0.48	1.48	0.60
Gelsenkirchen	261	7,091	-2.82	-0.17	5.65	2.30	31,031	-1.13	-0.06	0.68	0.47
Hamburg	1778	25,471	-2.30	1.08	3.63	1.40	31,600	-0.49	0.73	2.25	0.74
Hannover	523	15,734	-1.12	0.14	1.93	0.78	25,264	-0.19	0.22	1.12	0.34
Köln	995	34,312	-0.84	0.34	0.93	0.47	57,762	-0.53	0.20	1.22	0.53
Krefeld	236	8,640	-1.75	-0.25	1.62	0.94	18,863	-1.10	0.07	0.86	0.52
Leipzig	517	29,402	-4.41	-0.22	1.84	1.48	237,453	-0.53	0.03	0.28	0.26
Mannheim	312	12,234	-1.94	0.00	2.29	1.31	15,987	-0.99	0.25	1.48	0.64
Mönchengladbach	258	10,825	-2.31	-0.13	1.83	1.17	23,860	-0.37	0.19	1.03	0.35
München	1320	50,245	-0.86	0.95	3.05	1.04	57,311	-0.62	0.39	1.65	0.52
Nuernberg	503	18,892	-2.17	0.25	2.79	1.25	14,645	-0.50	0.56	1.70	0.65
Stuttgart	601	24,469	-2.04	0.11	1.59	0.84	25,773	-0.63	0.33	1.61	0.61
Wiesbaden	277	11,214	-2.32	0.27	2.18	1.03	19,922	-0.80	0.25	1.39	0.56
Wuppertal	352	18,880	-1.66	-0.14	1.43	0.76	37,150	-0.42	0.09	0.62	0.33
26 cities	18882	599,569	-0.81	0.30	1.09	0.52	1,198,488	-0.41	0.09	0.84	0.35

Notes: 1) "Min" stands for minimum; "Max" stands for maximum; and "SD" stands for standard deviation. 2) The population figures are taken from the database of German regional accounts VGRdL, see http://www.statistik.baden-wuerttemberg.de/Arbeitskreis_VGR/ergebnisse.asp#BIP_K and refer to 2009; population of Hannover is taken from the database of Landesbetrieb für Statistik und Kommunikationstechnologie Niedersachsen and refers to 30.12.2010.

Table 2: Estimation results of the flats' price models, 2010:7-2012:4

	No spatial effects					Spatial effects			
	I_{OLS}			P_{OLS}	FE_{OLS}	P_{MLE}^{SLM}	FE_{MLE}^{SLM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
	Minimum	Median	Maximum						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	-0.290	0.086	0.979**	0.139**		0.160***		0.168***	
β	-0.400**	0.293	0.607***	0.483***	0.380***	0.378***	0.282***	0.380***	0.284***
λ	—	—	—	—	—	—	—	0.012	0.006
ρ	—	—	—	—	—	0.044	0.032	—	—
R^2	0.009	0.146	0.376	0.227	0.143	0.149	0.196	0.151	0.087

Note: *** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.

Table 3: Estimation results of the flats' rent models, 2010:7-2012:4

	No spatial effects					Spatial effects			
	I_{OLS}			P_{OLS}	FE_{OLS}	P_{MLE}^{SLM}	FE_{MLE}^{SLM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
	Minimum	Median	Maximum						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	-0.002	0.171	0.656**	0.028***		0.175***		0.212***	
β	-0.011	0.369	0.841***	0.485***	0.403***	0.357***	0.277***	0.358***	0.275***
λ	—	—	—	—	—	—	—	0.103*	0.119**
ρ	—	—	—	—	—	0.135***	0.147***	—	—
R^2	0.000	0.181	0.723	0.232	0.161	0.168	0.196	0.163	0.112

Note: *** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.

Table 4: Quasi out-of-sample forecast accuracy of flats' price models (RMSFE), 2011:7-2012:4

Horizon	No spatial effects					Spatial effects			
	Individual			OLS		SLM		SEM	
	Past value	Average	AR	Pooled	Fixed-effects	Pooled	Fixed-effects	Pooled	Fixed-effects
			I_{OLS}	P_{OLS}	FE_{OLS}	P_{MLE}^{SLM}	FE_{MLE}^{SLM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
1	1.194	1.208	1.166	1.117	1.076	1.109	1.072	1.110	1.072
2	2.594	2.155	2.144	2.154	2.007	2.153	2.005	2.155	2.006
3	3.821	2.900	2.917	3.071	2.752	3.021	2.714	3.022	2.714
4	5.078	3.577	3.591	3.901	3.402	3.818	3.341	3.820	3.342
5	6.226	4.225	4.171	4.621	3.932	4.532	3.896	4.534	3.897
6	7.370	4.973	4.912	5.396	4.540	5.341	4.555	5.342	4.556
Relative RMSFE = $RMSFE_i/RMSFE_{AR}$									
1	1.02	1.04	1.00	0.96	0.92	0.95	0.92	0.95	0.92
2	1.21	1.00	1.00	1.00	0.94	1.00	0.94	1.00	0.94
3	1.31	0.99	1.00	1.05	0.94	1.04	0.93	1.04	0.93
4	1.41	1.00	1.00	1.09	0.95	1.06	0.93	1.06	0.93
5	1.49	1.01	1.00	1.11	0.94	1.09	0.93	1.09	0.93
6	1.50	1.01	1.00	1.10	0.92	1.09	0.93	1.09	0.93

Table 5: Quasi out-of-sample forecast accuracy of flats' rent models (RMSFE), 2011:7-2012:4

