Think national, forecast local: A case study of 71 German urban housing markets

a case study of 71 German urban housing markets

KOF

KOF Working Papers

Think national, forecast local:
A case study of 71 German urban housing markets

Konstantin A. Kholodilin and Boriss Siliverstovs

No. 372
February 2015

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

KOF

KOF Swiss Economic Institute
ETH Zurich
LEE G 116
Leonhardstrasse 21
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Think national, forecast local:

A case study of 71 German urban housing markets[¶]

Konstantin A. Kholodilin[*] Boriss Siliverstovs[§]

February 18, 2015

Abstract

In this paper, we evaluate the forecasting ability of 145 indicators and ten types of forecast combination schemes to predict housing prices and rents in 71 German cities. We are interested in whether local business confidence indicators facilitate substantial improvements of the forecasts, given the local nature of the real-estate markets. The forecast accuracy of different predictors is tested in a framework of a quasi out-of-sample forecasting. Its results are quite heterogeneous. No single indicator appears to dominate all the others for all cities and market segments. However, there are several predictors that are especially useful, namely price-to-rent ratios, the business confidence at the national level, and consumer surveys. We also find that combinations of individual forecasts are consistently selected among the top forecasting models/approaches. However, given a rather small sample size in our recursive forecasting exercise, the optimal combination weights is only possible to detect when using full-sample estimation information. On average, the forecast improvements attain about 20%, measured by a reduction in RMSFE, compared to the naïve models. In separate cases, however, the magnitude of improvement is about 40%.

Keywords: Housing prices and rents; forecast combinations; spatial dependence; Germany.

JEL classification: C21; C23; C53.

[¶]This paper was presented at the DIW Macroeconometric Workshop (Berlin, 2013), the Panel Survey Data and Business Cycle Analysis Workshop (German University in Cairo (Berlin campus), 2014), the 54th ERSA Conference (St. Petersburg, 2014) and the 32nd CIRET Conference (Hangzhou, 2014). The standard disclaimer applies.

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

[§]KOF Swiss Economic Institute, ETH Zurich, Leonhardstrasse 21, 8092 Zurich, Switzerland, e-mail: siliverstovs@kof.ethz.ch

Contents

List of Tables

List of Figures

1 Introduction

The role of the housing market in everyday life is difficult to overestimate. Housing rents and prices directly affect the standard of living of every person. In Germany, the housing wealth (6.3 trillions euros at the end of 2012) accounts for more than a half of wealth of private households (about 12.3 trillions euros), see SVR (2013).

It is well known that speculative price bubbles on real-estate markets are likely to trigger financial crises, which can, in turn, spillover to the real economy causing deep recessions with detrimental consequences for production and employment.

Since the end of 2010, after more than a decade of falling real housing prices, strong rent and especially price increases have been observed in Germany. This raised doubts and fears in German society. On the one hand, it is feared that Germany can follow the path of Spain, Ireland, and other bubble countries that ended with a severe economic crisis[1]. On the other hand, the tenants that constitute a majority of German population are afraid of substantial rent increases that will erode their welfare. The tenants' discontent takes a form of massive protests and manifestations endangering political stability in the country. For this reason one of the major issues debated during the 2013 Bundestag elections and included in the coalition treaty of the two leading German parties CDU/CSU and SPD, which form the 2013 government led by Angela Merkel, was the housing policy[2]. Therefore, it is very important to be able to predict the dynamics of home rents and prices in the nearest future.

There are very few studies on forecasting housing prices in Germany. an de Meulen et al. (2011) forecast German real estate prices for four different market segments (both new and existing houses and apartments) using AutoRegressive Distributed Lag (ARDL) and Vector AutoreRressive (VAR) models, that draw upon the information contained in 26 potentially relevant economic and financial variables potentially useful for prediction of the real-estate market, namely: consumer confidence indicators of the European Commission, business confidence indicators of the Ifo institute, and such macroeconomic indicators as consumer prices, stock exchange index, mortgage interest rate as well as new orders and building permits in construction. an de Meulen et al. (2011) also investigate whether pooling models by means of several forecast combination approaches is beneficial for predicting the real-estate market indices. Their study is based on monthly data provided by the

[1] Deutsche Bundesbank (2013) in its recent study stated that in several cities the house prices might be overvalued by 5-10%.

[2] For more details see the coalition treaty (CDU-CSU and SPD, 2013).

leading German Internet platform for real-estate announcements http://www.immobilienscout24.de, 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.

Kholodilin and Mense (2012) use a panel-data model with spatial effects to forecast the monthly growth rates of the prices and rents for flats in 26 largest German cities. A big shortcoming of their approach is that their forecasts are based only on the past growth in the city and in the neighboring city and ignore other indicators that could contain useful informations about the future price and rent dynamics.

In this paper, we intend to fill this gap and to use alternative predictors in forecasting housing prices and rents. In particular, we examine the forecasting performance of macroeconomic variables, consumer confidence as well as business confidence indicators. The latter variables, unlike all other, are available not just at the national level but also regionally. The regional business confidence indicators are produced by the local chambers of commerce and industry (CCI) for the whole economy of a region and for its separate branches, such as industry, construction, services, etc. A priori, one would expect that namely regional indicators should be more informative about regional price dynamics rather than national indicators based on aggregated nationwide information. Despite their potential usefulness, these indicators are neglected in the literature. To the best of our knowledge, the only paper that takes advantage of the CCI indices for forecasting purposes is that of Wenzel (2013), who uses regional business confidence indicators to forecast economic growth of German Bundesländer. Such a neglect of these data for economic analysis and research can be explained by a formidable task of decentralized collection them from various institutions, for example.

The paper has the following structure. Section 2 describes the data used in the paper. Section 3 introduces forecasting models and compares their out-of-sample forecast accuracy. Finally, section 4 concludes.

2 Data

This study forecasts four real-estate variables: square-meter prices and rents for the existing (secondary market) and newly built (primary market) housing. The data were provided by a Berlin-based research institute, *empirica*,[3] that computes the quarterly housing price/rent indices starting from the 1st quarter of 2004. Both prices and rents were calculated using hedonic approach. The prices refer to the owner-occupied apartments in the condominiums with total area of 100-150 m^2, whereas the rents refer to the rental apartments with total area of 60-80 m^2. Our data set includes prices and rents in 71 large German cities from 2004q1 through 2013q3. Thus, the dimensions of our dataset are $N = 71$ and $T = 39$. Figures 1 and 2 show the dynamics of the housing prices and rents at secondary market, respectively. Due to a high correlation between the primary and secondary market variables and in order to save space the graphs of prices and rents at primary markets are not reported.

The set of potential predictors comprises both macroeconomic variables (15 variables) and confidence indices (100 variables). The macroeconomic variables include the housing lending rates and volumes at different loan maturities as well as the German stock exchange price and performance indices DAX and CDAX, see Table 1. All of them are only available at the national level and, hence, are identical for all cities. The macroeconomic time series were downloaded from the webpage of the Deutsche Bundesbank[4].

The sentiment indices are available both at the national level (business confidence indices of Ifo and consumer confidence indices of the European Commission) and at the regional level (business confidence indices for East Germany, Bundesländer or cities). Table 2 lists the national and regional business confidence indices. "Frequency" refers to the number of times the indicators are published a year. It varies from 2 (semiannual) to 12 (monthly). The vast majority of the CCIs produce their indices at triannual frequency. In some cases, the surveying and publication frequency has been increased, say, from semiannual to triannual (2-3), or reduced, say, from quarterly to triannual (4-3). The all-German chamber of commerce and industry (Deutsche Industrie- und Handelskammertag e.V., or shortly DIHK) collects the data from individual regions and constructs aggregated indicators for the whole country and four large regions (North, South, East, and West). In addition, Dresden branch of the Ifo institute conducts it own surveys for East Germany and Saxony. Moreover, the NRW.Bank does the same for the Bundesland North Rhine-Westphalia. Furthermore, the sentiment indices of several regions from the same Bundesland are often aggregated at the Bundesland level (e.g., Low Saxony and Rhineland-Palatinate).

[3] http://www.empirica-institut.de/empi2007/startseite.html
[4] http://www.bundesbank.de/Navigation/DE/Statistiken/statistiken.html?nsc=true.

Figure 3 depicts the publication schedule of housing prices/rents and business confidence indicators. t corresponds to the 1st quarter of the year, while $t-1$ stands for the last quarter of the previous year. It can be seen that the data on prices/rents are published several weeks later after the end of the reference quarter. The Ifo indices are typically published on 25th-26th of the reference month. Each quarter sees three Ifo publications: $\text{Ifo}_{t,1}$ is the first month of quarter t, $\text{Ifo}_{t,2}$ is the second month of quarter t, and $\text{Ifo}_{t,3}$ is the third month of quarter t. The same publication cycle is valid for the Dresden subsidiary of Ifo and NRW.Bank. Thus, before the reference quarter ends and much earlier than the price/rent data will be published, some information on the state of the economy, which may be relevant for predicting the price/rent dynamics, is already available. By contrast, the DIHK publishes its indices only three times a year: in the beginning of the year (Jahresbeginn), in the early Summer (Frühsommer), and in the Fall (Herbst). Notice that no data are published in the second quarter. The exception to this rule are the CCI of Northern Germany (Hamburg, Bremen, and Low Saxony) that publish their business sentiment indices quarterly, and Saarland that produces its indices monthly.

Given that the dependent variable has quarterly frequency, while predictors have in many cases a lower observational frequency, we interpolated such regressors to the monthly frequency by using a linear spline. The interpolated time series are then sampled at the quarterly frequency, such that March corresponds to the 1st quarter, June to the 2nd quarter, September to the 3rd quarter, and December to the 4th quarter.

In order to obtain the time series of business confidence, we contacted all the relevant chambers of commerce and industry. Unfortunately, we were unable to obtain the sentiment indicators for all the cities of interest. In some cases, the local CCIs did not respond to our data requests, in other cases, they promised but never delivered the data (like the CCI Nürnberg für Mittelfranken). In some cases, we managed to find the data from the archives of the business survey indicators publications. When the business confidence indicators for a city itself are not available, we use those of its larger region. The latter indicator can sometimes be even better than the former one. It is known from the anecdotal evidence that in large cities, such as Berlin and Hamburg, the local construction firms, due to their higher costs, cannot compete with firms coming from neighboring regions. Hence, the local firms may have lower or even declining business confidence, despite booming building activity. Thus, using the indices based on the opinions of the local firms can sometimes be misleading.

The business confidence indices used here typically represent the differences between the percentage share of the positive answers (e.g., the economic situation is good or is going to improve) and the that of the negative answers (e.g., the economic situation is bad or is going to deteriorate):

$$B_{it} = 100 \times \frac{A_{it}^{+} - A_{it}^{-}}{A_{it}^{+} + A_{it}^{-} + A_{it}^{0}} \tag{1}$$

where A_{it}^{+} is the number of positive answers given by the firms in the region i in the period t, A_{it}^{-} is the number of negative answers, and A_{it}^{0} is the number of neutral answers. The index varies between -100 (all firms believe that the situation is bad) and 100 (all firms believe that the situation is good).

In this study, we utilize four business sentiment indices for forecasting purposes: current situation, future situation (next 12 months), investment plans, and employment plans. When possible, these are reported for the whole economy and for construction industry in particular. Thus, for each region we could have at most 8 different local business confidence indices.

The indices of the current and the future economic situation can be employed to construct a so-called **business climate index**:

$$BCI = \sqrt{(B_{it}^{c} + 100)(B_{it}^{f} + 100)} \tag{2}$$

where B_{it}^{c} is the current economic situation index and B_{it}^{f} is the future economic situation index. By construction, the BCI can take values between 0 indicating extremely bad business climate and 200 pointing to the excellent business climate.

For some cities only the business climate index is available. Therefore, we computed it also for those cities, for which we have its components. The BCI is used in the forecasts along with 8 other business confidence indices.

3 Forecasting

In this section, we describe the details of how forecasts of real-estate price indices were made. The four-quarter-ahead forecasts of the quarterly year-on-year growth rates of the real-estate variables were obtained using a direct forecasting approach (Marcellino et al., 2006). The forecasts are based on three different specifications of the forecasting model with gradually increasing information set. Observe that for each city we allow only one auxiliary indicator to enter the forecasting regression at a time. The first specification contains a single indicator as the only explanatory variable:

$$y_t^{(j)} = \mu_i^{(j)} + \beta_i^{(j)} x_{i,t-4}^{(j)} + \epsilon_{it}^{(j)}, \tag{3}$$

where $y_t^{(j)}$ denotes the quarterly year-on-year growth rate of one of the four real-estate price indices in question that is specific to a city (j). The auxiliary indicators are denoted by $x_{i,t}^{(j)}$, where the super-script (j) allows for a possibility that some of the indicators are specific to a particular city. Naturally, for national indicators this super-script can be suppressed.

The second specification of the forecasting model adds own lag of the dependent variable $y_{t-4}^{(j)}$ as an additional explanatory variable:

$$y_t^{(j)} = \mu_i^{(j)} + \alpha_i^{(j)} y_{t-4}^{(j)} + \beta_i^{(j)} x_{i,t-4}^{(j)} + \epsilon_{it}^{(j)}. \tag{4}$$

The third specification of the forecasting model adds a distance-weighted spatial lag of the dependent variable $y_{t-4}^{(W)}$ accounts for spatial correlation between price indices:

$$y_t^{(j)} = \mu_i^{(j)} + \alpha_i^{(j)} y_{t-4}^{(j)} + \beta_i^{(j)} x_{i,t-4}^{(j)} + \gamma_i^{(j)} y_{t-4}^{(W)} + \epsilon_{it}^{(j)}. \tag{5}$$

The spatial lag of the dependent variable $y_t^{(W)}$ was calculated using a spatial weights matrix W such that:

$$y_t^{(W)} = \sum_{j=1}^{N} w_{ij} y_t^{(j)}$$

A typical element of W is defined as:

$$w_{ij} = \frac{I_{ij} d_{ij}^{-2}}{\sum_{k=1}^{N} I_{ik} d_{ik}^{-2}} \tag{6}$$

where I_{ij} is the indicator function such that:

$$I_{ij} = \begin{cases} 1, \text{ if } d_{ij} \leq d_{0.25} \\ 0, \text{ otherwise} \end{cases}$$

where d_{ij} is the distance between city i and city j and $d_{0.25}$ is the first quartile of pairwise distances between all 71 cities.

