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ORIGINAL ARTICLE

Drivers of the great housing boom-bust: Credit conditions, beliefs, or both?

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Abstract

Two potential driving forces of house price fluctuations are commonly cited: credit conditions and beliefs. We posit some simple empirical calculations using direct measures of credit conditions and beliefs to consider their potentially distinct roles in house price fluctuations at the aggregate level. Changes in credit conditions are positively related to the fraction of riskier nonconforming debt in total mortgage lending, while measures of beliefs are unrelated to this ratio. Credit conditions explain quantitatively large magnitudes of the variation in quarterly house price growth and also predict future house price growth. Beliefs bear some relation to contemporaneous house price growth but have little predictive power. A structural vector autoregression analysis implies that exogenous changes in credit conditions have quantitatively important dynamic causal effects on house price changes.

1 | INTRODUCTION

The dawn of the 21st century was marked by a dramatic boom-bust cycle in residential real estate prices, a phenomenon of unprecedented magnitude and breadth that affected many countries and most regions within the United States. This cycle, which roughly spanned the years 2000–2010, has generated keen interest in the origins of house price movements. For brevity, we shall refer hereafter to this entire episode as the *Great Housing Cycle* (GHC), to the period of rapid home price appreciation from 2000 to 2006 as the *boom,* and to the period 2007 to the end of 2010 as the *bust*.

Two potential driving forces of house price fluctuations are commonly cited: credit conditions and beliefs. Perhaps, the boom was driven by cheaper and easier access to credit and the bust by a subsequent constriction in credit availability. Alternatively, the boom might have been propelled by a widespread exuberance about housing unexplained by economic fundamentals, while the bust came after a negative shift in beliefs. Theoretical studies have yet to reach consensus on the relative or even absolute importance of these two mechanisms, pointing to the need for empirical evidence.[1] Yet, even empirical researchers looking at similar data sets have arrived at divergent conclusions. One set of results suggests that the boom was driven by a nascent extension of credit to low-income and subprime borrowers, while the bust was caused by a subsequent reversal of credit. Evidence commensurate with this idea (e.g., Mian & Sufi, 2009, 2016) is often interpreted as consistent with the credit conditions view. Other evidence suggests that the boom was characterized by an increase in mortgage originations to households at all income levels, including higher income and prime borrowers often thought to be less constrained by credit conditions than subprime borrowers, while the bust was characterized by a rising share of defaults by many of these same higher income borrowers (e.g., Adelino, Schoar & Severino, 2016). This evidence is often interpreted as consistent with the beliefs view, since it comports with the idea that the boom was caused by a broadly shared optimism about housing by prime and subprime borrowers alike, while the bust was caused by a widespread shift toward pessimism.

Often, the credit conditions view and beliefs view are discussed as if they were mutually exclusive possibilities. In reality, both forces could be playing a role at the same time in the data. Greenwald (2017) provides evidence that the vast majority of prime borrowers take out the largest mortgage possible given their loan-to-value (LTV) limit and their monthly debt payment-to-income (PTI) limit[2] among other eligibility requirements, implying that any homebuyer who is not purchasing with cash is likely to be credit-constrained or nearly so. Higher income and prime borrowers with more borrowing capacity take out larger mortgages, but are not necessarily less constrained than lower income and subprime households. This suggests that the relationship between mortgage growth and income growth at the individual level may be no more (or no less) informative about credit conditions than it is about beliefs. What is missing from this analysis are direct measures of credit conditions and beliefs.[3]

In this paper, we posit some simple empirical calculations using direct measures of credit conditions and beliefs to consider their potentially distinct roles as drivers of house price fluctuations at the aggregate level. To measure credit conditions, we study a little utilized indicator of mortgage lending standards from a survey of banks: the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve. The quarterly survey asks senior loan officers at banks to state whether their lending standards for purchase mortgages have eased or tightened relative to the previous quarter. We use the net percentage of banks that have eased their lending standards on mortgage loans as a measure of credit supply, a variable we denote as ΔCS_t. To our knowledge, the only paper that has previously used this measure in the study of house price fluctuations is Favilukis, Kohn, Ludvigson, and Van Nieuwerburgh (2013) (FKLV). We extend this prior analysis by considering an updated sample and a more extensive empirical study using data on beliefs.

