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Predicting Housing Market Sentiment: The Role of Financial, Macroeconomic and Real Estate Uncertainties

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Abstract

Sentiment indicators have long been closely monitored by economic forecasters, notably to predict short-term moves in consumption and investment. Recently, housing sentiment indices have been developed to forecast housing market developments. Sentiment indices partly reflect economic determinants, but also more subjective factors, thereby adding information, particularly in periods of uncertainty, when economic relations are less stable than usual. While many studies have investigated the relevance of sentiment indicators for forecasting, few have looked at the factors which shape sentiment. In this paper, we investigate the role of different types of uncertainty in predicting housing sentiment, controlling for a wide set of economic and financial factors. We use a dynamic model averaging/selection (DMA/DMS) approach to assess the relevance of uncertainty and other factors in forecasting housing sentiment at different points in time. We find that housing sentiment forecast errors from models incorporating uncertainty measures are up to 40% lower at a two-year horizon, compared with models ignoring uncertainty. We also show, by examining DMS posterior inclusion probabilities, that uncertainty has become more relevant since the 2008 global financial crisis, especially at longer forecast horizons.

JEL Classifications: C53; E44; R31
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1 Introduction

Building on a long tradition of using confidence indicators in economic forecasting, Bork et al. (2019) have recently developed a housing sentiment index for the United States, exploiting information from the University of Michigan consumer survey. They show that their index explains a large share of house price variation and is a good predictor of house prices, compared to several macroeconomic variables traditionally used for this purpose. In most of the literature, which focuses on forecasting performance, sentiment is taken as exogenous. Nevertheless, from a behavioural point of view, it is interesting to examine how sentiment is shaped by fundamental and more subjective factors. This is also relevant to policymakers, insofar as their actions can influence subjective perceptions and expectations. Recent years have seen several spikes in economic and financial uncertainty, related in particular to the 2008 global financial crisis (GFC), Brexit, trade tensions and, most recently the COVID-19 outbreak (Baker et al., 2016).

Against this background, this paper investigates how uncertainty predicts housing sentiment. Following Jurado et al. (2015), Ludvigson et al. (forthcoming) and Nguyen Thanh et al. (2020), we distinguish different types of uncertainty, namely macro(economic), real (activity), financial and real estate uncertainty. As house price expectations generally contain a significant extrapolative component (Abraham and Hendershott, 1996; Muellbauer and Murphy, 2008), we include the change in real house prices as a potential driver of housing sentiment. We control for the impact of macroeconomic and financial variables, using the eight macro factors from Ludvigson and Ng (2009, 2011), which summarise information from a set of 131 indicators. We use the dynamic model averaging/selection (DMA/DMS) approach developed by Koop and Korobilis (2012), which allows both the model coefficients and the model itself to vary over time. This technique is particularly relevant for our purpose, since studies have shown that the relation between uncertainty and housing market variables is generally nonlinear and time varying (Antonakakis et al., 2015; André et al., 2017; Christou et al., 2019).

We find that models incorporating combinations of macro, real, financial and real estate uncertainty reduce housing sentiment forecast errors significantly, compared with models that only incorporate real house price changes and macroeconomic and financial factors. Moreover, the gain increases with the forecasting horizon, with 4-quarter ahead forecast errors reduced by up to 20% and 8-quarter ahead forecast errors cut by up to 40%. The dynamic model selection process provides insights into the importance of different factors at different points in time, through their posterior inclusion probabilities. The probabilities of inclusion of macro, real and financial uncertainty jump with the GFC at the medium (4-quarter) and long forecast horizon (8-quarter). While the inclusion probability of financial uncertainty recedes somewhat over time, those of macro and real uncertainty remain very high. Real estate uncertainty also has a high inclusion probability around the GFC. To sum up, macro, real, financial and real estate uncertainty are all relevant to forecast housing sentiment, especially after the GFC.

The paper is organized as follows. Section 2 briefly reviews the literature on the determinants of sentiment and the role of uncertainty in housing markets. Section 3 presents the methodology and data. Section 4 describes the empirical results. Section 5 concludes.

2 Brief literature review

This paper relates primarily to the literature on the determinants of sentiment, which is relatively scarce, as most studies take sentiment as exogenous to explain and forecast economic and financial variables. As residential property is both a consumer good, providing housing services, and an investment good, offering opportunities for wealth accumulation, the literatures on consumer and investor sentiment are both relevant. Sentiment surveys are rooted in psychological economics, which demonstrates that economic agents behaviour does not mechanically reflect the state of economic variables, but is affected by attitudes, perceptions and expectations (Katona, 1975). Several papers from the 1970s relate consumer sentiment to uncertainty, notably associated with rising inflation and unemployment, and show its usefulness for predicting demand for durable goods (Hymans. 1970; Juster and Wachtel, 1972; Lovell, 1975). In a similar vein, Mishkin (1978) argues that the consumer sentiment index could be interpreted as a measure of consumers perception of the risk of financial distress. When sentiment weakens, so does demand for durable goods, as consumers facing higher risks of distress prefer holding liquid financial assets, rather than illiquid durable goods. The liquidity hypothesis put forward by Mishkin for durable goods may also be relevant for potential homebuyers. Households facing risks of unemployment and income losses will be less positive about buying homes.