We elicit the informational content of the auxiliary indicators for the future development of the real-estate price indices by comparing out-of-sample forecast accuracy of the forecasts models in equations (3)—(5) with that of the benchmark models. Correspondingly, for those indicators that are informative about future price dynamics we should observe substantial increase in forecast accuracy compared to the forecasting performance of the benchmark models lacking this additional information. To this end, we use two benchmark models. The first benchmark model is a so-called random walk model that uses a historical mean of observed growth rate of the real-estate price indices as a forecast. This model is nested within each of the three specifications of the forecasting model as it imposes zero restrictions on the slope coefficients in equations (3)—(5), i.e., $\alpha_i^{(j)} = \beta_i^{(j)} = \gamma_i^{(j)} = 0$ for all i and j, whenever appropriate. The second benchmark model allows for the lagged dependent variable to enter the regression. This benchmark model is nested within the models in equations (4) and (5) with the restrictions $\beta_i^{(j)} = 0$ and $\beta_i^{(j)} = \gamma_i^{(j)} = 0$ for all i and j, respectively. Observe that the model specification in equation (3) does not nest the autoregressive benchmark model.

The (non-)nested structure of the benchmark and indicator-augmented forecasting models has implications on the choice of the statistical tests for comparing predictive ability of the competing models. In the case of non-nested models, we use the Diebold-Mariano test with the small-sample correction proposed in Harvey et al. (1997). When comparing forecasting accuracy of the nested models, we use the test of Clark and West (2007). In both cases, we pairwise tested the null hypothesis of equal predictive accuracy of an indicator-augmented and benchmark models against a one-sided alternative that the former model produces more accurate forecasts than the latter model.

In addition, we investigated forecasting performance of various forecast combination schemes (Timmermann, 2006). These include a simple average of all available forecasts (Mean), forecast combinations using weights from in-sample model fit measured by the Bayesian Information Criterion (BIC), and forecast combinations using weights derived from the recursively calculated measures of the past forecast performance. In the last group of forecast combinations, the weights are derived from inverse of recursively computed discounted mean squared forecast errors (MSFE(δ)), where δ denotes a value of chosen discount factor $\delta = \{1, 0.75, 0.50, 0.25\}$ (Watson and Stock, 2004). We also derived forecast weights by taking average of remaining forecasts after trimming a certain number of models with the worst forecasting performance (TRIM(τ)), where $\tau = \{0.75, 0.50, 0.25, 0.10\}$ denotes a quantile in distribution of model-specific MSFEs used as a threshold for discarding models with the MSFE surpassing this threshold. Last but not least we considered forecast combination based on ranks, i.e., the forecast weights were computed inversely proportional to model ranking based on the past forecasting performance in terms of MSFE.

An important aspect of computing forecast combinations, derived from the past forecasting performance, is that we calculated combination weights based on the information set available at the forecast origin, that is allowing for an appropriate information lag of the target variable when the out-of-sample forecast accuracy of the models can be evaluated. Thus, we simulated information flow to a forecaster under pseudo-real time conditions. As a result of this setup, forecast combination weights are time-varying as these were re-calculated every quarter. For the first few iterations, when the out-of-sample information on forecast accuracy was not available, we used the equal weighting scheme.

This recursive approach to computation of forecast weights allows us to compare forecasting accuracy of combinations using real-time information versus that of combinations using full-sample information. In the latter case, forecast combination weights are computed using the full-sample information and kept constant across all past forecast origins. Clearly, such model combinations are not feasible when one simulates real-time information flow in the past. However, in the first place, this way of combining forecasts helps to determine whether it is possible to detect optimal weights that could boost forecasting performance compared with benchmark as well as single-indicator-augmented models in a given sample. Secondly, since housing market developments draw constant attention from policy-makers and other market participants, this result can be used in future forecasting exercises when predicting housing market dynamics in real time.

We are interested in forecasting dynamics of real-estate price indices four quarters ahead. This choice of the forecast horizon is motivated by the fact that buying and selling housing property typically takes a formidable amount of time in contrast to stock market trading. Hence, property market participants are more interested in medium- to long-run forecasts rather than short-term forecasts.

The forecasting period is from 2009q1 until 2013q3. For each quarter in this period we computed four-quarter ahead forecasts by appropriately truncating the data set. Due to the fact that after the transformation of the price indices into the year-on-year growth rates, the earliest available observation is for 2005q1. This leaves us with a rather small estimation sample to initialize our forecasting procedure. Therefore, we used an expanding estimation window allowing us to use all available observations for estimation of regression coefficients. For example, the forecast for 2009q1 was produced using estimated coefficients of the models in equations (3), (4) and (5) as well as two benchmark models for the sample from 2006q1 until 2008q1.[5] The next forecast for 2009q2 was produced using estimation results for the 2006q1 until 2008q2, etc.

The results of out-of-sample forecasting are reported in Tables 3—9. Given a rather large number of alternative models and cities, which makes their pairwise comparison a challenging task, we summarize the predictive ability of various indicators and their combinations in various ways. For example, in Table 3 we report the incidence of how often a given indicator, which enters either forecasting model specification in equations (3)—(5), was selected among the top five forecasting models. Based on the information presented in the table a number of interesting observations can be made.

First, the naïve models (RW and AR) most of the times produced inferior forecast accuracy compared to the best five forecasting models. Each of the benchmark models was selected only once when forecasting rents the secondary and primary markets, respectively. This means that practically for every city we could find at least five indicators with better forecasting ability than the benchmark models. Secondly, the price-to-rent ratio variables (*P2R_Neubau* and *P2R_Bestand*), appropriately lagged, turn out to be among the most informative single indicators, especially when forecasting housing prices both in primary and secondary markets. This finding implies that for predicting future price dynamics, the current discrepancy between prices and rents is more informative than the current growth rates of respective prices alone. Third, we can compare the informational content of regional versus nationwide business confidence indicators. *A priori*, one would

[5]Four additional observations were lost due to incorporating the fourth-order lag of the dependent variables in the forecasting equation.

expect the former group of the business confidence indicators to take the lead as, arguably, they should better reflect the local information rather than national confidence indicators constructed by aggregation of regional information. Even though, when accounting for correction for the smaller number of cities, for which regional indicators are available, the tentative conclusion is that these regional indicators are of a relatively minor importance compared to national indicators. The regional indicators are selected most often only once or twice in the group of top five best indicators. Among the regional indicators such forward-looking indicators as *GE*(Future situation in a whole local economy), *NRW_GE*(Future situation in whole North Rhine-Westphalia's economy) and *Region_BauGE*(Future situation in the regional construction industry) score the best, especially in predicting rent in the primary and secondary housing markets. Among the national business confidence indicators the highest incidence is attributed to the following indicators: *Ifo_BauGL*(Economic situation in construction) released by Munich thinktank Ifo and *BUIL.Q2.F6S* (Q2: Main factors currently limiting your building activity, F6S: Other factors) of the European Commission. A rather high informative content can also be attributed recorded for selected indicators from the consumer survey of the European Commission. The highest selection frequency is recorded for the following indicators based on the corresponding questions *CONS.Q1* (Financial situation over last 12 months), *CONS.Q2* (Financial situation over next 12 months), *CONS.Q6*(Price trends over next 12 months), *CONS.Q8*(Major purchases at present) , *CONS.Q10* (Savings at present) and *CONS.Q12* (Statement on financial situation of household). It is interesting to observe that survey question directly asking about intentions about purchasing or building a home within the next 12 months (*CONS.Q14*) and home improvements over the next 12 months (CONS.Q15) are not selected as often as the other above mentioned survey questions. The best predictors of housing price indices among the macroeconomic indicators are those related to quarterly year-on-year growth of housing loans to households such as *D4Lend.HH.1year.Vol*, *D4Lend.HH.1.5year.Vol* and *D4Lend.HH.over10year.Vol*.

Last, but not least, and contrary to our expectations, the forecast combinations with recursively computed weights in pseudo-real time perform very poorly. In fact, none of these model combinations, including such a robust forecast combination method as simple averaging (*Mean*), was selected into top five forecasting models. However, the conclusion is reversed as soon as we consider model combinations based on the weights computed using the full-sample estimation results. The forecast combinations based on the in-sample Bayesian Information

Criterion (*BIC.FS*) and trimming of worst forecasting models out of sample at the 10% threshold (*TRIM.10.FS*) consistently display the highest selection incidence into the top five forecasting models across all four price indices in question. The third-best model combination is based on the weights derived from the inverse ranks (*RANK.FS*). The poor performance of the recursively computed forecast combinations can be attributed to the fact that due to data limitations the use of a rather short estimation sample, especially for the earlier forecast period, obscured the optimal weighting of individual models. Only using a sufficiently long estimation sample, covering the full-sample period 2006q1–2013q3, can the optimal weights be reliably determined. The evidence based on the full-sample weighting coincides with the with the results of an de Meulen et al. (2011), emphasizing the important role of forecast combinations in considerable enhancement of predictive power.

Tables 4—7 contain summary of forecasting performance of the best forecasting models selected for each city. We report the absolute measure of forecast accuracy of individual models and model combinations based on the root mean squared forecast error (RMSFE) as well as two relative measures of forecast accuracy; the ratio of RMSFE to that of the benchmark random-walk (*RW*) as well the benchmark autoregressive (AR) models. Since the RW benchmark model is nested within each of the individual models based on equations (3)—(5), we test the statistical significance of improvement in forecast accuracy using the test statistics of Clark and West (2007) (CW). Under the null hypothesis the best and RW models display equal predictive ability. The one-sided p-values of the CW test are reported in the respective column *CW p-value* of each table.

Testing statistical significance of improvement in forecast accuracy brought by individual indicators or model combinations in comparison to that of the benchmark AR model requires some caution. In particular, the AR model is still nested in models based on equations (4) and (5). Hence, the statistical testing of equal forecasting performance of the AR and indicator-augmented models still can be based on the test of Clark and West (2007). In cases when the best forecasting model corresponds to the model specification given in equation (3), we resort to the standard Diebold-Mariano test of equal forecast accuracy applicable for non-nested models. As mentioned above, we use the small-sample correction of Harvey et al. (1997) and report the p-values based on the one-sided test in column *MDM p-value* in each table. As noted in Clark and West (2007, p. 297), the CW test statistic is identical to that proposed in Harvey et al. (1998) for forecast encompassing test. Hence when comparing non-nested models, the marginal significance levels reported for the CW test statistic can be used in order to test the null hypothesis whether an indicator-augmented model forecast encompasses the benchmark model using the two- rather than one-sided alternative hypothesis.

The summary of the forecast accuracy of the best models in the forecast period is presented in Table 8. The relative forecast accuracy is measured by the ratio of model-specific RMSFE to that of the RW model.[6] The descriptive statistics are calculated using only those models, for which reported RMSFE was numerically smaller than the RMSFE of the benchmark RW model. The corresponding number of observations (71) is reported in the row # $\frac{RMSFE}{RMSFE_{RW}} < 1$ for each housing price index. The result, consistent with the evidence reported earlier in Table 3, indicates that for every city in our sample we are able to find an indicator-augmented model (or their combination) that beats the RW benchmark model in terms of forecast accuracy. The average reduction in the RMSFE for housing rent indices is 22% and 24%, whereas for housing prices—28% and 27% in the primary and secondary markets, respectively. However, the corresponding RMSFE ratio greatly varies in the range between values as small as 40% for price in the secondary market and values as large as 99% for price in the primary market.

In the row # $\text{CW}_{RW}(10\%)$ the number of cities, for which the null hypothesis of equal forecast accuracy with the benchmark random-walk model, was rejected at the 10% significance level by the test of Clark and West (2007) is reported. The number of cities, for which forecast accuracy of the best forecasting model was better than that of the benchmark RW model, varies from 67 (reported for rent in the primary market) to 70 (reported for rent in the secondary market and price in the primary market). For prices in the secondary market we can reject the null hypothesis for 68 cities at the chosen significance level. Finally, in the row # $\text{RMSFE}_{RW}/\text{RMSFE}_{AR} \leq 1$ we report the number of cities for which the random-walk benchmark model produced numerically smaller or equal relative RMSFEs compared with the autoregressive benchmark model: depending on the housing price index the number of cities varies from 53 to 60. In order to quantify differences between the entries reported in columns $\text{RMSFE}/\text{RMSFE}_{RW}$ and $\text{RMSFE}/\text{RMSFE}_{AR}$, we provide median estimates of the respective differences for those cities with more accurate AR- rather than RW-based forecasts.[7]

[6] As reported in Tables 4–7, the forecasting performance of the benchmark autoregressive benchmark model was only in few cases substantially better than that of the RW model. This is unsurprising, given that the autoregressive term enters with the fourth-order lag and the housing price indices displays no seasonality. As a result, in the overwhelming number of cases the RW model provides the benchmark that is more difficult to improve upon. This is the reason why we primarily focus on comparing forecasting performance of the indicator-augmented models with the benchmark RW model.

[7] The medians are negative since higher value of $\text{RMSFE}/\text{RMSFE}_{AR}$ than $\text{RMSFE}/\text{RMSFE}_{RW}$ indicate that the AR model produces more accurate forecasts that the RW model for a given city.

For all but one price (price in the primary market) and rent indices, the estimated median of differences in relative RMSFE is about of the same size (0.06-0.07 in absolute terms), for the price in the primary market it is 0.12 in absolute terms. The latter finding indicates that when predicting prices in the primary market for a handful of cities the benchmark AR model is more competitive than the RW model.