Horizon	No spatial effects					Spatial effects			
	Individual			OLS		SLM		SEM	
	Past value	Average	AR	Pooled	Fixed-effects	Pooled	Fixed-effects	Pooled	Fixed-effects
			I_{OLS}	P_{OLS}	FE_{OLS}	P_{MLE}^{SLM}	FE_{MLE}^{SLM}	P_{MLE}^{SEM}	FE_{MLE}^{SEM}
1	0.594	0.617	0.565	0.567	0.555	0.551	0.548	0.554	0.550
2	1.333	1.111	1.086	1.097	1.042	1.071	1.037	1.076	1.040
3	2.095	1.480	1.479	1.538	1.433	1.491	1.396	1.497	1.399
4	2.793	1.754	1.729	1.841	1.651	1.810	1.624	1.817	1.625
5	3.440	1.957	1.876	2.096	1.788	2.057	1.749	2.068	1.751
6	3.716	2.177	1.901	2.368	1.928	2.299	1.862	2.318	1.870
Relative RMSFE = $RMSFE_i/RMSFE_{AR}$									
1	1.05	1.09	1.00	1.00	0.98	0.98	0.97	0.98	0.97
2	1.23	1.02	1.00	1.01	0.96	0.99	0.95	0.99	0.96
3	1.42	1.00	1.00	1.04	0.97	1.01	0.94	1.01	0.95
4	1.62	1.01	1.00	1.06	0.95	1.05	0.94	1.05	0.94
5	1.83	1.04	1.00	1.12	0.95	1.10	0.93	1.10	0.93
6	1.96	1.15	1.00	1.25	1.01	1.21	0.98	1.22	0.98

Table 6: Predicted average growth rates of flats prices and rents, %, 2012:5-2012:10

City	Flats for sale			Flats for rent		
	I_{OLS}	FE_{OLS}	FE^{SLM}_{MLE}	AI_{OLS}	FE_{OLS}	FE^{SLM}_{MLE}
Aachen	1.40	1.38	1.46	0.73	0.71	0.75
Augsburg	0.56	0.57	0.58	0.45	0.41	0.42
Berlin	0.92	0.94	0.94	0.84	0.74	0.75
Bielefeld	0.29	0.33	0.30	0.11	0.11	0.14
Bochum	-0.07	-0.24	-0.23	0.25	0.23	0.26
Bonn	-0.17	-0.13	-0.16	0.39	0.40	0.38
Bremen	0.58	0.55	0.56	0.74	0.78	0.83
Dortmund	-0.11	-0.11	-0.11	0.71	0.32	0.32
Dresden	1.07	0.90	0.93	0.32	0.30	0.30
Düsseldorf	0.25	0.41	0.37	0.43	0.43	0.44
Duisburg	-0.37	-0.29	-0.28	0.04	0.09	0.07
Essen	-0.24	-0.31	-0.32	0.21	0.06	0.07
Frankfurt-am-Main	1.02	1.11	1.12	-0.08	0.38	0.40
Gelsenkirchen	-0.31	-0.20	-0.16	0.01	-0.02	0.00
Hamburg	1.31	1.26	1.32	0.72	0.75	0.77
Hannover	0.14	0.19	0.18	0.24	0.23	0.26
Köln	0.38	0.39	0.39	0.03	0.11	0.11
Krefeld	-0.35	-0.33	-0.35	0.13	0.11	0.13
Leipzig	-0.15	0.16	0.22	0.04	0.03	0.04
Mannheim	-0.12	-0.14	-0.15	0.22	0.24	0.23
Mönchengladbach	0.02	0.04	0.07	0.15	0.16	0.15
München	0.68	0.83	0.84	0.57	0.49	0.52
Nürnberg	0.15	0.17	0.14	0.96	0.66	0.68
Stuttgart	0.09	0.11	0.12	0.33	0.33	0.33
Wiesbaden	0.44	0.45	0.50	0.28	0.29	0.27
Wuppertal	-0.29	-0.20	-0.19	0.19	0.15	0.15

