DIW Weekly Report 32 2019

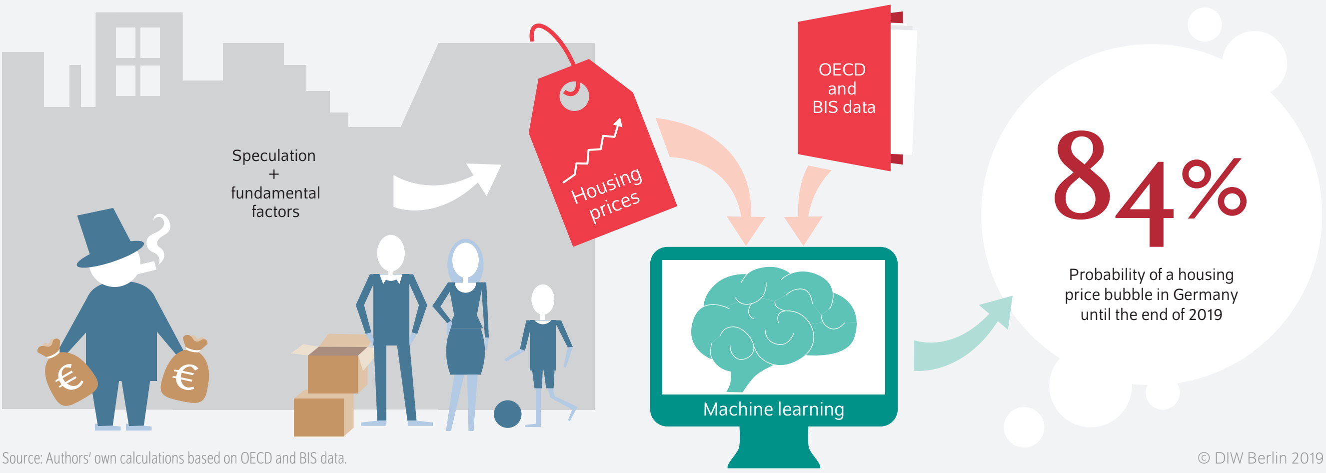
AT A GLANCE

High risk of a housing bubble in Germany and most OECD countries

By Konstantin Kholodilin and Claus Michelsen

- Housing bubbles are difficult to predict
- Modern machine learning methods improve forecast accuracy significantly
- High risk of a housing bubble in most OECD countries
- Risk in Germany will decrease somewhat over the course of the year at a high level
- Preventative measures in use are not sufficient

Machine learning can forecast housing bubbles, shows a high risk for Germany



Source: Authors' own calculations based on OECD and BIS data.

FROM THE AUTHORS

"We must be very careful with measures meant to prevent housing bubbles; there is always the danger that these measures can lead to the bubble bursting with devastating consequences. Our analyses are designed to help the regulatory authorities determine the right time to intervene."
— Konstantin Kholodilin —

MEDIA

Audio interview with K. Kholodilin (in German)
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High risk of a housing bubble in Germany and most OECD countries

By Konstantin Kholodilin and Claus Michelsen

ABSTRACT

Housing prices in many countries have increased significantly over the past years, fueling a fear that speculative price bubbles will return. However, it can be difficult for policymakers to recognize when regulatory interventions in the market are necessary to counteract bubbles. This report shows how modern machine learning methods can be used to forecast speculative price bubbles at an early stage. Early warning models show that many OECD countries have an increased risk of speculative bubbles. In Germany, there are explosive price developments that have decoupled from real estate earnings. However, the forecast model indicates that the risk will decrease somewhat over the coming months at a high level. Unfortunately, the preventative measures in Germany remain insufficient. For example, there is a lack of intervention options involving household debt ceilings, and it is unclear when the Federal Financial Supervisory Authority (BaFin) can begin intervening in the market.