Throop (1992) analyses the causes and effects of consumer sentiment, as measured in the University of Michigan survey. He finds that, while in normal times consumer sentiment moves with current economic conditions and shows a stable relation with key economic variables, it brings additional information to forecast the consumption of durable goods during exceptional economic or political events, like the 1990-91 Gulf war. Fuhrer (1993) finds that most of the variation in the Michigan sentiment index can be explained by macroeconomic variables, but that it contains independent information which improve consumption growth forecasts, albeit marginally. Caroll et al. (1994) also find that sentiment helps forecast household spending. Barsky and Sims (2012) find that unexplained variations in consumer confidence affect the future path of macroeconomic variables. They show that this effect can be almost entirely attributed to news about future productivity, as opposed to a causal effect of animal spirits on economic activity. Lahiri and Zhao (2016), using household level survey data, point to the role of household perceptions and expectations about the economy and individual economic conditions in shaping sentiment. They find responses to news to be cyclical, asymmetric and heterogeneous across households.

The literature has long acknowledged the importance of uncertainty for fixed investment, especially due to the option value associated with irreversibility (Bernanke, 1983; Pindyck, 1991). In the area of urban economics, Capozza and Helsley (1990) demonstrate that uncertainty delays the conversion of land from agricultural to urban use and reduces equilibrium city size. Recent papers investigate the determinants of stock market investor sentiment empirically. Kurov (2010) finds a significant effect of monetary policy on investor sentiment, especially in bear markets. Lutz (2015) finds a favorable effect on investor sentiment from both conventional and unconventional monetary policy easing. Apergis et al. (2018) find a negative association between oil and natural gas prices and US investor sentiment. Determinants of investor sentiment may also affect housing sentiment, even though to a different degree, as housing is also a consumption good, its risk and liquidity profile differs from that of equity investment, and homebuyers and stock market investors may have different investment horizons.

Our paper focuses on the impact of uncertainty on housing sentiment for two reasons. First, psychology has been shown to play an important role in housing markets (Shiller, 2008). As a result of extrapolative house price expectations, lagged appreciation of house prices tends to act as a bubble builder. However, at some point the deviation of house prices from fundamentals acts as a bubble burster (Abraham and Hendershott, 1996; Muellbauer and Murphy, 2008). The event triggering the reversal in expectations may be trivial (Kindleberger and Aliber, 2005). Hence, understanding what may drive housing sentiment, beyond economic and housing market fundamentals, is important. Second, the literature has documented a link between the economic policy uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016) and house prices, as well as a link between different measures of housing sentiment and house prices, but the link between uncertainty and housing sentiment remains largely unexplored. Our paper aims at filling this gap.

Regarding the link between uncertainty and house prices, Antonakakis et al. (2015) find negative correlations between housing market returns and EPU in the United States, controlling for economic and financial fundamentals, with time-varying correlations increasing sharply in times of high economic uncertainty, notably around recessions. André et al. (2017) find that EPU helps predict the level and volatility of US real housing returns. Christou et al. (2019) find a time-varying impact of uncertainty shocks on a range of US housing market variables, with the largest effects on house prices, permits and starts. Strobel et al. (2020) find that uncertainty shocks affect house prices, although not transaction volumes. They also show that the effect of uncertainty on the housing market dominates that of local labour demand shocks. Regarding the link between sentiment and house prices, Ling et al. (2015) find that changes in sentiment of homebuyers, homebuilders and lenders predict real house price changes, controlling for the impact of past house price changes, fundamentals, and market liquidity.

Bork et al. (2019) compute a housing sentiment index, which explains a large share of house price variation and improves forecasts, compared to models based on fundamental house price drivers. This housing sentiment index is constructed using household survey responses to questions about buying conditions for houses. Our paper investigates whether uncertainty measures help forecast this housing sentiment index, controlling for a large set of macroeconomic and financial variables. Ludvigson et al. (forthcoming) point to the need to differentiate macroeconomic from financial uncertainty in business cycle analysis. More specifically, they show that higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while financial uncertainty is a likely source of output fluctuations. Nguyen Thanh et al. (2020) propose a real estate sector-specific uncertainty measure, which explains a larger share of house price variation than other uncertainty indicators from the literature. They show that their real estate uncertainty index granger-causes both housing starts and prices. In our empirical analysis, we investigate the ability of the different uncertainty indices mentioned above to improve forecasts of housing sentiment and examine whether it has changed over time.

3 Methodology and data

3.1 Methodology

In order to study the different forces that drive future housing market sentiments, we use the innovative dynamic model averaging/selection (DMA/DMS) approach developed by Koop and Korobilis (2012) used in several studies (Wang et al., 2016; Marfatia, 2020; among others). This approach has the advantage of allowing the coefficients to vary over time (as in the time-varying parameter model), but more importantly of allowing the forecasting model itself to vary across time. We then trace out the extent to which housing market sentiments can be predicted at each point in time by macroeconomic factors and uncertainty. We follow Koop and Korobilis (2012) and specify the DMA model as:[1]

$$Y_t = z_t^{(k)}\theta_t^{(k)} + \epsilon_t^{(k)} \qquad \epsilon_t^{(k)} \overset{ind}{\sim} N(0, H_t^{(k)}) \tag{1a}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \eta_t^{(k)} \qquad \eta_t^{(k)} \overset{ind}{\sim} N(0, Q_t^{(k)}) \tag{1b}$$

where $Y_{n,t}$ is housing market sentiments, ϵ_t and η_t are shocks with variance-covariance matrix H_t and Q_t for the measurement equation (eq. 1a) and transition equation (eq. 1b), respectively. Coefficient θ_t is an m x 1 vector that capture the time-varying response of housing market sentiments to explanatory variables. We assume the errors to be mutually independent at all leads and lags. Since models themselves can vary across time, we have a set of models indexed by $k = 1, ..., K$; and K is the number of models used for forecasting housing market sentiments.