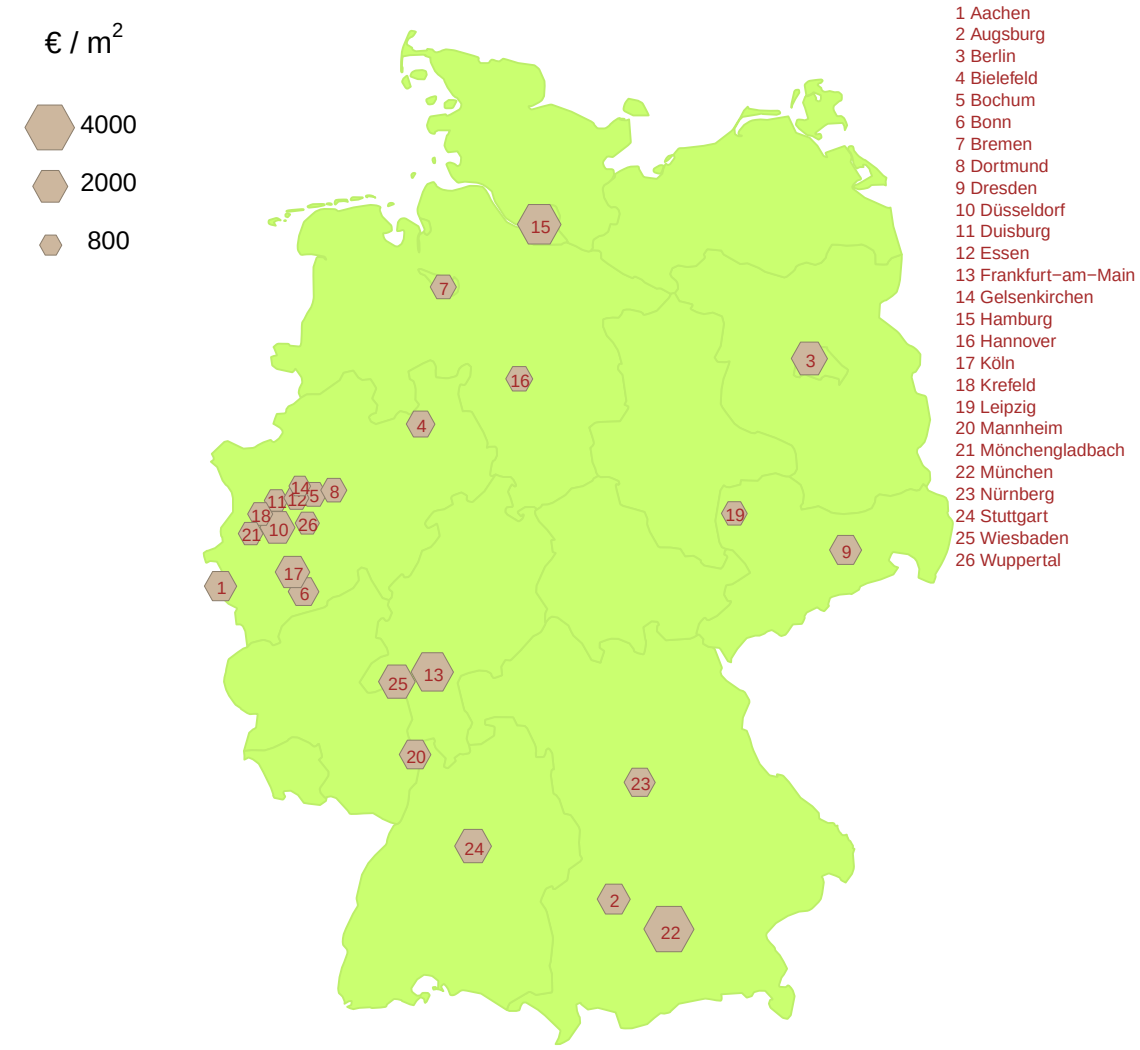

Figure 1: Geographical distribution of flats' prices in Germany, April 2012

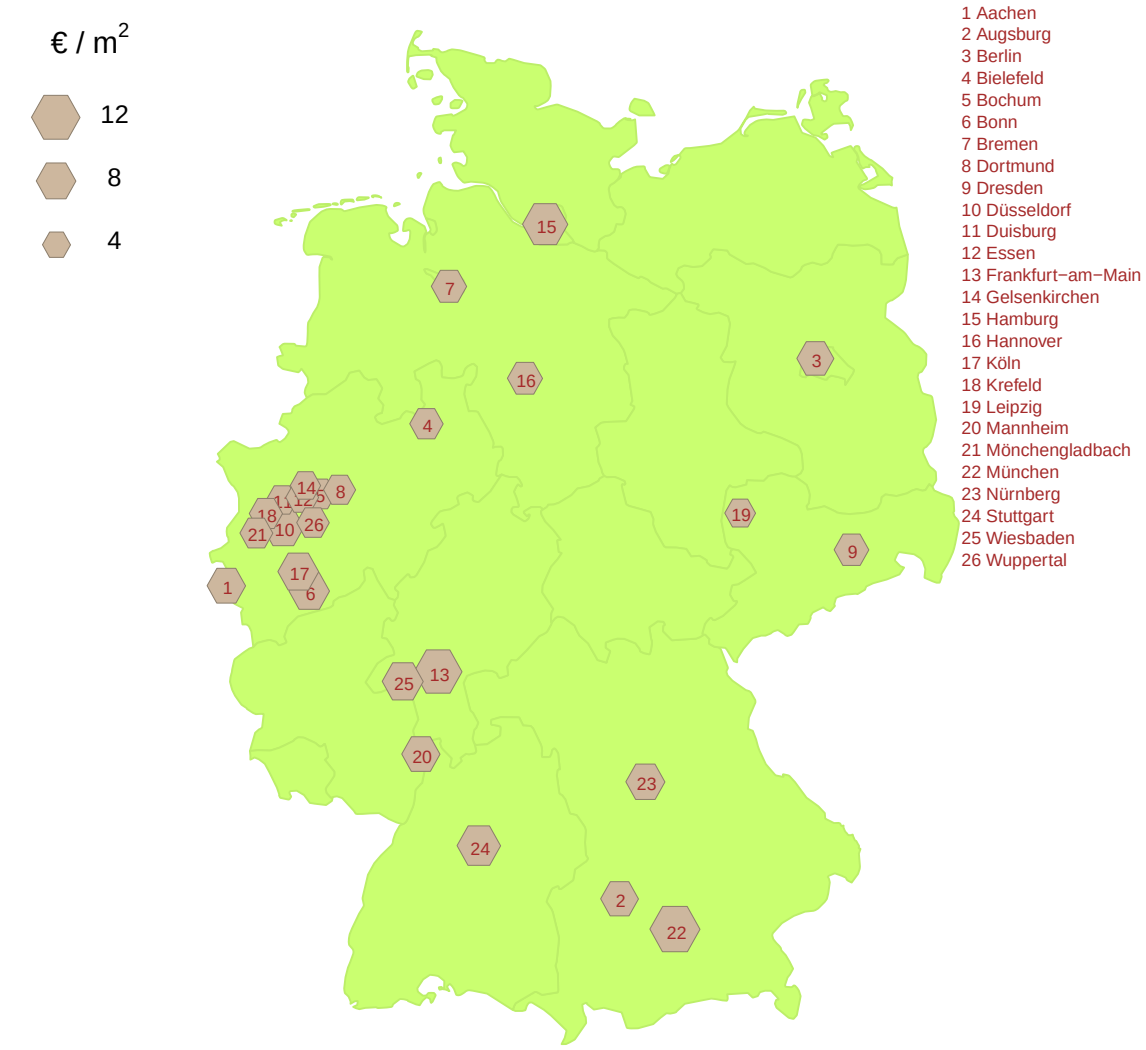

Figure 2: Geographical distribution of flats' rents in Germany, April 2012