[1] A growing body of theoretical work has addressed these questions in general equilbrium. See, for example, Davis and Heathcote (2005), Campbell and Hercowitz (2006), Kahn (2008), Kiyotaki, Michaelides, and Nikolov (2011), Piazzesi and Schneider (2008), Iacoviello and Pavan (2013), Sommer, Sullivan, and Verbrugge (2013), Landvoigt, Piazzesi, and Schneider (2015), Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Garriga and Hedlund (2017), Greenwald (2017), and Kaplan, Mitman, and Violante (2017).

[2] This limit is referred to as the “debt-to-income” limit in the mortgage industry even though the numerator is the monthly debt payment rather than the debt itself. We therefore follow other academic literature and refer to it as the PTI ratio, or PTI.

[3] Although not focused on credit conditions *per se*, at least one experimental study finds evidence that restrictions on the ability to trade in housing markets can generate large and persistent fluctuations in house prices relative to measures of fundamental value (Ikromov & Yavas, 2012).

To measure beliefs, we study four indicators. The first three are each distinct household-level survey indicators from the University of Michigan's Survey of Consumers (SOC) that ask specifically about the respondent's view on home prices. These include an overall *buying conditions index* (BCI) (whether now is a good or bad time to invest in a home), a measure created from the fraction of SOC respondents who say that conditions are good because house prices are expected to rise or stay high, and a survey point forecast for house price changes over the next year (available since 2007). As a fourth measure of beliefs, we make use of the index constructed by Soo (2018) that measures sentiment about housing based on a textual analysis of major news publications' coverage of the housing market. We then combine these data with data on national home prices in order to compile a set of statistical facts on the empirical relationships among these variables at the aggregate level.

Why should we care about whether boom-bust cycles in real estate prices are driven more by credit conditions or beliefs? One reason is that the answer to this question is likely to matter greatly for macroprudential policies, both those currently in place and those at the proposal stage. Most macroprudential policies, which are aimed at household balance sheets that tend to be dominated by mortgage credit, are effective only if credit conditions actually affect house prices. Similarly, postcrisis debt reduction and foreclosure policies are more efficacious if credit conditions matter for house prices. These points have been made recently by Greenwald and Guren (2019) who show that, in a model where home prices are driven mostly by beliefs, regulation restricting credit standards would have done nothing to dampen the boom in house prices, and would have been much less effective at restricting credit growth. By contrast, when credit matters for home prices, these policies work as intended.

With this as backdrop, we investigate several hypotheses. One concerns the relationship between credit conditions and the type of mortgages that are underwritten. If a reported net easing of bank lending standards means a relaxation of general underwriting standards, we would expect such easings to be associated with a shift in the composition of mortgages, away from less risky conforming loans and toward riskier nonconforming loans. The converse would be true of a reported net tightening of bank lending standards. By contrast, the type of broadly shared optimism or pessimism about housing necessary to drive significant fluctuations in aggregate real estate prices would presumably affect the demand for all types of credit, implying that they would change in rough proportion. So, we look at how the SLOOS survey measure of credit supply relates to mortgage growth and its composition over time.

A second and related hypothesis is that *lenders*' beliefs about future home prices altered their willingness to bear mortgage credit risk, with this willingness increasing when they were optimistic and decreasing when they turned pessimistic. Under this hypothesis, a shift in the composition of credit toward riskier nonconforming mortgages should occur when beliefs are bullish. So, we investigate whether our measures of house price beliefs are related to the shifts in the composition of mortgages.