In Table 9 we summarise best-predicting models in terms of the indicator categories. The table entries indicate number of cities for which an indicator was selected to be a best-performing model in Tables 4—7. We also distinguish between forecast combinations based on recursively calculated weights and those based on the full-sample information. For rents, the selection frequency is approximately evenly distributed for national business confidence indicators, consumer surveys and macroeconomic variables as well as full-sample combinations. For housing prices, the indicators from consumer surveys were most frequently selected as the best-forecasting model, followed by macroeconomic variables and price-to-rent ratios.

4 Conclusion

In this paper, we evaluate the forecasting ability of 145 indicators and ten types of forecast combination schemes to predict the housing prices and rents in 71 German cities. We are interested in whether the local business confidence indicators can allow for substantially improving the forecasts, given the local nature of the real-estate markets.

In order to test the forecast accuracy of different predictors a four-quarters-ahead out-of-sample forecasting exercise is undertaken. Its results are quite heterogeneous. No single indicator appears to dominate all the others. However, there are several predictors that are especially useful, in particular, price-to-rent ratios. To our surpise, we find that national business confidence indices tend to be more informative than regional ones. We also record a rather high informational content regarding future housing market dynamics of the consumer surveys published by the European Commission. Among the macroeconomic variables those reflecting lending volumes to households turn out to be the most informative indicators. On average, the forecast improvements attain about 20% to 30%, measured by reduction in RMSFE, compared to the naïve models represented by the random-walk and pure autoregressive models. In separate cases, however, the magnitude of improvement is about 40%. Given the short sample size, the combinations of individual forecasts do not improve the forecast accuracy when the weights are computed on the recursive basis. However, when the combination weights are computed using the full-sample information forecast combinations, e.g., based on in-sample fit like Bayesian Information Criterion (BIC) or based on the subset of models appropriately selected based on their out-of-sample forecasting performance, are among the best predictors.

The present analysis utilizes information from national and regional indicators for short-term predicting real-estate price dynamics. In the future research, the scope of regional or city-specific indicators needs to be enlarged by collecting local information on factors influencing demand-supply conditions in the real-estate market such as in-/out-migration, unemployment, vacant housing, housing stock, etc.

References

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

CDU-CSU and SPD (2013). *Deutschlands Zukunft gestalten. Koalitionsvertrag zwischen CDU, CSU und SPD. 18. Legislaturperiode.* Union Betriebs-GmbH: Rheinbach.

Clark, T. E. and K. D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics 138*(1), 291–311.

Deutsche Bundesbank (2013). Monatsbericht Oktober 2013.

Harvey, D., S. Leybourne, and P. Newbold (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting 13*(2), 281–291.

Harvey, D. I., S. J. Leybourne, and P. Newbold (1998). Tests for forecast encompassing. *Journal of Business & Economic Statistics 16*(2), 254–59.

Kholodilin, K. A. and A. Mense (2012). Forecasting the prices and rents for flats in large German cities. Discussion Papers of DIW Berlin 1207, DIW Berlin, German Institute for Economic Research.

Marcellino, M., J. H. Stock, and M. W. Watson (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics 135*(1-2), 499–526.

SVR (2013). Gegen eine rückwärtsgewandte Wirtschaftspolitik. Jahresgutachten 2013/14. Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung.

Timmermann, A. (2006). *Forecast Combinations*, Volume 1 of *Handbook of Economic Forecasting*, Chapter 4, pp. 135–196. Elsevier.

Watson, M. W. and J. H. Stock (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting 23*(6), 405–430.

Wenzel, L. (2013). Forecasting regional growth in Germany: A panel approach using business survey data. HWWI Research Papers 133, Hamburg Institute of International Economics (HWWI).

Appendix

Table 1: List of variables

Code	Description	Source	Frequency
	Prices and rents		
Rent_Neubau	Housing rent at primary market	empirica	4
Rent_Bestand	Housing rent at secondary market	empirica	4
Price_Neubau	Housing price at primary market	empirica	4
Price_Bestand	Housing price at secondary market	empirica	4
	Price-to-Rent ratio		
P2R_Neubau	Price-to-rent ratio at primary market	own calculation	4
P2R_Bestand	Price-to-rent ratio at secondary market	own calculation	4
	Business confidence (region)		
GE	Future situation in whole local economy	local CCIs	2 to 12
GL	Current situation in whole local economy	local CCIs	2 to 12
GK	Business climate in whole local economy	local CCIs	2 to 12
BeP	Employment plans in whole local economy	local CCIs	2 to 12
Inv	Investment plans in whole local economy	local CCIs	2 to 12
BauGE	Future situation in local construction	local CCIs	2 to 12
BauGK	Business climate in local construction	local CCIs	2 to 12
BauGL	Current situation in local construction	local CCIs	2 to 12
BauBeP	Employment plans in local construction	local CCIs	2 to 12
BauInv	Investment plans in local construction	local CCIs	2 to 12
RLP_BauGE	Future situation in Rhineland-Palatinate's construction	CCI Koblenz	3
RLP_BauGK	Business climate in Rhineland-Palatinate's construction	CCI Koblenz	4
RLP_BauGL	Current situation in Rhineland-Palatinate's construction	CCI Koblenz	3
RLP_BauBeP	Emploment plans in Rhineland-Palatinate's construction	CCI Koblenz	3
RLP_BauInv	Investment plans in Rhineland-Palatinate's construction	CCI Koblenz	3
RLP_GE	Future situation in whole Rhineland-Palatinate's economy	CCI Koblenz	3
RLP_GK	Business climate in whole Rhineland-Palatinate's economy	CCI Koblenz	3
RLP_GL	Current situation in whole Rhineland-Palatinate's economy	CCI Koblenz	3
RLP_BeP	Emploment plans in whole Rhineland-Palatinate's economy	CCI Koblenz	3
RLP_Inv	Investment plans in whole Rhineland-Palatinate's economy	CCI Koblenz	3
NRW_GE	Future situation in whole North Rhine-Westphalia's economy	NRW.Bank	12
NRW_GK	Business climate in whole North Rhine-Westphalia's economy	NRW.Bank	12
NRW_GL	Current situation in whole North Rhine-Westphalia's economy	NRW.Bank	12
Bayern_GE	Future situation in Bavaria's economy	Bavarian CCI	3
Bayern_GK	Business climate in Bavaria's economy	Bavarian CCI	3
Bayern_GL	Current situation in Bavaria's economy	Bavarian CCI	3
Bayern_BauGE	Future situation in Bavaria's construction	Bavarian CCI	3

Table 1: List of variables (continued)

Code	Description	Source	Frequency
Bayern_BauGK	Business climate in Bavaria's construction	Bavarian CCI	3
Bayern_BauGL	Current situation in Bavaria's construction	Bavarian CCI	3
Bayern_BeP	Emploment plans in Bavaria's economy	Bavarian CCI	3
Bayern_Inv	Investment plans in Bavaria's economy	Bavarian CCI	3
Sachsen_GE	Future situation in whole Saxony's economy	Ifo Dresden	12
Sachsen_GK	Business climate in whole Saxony's economy	Ifo Dresden	12
Sachsen_GL	Current situation in whole Saxony's economy	Ifo Dresden	12
Sachsen_BauGE	Future situation in Saxony's construction	Ifo Dresden	12
Sachsen_BauGL	Current situation in Saxony's construction	Ifo Dresden	12
Sachsen_BauGK	Business climate in Saxony's construction	Ifo Dresden	12
Niedersachsen_BauGE	Future situation in Lower Saxony's construction	CCI Lüneburg-Wolfsburg	4
Niedersachsen_BauGK	Business climate in Lower Saxony's construction	CCI Lüneburg-Wolfsburg	4
Niedersachsen_BauGL	Current situation in Lower Saxony's construction	CCI Lüneburg-Wolfsburg	4
Niedersachsen_BauBeP	Emploment plans in Lower Saxony's construction	CCI Lüneburg-Wolfsburg	4
Niedersachsen_BauInv	Investment plans in Lower Saxony's construction	CCI Lüneburg-Wolfsburg	4
Niedersachsen_GE	Future situation in whole Lower Saxony's economy	CCI Lüneburg-Wolfsburg	4
Niedersachsen_GK	Business climate in whole Lower Saxony's economy	CCI Lüneburg-Wolfsburg	4
Niedersachsen_GL	Current situation in whole Lower Saxony's economy	CCI Lüneburg-Wolfsburg	4
Niedersachsen_BeP	Emploment plans in whole Lower Saxony's economy	CCI Lüneburg-Wolfsburg	4
Niedersachsen_Inv	Investment plans in whole Lower Saxony's economy	CCI Lüneburg-Wolfsburg	4
Ostdeutschland_BauGE	Future situation in East German construction	Ifo Dresden	12
Ostdeutschland_BauGK	Business climate in East German construction	Ifo Dresden	12
Ostdeutschland_BauGL	Current situation in East German construction	Ifo Dresden	12
Ostdeutschland_GE	Future situation in whole East German economy	Ifo Dresden	12
Ostdeutschland_GK	Business climate in whole East German economy	Ifo Dresden	12
Ostdeutschland_GL	Current situation in whole East German economy	Ifo Dresden	12
Region_BauGE	Future situation in big region's construction	DIHK	3
Region_BauGK	Business climate in big region's construction	DIHK	3
Region_BauGL	Current situation in big region's construction	DIHK	3
Region_BauBeP	Emploment plans in big region's construction	DIHK	3
Region_BauInv	Investment plans in big region's construction	DIHK	3
Region_GE	Future situation in whole big region's economy	DIHK	3
Region_GK	Business climate in whole big region's economy	DIHK	3
Region_GL	Current situation in whole big region's economy	DIHK	3
Region_BeP	Emploment plans in whole big region's economy	DIHK	3
Region_Inv	Investment plans in whole big region's economy	DIHK	3
Macroeconomic			

Table 1: List of variables (continued)

Code	Description	Source	Frequency
Lend.HH.1year.EIR	Effective interest rates of German banks / New business / Housing loans to households with an initial rate fixation, floating rate or up to 1 year	Deutsche Bundesbank	12
Lend.HH.1year.Vol	New business (volumes) of German banks / Housing loans to households with an initial rate fixation, floating rate or up to 1 year	Deutsche Bundesbank	12
Lend.HH.1.5year.EIR	Effective interest rates of German banks / New business / Housing loans to households with an initial rate fixation of over 1 year and up to 5 years	Deutsche Bundesbank	12
Lend.HH.1.5year.Vol	New business (volumes) of German banks / Housing loans to households with an initial rate fixation of over 1 year and up to 5 years	Deutsche Bundesbank	12
Lend.HH.5.10year.EIR	Effective interest rates of German banks / New business / Housing loans to households with an initial rate fixation of over 5 years and up to 10 years	Deutsche Bundesbank	12
Lend.HH.5.10year.Vol	New business (volumes) of German banks / Housing loans to households with an initial rate fixation of over 5 years and up to 10 years	Deutsche Bundesbank	12
Lend.HH.over10year.EIR	Effective interest rates of German banks / New business / Housing loans to households with an initial rate fixation of over 10 years	Deutsche Bundesbank	12
Lend.HH.over10year.Vol	New business (volumes) of German banks / Housing loans to households with an initial rate fixation of over 10 years	Deutsche Bundesbank	12
Lend.HH.EIR	Effective interest rates of German banks / New business / Housing loans to households	Deutsche Bundesbank	12
Lend.HH.Vol	New business (volumes) of German banks / Housing loans to households	Deutsche Bundesbank	12
Lend.HH.Cost	Effective interest rates of German banks / New business / Housing loans to households (annual percentage rate of charge, total cost of loan)	Deutsche Bundesbank	12
DAX_price	DAX price index / End 1987 = 1000 / End of month	Deutsche Bundesbank	12
DAX_performance	DAX performance index / End 1987 = 1000 / End of month	Deutsche Bundesbank	12
CDAX_price	CDAX price index / End 1987 = 100 / End of month	Deutsche Bundesbank	12
CDAX_performance	CDAX performance index / End 1987 = 100 / End of month	Deutsche Bundesbank	12
Business confidence (nation)			
Ifo_BauGK	Business climate in German construction	Ifo	12
Ifo_BauGL	Current situation in German construction	Ifo	12
Ifo_BauGE	Future situation in German construction	Ifo	12
Ifo_GE	Future situation in whole German economy	Ifo	12
Ifo_GK	Business climate in whole German economy	Ifo	12
Ifo_GL	Current situation in whole German economy	Ifo	12
DIHK_BauGE	Future situation in German construction	DIHK	3
DIHK_BauGK	Business climate in German construction	DIHK	3
DIHK_BauGL	Current situation in German construction	DIHK	3
DIHK_BauBeP	Employment plans in German construction	DIHK	3
DIHK_BauInv	Investment plans in German construction	DIHK	3

Table 1: List of variables (continued)