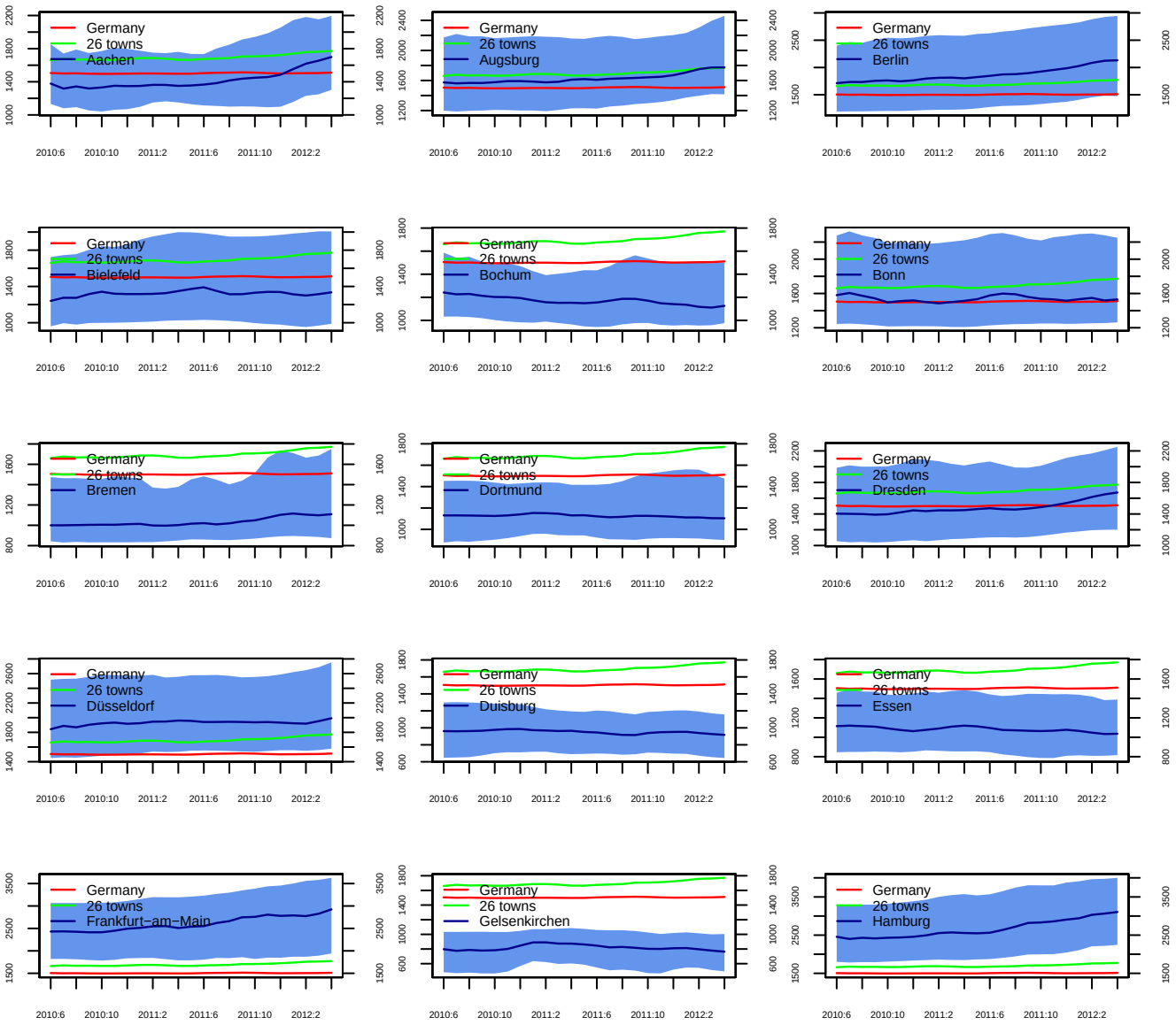

Figure 3: Flat price dynamics in 26 large German cities, 2010:6-2012:4

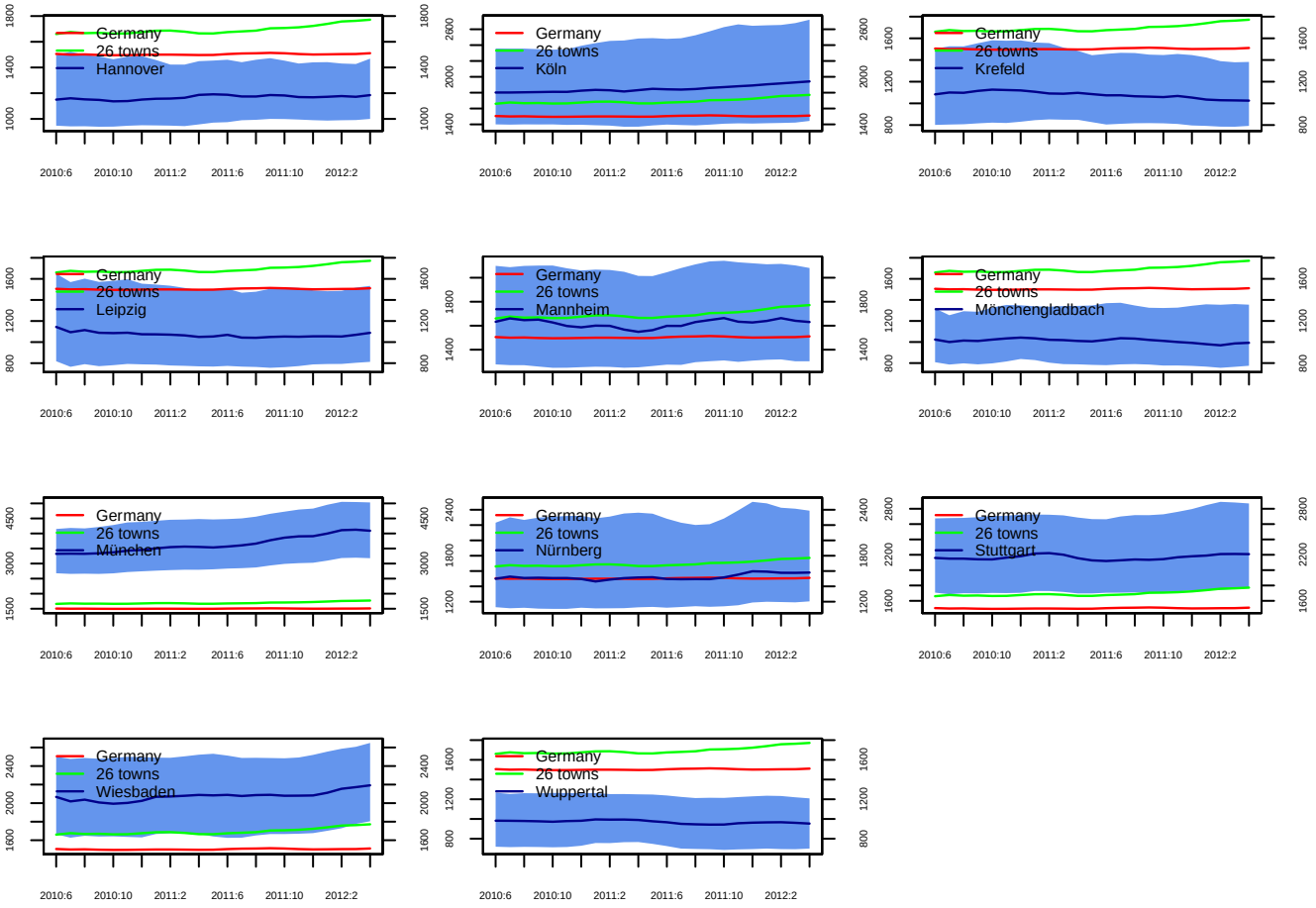

Figure 4: Flat price dynamics in 26 large German cities, 2010:6-2012:4 (continued)