A third question is whether either credit conditions or beliefs contain explanatory power for national home price growth that is independent of the explanatory power contained in the other variable, and in economic fundamentals. An important question for the literature on behavioral biases is whether beliefs pushed house prices beyond what would be justified by fundamentals, in which case beliefs should contain information about house price growth that is independent of credit conditions and other economic fundamentals. So, we ask whether bank credit supply contains information about current house price growth that is not contained in beliefs (and vice versa). We further investigate which forces are more quantitatively important for explaining the variation in house price changes.

A fourth hypothesis is that beliefs in the form of expectations about *future* house prices contain information about home prices that is independent of that in economic fundamentals or credit conditions (e.g., Kaplan et al., 2017). So, we investigate whether beliefs predict future house price changes, once credit conditions, fundamentals, and lagged house prices are controlled for.

A fifth hypothesis is that there is no genuine causality running from credit conditions to house price changes, even if there is a positive correlation between the two. Credit conditions could be responding to a change in home prices, as opposed to influencing them. To identify exogenous movements in credit conditions, we use the shock-restricted identification approach of Ludvigson, Ma, and Ng (2019a, b) applied to a bivariate structural vector autoregression (SVAR) with observations on ΔCS_t and house price growth. The approach allows us to locate movements in aggregate credit conditions that are not a response to changes in aggregate house prices. These movements may then be used to estimate the dynamic causal effects of an impulse to credit conditions on house price growth.[4]

Our main findings may be summarized as follows. First, changes in credit supply, as measured by ΔCS_t, are positively related to the fraction of riskier nonconforming debt in total mortgage lending. The measures of beliefs we study, however, are unrelated to this ratio. This underscores the role of easier credit in the proliferation of nonconforming debt during the housing boom and its subsequent reversal during the bust.

Second, ΔCS_t explains quantitatively large magnitudes of the variation in quarterly house price growth and is strongly statistically significant. It explains 31% of the variation in quarterly house price growth in the full sample from 1991:Q4 to 2017:Q4, and 54% in the GHC subsample. Several measures of beliefs also have statistically significant explanatory power for changes in home values, although they explain lower fractions of the variation in house price growth compared to changes in credit conditions. Once key macroeconomic fundamentals such as interest rates and expected economic growth are controlled for, ΔCS_t retains its strong statistically significant explanatory power but only two measures of beliefs do so. Both of these measures add more modestly to the fraction of variation explained in contemporaneous house price growth compared to ΔCS_t.

Third, ΔCS_t is found to be a strong marginal predictor of house price growth, both in terms of statistical significance and in terms of economic magnitudes, over horizons ranging from one- to four-quarters-ahead, controlling for economic fundamentals, lagged house price growth, and beliefs. We find little evidence that beliefs have predictive power for future house price changes, once credit conditions, fundamentals, and lagged house price growth are controlled for.

Fourth, the SVAR analysis finds that credit conditions have quantitatively important dynamic causal effects on house price changes, with positive shocks (an easing of credit) increasing home values and negative shocks (a tightening of credit) decreasing them. Although the set identified procedure produces a range of estimates, the bounds of the set are nevertheless informative. They imply that a one-standard-deviation shock to ΔCS increases real quarterly house price growth by anywhere from 0.8% to 1.4% on impact, or roughly 3.2% to 5.7% at an annual rate.

The rest of this paper is organized as follows. The next section discusses the data. Section 3 reports the empirical findings. This section includes subsections on the relation between mortgages, credit conditions, and beliefs (Section 3.1), on explaining contemporaneous house price changes (Section 3.2), on predicting future house price changes (Section 3.3), and on the SVAR analysis of credit conditions shocks on house prices (Section 3.4). Section 4 concludes.

