Waves of Optimism: House Price History, Biased Expectations and Credit Cycles

Alessia De Stefani[*]

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Abstract

Using the Michigan Survey of Consumers, I show that American households have heterogeneous expectations about the future of house prices, which largely depend upon the history of past house price realizations in the local area of residence. House price expectations are also systematically biased and inefficient: beliefs are over-optimistic following good times and over-pessimistic following bad ones. This systematic bias matters because consumers make financial decisions on the basis of their house price beliefs. Exploiting an exogenous shift in housing sentiment, based on the outcome of US Presidential elections, I show that when individuals expect the value of their properties to rise, they borrow against the anticipated increase in home equity. One standard deviation increase in one-year-ahead house price expectations changes the average leverage ratios on long-term fixed-rates mortgages by 6% of a standard deviation.

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[*]Danmarks Nationalbank, Research Department: Havnegade 5, DK-1093 Copenhagen K. e-mail: ads@nationalbanken.dk. This paper is a revised version of a chapter of my Ph.D. dissertation presented at the University of Edinburgh in August 2016. I would like to thank Liang Bai, Michele Belot, Stephan Heblich, Ed Hopkins, Moritz Schularick and Robert Zymek as well as seminar participants at the 2017 CEPR European Conference on Household Finance, University of Edinburgh, University of Bonn and Danmarks Nationalbank for useful advice and comments. I am grateful to the Survey Research Center at the University of Michigan for their technical support and to the Edinburgh School of Economics and the Economic and Social Research Council for financial support. This paper represents the view of the author and does not in any way reflect the opinions of the Danish Central Bank, its Board of Directors, or its staff.

1 Introduction

The expectations of households and firms play a central role in macroeconomics. Ahead of the 2007-2008 financial crisis American consumers channeled their savings into the real estate market largely because of the expectation of significantly positive returns on investment (Piazzesi and Schneider 2009; Case, Shiller, and Thompson 2012; Adelino, Schoar, and Severino 2016). There is evidence that this optimistic attitude was shared by mortgage lenders: sophisticated investors appeared to be for the most part oblivious to the risk of a substantial downturn in the housing market.[1] The 2007-2008 crisis proved these expectations to be largely misguided.

Some models attempt to reconcile the burst of financial bubbles with rational expectations theory by framing them as the investors' reaction to *rare* events (Martin and Ventura 2011; Caballero and Simsek 2013).[2] This view is however hard to reconcile with the evidence that financial crises, and housing market crashes in particular, occur relatively frequently.[3] The generalized underestimation of risk which occurred in the run-up to the 2007 financial crisis might therefore stem from some form of cognitive limitation: investors could be applying simple heuristics to predict price changes in the future (Glaeser (2013)). In particular, the excessive weight given to recent events when forming expectations might lead investors to highly discount the probability of a market downturn in good times, and *vice versa* (Gennaioli, Shleifer, and Vishny (2015); Bordalo, Gennaioli, and Shleifer (2016)). In this case, a form of "irrational exuberance" may have been a main driver of housing market dynamics in the pre-crisis period (Shiller (2015)).

This paper shows that consumers' house price expectations depend positively on the recent growth in house prices in the local area of residence, which is consistent with the results provided by Case, Shiller, and Thompson (2012) and Kuchler and Zafar (2015). My contributions are to show that this adaptive component of the expectation formation process is symmetric across the business cycle (people extrapolate from losses as much as from gains); that extrapolation leads people to make *systematic* forecasting mistakes, and

[1] Coval, Jurek, and Stafford (2009); Foote, Gerardi, and Willen (2012); Cheng, Raina, and Xiong (2014); Chernenko, Hanson, and Sunderam (2016)

[2] In other words, during boom phases agents are not blind to the possibility of a market downturn, but given the probability distribution of outcomes, it may be rational to invest in a given asset despite acknowledging its overvaluation. The burst of the bubble, on the other hand, occurs due to stochastic and exogenous processes, to which agents attach an extremely low probability ex-ante because they are rare events. Some classes of these models rely on frictions, others on asymmetric information: see Brunnermeier and Oehmke (2013) for a comprehensive review of the literature on rational bubbles.

[3] Developed economies have experienced at least twenty housing market crashes in the post-World War II period all of which were followed by a recession Jordà, Schularick, and Taylor (2015). Regional housing bubbles also have a long tradition: in the US, for example, they date back all the way to the frontier land boom of the late 18th century (Glaeser (2013)).

expectations become over-pessimistic(optimistic) after a string of bad(good) news; that this dynamic has important aggregate implications, because house price expectations directly drive the mortgage credit cycle. When consumers expect house prices to increase, their mortgage leverage ratios rises accordingly, particularly with respect to home equity extraction.

I use the micro data contained in the Michigan Survey of Consumers and exploit its variation along the lines of geography and time to analyse how American households formed house price expectations between 2007 and 2014. I show that households have heterogeneous beliefs about the future of the housing market, which systematically depend upon household characteristics and upon the history of past house price realizations in the state of residence. The intuition that people might be extrapolating from the past of house price realizations into the future builds on the work of Case, Shiller, and Thompson (2012) and Kuchler and Zafar (2015), who study how house price expectations develop in relationship to aggregate and personal experiences. My result confirms their findings: experiencing a state-level house price increase worth 1 percentage point (on average over the previous year) leads households to forecast a price increase 0.1 percentage points higher, at the one-year horizon (10% of a standard deviation in the dependent variable). This coefficient is very close to the elasticity estimated by Kuchler and Zafar (2015), a similarity that provides evidence of the robustness of this result across data sources, levels of geographic aggregation (I use US states rather than ZIP codes) and time (I include the years of the crisis and the Recession). I extend Kuchler and Zafar (2015)'s result in three dimensions. First of all, my results show that the dynamic of extrapolation in the housing market is not limited to boom periods, but rather, it is symmetrical across the business cycle, and can be observed also during a downturn.[4] This is important, because it suggests that people extrapolate from losses as much as from gains. In my estimations, the extent of extrapolation from past house price growth remains largely unchanged during the crisis years (2007-2008) and only marginally decreases during the Recession (2009-2011) holding throughout the recovery (2012 onward).

In addition, I develop upon earlier literature by studying whether the formation of house price expectations is consistent with the standard predictions of economic theory. I construct individual-level house price *forecast errors* and show that such errors are predictable from individual characteristics and from information publicly available at the time the forecast was made: in particular they depend positively from *recent house price growth* in the state of residence. In other words, I show that extrapolation from recent house price changes induces a *systematic extrapolative bias* in beliefs. Controlling

[4]Kuchler and Zafar (2015)' sample starts after the official end of the Recession, in 2012

for individual-level time-invariant heterogeneity proves crucial for this result, and reverses the evidence provided by Case, Shiller, and Thompson (2012), which suggested that in a growth phase people *under-react* to news about the housing market. By including individual-level fixed effects I show that individuals that experience a state-level house price increase (decrease) in the past year worth 1 percentage point, become 0.21 percentage points more over-optimistic (pessimistic) than they were before. This result is also symmetric across the business cycle, holding both during the housing bust, the recession, and the subsequent recovery.

House price expectations seem therefore to follow a representativeness heuristic, as defined by Bordalo, Gennaioli, and Shleifer (2016), where agents overweight information they recently acquired when making predictions about the future. The local nature of my estimations suggests caution in interpreting these results as a rejection of "rational" expectations, since the years between 2007 and 2014 might not be representative of the true long-term dynamics of the US housing cycle. The predictability of forecast errors from past house price information could in principle be reflecting a (long) series of unanticipated shocks in this time frame; moroever, the result might depend on the the fact that "public" information, such as recent growth in house prices, might itself be observed with noise. Nevertheless, this evidence is suggestive that the way consumers form expectations may depart substantially from the standard predictions of economic theory, at least temporarily.

Finally, this paper adds to the existing literature by directly linking expectations to consumers' financial decisions. I use Freddie Mac's Single Family Loan-Level microdata, merged with state/quarter averages of house price expectations measured by the Michigan Survey, to show that house price expectations have a direct, positive, effect on mortgage leverage. The identification of a causal relationship between house price expectations and mortgage leverage is challenging, due to concerns over simultaneity and omitted variables. Therefore, in order to identify the effect of an exogenous shift in housing sentiment on the American mortgage market I exploit an instrumental variable strategy. Mian, Sufi, and Khoshkhou (2015) use the interaction of constituent ideology prior to presidential elections with election timing to show that more progressive (conservative) counties experience a positive shift of feelings about the government whenever the Democrats (Republicans) win the White House. In a similar fashion, I use the interaction of constituent ideology prior to the 2008 presidential election with election timing to show that more progressive states experienced a more positive *housing sentiment* shift around the time of the election, after controlling for pre-electoral trends. I show that this change in house price expectations can be considered exogenous to changes in fundamentals and to post-electoral policy changes that might affect the housing or mortgage markets directly. Most importantly, the shift in housing sentiment appears to be unaffected by changes in other sentiment variables, including feelings about the government as measured by Mian, Sufi, and Khoshkhou (2015).

I exploit this methodology to show that when state-level house price expectations increase by one standard deviation, the leverage ratios on individual-level 30 years fixed-rates mortgages increases by 6% of a standard deviation. In terms of magnitude, this implies that when home buyers expect a one percentage point increase in house prices within the year, their mortgage loan-to-value ratios increase by 0.7 percentage points. The effect is much larger for cash-out refinancing mortgages (1.3 percentage points). This result holds to controlling for an extensive set of individual loan and borrower characteristics; to controls for aggregate time trends (reflecting, among other factors, shifts in federal macroeconomic policy); to the inclusion of geographic area fixed-effects, which capture the state-level time-invariant characteristics that might affect housing markets; and to the inclusion of a wide set of regional time varying controls (including the direct effect of past house price growth).

Moreover, the relationship between sentiment and leverage seems to reflect more strongly a shift in the expectations of consumers, rather than in those of professionals forecasters. The expectations of home builders about the short-term future of regional housing markets do not change in a way that is systematically correlated with regional voting patterns, around election time. In other words, the effect of sentiment on mortgage leverage seems to reflect a shift in the demand of credit, rather than in its supply. This evidence should not be interpreted as implying that changes in credit supply (or lenders' expectation) are irrelevant in determining the equilibrium leverage ratio in the economy. On the other hand my results suggest that, taking credit supply as given, consumer demand and expectations may have an independent role in determining the leverage cycle. This is in line with the results proposed by Adelino, Schoar, and Severino (2016), Albanesi, Giorgi, and Nosal (2017) and Kaplan, Mitman, and Violante (2017), whose contributions indicate that the housing cycle around 2007-2008 has been in part been driven by the expectations of a large cross-section of home buyers, rather than simply by a reduction of the credit constraints on the poorer segments of the population.

This paper draws inspiration from several strands of literature. In particular, my work is closely related to the empirical efforts analysing the expectation formation process, which generally shows that expectations are heterogeneous among agents (Carroll 2003; Branch 2004; Souleles 2004). Recent evidence strongly points in the direction of an extrapolative bias affecting different types of expectations (Malmendier and Nagel

2016; Madeira and Zafar 2015; Greenwood and Shleifer 2014).[5] This paper is most closely related to, and draws inspiration from, Case, Shiller, and Thompson (2012) and Kuchler and Zafar (2015). Case, Shiller, and Thompson (2012) describe house price forecasts using proprietary data on four US metropolitan areas before the crisis, and find evidence of unrealistic long term expectations. Kuchler and Zafar (2015) find that people extrapolate from their personal experiences in two crucial dimension of the macroeconomy: the housing and labour markets. Their beliefs about the future change in a way that is positively correlated with the past. This mechanism might be crucial in explaining the emergence of boom bust cycles in employment and aggregate demand (Eeckhout and Lindenlaub (2015)).[6]

My findings are consistent with theirs, and extend them by describing how extrapolation is symmetrical across the business cycle, taking place in booms as well as in busts. Moreover, by focusing on individual-level forecast errors, this paper is to my knowledge the first to provide evidence of a *systematic* bias in house price expectations formed by American consumers over this time frame.[7]

My work is also related to the literature evaluating whether sentiment has any real effects on consumer and investor behaviour. A recent literature analyses the feedback effects of house price expectations, or their capacity to be self-fulfilling prophecies. In particular, Lambertini, Mendicino, and Punzi (2013) show that during housing booms, expectations about future house price growth account for a large fraction of macroeconomic fluctuations. Ling, Ooi, and Le (2015), Soo (2015) and Wang (2014) show how different measures of housing sentiment can predict subsequent movements in house prices. Using microdata from the Survey of Consumer Finances, Kuchler and Zafar (2015) show that house price expectations are positively correlated with self-reported intentions to invest, while Armona, Fuster, and Zafar (2016) rely on an experimental design to investigate how people form and update their expectations, finding that

[5] Malmendier and Nagel (2011) and Malmendier and Nagel (2016) show that expectations and financial choices depend more strongly on lifetime experiences than on other publicly available data. Madeira and Zafar (2015) confirm this finding with respect to short-term inflation expectations and find that publicly available information matters more for longer horizons. However, evidence of an extrapolative bias is not confined only to inflation expectations. Greenwood and Shleifer (2014) show expected stock market returns are extrapolative in nature, and as such incompatible with rational expectations models of returns.

[6] Two other papers also study the house price expectation formation process: Bover (2015) focuses on the Spanish case, and shows how expectations are heterogeneous and depend upon household-specific characteristics; Niu, Soest, and Arthur (2014) using the Rand American life panel also present evidence that American households failed to anticipate the fall in house prices between 2009 and 2011. My results are consistent with their findings.

[7] The only other contributions testing the rationality of house price expectations is, to my knowledge, Zhang (2016), who focuses on professional forecasters. Zhang (2016), finds evidence of systematic over-optimistic forecasts, but not of inefficiency.

individuals allocate a larger share of resources to the housing budget whenever they expect prices to increase. This paper extends the existing literature by linking house price expectations to *actual* (as opposed to elicited) choices. Closely related is also more recent work by Bailey et al. (2017), who use information on social connections on Facebook to study how beliefs about the future of the housing market shifts consumers' mortgage leverage ratios. Using a proxy for expectations based on individuals' social network, Bailey et al. (2017) find that people with higher expectations have *lower* mortgage leverage at the time of purchase. They interpret this result as evidence that the housing "consumption" channel dominates the housing "investment" channel, which would instead predict higher leverage when expectations increase. The discrepancy between my results and theirs might stem from different factors, particularly the fact that their sample is limited to mortgages for purchase[8], that their geographical focus is limited to the Los Angeles metro area[9] and that they study a very particular demographic group, rather than a representative cross-section of US households.[10] Overall, the literature seems predominantly to point towards a strong feedback effect of house price sentiment on housing market equilibria.