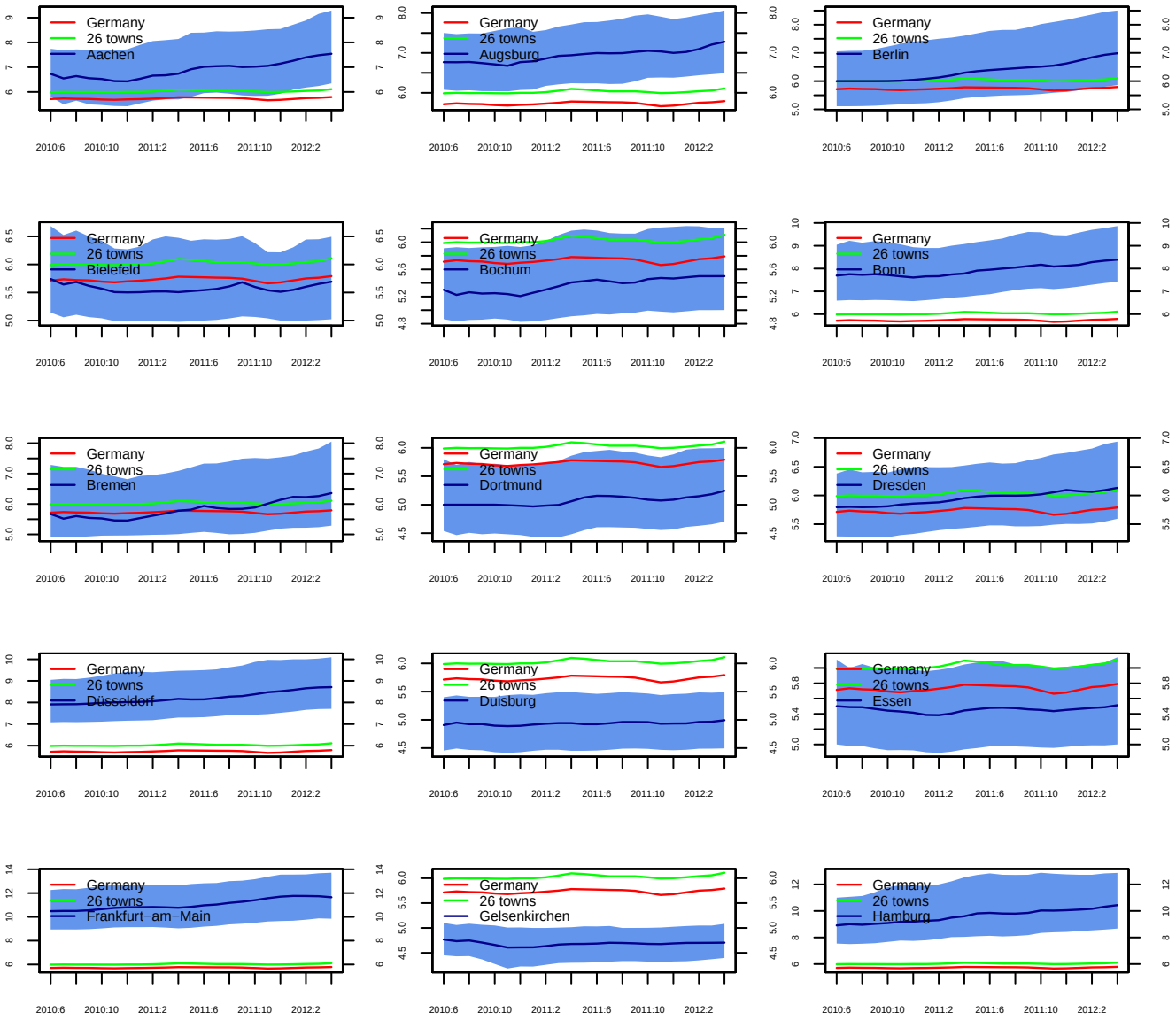

Figure 5: Flat rent dynamics in 26 large German cities, 2010:6-2012:4

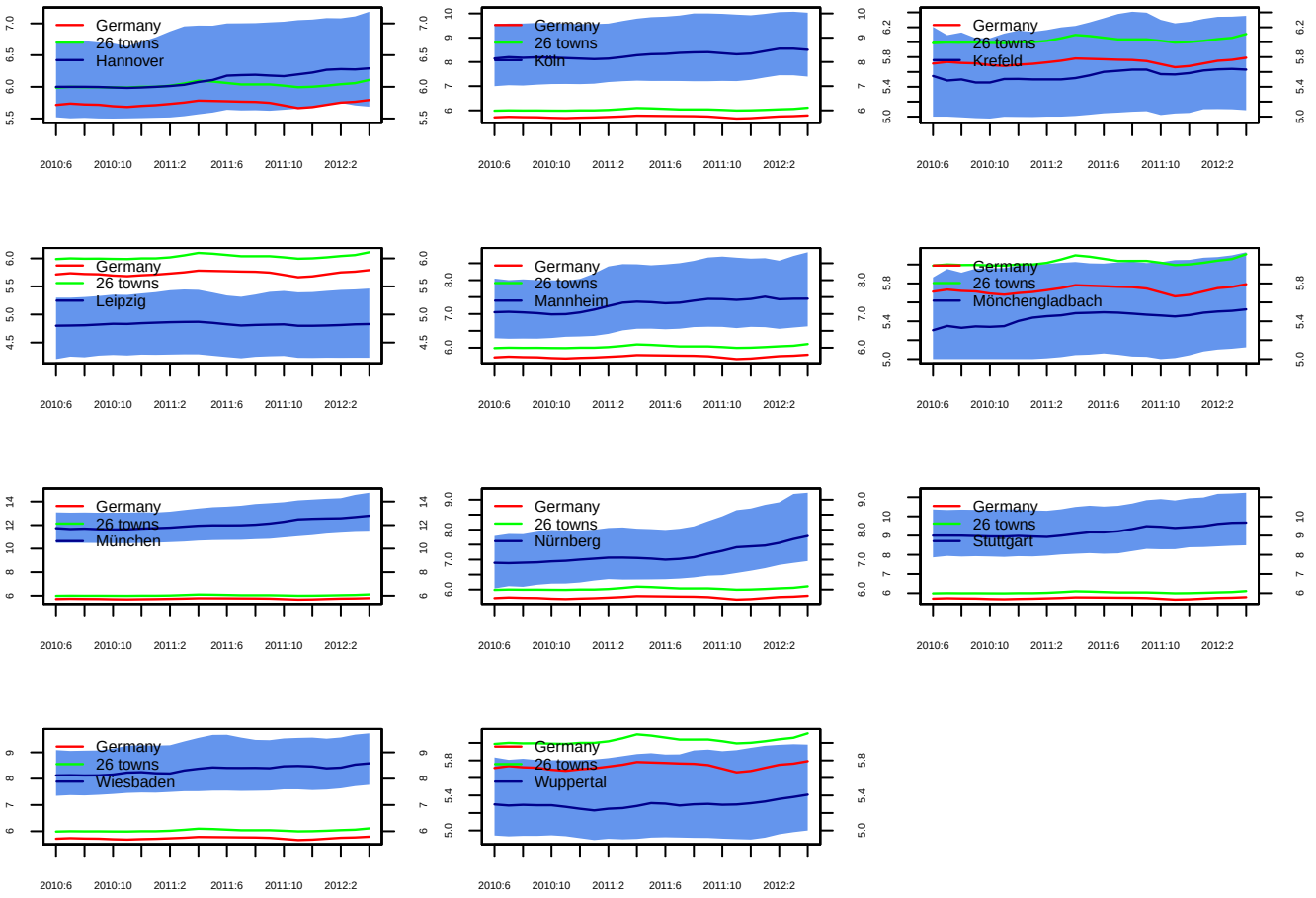

Figure 6: Flat rent dynamics in 26 large