Rising real estate prices and a prolonged period of low interest rates in most developed economies are warning signs of new housing bubbles. Ten years following the financial crisis, housing prices are rising again in many countries (Figure 1). Factors determining real estate value—such as income and population developments or long-term interest rate levels—can no longer fully explain this price development. Price increases become dangerous when prices develop based on the expectation that a buyer will be willing to pay a higher price for a dwelling in the future, regardless of how the fundamental factors change. In these cases, price developments are purely speculative. This type of speculative price development triggered the major real estate market crisis in the USA in 2008, dragging the global economy into a deep recession.

The devastating effects of the housing bubble burst can be traced back to extensive credit financing.[1] Extremely loose lending fueled the real estate market boom. The increasing number of loan defaults weighed on banks' balance sheets and ultimately led to a collapse of the interbank market,[2] a lack of financing opportunities for companies, and extreme uncertainty among economic players. Countries were only able to gradually compensate for the resulting slump in global industrial production, and some are still grappling with the effects of the crisis today.

Despite the serious consequences of the crisis, banking regulations and monitoring of the housing market remain insufficient in many countries due to a lack of data. Often, speculative bubbles can be dated with certainty only *after* they have burst. As a result, it is difficult to detect undesirable developments at an early stage and to implement countermeasures

1 Moritz Schularick and Alan M. Taylor, "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008," *American Economic Review* 102, no. 2 (2012): 1029-61. Frederic S. Mishkin, "Over the cliff: From the subprime to the global financial crisis," *Journal of Economic Perspectives* 25, no. 1 (2011): 49–70.

2 Rajkamal Iyer et al., "Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007-2009 crisis," *The Review of Financial Studies* 27, no. 1 (2013): 347–372.

DOI: https://doi.org/10.18723/diw_dwr:2019-32-1

in time. This report presents a forecast model for the early recognition of housing price bubbles for 20 OECD countries (Box 1) and compares the accuracy of various forecast methods. A simple *probability model* (panel logit regression) is compared with three modern machine learning methods: decision tree, random forest, and support vector machine (Box 2).

Forecasting housing price bubbles is challenging

There have been countless efforts to establish early warning systems for housing price bubbles. The most common forecast method in the literature involves estimating the probability of a price bubble as a binary event depending on observed influencing factors using a probability model (e.g., panel logit regression) and then forecasting.[3] Other methods have also been used, including a signaling approach that sends out warnings when certain thresholds are reached—for example, when the ratio of real estate loans to aggregate economic performance exceeds a certain level.[4] Time-series models, which model long-term equilibrium relationships of individual variables and interpret deviations as signs of undesirable trends, are also applied.[5]

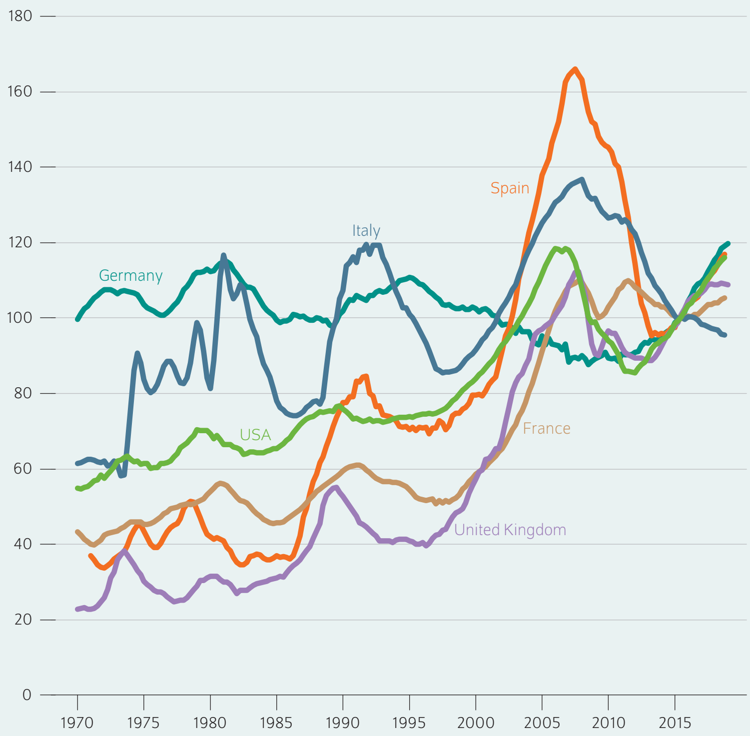
All approaches help improve the current understanding of housing bubbles. Even so, a consensus on a forecast model has not been reached. One significant commonality among the approaches is the list of explanatory variables to be used. It is generally agreed upon that financial market indicators, such as the volume of lending, money supply, or interest rates, influence the probability of a housing price bubble. However, public debt, economic growth, or debt-to-GDP ratios have also become established financial market indicators (Table 1).