[4]In a recent paper, using cross-sectional data, Greenwald and Guren (2019) also provide evidence that credit conditions have quantitatively large causal effects on home prices. They identify exogenous movements in credit conditions using an instrumental variable based on the idea that changes in the nation-wide Fannie Mae and Freddie Mac conforming loan limit should have larger effects in cities with more homes priced near the limit. Because the regression is cross-sectional and time effects are removed, it is not possible to identify the aggregate effects (across all cities) of changing conditions, in contrast to the approach here using aggregate data.

2 | DATA

This section describes the data. Details and sources for all data may be found in the Internet Appendix.

2.1 | Data on credit conditions

Our measure of credit conditions is based on the Federal Reserve's SLOOS survey. The survey asks banks to explicitly distinguish between changes in the supply of credit (whether it has eased or tightened) as distinct from the demand for credit, on bank loans to businesses and households over the past 3 months. We focus on questions related to *mortgage* credit supply to *households*. The detailed information is considered highly reliable because the surveys are carried out by central banks that also function as bank regulators with access to a large amount of information about a bank's operations, including those reflected in loan applications and balance sheet data.

For the SLOOS survey, banks indicate easing, tightening, or no change in lending standards on purchase mortgages compared to the previous 3 months. Thus, this variable indicates whether there has been any *change* in lending standards from the previous quarter. We use the net percentage of banks that have eased their lending standards on mortgage loans as a measure of credit supply, and denote this variable as ΔCS_t. The net percentage is the difference between the percentage of banks reporting easing and the percentage of banks reporting tightening; thus, a positive figure indicates a net easing of lending standards, considering all bank respondents. To facilitate the interpretation of results below, we standardize this variable. These data begin in 1990:Q2.

Figure 1 displays the credit supply variable ΔCS_t over time. This variable is persistent, with an autoregressive coefficient of 0.9, but statistical tests indicate that it is stationary. According to this measure, there was a notable easing of standards from 2002 to 2006, and a very sharp tightening afterward. This measure does not weight banks by their relative importance in the mortgage market, nor does it weight the responses by the degree of tightening. Thus, it is not an indicator of the strength of credit easing or tightening only of its breadth. Moreover, until 2007, the survey did not distinguish between prime and subprime mortgages. Subsequent to this time, the SLOOS survey asks banks about lending on different categories of mortgages. The Online Appendix explains how we weight these to arrive at the overall index. The figure shows a marked broad tightening of credit standards beginning at the end of 2006. A cursory examination of the figure suggests that the easing of standards in the boom was more modest. One must be careful in interpreting this series, however. A string of observations starting in 2002 and continuing through 2006 shows that standards were eased in every quarter. Recall that the survey asks banks about how their standards have changed *relative to the pervious 3 months*. Thus, a series of observations indicating easier credit conditions relative to previous quarters by a few important banks in the mortgage space, once cumulated, could indicate a significant relaxation of underwriting standards. As a crude measure of the magnitude of credit standard easing or tightening, the bottom panel of Figure 1 reports the fitted value of ΔCS_t over time that would be predicted by the actual changes in government-sponsored enterprise (GSE)-backed conforming loans outstanding and nonconforming "asset-backed securities" (ABS) outstanding, categories defined explicitly below. This estimate points to a quantitatively large easing of standards from 2002 to 2006, and a sharp tightening afterward.

It is worth noting that other indicators of credit conditions, even for conforming mortgages, also imply that credit standards were significantly relaxed during the boom and then subsequently tightened in the bust. For example, Figure 2 exhibits the fraction, over time, of mortgage originations purchased by the Federal National Mortgage Association (Fannie Mae) with PTI ratios greater than either 35%,