The vector Z_t is a 1 x m vector of potential predictors (explanatory variables), which includes the constant and lagged values of dependent variable (to capture persistence), real house price changes and eight macro factors in Ludvigson and Ng (2009) (as controls), and alternative measures of macro and financial uncertainty. The measures of macro and financial uncertainty include macro uncertainty (MU), financial uncertainty (FU), real estate uncertainty (REU), and real uncertainty (RU) at 3 or 12 months in each case. We convert the monthly data to quarterly values by taking three-month averages, corresponding to 1- and 4-quarter respectively, which we label as MU1, FU1, REU1, RU1 and MU4, FU4, REU4, RU4. Since macro uncertainty and real uncertainty are similar measures, we consider four alternative model specifications: In addition to real house returns, and the 8 factors in each specification, model 1 includes MU1, FU1, REU1; model 2 includes MU4, FU4, REU4; model 3 includes RU1, FU1, REU1; and model 4 includes RU4, FU4, REU4.

Note that in the equation 1a, the coefficients as well as the forecasting models are time-varying. Since the models themselves change over time, next we specify how these models evolve, that is, how predictors enter/leave the model at each point in real time.[2] We use an innovative algorithm

[1]This is similar to the standard state-space version of the time-varying parameter model widely used in the literature (Bovin 2006; Kishor and Marfatia 2013; Korobilis 2013; Marfatia 2014, 2015; Marfatia et al. 2017, 2019, Mbarek et al, 2019).

[2]One approach is to specify a Markov switching transition matrix which requires estimating transition probabilities of switching from model i to model j at each time period t for all the k model. However, with several predictors and a large transition matrix, this can become infeasible, lead to imprecise estimates/inference, and imply a significant computational burden. See, Chen and Liu (2000) and Koop and Korobilis (2012) for more details.

proposed by Raftery et al. (2010), which involves specifying the two "*forgetting factors*" for the coefficients (λ) and the models (α). These factors are the weights assigned to predictors and models in the previous period for the purpose of forecasting in the present period t. Raftery et al. (2010) show that an efficient algorithm can be achieved by setting

$$Q_t = (1 - \lambda^{-1})\Sigma_{t-1|t-1} \tag{2}$$

where Σ_t is the covariance matrix of the prediction error in the Kalman filter and λ is the forgetting factor for the coefficient. Thus, the observations that are j periods in the past get a weight of λ^j. A lower value of λ indicates with larger time variation (greater parameter instability), with $\lambda = 1$ implying that the coefficients are constant over time.[3] The other forgetting factor (α) has a similar interpretation, except that it applies in the context of the evolution of model probabilities over time. Let $\pi_{t|r,k} = Pr(L_t = k|y^r)$ be the probability of the selected model at time t based on the information available through time r. Following Raftery et al. (2010) and Koop and Korobilis (2012), we then have,

$$\pi_{t|t-1,l} = \frac{\pi^{\alpha}_{t-1|t-1,k}}{\sum_{k=1}^{K} \pi^{\alpha}_{t-1|t-1,t}} \tag{3}$$

where $0 < \alpha < 1$ and is generally set to a value very close to one. The interpretation of α is similar to that of λ. For the purposes of forecasting, we use two alternatives. First, we obtain forecasts by selecting the model with the highest probability $\pi_{t|r,k}$. This is the dynamic model selection (DMS). Second, we obtain forecasts by using a weighted average of all the models, with weights governed by the probability of each model. This is the dynamic model average (DMA). In discussing the posterior inclusion probabilities, we consider $\alpha = 0.95$ and $\lambda = 0.99$ for short (1-quarter), medium (4-quarter) and long (8-quarter) run forecast horizons. This is consistent with the literature (Koop and Korobilis, 2012; Marfatia, 2020).

[3]For example, for a quarterly data, when the value of λ is set to 0.99 (0.95), it implies that the observations five years ago get 81.8% (35.8%) of the weight of the last period's observation.

3.2 Data

As discussed in the introduction, our data set covers the quarterly period of 1975:3 to 2017:3, with the start and end date being driven by the availability of respectively the housing sentiment index developed by Bork et al. (2019) and the real estate uncertainty indicator developed by Nguyen et al. (2018). Bork et al. (2019) use time series data from the consumer surveys of the University of Michigan to generate the housing sentiment index, with housing sentiment defined as the general attitude of households about house buying conditions. In particular, Bork et al. (2019) consider the underlying reasons for households' views about house buying conditions. The part of the University of Michigans consumer survey related to house buying conditions starts with the question: "Generally speaking, do you think now is a good time or a bad time to buy a house?", with the follow-up question: "Why do you say so?". In constructing the index, Bork et al. (2019) focused on the responses to the follow-up question, as the idea is to draw on the information in the underlying reasons why households believe that it is a bad or good time to buy a house. Specifically, the housing sentiment index is based on the following ten time series: good time to buy; prices are low, good time to buy; prices are going higher, good time to buy; interest rates are low, good time to buy; borrow-in-advance of rising interest rates, good time to buy; good investment, good time to buy; times are good, bad time to buy; prices are high, bad time to buy; interest rates are high, bad time to buy; cannot afford, bad time to buy; and uncertain future, bad time to buy. Then Bork et al. (2019) used partial least squares (PLS) to aggregate the information contained in each of the ten time series into an easy-to-interpret index of housing sentiment, with PLS filtering out idiosyncratic noise from the individual time series and summarizing the most important information in a single index.[4]