Machine learning improves forecast accuracy

Recent advances in computing capacities have made it possible to use more complex methods to select forecast models and to use machine learning in order to forecast price bubbles. In fact, these approaches show a significant improvement in the accuracy of forecasting housing bubbles (Table 2).

Figure 1

Development of real housing prices between the first quarter of 1970 and the first quarter of 2019
Index: 2015=100



Source: OECD data.

Housing prices are once again increasing in many countries after the financial crisis caused them to fall sharply in 2008.

Table 1

Data sources

Variable	Definition	Source	Time period
P2R	Price-rent ratio	OECD	1970q1–2019q1
TLoan	Total loans to non-financial private sector; nominal; local currency	BIS	1940q2–2018q3
LTIR	Long-term interest rate, percent per year	OECD	1953q2–2019q1
STIR	Short-term interest rate, percent per year	OECD	1956q1–2019q1
CPI	Growth rate of consumer price index	OECD	1914q2–2019q1
GDP_growth	Growth rate of GDP	OECD	1948q1–2019q1
Share_price	Growth rate of share index	OECD	1950q1–2019q1
Loan2GDP	Total loan to GDP ratio	Authors' own calculations	1953q2–2019q1

Note: OECD = Organization for Economic Cooperation and Development; BIS = Bank for International Settlements; time series in quarters (for example, 1970q1 = first quarter of 1970).

Source: OECD and BIS data.

3 Cf. for example Luca Agnello and Ludger Schuknecht, "Booms and busts in housing markets: Determinants and implications," *Journal of Housing Economics* 20, no. 3 (2011): 171–190. Dieter Gerdesmeier, Hans-Eggert Reimers, and Barbara Roffia, "Early warning indicators for asset price booms," *Review of Economics and Finance* 3 (2011): 1–20. Òscar Jordà, Moritz Schularick, and Alan M. Taylor, "Leveraged bubbles," *Journal of Monetary Economics* 76 (2015): 1-20; André K. Anudsen et al., "Bubbles and crises: The role of house prices and credit," *Journal of Applied Econometrics* 31, no. 7 (2016): 1291–1311.

4 Cf. for example Lucia Alessi and Carsten Detken, "Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity," *European Journal of Political Economy* 27, no. 3 (2011): 520–533.

5 Cf. Michael D. Bordo and Olivier Jeanne, "Boom-busts in asset prices, economic instability, and monetary policy," NBER working paper no. 8966 (available online). Charles Goodhart and Boris Hofmann, "House prices, money, credit, and the macroeconomy," *Oxford Review of Economic Policy* 24, no. 1 (2008): 180–205.

Box 1

Identifying speculative bubbles

Empirical tests for speculative housing price bubbles are based on two assumptions: the price is exclusively determined by the present value of future rental income and market participants are fully informed and rational. In other words, housing prices are coupled to rental price trends in the long term. Since the assumption implies that all known information immediately affects valuation, the relationship between prices and rents follows a "random walk" process, meaning that it does not systematically deviate from the fundamentally justified value. In this approach, if prices are not a perfect reflection of returns, the only explanation for the price deviations is speculation. This leads to expected future increases in real estate prices co-determining price trends alongside the expected trend of real demand. If such estimates become the consensus of market participants, a speculative bubble builds up in which prices are increasingly decoupled from fundamental demand.