Code	Description	Source	Frequency
DIHK_GE	Future situation in whole German economy	DIHK	3
DIHK_GK	Business climate in whole German economy	DIHK	3
DIHK_GL	Current situation in whole German economy	DIHK	3
DIHK_BeP	Employment plans in whole German economy	DIHK	3
DIHK_Inv	Investment plans in whole German economy	DIHK	3
BUIL.COF	Construction confidence indicator (Q3 + Q4) / 2	European Commission	12
BUIL.Q1	Building activity development over the past 3 months	European Commission	12
BUIL.Q2.F1S	Factors limiting activity: None	European Commission	12
BUIL.Q2.F2S	Factors limiting activity: Insufficient demand	European Commission	12
BUIL.Q2.F3S	Factors limiting activity: Weather conditions	European Commission	12
BUIL.Q2.F4S	Factors limiting activity: Shortage of labour force	European Commission	12
BUIL.Q2.F5S	Factors limiting activity: Shortage of material and/or equipment	European Commission	12
BUIL.Q2.F6S	Factors limiting activity: Other factors	European Commission	12
BUIL.Q2.F7S	Factors limiting activity: Financial constraints	European Commission	12
BUIL.Q3	Evolution of your current overall order books	European Commission	12
BUIL.Q4	Employment expectations over the next 3 months	European Commission	12
BUIL.Q5	Prices expectations over the next 3 months	European Commission	12
BUIL.Q6	Operating time ensured by current backlog (in months)	European Commission	12
Immokonjunktur_BG	Deutsche Hypo Immobilienkonjunktur-Index	Bulwiengesa AG	12
	Consumer confidence		
CONS.COF	Consumer confidence indicator (Q2 + Q4 - Q7 + Q11) / 4	European Commission	12
CONS.Q1	Financial situation over last 12 months	European Commission	12
CONS.Q2	Financial situation over next 12 months	European Commission	12
CONS.Q3	General economic situation over last 12 months	European Commission	12
CONS.Q4	General economic situation over next 12 months	European Commission	12
CONS.Q5	Price trends over last 12 months	European Commission	12
CONS.Q6	Price trends over next 12 months	European Commission	12
CONS.Q7	Unemployment expectations over next 12 months	European Commission	12
CONS.Q8	Major purchases at present	European Commission	12
CONS.Q9	Major purchases over next 12 months	European Commission	12
CONS.Q10	Savings at present	European Commission	12
CONS.Q11	Savings over next 12 months	European Commission	12
CONS.Q12	Statement on financial situation of household	European Commission	12
CONS.Q13	Intention to buy a car within the next 12 months	European Commission	12
CONS.Q14	Purchase or build a home within the next 12 months	European Commission	12
CONS.Q15	Home improvements over the next 12 months	European Commission	12

Table 2: Business confidence indicators

City	Region	Frequency	Source
Augsburg	IHK-Bezirk Bayerisch-Schwaben	3	IHK Schwaben
Berlin	Berlin	3	IHK Berlin
Bielefeld	Ostwestfalen	2	IHK Ostwestfalen zu Bielefeld
Bochum	Mittleres Ruhrgebiet	2	IHK Mittleres Ruhrgebiet
Bonn	Bonn/Rhein-Sieg	3	IHK Bonn/Rhein-Sieg
Bottrop	Nord Westfalen	2	IHK Nord Westfalen
Braunschweig	Braunschweig (only industry)	4	IHK Braunschweig
Bremen	HK Bremen	4	HK Bremen
Bremerhaven	Bremerhaven	2-4	IHK Bremerhaven
Chemnitz	IHK Südwestsachsen	2-3	IHK Chemnitz
Cottbus	Südbrandenburg	3	IHK zu Cottbus
Dortmund	Ruhrgebiet	2	IHK zu Essen
Dresden	Kammerbezirk Dresden	2-3	IHK Dresden
Duisburg	Ruhrgebiet	2	IHK zu Essen
Düsseldorf	Düsseldorf und Mittlerer Niederrhein	2-3	IHK zu Düsseldorf
Erfurt	Region Nord- und Mittelthüringen	3	IHK Erfurt
Erlangen	Mittelfranken	3	IHK Nürnberg für Mittelfranken
Essen	Ruhrgebiet	2	IHK zu Essen
Frankfurt am Main	Frankfurt (all) and IHK-Bezirk Frankfurt (construction)	3	IHK Frankfurt am Main
Fürth	Mittelfranken	3	IHK Nürnberg für Mittelfranken
Gelsenkirchen	IHK Nord Westfalen	2	IHK Nord Westfalen
Halle (Saale)	IHK Bezirk Halle-Dessau	4	IHK Halle-Dessau
Hamburg	Hamburg	4	IHK Hamburg
Hannover	IHK-Bezirk Hannover	4	IHK Hannover
Heilbronn	IHK Bezirk Heilbronn-Franken	4	IHK Heilbronn-Franken
Jena	Region Nord- und Mittelthüringen	3	IHK Erfurt
Karlsruhe	TechnologieRegion Karlsruhe	4-3	IHK Karlsruhe
Kassel	Nordhessen (only business climate)	3	IHK Kassel-Marburg
Kiel	Schleswig-Holstein	4	IHK zu Kiel
Koblenz	Bezirk der IHK Koblenz	4-3	IHK Koblenz
Köln	Stadt Köln	3	IHK Köln
Leipzig	Kammerbezirk Leipzig	2-3	IHK Leipzig
Ludwigshafen	Pfalz	3	IHK für die Pfalz in Ludwigshafen am Rhein
Lübeck	Schleswig-Holstein	4	IHK zu Kiel
Magdeburg	Sachsen-Anhalt	4	IHK Magdeburg
Mainz	Rheinhessen	3	IHK für Rheinhessen
München	Region München	3	IHK München und Oberbayern
Münster	Nord Westfalen	2	IHK Nord Westfalen
Nürnberg	Mittelfranken	3	IHK Nürnberg für Mittelfranken
Oldenburg	Oldenburger Land	4	Oldenburgische IHK
Osnabrück	Osnabrück - Emsland - Grafschaft Bentheim	4	IHK Osnabrück - Emsland - Grafschaft Bentheim
Pforzheim	Nordschwarzwald	2	IHK Nordschwarzwald
Potsdam	Westbrandenburg	2	IHK Potsdam
Regensburg	Region Oberpfalz-Kelheim	3	IHK Regensburg für Oberpfalz/Kelheim
Rostock	IHK-Bezirk Rostock	3	IHK zu Rostock
Saarbrücken	Saarland	12	IHK des Saarlandes
Trier	Region Trier	3	IHK Trier
Ulm	IHK-Region Ulm	4-3	IHK Ulm
Wiesbaden	Rhein-Main-Gebiet	3	IHK Wiesbaden
Wolfsburg	Lüneburg-Wolfsburg (all), Niedersachsen (construction)	4	IHK Lüneburg-Wolfsburg
Wuppertal	IHK-Bezirk Wuppertal-Solingen-Remscheid	2-3	IHK Wuppertal-Solingen-Remscheid
Würzburg	Mainfranken	3	IHK Würzburg-Schweinfurt
Germany and big regions (North, South, West, East)		3	DIHK
Saxony and East Germany		12	Ifo Dresden
North Rhine-Westphalia		12	NRW.Bank
Niedersachsen		4	IHK Lüneburg-Wolfsburg
Rheinland-Pfalz		4-3	IHK Koblenz

Table 3: Selection frequency of indicator models into top five forecasting models for each city

Indicator	RN%	RB%	PB%	PN%	# City
			Naive		
RW	0	1	0	0	71
AR	1	0	0	0	71
			Price-to-Rent ratio		
P2R_Neubau	2	8	28	16	71
P2R_Bestand	8	7	22	23	71
			Business confidence (region)		
GE	7	4	4	2	44
GK	2	0	0	0	45
GL	0	2	0	0	45
BeP	0	0	1	1	29
Inv	2	1	0	0	27
BauGE	1	0	0	0	26
BauGK	1	0	0	0	28
BauGL	2	1	1	1	26
BauBeP	0	0	0	0	20
BauInv	0	0	0	0	19
RLP_GE	1	1	0	1	3
RLP_GK	0	0	0	0	3
RLP_GL	0	0	0	0	3
RLP_BeP	0	0	0	0	3
RLP_Inv	0	0	0	0	3
RLP_BauGE	1	0	0	0	3
RLP_BauGK	0	0	0	0	3
RLP_BauGL	1	0	0	0	3
RLP_BauBeP	0	0	0	0	3
RLP_BauInv	0	0	0	0	3
NRW_GE	5	2	1	1	25
NRW_GK	2	2	0	0	25
NRW_GL	1	0	0	0	25
Bayern_GE	1	0	1	0	8
Bayern_GK	0	0	0	0	8
Bayern_GL	0	0	0	0	8
Bayern_BauGE	0	0	0	0	8
Bayern_BauGK	0	0	0	0	8
Bayern_BauGL	2	1	0	1	8
Bayern_BauBeP	0	1	0	0	8
Bayern_BauInv	0	0	0	0	8
Sachsen_GE	0	0	0	0	3
Sachsen_GK	0	0	0	0	3
Sachsen_GL	0	0	0	0	3
Sachsen_BauGE	0	0	0	0	3
Sachsen_BauGK	0	0	0	0	3
Sachsen_BauGL	0	0	0	0	3
Niedersachsen_GE	0	0	0	0	9
Niedersachsen_GK	0	0	0	0	9
Niedersachsen_GL	0	0	0	1	9
Niedersachsen_BeP	0	0	0	0	9
Niedersachsen_Inv	0	0	0	0	9
Niedersachsen_BauGE	0	0	0	0	9
Niedersachsen_BauGK	0	0	0	0	9
Niedersachsen_BauGL	0	0	0	0	9
Niedersachsen_BauBeP	1	0	0	0	9
Niedersachsen_BauInv	0	0	0	0	9
Ostdeutschland_GE	0	0	0	0	11
Ostdeutschland_GK	0	0	0	0	11
Ostdeutschland_GL	0	0	1	0	11
Ostdeutschland_BauGE	0	0	1	0	11

Indicator	RN%	RB%	PB%	PN%	# City
Ostdeutschland_BauGK	0	0	0	0	11
Ostdeutschland_BauGL	0	0	0	2	11
Region_GE	5	6	4	3	71
Region_GL	1	0	0	0	71
Region_GK	0	2	0	1	71
Region_BeP	0	1	1	0	71
Region_Inv	0	0	1	1	71
Region_BauGE	0	2	1	0	71
Region_BauGK	0	1	1	0	71
Region_BauGL	5	4	2	4	71
Region_BauBeP	1	2	0	0	71
Region_BauInv	0	0	0	0	71
			Business confidence (nation)		
Ifo_GE	4	2	2	1	71
Ifo_GK	3	2	1	1	71
Ifo_GL	1	1	0	0	71
Ifo_BauGE	0	0	0	0	71
Ifo_BauGK	2	6	0	0	71
Ifo_BauGL	14	22	7	19	71
DIHK_GE	5	7	3	3	71
DIHK_GK	0	0	0	0	71
DIHK_GL	2	1	0	0	71
DIHK_BeP	0	0	0	1	71
DIHK_Inv	1	1	2	0	71
DIHK_BauGE	0	0	0	0	71
DIHK_BauGK	1	1	2	0	71
DIHK_BauGL	4	4	2	6	71
DIHK_BauBeP	1	0	0	0	71
DIHK_BauInv	0	0	0	0	71
BUIL.COF	1	1	0	0	71
BUIL.Q1	1	2	0	1	71
BUIL.Q2.F1S	0	1	0	0	71
BUIL.Q2.F2S	3	2	0	1	71
BUIL.Q2.F3S	0	3	4	2	71
BUIL.Q2.F4S	4	3	3	5	71
BUIL.Q2.F5S	1	0	1	0	71
BUIL.Q2.F6S	2	6	15	20	71
BUIL.Q2.F7S	3	0	4	2	71
BUIL.Q3	1	0	1	3	71
BUIL.Q4	0	2	0	0	71
BUIL.Q5	3	2	0	1	71
BUIL.Q6	2	0	2	5	71
Immokonjunktur_BG	0	0	0	0	71
			Consumer confidence		
CONS.COF	2	0	1	0	71
CONS.Q1	5	3	14	15	71
CONS.Q2	4	1	10	9	71
CONS.Q3	5	4	3	2	71
CONS.Q4	2	3	2	1	71
CONS.Q5	1	0	4	3	71
CONS.Q6	14	8	3	2	71
CONS.Q7	2	3	0	0	71
CONS.Q8	7	10	3	2	71
CONS.Q9	5	3	4	1	71
CONS.Q10	3	6	4	17	71
CONS.Q11	2	1	2	2	71
CONS.Q12	3	3	10	15	71
CONS.Q13	7	3	2	2	71

Indicator	RN%	RB%	PB%	PN%	# City
CONS.Q14	1	0	3	4	71
CONS.Q15	1	2	4	3	71
			Macroeconomic		
Lend.HH.1year.EIR	5	3	5	1	71
Lend.HH.1year.Vol	3	2	1	1	71
Lend.HH.1.5year.EIR	3	3	5	2	71
Lend.HH.1.5year.Vol	2	3	1	1	71
Lend.HH.5.10year.EIR	1	1	6	5	71
Lend.HH.5.10year.Vol	4	2	4	0	71
Lend.HH.over10year.EIR	1	0	5	4	71
Lend.HH.over10year.Vol	1	0	1	0	71
Lend.HH.EIR	0	2	6	6	71
Lend.HH.Vol	3	4	4	2	71
Lend.HH.Cost	0	2	4	4	71
DAX_price	3	3	2	2	71
DAX_performance	1	1	0	0	71
CDAX_price	6	3	4	3	71
CDAX_performance	1	0	0	0	71
D1Lend.HH.1year.Vol	0	1	0	1	71
D1Lend.HH.1.5year.Vol	0	0	0	2	71
D1Lend.HH.5.10year.Vol	1	2	0	1	71
D1Lend.HH.over10year.Vol	1	1	0	3	71
D1Lend.HH.Vol	0	0	1	0	71
D1DAX_price	2	2	1	0	71
D1DAX_performance	1	3	1	0	71
D1CDAX_price	3	2	1	0	71
D1CDAX_performance	1	0	1	0	71
D4Lend.HH.1year.Vol	10	6	2	2	71
D4Lend.HH.1.5year.Vol	12	8	5	3	71
D4Lend.HH.5.10year.Vol	1	0	1	4	71
D4Lend.HH.over10year.Vol	8	6	6	7	71
D4Lend.HH.Vol	1	0	0	6	71
D4DAX_price	3	5	4	1	71
D4DAX_performance	2	5	4	1	71
D4CDAX_price	2	5	3	1	71
D4CDAX_performance	1	4	3	1	71
			Model combinations		
Mean	0	0	0	0	71
BIC.RT	0	0	0	0	71
MSFE.1..RT	0	0	0	0	71
MSFE.0.75..RT	0	0	0	0	71
MSFE.0.50..RT	0	0	0	0	71
MSFE.0.25..RT	0	0	0	0	71
TRIM.75..RT	0	0	0	0	71
TRIM.50..RT	0	0	0	0	71
TRIM.25..RT	0	0	0	0	71
TRIM.10..RT	0	0	0	0	71
RANK.RT	0	0	0	0	71
BIC.FS	31	34	38	37	71
MSFE.1..FS	1	1	0	0	71
MSFE.0.75..FS	1	0	0	0	71
MSFE.0.50..FS	0	0	0	0	71
MSFE.0.25..FS	0	0	0	0	71
TRIM.75..FS	1	0	0	0	71
TRIM.50..FS	1	1	0	0	71
TRIM.25..FS	5	9	2	3	71
TRIM.10..FS	35	39	24	25	71
RANK.FS	21	24	22	19	71

The entries are selection frequency of each indicator model (Equations (3)—(5)) into top five forecasting models. The column # *City* reports the number of cities for which a given indicator is available. The letters *D1* and *D4* in front of the *macroeconomic* indicator names indicate one- and four-quarter growth rates of the respective indicators.