The paper proceeds as follows. Section 2 describes the Michigan Survey of Consumers, presents the results related to how house price expectations depend on individual-level characteristics and studies the formation of house price forecast errors. Sections 3 presents the mortgage-level data, the identification strategy, and the results that relate shifts in housing sentiment to mortgage leverage decisions. Section 4 concludes.

[8]My sample includes refinancing mortgages, while Bailey et al. (2017)'s does not. In their model the "downpayment" motive is crucial to explain how more pessimistic beliefs may lead to higher leverage and *vice versa*, but such motive is absent in the utility function of refinancing homeowners, who do not have to save for a downpayment. These mortgages constitute 67% of my sample- and of US mortgages-and my results suggest that refinancing-cash-out mortgages respond more strongly to shifts in expectations than all other mortgage types.

[9]Their model (and the consumption channel) crucially relies on the possibility of a virtually costless default, allowing purchasers to walk-away from underwater mortgages. This assumption holds in their sample, since they focus exclusively on the Los Angeles metro area, where non-recourse applies (by California law); however, the states where non-recourse applies are a minority in the US (and in my sample).

[10]Their sample (Facebook users in 2015) is very young (38 years old on average) and is composed mainly of first-time home buyers. Clearly, life cycle motives (and income) may lead to different individual to act differently in response to changes in expectations. The consumption channel might dominate early in life, but the investment channel might be more dominant in relatively older cohorts-and as a result in the cross section.

2 Empirical analysis of house price expectations

This section describes the Michigan Survey of Consumers, the data source used to analyse individual-level expectations. It also provides some descriptive analyses of the determinants of individual-level expectations and shows how the data can be used to test the rational expectations hypothesis. Finally, it presents the results of these tests.

2.1 Data: Expectations in the Michigan Survey of Consumers

Data on expectations comes from the University of Michigan Survey of Consumers, the source used to produce the Consumer Sentiment Index. This survey is nationally representative and has been conducted every month since 1978 on a rotating panel of about 6000 US households (500 per month).

The interviews are conducted with one individual per household and include household-level demographics such as income, educational attainment, and family composition, as well as a vast array of sentiment and expectations indicators. In particular, respondents are required to indicate their forecast of the one-year-ahead percentage change in inflation, personal income, and local area house prices. These questions are phrased as:

By about what percent do you expect prices of homes like yours in your community to go (up/down), on the average, over the next 12 months?

Similar questions are asked about the development of personal income and inflation.[11] The descriptive statistics for this sample are provided in panel A of Table 1.

To analyse how individuals' experiences and characteristics influence the expectation-formation process, I estimate the following equation:

$$Expectation_{ist} = \alpha + \Gamma^{I}_{ist} + \Theta^{I}_{st} + \phi_s + \tau_t + \varepsilon_{ist} \tag{1}$$

Where the outcome variable is the individual-level expectation about the change in income, inflation, and house prices in 12 months for individual i living in state s during quarter t. Γ^I is a vector of individual respondent characteristics, such as income, a variety of demographics, and recent experiences. Θ^I measures aggregate dynamics at the state

[11] House price forecasts are only available since 2007 and only for homeowners. For consistency, I therefore drop non-homeowners from the sample altogether. Homeowners constitute 78% of surveyed households.

level in a given quarter, such as recent house price changes, or unemployment rates.[12] Quarter fixed-effects have the purpose of controlling for aggregate shocks affecting all states at the same time, and state fixed effects control for time-invariant factors that might affect all families living in the same state across time.

2.2 Determinants of individual expectations

Aggregate expectations on the growth rates of income, inflation and house prices display a strong correlation with the US business cycle (Figure 1). Both income and house price expectations drop in the aftermath of the 2007/2008 financial crisis. Income growth expectations drop from 3% per year in 2007 to about 1%, and start recovering only in 2013. House price growth expectations follow a similar pattern: they become negative in 2008 and stay negative until 2012. Throughout this time, American consumers were consistently expecting a wealth loss. Expectations about inflation rates, by comparison, have been remarkably stable throughout this time frame. With the exception of a spike in the second quarter of 2008, inflation expectations have been averaging around 4% over this time frame.

Table 2 sheds some light on how household-level demographics are correlated with different measures of expectations. Richer and older couples have on average lower income expectations than younger, poorer, and single individuals (Column 1). This probably reflects the lifecycle of earnings. On the other hand, men and people with a college degree expect their earnings to grow more than other demographic groups. People who report experiencing negative income shock in the previous year (measured as job loss or reduced wages/working hours) expect their income to grow 2 percentage points less than others. This is coherent with recent evidence showing that negative shocks at the personal level cast a shadow of pessimism on agents' beliefs about the future. For example, individuals who experienced a negative stock market shock are more risk-averse and less likely to predict high returns on investment (Malmendier and Nagel 2011).

The effect of unemployment rates confirms this intuition: one standard deviation increase in state-level unemployment rates reduces individual income expectations by 4% of a standard deviation. This can be considered evidence corroborating the findings of Kuchler and Zafar (2015), who find that experiencing unemployment systematically makes people more pessimistic about the future of the labour market.

[12] Details of the state-level control variables can be found in Appendix A.1 and the relative descriptive statistics in Panel C of Table 1.

Inflation expectations display different correlations with household demographics (Column 2). Richer and more educated males expect future inflation to be lower than poorer and less educated women, or older people. This is consistent with the results presented by Madeira and Zafar (2015), who find that women, ethnic minorities, less educated and lower-income people predict higher inflation, on average. They also find that these social groups are slower in updating their expectations, and make more prediction errors. Madeira and Zafar (2015) interpret their results as indicative of differentials in the ability to collect and process public information across different types of agents.

My results also indicate that stock owners expect lower levels of future inflation. If social groups with lower inflation expectations are also generally correct more often, as Madeira and Zafar (2015) suggest, this evidence may be consistent with a theory of the heterogeneity in expectations being based on information. Stock market exposure may induce people to follow financial news more closely, and this may in turn develop their ability to better assess market conditions. On the other hand, people who are more financially literate probably also self-select in stock ownership. Access to information, as well as information processing ability (financial literacy) may therefore play a crucial role in explaining heterogeneity in inflation expectations, as suggested by Burke and Manz (2014). People who recently experienced a negative income shock, on the other hand, forecast future inflation to be higher, giving further credit to the idea that personal experiences matter for relative optimism/pessimism about the future.

Despite the relative stability of house price expectations over time (Figure 1), both house price expectations and changes in actual house prices display a large degree of variation, in the cross section (Figure 2). Column 3 of Table 2 studies the sources of this heterogeneity. Richer households, men, and college graduates expect house prices to grow more, as do people who own stocks. This might in part be due to unobserved within-state heterogeneity: these households may be more likely to reside in cities, where house prices are likely to have different price dynamics than the state average.[13] On the other hand, it may also be that these households are actually better informed, and correctly anticipated the decline in prices around 2008 and a more rapid recovery in the post-crisis period. Less informed households may be more prone to cognitive biases and may be slower in updating expectations, as suggested by Madeira and Zafar (2015). They may therefore have projected the housing market shock to continue well beyond 2011. Once again, people who recently experienced a negative income shock are less optimistic about the future.

An interesting result of the specification in Table 3, Column 3, is that the average yearly

[13] I observe the state of residence for any given household, but not the county or ZIP code.

house price growth in the state of residence (measured as the average percentage change in the year prior to the interview) is a strong predictor of expectations about future house price growth. A household experiencing a 1 percentage point increase (decrease) in state-level house prices in the previous four quarters predicts the one-year-ahead increase(decrease) in local house prices to be 0.13 percentage points higher(lower), which corresponds to 10% of a standard deviation in the dependent variable. This coefficient is significant at the 1% level and is close to the elasticity of 0.23 estimated by Case, Shiller, and Thompson (2012), and virtually identical to that of 0.1 estimated by Kuchler and Zafar (2015), in a similar exercises, albeit using different data.[14]

This result is confirmed when measuring house price expectations in *real* terms, defined as individual house price expectations minus the individual 1 inflation expectations at the one-year horizon (Table 2, Column 4). When people experience house price growth, they expect house prices in their community to grow faster *than other prices*. The sign, magnitude and significance of this coefficient are very close to the coefficient estimated for simple house price expectations (Column 3). In other words, when people experience house price increase they expect house prices to grow *more* than general CPI.

This evidence suggests an extrapolative pattern: if individuals experience house price growth in their state of residence, they expect the trend to continue in the near future. Such result is consistent with other recent empirical studies focusing on different kinds of expectations and provide evidence for an extrapolative component of investors'beliefs about the future that largely depends on recent experiences (Malmendier and Nagel 2016; Madeira and Zafar 2015; Greenwood and Shleifer 2014; Kuchler and Zafar 2015).

The extrapolative pattern in house price expectations is heterogenous across the population (Table 3). Interaction terms between state-level price growth and individual demographics suggests that this effect is stronger in people with higher income and education, and weaker in older people (Columns 1, 2 and 3). This is likely to reflect the role of some unobservables factors, in particular the precise geographic location of these households in any given state. Younger, richer and more educated individuals are more likely to live in cities, and it is possible that house price dynamics in urban contexts differ substantially from state-level averages.

The extrapolation from past price growth does is not significantly different between the years of the crisis (2007-2008) and the rest of the time frame (Column 4). Albeit individuals interviewed during the Recession (2009-2011) are less likely to extrapolate from recent house price changes than in other periods (Column 5), the cofficient is still

[14] Kuchler and Zafar (2015) use the Survey of Consumer Finances, study a different time frame (2012 onward), and measure house prices at the local (ZIP) code area rather than at the state level. Case, Shiller, and Thompson (2012) focus on the pre-crisis period and on four metropolitan areas.

positive even during this time frame.

Overall, this section shows that expectations are highly heterogeneous across households. Different demographic groups display systematic differences in the way they think about the future. This seems to contradict the tenet that private information plays no role in the expectation formation process, and that therefore all expectations can be approximated by those of a representative agent (Muth 1961). On the other hand, it does not necessarily contradict the hypothesis that expectations are formed efficiently overall, since from the point of view of the individual it may be optimal to choose different forecasting methods depending on personal circumstances, or different individuals might have differential access to information (Pesaran and Weale 2006).

2.3 Testing the efficiency of expectations: methodology

Tables 2 and 3 show that people form expectations about the future based on the information available to them at the time they make the forecast. Economic theory adds to this tenet the notion of *optimality* in the use of publicly available information: individuals might make mistakes in their predictions, but the economic system in the aggregate does not waste information. In this sense, expectations are assumed to be rational, or consistent with the predictions of the relevant economic theory (Muth 1961).

Muth (1961) postulates that private information plays no role in the formation of macroeconomic expectations. Moreover, expectations should be *fully efficient* with respect to publicly available information. Given a variable Y, its value at time t, (Y_t) should be perfectly predicted by the ex-ante expectations of the representative agent, defined as $E_{t-n}(Y_t)$. Any vector of public information available to the agent at time *t-n* (X_{t-n}) should have no additional explanatory power towards Y_t. Formally:

$$Y_t = \alpha + \beta_1 E_{t-n}(Y_t) + \beta_2 X_{t-n} + \varepsilon_t \tag{2}$$

with $\alpha = \beta_2 = 0; \beta_1 = 1; E(\varepsilon_t) = 0$.

Forecasts may diverge from realizations, but the errors will average out to zero over time, and they won't be *systematic*. This, in turn, implies orthogonality between ex-post forecast errors (FE_t) and all public information available to the agent at the time the forecast $E_{t-n}(Y_t)$ was made:

$$FE_t = Y_t - E_{t-n}(Y_t) = \alpha + \beta_2 X_{t-n} + \varepsilon_t \tag{3}$$

with with $\alpha = \beta_2 = 0; E(\varepsilon_t) = 0$.

In other words, under rational expectations forecast errors should be unpredictable given the set of public information available to the agent at the time the prediction was made (Muth 1961; Lovell 1986).

To study the (in)efficiency in the development of expectations, I construct individual-level house price *forecast errors*, defined as follows:

$$FE_{ist} = E_{ist-4}(HPI_{st}) - HPI_{st} \tag{4}$$

Where $E_{ist-4}(HPI_{st})$ is the expectation that individual i living in state s at quarter *t-4* has about house price growth in state s at time t (percentage house price growth in one year). This forecast is compared with the actual annualized change in house prices recorded in quarter t for state s, as measured by the Federal Housing Finance Agency (FHFA) quarterly repeated sales house price index, HPI_{st}.[15] FE_{ist} therefore represents individual-level *forecast errors*: unlike in equation (3), a larger value implies over-optimism.

Note that equation (4) introduces individual-level heterogeneity in the definition of forecast errors, which was absent from equation (3). The presence of individual-level heterogeneity in expectations, described in the previous section of this paper, suggests that also the forecast errors FE_{ist} are unlikely to be orthogonal to the private information set, defined by individual characteristics.

It is not clear yet how to test for efficiency of forecasts in the presence of individual-level heterogeneity (Pesaran and Weale 2006). Heterogeneous individuals may have different information processing costs, and it may be optimal for them to choose different forecasting methods (Pesaran and Weale 2006). Moreover, agents may have differential access to information. I will therefore focus on whether *public* information (specifically past house price growth in the area of residence) is processed efficiently, on average.

I therefore exploit the panel component of the survey, which provides two observations

[15] Information about the house price index, together with other aggregate controls, can be found in Appendix A1.

per individual, to study how public information translates into changes in individual-level forecast errors.[16] To do so, I use a model in first-differences:

$$\Delta FE_{ist} = \alpha + \beta_1 \Delta\Gamma^I_{ist} + \beta_2 \Delta\Theta^I_{st-n} + \tau_t + \phi_s + \varepsilon_{ist} \tag{5}$$

Where $\Delta FE_{ist} = FE_{ist} - FE_{ist-2} = [E_{ist-4}(HPI_{st}) - HPI_{st}] - [E_{ist-6}(HPI_{st-2}) - HPI_{st-2}]$ is the difference between individual i's forecast errors between the first and the second interview (which are two quarters apart from each other), where s and t indicate state and quarter, respectively. $\Delta\Gamma^I_{ist}$is a vector of changes in family-specific controls between the first interview and the second one, such as household income, plus the same household-level demographics used in equation (1) measured at the time of the latest interview. $\Delta\Theta^I_{st-n}$ defines changes in state/quarter variables, such as the average yearly growth in house price (measured in the quarter *prior* to each interview, since this vector needs to reflect information *available* to individuals *when they made the forecast*).