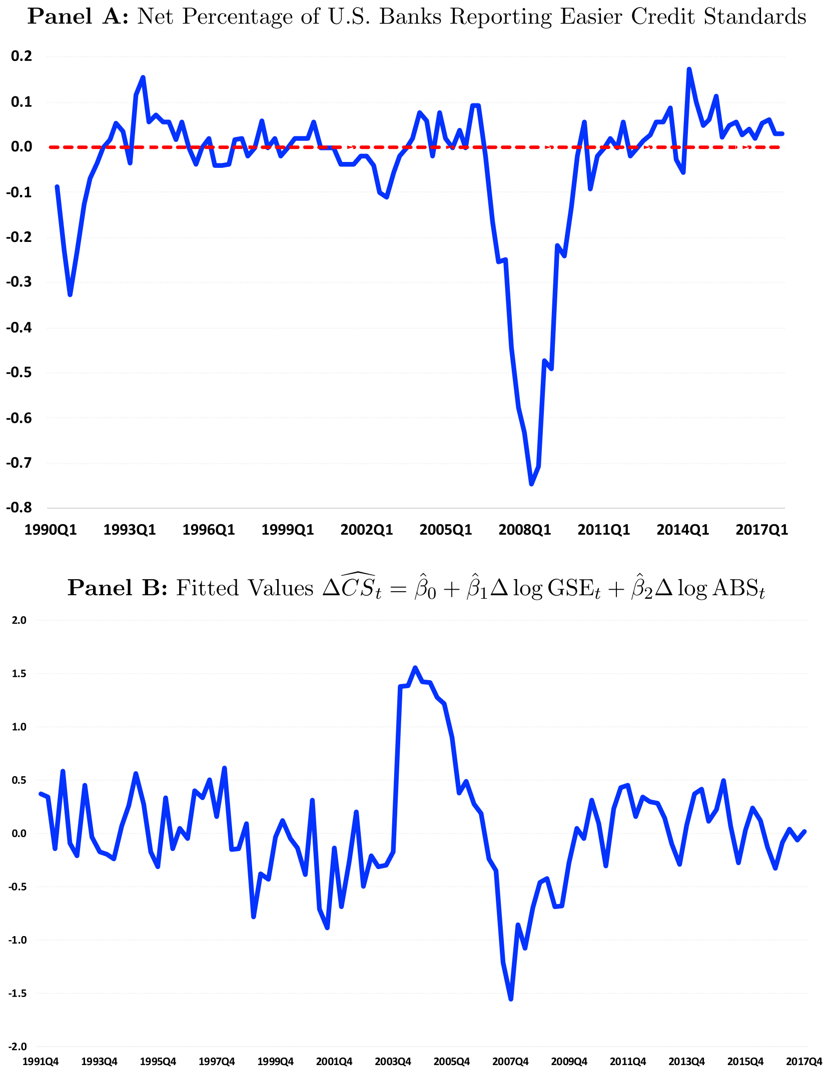


FIGURE 1 Credit supply measures [Color figure can be viewed at wileyonlinelibrary.com]

Notes: Panel A presents the net percentage of banks that reported easier credit standards on mortgages. A positive number indicates that more banks report easing than tightening. A negative number indicates the opposite (more banks tightening than easing). Panel B presents the quarterly growth of *normalized credit supply* (blue line) and the fitted values of a regression on the quarterly growth of mortgages held by GSE and ABS for the full sample (1991Q4–2017Q4) and the GHC sample (2000Q1–2010Q4).

Source: Federal Reserve—Senior Loan Officer Opinion Survey on Bank Lending Practices.

45%, or 50%, weighted by loan balance. The figure shows that PTI ratios increased dramatically from 2000 to the end of 2006. The largest increase was for the fraction that exceeded 50%, which rose by 85% over this period, followed by the fraction that exceeded 45%, which rose 66%, and the fraction that exceeded 36%, which rose 28%. All three were sharply reduced in the bust, with the fraction exceeding 50% driven to zero shortly after 2010, in part because of the Dodd–Frank act, which explicitly limits PTI ratios on conforming loans. Because these data are available only annually since 2000, we do not use them in our empirical analysis below, instead focusing on the SLOOS measure, which is available quarterly and over a longer time frame. But theoretical evidence in Greenwald (2017)