Table 4: Rent in primary market: Best forecasting model

	City	Indicator	Eqn	RMSFE	$\frac{RMSFE}{RMSFE_{RW}}$	CW p-value	$\frac{RMSFE}{RMSFE_{AR}}$	CW p-value	MDM p-value
1	Aachen	D4DAX_price	Eq.(3)	3.48	0.85	0.08	0.64	0.03	0.10
2	Augsburg	CONS.Q1...AR	Eq.(4)	1.60	0.51	0.00	0.42	0.00	0.03
3	Berlin	D4Lend.HH.1.5year.Vol...SARAR	Eq.(5)	4.00	0.58	0.01	0.50	0.00	0.05
4	Bielefeld	BIC.FS	Comb.	2.54	0.72	0.08	0.71	0.07	0.21
5	Bochum	GE	Eq.(3)	2.28	0.80	0.00	0.73	0.00	0.00
6	Bonn	P2R_Neubau	Eq.(3)	4.46	0.92	0.14	0.89	0.00	0.08
7	Bottrop	CONS.Q6	Eq.(3)	1.52	0.61	0.02	0.59	0.01	0.04
8	Braunschweig	P2R_Bestand...SARAR	Eq.(5)	2.86	0.87	0.04	0.79	0.00	0.01
9	Bremen	D4Lend.HH.1.5year.Vol	Eq.(3)	4.02	0.80	0.08	0.74	0.04	0.14
10	Bremerhaven	Lend.HH.Vol	Eq.(3)	5.26	0.95	0.01	0.70	0.06	0.11
11	Chemnitz	Ifo_BauGL	Eq.(3)	2.44	0.96	0.13	0.94	0.04	0.21
12	Cottbus	CONS.Q3	Eq.(3)	2.13	0.75	0.01	0.67	0.01	0.03
13	Darmstadt	Ifo_GK...SARAR	Eq.(5)	2.45	0.75	0.03	0.59	0.04	0.06
14	Dortmund	D4Lend.HH.1year.Vol	Eq.(3)	1.75	0.72	0.05	0.62	0.01	0.07
15	Dresden	BIC.FS	Comb.	2.72	0.65	0.01	0.67	0.03	0.10
16	Duesseldorf	D4CDAX_price	Eq.(3)	4.07	0.86	0.04	0.50	0.08	0.15
17	Duisburg	P2R_Neubau	Eq.(3)	2.73	0.88	0.07	0.74	0.06	0.11
18	Erfurt	Lend.HH.1year.EIR	Eq.(3)	4.91	0.88	0.01	0.77	0.01	0.10
19	Erlangen	TRIM.10..FS	Comb.	1.91	0.84	0.03	0.92	0.02	0.10
20	Essen	D4Lend.HH.over10year.Vol	Eq.(3)	1.98	0.79	0.00	0.77	0.00	0.01
21	Frankfurt	BauGL...AR	Eq.(4)	2.23	0.76	0.04	0.65	0.00	0.02
22	Freiburg	D1CDAX_price...SARAR	Eq.(5)	4.26	0.72	0.00	0.81	0.01	0.18
23	Fuerth	BIC.FS	Comb.	2.15	0.77	0.00	0.74	0.00	0.06
24	Gelsenkirchen	NRW_GE	Eq.(3)	2.94	0.91	0.06	0.63	0.05	0.09
25	Hagen	CONS.Q7...SARAR	Eq.(5)	1.92	0.86	0.00	0.89	0.03	0.13
26	Halle	BIC.FS	Comb.	1.59	0.72	0.00	0.68	0.00	0.03
27	Hamburg	CONS.Q13	Eq.(3)	2.78	0.87	0.00	0.49	0.09	0.14
28	Hamm	D4Lend.HH.1year.Vol	Eq.(3)	3.91	0.83	0.02	0.75	0.00	0.13
29	Hannover	Region_GE	Eq.(3)	3.91	0.75	0.00	0.63	0.02	0.05
30	Heidelberg	CONS.Q8...AR	Eq.(4)	1.69	0.83	0.00	0.97	0.12	0.24
31	Heilbronn	CONS.Q1...AR	Eq.(4)	2.33	0.72	0.00	0.74	0.00	0.05
32	Herne	CONS.Q6...AR	Eq.(4)	3.12	0.71	0.02	0.62	0.01	0.04
33	Ingolstadt	CONS.Q13	Eq.(3)	4.02	0.92	0.02	0.88	0.00	0.05
34	Jena	CONS.Q6...SARAR	Eq.(5)	3.02	0.79	0.01	0.73	0.00	0.04
35	Karlsruhe	TRIM.10..FS	Comb.	2.45	0.79	0.01	0.69	0.00	0.04
36	Kassel	CONS.Q6...SARAR	Eq.(5)	3.31	0.72	0.03	0.78	0.01	0.06
37	Kiel	BIC.FS	Comb.	3.00	0.71	0.00	0.57	0.00	0.01
38	Koblenz	TRIM.10..FS	Comb.	1.57	0.82	0.05	0.64	0.03	0.08
39	Koeln	Inv	Eq.(3)	3.76	0.77	0.05	0.62	0.01	0.06
40	Krefeld	DIHK_BauGL	Eq.(3)	1.78	0.57	0.01	0.52	0.00	0.00
41	Leipzig	Ifo_BauGL	Eq.(3)	1.96	0.85	0.07	0.80	0.07	0.16
42	Leverkusen	Ifo_GE	Eq.(3)	2.63	0.86	0.08	0.72	0.03	0.13
43	Ludwigshafen	CDAX_price	Eq.(3)	1.74	0.82	0.00	0.70	0.01	0.05
44	Luebeck	CONS.Q13	Eq.(3)	2.40	0.87	0.03	0.76	0.01	0.13
45	Magdeburg	D4Lend.HH.1.5year.Vol...SARAR	Eq.(5)	2.82	0.66	0.00	0.60	0.00	0.00
46	Mainz	BIC.FS	Comb.	2.60	0.71	0.04	0.72	0.04	0.07
47	Mannheim	Ifo_BauGL	Eq.(3)	1.35	0.82	0.03	0.76	0.01	0.05
48	Moenchengladbach	D4Lend.HH.1.5year.Vol	Eq.(3)	1.65	0.77	0.06	0.73	0.03	0.13
49	Muelheim	Lend.HH.over10year.EIR...SARAR	Eq.(5)	3.31	0.90	0.13	0.84	0.06	0.15
50	Muenchen	BUIL.Q2.F4S	Eq.(3)	1.62	0.56	0.02	0.43	0.00	0.02
51	Muenster	CONS.Q6	Eq.(3)	3.12	0.94	0.13	0.90	0.04	0.15
52	Nuernberg	CONS.Q9	Eq.(3)	1.64	0.71	0.00	0.39	0.08	0.16
53	Oberhausen	BUIL.Q2.F4S...AR	Eq.(4)	1.59	0.74	0.03	0.72	0.02	0.09
54	Offenbach	Ifo_BauGL...AR	Eq.(4)	1.62	0.80	0.02	0.78	0.02	0.05
55	Oldenburg	D4Lend.HH.over10year.Vol	Eq.(3)	5.06	0.93	0.00	0.68	0.02	0.06
56	Osnabrueck	Lend.HH.1year.EIR...AR	Eq.(4)	2.67	0.86	0.00	0.82	0.00	0.13
57	Pforzheim	CONS.Q2...AR	Eq.(4)	1.19	0.65	0.00	0.84	0.00	0.12
58	Potsdam	BIC.FS	Comb.	2.45	0.64	0.03	0.56	0.03	0.13
59	Regensburg	BIC.FS	Comb.	0.91	0.74	0.00	0.63	0.00	0.00
60	Remscheid	NRW_GE	Eq.(3)	1.80	0.96	0.02	0.85	0.00	0.08
61	Rostock	CONS.Q6	Eq.(3)	3.55	0.70	0.05	0.59	0.02	0.05
62	Saarbruecken	BIC.FS	Comb.	1.68	0.63	0.00	0.56	0.00	0.03
63	Salzgitter	BIC.FS	Comb.	4.19	0.84	0.01	0.61	0.06	0.16
64	Solingen	CONS.Q7...SARAR	Eq.(5)	2.98	0.72	0.01	0.73	0.00	0.05
65	Stuttgart	Ifo_BauGL	Eq.(3)	1.72	0.57	0.03	0.66	0.01	0.06
66	Trier	RLP_GE...AR	Eq.(4)	1.91	0.89	0.00	0.91	0.01	0.14
67	Ulm	RANK.FS	Comb.	7.33	0.57	0.02	0.63	0.01	0.06
68	Wiesbaden	CDAX_price	Eq.(3)	3.60	0.92	0.01	0.77	0.00	0.03
69	Wolfsburg	D4Lend.HH.over10year.Vol	Eq.(3)	7.59	0.91	0.03	0.83	0.01	0.09
70	Wuerzburg	TRIM.10..FS	Comb.	4.09	0.90	0.02	0.79	0.05	0.15
71	Wuppertal	CONS.Q11	Eq.(3)	0.97	0.86	0.00	0.86	0.03	0.30