By first-differencing the outcome variable, the model controls for all time invariant household-level characteristics related to idiosyncratic perceptions of the housing market.[17] First-differencing should also control for all individual level heterogeneity that can be reasonably assumed to be constant for a given individual within six months, such as information processing capacity and financial literacy. With only two time periods, this model is equivalent to an individual-level fixed effects estimation (albeit in a limited sense, since ideally one would want to control for the individual trend over a longer time series).

The model in equation (5) allows for the identification of systematic components in consumers' forecast errors. From the point of view of theory, significant coefficients on any variable within the information set available to the agent at the time they produce the forecast (any β_1 or $\beta_2 \neq 0$), imply a departure from a strong form of rational

[16]An alternative would be to estimate a model with state-level averages in house price forecast errors as a dependent variable. The results are very similar in nature, magnitude and significance, with respect to this model in changes. I therefore prefer to maintain micro-level variation and use a model in changes at the individual level instead.

[17]For example, individuals might be forecasting house price growth for their local area of residence (ZIP code or city) rather than for their state. Since I construct individual-level forecast errors as a the difference between the individual-level expectation and the state-level realization, the dependent variable might contain measurement error (the difference between local and state-level house price growth). As long as this difference is constant over six months (and individuals don't change their place of residence over the interviews), the model in changes should take into account this unobserved variation. However, even if the difference between state and local area house price growth were to change over time, this difference will appear as measurement error in the *dependent* variable. As long as the measurement error in the dependent variable is uncorrelated with the right-hand side of equation (5), the estimation will be consistent.

expectations (Lovell 1986). On the other hand, for even a weak form of unbiasedeness and efficiency (rationality) to hold, the prediction errors must at least be independent from historical information on prior realizations of the variable being forecast: formally, β_2 must be equal to zero, whenever Θ_{st-n} measures past house price realizations (Lovell 1986).[18]

2.4 Results: house price forecast errors

House price forecast errors do not cancel each other out in the aggregate, and display a strong time component in this sample (Figure 3). They are systematically positive, implying excessive optimism, at the beginning of the financial crisis (2007q1 until 2010q4). In mid-2011 they turn to be consistently negative, or over-pessimistic, indicating that American consumers have on average underestimated the recent recovery of the US housing market.

The first two columns of Table 4 analyses how forecast errors depend on household characteristics. Column (1) describes forecast precision: the dependent variable is the absolute value of forecast errors. The closer this value is to zero, the higher the precision of the forecast. Richer households, men, people with higher education degrees and households who invest in the stock market have more accurate estimates about the future of the housing market. The effect of owning stocks is small, but strongly significant: stock owners make predictions that are on average 0.3 percentage points more accurate than non-stock owners (or 5.7% of a standard deviation in the dependent variable). This is also true of more educated families: the effect of having a college degree improves the accuracy of the house price forecast by 0.14 percentage points, or 2.6% of a standard deviation in the dependent variable. This seems consistent with what Madeira and Zafar (2015) find about household-level heterogeneity in inflation expectations: women, less educated people, and poorer households tend to have more imprecise forecasts. This result provides further support for the hypothesis that access to information, or the ability to process it, might play a crucial role in the expectation formation process. People who recently experienced negative income shocks also tend to have less precise forecasts. It is interesting to notice that errors do not cancel out over time:the constant in this model is significantly different from zero (+6 percentage points, significant at 1% level).

However, forecast errors can also be analysed with respect to their relative degree of

[18] This version of the rational expectations hypothesis is weak in that it only requires the agent to efficiently process the information related to the historical realizations of the variable s/he is forecasting rather than *all* available public information.

optimism and pessimism, rather than in absolute values. Column (2) shows the results of a model with the forecast error defined as in equation (4): a positive value in the dependent variable now implies excessive optimism about the future of local house prices. Richer households, men, and college graduates tend to have more positive forecast errors: in other words they are wrong less often (as shown in Column 1), but when they are, their mistakes are on the optimistic side. A negative income shock, on the other hand, makes people excessively pessimistic about housing market returns (Column 2): a family declaring a negative income shock in the previous year predicts a house price growth at the on-year horizon 0.74 percentage points lower than the actual realization (about 10% of a standard deviation in the dependent variable).

The simple correlation between forecast errors and past house price growth seems to suggest that individuals under-react to recent news about the housing market, expecting excessive mean reversion in house prices (Table 4, Column 3). However, this effect differs over time. Ahead of the housing crisis (2007 and early 2008), a house price growth (decline) in the state of residence was correlated with over-optimism (pessimism) about the future of the housing market (Column 4), implying extrapolation from recent price trends. After the crisis, and during the recession and recovery, there is a sign switch and house price growth (decline) at the state level was correlated with average over-pessimism (optimism), implying that individuals who experienced losses were expecting excessive gains in the housing market, and *vice versa* (Column 5). This evidence, estimated during a time frame of recovery, would confirm the results of Case, Shiller, and Thompson (2012), who find evidence of unrealistic long-term expectations but of under-reaction (excessive mean reversion expectations) in the short term.

These results suggest some inefficiencies in the use of information, when consumers form expectations about the future. However, such heterogeneity and the predictability of forecast errors could be caused by the fact that different individuals have differential access to public information; or that private information plays a role in determining house price expectations; or, again, that the same public information is optimally processed in different ways by different individuals. So far, consensus has not emerged yet on how to distinguish between these alternative hypotheses (Pesaran and Weale 2006). In other words, the results presented in Table 4 do not allow to understand whether public information (such as recent house price growth) is processed efficiently by the aggregate economy, of whether such inefficiencies instead depend upon unobserved individual characteristics.

Table 5 therefore shows the results of a model in first-differences at the individual level, in order to control for time-invariant individual-level heterogeneity-or the baseline level of over-optimism (pessimism) of each respondent. This is an attempt to mitigate any differences due to *private* information and household-specific characteristics, such as financial literacy, forecasting methods, area of residence within a state, which can be reasonably be assumed to be time invariant over six months. This specification, in other words, attempts to evaluate whether the economy in the aggregate processes *public* information efficiently, by analyzing whether changes in individual forecast errors are efficient with respect to past information about local area house price growth.

Even in such a restrictive model, a recent history of housing appreciation is strong predictor of changes in forecast errors (Table 5, Column 1).[19] An increase in state-level house prices worth 1 percentage point in the year before the forecast was initially made is correlated with an increase in individual forecast errors worth 0.21 percentage points(significant at the 1% level). In other words, if individuals experienced a state-level house price increase (decrease) in the past year worth 1 percentage point, their forecast errors about the future of the housing market tend to become 0.21 percentage points more over-optimistic(pessimistic). By comparison, a similar increase in personal income between the two interviews affects forecast errors by 0.3 percentage points, but the estimate is much more imprecise. The extrapolation bias in house price expectations is detectable both before and after the year 2008 (Column 2 and Column 3). In fact, from 2009 onward the extrapolation from recent house price growth gained strength (Column 4).

These results hold to controls for a variety of individual-level controls as well as aggregate time trends (quarter fixed effects) and state-specific characteristics. The inclusion of quarter fixed effects should also rule out the possibility that the forecast errors may be due to unexpected US-wide macroeconomic shocks, since all aggregate time trends are taken into account.

The latter result suggests that households may not be efficiently processing public information about house price growth. Consumers attach too much weight to recent house price movements, and forecasts have a tendency to become over-optimistic when they are formulated after a period of house price growth, and *vice versa*.[20] Taken literally, this result supports the idea that house price expectations may not conform to (weak) rational expectations theory and as a consequence that housing markets may be subject

[19]To avoid simultaneity, past housing appreciation is measured as the average yearly house price growth measured in the year ahead of the first interview.

[20]Table 1 in Appendix A2 shows the extrapolative bias is particularly pronounced for certain socio-demographic groups. In particular richer and more educated people seem more subject to extrapolation from recent price movements. Investigating the reasons for these differences would require more detailed information on the respondents,particularly about the geographic area of residence of each given household, to rule out the possibility that this heterogeneity stems from the particular characteristics of the areas where they live.

to purely belief-driven boom and bust cycles, in which prices can be largely detached from fundamentals and be subject to endogenous excess volatility (Bordalo, Gennaioli, and Shleifer (2016)). I nevertheless refrain from attaching such a strong interpretation to these results: the possibility that people were hit by a long series of state/time varying unexpected shocks in this time period remains, and therefore the non-convergence of forecasts errors to zero over time might reflect such shocks, rather than a departure from rational expectations. Also, it is plausible that the time frame upon which consumers' expectations average out to zero (the constant in equation 5) is longer than ten years, due to the particular "length" of the housing cycle. Regarding the predictability of forecast errors from past local house price growth, it is important to stress that most people make very few housing transactions in their lifetimes and therefore might never be able to fully internalize "public" information. Nevertheless, these results are suggestive that the expectation formation process might depart substantially from the predictions of the relevant theory, at least temporarily.

3 House price expectations and the credit cycle

Understanding how consumers form expectations matters, if expectations help understanding fluctuations in real economic activity. Expectations data based on survey responses may contain large amounts of noise, but the question of whether such data contains also useful information is ultimately an empirical one. Its answer relies on the capacity that expectations have in predicting people's *actual* (as opposed to elicited) choices.

Given the link between housing collateral and mortgage debt (Mian and Sufi 2011), it is particularly interesting to study whether house price expectations affect mortgage borrowing behavior. In this section, I first describe the problem of identifying a causal relationship between house price expectations and mortgage markets, and present the empirical strategy I will use to address this problem. I then describe the mortgage data, which is derived from a publicly available, lender-side source. Finally, I present evidence of the empirical relationship between house price expectations and mortgage borrowing.

3.1 The identification problem: IV strategy

House price expectations display a strong positive correlation over time with average mortgage leverage recorded among American households (Figure 4). If individuals expect the value of their properties to rise, they might borrow against the expected increase in home equity, because a part of the loan will be automatically repaid by the price increase. At the same time banks might be willing to lend larger sums, because of the expectations of higher collateral in the near future.

The Michigan Survey of Consumers does not provide data on financial liabilities, but information on mortgage leverage at the household level is available from other publicly available data sources. Micro data on individual mortgage originations can be merged with state/quarter averages of house price expectations observed in the Michigan Survey of Consumer to estimate a model of the type:

$$LTV_{ist} = \alpha + \beta_1 Exp_{st} + \beta_2 \Gamma^I_{ist} + \beta_3 \Theta^I_{st} + \phi_s + \tau_t + \epsilon_{ist} \tag{6}$$

Where LTV_{ist} is the individual mortgage loan-to-value ratio, a measure of leverage, for family i residing in state s in quarter t. Exp_{st} defines the weighted average of expectations in state s at quarter t recorded by the Michigan Survey of Consumers. Γ^I_{ist} is a vector of household-level controls, which includes the credit score of the borrower, interest rate, length and purpose of the loan. Θ^I_{st} defines control variables recorded at the state/quarter cell, which might contemporaneously affect expectations and the dependent variable (such as recent state-level house price growth).

Quarter fixed effects allow to control for economy-wide shocks, for example federal policy changes affecting all states at the same time. State fixed-effects instead control for time-invariant state-specific characteristics, which could be correlated with both sentiment and mortgage markets. The use of micro data combined with geographic and time fixed effects assimilates equation (6) to a fuzzy difference-in-differences approach: β_1 measures whether how change in state-level expectations over time affects leverage ratios on mortgages that are otherwise similar over a set of characteristics Γ^I_{ist} and Θ^I_{st}.

However, the change in expectations in equation (6) is not exogenous; in fact, this model is subject to several endogeneity concerns. First of all a higher availability of credit is likely to trigger a change in aggregate expectations about the future of house prices, generating concerns about reverse causality. Furthermore, expectations and outcomes are likely to be simultaneously affected by various unobserved factors occurring at the state/time level (such as changes in policy). In order to identify the effect of a shift in house price expectations, I therefore rely on an instrumental variable strategy.

Mian, Sufi, and Khoshkhou (2015) show that that the ideological predisposition of residents in a county (Republican VS Democrats) is a strong predictor of within-county changes in sentiments regarding government policy, anytime there is a *change* of government in the White House. In particular, Republican-leaning counties become more pessimistic about government policy when Democrats win the presidential elections, and *vice versa*.

However, there is evidence that large-scale electoral events shift all measures of consumer sentiment, and not just views of the government. Gerber and Huber (2009) and Gerber and Huber (2010) exploit an unanticipated change in political power (the Democrat takeover of Congress occurring in 2006) to show that pre-electoral political leanings have a strong effect on the changes in *economic opinions* after the election. Immediately after the event, Democrats become more optimistic about the general economy than they were the month before, and Republicans' sentiment shifts in the opposite direction.

This suggests that housing expectations might also be subject to changes around election time, whenever there is a change in party at the White House. The housing market could be particularly affected by elections due to the role of pre-electoral uncertainty. Pre-electoral uncertainty may reduce investments that are costly to reverse: Canes-Wrone and Park (2014) find evidence of this effect across the US at the turn of the 2008 Presidential election. The extent of the reversal of this uncertainty after the election may depend upon the ex-ante political views of a certain electorate and interact with the party change at the White House. I exploit this idea to evaluate how the change in house price expectations following the 2008 presidential election affects mortgage leverage ratios.

My empirical strategy is formally expressed by equations (7) and (8).[21] The first stage relationship measures the within-state change in expectations occurring after the presidential elections that resulted in a change in party at the White House. This equation takes the form:

$$E_{st} = Z_{st} + D_{st} + \delta_t + X^I_{st} + \Lambda^I_{ist} + \phi_s + \tau_t + \varepsilon_{st} \tag{7}$$

Where E_{st} are state-level expectations about one-year change in house prices, measured as a weighted average of the individual level forecasts provided by the Michigan Survey in a given state s and quarter t. Z_{st} is the interaction term between the vote share for the Democratic Party in a given presidential election (D_{st}) and the post electoral period δ_t (the quarter of the election is excluded from the analysis). State fixed effects,

[21]I apply a very similar methodology to Mian, Sufi, and Khoshkhou (2015) although I rely on state-level measures of sentiment and political leanings, rather than on county-level data. Also, my time series is shorter, because the Michigan Survey only began collecting information on house price expectations in 2007.

ϕ_s, capture time-invariant state characteristics while quarter fixed effects, τ_t, control for economy-wide time trends such as the US-wide shift in housing sentiment occurring in 2007. If Z_{st} is significant and positive, progressive states get more optimistic about the housing market than conservative states, and this shift occurs *after* the electoral period.