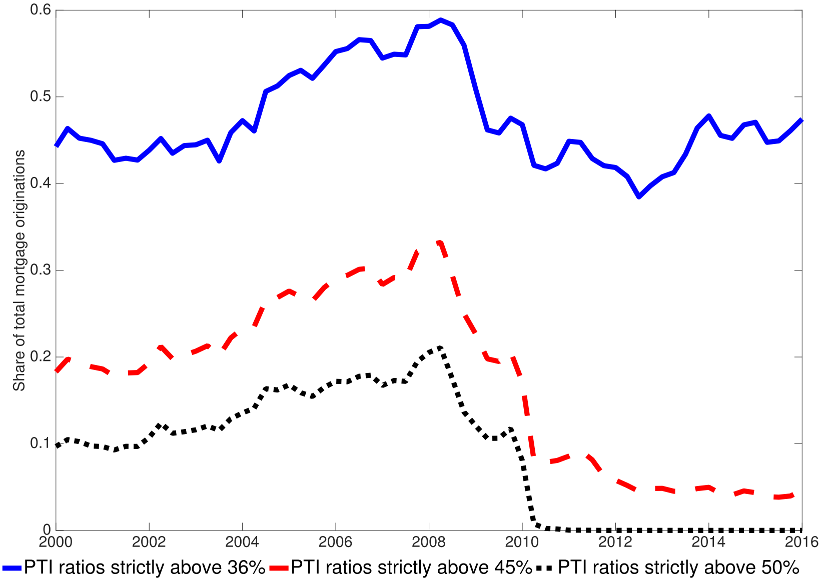


FIGURE 2 Share of originations with minimum payment to income ratio (PTI) [Color figure can be viewed at wileyonlinelibrary.com]

Notes: The figure displays the fraction, over time, of mortgage originations purchased by Fannie Mae with PTI ratios greater than 36%, 45%, and 50%, weighted by loan balance. The sample spans the period 2000:Q1–2016:Q1.

Source: Fannie Mae Single Family Dataset.

suggests that time variation in these PTI constraints has an important influence on home prices in general equilibrium.[5]

2.2 | Data on beliefs

We use four measures of beliefs about home values. The first three of these are available from the University of Michigan's SOC. The first is an index of perceived buying conditions that goes back to 1978. The SOC asks, "Generally speaking, do you think now is a good time or a bad time to buy a house?" We construct a net BCI by taking the number of "good" answers, subtracting the number of "bad" answers and adding 100. This index is plotted over time in the upper panel of Figure 3. A slightly different measure, the *fraction* of respondents who answer that now is a "good time to buy," is shown in the lower panel and behaves similarly over time. Below, we investigate the relation between the log difference in house prices and possible covariates such as beliefs and credit conditions. Thus, our empirical analysis uses the quarterly log difference in all belief indicators, including BCI. The log difference in BCI is denoted by Δbci.

Our second measure of beliefs is taken from a follow-up question of the SOC on buying conditions. There may be many reasons respondents answer that it is a good time to buy a house. The SOC asks households to give up to two reasons. This is an open-ended question, but the SOC groups the answers into six categories. Figure 4 plots the fraction of respondents who have a positive view about buying conditions along with the three most important reasons given for that view, again in terms of the

[5]Greenwald (2017) uses the Fannie Mae data to calibrate a general equilibrium model with prepayable debt and a limit on the ratio of mortgage payments to income. He finds that a relaxation of PTI standards has large effects on home prices and price–rent ratios in the model.