Table 5: Rent in secondary market: Best forecasting model

	City	Indicator	Eqn	RMSFE	$\frac{RMSFE}{RMSFE_{RW}}$	CW p-value	$\frac{RMSFE}{RMSFE_{AR}}$	CW p-value	MDM p-value
1	Aachen	D4DAX_price	Eq.(3)	3.28	0.81	0.06	0.64	0.02	0.09
2	Augsburg	CONS.Q1...AR	Eq.(4)	1.93	0.57	0.00	0.53	0.00	0.02
3	Berlin	BIC.FS	Comb.	3.44	0.59	0.02	0.58	0.00	0.04
4	Bielefeld	BIC.FS	Comb.	2.38	0.68	0.00	0.65	0.00	0.03
5	Bochum	GE	Eq.(3)	1.89	0.76	0.00	0.70	0.00	0.01
6	Bonn	TRIM.10..FS	Comb.	4.57	0.87	0.00	0.85	0.01	0.08
7	Bottrop	GL	Eq.(3)	0.96	0.44	0.00	0.42	0.00	0.00
8	Braunschweig	Ifo_BauGL...SARAR	Eq.(5)	3.60	0.84	0.09	0.79	0.02	0.10
9	Bremen	D4Lend.HH.1.5year.Vol	Eq.(3)	4.62	0.80	0.08	0.75	0.05	0.17
10	Bremerhaven	TRIM.10..FS	Comb.	1.55	0.82	0.00	0.86	0.03	0.12
11	Chemnitz	D4Lend.HH.1.5year.Vol	Eq.(3)	1.17	0.92	0.14	0.89	0.06	0.22
12	Cottbus	BIC.FS	Comb.	1.47	0.66	0.00	0.64	0.00	0.02
13	Darmstadt	Ifo_BauGL	Eq.(3)	2.23	0.90	0.09	0.64	0.05	0.13
14	Dortmund	D4Lend.HH.1year.Vol...SARAR	Eq.(5)	2.61	0.74	0.01	0.72	0.00	0.06
15	Dresden	CONS.Q12...SARAR	Eq.(5)	2.47	0.61	0.00	0.62	0.00	0.01
16	Duesseldorf	GE	Eq.(3)	3.79	0.79	0.00	0.51	0.09	0.14
17	Duisburg	CONS.Q4	Eq.(3)	1.80	0.86	0.06	0.77	0.06	0.12
18	Erfurt	CDAX_price	Eq.(3)	2.43	0.84	0.01	0.72	0.01	0.03
19	Erlangen	P2R_Neubau	Eq.(3)	2.38	0.76	0.00	0.71	0.02	0.11
20	Essen	D4CDAX_price	Eq.(3)	1.96	0.80	0.00	0.71	0.01	0.04
21	Frankfurt	Ifo_BauGL...SARAR	Eq.(5)	2.59	0.77	0.08	0.66	0.02	0.07
22	Freiburg	D1DAX_price...SARAR	Eq.(5)	4.80	0.73	0.01	0.79	0.02	0.14
23	Fuerth	Ifo_BauGL...AR	Eq.(4)	1.97	0.74	0.01	0.71	0.02	0.08
24	Gelsenkirchen	Lend.HH.1year.EIR	Eq.(3)	2.69	0.90	0.09	0.62	0.06	0.13
25	Hagen	CONS.Q13...AR	Eq.(4)	1.18	0.62	0.00	0.86	0.00	0.13
26	Halle	TRIM.10..FS	Comb.	1.63	0.89	0.02	0.80	0.01	0.05
27	Hamburg	CONS.Q9	Eq.(3)	3.13	0.90	0.01	0.49	0.08	0.15
28	Hamm	Region_BauGE...SARAR	Eq.(5)	1.41	0.56	0.01	0.46	0.03	0.13
29	Hannover	Region_GE	Eq.(3)	3.01	0.85	0.00	0.78	0.01	0.04
30	Heidelberg	Lend.HH.1.5year.Vol...AR	Eq.(4)	1.64	0.77	0.00	0.93	0.07	0.22
31	Heilbronn	BIC.FS	Comb.	1.96	0.72	0.02	0.69	0.01	0.09
32	Herne	CONS.Q6...AR	Eq.(4)	1.81	0.56	0.02	0.60	0.01	0.07
33	Ingolstadt	Bayern_BauBeP...SARAR	Eq.(5)	3.92	0.93	0.01	0.90	0.02	0.25
34	Jena	CONS.Q6...SARAR	Eq.(5)	2.76	0.82	0.01	0.82	0.02	0.12
35	Karlsruhe	Ifo_BauGK...AR	Eq.(4)	1.67	0.73	0.00	0.66	0.00	0.01
36	Kassel	P2R_Neubau	Eq.(3)	2.77	0.73	0.04	0.91	0.09	0.32
37	Kiel	BIC.FS	Comb.	2.93	0.85	0.02	0.69	0.03	0.09
38	Koblenz	TRIM.10..FS	Comb.	1.66	0.75	0.03	0.61	0.01	0.05
39	Koeln	Inv...AR	Eq.(4)	4.17	0.74	0.00	0.59	0.01	0.03
40	Krefeld	DIHK_BauGL	Eq.(3)	2.08	0.83	0.00	0.69	0.00	0.03
41	Leipzig	BUIL.Q2.F6S	Eq.(3)	2.08	0.80	0.02	0.76	0.01	0.07
42	Leverkusen	TRIM.10..FS	Comb.	2.35	0.84	0.04	0.72	0.02	0.07
43	Ludwigshafen	Lend.HH.1.5year.EIR	Eq.(3)	1.70	0.71	0.00	0.62	0.01	0.06
44	Luebeck	TRIM.10..FS	Comb.	1.52	0.80	0.00	0.73	0.02	0.07
45	Magdeburg	P2R_Neubau	Eq.(3)	0.86	0.67	0.04	0.58	0.01	0.09
46	Mainz	BIC.FS	Comb.	2.75	0.62	0.04	0.64	0.04	0.08
47	Mannheim	Ifo_BauGL	Eq.(3)	1.77	0.72	0.04	0.69	0.02	0.07
48	Moenchengladbach	D4Lend.HH.1.5year.Vol...AR	Eq.(4)	1.90	0.83	0.08	0.85	0.12	0.26
49	Muelheim	TRIM.10..FS	Comb.	1.96	0.84	0.00	0.73	0.01	0.04
50	Muenchen	BUIL.Q2.F4S	Eq.(3)	1.95	0.56	0.03	0.45	0.00	0.02
51	Muenster	Lend.HH.Vol	Eq.(3)	2.96	0.96	0.07	0.94	0.01	0.11
52	Nuernberg	CONS.Q8	Eq.(3)	1.87	0.67	0.00	0.38	0.09	0.15
53	Oberhausen	BUIL.Q2.F3S	Eq.(3)	1.21	0.76	0.00	0.77	0.00	0.05
54	Offenbach	Ifo_BauGL...AR	Eq.(4)	1.78	0.86	0.03	0.84	0.03	0.10
55	Oldenburg	D4Lend.HH.over10year.Vol	Eq.(3)	3.77	0.93	0.00	0.74	0.02	0.08
56	Osnabrueck	Lend.HH.1.5year.EIR...AR	Eq.(4)	2.15	0.72	0.00	0.73	0.00	0.04
57	Pforzheim	Ifo_BauGK	Eq.(3)	1.18	0.78	0.07	0.78	0.05	0.14
58	Potsdam	D1DAX_price...SARAR	Eq.(5)	2.11	0.79	0.00	0.70	0.00	0.10
59	Regensburg	BIC.FS	Comb.	1.08	0.68	0.00	0.57	0.00	0.01
60	Remscheid	Ifo_GK...AR	Eq.(4)	1.55	0.84	0.00	0.90	0.00	0.03
61	Rostock	CONS.Q6...AR	Eq.(4)	2.90	0.77	0.04	0.83	0.09	0.29
62	Saarbruecken	CONS.Q10...AR	Eq.(4)	1.74	0.70	0.02	0.66	0.02	0.07
63	Salzgitter	BIC.FS	Comb.	4.39	0.81	0.03	0.57	0.07	0.15
64	Solingen	CONS.Q7...AR	Eq.(4)	3.19	0.70	0.02	0.76	0.01	0.06
65	Stuttgart	Ifo_BauGL	Eq.(3)	2.19	0.60	0.03	0.68	0.02	0.08
66	Trier	RLP_GE...AR	Eq.(4)	2.09	0.80	0.00	0.89	0.06	0.21
67	Ulm	RANK.FS	Comb.	6.90	0.61	0.05	0.69	0.05	0.13
68	Wiesbaden	CONS.Q10	Eq.(3)	3.37	0.83	0.02	0.75	0.01	0.11
69	Wolfsburg	DIHK_BauGL	Eq.(3)	10.23	0.89	0.02	0.84	0.00	0.04
70	Wuerzburg	CONS.Q8	Eq.(3)	5.23	0.93	0.07	0.83	0.07	0.18
71	Wuppertal	TRIM.10..FS	Comb.	1.00	0.83	0.00	0.89	0.03	0.12

Table 6: Price in primary market: Best forecasting model

	City	Indicator	Eqn	RMSFE	$\frac{RMSFE}{RMSFE_{RW}}$	CW p-value	$\frac{RMSFE}{RMSFE_{AR}}$	CW p-value	MDM p-value
1	Aachen	Region_GE...SARAR	Eq.(5)	3.74	0.79	0.01	0.77	0.00	0.07
2	Augsburg	BUIL.Q2.F3S...SARAR	Eq.(5)	3.33	0.66	0.04	0.68	0.03	0.12
3	Berlin	BIC.FS	Comb.	2.42	0.46	0.00	0.86	0.02	0.26
4	Bielefeld	BIC.FS	Comb.	2.08	0.70	0.00	0.62	0.00	0.11
5	Bochum	RANK.FS	Comb.	1.26	0.92	0.07	0.91	0.04	0.18
6	Bonn	CONS.Q12	Eq.(3)	3.40	0.83	0.01	0.72	0.00	0.01
7	Bottrop	CONS.Q8...AR	Eq.(4)	2.70	0.80	0.02	0.97	0.10	0.28
8	Braunschweig	P2R_Bestand	Eq.(3)	4.38	0.59	0.00	0.58	0.00	0.02
9	Bremen	BUIL.Q2.F6S...AR	Eq.(4)	4.29	0.55	0.02	0.77	0.03	0.07
10	Bremerhaven	D4Lend.HH.1year.Vol	Eq.(3)	5.27	0.83	0.12	0.65	0.05	0.16
11	Chemnitz	BIC.FS	Comb.	2.84	0.70	0.00	0.59	0.00	0.02
12	Cottbus	P2R_Neubau	Eq.(3)	5.38	0.69	0.01	0.67	0.00	0.16
13	Darmstadt	D4Lend.HH.over10year.Vol	Eq.(3)	7.15	0.94	0.00	0.72	0.01	0.03
14	Dortmund	CONS.Q14	Eq.(3)	3.17	0.75	0.02	0.65	0.00	0.03
15	Dresden	P2R_Neubau...AR	Eq.(4)	1.98	0.45	0.00	0.40	0.00	0.02
16	Duesseldorf	Region_GE...SARAR	Eq.(5)	3.09	0.57	0.00	0.81	0.00	0.10
17	Duisburg	CONS.Q9...SARAR	Eq.(5)	2.39	0.67	0.00	0.61	0.00	0.01
18	Erfurt	BUIL.Q2.F7S...SARAR	Eq.(5)	3.27	0.92	0.03	0.93	0.04	0.27
19	Erlangen	CONS.Q10	Eq.(3)	5.68	0.79	0.00	0.61	0.02	0.07
20	Essen	Lend.HH.1year.EIR...SARAR	Eq.(5)	3.76	0.83	0.01	0.53	0.07	0.13
21	Frankfurt	D4Lend.HH.over10year.Vol	Eq.(3)	4.23	0.83	0.00	0.78	0.09	0.22
22	Freiburg	BUIL.Q2.F7S	Eq.(3)	9.94	0.99	0.05	0.60	0.11	0.16
23	Fuerth	CDAX_price	Eq.(3)	5.03	0.88	0.04	0.68	0.08	0.15
24	Gelsenkirchen	Lend.HH.1year.EIR	Eq.(3)	3.84	0.84	0.02	0.77	0.07	0.14
25	Hagen	Lend.HH.over10year.Vol...SARAR	Eq.(5)	2.20	0.81	0.07	0.73	0.03	0.10
26	Halle	P2R_Neubau	Eq.(3)	3.81	0.77	0.01	0.71	0.02	0.11
27	Hamburg	CONS.Q12	Eq.(3)	5.21	0.81	0.01	0.76	0.02	0.09
28	Hamm	Lend.HH.5.10year.EIR...AR	Eq.(4)	3.31	0.59	0.01	0.47	0.00	0.03
29	Hannover	CONS.Q12	Eq.(3)	4.76	0.76	0.02	0.83	0.09	0.22
30	Heidelberg	BUIL.Q6	Eq.(3)	2.80	0.71	0.00	0.59	0.00	0.02
31	Heilbronn	Lend.HH.1year.Vol...SARAR	Eq.(5)	4.15	0.79	0.01	0.77	0.00	0.00
32	Herne	CONS.Q1...AR	Eq.(4)	3.54	0.72	0.01	0.64	0.00	0.02
33	Ingolstadt	CONS.Q10	Eq.(3)	3.99	0.63	0.00	0.67	0.03	0.11
34	Jena	GE...SARAR	Eq.(5)	3.63	0.65	0.01	0.56	0.01	0.10
35	Karlsruhe	RANK.FS	Comb.	1.30	0.69	0.07	0.57	0.01	0.06
36	Kassel	P2R_Neubau	Eq.(3)	4.48	0.96	0.02	0.56	0.01	0.08
37	Kiel	Lend.HH.over10year.EIR	Eq.(3)	6.35	0.80	0.04	0.60	0.09	0.14
38	Koblenz	P2R_Bestand	Eq.(3)	1.97	0.63	0.00	0.61	0.00	0.02
39	Koeln	CONS.Q1	Eq.(3)	2.68	0.52	0.01	0.48	0.02	0.05
40	Krefeld	BIC.FS	Comb.	2.64	0.65	0.06	0.53	0.04	0.08
41	Leipzig	Lend.HH.5.10year.EIR	Eq.(3)	3.80	0.79	0.06	0.70	0.07	0.13
42	Leverkusen	BIC.FS	Comb.	2.31	0.66	0.00	0.61	0.00	0.03
43	Ludwigshafen	D4CDAX_price	Eq.(3)	4.00	0.74	0.00	0.55	0.01	0.02
44	Luebeck	P2R_Neubau	Eq.(3)	3.36	0.53	0.01	0.46	0.00	0.01
45	Magdeburg	P2R_Bestand	Eq.(3)	6.14	0.78	0.00	0.73	0.00	0.07
46	Mainz	CONS.Q1	Eq.(3)	5.03	0.71	0.01	0.57	0.05	0.09
47	Mannheim	CONS.Q8...AR	Eq.(4)	3.10	0.63	0.00	0.75	0.05	0.11
48	Moenchengladbach	CONS.Q2	Eq.(3)	3.61	0.82	0.04	0.65	0.08	0.14
49	Muelheim	P2R_Neubau	Eq.(3)	4.32	0.72	0.01	0.55	0.00	0.02
50	Muenchen	CONS.Q1	Eq.(3)	6.67	0.68	0.02	0.65	0.00	0.00
51	Muenster	Lend.HH.1.5year.EIR	Eq.(3)	4.01	0.62	0.00	0.47	0.04	0.08
52	Nuernberg	D4Lend.HH.1.5year.Vol...SARAR	Eq.(5)	3.33	0.67	0.05	0.62	0.04	0.09
53	Oberhausen	Lend.HH.Vol...AR	Eq.(4)	1.63	0.79	0.00	0.77	0.00	0.00
54	Offenbach	P2R_Neubau	Eq.(3)	4.14	0.78	0.00	0.66	0.00	0.01
55	Oldenburg	P2R_Neubau	Eq.(3)	3.24	0.55	0.00	0.51	0.00	0.08
56	Osnabrueck	Region_GE...SARAR	Eq.(5)	5.64	0.80	0.00	0.79	0.02	0.14
57	Pforzheim	CONS.Q10	Eq.(3)	3.81	0.76	0.01	0.77	0.05	0.11
58	Potsdam	BIC.FS	Comb.	3.69	0.72	0.00	0.54	0.02	0.08
59	Regensburg	CONS.Q3...SARAR	Eq.(5)	3.65	0.57	0.01	0.44	0.04	0.10
60	Remscheid	CONS.Q2	Eq.(3)	4.22	0.74	0.01	0.55	0.06	0.12
61	Rostock	CONS.Q14...SARAR	Eq.(5)	3.63	0.44	0.01	0.42	0.02	0.09
62	Saarbruecken	Ifo_BauGL	Eq.(3)	4.53	0.83	0.05	0.63	0.10	0.16
63	Salzgitter	CDAX_price	Eq.(3)	3.44	0.62	0.02	0.52	0.01	0.04
64	Solingen	P2R_Neubau	Eq.(3)	2.88	0.91	0.00	0.81	0.01	0.10
65	Stuttgart	D4DAX_price...SARAR	Eq.(5)	2.34	0.43	0.01	0.68	0.01	0.09
66	Trier	P2R_Bestand	Eq.(3)	2.51	0.79	0.00	0.66	0.00	0.04
67	Ulm	CONS.Q1	Eq.(3)	4.55	0.67	0.02	0.53	0.01	0.12
68	Wiesbaden	CONS.Q2	Eq.(3)	4.46	0.70	0.01	0.63	0.00	0.01
69	Wolfsburg	BeP	Eq.(3)	6.51	0.89	0.08	0.81	0.06	0.17
70	Wuerzburg	BIC.FS	Comb.	3.39	0.64	0.00	0.57	0.02	0.06
71	Wuppertal	P2R_Neubau	Eq.(3)	4.14	0.81	0.00	0.77	0.00	0.01