As far as the predictors are concerned, we consider alternative forms of uncertainties. The methodological framework for the construction of the real estate uncertainty (REU) index developed by Nguyen Thanh et al. (2018) follows that of Jurado et al. (2015). The macroeconomic uncertainty (MU) and financial uncertainty (FU) measures of Jurado et al. (2015) and Ludvigson et al. (forthcom-

[4]The data is available for download from: https://www.dropbox.com/s/al3sddq1026xci2/Online%20data.xlsx?dl=0.

ing) are the average time-varying variances in the unpredictable component of 134 macroeconomic and 148 financial time-series respectively. They attempt to capture the average volatility in the shocks to the factors that summarize real and financial conditions.[5] We also conduct our empirical analysis using a narrower measure of macroeconomic uncertainty also developed by Ludvigson et al. (forthcoming), real uncertainty (RU) obtained from 73 variables related to real activity, instead of MU. Building on the idea behind MU (or RU) and FU, Nguyen Thanh et al. (2018) link uncertainty directly to the predictability of 40 housing market variables.[6] The various uncertainty indices are available monthly for three forecasting horizons of one-, three-, and twelve-month-ahead, but given that the housing sentiment index is available quarterly, we convert these monthly indices into quarterly values by taking three-month averages, and only consider the uncertainty indices at the 3- and 12-month horizons, as they correspond to 1- and 4-quarter respectively, which we call MU1, RU1, FU1, REU1, and MU4, RU4, FU4, REU4.

While, the focus is on the role of uncertainty in explain the movements in housing market sentiment, we also include additional controls. We include in the list real house price log-returns, based on the Federal Housing Finance Agency (FHFA) all-transactions nominal house price index deflated by the Consumer Price Index (CPI), with the latter extracted from the FRED database of the Federal Reserve Bank of St. Louis. Note that the FHFA all-transactions index is constructed using repeat-sales and refinancings on the same single-family properties. We also use 8 factors (F1, F2, F3, F4, F5, F6, F7, F8) derived from the 134 macroeconomic variables by Ludvigson and Ng (2009, 2011),[7] given the widespread evidence that the housing market is affected by a large number of macroeconomic variables (Christou et al., 2019). These factors are converted to quarterly values from their monthly frequency by using averages over three months. Ludvigson and Ng (2009, 2011), identified these 8 factors such that, F1 is a real activity factor (that loads heavily on employment and

[5]The MU and FU indices are available for download from: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

[6]The REU index is available for download from: https://sites.google.com/site/johannespstrobel/.

[7]The factors are available for download from: https://www.sydneyludvigson.com/data-and-appendixes, with the underlying data derived from the FRED-MD database developed by McCracken and Ng (2016). The dataset represent broad categories of macroeconomic time series. The majority of these are real activity measures: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, and capacity utilization measures. The dataset also includes commodity and price indexes and a handful of bond and stock market indexes, and foreign exchange measures.

output data), F2 loads heavily on interest rate spreads, while F3 and F4 factors load on prices, F5 loads on interest rates (much more strongly than the interest rate spreads), F6 loads predominantly on the housing variables, F7 loads on measures of the money supply, and F8 loads on variables relating to the stock market.

4 Empirical Results

Table 1 presents the ratio of mean square forecast errors (MSFE) from the models with uncertainty measures over the MSFE of the corresponding model without uncertainty measures. A ratio lower than one indicates that the models with uncertainty forecast housing sentiments more accurately than the corresponding model without uncertainty measures. This reflects the usefulness of the incremental information contained in macro and financial uncertainty measures in predicting housing market settlements. For each specification, we evaluate the forecast performance at short (1-quarter), medium (4-quarter) and long (8-quarter) run forecast horizons.

Results show that the forecast performance of models with macroeconomic and financial uncertainty is at par or superior to that of models without these uncertainty measures. For example, when we combine macroeconomic uncertainty (MU) with financial (FU) and real estate uncertainty (REU), the errors in forecasting 8-quarter-ahead housing market sentiments is on average 40% lower than when using the model without these uncertainty measures.

Results show that the MSFEs are lower at the longer horizon (8-quarter) than at the short forecast horizon (1-quarter) for all model specifications. The ratio of the MSFEs from the model with uncertainty measures over the MSFE of models without uncertainty measures is around 0.99, 0.82, and 0.65 for 1-quarter, 4-quarter, and 8-quarter-ahead forecasts, respectively. Using McCracken's (2007) MSE-F test suitable for nested models, we find that the forecasts from the DMA and DMS with uncertainties for 4-quarter and 8-quarter-ahead outperform the corresponding models without uncertainties in a statistically significant manner at the 1% level, except at h=4 under DMS, where significance holds at 5% level.