German cities, 2010:6-2012:4 (continued)

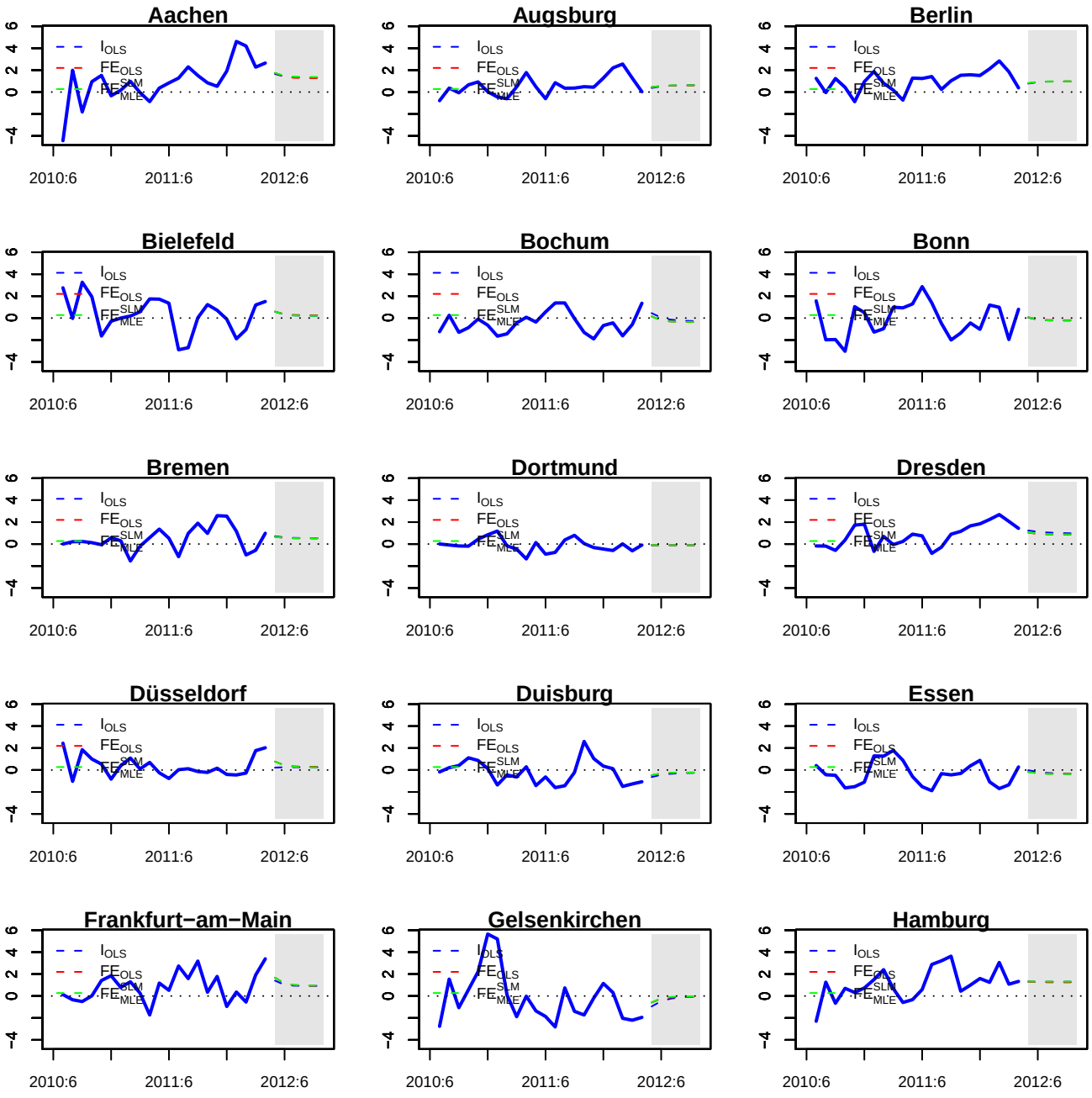

Figure 7: Monthly growth rates of flat prices in 26 large German cities: actual and predicted, 2010:7-2012:10