Table 7: Price in secondary market: Best forecasting model

	City	Indicator	Eqn	RMSFE	$\frac{RMSFE}{RMSFE_{RW}}$	CW p-value	$\frac{RMSFE}{RMSFE_{AR}}$	CW p-value	MDM p-value
1	Aachen	BIC.FS	Comb.	3.40	0.68	0.01	0.69	0.00	0.03
2	Augsburg	D4Lend.HH.over10year.Vol...SARAR	Eq.(5)	4.95	0.59	0.03	0.71	0.02	0.06
3	Berlin	Ifo_BauGL...AR	Eq.(4)	3.14	0.45	0.00	0.78	0.03	0.10
4	Bielefeld	BUIL.Q2.F6S	Eq.(3)	3.61	0.79	0.02	0.76	0.00	0.01
5	Bochum	TRIM.10..FS	Comb.	1.85	0.93	0.01	0.91	0.04	0.21
6	Bonn	CONS.Q11...SARAR	Eq.(5)	4.27	0.70	0.02	0.64	0.01	0.02
7	Bottrop	TRIM.10..FS	Comb.	2.96	0.75	0.05	0.97	0.20	0.36
8	Braunschweig	CONS.Q1	Eq.(3)	6.21	0.73	0.03	0.72	0.00	0.02
9	Bremen	BUIL.Q2.F6S...AR	Eq.(4)	4.18	0.53	0.04	0.69	0.00	0.01
10	Bremerhaven	CONS.Q15...SARAR	Eq.(5)	11.58	0.72	0.02	0.70	0.02	0.09
11	Chemnitz	BIC.FS	Comb.	2.93	0.66	0.00	0.60	0.00	0.01
12	Cottbus	CONS.Q12	Eq.(3)	7.63	0.68	0.03	0.53	0.05	0.11
13	Darmstadt	D4Lend.HH.over10year.Vol	Eq.(3)	7.66	0.93	0.00	0.81	0.00	0.00
14	Dortmund	CONS.Q15	Eq.(3)	3.05	0.73	0.03	0.63	0.02	0.09
15	Dresden	BUIL.Q2.F6S	Eq.(3)	2.89	0.54	0.01	0.50	0.01	0.04
16	Duesseldorf	Region_GE...SARAR	Eq.(5)	5.56	0.79	0.00	0.87	0.00	0.00
17	Duisburg	CONS.Q5...AR	Eq.(4)	2.13	0.66	0.00	0.60	0.00	0.00
18	Erfurt	TRIM.10..FS	Comb.	2.38	0.83	0.00	0.85	0.02	0.07
19	Erlangen	CONS.Q10	Eq.(3)	4.66	0.73	0.00	0.59	0.02	0.07
20	Essen	P2R_Bestand...AR	Eq.(4)	2.96	0.81	0.01	0.79	0.01	0.05
21	Frankfurt	BauGL...SARAR	Eq.(5)	4.93	0.80	0.01	0.75	0.01	0.07
22	Freiburg	CONS.Q10	Eq.(3)	6.96	0.87	0.01	0.85	0.00	0.02
23	Fuerth	BUIL.Q2.F6S	Eq.(3)	6.75	0.79	0.03	0.69	0.00	0.03
24	Gelsenkirchen	CONS.Q1	Eq.(3)	5.00	0.90	0.12	0.80	0.08	0.15
25	Hagen	P2R_Neubau	Eq.(3)	2.57	0.81	0.00	0.76	0.00	0.02
26	Halle	P2R_Neubau	Eq.(3)	7.31	0.83	0.01	0.82	0.01	0.14
27	Hamburg	CONS.Q12	Eq.(3)	6.28	0.80	0.01	0.72	0.03	0.10
28	Hamm	CONS.Q6	Eq.(3)	2.44	0.82	0.07	0.49	0.05	0.10
29	Hannover	P2R_Bestand	Eq.(3)	9.05	0.80	0.01	0.34	0.12	0.17
30	Heidelberg	BUIL.Q2.F4S	Eq.(3)	4.24	0.77	0.07	0.64	0.01	0.11
31	Heilbronn	CONS.Q10	Eq.(3)	4.01	0.66	0.01	0.73	0.00	0.01
32	Herne	D1Lend.HH.over10year.Vol...AR	Eq.(4)	3.35	0.97	0.06	0.97	0.07	0.22
33	Ingolstadt	Lend.HH.5.10year.EIR...SARAR	Eq.(5)	3.71	0.51	0.02	0.58	0.01	0.08
34	Jena	GE...SARAR	Eq.(5)	4.17	0.77	0.06	0.69	0.06	0.21
35	Karlsruhe	P2R_Neubau	Eq.(3)	2.22	0.68	0.01	0.56	0.00	0.01
36	Kassel	BIC.FS	Comb.	4.59	0.59	0.05	0.59	0.04	0.08
37	Kiel	CONS.Q10	Eq.(3)	8.57	0.84	0.02	0.84	0.01	0.10
38	Koblenz	TRIM.10..FS	Comb.	4.23	0.74	0.01	0.69	0.02	0.02
39	Koeln	CONS.Q1	Eq.(3)	4.26	0.64	0.01	0.63	0.00	0.01
40	Krefeld	BIC.FS	Comb.	3.23	0.66	0.04	0.57	0.04	0.08
41	Leipzig	CONS.Q14	Eq.(3)	4.73	0.80	0.06	0.68	0.09	0.15
42	Leverkusen	P2R_Bestand	Eq.(3)	2.93	0.79	0.00	0.72	0.00	0.06
43	Ludwigshafen	D4Lend.HH.over10year.Vol...SARAR	Eq.(5)	5.07	0.84	0.10	0.83	0.04	0.10
44	Luebeck	CONS.Q1...AR	Eq.(4)	4.01	0.68	0.04	0.58	0.02	0.05
45	Magdeburg	P2R_Bestand	Eq.(3)	6.91	0.85	0.02	0.81	0.01	0.09
46	Mainz	CONS.Q1	Eq.(3)	4.31	0.73	0.03	0.68	0.04	0.10
47	Mannheim	CONS.Q12	Eq.(3)	5.45	0.81	0.06	0.80	0.01	0.06
48	Moenchengladbach	CONS.Q12	Eq.(3)	3.03	0.69	0.02	0.60	0.04	0.08
49	Muelheim	P2R_Bestand	Eq.(3)	2.81	0.64	0.00	0.53	0.00	0.04
50	Muenchen	CONS.Q1	Eq.(3)	8.03	0.70	0.02	0.77	0.00	0.00
51	Muenster	Lend.HH.1.5year.EIR	Eq.(3)	5.57	0.70	0.00	0.69	0.01	0.02
52	Nuernberg	D4Lend.HH.1.5year.Vol...SARAR	Eq.(5)	4.96	0.53	0.08	0.59	0.06	0.11
53	Oberhausen	BIC.FS	Comb.	2.46	0.78	0.00	0.77	0.00	0.04
54	Offenbach	P2R_Bestand	Eq.(3)	4.29	0.82	0.00	0.80	0.00	0.02
55	Oldenburg	P2R_Bestand	Eq.(3)	3.65	0.61	0.00	0.53	0.00	0.05
56	Osnabrueck	CONS.Q10...AR	Eq.(4)	4.43	0.68	0.06	0.60	0.01	0.05
57	Pforzheim	BUIL.Q2.F6S	Eq.(3)	4.05	0.79	0.03	0.75	0.00	0.02
58	Potsdam	RANK.FS	Comb.	5.59	0.75	0.01	0.60	0.00	0.01
59	Regensburg	D4Lend.HH.Vol...SARAR	Eq.(5)	5.38	0.55	0.03	0.48	0.03	0.09
60	Remscheid	CONS.Q1...SARAR	Eq.(5)	3.06	0.68	0.00	0.54	0.02	0.07
61	Rostock	BUIL.Q2.F3S...SARAR	Eq.(5)	10.65	0.84	0.00	0.89	0.03	0.14
62	Saarbruecken	Lend.HH.over10year.EIR	Eq.(3)	4.89	0.81	0.04	0.68	0.06	0.13
63	Salzgitter	DAX_price	Eq.(3)	4.13	0.80	0.01	0.73	0.02	0.02
64	Solingen	BUIL.Q2.F6S	Eq.(3)	2.12	0.64	0.01	0.60	0.01	0.02
65	Stuttgart	Region_GE...SARAR	Eq.(5)	4.34	0.63	0.03	0.70	0.00	0.05
66	Trier	BUIL.Q6	Eq.(3)	4.09	0.90	0.14	0.83	0.07	0.22
67	Ulm	CONS.Q1	Eq.(3)	3.27	0.40	0.01	0.31	0.00	0.02
68	Wiesbaden	CONS.Q1	Eq.(3)	5.04	0.70	0.02	0.69	0.00	0.02
69	Wolfsburg	P2R_Bestand	Eq.(3)	7.63	0.80	0.01	0.67	0.03	0.16
70	Wuerzburg	CONS.Q8...SARAR	Eq.(5)	4.17	0.73	0.00	0.68	0.00	0.04
71	Wuppertal	D4Lend.HH.Vol...SARAR	Eq.(5)	2.80	0.76	0.02	0.84	0.04	0.19

Table 8: Summary of forecast accuracy (2009Q1-2013Q3)

	Rent		Price	
	primary market (RN%)	secondary market (RB%)	primary market (PN%)	secondary market (PB%)
mean	0.78	0.76	0.72	0.73
st. dev.	0.11	0.11	0.13	0.11
min	0.51	0.44	0.43	0.40
max	0.96	0.96	0.99	0.97
# $\frac{RMSFE}{RMSFE_{RW}} < 1$	71	71	71	71
# CW$_{RW}$ (10%)	67	70	70	68
# $\frac{RMSFE_{RW}}{RMSFE_{AR}} \leq 1$	58	53	60	57
median $\left[\frac{RMSFE}{RMSFE_{RW}} - \frac{RMSFE}{RMSFE_{AR}} < 0\right]$	-0.06	-0.06	-0.12	-0.07

The entries in columns are descriptive statistics of the relative forecast accuracy of the best models achieved during the forecast training period from 2009Q1-2013Q3 at the four-quarter forecast horizon. The relative forecast accuracy is measured by the ratio of model-specific RMSFE to that of the random-walk model. The descriptive statistics is calculated using only those models for which reported RMSFE was numerically smaller than the RMSFE of the benchmark random-walk model. The corresponding number of observations is reported in the row # $\frac{RMSFE}{RMSFE_{RW}} < 1$. Below the number of cities for which the null hypothesis of equal forecast accuracy with the benchmark random-walk model was rejected at the 10% significance level by the test of Clark and West (2007) is reported in the row # CW$_{RW}$ (10%). The number of cities for which the benchmark random-walk model produces not worse forecasts than the benchmark autoregressive model is reported in the row # $\frac{RMSFE_{RW}}{RMSFE_{AR}} \leq 1$.

Table 9: Distribution of the best-forecast indicators according to categories

	Rent		Price	
	primary market (RN%)	secondary market (RB%)	primary market (PN%)	secondary market (PB%)
Naïve	0	0	0	0
Price-to-Rent ratio	3	3	14	11
Business confidence (region)	7	8	5	4
Business confidence (nation)	10	15	6	10
Consumer confidence	18	13	20	25
Macroeconomic	18	15	17	11
Model combination (Real-Time)	0	0	0	0
Model combination (Full-Sample)	15	17	9	10

The entries in columns are selection incidence of indicators pertaining to the best-forecasting models, as reported in Tables 4—7, foe each indicator category.