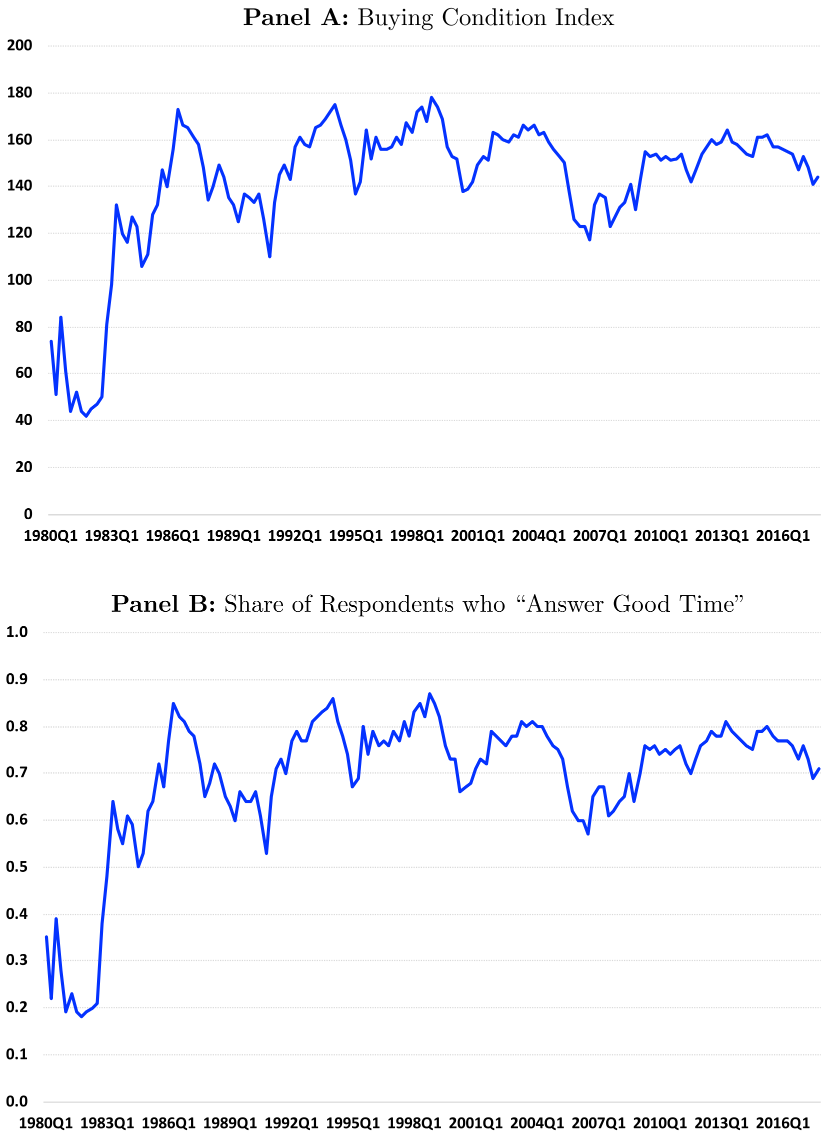


FIGURE 3 Buying condition for houses [Color figure can be viewed at wileyonlinelibrary.com]
Notes: Panel A: Buying condition index constructed by taking the number of "good" answers, subtracting the number of "bad" answers, and adding 100. Panel B: Fraction of respondents who answer that now is a "good time" to buy a house.
Source: Survey of Consumers, University of Michigan.

fraction of respondents who hold that view for that reason. As pointed out previously by Piazzesi and Schneider (2009), the most commonly given reason that households have a positive view of buying conditions is that *credit conditions are good*. Good credit conditions are expressed by referring to low interest rates, lower down payment requirements, or more general ease in obtaining credit.[6] The next two most important reasons given in the case of *good time to buy* are *current prices are low* and

[6]The SOC refers to this category as "interest rates low." We refer to it as "good credit" because the respondents include all those giving any of the four following reasons for their favorable outlook: (a) lower down payment; (b) interest rates are low; (c) credit easy to get, easy money; and (d) variable mortgage rate.