The dynamic model selection (DMS) allows assessing the role of uncertainty and fundamental variables at different points in time by looking at their posterior inclusion probabilities. The posterior inclusion probabilities of each variable in different model specifications for short-, medium-, and long-term forecast horizons are plotted in Figures 1, 2, and 3, respectively. For each model, we have a set of 12 predictors - real house price changes, 8 factors, and 3 measures of uncertainty. In each figure, we plot posterior probabilities of real house price changes and 8 factors in panel a from model 1 and the three measures of uncertainty across 4 model specifications in panel b.[8]

At the short forecast horizon (1-quarter), the posterior inclusion probabilities of macro, real and real estate uncertainty [Fig. 1(b)] are relatively modest and fairly stable throughout the sample. Financial uncertainty also shows modest inclusion probabilities, although higher in the late 1970s and after the GFC than in the middle of the sample. The relatively low inclusion probabilities of uncertainty variables is consistent with the limited gains in MSFE from including these variables at this forecasting horizon. The dominant factor is real activity (F1) over most of the sample, but even more so during the boom period from the mid-1990s to 2006. Real house prices (RHPI) also have a relatively high inclusion probability around the early 1990s recession and the GFC. Factors associated with interest rates (F5), housing (F6), money supply (F7) and the stock market (F8) display fairly high inclusion probabilities towards the end of the sample, which could reflect the role of accommodative monetary policy (including unconventional) in lifting asset prices and driving expectations.

At the medium forecast horizon (4-quarter), uncertainty variables inclusion probabilities show more time variation [Fig. 2(b)]. The most salient feature is the spike in the inclusion probabilities of macro, real and financial uncertainty in the wake of the GFC. While financial uncertainty subsequently subsides, macro and real uncertainty remain high. Real estate uncertainty inclusion probabilities are also relatively high at this horizon. In particular, 4-quarter ahead uncertainty spikes around the early 1990s crisis and the GFC. Looking at real and financial variables, several

[8]To maintain brevity, we do not include plots of posterior inclusion probabilities of real house price changes and 8 factors estimated from other model specifications because they are both quantitatively and qualitatively similar across model specifications. However, these are available upon request.

points are worth noting. Real house prices play an important role in the 1990s. The interest rate spread factor (F2) and the first price factor (F3) peak with the GFC. The former remains high, reflecting persistent tensions in financial markets, while the latter falls back, as inflation picks up. The housing factor (F6), loading on building starts and permits, also has a higher inclusion probability after the GFC than before, which may be related to the overhang of homes following the subprime mortgage crisis. Finally, the interest rate factor (F5) and one of the price factors (F4) show a strong rising trend in their inclusion probabilities. This is consistent with the fall in interest rates making housing more affordable, all else equal, during the period. Ludvigson and Ng (2009) note that F4 is strongly correlated with nominal interest rates, which have been shown to impact house prices, above the impact from real interest rates. This is because high nominal rates, by frontloading mortgage repayments, act as a credit constraint (Meen, 1996).

At the long forecast horizon (8-quarter), the inclusion probabilities of macro, real and financial uncertainty plotted in Figure 3(b) are generally higher than at shorter horizons. This is particularly true after the GFC, when inclusion probabilities are close to one. The financial uncertainty inclusion probability falls somewhat towards the end of the sample, while those of macro and real uncertainty remain close to one. Real estate uncertainty also has a high inclusion probability, especially 4-quarter ahead uncertainty around the GFC. Regarding real and financial variables, real house prices clearly dominate during the long upswing from the early 1990s to the GFC. Thereafter, the interest rate (F5), real activity (F1) and interest rate spread (F2) factors become most important. The first price factor (F3) spikes with the GFC, but as in the medium horizon forecasts, the jump is relatively short-lived. The factor strongly correlated with nominal interest rates (F4) shows the same steady upward trend as in the medium horizon forecasts.

5 Conclusions

In this paper, we have tested whether different kinds of uncertainty help forecast housing sentiment, using a dynamic model averaging/selection (DMA/DMS) approach. We found that housing sentiment forecast models incorporating uncertainty measures perform only slightly better than those ignoring uncertainty variables at a short (1-quarter) forecast horizon, suggesting that fundamental variables capture most of the relevant information for very short-term forecasts. However, the relative forecasting performance of models incorporating uncertainty measures improves as the forecast horizon lengthens, with a gain in MSFE of about 20% at a 4-quarter horizon and up to 40% at a 8-quarter horizon. This demonstrates a high contribution of uncertainty to predicting housing sentiment, over and above fundamental variables. Moreover, uncertainty variables have become more relevant since the GFC. While the inclusion probabilities of real estate uncertainty and to a lesser extent financial uncertainty have fallen back gradually, those of macro and real uncertainty have remained very high. To sum up, uncertainty is now a key driver of housing sentiment. High uncertainty in the wake of the COVID-19 pandemic is likely to drag down housing sentiment, and possibly house prices, although some offsetting factors, like more expansionary monetary policy and changes in preferences could have offsetting effects. This is an area for future research, when the data covering the crisis period become available.

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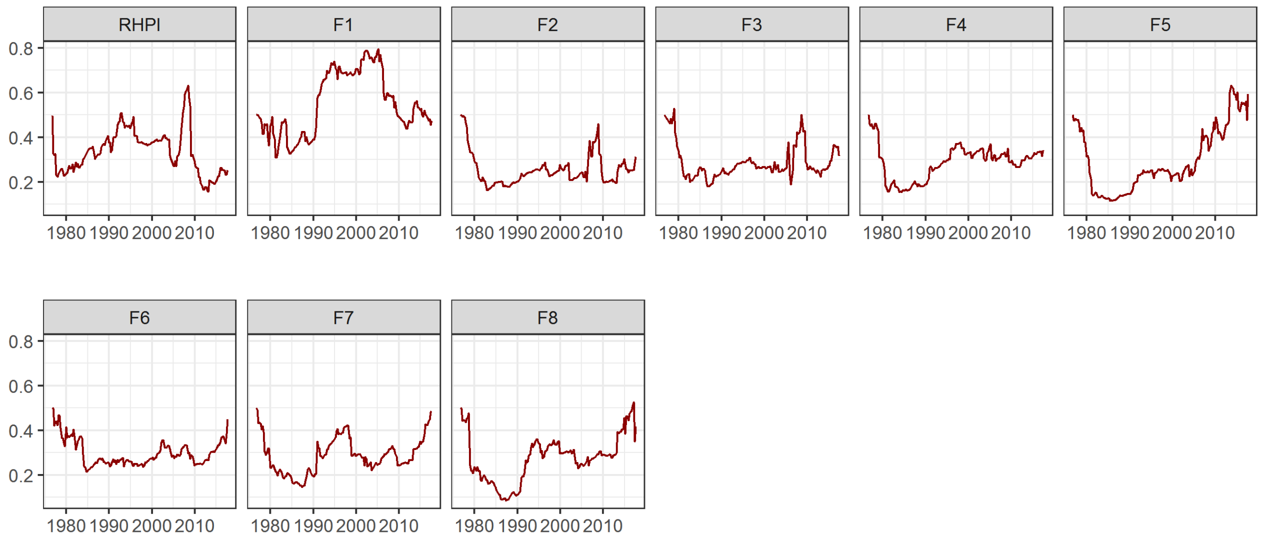
Table 1: Forecast performance of model with macro and financial uncertainty

The table presents the ratio of mean squared forecast errors (MSFE) with uncertainty measures over mean square forecast errors (MSFE) without uncertainty measure. The ratios are presented for both dynamic model selection (DMS) and dynamic model average (DMA) at short-term (h=1), medium-term (h=4), and long-term (h=8) forecast horizons. Each model specification includes real house price changes (as a control), the eight macro factors in Ludvigson and Ng (2009), and alternative measures of macro and financial uncertainty. The measures of macro and financial uncertainty include macro uncertainty (MU), financial uncertainty (FU), real uncertainty (RU), and real estate uncertainty (REU) at 1 or 4 quarters in each case. The statistical significance of McCracken's (2007) MSE-F nested model forecast comparison test at 1% and 5% levels is shown by $***$ and $**$ respectively.

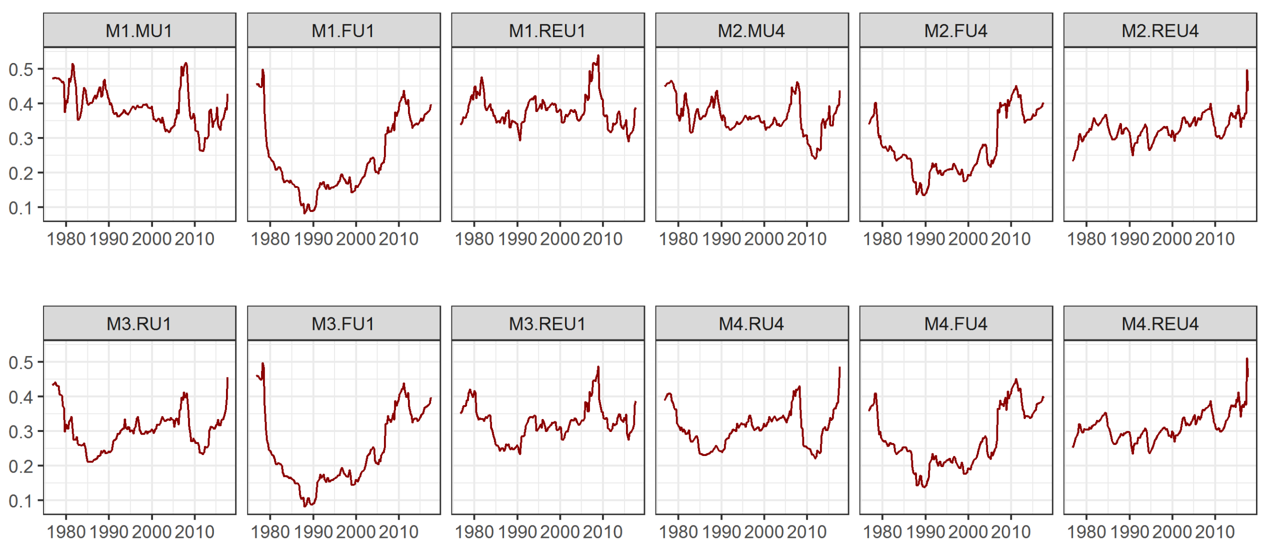
		h=1 (1-quarter)		h=4 (1-year)		h=8 (2-year)	
Model	Specification	DMA	DMS	DMA	DMS	DMA	DMS
M1	MU1, FU1, REU1	1.01	1.00	0.84^{***}	0.97^{**}	0.61^{***}	0.64^{***}
M2	MU4, FU4, REU4	1.00	0.99	0.85^{***}	0.81^{***}	0.67^{***}	0.67^{***}
M3	RU1, FU1, REU1	1.02	1.00	0.82^{***}	0.82^{***}	0.61^{***}	0.61^{***}
M4	RU4, FU4, REU4	1.00	1.00	0.83^{***}	0.81^{***}	0.64^{***}	0.62^{***}

Figure 1: Posterior inclusion probabilities (Short horizon forecast)

The plots show posterior inclusion probabilities for each model specification at short horizon forecast (h=1). Each model specification - M1 through M4 - includes real house price changes (rhpi), the eight macro factors in Ludvigson and Ng (2009) labeled F1 through F8, and macro and financial uncertainty, that is, macro uncertainty (MU), financial uncertainty (FU), and real estate uncertainty (REU) at 1 or 4 quarters.