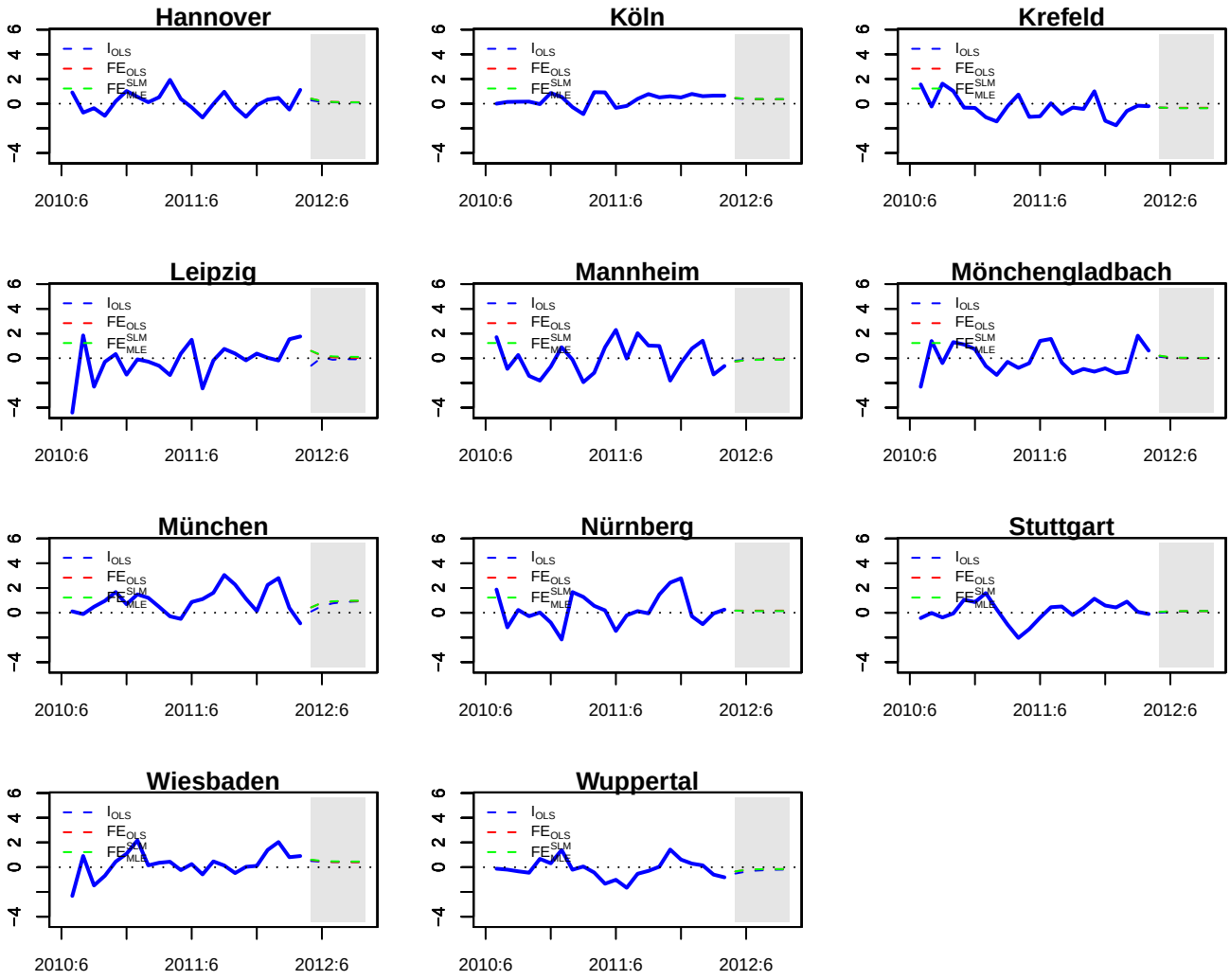

Figure 8: Monthly growth rates of flat prices in 26 large German cities: actual and predicted, 2010:7-2012:10 (continued)