It is important to stress that the vote shares for the Democratic party are *not* assumed exogenous in this model: partisan leanings can be strongly correlated with long-term housing price dynamics, such as the willingness to issue new building permits (Kahn 2011).[22] The validity of the instrumental variable strategy relies on the exogeneity of the *interaction* between partisanship and electoral timing.

The vector X^I_{st} is a set of variables that proxy for changes in fundamentals which could impact states exactly at the time of the elections. This set of controls includes past changes in house prices, which might affect both expectations and loan-to-value ratios directly. The vector Λ^I_{ist} includes individual-level characteristics: average income, age, credit score of the borrower, and some of the characteristics of the loan (length in years, interest rate, type and purpose of the mortgage, use of the property).[23] The inclusion of these variables has the purpose of building further credibility to the orthogonality condition: the exclusion restriction is valid after partialling out for these shocks in fundamentals.

I will run a series of robustness tests on the first stage relationship to show that the switch in housing sentiment can be considered exogenous to a set of macroeconomic fundamentals. I also show that the switch cannot be attributed to multiple changes in state-level housing policy taking place after the elections and that it is robust to shifts in other expectations and sentiment variables occurring at the same time, including views of the government (as measured by Mian, Sufi, and Khoshkhou (2015)).

The second stage relationship exploits mortgage-level data to measure how house price expectations affect borrowing/lending. This relationship is defined as follows:

$$LTV_{ist} = \alpha + \widehat{E_{st}} + D_{st} + \delta_{st} + \Lambda^I_{ist} + X^I_{st} + \phi_s + \tau_t + \varepsilon_{st} \tag{8}$$

Where LTV_{ist} is loan-to-value ratio for household i, in state s, at time t. The dependent variable is regressed upon the same set of controls in (7), with the housing sentiment

[22]In practice, given that my time series only includes one change in party in the White House (the 2008 presidential election, D_{st} is time-invariant at the state level and is absorbed by state fixed-effects.

[23]The inclusion of this vector in the first-stage relationship is necessary for the consistency of the IV estimator.

variable at time t ($\widehat{E_{st}}$) instrumented by Z_{st}.

The validity of this instrumental variable strategy deserves some further discussion. Mian, Sufi, and Khoshkhou (2015) use the change in presidency to evaluate how sentiment *towards the government* affects household consumption. This might somewhat undermine the credibility of my empirical results, because the exclusion restriction in equation (8) might be violated. In particular, the concern might be that feelings about the government might be driving the second stage results, rather than house price expectations. However, my results are robust to the inclusion of controls for other sentiment variables: not only feelings about the government, but expectations about future income, inflation and interest rates. Often, such variables display a much lower correlation with mortgage leverage ratios (and with election cycles) than house prices expectations do, both over time and in the cross-section. Moreover, I believe this particular concern about the validity of the instrument to be of second-order relevance: Mian, Sufi, and Khoshkhou (2015) show that shifts in government sentiment after the election have *no significant effect* on household consumption over the same time period. If feelings about the government do not shift short-term consumption habits, there is no reason to believe that they will influence long-term saving decisions such as mortgage borrowing.

3.2 Mortgage data

The Michigan Survey does not include data on households' balance sheets. In order to identify whether house price expectations matter for mortgage leverage choices I rely on a different data source.

The data on individual-level mortgage transactions comes from the Single Family Loan-Level Data set, provided by the Federal Home Loan Mortgage Corporation (Freddie Mac). While some surveys collect information about American households' financial liabilities, using mortgage information provided by the lender provides several advantages. The first is coverage: Freddie Mac's database collects information about over 20 million residential mortgages securitized across the United States between 1999 and 2015. Freddie Mac's share of mortgage-backed securities currently corresponds to roughly a third of the American market in terms of number of loans, and 14% in terms of volume.[24] The second advantage of this data set is its precision and quality. As this is lender-level data, it is much less likely to contain measurement error. It also provides information

[24] http://www.freddiemac.com/investors/pdffiles/investor-presentation.pdf; Federal Reserve Board Data, Mortgage Debt Outstanding, March 2016.

unavailable in most surveys, such as credit score of the borrower or the length of the mortgage in years.

Freddie Mac provides a sample of about fifty-thousand observations per year which are randomly drawn from the overall population. I rely on this sample because it makes the estimations less computationally intensive while matching the moments of the distribution of the overall population very closely.[25]

After the Federal Housing Finance Regulatory Reform Act of 2008, the Agencies (as Freddie Mac and Fannie Mae are commonly referred to) were put under federal administration and are now running under the conservatorship of the Federal Housing Finance Agency (FHFA). Since the federal government is ultimately responsible for the Agencies' solvency, both have strict rules about the characteristics of the mortgages that fall under their umbrella. Loan values cannot exceed certain nominal limits, which are determined annually by the FHFA, depending on the geographical area where the house is located. The Agencies are also required to back only prime mortgages, and jumbo loans are excluded from their portfolios. This data set in particular is composed only of 30-year fixed-rate single-family mortgages, which nevertheless constitute the most common type of mortgage on the American market, making up on average 83% of the stock of loans originated in a given year (Fuster and Vickery 2015). In this sense, this data set represents the most conservative side of the American mortgage market, both in terms of lending risk and overall leverage.

The descriptive statistics for this sample can be found in panel B of Table (1). The outcome variable I will consider is the individual mortgage loan-to-value ratio. This is the ratio of the loan to the value of the property as appraised by the lender (or the original property value at the time of purchase, if the owner can prove that the value of the property has not declined since then). Clearly, this is an equilibrium variable, because it reflects credit supply and credit demand at the same time.

The average mortgage securitized by Freddie Mac in this time frame is worth 69% of the property value and its length is 26 years. About 47% of the families have not been homeowners in the past three years and as such are labelled in the database as first-time home buyers. The vast majority of borrowers live in the property, since investment loans are only 6% of the total. On the other hand, a large fraction of the loans have the purpose of refinancing since purchase mortgages are the minority (37%).

[25] All relevant comparisons between the sample and the population are included in the material provided by Freddie Mac at http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.html

3.3 First stage: housing sentiment and elections

Column 1 of Table 6 estimates equation (7), the first-stage relationship. The relationship between house price expectations, partisan leanings and electoral outcomes is strong: the interaction between ex-ante state-level voting share for the Democratic Party, and a dummy indicating the post 2008q4 period, displays an elasticity of +0.06 (significant at 1 percent level). Since this model includes state fixed-effects, it reflects the change within the state over time, so it controls for pre-electoral trends. Moreover, the general change in sentiment occurring after the election (or US-wide policy changes) that affect all states equally at any given point in time are captured by quarter fixed-effects. This coefficient reflects the higher-than-average optimism about the future of the housing market occurring in democratic-leaning states after the election (after controlling for their pre-electoral trends in expectations).

This model also includes controls for whether this shock was due to changes in fundamentals. For example, if Democratic states experienced an income shock after the election, or a stronger house price growth, the coefficient associated with the interaction term would be capturing a spurious correlation between the electoral outcomes and the sentiment variable. Consistently with the results presented in the first section, house price expectations are strongly correlated with past house price growth, but other controls, such as changes in aggregate income, unemployment rates or population growth are not significant.

Also, the relationship between the interaction term and the post-electoral shift in house price expectations holds to the inclusion of other sentiment variables, such as inflation expectations and feelings about the government (which are likely to shift with changes in party at the White House). The coefficient associated with the interaction term is still positive, similar in magnitude and significant at the 1% level.

Given that the shift in presidency in 2008 affects house price expectations, if house price expectations affect mortgages a relationship between the potential instrument and loan-to-value ratios should emerge. The reduced-form equation (Column 3) shows that the coefficient associated with the interaction term is positive (+0.05) and statistically significant at the 1% level. Other sentiment variables do not, on the other hand, show any statistically significant relationship with mortgage leverage ratios.

The Democratic vote share in a given state is positively associated with an increase in the individual-level loan-to-value ratios, in the post-electoral period. In the remaining part of this section, I run a series of robustness tests aimed at verifying the validity of this instrument and testing the credibility of the exclusion restriction.

Post electoral policy changes

Political leanings might directly affect housing markets in the post-electoral period, for example by changing the local housing policy. Local housing policy might lead people to act differently with respect to the housing market, independently from house price expectations. In this case the exclusion restriction would be violated. For example, if Democratic states changed the provision of housing benefits after the 2008 election, a fraction of poorer citizens might have been pushed into the private residential market, changing the overall leverage ratios in the economy.

Table 7 runs some robustness checks, testing whether Democratic-leaning states experience relevant policy changes in the housing sector in the post-electoral period. More progressive states did not change housing benefits in the post-electoral period. The percentage of citizens relying on public housing is not significantly affected by political leanings in the post-electoral period (Column 2), nor is the number of people relying on rent subsidies (Column 3).

A different kind of concern relates to Democratic states receiving a more favorable treatment in the post electoral period from the Federal government, for example in terms of real estate taxation. If Democratic constituencies experienced a decrease in property taxes after the election, this might increase people's willingness to buy a house, and possibly increase average loan-to-value ratios. Column 4 shows that this is not the case: the coefficient of the interaction term on average property taxes (in logs) is positive and not significant.

Finally, political views might change the housing supply dynamic after elections such as a change in the regulatory framework. However, the housing regulatory framework, proxied by the number of building permits issued in a given state/year, is not significantly affected by the interaction between Democratic vote shares and the post-electoral period (Column 5). Ex-ante political leaning doesn't seem to change housing supply dynamics also when looking at construction costs (Column 6): the average wages in the construction sector, which are the component of building costs more likely to differ across states, are also unaffected by partisanship and election timing.

Overall, there is no clear relationship between ex-ante political views and within-state policy changes in the post-electoral period which might impact the housing or mortgage markets directly.

Other sentiment variables

The baseline specification presented in Table 6 controls for some of the fundamentals which might affect the regional economies at the time of the elections. However, the change in party at the White House might affect other sentiment variables, which could also have an impact on borrowing and saving decisions. It is important to understand if the post-electoral shift in housing sentiment is not actually concealing a more general optimism about the economy. In particular, Mian, Sufi, and Khoshkhou (2015) show that the percentage of the population expressing a positive opinion about the government shifts dramatically after the US presidential elections, the direction of such change depending on the partisan leanings of a given constituency. Other expectations about macroeconomic policy, such as inflation rates and interest rates, might also be influenced by a change in government. Therefore, it is necessary to clarify the role of other expectations in the first-stage relationship.

Table 8 addresses this issue by studying the state-quarter average of other sentiment variables measured by the Michigan Survey of Consumers. The interaction between ex-ante political views and electoral outcomes has no significant effect on personal income expectations(Column 1). However, more progressive states view the election of a Democratic president as beneficial for their income in real terms, as they expect the inflation rate to be lower in the subsequent 12 months (Column 2). Consistently with Mian, Sufi, and Khoshkhou (2015), I find that the proportion of individuals reporting a positive view of the government increases substantially after 2008, depending on the share of votes that the Democratic party received in the election (Column 3). Interestingly, there is no change in interest rates expectations following the election (Column 4). This is reassuring, as interest rate expectations may be a main driver of mortgage market dynamics.

Moreover, the first-stage relationship is robust to the inclusion of other sentiment variables. The coefficient associated with the interaction term maintains its sign, magnitude and significance when expectations about income, inflation, interest rates and views of the government are included in the model (Column 5). As a further robustness test, Column 6 tests whether real house price expectations (deflated by state/quarter averages of inflation expectations) also change after the election. Indeed, this is the case: progressive-leaning states shift their expectations towards optimism in the post-electoral period, expecting the value of their homes to grow more than inflation.

In sum, partisan leanings are a strong predictor of changes in house prices and inflation expectations as well as in the views of the government, after the 2008 presidential election. However, the first-stage relationship between elections and housing sentiment holds after controlling for these factors.

Placebo test

The mechanism through which a change in party at the White House may affect house price expectations is through a reversal of pre-electoral perceptions regarding the government capacity to run the economy. When there is a change in party, voters who voted for the winning candidate naturally trust the government more than those who voted for the losing party, and become more optimistic about their future economic perspectives. This optimism reflects in particular on housing, since pre-electoral uncertainty may reduce investments that are costly to reverse. Canes-Wrone and Park (2014) find evidence of this effect across the US precisely at the turn of the 2008 Presidential election.

House price expectations for Democratic states indeed shifted dramatically between q3-2008 and q1 2009, and remained on average higher than expectations in Republican-leaning states throughout the Obama presidency (Figure 5).[26] In 2012, however, when the incumbent President ran for office and obtained a second term, there was no reason for Democratic (or Republican) constituencies to significantly shift their expectations, since the party in charge remained the same. The shift in house price expectations after the third quarter of 2012 is much weaker than in 2008 (Figure 5).

In other words, as Mian, Sufi, and Khoshkhou (2015) point out, the within-region change in sentiment should be driven by a *change* in party in the White House. This provides a placebo test. If the first-stage equation really reflects a shift in sentiment, rather than a change in unobservables, I should not register a significant shift in house price expectations after the victory of an incumbent President in 2012.

Table 9 confirms that this is indeed the case. When constructing the same instrument using voting shares in the 2012, rather than the 2008, Presidential election the coefficient on the interaction term is positive but not statistically significant (Column 2). Also, its magnitude is three times smaller than in the same model for the 2008 presidential election (Column 1).

The results of this section suggest that there was a shift in housing market sentiment at the time when the Democrats won the White House in 2008. This shift was positively correlated with the ex-ante political views of a state's population: Democratic-leaning states became more optimistic than Republican-leaning states, even after controlling for their general level of optimism/pessimism over time (pre-electoral trends). This shift does not seem to be due to changes in housing or federal policies, or due to a generalized optimistic view about the economy. Rather, it seems to reflect largely a shift in housing sentiment.

Therefore, conditional on a set of covariates, the interaction between partisanship and electoral timing appears to be a relevant and valid instrument to analyze the effects of a

[26]In this graph, Democratic states are states in the 5th quintile in the distribution of voting shares for the democratic party in the 2008 election. Republican states are states in the 1st quintile.

change in house price expectations on mortgage borrowing.

3.4 Second stage: expectations and mortgage leverage

Table 10 presents the analysis of the effects of housing sentiment on mortgage leverage ratios. Individual mortgages' loan-to-value ratios (LTVs) are regressed on a set of covariates, including different measures of sentiment in the same quarter/state cell.