The PSY test was developed by Phillips, Shi, and Yu to identify multiple speculative price bubbles.[1] By applying this test to quarterly time series on the housing price-to-rent ratio, the turning points of housing price cycles can be determined. The PSY test is based on a rolling regression model.

The test's null hypothesis is that the housing price-to-rent ratio follows a random walk. Based on the regression, an augmented Dicky Fuller test (ADF) is calculated for the sequence of forward-expanding samples.

A major advantage of the PSY test is that it can be used to identify multiple bubbles in a time series. Other tests[2] focus on single speculative bubbles. In the approach used in this report, each country is analyzed separately. A p-value of 10 is used as the critical value.[3]

1 Cf. Peter C. B. Phillips, Shuping Shi, and Jun Yu, "Explosive behavior in the 1990s NASDAQ: when did exuberance escalate asset values?" *International Economic Review* 52, no. 1 (2011): 201–226.

2 Cf. for example Ulrich Homm and Jörg Breitung, "Testing for speculative bubbles in stock markets: a comparison of alternative methods," *Journal of Financial Econometrics* 10, no. 1 (2012): 198–231. Phillips, Shi, and Yu, "Explosive behavior in the 1990s NASDAQ."

3 A p value of exactly 10 percent would show that the null hypothesis is rejected with a probability of 10 percent although it is correct.

Forecasting accuracy improves for forecast horizons of different lengths when using decision tree, random forest, and support vector machine models, particularly in comparison to panel logit regression models (Box 2). Each of the above-mentioned models is estimated for a training period using the same explanatory variables. Then, in the test period, it is reviewed if the price bubble was correctly predicted. Price bubbles are dated using real estate prices. If price time series behave "explosively," speculative investor behavior is assumed (Box 1).[6]

The first training period ended in the fourth quarter of 2013. Based on the predictions, the likelihood of a price bubble for the first quarter of 2014 is forecast. Subsequently, the training period is extended to the first quarter of 2014 and a forecast for the second quarter of 2014 is made. The entire test period includes the first quarter of 2014 up to the fourth quarter of 2018 for a total of 20 quarters.

The forecasting quality (Box 3) of all four methods is shown for four different time horizons (Table 2). The traditional panel logit regression model serves as a benchmark for comparison. All other models provide significantly better forecasts than the panel logit regression model, with the random forest method providing the best forecasts for all horizons. Its forecasting accuracy is highest for the forecast horizon of one quarter and decreases with the length of the forecast horizon. For example, the accuracy of forecasting in the first quarter is 61 percent according to the Cramer measure (Box 3). However, even with a forecast horizon of four quarters, bubble and non-bubble periods are correctly forecast in more than half the cases (Figure 2). Forecasts could be improved further by including better early indicators; however, the timely availability of data sets clear limits here.

Risk of price bubbles high in many OECD countries

The random forest model, whose forecast accuracy has proven to be superior to the alternatives, can be used to forecast the bubble probability for the current year using the available values of the early indicators (Figure 3). A value of 100 means that a speculative bubble is very likely, while a value near zero indicates a very low danger of a bubble.

The probability of speculative housing bubbles is very high this year in some OECD countries, including the United States, Sweden, Norway, Denmark, Belgium, Switzerland, and Japan. There is also a high probability of a bubble in Germany, although this will decrease somewhat during the forecast period. The high probability reflects the recent slowdown in real estate price development, especially in the large German cities. Real estate investment financing in Germany appears to be relatively sound, credit volumes are not showing any conspicuous trends, and the fixed interest rate periods are long.

6 Konstantin A. Kholodilin and Claus Michelsen, "Signs of New Housing Bubble in Many OECD Countries – Lower Risk in Germany," *DIW Weekly Report* no. 30/31 (2018): 657–667 (available online).

Box 2

Forecasting methods

Predicting speculative bubbles is a problem of classification. The task is to distinguish between bubble and non-bubble situations as well as possible using a series of indicators. There are a variety of methods to perform this classification. This report compares the forecast accuracy of the four most common methods.