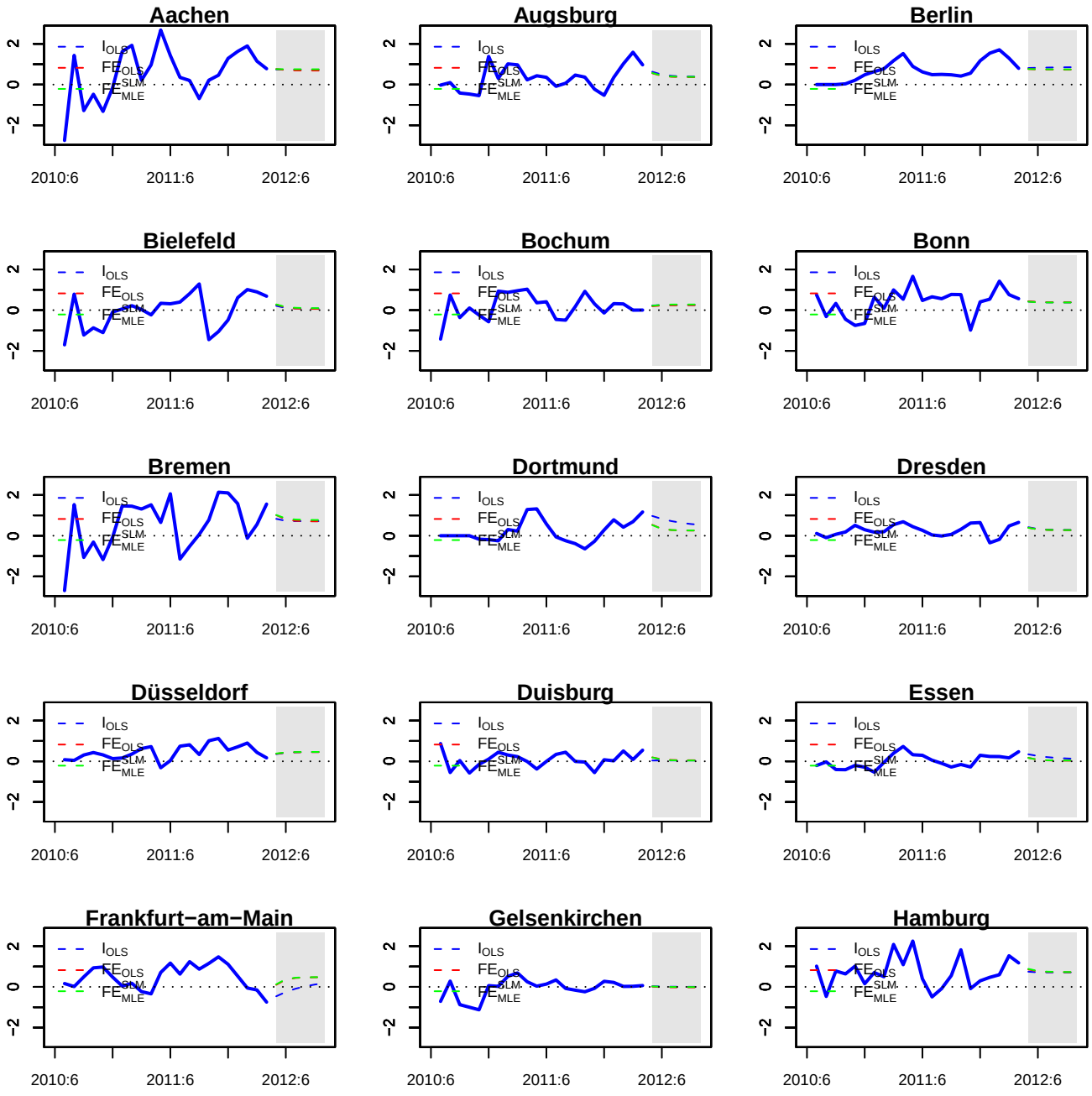

Figure 9: Monthly growth rates of flat rents in 26 large German cities: actual and predicted, 2010:7-2012:10

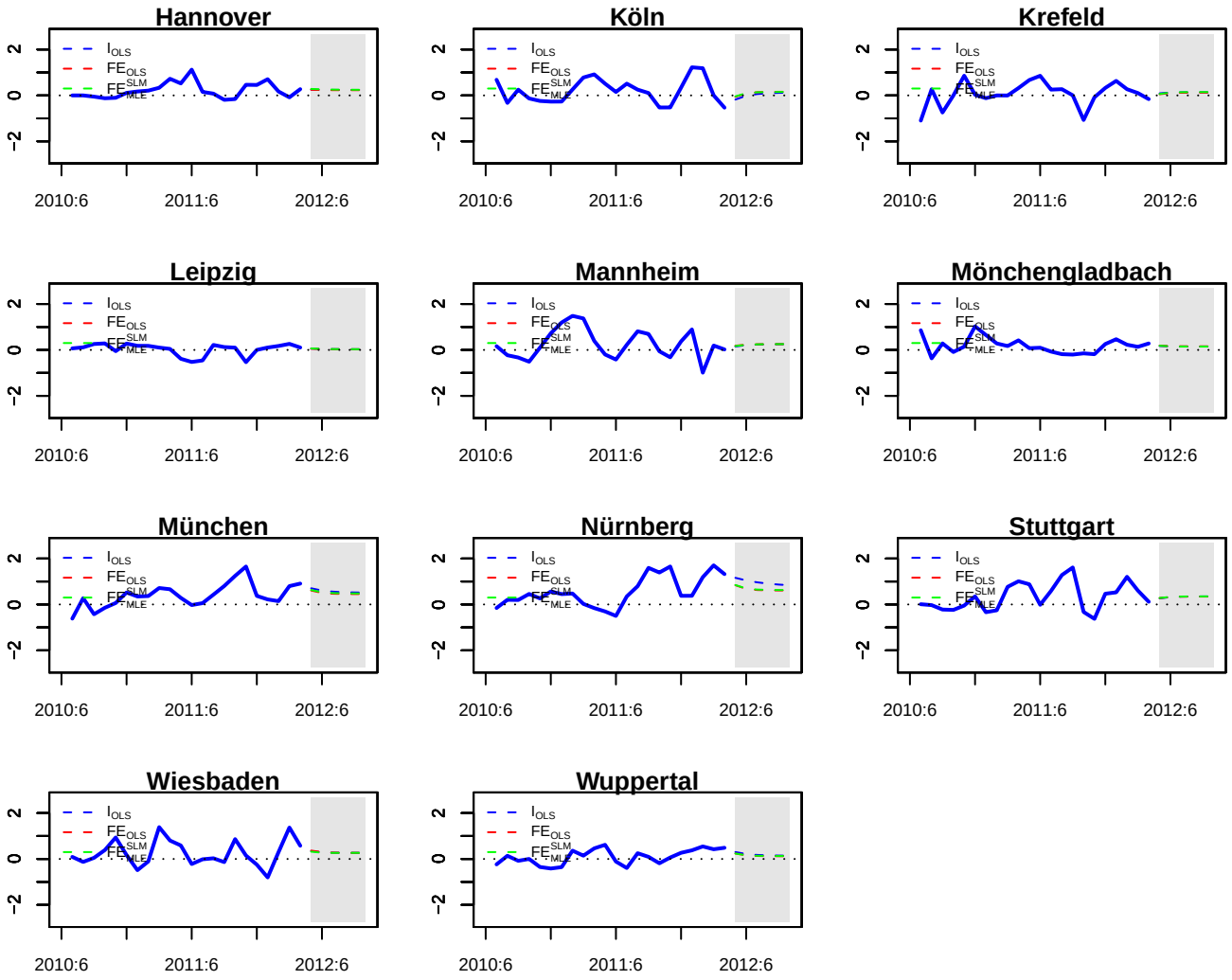

Figure 10: Monthly growth rates of flat rents in 26 large German cities: actual and predicted, 2010:7-2012:10 (continued)