In the OLS estimation, state/quarter averages of house price expectations are positively but not significantly correlated with mortgage borrowing (Column 1). The loan-level characteristics have the expected signs: longer mortgages have higher LTVs and homeowners with higher credit scores are generally less heavily in debt. Interest rates are positively correlated with loan-to-value ratios, which is probably explained by the credit risk associated to lending a larger proportion of a property's appraisal value. First-time home buyers, on average, receive less lending on similar properties (probably reflecting a shorter credit history). Loans on investment properties are also about 2.5 percentage points lower than loans on owner-occupied properties. Finally, mortgages that have the purpose of purchasing a property have a loan-to-value ratio that is on average 11 percentage points higher than refinancing mortgages, indicating that on average homeowners (who wish to extract equity out of their properties) borrow less than home-buyers.

Column 2 of Table 10 instruments state-level house price expectations with the interaction between state-level political leanings and election timing. I can reject the null at the 1% level (with an estimated elasticity of +0.63). The model includes state and quarter fixed-effects, so it reflects the within-state change over time taking into account all time-variant US-wide policy changes (i.e. federal interest rates) affecting all states equally at any given point in time. It also includes a set of state/time varying controls (including past house price growth). The sign and magnitude of mortgage-level coefficients is unchanged.

This suggests that when state-level house price expectations increase by one standard deviation (1.7 percentage points), the leverage ratios on individual-level 30 years fixed-rates mortgages increases by one percentage point (6% of a standard deviation). The difference between this coefficient and the OLS coefficient could be explained by the LATE interpretation of the IV estimation: this model reflects the effect of a shift in housing sentiment for the subgroup of the population which is affected by the instrument, or for those states for which sentiment shifts after the election. In some states, the population was roughly equally split between the Democratic and the Republican party:

this included popolous states, wh like Florida, Ohio North Carolina or Virginia. The OLS estimate will pick up the average effect on the population (ATE), rather than the local average treatment effect (LATE). In this scenario, the OLS coefficient will tend to be smaller than the IV coefficient.

Using real house price expectations (deflated by average inflation expectations at the state-year level) yields similar results. The OLS estimate, while positive, is downward biased (Column 3) with respect to the coefficient estimated via 2SLS (Column 4). Using real house price expectations, is more conservative than estimating the same model using simple' expectations, because the coefficient measures the effect on loans of an increase in house price expectations that exceeds the expectations regarding the general level of prices in the economy. Real house price expectations shift loan-to-value ratios by magnitude that is similar to that associated with "simple" house price expectations .[27]

Moreover, the result holds to controlling for interest rate expectations, which have a positive effect on loan-to-value ratios. This sign is coherent with the fact that the Freddie Mac Single Family Loan Level Data set records only fixed rate mortgages, and in this context an expectation of a price increase should lead consumers to borrow/refinance when rates are more favorable.

3.5 Robustness: heterogeneous effects of expectations

The first possible source of heterogeneity in the effects of expectations on mortgage leverage relates to geography. For example, policy response to the financial crisis and the Recession differed across US states. Some regions that predominantly voted for the Democratic party in the 2008 election were the states in which the automotive industry was a crucial part of the industrial ecosystem. Such states (a large part of those commonly denominated as the American Rust Belt) received heavy subsidies in 2008 and 2009 to keep the automotive industry afloat during the Recession. Public subsidies of this magnitude might not only have shifted consumers' expectations, but their spending capacity directly, by containing unemployment rates in a context in which many establishments throughout the country were closing. This might have affected propensity to borrow and lend in such Democratic states, independently from

[27] One possible source of concern with these estimations is the relative representativeness of the expectations sample. The total number of elicited house price forecasts in the Michigan Survey between 2007 and 2014 is around 36000, less than 5000 per year. This implies using little more than 1000 observations per quarter, roughly 22 per state/quarter cell (the unit of observation). However, Table 2 in Appendix A2 shows that when aggregating expectations at the state/year level (100 observations per cell) rather than state/quarter level, the coefficients associated with both the OLS and 2SLS estimations presented in Table 10 remain largely unchanged.

expectations.

However, excluding Michigan, Indiana, Illinois, Pennsylvania and Ohio from the analysis does not change the results in any significant way (Table 11). Results are very close to the average reported for the entire United States both when considering simple expectations (Column 1) and real expectations (Column 2).

Another dimension of heterogeneity regards mortgage typology. Loans included in Freddie Mac's portfolio serve different purposes. About 37% are loans to buy a property and the remaining 63% of the loans are refinancing mortgages. This type of loans are meant to extract equity from *already occupied* properties. Among refinancing mortgages, a further distinction needs to be made between *cash-out* loans and *non-cash-out* loans. The former type is free from any specific purpose, however the latter is a mortgage that has the intent to pay off existing mortgage and house-related debt.[28] The three types of loans are roughly equally represented in Freddie Mac's portfolio between 2007 and 2014: purchase mortgages constitute 37% of the total, cash out mortgages 28%, and non-cash-out ones about 34%.

However, these three types of mortgages might be affected by house price expectations in different ways. Borrowing in the expectation of house price increases makes sense if households are liquidity constrained, desire higher consumption (whether housing-related or not), and bet on home appreciation to pay off a part of their debts in the near future. This type of logic is less likely to apply to households who are opening a second mortgage in order to pay off existing debts. In this latter case, the decision to refinance is most likely due to the desire to change the mortgage conditions (length, or structure of the interest rates) due to changes in policy or to unforeseen circumstances, such as the loss of employment.

Table 11 explores the effect of house price expectations on these three different types of mortgages. House price expectations display an elasticity of +0.67 on purchase mortgages (Column 3, significant at the 5% level), but the effect is almost double on cash-out refinancing mortgages (+1.3, Column 4, significant at 1% level). On the other hand, the coefficient associated with house price expectations on non-cash-out refinancing mortgages is substantially smaller (+0.3, Column 5) and statistically insignificant.[29]

[28] The loan is limited to being used to: pay off the first mortgage, regardless of its age; pay off any junior liens secured by the mortgaged property, that were used in their entirety to acquire the subject property; pay related closing costs, financing costs and prepaid items; disburse cash out to the borrower (or any other payee) not to exceed 2% of the new refinance mortgage loan or $2,000, whichever is less.

[29] Aggregate level controls support the idea that non-cash out refinancing mortgage borrowing is driven mainly by negative circumstances, rather than by speculation about the future of the housing market. One standard deviation increase in the unemployment rate is correlated with an increase in non-cash-out refinancing borrowing worth 0.46 percentage points (2.7% of a standard deviation). Average wages in the construction sector (a proxy for the average level of wages in a state) are also

Finally, I address the concern of unobserved fundamental shock that could be correlated with state ideology and emerges long *after* the election. As a robustness check, Table 12 presents the estimates of equation (8) again, including only the first three quarters of 2008 and the year 2009 (2008q4, or the election quarter, is excluded). Analyzing the effect of expectations in a temporal span so close to the election helps to further reduce the concern that my results could be driven by unobservable shocks affecting more progressive states in the post-electoral period.

Column 1 shows that between 2008 and 2009, leverage on purchased properties was not significantly affected by changes in house price expectations. The coefficient (+0.2) is positive, but not statistically significant. The same is true of mortgage refinancing to pay off existing debt, for which the coefficients is negative and ind not significant (Column 3). On the other hand, the estimated elasticity on cash-out refinancing mortgages (+2.09) is statistically significant at the 5% level (Column 2). The magnitude of this effect implies that an increase one standard deviation increase in state-level averages in house price expectations (1.7 percentage) generates an increase in cash-out refinancing mortgage leverage ratios worth 3.4 percentage points, or 21% of a standard deviation in the dependent variable.

Overall, the effects of a shift in housing sentiment on mortgage leverage are significantly positive and robust to different specifications. If consumers on average expect house prices to rise in the near future, the individual leverage ratio increases, and as a consequence so does the leverage ratio of the aggregate economy.

3.6 Robustness: the expectations of professional forecasters

Leverage ratios on new mortgage originations is an expression of the equilibrium between credit supply and credit demand. An important question therefore, remains: does the change in mortgage leverage driven by house price expectations originate on the demand or supply side? Indeed, Cheng, Raina, and Xiong (2014) show that professionals were also heavily invested in the housing market prior to the crisis, and that they failed to anticipate the looming burst of the housing bubble.

The instrumental variable methodology presented in this paper exploits heterogeneity in expectations across geographical regions and over time. This implies that, for credit supply to be driving the main result, the regional expectations of professional forecasters need to shift in a similar direction and at the same time as the expectations of the

negatively and significantly correlated with loan-to-value ratios. These results are not reported in the table for brevity.

general public. Indeed, the expectations of professional forecasters at the level of US Census divisions present a high degree of co-movement over time with the expectations recorded in the Michigan Survey for the same Census divisions/quarters (Figure 6). The expectations of professional forecasters are measured by the quarterly averages of the National Association of Home Builders (NAHB)/Wells Fargo Regional Housing Market Index (historical data).[30] While this indicator does not precisely measure lender/builder expectations about future house price *percentage growth*, it proxies it by reflecting the expectations about sales in the near future. Its high degree of correlations with the expectations of consumers, moreover, indicates that the two indicators are measuring similar concepts.

US Census divisions are the lowest level of geographical aggregation for which the NAHB/Wells Fargo data is available. At this level of geographical aggergation, the first stage relationship between the instrument and consumer expectations (recorded by the Michigan Survey of Consumers) is much weaker than when measured for US states (Table 13, column 1), but still positive and significant.[31]

However, the expectations of professional forecasters about the future of the housing market do not display a systematic discontinuity in proximity of the 2008 election. The coefficient associated with the expectations of professional forecasters, while similar in magnitude to that of consumers'expectations, is not significant (Table 13, column 2). The reduced form relationship between mortgage LTVs and expectation variables also favors the hypothesis that consumer expectations are driving the result. When loan-to-value ratios are regressed over expectation variables, the coefficient associated with consumer expectations is positive and significant (Column 3) while the expectations of professional forecasters returns a negative and non-significant coefficient (Column 4).

Finally, consumer expectations (instrumented with partisan leaning and election timing) returns a positive and significant coefficient on mortgage loan-to-value ratios, even when controlling for the expectations of professional forecasters, which actually tend

[30]This is the only publicly available data source on professional house price expectations that contains a regional (sub-national) dimension. The index is based on a monthly survey of NAHB members, asking respondents to rate market conditions for the sale of new homes at the present time and in the next six months as well as the traffic of prospective buyers of new homes. The index ranges from 0 to 100, with higher values implying higher optimism about the future of housing sales in any given region. (http://www.nahb.org/en/research/housing-economics/housing-indexes/housing-market-index.asp). The only other publicly available surveys of professional forecasters that include house price expectations are the Philadelphia Fed Survey of Professional Forecasters and the Wall Street Journal Survey. Unfortunately, both lack a regional dimension.

[31]The result is weaker because Census divisions bundle together multiple constituencies, which often have very different electoral preferences. For example, the Western Census division pools Democratic-leaning states like California and Oregon with Republican-leaning ones like Utah and Montana. The fact that the shift in sentiment is detectable despite this level of geographic aggregation should in fact be considered as proof of the robustness of the original result expressed at the level of states.

to be negatively correlated with LTVs (Column 5). This estimation is not conclusive, as the F statistics suggests that this model suffers from a weak instrument problem. Nevertheless, the evidence suggests that the change in mortgage leverage ratios that can be detected as a result of shifting consumer expectations is unlikely to be suffering from an omitted variable bias in the form of supply-side expectations. In other words, the effect of expectations on mortgage leverage is likely to reflect a shift in credit demand, rather than a shift in credit supply.

These results should not be interpreted as suggesting that credit supply is irrelevant in determining the credit cycle, but rather as implying that, holding supply constraints constant, credit demand fueled by consumer expectations may have independent role in determining the mortgage-housing cycle (Adelino, Schoar, and Severino (2016); Kaplan, Mitman, and Violante (2017)).

4 Conclusions

In this paper, I document the pattern of house price expectations formed by American consumers in turn of the 2007-2008 financial crisis. I show that expectations are heterogeneous across the population and that they contain a component of systematic extrapolative bias which leads people to be over-optimistic after experiencing house price growth, and over-pessimistic when experiencing house price decline. I also study whether these (biased) house price expectations might be considered a fundamental driver of mortgage borrowing and lending behavior. By exploiting an exogenous shift in housing sentiment that occurred after the 2008 presidential election, I show that a change in house price expectations has substantial effects on mortgage leverage, which increases whenever there is an expected increase in home equity. This effect is particularly strong for refinancing mortgages, and seems to be reflecting more strongly a shift in consumers'expectations, rather than in the expectations of professionals in the housing sector.

These results provide evidence for an expectation-based explanation of the events unfolding around 2007 (Adelino, Schoar, and Severino 2016). Consumers who extrapolate from recent price trends can becom over-optimistic over the medium-long run, and are bound to be disappointed, eventually. Conversely, their extrapolation from negative trends may lead them to be slow to adjust and update their beliefs to positive news after a prolonged downturn. Since house price expectations are a driver of their consumption(borrowing) decisions, the extrapolative heuristic in house price expectations helps explaining not only endogenous cycles in the asset markets (Bordalo, Gennaioli, and Shleifer (2016)) but they may also be responsible for the slow recovery after the Great Recession (Nardi, French, and Benson 2011; Mitman, Violante, and Kaplan 2015).

A theme that connects recent empirical research on expectations is the role of personal experiences, as opposed to public information, in shaping individuals' beliefs about the future. For example, cross-sectional contagion among peers affects the average consumer's decisions about investing in the housing market more than objective economic data (Kuchler and Zafar 2015; Bayer, Mangum, and Roberts 2016; M. Bailey et al. 2016). The evidence on heterogeneity in expectations presented in this paper may indeed arise from private information, but also from differential access to public information or even from different forecasting models: my work can be improved by distinguishing between these alternative channels. Analyzing the drivers of expectations' heterogeneity may constitute the empirical basis upon which to develop a new theory of how consumers are likely to react to news, a theory that does not rely on the assumption that all agents are perfectly informed and efficient in their forecasting methods. Indeed, this paper shows that full-information rational expectations theory may not be entirely capturing the dynamics of the housing market. Developing a more realistic model of how beliefs are formed seems particularly important because expectations are more than just noise: the evidence I present suggests that they directly affect the credit cycle.

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Figures

Figure 1 Expectations on income, inflation and house price growth rates at the 1-year horizon. US average, 2007-2014. Source: Michigan Survey of Consumers.