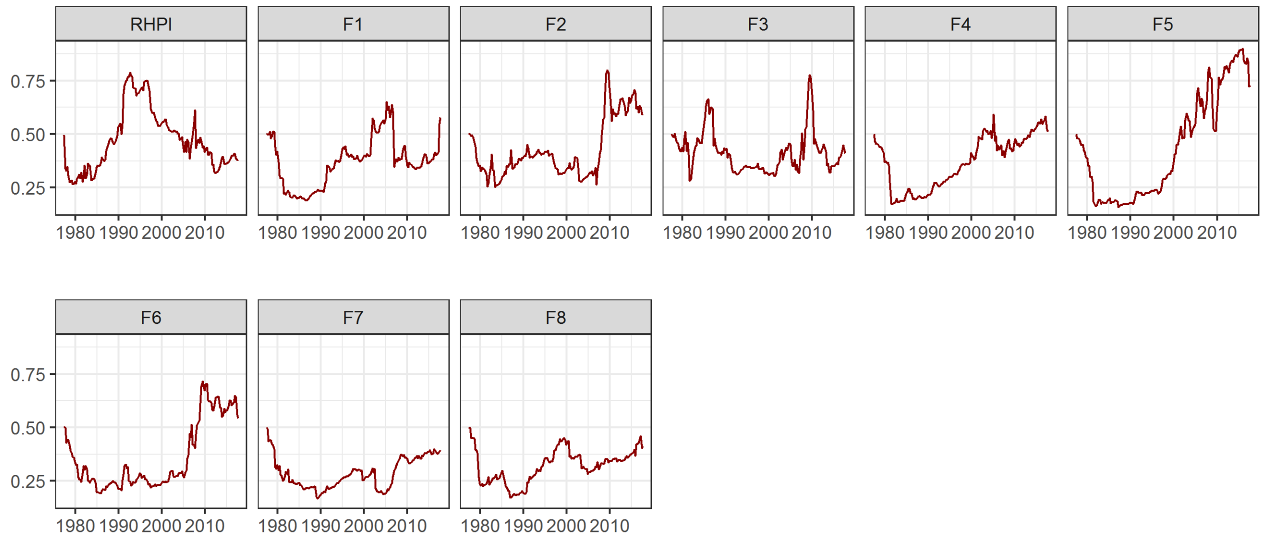
(a) RHPI and the eight factors



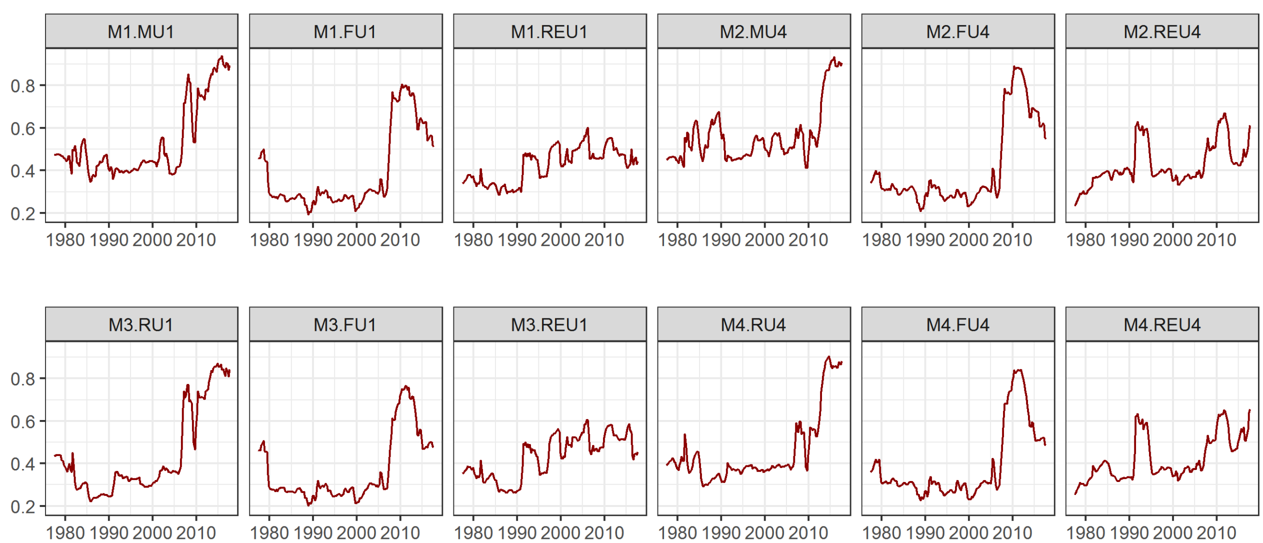
(b) Macro and financial uncertainty

Figure 2: Posterior inclusion probabilities (Medium horizon forecast)

The plots show posterior inclusion probabilities for each model specification at medium horizon forecast (h=8). Each model specification - M1 through M4 - includes real house price changes (rhpi), the eight macro factors in Ludvigson and Ng (2009) labeled F1 through F8, and macro and financial uncertainty, that is, macro uncertainty (MU), financial uncertainty (FU), and real estate uncertainty (REU) at 1 or 4 quarters.