Logistic panel regression model: This classic probability model is often used to explain and forecast speculative bubbles. In contrast to machine learning methods, researchers must determine the relationship between the explanatory variables and the bubble probability before estimating the model and it is therefore assumed to be known.

Decision tree: This method selects a threshold for each explanatory variable that triggers the transition from one probability group to another. When diagrammed, it resembles a tree. Two branches result from every decision, which in turn have their own branches (Figure). CART (Classification and Regression Trees) is a popular method for constructing decision trees.[1] However, decision trees do have a problem with overfitting, causing the model's forecast accuracy for the training period to be significantly higher than that of the test period, which was not used to estimate the model.

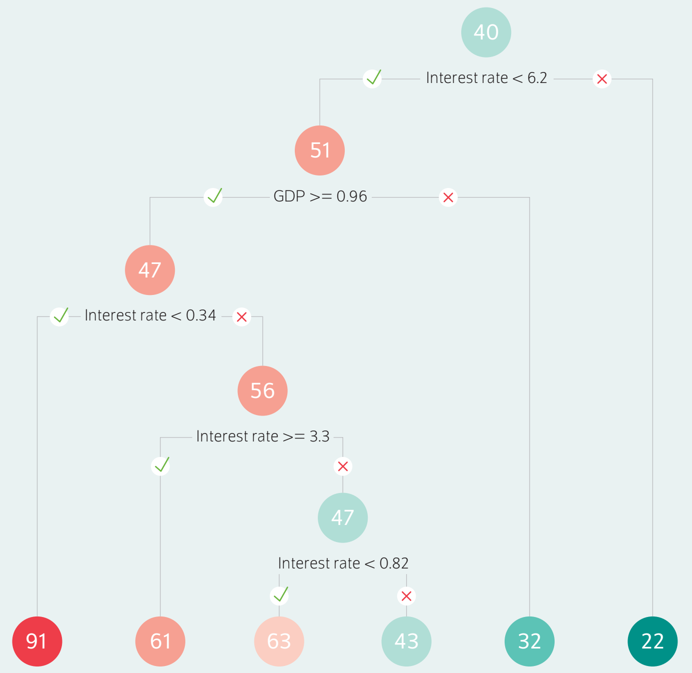
Random forest: This method is closely related to decision trees but drastically reduces the issue of overfitting.[2] It divides the sample into several independent sub-samples and calculates a decision tree for each of them. The final forecast is a combination of the forecasts from all trees.

Support-vector machine: As in all of the methods discussed here, observations are classified as bubbles or non-bubbles.[3] The advantage of this model is that it enables relatively robust forecasts even for small samples. In the process, overfitting is penalized by a cost parameter, thus limiting the complexity of the model.

The data used (Table 1) are available for 20 countries (Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, South Korea, Sweden, Switzerland, and the United States). The number of observations differ from country to country from between 66 for Japan (third quarter of 2002 to fourth quarter of 2018) to 170 for Canada (third quarter of 1976 to fourth quarter of 2018).

Figure

Bubble probabilities in percent for a stylized decision tree



Source: Authors' own depiction.

If the real long-term interest rate is below 6.2 percent, the probability of a housing price bubble is 51 percent.

1 Leo Breiman et al., *Classification and regression trees, Wadsworth & Brooks/Cole* (Advanced Books & Software, 1984).

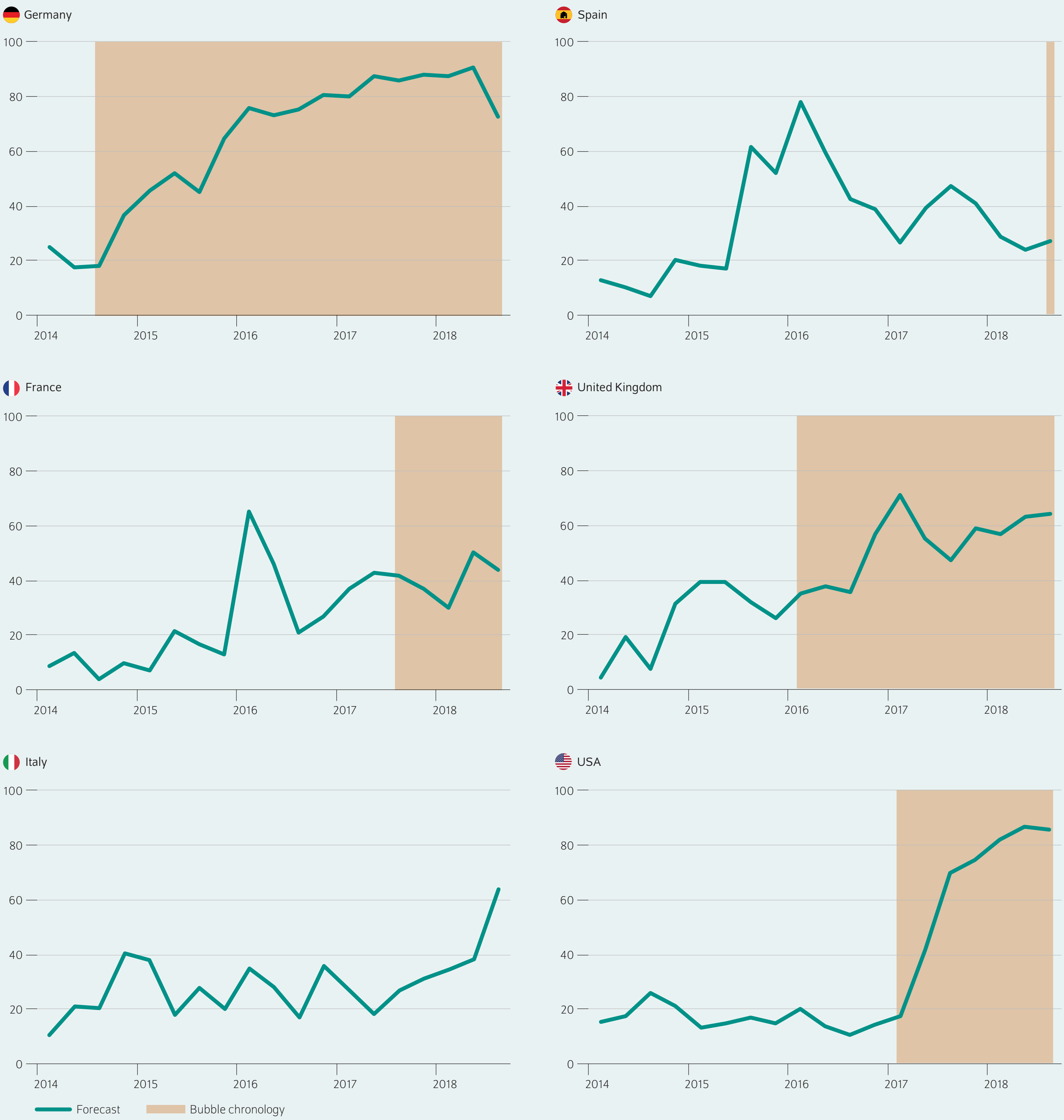
2 Leo Breiman, "Random forests," *Machine Learning* 45, no. 1 (2001): 5–32.

3 Corinna Cortes and Vladimir Vapnik, "Support-vector networks," *Machine Learning* 20, no. 3 (1995): 273–297.

Figure 2

Chronology of speculative bubbles and forecasted bubble probabilities according to the random forest method

Bubble probabilities in percent; periods with bubbles



Source: Authors' own calculations based on OECD and BIS data.

The random forest method forecasts a high probability of speculative housing price bubbles for each country.

A low likelihood of a speculative price bubble was forecast for Australia, New Zealand, and South Korea as well as Finland, the Netherlands, Ireland, and Italy. The result for Italy may not be too surprising considering the country is in the midst of a serious economic crisis. Nevertheless, even countries like Ireland, whose housing prices have risen markedly since the financial crisis, still have to recover from its negative effects.

Conclusion: preventative measures needed to combat the high risk of speculative bubbles

Housing prices have risen significantly in many countries in recent years. As the fear of undesirable trends is growing, identifying speculative price bubbles in the early stages remains a challenge. It is incredibly difficult for policymakers—who make the decisions regarding regulatory market interventions—to recognize the correct time to take action. This report shows that modern machine learning methods can significantly improve early recognition of housing bubbles.

The forecast models show that risk of speculative bubbles is once again very high in many countries—above all in the United States, where real estate prices have recovered rapidly since the financial crisis. There are warning signs in Germany as well, where an explosive price development has decoupled from the rental returns. However, the forecast model indicates that this risk will decrease somewhat over the coming months. This is consistent with observations by real estate market analysts who have observed weaker price development. Financing developments also appear to be less problematic: the fixed-interest period is long and credit volume development is largely inconspicuous.

However, this does not mean that policymakers can sit back and relax. On the contrary, preventative measures are still inadequate in Germany. For example, there is a lack of intervention options involving household debt ceilings. It is also unclear according to which criteria the Federal Financial Supervisory Authority can intervene in the market, as there is a lack of thresholds to determine when intervention is necessary. This report presents one way of determining these thresholds.

Box 3

Measuring forecast accuracy

Forecast accuracy is usually measured by analyzing the concordance between forecasts and bubble chronology. However, there are significantly fewer periods with speculative bubbles than without overall, so models that systematically underestimate the probability of a speculative bubble nevertheless show very good forecast accuracy according to the standard measure.

Therefore, the Cramer measure of forecast accuracy[1] is used as an indicator.

$$\lambda = \frac{\sum_{t=1}^{T} C_t \hat{F}_t}{T_1} - \frac{\sum_{t=1}^{T} (1 - C_t)\hat{F}_t}{T_0}$$

where C_t is the bubble chronology, $\hat{F}_t$ is the forecast probability of speculative bubbles, and T_0 and T_1 the number of observations in non-bubble and bubble periods. Cramer's λ explicitly takes into account the fact that some events, such as speculative bubbles, occur less frequently and is therefore a better measure for evaluating forecasts in this study.

1 Jan S. Cramer, "Predictive performance of the binary logit model in unbalanced samples," *Journal of the Royal Statistical Society: Series D (The Statistician)* 48, no. 1 (1999): 85–94.

Table 2

Forecast accuracy for the first quarter of 2014 to the third quarter of 2018 (Cramer measure)

Probability of an accurate housing price bubble forecast in percent

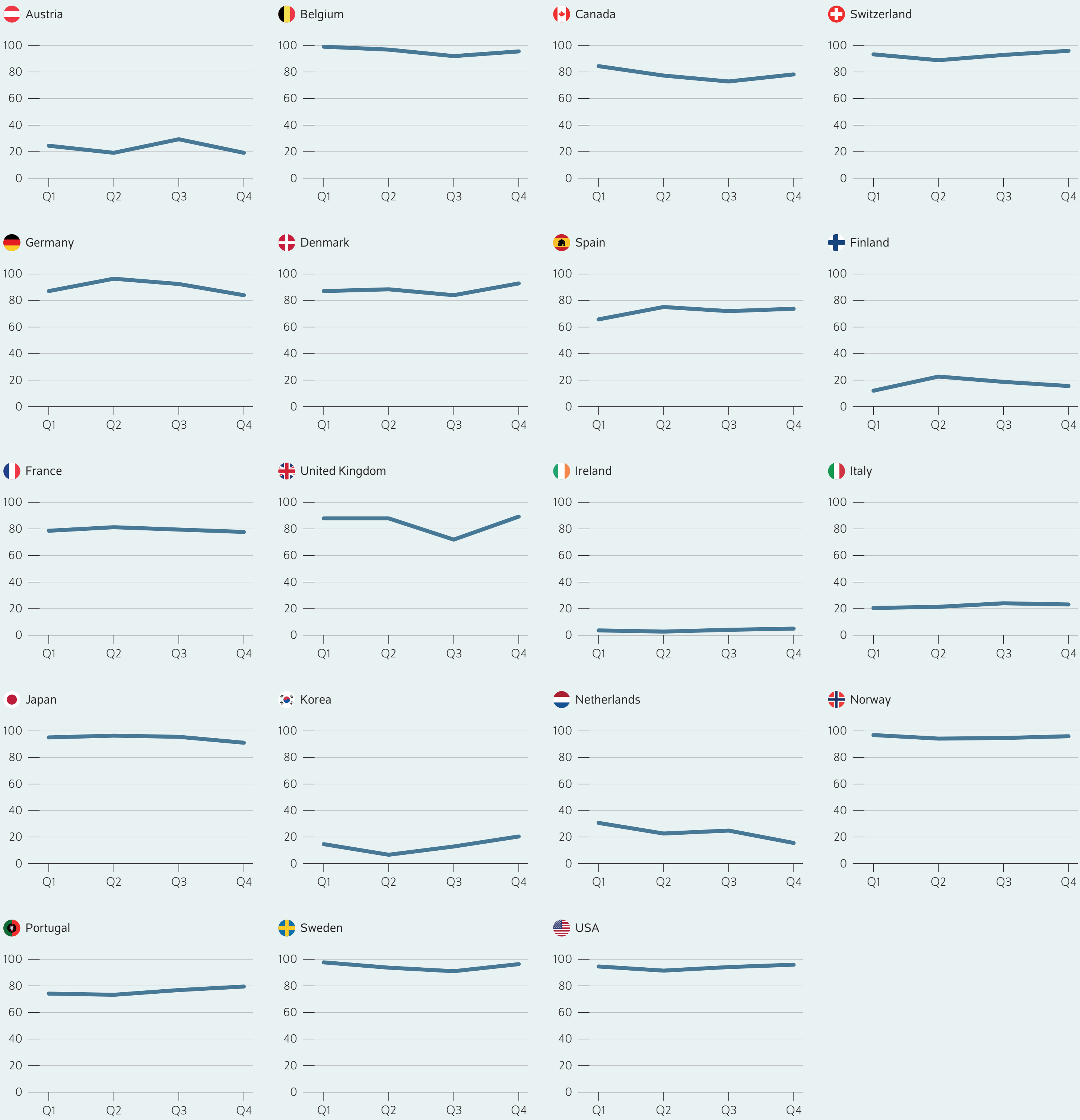
Model	Lag in quarters of a year between used information and the forecast period			
	1	2	3	4
Panel logit model	11.5	5.5	9.4	8.0
Decision tree	33.4	31.8	26.5	23.0
Random forest	60.7	55.9	55.1	53.7
Support vector machine	23.4	22.8	26.9	23.0

Source: Authors' own calculations based on OECD and BIS data.

Figure 3

Speculative housing price bubble forecast in OECD countries for the current year

Probabilities in percent for Q1–Q4 of 2019



Source: Authors' own calculations based on OECD and BIS data.

There is a high probability of speculative housing price bubbles in most OECD countries.

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JEL: C25, C53, E32

Keywords: Early warning system, speculative housing price bubble, panel logit, decision tree, random forest, support vector machine

LEGAL AND EDITORIAL DETAILS

DIW BERLIN

DIW Berlin — Deutsches Institut für Wirtschaftsforschung e. V.
Mohrenstraße 58, 10117 Berlin
www.diw.de
Phone: +49 30 897 89–0 Fax: –200
Volume 9 August 7, 2019

Sale and distribution
DIW Berlin Leserservice, Postfach 74, 77649 Offenburg
leserservice@diw.de
Phone: +49 1806 14 00 50 25 (20 cents per phone call)

Layout
Roman Wilhelm, DIW Berlin

Cover design
© imageBROKER / Steffen Diemer

Composition
Satz-Rechen-Zentrum Hartmann + Heenemann GmbH & Co. KG, Berlin

ISSN 2568-7697