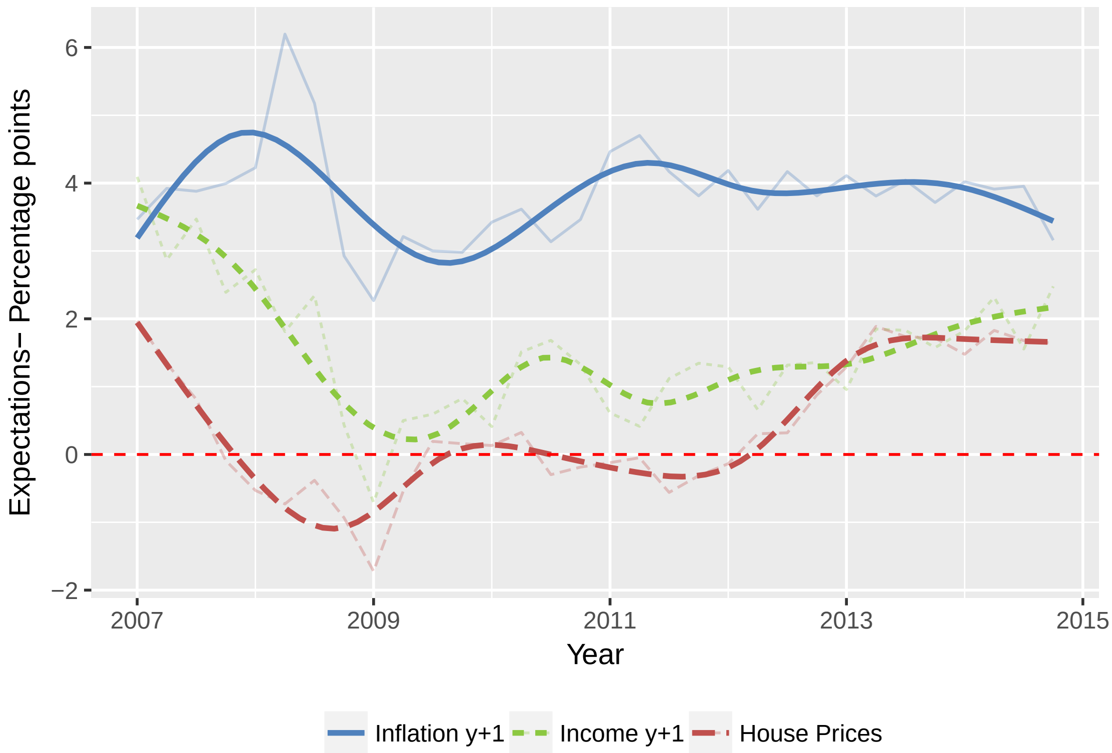


Figure 2 Dispersion in house price expectations and house price growth rates (year-on year). State/year averages. Sources: Michigan Survey of Consumers; FHFA

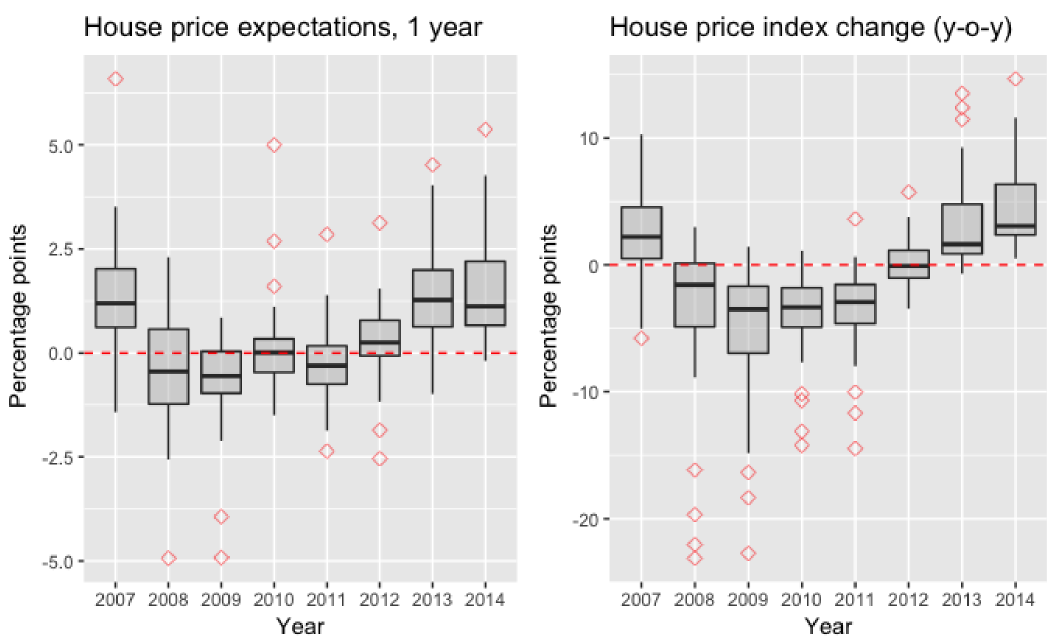


Figure 3 House price forecast errors by date. Sources: Michigan Survey of Consumers; FHFA repeated sales index

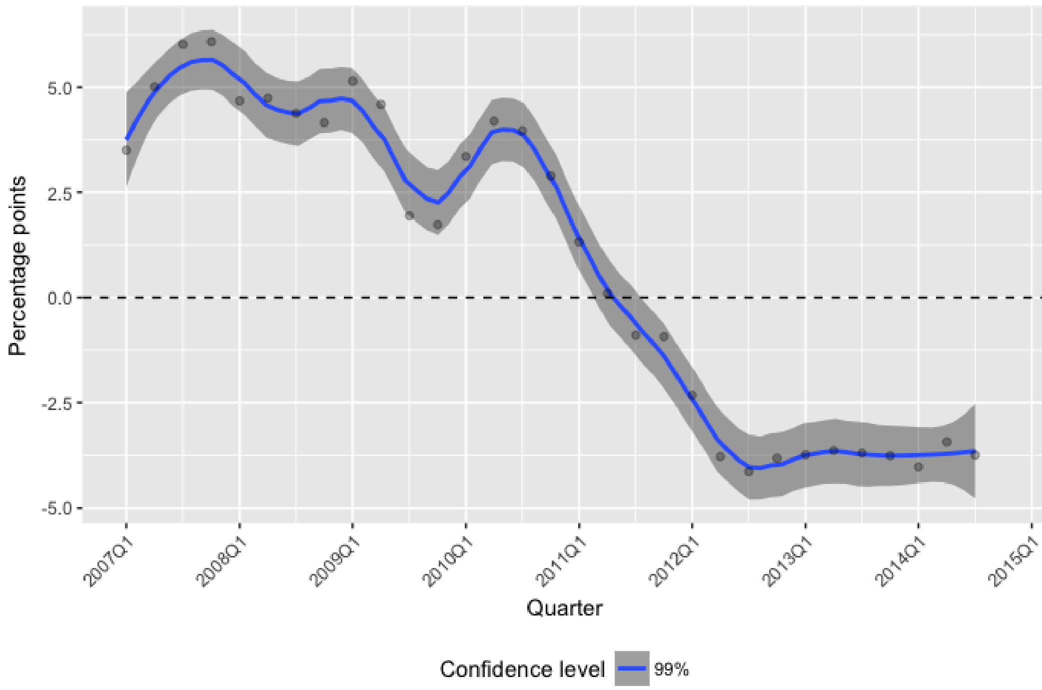


Figure 4 Average mortgage loan-to-value ratios and average house price expectations by date. Sources:Michigan Survey of Consumers; Freddie Mac Single Family Loan-Level Dataset

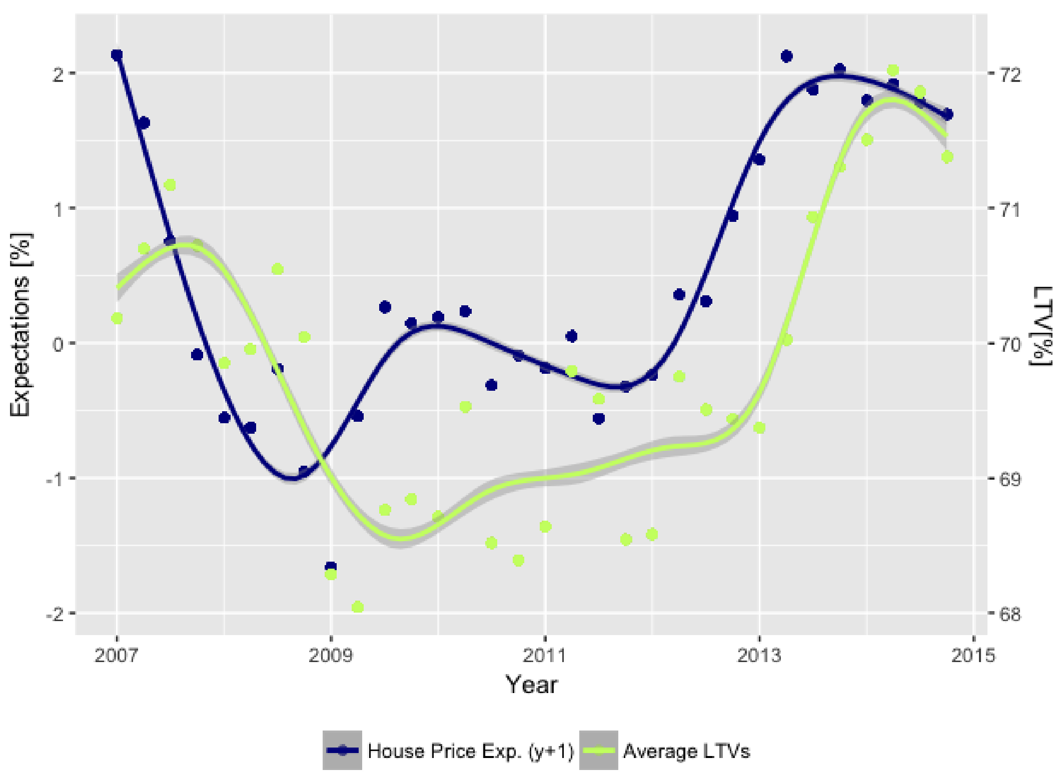


Figure 5 Change in house price expectations at Presidential elections. % points difference from US average expectations. Source:Michigan Survey of Consumers

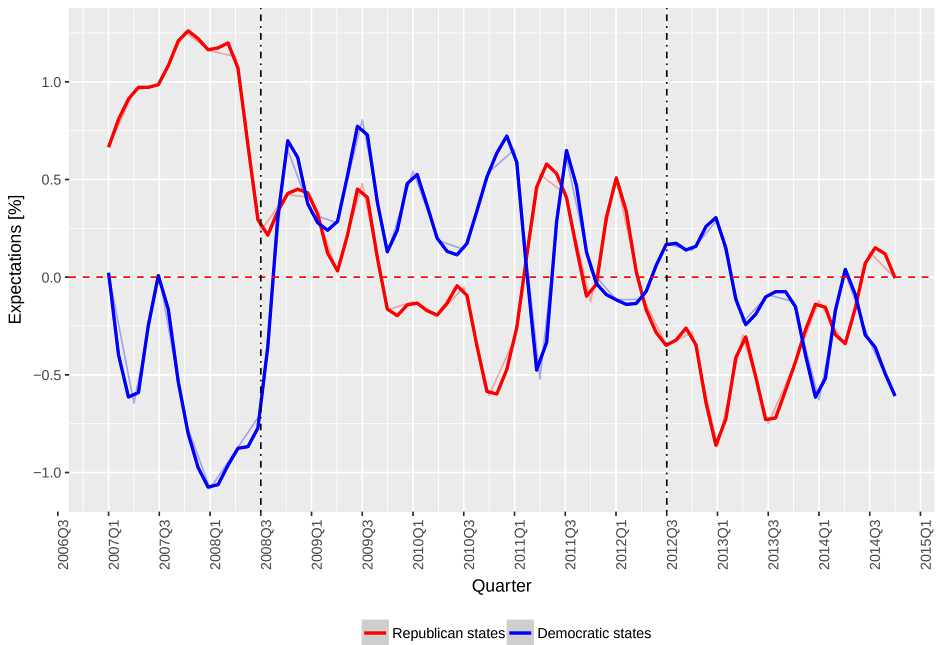
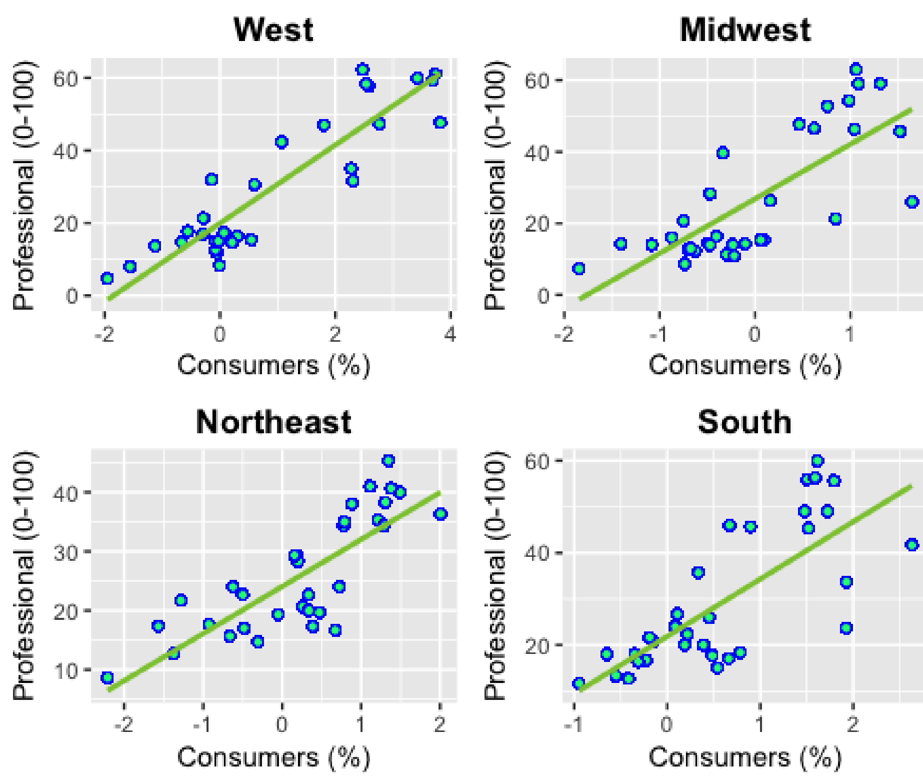


Figure 6 Professionals' house price expectations VS consumer expectations. US Census regions, 2007-2014. Sources:Michigan Survey of Consumers; NAHB/Wells Fargo Regional Housing Market (historical index)