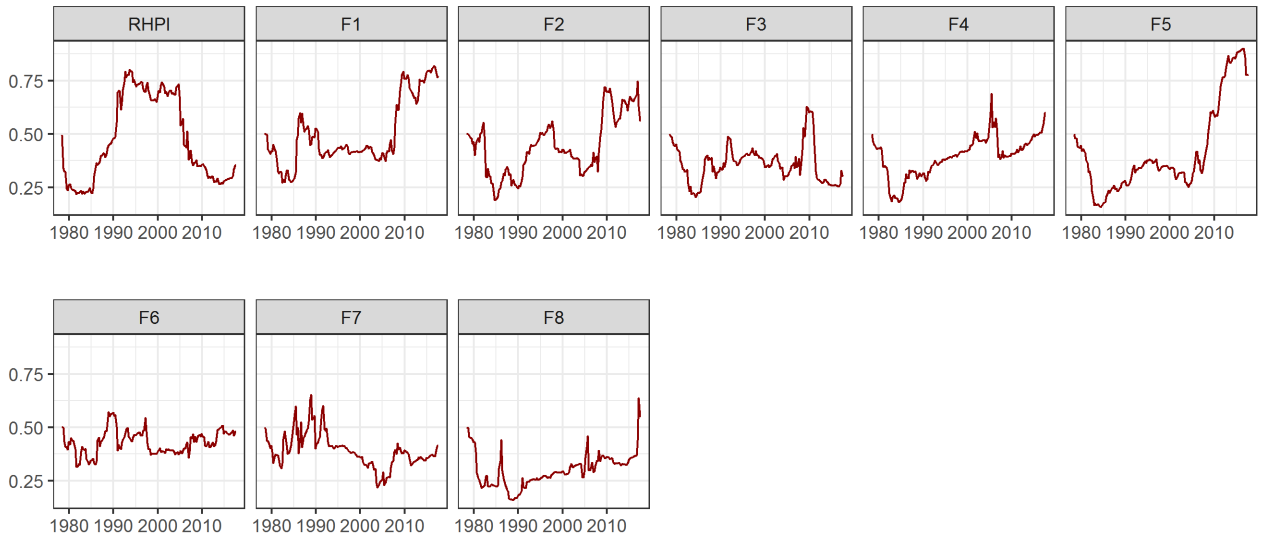
(a) RHPI and the eight factors



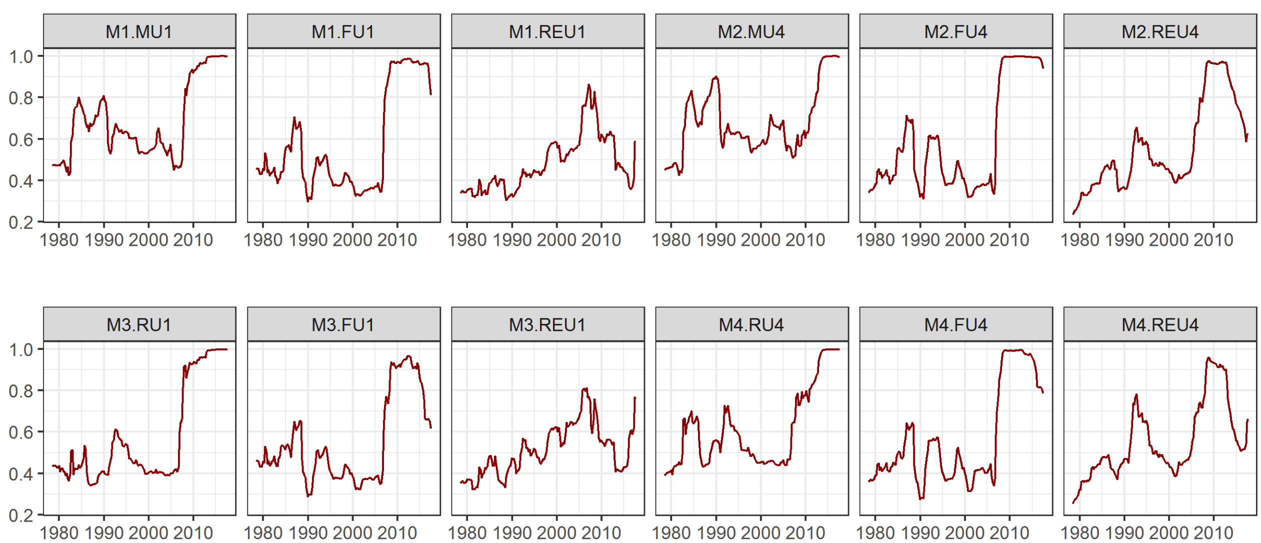
(b) Macro and financial uncertainty

Figure 3: Posterior inclusion probabilities (Long horizon forecast)

The plots show posterior inclusion probabilities for each model specification at long horizon forecast (h=12). Each model specification - M1 through M4 - includes real house price changes (rhpi), the eight macro factors in Ludvigson and Ng (2009) labeled F1 through F8, and macro and financial uncertainty, that is, macro uncertainty (MU), financial uncertainty (FU), and real estate uncertainty (REU) at 1 or 4 quarters.



(a) RHPI and the eight factors



(b) Macro and financial uncertainty