Figure 1: Secondary market price in large German cities (euros per m^2), 2004Q1-2013Q3

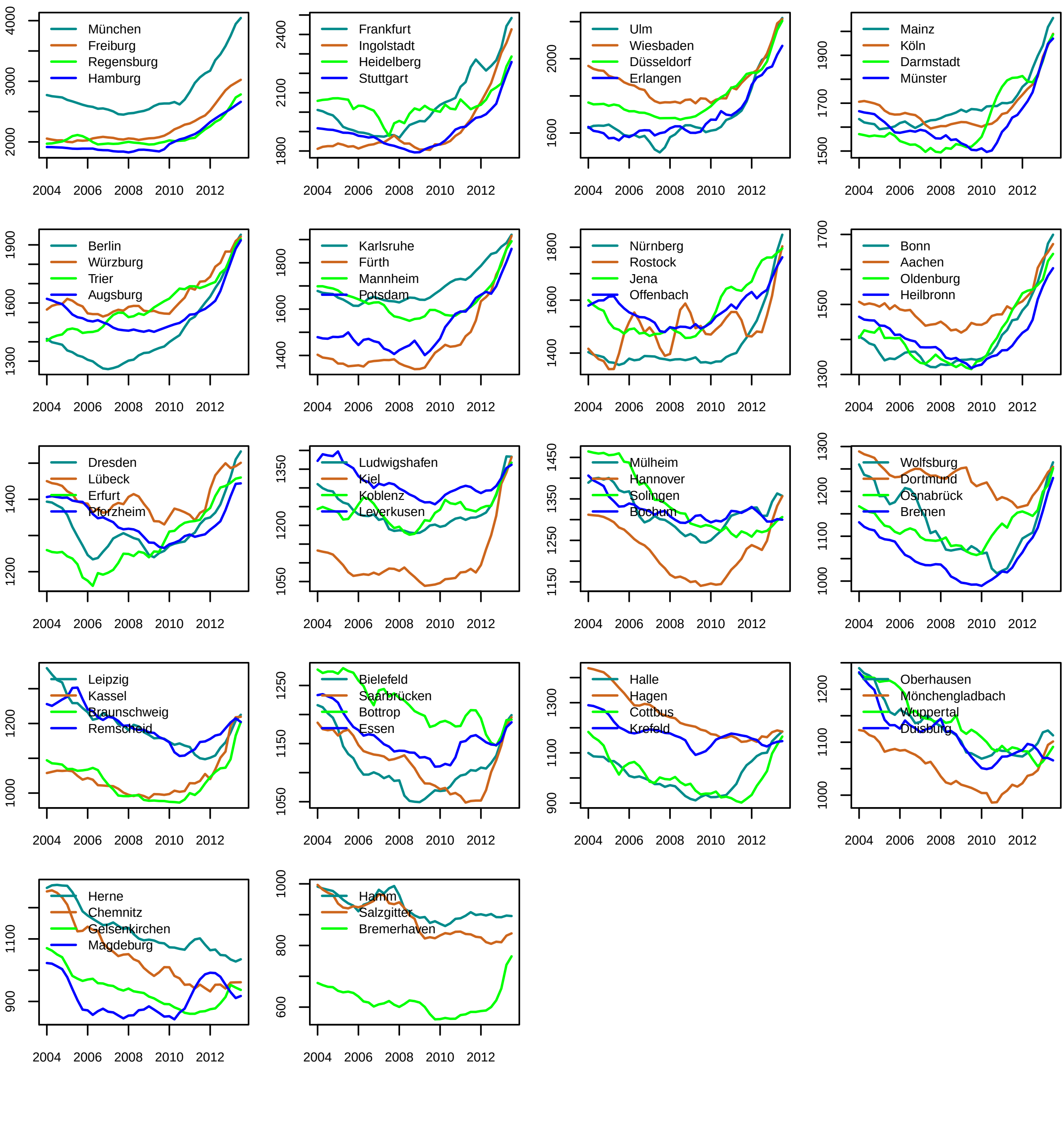

Figure 2: Secondary market rent for existing housing in large German cities (euros per m^2), 2004Q1-2013Q3

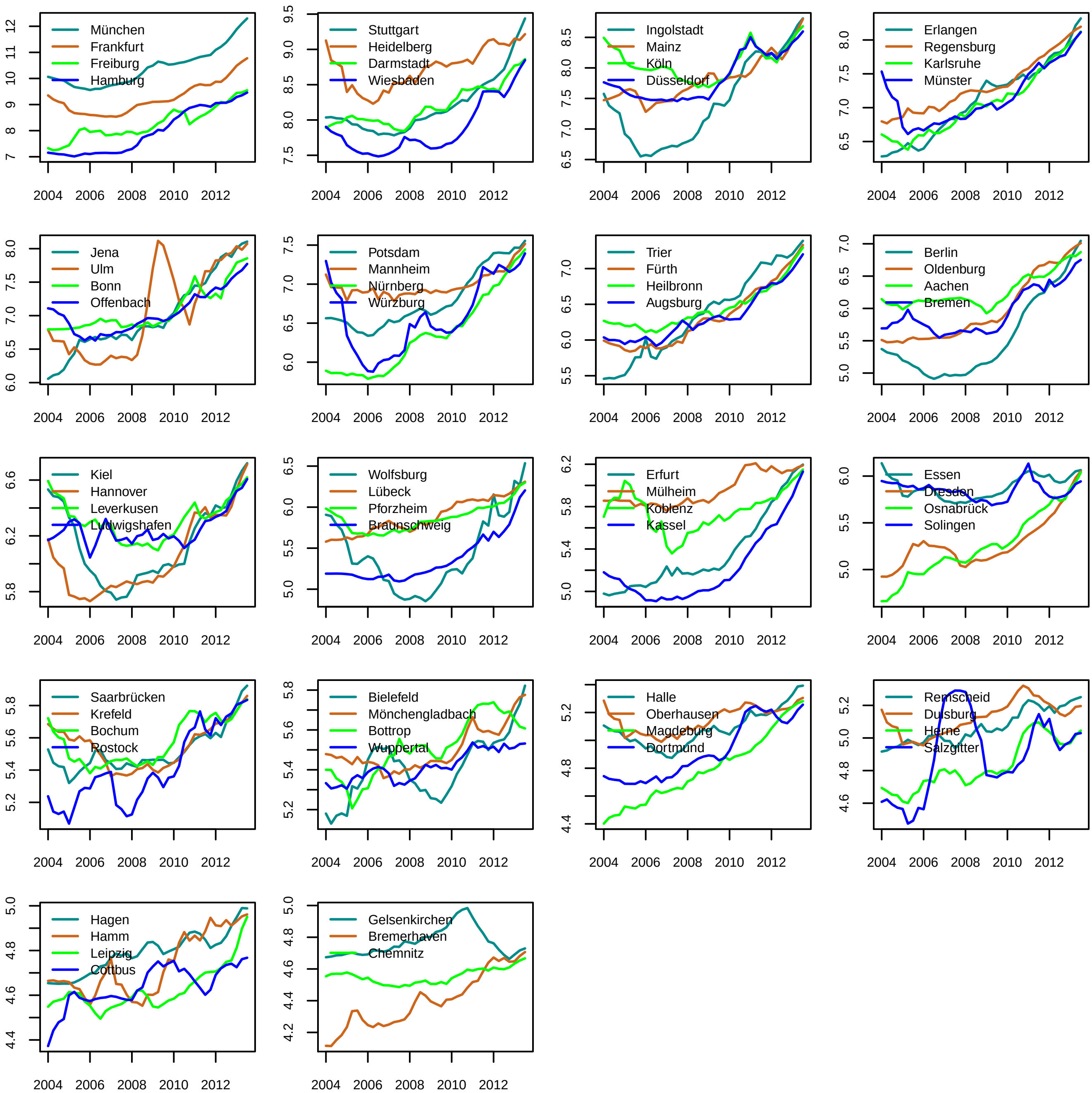

Figure 3: Publication schedule of housing prices/rents, DIHK and Ifo business confidence indices

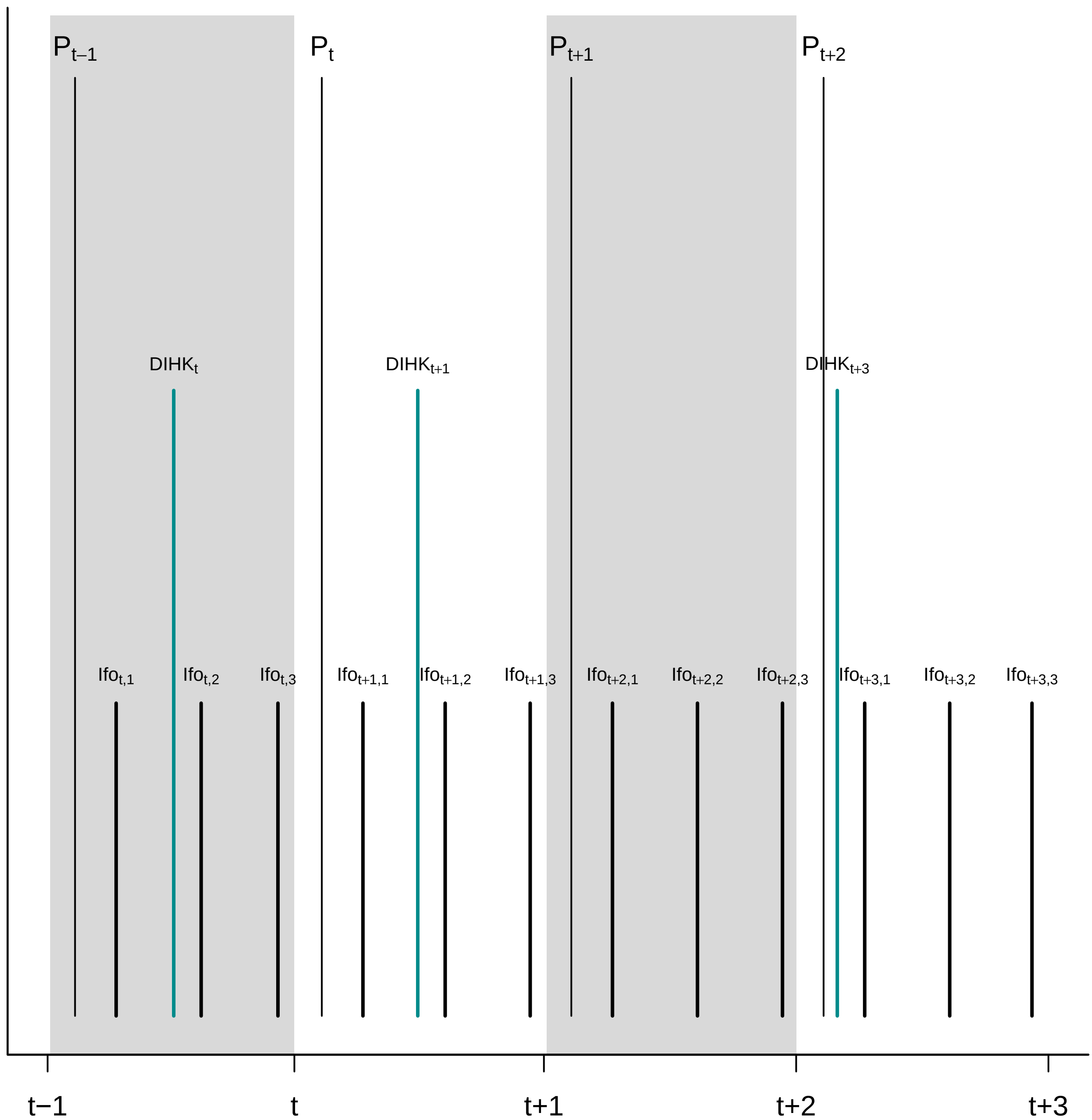

Figure 4: National and regional business climate indices for construction: Ifo vs. DIHK, 2001M1-2013M9

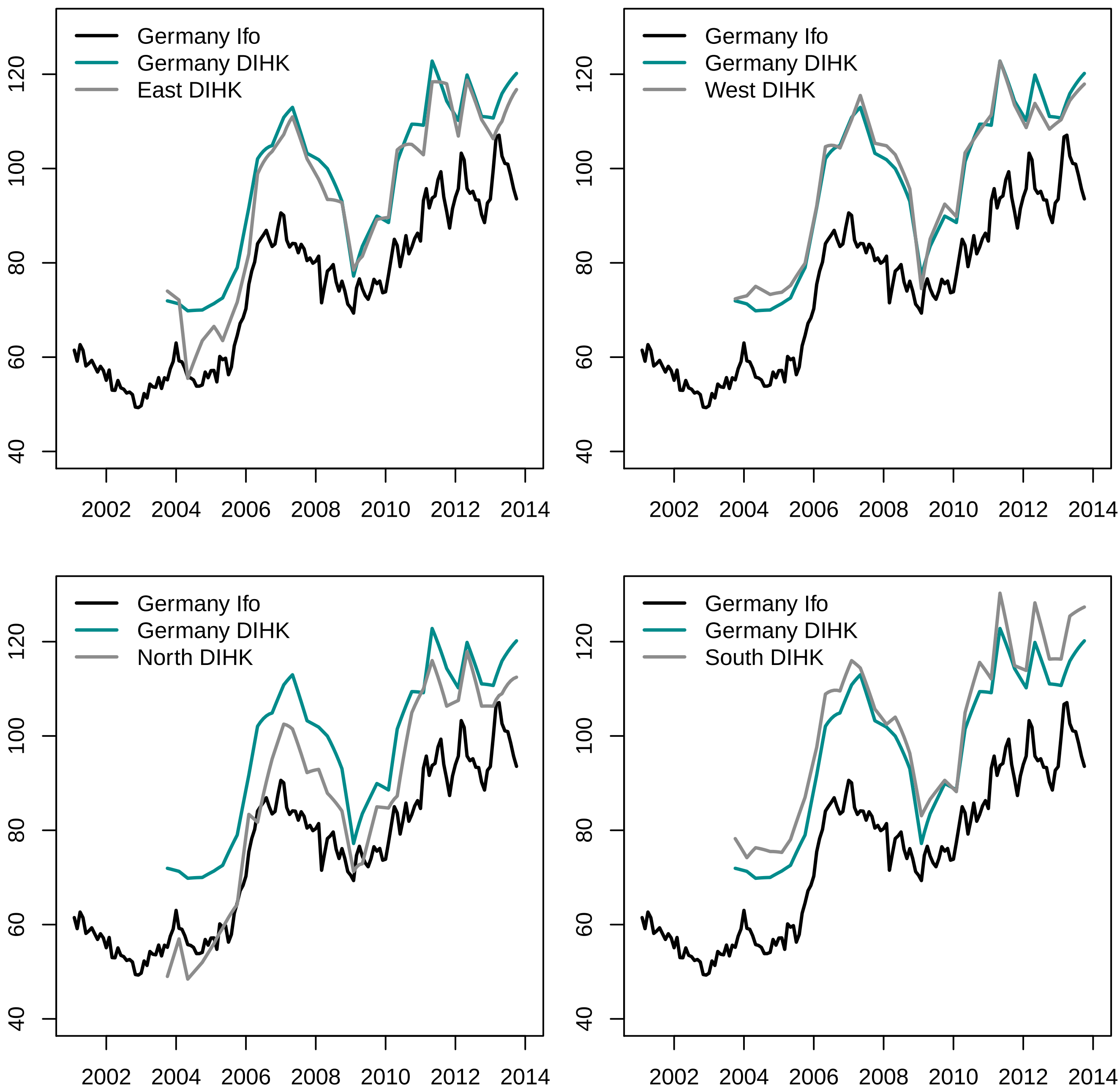

Figure 5: Business climate indices of individual cities for construction, 2001Q1-2013Q3