Tables

Table 1 Summary statistics

Summary Statistics, 2007-2014

Variable	Units	Obs	Mean	Std.Dv	Min	Max
Panel A			Michigan Survey of Consumers			
HH Income	Yearly, US $	48896	84074.71	73331.61	2400.00	500000.00
Age	Years	52304	55.17	56.59	18.00	97.00
Male	Dummy	52548	0.46	16.59	0.00	1.00
Married	Dummy	52548	0.67	0.46	0.00	1.00
Adults	#	52548	1.90	0.70	1.00	5.00
Children	#	52521	0.61	1.03	0.00	5.00
College Educ.	Dummy	52548	0.52	0.50	0.00	1.00
Stock Owner	Dummy	52548	0.70	0.45	0.00	1.00
Exp. Hprice 1 Y	% growth	36404	0.34	5.30	-25.00	25.00
Exp. Income 1Y	% growth	50371	1.77	14.09	-50.00	95.00
Exp. Inflation 1Y	% growth	47047	3.84	4.15	-10.00	20.00
Forecast Error Hprice	%	35137	0.85	7.04	-30.85	25.00
Absoulute Value For.Err.	%	36313	5.12	4.85	0.00	30.85
Panel B			Freddie Mac Single-Family Loan Level Dataset			
Loan to Value	%	399296	69.48	17.36	6.00	100.00
Length Mortgage	Years	399304	26.12	6.60	5.00	43.00
Credit Score	Points	399239	753.69	46.71	333.00	844.00
Interest Rate	%	399304	4.76	1.06	2.25	9.13
First Time Buyer	Dummy	399304	0.47	0.50	0.00	1.00
Investment Property	Dummy	399304	0.06	0.24	0.00	1.00
Purchase	Dummy	399304	0.37	0.48	0.00	1.00
Panel C			State-Level Controls			
Change House Price t-1	Percentage points	395324	0.00	0.02	-0.08	0.06
Unemployment Rate	Percentage points	395324	0.06	0.02	0.02	0.12
Population Growth	Percentage points	390182	0.01	0.01	-0.03	0.05
Building Permits	# per year	390182	33796.58	34736.81	536.00	176992.00
Wage Construction Sector	Monthly, US $	389732	4312.46	637.01	2724.00	6756.00
Property Tax	Yearly, US $	397938	2011.87	836.06	462.01	5346.01
Public Housing	Percentage/ pop.	397938	0.01	0.01	0.00	0.08
Rent Subsidies	Percentage/ pop.	397938	0.01	0.07	0.00	1.00

Table 2 Determinants of individual expectations

	(1)	(2)	(3)	(4)
VARIABLES	E. Income t+1	E. Inflation t+1	E. H. Price t+1	Real E. H.Price t+1
Household-level variables				
HH Income (log)	-1.484***	-0.436***	0.212***	0.735***
	(0.149)	(0.038)	(0.072)	(0.063)
Age head	-0.301***	0.046***	-0.037**	-0.084***
	(0.047)	(0.008)	(0.014)	(0.017)
Age^2	0.001***	-0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.873***	-0.501***	0.200**	0.694***
	(0.186)	(0.054)	(0.076)	(0.097)
College degree	1.895***	-0.334***	0.287***	0.573***
	(0.217)	(0.056)	(0.070)	(0.082)
Married	-0.531**	0.212***	0.082	-0.170*
	(0.205)	(0.044)	(0.069)	(0.099)
# Children	0.100	-0.012	-0.105***	-0.062
	(0.116)	(0.023)	(0.038)	(0.045)
Change HH Income	0.063	0.530	0.367	-1.653*
	(1.744)	(0.558)	(0.830)	(0.985)
Stock ownership	-0.146	-0.325***	0.244***	0.492***
	(0.208)	(0.065)	(0.083)	(0.107)
Negative Income Shock	-2.253***	0.889***	-0.853***	-1.694***
	(0.163)	(0.050)	(0.067)	(0.096)
State-Level variables				
Change HPrice (State, YoY)	-0.040*	0.005	0.134***	0.130***
	(0.022)	(0.005)	(0.011)	(0.011)
Gini Coefficient (State)	7.181	-5.485**	4.127	14.677**
	(8.082)	(2.459)	(4.643)	(5.749)
Unemployment rate	-38.361***	-3.430	5.080	3.220
	(11.626)	(2.887)	(6.260)	(7.529)
Constant	30.815***	10.350***	-3.324	-16.990***
	(4.533)	(1.272)	(2.794)	(3.039)
State FE	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes
Observations	47,047	43,998	34,029	31,385
R-squared	0.056	0.066	0.064	0.082

The dependent variable in column 1 is the expected % personal income change in one year; in column 2 is the expected inflation change in one year; in column 3 is expected house price growth in 12 months and in column 4 is the real expected appreciation on housing, discounted by inflation expectations (Exp House prices t+1- Exp Inflation T+1). Source: Michigan Survey of Consumers, 2007 to 2014. Only homeowners are included. House price appreciation is measured via the FHFA repeated sale index; other state-level controls are derived from the March CPS. Standard errors are robust to heteroskedasticity and clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 3 Determinants of house price expectations: interaction between house price growth and individual demographics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	E. H. Price t+1	E. H. Price t+1	E. H. Price t+1	E. H. Price t+1	E. H. Price t+1
Interactions demographics					
ChangePrice*Income	0.029***				
	(0.008)				
ChangePrice*Age		-0.001***			
		(0.000)			
ChangePrice*College			0.034***		
			(0.011)		
HHIncome(logs)	0.327***	0.272***	0.271***	0.270***	0.268***
	(0.083)	(0.070)	(0.069)	(0.069)	(0.069)
Age	-0.057***	0.002	0.003	0.004	0.004
	(0.015)	(0.002)	(0.003)	(0.003)	(0.003)
College	0.325***	0.320***	0.362***	0.317***	0.317***
	(0.069)	(0.069)	(0.066)	(0.069)	(0.069)
Interactions by time					
ChangePrice*Crisis				-0.029	
				(0.022)	
Crisis				-0.619**	
				(0.231)	
ChangePrice*Recession					-0.101***
					(0.015)
Recession					0.268
State-level variables					
Change HPrice (State, YoY)	-0.187*	0.193***	0.119***	0.153***	0.162***
	(0.101)	(0.017)	(0.012)	(0.018)	(0.012)
State FE	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes
Constant	-2.973***	-3.798***	-3.870***	-2.295***	-3.587***
	(0.739)	(0.714)	(0.729)	(0.839)	(0.707)
Observations	34,029	34,029	34,029	34,029	34,029
R-squared	0.058	0.057	0.057	0.057	0.058

This table displays how the effects of state-level house price -Change HPrice (State, YoY)- differs along demographic characteristics of the household and over time. The dependent variable is expected house price growth in 12 months (%). The change in house prices is measured at the state level by the FHFA repeated sales index. In column 1 Change HPrice is interacted with HH income; in Column 2 with age of the household head; in Column 3 with educational attainment of the household head. In column 4 the change in house prices is interacted with a dummy variable that equals 1 if the year is post-2008; in Column 5 the change in house prices is interacted with a dummy variable that equals 1 if the year is 2009 or 2010. Household-level controls include HH income; age, age squared, gender education and marital statust of the household head as well as an indicator for stock ownership. Source: Michigan Survey of Consumers, 2007 to 2014. Only homeowners are included. Standard errors are robust to heteroskedasticity and clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 4 Determinants of house price forecast errors

VARIABLES	(1) Inaccuracy Forecast	(2) Forecast Error	(3) Forecast Error Whole sample	(4) Forecast Error 2007-2008	(5) Forecast Error 2009+
Change HPrice (State, YoY)			-0.412***	0.261**	-0.325***
			(0.051)	(0.104)	(0.108)
HH Income (logs)	-0.252***	0.289***	0.225***	-0.219*	0.342***
	(0.062)	(0.092)	(0.078)	(0.125)	(0.080)
Age head	0.018*	-0.041**	-0.033*	-0.045	-0.037**
	(0.011)	(0.019)	(0.018)	(0.028)	(0.016)
Age^2	-0.000**	0.000**	0.000**	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.265***	0.246***	0.278***	-0.012	0.402***
	(0.049)	(0.086)	(0.081)	(0.153)	(0.088)
College degree	-0.144**	0.321***	0.309***	0.189	0.360***
	(0.059)	(0.094)	(0.090)	(0.116)	(0.089)
Married	-0.081	0.069	0.107*	0.023	0.112
	(0.088)	(0.068)	(0.062)	(0.167)	(0.083)
#Children	-0.044	-0.127***	-0.113***	-0.008	-0.156***
	(0.030)	(0.042)	(0.037)	(0.073)	(0.045)
Stock Owner	-0.300***	0.199	0.208*	0.041	0.311***
	(0.077)	(0.127)	(0.111)	(0.190)	(0.094)
Negative Income Shock	0.259***	-0.743***	-0.861***	-0.633***	-0.910***
	(0.078)	(0.079)	(0.061)	(0.160)	(0.062)
State FE	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes
Constant	6.515***	-6.594***	-0.602	2.525	-4.932***
	(0.605)	(1.954)	(1.098)	(1.820)	(0.936)
Observations	32,844	32,844	32,844	8,425	24,419
R-squared	0.262	0.317	0.370	0.423	0.341

The dependent variable in Column 1 is the absolute value of the house price forecast error: the further away from zero, the higher the inaccuracy of the forecast. In Columns 2-5 the dependent variable is the forecast error, defined as in Equation (6): a higher value implies excessive optimism with respect to future house price realizations. Source: Michigan Survey of Consumers, 2007 to 2014. Only homeowners are included. House price appreciation is measured via the FHFA repeated sale index; other state-level controls are derived from the March CPS. Standard errors are robust to heteroskedasticity and clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 5 Determinants of house price forecast errors: fixed effects

VARIABLES	(1) Δ Forecast Error	(2) Δ Forecast Error 2007-2008	(3) Δ Forecast Error 2009+	(4) Δ Forecast Error
Δ HPrice (State)	0.216***	0.614***	0.23***	0.178***
	(0.046)	(0.036)	(0.063)	(0.039)
Δ Personal Income(%)	0.291*	0.318	0.277	0.317*
	(0.168)	(0.38)	(0.207)	(0.170)
ΔHPrice*Crisis				0.071**
				(0.031)
Crisis				-2.44***
				(0.682)
State FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Constant	-2.436**	2.27**	-4.22***	-1.33
	(1.039)	(2.47)	(1.277)	(1.14)
Observations	11,786	2,468	9,318	11,809
R-squared	0.097	0.149	0.098	0.081

Δ Forecast errors measures the change in individual-level forecast errors measured between the two interviews (which are 6 months apart). A positive value implies a relative increase in overoptimism/overpessimism at the level of the individual. Δ HPrice (State) is the change in house prices at the state level in the previous year, measured by the FHFA repeated sales index. Individual-level controls include the change in personal income between the two interviews (Δ Personal Income(%) , the log of income, age gender, marital status and education of the household head, plus indicators for stock ownership. Column 4 includes an interaction term between the change in house prices (Δ HPrice (State) and a dummy=1 if the year is after 2008. Source: Michigan Survey of Consumers, 2007 to 2014 (only homeowners are included in the analysis). Standard errors are robust to heteroskedasticity and clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 6 First stage: changes in house price expectations and political outcomes

VARIABLES	(1) Exp. H. Price t+1 OLS First Stage	(2) Exp. H. Price t+1 OLS First Stage	(3) Loan To Value Ratio OLS Reduced Form
Dem Share(08)*PostElection(08)	0.063***	0.050***	0.047***
	(0.013)	(0.014)	(0.017)
State-level variables			
Exp. Inflation		-0.041	0.003
		(0.042)	(0.038)
Views of Government		1.968***	-0.113
		(0.645)	(0.454)
Aggregate Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Unempl.rate	-6.002	-5.241	14.59**
	(5.346)	(5.384)	(6.79)
Change HPrice (State, YoY)	0.123***	0.123***	2.27
	(0.849)	(0.859)	(1.532)
Pop. growth	-2.483	-2.593	5.26
	(9.579)	(9.867)	(16.240)
Household-Level Demographics	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Constant	3.172***	2.269***	33.898***
	(0.568)	(0.675)	(4.397)
Observations	373,211	373,211	373,406
R-squared	0.553	0.559	0.282

This table shows first-stage and reduced form relationships between electoral outcomes, house price expectations and loan-to-value ratios. The dependent variable in Columns(1)-(2) is the quarter/state average of one-year house price expectations recorded by the Michigan Survey of Consumers (2007-2014). In Column.(3) the dependent variable is the individual-level mortgage loan-to-value ratio recorded by the Freddie Mac Single Family Loan level dataset (2007-2014). Columns 2-3 include controls for inflation expectations and for perceptions of the government (state-quarter averages from Michigan Survey). Individual level demographics are also derived from Freddie Mac Single Family and include Income of the borrower, their credit score, the length of the mortgage in years, the interest rate charged on the loan, whether the borrower is a first-time homebuyer, wehther they are buying for investment or as live-in owners and whether the loan has the purpose of purchasing or refinancing. State-level variables are derived from the March CPS and stat-level house price growth from the FHFA repeated sales index. Standard errors allow for *heteroskedasticity and are* clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 First Stage robustness: post-electoral policy change?

VARIABLES	(1) E. HPrice y+1	(2) Public Housing y+1	(3) Rent subsidies y+1	(4) Property tax y+1	(5) Building Permits y+1	(6) Wage Construction y+1
DemShare(08)*Post Election(08)	0.056***	-0.000	0.001	0.001	-50.145	-0.000
	(0.016)	(0.000)	(0.001)	(0.003)	(107.332)	(0.000)
Aggregate Income	1.399	-0.002	-0.013	0.439***	10,927.144	0.145
	(1.108)	(0.003)	(0.078)	(0.138)	(8,554.554)	(0.098)
Unempl.Rate	-2.414	-0.015	-0.461	-0.277	-90,342.721	-0.631***
	(7.779)	(0.026)	(0.751)	(1.162)	(56,421.711)	(0.228)
Change HPrice (State, YoY)	0.128***	-0.001	0.076	-0.201	36,726.703*	-0.261**
	(1.296)	(0.005)	(0.093)	(0.265)	(19,203.099)	(0.106)
Population growth	-17.089	-0.036	-0.345	-0.561	157,286.027**	1.209**
	(13.974)	(0.045)	(0.777)	(0.727)	(62,024.018)	(0.461)
State FE	yes	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes	yes
Constant	-34.880	0.075	0.391	-4.377	-258,150.277	4.412*
	(29.299)	(0.079)	(2.041)	(3.639)	(224,965.387)	(2.591)
Observations	1,409	1,367	1,367	1,367	1,367	1,367
R-squared	0.280	0.016	0.022	0.511	0.416	0.852
Number of states	46	46	46	46	46	46

Relationship between electoral outcomes and state-level housing-related policy at year+1. The dependent variables are averages at the state/year leve Average house price expectation at year+1 (Column 1) Percentage of citizens living in public housing (Column 2); Percentage of renters who receiv rent subsidies (Column 2); Average property taxes on residential housing (Column 3); Yearly building permits issued by the local authorities (Col.4 Average Wages in the construction Sector (Column 5). State-level controls originate from the March CPS, except for the change in house prices at th state level, measured by the FHFA repeated sale index. Sources: March CPS, thBureau of Labour Statistics and the Census Bureau, Michigan Survey c Consumers. Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 8 First stage robustness: other expectations?