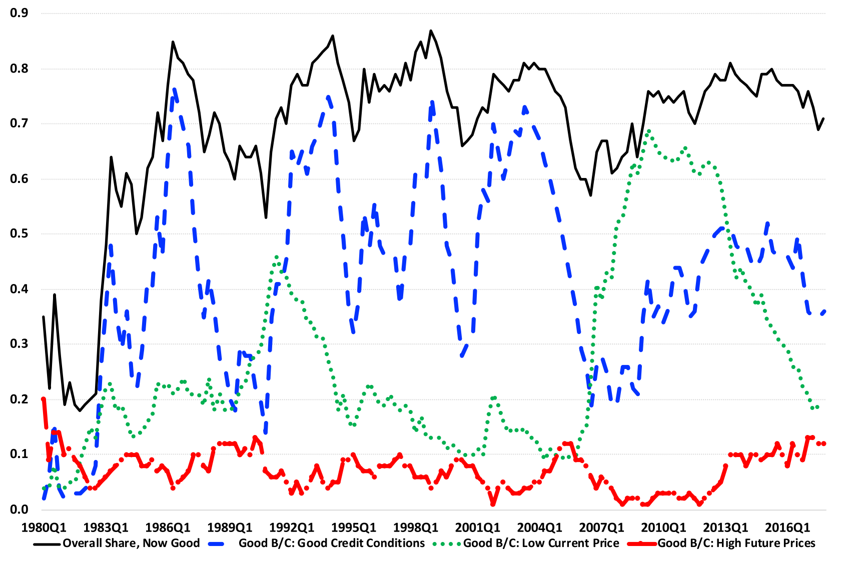


FIGURE 4 Reasons for which it is a good time to buy a house [Color figure can be viewed at wileyonlinelibrary.com]

Notes: The black line presents the share of all respondents who answer that now is a "good time" to buy a house. We present the three most important reasons that respondents give when surveyed. The blue line presents the share of respondents who answer that it is a good time to buy a house because *credit conditions are favorable*, the SOC classifies it as *low interest rates*. The green line presents the share of respondents who answer that it is a good time to buy a house because *current prices are low*. The red line presents the share of respondents who answer that it is a good time to buy a house because of *potential higher future prices*. Note that each respondent may give up to two reasons; hence, these shares do not necessarily sum up to 100%.
Source: Survey of Consumers, University of Michigan.

future prices will be higher. Note that relatively few individuals cite an expectation of future price growth as a reason to buy. Nevertheless, this latter series—the fraction of respondents who say that buying conditions are good because future house prices will be high—hones in on the expectations component of beliefs that is central, in some theories, to driving house price variation. In some models, it is crucial that all agents in the economy share the same beliefs (e.g., Kaplan et al., 2017). But in other models, this is not the case. Piazzesi and Schneider (2009) point out that in a search market with high transaction costs, even a small number of optimistic (pessimistic) buyers can drive up (down) the average transaction price without a large increase in trading volume. This insight motivates us to use the fraction of respondents who say that buying conditions are good because future house prices will be high as a third measure of house price beliefs. Our empirical analysis uses the log difference in this fraction, denoted by $\Delta bci_t^{high\,FP}$. This measure is available over the same time period as the overall BCI.

The third measure available from the SOC asks households for a point forecast on house price changes over the next 12 months. This measure is available from 2007:Q1 onward. This question asks respondents *By about what percent do you expect prices of homes like yours in your community to go (up/down), on average, over the next 12 months?* The SOC asks the analogous question for expected inflation over the next 12 months. We use either the median or mean responses to both questions to construct a measure of real house price expectations (Δp_t^e). For example, the median response is calculated as

$$\Delta p_t^{e,med} = E_t^{med} \Delta \log P_{t+4} - E_t^{med} \pi_{t+4}, \tag{1}$$

where "E_t^{med}" denotes the median value of the survey expectation for house prices and inflation. The mean response for house price growth is constructed in an analogous fashion and denoted by $\Delta p_t^{e,avg}$.

Our fourth measure of beliefs is the national version of Soo's (Soo, 2018) housing media sentiment index. