CENTRE FOR APPLIED MACRO – AND PETROLEUM ECONOMICS (CAMP)

CAMP Working Paper Series
No 8/2017

Residential investment and recession predictability

Knut Are Aastveit, Andre K. Anundsen and Eyo I. Herstad

NORWEGIAN
BUSINESS SCHOOL

Residential investment and recession predictability*

Knut Are Aastveit[†] André K. Anundsen[‡] Eyo I. Herstad[§]

December 2017

Abstract

We assess the importance of residential investment in predicting economic recessions for an unbalanced panel of 12 OECD countries over the period 1960Q1–2014Q4. Our approach is to estimate various probit models with different leading indicators and evaluate their relative prediction accuracy using the receiver operating characteristic curve. We document that residential investment contains information useful in predicting recessions both in-sample and out-of-sample. This result is robust to adding typical leading indicators, such as the term spread, stock prices, consumer confidence surveys and oil prices. It is shown that residential investment is particularly useful in predicting recessions for countries with high home-ownership rates. Finally, in a separate exercise for the US economy, we show that the predictive ability of residential investment is robust to employing real-time data.

Keywords: *Recession predictability; Housing; Leading indicators; Real-time data*

JEL classification: *C33; C53; E32; E37*

*This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. We thank Gunnar Bårdsen, Joe Gyourko, Nina Larsson Midthjell, Kjersti Næss Torstensen, Stuart Rosenthal, Phil Rothman, Albert Saiz, Jim Stock and Carl Walsh as well as seminar and conference participants at Norges Bank, the SNDE in Tuscaloosa and the Annual Meeting of the Norwegian Association of Economists for useful comments.

[†]Norges Bank and Centre for Applied Macro and Petroleum Economics, BI Norwegian Business School, knut-are.aastveit@norges-bank.no.

[‡]Norges Bank, andre-kallak.anundsen.@norges-bank.no.

[§]University of Chicago, eyoherstad@gmail.com.

1 Introduction

Economic policy decisions depend on whether the economy is in an expansion or a recession. Accurate predictions of business cycle turning points, and impending economic recessions in particular, are therefore of great importance to central banks and other policy institutions. A vast amount of research has shown that a variety of economic and financial variables contain predictive information about future recessions, see e.g. Marcellino (2006) and Liu and Moench (2016). In particular, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) have documented that the slope of the term structure has strong predictive power for US recessions.[1] Several other variables have also been regarded as leading recession indicators, including stock prices (Estrella and Mishkin (1998) and Stock and Watson (2003)), the index of leading economic indicators (Berge and Jordà (2011) and Stock and Watson (1989)), oil prices (Hamilton (1983, 1996) and Ravazzolo and Rothman (2013, 2016)) and survey data (Hansson et al. (2005), Claveria et al. (2007) and Aastveit et al. (2016)).[2]

While the Great Recession has triggered a new search for methods and leading indicators that may be useful for calling recessions in real time, it has also highlighted the importance of understanding the linkages between the housing market, macroeconomic activity and financial stability, see e.g. Iacoviello and Neri (2010), Claessens et al. (2012), Mian et al. (2013), Mian and Sufi (2014), Jordà et al. (2015), Leamer (2007, 2015) and Kydland et al. (2016). More specifically, Leamer (2007) argues that real estate markets were grossly understudied by macroeconomists and policymakers interested in understanding business cycle dynamics. Considering the cumulative detrended contribution of each aggregate demand component to GDP growth before, during and after US recessions, he documents that residential investment offers by far the best early warning indicator of oncoming recessions. He concludes that a fall in the contribution of residen-

[1]Interestingly, Rudebusch and Williams (2009) also document that the term spread consistently outperforms professional forecasters in predicting recessions.

[2]As highlighted by, e.g., Evans (2005), Giannone et al. (2008), and Aastveit et al. (2014), an advantage of surveys and financial market data is that they are timely available, with little revision.

tial investment to GDP growth is a reliable harbinger of a future recession.[3] Despite this focus, studies that use housing-related variables to forecast recessions are scarce. In this paper, we aim to fill this gap in the literature.

We evaluate both the in- and out-of-sample performance of the contribution of residential investment to GDP growth in predicting economic recessions for a panel of 12 OECD countries over the period 1960Q1–2014Q4. Our main question is whether residential investment contains predictive information about future recessions over and above other typical leading indicators, such as the term spread, stock prices, consumer confidence surveys and oil prices. For the US, we use the business cycle dating chronology provided by the National Bureau of Economic Research (NBER) to date business cycle turning points. For the other countries, we use the business cycle chronology provided by the Economic Cycle Research Institute (ECRI). While these recession indicators are binary variables, most leading indicators have continuous distributions. We follow custom (see e.g. Estrella and Hardouvelis (1991) and Liu and Moench (2016)) and estimate non-linear probit models to map the changes in predictor variables into recession forecasts.[4]

When assessing the accuracy of a given probit model in predicting recessions, we follow Berge and Jordà (2011) and Liu and Moench (2016) and calculate the receiver operating characteristic (ROC) curve. To summarize the forecast performance implied by each ROC curve, we integrate the area under the curve (AUROC).

Recession predictability is evaluated both in-sample and in a quasi real-time out-sample forecasting exercise, where we recursively predict recessions for the 1990-2014 sample. In a final exercise, we assess the importance of data revisions for recession predictability, using real-time data for the US obtained from the ALFRED (ArchivaL Federal Reserve Economic Data) database maintained by the Federal Reserve Bank of

[3] Ghent and Owyang (2010), however, do not find similar results when studying the relationship between housing and business cycles using data for US metro areas. They find no consistent evidence that housing-related variables influence the city's business cycle. Instead they suggest the possibility that housing is merely a proxy for other consumption or wealth indicators.

[4] Two alternative parametric approaches that allow for recession forecasts are the threshold autoregressive model, see e.g. Potter (1995), Tommaso (1998), Ferrara and Guégan (2005), and Billio et al. (2013), and the Markov-switching model, see e.g. Hamilton (1989), Chauvet (1998) and Chauvet and Piger (2008).

St. Louis.

We have three main findings. First, residential investment is useful in predicting recessions, both in-sample and out-of-sample. This holds true also when we include the term spread, stock prices, consumer confidence surveys and oil prices. In all cases the AUROC increases significantly when residential investment is added to the model. This result holds irrespective of forecasting horizon (from nowcast to three quarters ahead forecasts) and whether we estimate each country separately or together as a panel.

Second, we find that residential investment improves predictability the most for countries with high home-ownership rates. For instance, we find substantial forecast improvements by including residential investments as a recession predictor for Spain, Norway and the US – all of which have a high home-ownership rate. For countries with low home-ownership rates, such as Japan and South Korea, residential investment does not contain predictive information about future recessions above other leading indicators.

Third, the real-time data exercise shows that the predictive ability of residential investment is maintained when we account for data revisions. However, as expected, the forecast accuracy falls relative to the case where real-time data is not considered. Thus, with even more accurate data on residential construction activity, e.g. the number of cranes at work at each point in time, real-time recession forecasts could be improved even further.

Our paper contributes to the vast number of papers that estimate and predict business cycle turning points (see e.g., Anas et al. (2008), Darné and Ferrara (2011) and Billio et al. (2012) for applications to the euro area, Chauvet (1998), Chauvet and Piger (2008), Harding and Pagan (2002, 2006), Hamilton (2011) and Stock and Watson (2014) for applications to the US) by documenting that residential investment contains information over and above other typical leading indicators. We therefore corroborate and extend the findings in Leamer (2007, 2015) by showing that residential investment is important for predicting recessions also in a cross-country setting – especially in countries with a high home-ownership rate.

The rest of the paper is structured as follows. Section 2 discusses the empirical methodology used to predict recession probabilities and evaluate the classification of future recessions. Section 3 provides a description of the international panel data and the US real-time data used in our analysis. Section 4 presents results from the panel data exercise and the real-time analysis on US data. The final section concludes the paper.

2 Empirical methodology

2.1 A probit approach for predicting recessions

The state of the business cycle is a binary variable, taking the value one during recessions and zero otherwise. Most leading indicators are, however, continuous variables. In order to account for this, it is customary to consider a probit model for recession predictions, see e.g. Estrella and Hardouvelis (1991) and Liu and Moench (2016), which allows a mapping from a set of continuous explanatory variables onto a binary dependent variable.

Our probit model is then:

$$y_{i,t} = \begin{cases} 1 & \text{if there is a recession in the quarter} \\ 0 & \text{if there is not a recession in the quarter} \end{cases} \tag{1}$$

$$E(y_t|y_t^*) = P(y_t|y_t^*) = f(y_t^*) \tag{2}$$

$$y_{i,t}^* = \alpha_i + \sum_{j=1}^{k} \boldsymbol{X}_{i,t-j}\ \boldsymbol{\beta}_j + \sum_{j=1}^{k} \gamma_j IP_{t-j} \tag{3}$$

where $f(y^*)$ is the cdf of the normal distribution, and $\boldsymbol{X}$ is a vector of explanatory variables used to forecast recession probabilities. IP is the industrial production index for advanced economies, used as a proxy for the global business cycle, whereas α_i is a country-specific intercept. We set the lag length, k, to 4 in all estimations.

We consider three different ways of estimating the model. First, we estimate the model using all available data, referred to as the full-sample estimate. Second, we estimate the model recursively using at each point in time only observations that are available at that particular point in time. This exercise is conducted using the final data vintage. Lastly, we estimate the model recursively using real-time vintage data for each period. Using real-time data, we get a recession probability estimate that is based on data that were available at the forecast origin. Due to lack of data availability, the real-time estimation is only done for the US.

2.2 Forecast evaluation

For a given model, m, a recession signal is issued whenever the estimated probability of a recession from that model, $\hat{p}_m$, exceeds some threshold level, τ. There are two types of errors that can be made: the model fails to predict a recession (Type I error), or the model issues a false recession signal (Type II error).

Let the true positive rate ($TPR_m(\tau)$) denote the share of all recessions in which a correct signal is issued, i.e. one minus the share of Type I errors. Further, let the false positive rate ($FPR_m(\tau)$) be the fraction of all non-recession events in which a false signal is issued (the share of Type II errors). Lowering the value of the threshold parameter will in general imply that the model issues more signals. While this increases the share of correctly predicted recessions, it comes at the cost of issuing more false alarms. The opposite is true if the value of the threshold parameter is increased.[5] Determining the optimal threshold requires knowledge of the policymaker's preferences regarding the trade-off between Type I and Type II errors, which depends (among other things) on the relative cost of the different outcomes, as well as the frequency at which recessions occur. One way of formalizing this trade-off is by formulating a loss function. For model m, a

[5]Thus, $\underset{\tau\to 0}{TPR}(\tau) = \underset{\tau\to 0}{FPR}(\tau) = 1$ and that $\underset{\tau\to 1}{TPR}(\tau) = \underset{\tau\to 1}{FPR}(\tau) = 0$. A perfect model never issues any false signals ($FPR = 0$), while it always correctly predicts all recession episodes ($TPR = 1$). Thus, for any $\tau \in (0, 1)$, an informative model should deliver a $TPR(\tau) > FPR(\tau)$.

linear loss function could take the following form (see e.g. Sarlin (2013)):

$$L_m(\theta, \tau) = \theta p(1 - TPR_m(\tau)) + (1 - \theta)(1 - p)FPR_m(\tau) \tag{4}$$

where p is the unconditional probability of a recession, or the frequency of recessions in the sample under consideration, whereas θ is the relative weight that the policymaker attaches to missing a recession. A reasonable assumption is that $\theta \in [0.5, 1]$, i.e. the policymaker is at least as concerned with missing a recession as issuing false alarms (see also Sarlin (2013) and Behn et al. (2013)).

A complementary tool that has been used to compare the classification abilities of early warning models is the *Receiver Operating Characteristic* (ROC), which plots the full mapping of the false positive rate, $FPR_m(\tau)$, and the true positive rate, $TPR_m(\tau) = TPR_m(FPR_m(\tau))$, across different values of the threshold parameter τ (see e.g. Jordà and Taylor (2011),Berge and Jordà (2011),Jordà and Taylor (2012) and Anundsen et al. (2016) for further details). To assess the recession classification abilities of various leading indicators, we follow Berge and Jordà (2011) and Liu and Moench (2016) and calculate the *Area Under Receiver Operating Characteristic* (AUROC), which takes into account every point on the ROC curve. More formally, the AUROC is defined as:

$$AUROC_m = \int_{\tau=0}^{1} TPR_m(FPR_m(\tau))FPR'_m(\tau)d\tau \tag{5}$$

The advantage of AUROC is that it is independent of the policymaker's preferences and it covers all possible preference parameters (see Elliott and Lieli (2013)). When comparing the performance of model m relative to model c, model m is preferred to model c if $AUROC_m > AUROC_c$, i.e. model m has a higher TPR for a given FPR than model c on average.[6]

As shown in DeLong et al. (1988), a numerical estimate of AUROC can be achieved

[6] A perfect model has $AUROC = 1$, while a completely uninformative model has $AUROC = 0.5$.

by considering a discrete time version of (5):

$$AUROC = \frac{1}{qr}\sum_{j=1}^{r}\sum_{i=1}^{q}\psi(Y_i, Z_j) \tag{6}$$

and then calculate the mean of the kernel ψ, where

$$\psi(Y,Z) = \begin{cases} 1 \text{ if } Z < Y \\ \frac{1}{2} \text{ if } Z = Y \\ 0 \text{ if } Z > Y \end{cases} \tag{7}$$

with Y denoting the q implied probabilities in recessionary states and Z denoting the r implied probabilities in non-recessionary states. This object is asymptotically normal with variance and covariance, as shown in DeLong et al. (1988). This allows us to test if models including residential investment have a higher probability of correctly assigning higher probabilities to recessionary states. Pepe et al. (2009) and Janes et al. (2009) suggest the following Wald type test statistic to compare model m to model c (see Berge and Jordà (2011) and Anundsen et al. (2016) for economic applications):

$$W_{\text{AUROC}} = \frac{\text{AUROC}_m - \text{AUROC}_c}{se\left(\text{AUROC}_m - \text{AUROC}_c\right)}$$

W_{AUROC} follows a standard normal distribution under the null hypothesis of no difference. Thus, when formally testing whether model m is preferred to model c, we compare W_{AUROC} to the relevant critical value from a standard normal distribution.

3 Data

3.1 International data

We use quarterly data for 12 OECD countries; Australia, Canada, France, Italy, Japan, South Korea, New Zealand, Norway, Spain, Sweden, the UK and the US. For each country the dependent variable is a binary recession indicator, which takes the value one during recessions and zero otherwise. For the US, we use the business cycle dating chronology provided by the National Bureau of Economic Research (NBER) to date business cycle turning points. For the other countries, we use the business cycle chronology provided by the Economic Cycle Research Institute (ECRI).[7] However, since ECRI does not provide a business cycle chronology for Norway, we use the business cycle turning point dates from Aastveit et al. (2016) as the reference cycle for Norway.

We have an unbalanced panel, which at most covers the period 1960Q1 to 2014Q4, see Table A.1 in the appendix for details on data coverage for each country and each variable. For each of the countries, we consider the contribution of residential investment to GDP growth, term spread, stock prices, consumer confidence survey, oil prices and an industrial production index for advanced economies as explanatory variables. The data on residential investment and GDP are taken from the OECD Economic Outlook. The contribution of residential investment to GDP growth is calculated in a similar way as in Leamer (2007, 2015). Most other series are collected from the Global Financial Database (GFD).[8] The exceptions are the interest rate series for South Korea and the stock price series for Canada and France, which are taken from the GVAR database,[9] as well as the series for industrial production for advanced economies and the West Texas Intermediate (WTI) oil price, which are provided by the IMF and Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.

3.2 US real time data

Accounting for data revisions may be relevant when assessing the importance of various leading indicators for out-of-sample predictability of economic recessions. Unfortunately, a real-time database for the variables we use for the 12 countries in the panel data set

[7]See `https://www.businesscycle.com/ecri-business-cycles` for more details about the business cycle dates provided by ECRI.

[8]`https://www.globalfinancialdata.com/`

[9]`https://sites.google.com/site/gvarmodelling/data`

does not exist. However, in order to shed some light on the importance of real-time data for out-of-sample predictability of economic recessions, we use real-time data for the US obtained from the ALFRED (ArchivaL Federal Reserve Economic Data) database maintained by the Federal Reserve Bank of St. Louis. This database consists of collections of real-time vintages of data for each of the variables that we use, and the first vintage starts in 1966Q1. Vintages vary across time as either new data are released or existing data are revised by the relevant statistical agency. Using data from this database ensures that we only use data that were available at the date of the forecast origin. For the importance of using real-time data for macroeconomic forecasting, see Croushore and Stark (2001) and Croushore (2006).

4 Empirical Analysis

In this section, we describe our results from comparing various probit model specifications at different horizons. In doing so, we use an unbalanced panel for the 12 OECD countries described in Section 3. For some countries, such as the US, Australia and Japan, residential investment, the term spread and stock prices are available for the full sample, covering the period 1960Q1-2014Q4. For other countries, such as Spain, Norway and Sweden, some of these variables are first available in the 1970s or early 1980s. On the other hand, consumer confidence indicators are available only for a shorter sample for all countries except the US. While for most countries they are available sometime during the 1970s or early 1980s, for Sweden and South Korea they are first available in 1995 and 1998, respectively.

4.1 Forecasting exercise

We carry out both an in-sample and an out-of-sample analysis. In both exercises, we consider one-to-four step ahead forecasts, where the one-step ahead forecasts corresponds to a nowcast. At each horizon, we begin by estimating baseline probit models with four lags, including only one explanatory variable. Then, since our main interest is to assess the importance of residential investment for in- and out-of-sample predictability of economic recession, we augment each baseline specification with four lags of the contribution of residential investment to GDP growth. Following this procedure, we can formally test whether residential investment contains predictive information over and above what is contained in other explanatory variables traditionally considered in the recession forecasting literature. We use AUROC to evaluate the performance of each model and also to compare the forecasting ability of each model with the baseline models. For each specification, we provide information on the bootstrapped distribution of AUROCs. We can therefore evaluate the uncertainty around the estimates and assess whether adding residential investment to the models including standard recession predictors leads to a significant increase in recession forecasting accuracy.

4.2 Panel results

We report results from our in-sample and out-of-sample exercise in Table 1. Starting with the in-sample results, we report the AUROC values for the various baseline models with one explanatory variable in the second column. We have two interesting results. First, for all models forecasting performance is better the shorter is the forecasting horizon. Thus, the predictability of a recession is higher for the nowcast than for the three-quarters ahead forecast. Second, among the various specifications, the models including the contribution of residential investment to GDP growth achieve the highest AUROC values at all horizons.[10]

Next, we proceed to study whether or not residential investment contains predictive information about future recessions over and above the standard leading indicators considered in the literature, i.e., the term spread, stock prices, consumer confidence survey

[10]Note that the data samples for the various leading indicators differ, see Table A.1 in the appendix for details. The results reported in the various rows are therefore based on different estimation samples. Thus, the results for the relative performance based on the various leading indicators are therefore not strictly comparable. Results based on using exactly the same data sample for all the various leading indicators are reported in Table A.3 and results are similar.

and oil prices. We therefore augment each baseline specification with four lags of residential investment. In the third column of Table 1, we report the achieved gains (increase in AUROC) from this approach. Our findings suggest that the gain in AUROC is statistically significant for all specifications and at all horizons when residential investment is added to the model. Our in-sample results therefore suggest that residential investment contains important predictive information about future recessions over and above other leading indicators.

To assess whether the forecasting performance documented for the full sample extends to an out-of-sample setting, we conduct a recursive forecasting exercise for the period 1990Q1-2014Q4. We perform the following exercise: First, each probit model is estimated using all data until 1989Q4. Then, the estimated parameters are used to predict recession probabilities over the next four quarters: 1990Q1 (nowcast) to 1990Q4 (three-quarter ahead forecast). Next, we re-estimate the models, now using data until 1990Q1, and use the new estimated parameters to predict recessions for 1990Q2-1991Q1. We continue like this until we have forecasted recession probabilities for the end of the sample.

Similar to the in-sample exercise, we report the AUROC values for the out-of-sample exercise for the various baseline models with one explanatory variable (fourth column) and for the baseline specifications augmented by the contribution of residential investment to GDP growth (fifth column).

The out-of-sample exercise corroborates the results of the in-sample exercise. As expected, the AUROC values are somewhat smaller in this case, but the general patterns are the same as in the in-sample exercise: For all models, the forecasting performance is better the shorter is the forecasting horizon, and for each forecast horizon, models including the contribution of residential investment to GDP growth obtain the highest AUROC. Finally, the results show that residential investment contains out-of-sample predictive information about future recessions over and above the other leading indicators. For all baseline specifications, the increase in AUROC is statistically significant, and by a magnitude of around 0.1, when the model is augmented by residential investment.

Table 1: AUROC values and gain from including residential investment – Panel results.

	In-sample		Out-of-sample	
Variable	AUROC	Gain	AUROC	Gain
Nowcasting				
Resinvest	0.8295		0.7932	-
	(0.0158)		*(0.0145)*	
Spread	0.7321	0.1017***	0.6920	0.1012***
	(0.0184)	*(0.0133)*	*(0.0198)*	*(0.0121)*
Stocks	0.7836	0.0740***	0.7464	0.0786***
	(0.0158)	*(0.0111)*	*(0.0172)*	*(0.0099)*
C.Conf	0.7755	0.0853***	0.7489	0.0785***
	(0.0185)	*(0.0146)*	*(0.0195)*	*(0.0136)*
Oilprice	0.7176	0.1109***	0.6597	0.1220***
	(0.0188)	*(0.0143)*	*(0.0205)*	*(0.0137)*
1-step				
Resinvest	0.7973	-	0.7470	-
	(0.0174)		*(0.0159)*	
Spread	0.7143	0.0976***	0.6707	0.0930***
	(0.0186)	*(0.0124)*	*(0.0201)*	*(0.0110)*
Stocks	0.7514	0.0800***	0.7012	0.0856***
	(0.0166)	*(0.0116)*	*(0.0181)*	*(0.0100)*
C.Conf	0.7556	0.0854***	0.7116	0.0884***
	(0.0190)	*(0.0150)*	*(0.0202)*	*(0.0138)*
Oilprice	0.6797	0.1184***	0.6159	0.1177***
	(0.0192)	*(0.0139)*	*(0.0208)*	*(0.0118)*
2-step				
Resinvest	0.7683	-	0.6993	-
	(0.0184)		*(0.0168)*	
Spread	0.7062	0.0901***	0.6541	0.0845***
	(0.0184)	*(0.0117)*	*(0.0199)*	*(0.0099)*
Stocks	0.7143	0.0867***	0.6508	0.0870***
	(0.0174)	*(0.0120)*	*(0.0186)*	*(0.0095)*
C.Conf	0.7415	0.0869***	0.6860	0.0910***
	(0.0192)	*(0.0159)*	*(0.0206)*	*(0.0142)*
Oilprice	0.6492	0.1179***	0.5774	0.1036***
	(0.0191)	*(0.0134)*	*(0.0205)*	*(0.0098)*
3-step				
Resinvest	0.7447	-	0.6565	-
	(0.0192)		*(0.0174)*	
Spread	0.7106	0.0750***	0.6519	0.0656***
	(0.0179)	*(0.0106)*	*(0.0194)*	*(0.0079)*
Stocks	0.6754	0.0879***	0.5937	0.0801***
	(0.0183)	*(0.0126)*	*(0.0193)*	*(0.0090)*
C.Conf	0.7343	0.0765***	0.6730	0.0794***
	(0.0196)	*(0.0162)*	*(0.0206)*	*(0.0139)*
Oilprice	0.6406	0.1044***	0.5621	0.0818***
	(0.0187)	*(0.0128)*	*(0.0203)*	*(0.0087)*

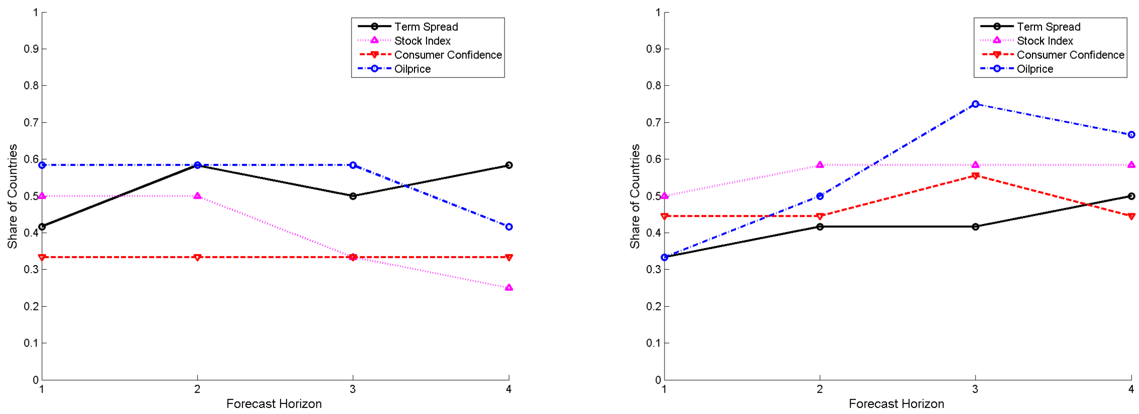
Note: This table shows AUROC values for probit models using various leading indicators and the AUROC gain when augmenting each probit specification with residential investment as an additional regressor. The second and third columns report results from models estimated on the full sample (in-sample forecasting exercise), while the fourth and fifth columns report results from the recursive out-of-sample forecasting exercise. All the models are evaluated based on the time period 1990Q1 to 2014Q4. Differences in accuracy that are statistically different from zero at a 10%, 5% and 1% significance level are denoted by one, two and three asterisks, respectively.

As a final exercise, we study whether or not the term spread, stock prices, consumer confidence survey and oil prices contain predictive information about future recessions over and above residential investment. Table A.2 in the appendix reports AUROC gains when augmenting a probit model with four lags of residential investment with four lags of each of the alternative leading indicators separately. The table shows results from both the in-sample and out-of-sample forecasting exercise. Both the in-sample and out-of sample results suggest that there is no gain from adding oil prices to a model containing residential investment. For stock prices, consumer confidence surveys and for longer horizons of the term spread, we find some predictive information about future recessions over and above residential investment. That said, the gains are considerably smaller in this case than when we conduct the opposite exercise, i.e. adding residential investment to models containing these indicators.

4.3 Country-specific results

Results from the panel analysis suggest a significant improvement in recession predictability when residential investment is added to the information set. In order to investigate the generality of this finding across countries, Figure 1 displays the share of countries where the AUROC increases significantly by augmenting the baseline specification with residential investment. The figure reports results for each baseline specification, both for the in-sample (Panel a) and out-of-sample (Panel b) exercise. Whereas the share is around 0.5 on average in the in-sample exercise, it tends to exceed 0.5 for most specifications and at most horizons for the out-of-sample exercise. Thus, for a majority of the countries in our sample, including residential investment contributes to improving the forecasting accuracy of future recessions.

Figure 1: Share of countries where residential investment is a significant recession predictor



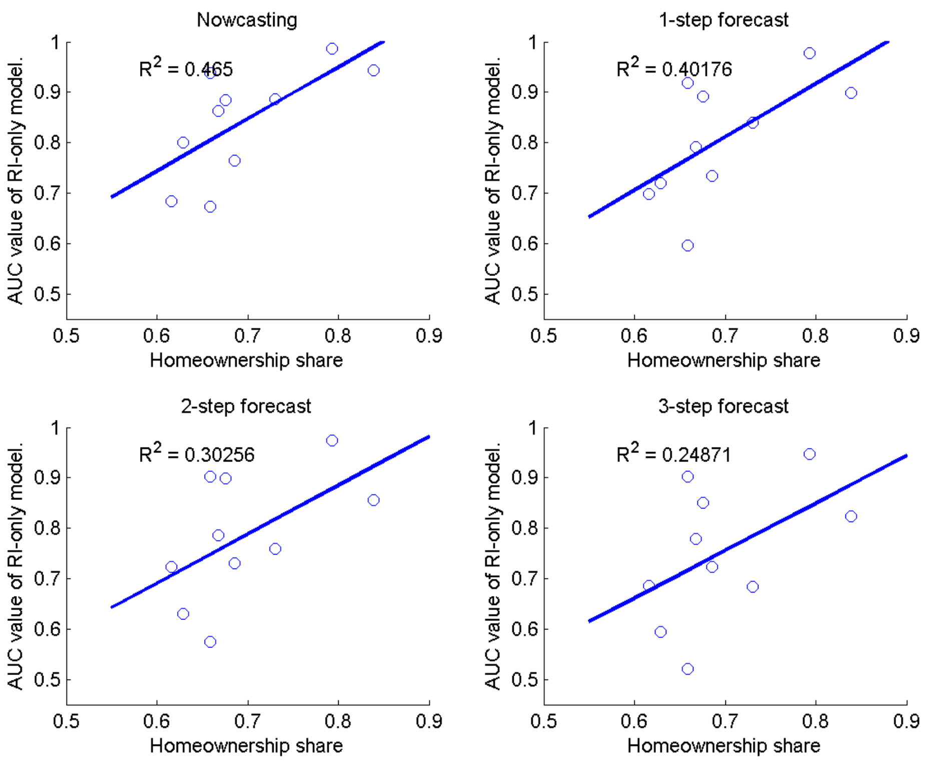
(a) In-sample (b) Out-of-sample

The figure shows the share of countries where we reject that the AUROC value based on predictions from the baseline model is equal to predictions from the baseline model augmented with residential investment. We report the result for both the in-sample and out-of-sample analysis. We use a significance level of 5%.

Tables A.4-A.11 in the appendix highlight this heterogeneity in even more detail by reporting the AUROC values for all individual countries for both the in-sample and out-of-sample exercise. The results indicate a high degree of heterogeneity in the predictive ability of residential investment across countries. Residential investment seems to be particularly important in predicting future recessions for countries such as Spain, Norway and the US. These are all countries with relatively high home-ownership rates. In contrast, for countries such as South Korea and Japan, where home-ownership rates are relatively low, residential investment does not contain predictive information about future recessions over and above the other leading indicators.

To shed some more light on this, Figure 2 shows a scatter plot of the AUROC from baseline models only containing residential investment at each forecast horizons against home-ownership rates. For all forecast horizons, there is a strong positive relationship between the AUROC and home-ownership rates. This suggests that residential investment is a stronger predictor of future recessions in countries with higher home-ownership rates.

Figure 2: Scatter plot of AUROC values and home-ownership rates.



The figure shows scatter plots of AUROC and home-ownership rates, as well as a fitted line and its corresponding R^2 value for different forecast horizons.

4.4 Real-time results for the US

It is important to account for data revisions when assessing the importance of various leading indicators for out-of-sample predictability of economic recessions. While data for the term spread, stock prices and oil prices are not revised, data on residential investment and its contribution to GDP growth are revised over time. It is therefore important to study whether the results in Section 4.2 and 4.3 are affected by accounting for data revisions.

Unfortunately, a real-time database for residential investment does not exist for the 12 countries in the panel. However, to shed light on whether data revisions affect the out-of-sample predictability of residential investment in forecasting economic recessions, we use real-time data for the US. In doing so, we conduct a recursive real-time out-of-sample forecasting exercise for the period 1966Q1-2014Q4, covering a total of seven recessions. Note that this is a considerably longer forecasting sample than the one used in the cross-country panel study. Therefore the relative performance of the different indicators differs from that obtained for the US in the panel study.

Table 2 reports results for the real-time out-of-sample forecasting exercise for the US. The second and third columns report AUROC and the gains in AUROC from adding residential investment to each model specification for the recursive quasi real-time exercise. In the fourth and fifth columns, we report similar results for the recursive real-time exercise. Note that the main goal of this exercise is to investigate whether accounting for data revisions affects forecast performance, and not to compare the performance of the various leading indicators per se. The relevant comparison is therefore to check whether the AUROC gains and their statistical significance change between the quasi real-time exercise and the real-time exercise, i.e. comparing the third and the fifth columns.

The results from the real-time exercise are broadly in line with the ones from the quasi real-time exercise. As expected, the results show that for most specifications the AUROC gains are smaller when data revisions are taken into account. However, in most cases the differences in AUROC gains are fairly small, and statistical significance are mostly not affected. This indicates that the results from our cross-country analysis are broadly robust to the use of real-time data.

Table 2: AUROC values and gain from including residential investment – US results. Estimated on 1953Q2 - 2014Q4, Evaluated on 1966Q1-2014Q4

	Out-of-sample		Real-Time	
Variable	AUROC	Gain	AUROC	Gain
Nowcasting				
Resinvest	0.8957	-	0.8863	-
	(0.0277)		*(0.0109)*	
Spread	0.8661	0.0456*	0.8661	0.0421*
	(0.0331)	*(0.0253)*	*(0.0331)*	*(0.0252)*
Stocks	0.8902	0.0544*	0.8902	0.0440
	(0.0344)	*(0.0287)*	*(0.0344)*	*(0.0270)*
C.Conf	0.8852	0.0403	0.8852	0.0204
	(0.0370)	*(0.0306)*	*(0.0370)*	*(0.0290)*
Oilprice	0.5466	0.2891***	0.5466	0.2124***
	(0.0741)	*(0.0637)*	*(0.0741)*	*(0.0580)*
1-step				
Resinvest	0.8727	-	0.8380	-
	(0.0293)		*(0.0136)*	
Spread	0.8494	0.0182	0.8494	-0.0037
	(0.0351)	*(0.0155)*	*(0.0351)*	*(0.0148)*
Stocks	0.8203	0.0785**	0.8203	0.0473*
	(0.0457)	*(0.0325)*	*(0.0457)*	*(0.0274)*
C.Conf	0.8120	0.0544*	0.8120	0.0495
	(0.0491)	*(0.0312)*	*(0.0491)*	*(0.0336)*
Oilprice	0.6019	0.2330***	0.6019	0.2093***
	(0.0671)	*(0.0550)*	*(0.0671)*	*(0.0495)*
2-step				
Resinvest	0.8045	-	0.7646	-
	(0.0444)		*(0.0279)*	
Spread	0.8591	-0.0261*	0.8591	-0.0467**
	(0.0331)	*(0.0144)*	*(0.0331)*	*(0.0218)*
Stocks	0.7326	0.0866**	0.7326	0.0616*
	(0.0499)	*(0.0348)*	*(0.0499)*	*(0.0358)*
C.Conf	0.7197	0.0585*	0.7197	0.0348
	(0.0594)	*(0.0302)*	*(0.0594)*	*(0.0400)*
Oilprice	0.5970	0.1546***	0.5970	0.1132***
	(0.0721)	*(0.0505)*	*(0.0721)*	*(0.0408)*
3-step				
Resinvest	0.6890	-	0.6693	-
	(0.0652)		*(0.0210)*	
Spread	0.8503	-0.0331*	0.8503	-0.0491**
	(0.0407)	*(0.0172)*	*(0.0407)*	*(0.0204)*
Stocks	0.6066	0.0899**	0.6066	0.0640
	(0.0593)	*(0.0414)*	*(0.0593)*	*(0.0497)*
C.Conf	0.6062	0.0806*	0.6062	0.0603
	(0.0684)	*(0.0420)*	*(0.0684)*	*(0.0558)*
Oilprice	0.6183	0.0261	0.6183	-0.0008
	(0.0633)	*(0.0406)*	*(0.0633)*	*(0.0502)*

Note: This table shows AUROC values for probit models using various leading indicators and the AUROC gain when augmenting each probit specification with residential investment as an additional regressor. The first two columns report results from models estimated on the full sample (in-sample forecasting exercise), the third and fourth columns report results from the recursive out-of-sample forecasting exercise, while the fifth and sixth columns report results for the recursive real-time out-of-sample forecasting exercise. The models are evaluated based on the time period 1966Q1 to 2014Q4 and estimated on the sample 1953Q2 - 2014Q4. Differences in accuracy that are statistically different from zero at a 10%, 5% and 1% significance level are denoted by one, two and three asterisks, respectively.

Finally, the relative performance of the different indicators for the quasi real-time exercise, reported in the second and third columns in Table 2, differs somewhat from that obtained for the US in the panel study in section 4.3. Although the main finding that residential investment is a good predictor of US recessions is still maintained, residential investment does not contain out-of-sample predictive information about future recessions over and above the term spread for the longer horizons.

5 Conclusion

0pi8In this paper, we have investigated whether the contribution of residential investment to GDP growth helps to predict recessions over and above what is captured by standard leading indicators. Our results strongly suggest that recession predictability is improved, both in- and -out-of-sample, when residential investment is included. Conducting the reverse exercise, namely adding each of the alternative indicators to a model containing residential investment, we find much less improvement in recession predictability. Moreover, our results suggest that residential investment is a particularly good indicator of the business cycle in countries where home-ownership rates are high. For the US, we test the robustness of these findings to accounting for data revisions. Our results are robust to applying real-time data.

These results are important, since they suggest that the probability of timely recession detection by central banks and other policy institutions may be improved by taking into account the developments in residential investment – especially in countries with high home-ownership rates. Moreover, with even more accurate data on residential construction activity, e.g. satellite pictures of the number of cranes at work each quarter, real-time recession forecasts could be improved even further.

References

Aastveit, K., K. Gerdrup, A. Jore, and L. Thorsrud (2014). Nowcasting GDP in real time: A density combination approach. *Journal of Business and Economic Statistics 32*(1), 48–68.

Aastveit, K. A., A. S. Jore, and F. Ravazzolo (2016). Identification and real-time forecasting of Norwegian business cycles. *International Journal of Forecasting 32*(2), 283–292.

Anas, J., M. Billio, L. Ferrara, and G. L. Mazzi (2008). A System for Dating and Detecting Turning Points in the Euro Area. *The Manchester School 76*, 549–577.

Anundsen, A. K., K. Gerdrup, F. Hansen, and K. Kragh-Sørensen (2016). Bubbles and crises: The role of house prices and credit. *Journal of Applied Econometrics 31*(7), 1291–1311.

Behn, M., C. Detken, T. A. Peltonen, and W. Schudel (2013). Setting countercyclical capital buffers based on early warning models: Would it work? Working Paper Series 1604, European Central Bank.

Berge, T. J. and O. Jordà (2011). Evaluating the classification of economic activity into recessions and expansions. *American Economic Journal: Macroeconomics 3*(2), 246–77.

Billio, M., R. Casarin, F. Ravazzolo, and H. van Dijk (2012). Combination schemes for turning point predictions. *Quarterly Review of Economics and Finance 52*(4), 402–412.

Billio, M., L. Ferrara, D. Guégan, and G. L. Mazzi (2013). Evaluation of Regime Switching Models for Real-Time Business Cycle Analysis of the Euro Area. *Journal of Forecasting 32*(7), 577–586.

Chauvet, M. (1998). An econometric characterization of business cycle dynamics with factor structure and regime switching. *International Economic Review 39*(4), 969–996.

Chauvet, M. and J. Piger (2008). Comparison of the real-time performance of business cycle dating methods. *Journal of Business and Economic Statistics 26*, 42–49.

Claessens, S., M. A. Kose, and M. E. Terrones (2012). How do business and financial cycles interact? *Journal of International Economics 87*(1), 178–190.

Claveria, O., E. Pons, and R. Ramos (2007). Business and consumer expectations and macroeconomic forecasts. *International Journal of Forecasting 23*(1), 47–69.

Croushore, D. (2006). *Forecasting with Real-Time Macroeconomic Data*, Volume 1 of *Handbook of Economic Forecasting*, Chapter 17, pp. 961–982. Elsevier.

Croushore, D. and T. Stark (2001). A real-time data set for macroeconomists. *Journal of Econometrics 105*(1), 111–130.

Darné, O. and L. Ferrara (2011). Identification of Slowdowns and Accelerations for the Euro Area Economy. *Oxford Bulletin of Economics and Statistics 73*(3), 335–364.

DeLong, E. R., D. M. DeLong, and D. L. Clarke-Pearson (1988). Comparing the areas under two or more correlated receiver operating characteristic curves: A nonparametric approach. *Biometrics 44*(3), 837–845.

Elliott, G. and R. P. Lieli (2013). Predicting binary outcomes. *Journal of Econometrics 174*(1), 15–26.

Estrella, A. and G. A. Hardouvelis (1991). The Term Structure as a Predictor of Real Economic Activity. *Journal of Finance 46*(2), 555–576.

Estrella, A. and F. S. Mishkin (1998). Predicting U.S. Recessions: Financial Variables As Leading Indicators. *Review of Economics and Statistics 80*(1), 45–61.

Evans, M. D. (2005). Where are we now? real-time estimates of the macro economy. *International Journal of Central Banking 1*(2), 127–175.

Ferrara, L. and D. Guégan (2005). Detection of the Industrial Business Cycle using SETAR Models. *Journal of Business Cycle Measurement and Analysis 2005*(3), 353–371.

Ghent, A. C. and M. T. Owyang (2010). Is housing the business cycle? Evidence from US cities. *Journal of Urban Economics 67*(3), 336–351.

Giannone, D., L. Reichlin, and D. Small (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics 55*(4), 665–676.

Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy 91*(2), 228–248.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica 57*, 357–384.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics 38*(2), 215–220.

Hamilton, J. D. (2011). Calling recessions in real time. *International Journal of Forecasting 27(4)*, 1006–1026.

Hansson, J., P. Jansson, and M. Löf (2005). Business survey data: Do they help in forecasting GDP growth? *International Journal of Forecasting 21*, 377–389.

Harding, D. and A. Pagan (2002). Dissecting the Cycle: A Methodological Investigation. *Journal of Monetary Economics 49*, 365–381.

Harding, D. and A. Pagan (2006). Synchronization of cycles. *Journal of Econometrics 132*(1), 59–79.

Iacoviello, M. and S. Neri (2010). Housing Market Spillovers: Evidence from an Estimated DSGE Model. *American Economic Journal: Macroeconomics 2*(2), 125–164.

Janes, H., G. Longton, and M. Pepe (2009). Accommodating covariates in ROC analysis. *Stata Journal 9*(1), 17–39.

Jordà, O., M. Schularick, and A. M. Taylor (2015). Betting the house. *Journal of International Economics 96*(S1), 2–18.

Jordà, O. and A. M. Taylor (2011). Performance Evaluation of Zero Net-Investment Strategies. NBER Working Papers 17150, National Bureau of Economic Research, Inc.

Jordà, O. and A. M. Taylor (2012). The carry trade and fundamentals: Nothing to fear but (FEER) itself. *Journal of International Economics 88*(1), 74–90.

Kydland, F. E., P. Rupert, and R. Sustek (2016). Housing Dynamics over the Business Cycle. *International Economic Review 57*(4), 1149–1177.

Leamer, E. E. (2007). Housing IS the business cycle. In *Housing, Housing Finance, and Monetary Policy*, pp. 149–233. Proceedings, Federal Reserve Bank of Kansas City.

Leamer, E. E. (2015). Housing really is the business cycle: What survives the lessons of 2008-09? *Journal of Money, Credit and Banking 47*(1), 43–50.

Liu, W. and E. Moench (2016). What predicts US recessions? *International Journal of Forecasting 32*(4), 1138–1150.

Marcellino, M. (2006). Leading indicators. In G. Elliott, C. W. J. Granger, and A. Timmermann (Eds.), *Handbook of Economic Forecasting*, Volume 1, pp. 879–960. Amsterdam: Elsevier.

Mian, A., K. Rao, and A. Sufi (2013). Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics 128*(4), 1687–1726.

Mian, A. and A. Sufi (2014). What explains the 2007-2009 drop in employment? *Econometrica 82*(6), 2197–2223.

Pepe, M., H. Janes, and H. Longton (2009). Estimation and comparison of receiver operating characteristic curves. *Stata Journal 9*(1), 1–16.

Potter, S. M. (1995). A Nonlinear Approach to U.S. GNP. *Journal of Applied Econometrics 10*, 109–125.

Ravazzolo, F. and P. Rothman (2013). Oil and U.S. GDP: A Real-Time Out-of-Sample Examination. *Journal of Money, Credit and Banking 45*(2-3), 449–463.

Ravazzolo, F. and P. Rothman (2016). Oil-price density forecasts of US GDP. *Studies in Nonlinear Dynamics & Econometrics 20*(4), 441–453.

Rudebusch, G. D. and J. C. Williams (2009). Forecasting Recessions: The Puzzle of the Enduring Power of the Yield Curve. *Journal of Business & Economic Statistics 27*(4), 492–503.

Sarlin, P. (2013). On policymakers' loss functions and the evaluation of early warning systems. *Economics Letters 119*(1), 1–7.

Stock, J. H. and M. W. Watson (1989). New indexes of coincident and leading economic indicators. In *NBER Macroeconomics Annual 1989, Volume 4*, NBER Chapters, pp. 351–409. National Bureau of Economic Research, Inc.

Stock, J. H. and M. W. Watson (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature 41*(3), 788–829.

Stock, J. H. and M. W. Watson (2014). Estimating turning points using large data sets. *Journal of Econometrics 178*(P2), 368–381.

Tommaso, P. (1998). Characterizing Asymmetries in Business Cycles Using Smooth-Transition Structural Time-Series Models. *Studies in Nonlinear Dynamics & Econometrics 3*(3), 1–18.

Appendix

Table A.1: Country-specific sample starts for the various leading indicators

Country	RI	Spread	Stocks	Con. conf
AUS	1960	1960	1960	1974
CAN	1961	1961	1979	1979
FRA	1960	1960	1979	1972
ITA	1960	1960	1960	1972
JPN	1960	1960	1960	1982
KOR	1970	1979	1970	1998
NZL	1962	1978	1962	1988
NOR	1960	1984	1970	-
ESP	1960	1982	1960	1986
SWE	1970	1970	1980	1995
UK	1966	1966	1966	1973
USA	1960	1960	1960	1960

Note: This table reports the sample start data for the various leading indicators for each country.

Table A.2: AUROC gains from adding various leading indicators to a model with residential investment – Panel results

Variable	In-sample Gain	Out-of-sample. Gain
Nowcasting		
Spread	0.0043	-0.0000
	(0.0063)	*(0.0091)*
Stocks	0.0284***	0.0324***
	(0.0072)	*(0.0083)*
C.Conf	0.0262***	0.0319***
	(0.0085)	*(0.0123)*
Oilprice	-0.0010	-0.0115***
	(0.0036)	*(0.0043)*
1-step		
Spread	0.0146	0.0167
	(0.0094)	*(0.0116)*
Stocks	0.0345***	0.0404***
	(0.0089)	*(0.0102)*
C.Conf	0.0341***	0.0484***
	(0.0095)	*(0.0128)*
Oilprice	0.0008	-0.0134*
	(0.0058)	*(0.0069)*
2-step		
Spread	0.0280**	0.0393***
	(0.0116)	*(0.0136)*
Stocks	0.0333***	0.0392***
	(0.0104)	*(0.0113)*
C.Conf	0.0444***	0.0670***
	(0.0108)	*(0.0144)*
Oilprice	-0.0011	-0.0183*
	(0.0081)	*(0.0101)*
3-step		
Spread	0.0408***	0.0610***
	(0.0133)	*(0.0157)*
Stocks	0.0193**	0.0181
	(0.0094)	*(0.0110)*
C.Conf	0.0459***	0.0801***
	(0.0114)	*(0.0164)*
Oilprice	0.0003	-0.0126
	(0.0082)	*(0.0103)*

Note: This table reports the additional AUROC gains from augmenting a probit model with residential investments with an additional leading indicator as regressor. The second column reports results from models estimated on the full sample (in-sample forecasting exercise), while the third column reports results from the recursive out-of-sample forecasting exercise. All the models are evaluated based on the time period 1990Q1 to 2014Q4. Differences in accuracy that are statistically different from zero at a 10%, 5% and 1% significance level are denoted by one, two and three asterisks, respectively.

Table A.3: AUROC values and gain from including residential investment – Panel results. Fixed sample across rows.

	In-sample		Out-of-sample	.
Variable	AUC	Gain	AUC	Gain
Nowcasting				
Resinvest	0.8451	-	0.8179	-
	(0.0159)		*(0.0147)*	
Spread	0.7411	0.1051***	0.7124	0.1034***
	(0.0194)	*(0.0158)*	*(0.0213)*	*(0.0150)*
Stocks	0.7921	0.0723***	0.7515	0.0798***
	(0.0171)	*(0.0137)*	*(0.0183)*	*(0.0139)*
C.Conf	0.7755	0.0852***	0.7471	0.0787***
	(0.0185)	*(0.0147)*	*(0.0195)*	*(0.0136)*
Oilprice	0.7350	0.1116***	0.6867	0.1250***
	(0.0198)	*(0.0164)*	*(0.0215)*	*(0.0168)*
1-step				
Resinvest	0.8137	-	0.7765	-
	(0.0177)		*(0.0165)*	
Spread	0.7182	0.0995***	0.6859	0.0984***
	(0.0196)	*(0.0152)*	*(0.0216)*	*(0.0137)*
Stocks	0.7591	0.0770***	0.7085	0.0867***
	(0.0181)	*(0.0142)*	*(0.0193)*	*(0.0138)*
C.Conf	0.7555	0.0856***	0.7098	0.0901***
	(0.0190)	*(0.0151)*	*(0.0201)*	*(0.0140)*
Oilprice	0.6997	0.1185***	0.6373	0.1341***
	(0.0205)	*(0.0165)*	*(0.0220)*	*(0.0165)*
2-step				
Resinvest	0.7920	-	0.7433	-
	(0.0187)		*(0.0172)*	
Spread	0.7051	0.0966***	0.6665	0.0990***
	(0.0198)	*(0.0155)*	*(0.0219)*	*(0.0133)*
Stocks	0.7208	0.0921***	0.6597	0.1006***
	(0.0193)	*(0.0159)*	*(0.0203)*	*(0.0145)*
C.Conf	0.7411	0.0873***	0.6839	0.0943***
	(0.0192)	*(0.0162)*	*(0.0205)*	*(0.0143)*
Oilprice	0.6767	0.1218***	0.6003	0.1374***
	(0.0204)	*(0.0171)*	*(0.0220)*	*(0.0161)*
3-step				
Resinvest	0.7729	-	0.7142	-
	(0.0196)		*(0.0179)*	
Spread	0.7083	0.0829***	0.6599	0.0903***
	(0.0194)	*(0.0151)*	*(0.0220)*	*(0.0128)*
Stocks	0.6924	0.0933***	0.6111	0.1081***
	(0.0202)	*(0.0173)*	*(0.0213)*	*(0.0151)*
C.Conf	0.7334	0.0770***	0.6684	0.0854***
	(0.0197)	*(0.0165)*	*(0.0207)*	*(0.0143)*
Oilprice	0.6731	0.1077***	0.5800	0.1298***
	(0.0198)	*(0.0175)*	*(0.0218)*	*(0.0161)*

Note: This table shows AUROC values for probit models using various leading indicators and the AUROC gain when augmenting each probit specification with residential investment as an additional regressor. The second and third columns report results from models estimated on the full sample (in-sample forecasting exercise), while the fourth and the fifth columns report results from the recursive out-of-sample forecasting exercise. All the models are evaluated based on the time period 1990Q1 to 2014Q4. Differences in accuracy that are statistically different from zero at a 10%, 5% and 1% significance level are denoted by one, two and three asterisks, respectively.

Table A.4: AUROC individual countries, in-sample, Nowcasting

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8684	0.8175	0.7772	0.3754	0.5404
CAN	0.8507	0.9228	0.8157	0.7853	0.7176
FRA	0.8068	0.7227	0.8772	0.8299	0.8171
ITA	0.8769	0.5360	0.6902	0.6466	0.7412
JPN	0.6849	0.5738	0.7353	0.6579	0.5786
KOR	0.7036	0.7857	0.6809	-	0.3146
NZL	0.6650	0.6585	0.6418	0.6791	0.4981
NOR	0.9467	0.8416	0.7749	-	0.7271
ESP	0.9840	0.5108	0.7746	0.7080	0.6845
SWE	0.7559	0.9456	0.8662	-	0.7647
UK	0.7553	0.5886	0.7230	0.6455	0.6399
USA	0.9414	0.9202	0.8919	0.9778	0.8475

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports in-sample nowcasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.5: AUROC individual countries, in-sample, 1-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8842	0.8544	0.7561	0.3596	0.4982
CAN	0.7868	0.9118	0.7413	0.7618	0.6368
FRA	0.7208	0.6348	0.8026	0.7535	0.7112
ITA	0.8488	0.4940	0.6577	0.6326	0.6787
JPN	0.6877	0.4952	0.7000	0.6611	0.4905
KOR	0.7052	0.8359	0.6900	-	0.3541
NZL	0.5963	0.7246	0.6168	0.7445	0.5212
NOR	0.8847	0.8094	0.7098	-	0.6745
ESP	0.9789	0.4826	0.7601	0.7268	0.6446
SWE	0.6794	0.9426	0.8471	-	0.6640
UK	0.7330	0.5569	0.6722	0.5530	0.5674
USA	0.9192	0.8919	0.8505	0.8909	0.7404

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports one quarter ahead in-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.6: AUROC individual countries, in-sample, 2-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8912	0.9298	0.7632	0.4228	0.5123
CAN	0.7868	0.9397	0.6695	0.7618	0.6272
FRA	0.6316	0.5899	0.7013	0.7015	0.5828
ITA	0.7778	0.4530	0.6196	0.6151	0.5721
JPN	0.7131	0.4544	0.6873	0.7234	0.4524
KOR	0.6748	0.8161	0.6717	-	0.4073
NZL	0.5526	0.7516	0.5745	0.7696	0.5475
NOR	0.8463	0.7569	0.5859	-	0.6259
ESP	0.9784	0.4873	0.7671	0.7202	0.6207
SWE	0.5949	0.9279	0.8059	-	0.5691
UK	0.7152	0.5474	0.6589	0.5741	0.5658
USA	0.8889	0.8808	0.7535	0.7798	0.6273

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports two quarters ahead in-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.7: AUROC individual countries, in-sample, 3-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8561	0.9789	0.6456	0.5228	0.6140
CAN	0.7824	0.9603	0.5656	0.7412	0.6382
FRA	0.6046	0.5834	0.6586	0.6707	0.5026
ITA	0.6957	0.4269	0.6116	0.5861	0.4870
JPN	0.6940	0.4433	0.6155	0.7778	0.4425
KOR	0.7036	0.8374	0.5684	-	0.4666
NZL	0.5039	0.7728	0.5173	0.7869	0.5565
NOR	0.8486	0.7412	0.4957	-	0.7153
ESP	0.9601	0.4897	0.7160	0.7155	0.5465
SWE	0.5522	0.9324	0.7390	-	0.5640
UK	0.7046	0.5351	0.6605	0.6622	0.6182
USA	0.9010	0.8859	0.6444	0.6667	0.6465

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports three quarters ahead in-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.8: AUROC individual countries, out-of-sample, Nowcasting

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8351	0.8333	0.7544	0.5439	0.4667
CAN	0.8309	0.8993	0.8141	0.8640	0.5978
FRA	0.7715	0.6932	0.8253	0.7786	0.8017
ITA	0.8514	0.5866	0.6992	0.6732	0.7297
JPN	0.6401	0.5631	0.7405	0.6498	0.5790
KOR	0.6231	0.7766	0.5684	-	0.3085
NZL	0.6573	0.6849	0.6258	0.6094	0.5218
NOR	0.9129	0.8863	0.8439	-	0.8384
ESP	0.9746	0.6531	0.8038	0.7897	0.7366
SWE	0.8485	0.9610	0.8816	-	0.8331
UK	0.7598	0.5730	0.7213	0.7163	0.6555
USA	0.9364	0.9030	0.8606	0.9768	0.8141

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports out-of-sample nowcasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.9: AUROC individual countries, out-of-sample, 1-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.8105	0.8614	0.6947	0.4825	0.3982
CAN	0.7294	0.8787	0.7350	0.7816	0.5294
FRA	0.6643	0.6085	0.7306	0.6932	0.6675
ITA	0.8138	0.5345	0.6692	0.6672	0.6642
JPN	0.6262	0.5040	0.6857	0.6236	0.5020
KOR	0.5790	0.7371	0.5456	-	0.2903
NZL	0.6155	0.7144	0.6008	0.6338	0.5353
NOR	0.8298	0.8541	0.7796	-	0.7318
ESP	0.9615	0.6075	0.7887	0.7845	0.6939
SWE	0.7993	0.9449	0.8287	-	0.7331
UK	0.7146	0.5435	0.6656	0.6288	0.5697
USA	0.9010	0.8626	0.8010	0.8717	0.7000

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports one quarter ahead out-of-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.10: AUROC individual countries, out-of-sample, 2-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.7596	0.9105	0.6456	0.4404	0.4158
CAN	0.6787	0.9022	0.6758	0.7824	0.4618
FRA	0.5732	0.5847	0.6172	0.6463	0.5635
ITA	0.7442	0.4865	0.6186	0.6016	0.5776
JPN	0.6187	0.4778	0.6512	0.6367	0.4690
KOR	0.5441	0.7295	0.5471	-	0.3191
NZL	0.5687	0.7176	0.5359	0.6236	0.5315
NOR	0.7294	0.8039	0.6588	-	0.6204
ESP	0.9441	0.5939	0.7535	0.7737	0.6469
SWE	0.7257	0.9169	0.7426	-	0.6404
UK	0.6644	0.5212	0.6193	0.6182	0.5011
USA	0.8333	0.8404	0.6737	0.7424	0.5455

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports two quarters ahead out-of-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Table A.11: AUROC individual countries, out-of-sample, 3-step

Country	RI	Spread	Stocks	Con. conf	Oil Price
AUS	0.7018	0.9789	0.5684	0.5316	0.4649
CAN	0.5809	0.9507	0.5725	0.7625	0.4140
FRA	0.5398	0.5783	0.5277	0.6142	0.4763
ITA	0.6897	0.4515	0.5871	0.5761	0.5045
JPN	0.5770	0.4385	0.5484	0.6331	0.4635
KOR	0.5517	0.7796	0.4422	-	0.3602
NZL	0.5167	0.7246	0.4487	0.6171	0.4942
NOR	0.6980	0.7812	0.6133	-	0.6753
ESP	0.9075	0.5906	0.6817	0.7371	0.5601
SWE	0.7103	0.9309	0.6794	-	0.6051
UK	0.6081	0.5022	0.6137	0.6834	0.5006
USA	0.7838	0.8616	0.5677	0.6273	0.5758

Note: This table reports country-specific AUROC values from panel probit models using residential investment, term spread, stock prices, consumer confidence survey and oil price, respectively, as regressor. The table reports three quarters ahead out-of-sample forecasts evaluated on the time period 1990Q1 to 2014Q4.

Centre for Applied Macro - and Petroleum economics (CAMP)
will bring together economists working on applied macroeconomic issues, with special emphasis on petroleum economics.

BI Norwegian Business School
Centre for Applied Macro - Petroleum economics (CAMP)
N-0442 Oslo

http://www.bi.no/camp

CAMP Working Paper Series
ISSN: 1892-2198