VARIABLES	(1) E.Income Y+1	(2) E.Inflation Y+1	(3) View of Govt.	(4) E.Int Rate Y+1	(5) E.HPrice Y+1	(6) Real E.HPrice Y+1
DemShare(08)*PostEl.(08)	-0.004	-0.032***	0.007***	-0.002	0.040**	0.085***
	(0.026)	(0.010)	(0.001)	(0.002)	(0.016)	(0.017)
View of Govt					1.877**	
					(0.761)	
E.Int Rate y+1					-0.252	
					(0.323)	
E.Income y+1					0.025*	
					(0.013)	
E.Inflation y+1					-0.056	
					(0.053)	
State/quarter controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,415	1,414	1,415	1,415	1,408	1,408
R-squared	0.070	0.291	0.291	0.332	0.302	0.271
Number of states	48	48	48	48	46	46

Relationship between electoral outcomes and state/quarter averages of expectations recorded by the Michigan Survey of Consumers (2007-2014). The dependent variables are: expectations about personal income (% growth) in one year (Column 1); about inflation (% growth) in one year (Column 2); about whether the respondent has a positive view of the government's policy (Column 3); about whether interest rates will go up/down in one year (Column 4);. House Price expectations (Column 5). Column 5 also includes all other sentiment variables as controls. In Column 6 the dependent variable is the difference between average house price expectations (1 year) and inflation expectations (1 year). State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS). Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 9 Placebo test: 2012 election

VARIABLES	(1) Exp. HPrice Y+1	(2) ExpHPrice Y+1
Dem(12)*PostElection(12)		0.014
		(0.010)
Dem(08)*PostElection(08)	0.055***	
	(0.016)	
State/quarter controls	Yes	Yes
State FE	Yes	Yes
Quarter FE	Yes	Yes
Constant	-21.739	-11.324
	(33.964)	(33.870)
Observations	1,408	1,407
R-squared	0.286	0.287
Number of states	46	46

This table displays the relationship between the two presidential election outcomes and house price expectations. The dependent variable is the state/quarter average of one-year house price expectations (Michigan Survey of Consumers, 2007 to 2014). Column 1 displays the change in house price expectations after the 2008 election; Column 2 displays the change after the 2012 election. State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS). Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 10 Second stage: house price expectations and mortgage leverage

VARIABLES	(1) LTV OLS	(2) LTV 2SLS	(3) LTV OLS	(4) LTV 2SLS	(5) LTV 2SLS
Exp. HPrice y+1	0.080	0.637**			
	(0.051)	(0.260)			
Real E.Hprice y+1			0.052	0.472**	0.474**
			(0.031)	(0.197)	(0.187)
Exp. Int Rate					0.928***
					(0.309)
Mortgage-variables					
Length mortgage	0.317***	0.317***	0.317***	0.317***	0.317***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Income borrower	3.306***	3.314***	3.306***	3.312***	3.314***
	(0.241)	(0.238)	(0.241)	(0.238)	(0.238)
Credit Score	-0.043***	-0.043***	-0.043***	-0.043***	-0.043***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Interest Rate	4.972***	4.973***	4.973***	4.975***	4.979***
	(0.259)	(0.250)	(0.259)	(0.251)	(0.251)
First time buyer?	-1.416***	-1.399***	-1.416***	-1.403***	-1.401***
	(0.181)	(0.172)	(0.182)	(0.175)	(0.175)
Investment	-2.433***	-2.432***	-2.434***	-2.435***	-2.436***
	(0.181)	(0.180)	(0.181)	(0.180)	(0.180)
Purchase	11.475***	11.457***	11.476***	11.461***	11.457***
	(0.583)	(0.571)	(0.584)	(0.573)	(0.573)
State/quarter vars.	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes
Constant	147.258***	155.388***	146.912***	153.568***	151.258***
	(32.399)	(34.477)	(33.054)	(37.470)	(35.215)
F Stat		21.31		35.42	36.26
Observations	372,755	372,755	372,755	372,755	372,755
R-squared	0.273	0.272	0.273	0.272	0.272

This table displays the estimations of the effects of changes in house price expectations on mortgage borrowing. The dependent variable is individual-level loan-to-value ratio (Freddie Mac Single family loan level dataset). Cols. 1 and 3 are estimated via OLS; Columns. 2, 4 and 5 via 2SLS. Columns 1-2 evaluate the effect of a change in house price expectations and cols 3-5 the effect of a change in the real house price expectations (house price-inflation expectations). State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS); Average taxes on residential property (Census Bureau); Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 11 Second stage robustness: heterogeneous effects

VARIABLES	(1) LTV 2SLS	(2) LTV 2SLS	(3) LTV 2SLS	(4) LTV 2SLS	(5) LTV 2SLS
Exp HPrice y+1	0.691**		0.675**	1.292***	0.307
	(0.269)		(0.338)	(0.376)	(0.468)
Real Exp HPrice y+1		0.545**			
Mortgage variables	Yes	Yes	Yes	Yes	Yes
State/quarter variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Constant	180.982***	181.218***	131.744**	202.496***	170.786***
	(39.004)	(43.167)	(60.594)	(52.152)	(63.903)
F Stat	17.19	26.58	20.61	17.92	20.46
Observations	302,452	302,452	138,789	105,009	131,199
R-squared	0.274	0.274	0.128	0.111	0.155

This table displays the estimations of the effects of changes in house price expectations on mortgage borrowing. Expectations are measured as quarter-year averages recorded in the Michigan Survey of Consumers. The dependent variable is individual-level loan-to-value ratio (Freddie Mac Single family loan level dataset).. Columns 1 estimates a 2SLS excluding Michigan, illinois, Pennsylvania, Ohio and Indiana. Column 2 runs the same model of Column 1 but using real house price expectations (House price expectations-inflation expectations). Column 3 observes the effects of a change in expectation on mortgages to purchase a house; Column 4 on mortgages that have the purpose of cash-out refinancing on an exisiting property; Column 5 on mortgages that have the purpose of refinancing on an exisiting property but where the loan can only be used to repay existing housing debt.). Individual level mortgage demographics are also derived from Freddie Mac Single Family and include Income of the borrower, their credit score, the length of the mortgage in years, the interest rate charged on the loan, whether the borrower is a first-time homebuyer, whether they are buying for investment or as live-in owners. State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS); Average taxes on residential property (Census Bureau). Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 12 Second stage robustness: effects close to the 2008 election

VARIABLES	(1) LTV Purchase	(2) LTV Cash out	(3) LTV Non-cash out
Exp HPrice y+1	0.207	2.091**	-0.073
Mortgage variables	Yes	Yes	Yes
State/quarter variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Constant	43.896***	27.853***	76.083***
	(4.419)	(6.201)	(4.713)
F stat			
Observations	25,206	26,436	30,318
R-squared	0.107	0.119	0.159

The dependent variable is individual-level loan-to-value ratio (Freddie Mac Single family loan level dataset between 2008q1 and 2009q4.. Column 1 observes the effects of a change in expectation on mortgages to purchase a house; Column 2 on mortgages that have the purpose of cash-out refinancing on an existing property; Column 3 on mortgages that have the purpose of refinancing on an existing property but where the loan can only be used to repay existing housing debt.). Individual level mortgage demographics are also derived from Freddie Mac Single Family and include Income of the borrower, their credit score, the length of the mortgage in years, the interest rate charged on the loan, whether the borrower is a first-time homebuyer, whether they are buying for investment or as live-in owners. State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS); Average taxes on residential property (Census Bureau). Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Table 13 Second stage robustness: expectations of professional forecasters

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Exp. HPrice (Census)	Professional Exp (Census)	LTV	LTV	LTV
	First Stage	First Stage			Second stage
	OLS	OLS	OLS	OLS	2SLS
DemShare(08)*PostEl(08)	0.024*	0.024			
	(0.010)	(0.153)			
Exp. HPrice (CensusDiv)			0.260*		1.718***
			(0.085)		(0.565)
Professional Exp (Census Div).				-0.008	-0.065***
				(0.019)	(0.025)
Mortgage-level controls	Yes	Yes	Yes	Yes	Yes
State/quarter controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Constant	-17.650	-202.917	161.248**	156.971**	151.632***
	(39.802)	(449.628)	(31.885)	(36.386)	(24.230)
F Stat					5.8
Observations	372,992	372,992	372,986	372,986	372,986
R-squared	0.867	0.945	0.273	0.273	0.272

This table compares the effects of expectations recorded by the Michigan Survey of consumers with the expectations formed by professional forecasters in the same time frame. Expectations variables are expressed at the region/quarter cell (Midwest, West, South, Northeast). In column 1 the dependent variable is the region/quarter average of house price expectations recorded by the Michigan Survey of consumers (2007-2014). In Column 2 it is the region/quarter average of expectations recorded by the National Association of HomeBuiders (2007-2014). In Columns 3-5 it is the mortgage Loan-to-Value ratio recorded by the Freddie Mac Single Family Loan Level dataset (2007-2014).). Individual level mortgage demographics are also derived from Freddie Mac Single Family and include Income of the borrower, their credit score, the length of the mortgage in years, the interest rate charged on the loan, whether the borrower is a first-time homebuyer, whether they are buying for investment or as live-in owners. State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS); Average taxes on residential property (Census Bureau). Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Appendix A1: Additional data sources

Aggregate, state-level variables control for the characteristics of the housing market and the general economy in a given state and quarter. In both sets of estimations (on expectations and on mortgage leverage) I include past house price growth, measured at the state level, defined as the growth rate in the previous four quarters (Federal Housing Finance Agency repeated sales index). Some models control for time-varying fundamental shock (income growth, unemployment rates, homeownership rates (from the March CPS) and for changes in local housing policy (average property taxes, percentage of residents living in public housing, percentage of residents paying lower rent due to government subsides). These variables are derived from the March CPS. Both expectations and mortgage markets are likely to be affected by changes in regulation or other factors restricting housing supply, such as higher building costs. I proxy for production costs using average wages in the construction sector (Bureau or Labour Statistics, NAICS 23). The changes in the restrictiveness of regulation are proxied by the yearly number of building permits issued in a given state, which are here used as a measure of housing supply elasticity, as in (Kahn 2011).

Appendix A2: Robustness tests

Table A1: Forecast errors and past price growth: interaction with individual characteristics

VARIABLES	(1) Δ Forecast Error	(2) Δ Forecast Error	(3) Δ Forecast Error
Δ HPrice*Income	0.056***		
	(0.016)		
Δ HPrice*age		-0.005	
		(0.003)	
Δ HPrice*college			0.112**
			(0.051)
Δ Personal Income(%)	0.319*	0.321*	0.320*
	(0.170)	(0.164)	(0.172)
Age	0.035*	0.037*	0.034*
	(0.020)	(0.021)	(0.020)
College degree	0.048	0.115	0.025
	(0.158)	(0.155)	(0.150)
HH Income (logs)	0.163	0.179*	0.183*
	(0.099)	(0.097)	(0.099)
Δ HPrice (State)	-0.488***	0.185	0.076*
	(0.175)	(0.128)	(0.039)
State FE	yes	yes	yes
Quarter FE	yes	yes	yes
Constant	-1.714	-0.123	-1.908
	(1.354)	(0.701)	(1.361)
Observations	11,809	11,809	11,809
R-squared	0.081	0.080	0.082

This table displays how the effects of state-level house price change between the two interviews -Δ HPrice (State))- differs along demographic characteristics of the household . The dependent variable-Δ Forecast error- measures the change in individual-level forecast errors measured between the two interviews (which are 6 months apart). A positive value implies a relative increase in overoptimism/overpessimism at the level of the individual. Δ HPrice (State) is the change in house prices at the state level between the two interviews, measured by the FHFA repeated sales index. In column 1 Change HPrice is interacted with HH income; in Column 2 with age of the household head; in Column 3 with educational attainment of the household head. Individual-level controls include the change in personal income between the two interviews (Δ Personal Income(%) , the log of income, age gender, marital status and education of the household head, plus indicators for stock ownership. Source: Michigan Survey of Consumers, 2007 to 2014. Only homeowners are included. Standard errors are robust to heteroskedasticity and clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2: Second stage robustness: expectations measured as state/year averages

VARIABLES	(1) LTV OLS	(2) LTV 2SLS	(3) LTV OLS	(4) LTV 2SLS
HPrice y+1	0.180	0.529**		
	(0.134)	(0.228)		
Real HPrice y+1			0.111	0.406**
			(0.105)	(0.170)
Mortgage variables	Yes	Yes	Yes	Yes
State/quarter variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Constant	79.331**	78.226**	80.456**	81.937**
	(37.558)	(36.686)	(38.518)	(39.698)
F Stat		16.07		31.61
Observations	372,908	372,908	372,908	372,908
R-squared	0.270	0.270	0.270	0.270

This table displays the estimations of the effects of changes in house price expectations on mortgage borrowing. Expectations are measured as state-year averages recorded in the Michigan Survey of Consumers, unlike in all other tables, where they are expressed as state/quarter averages. The dependent variable is individual-level loan-to-value ratio (Freddie Mac Single family loan level dataset). Cols. 1 and 3 are estimated via OLS; Columns. 2 and 4 via 2SLS. Columns 1-2 evaluate the effect of a change in house price expectations and cols 3-5 the effect of a change in the real house price expectations (house price-inflation expectations). State-level time varying controls include the sum of state incomes (March CPS); unemployment rates (March CPS); average house price growth in the previous three quarters (FHFA repeated sale index); average wages in the construction sector (Bureau of Labour Statistics) ; number of building permits (Census Bureau) ; population growth (March CPS); Average taxes on residential property (Census Bureau). Individual level demographics are also derived from Freddie Mac Single Family and include Income of the borrower, their credit score, the length of the mortgage in years, the interest rate charged on the loan, whether the borrower is a first-time homebuyer, wehther they are buying for investment or as live-in owners and whether the loan has the purpose of purchasing or refinancing. Errors are robust to heteroskedasticity and are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1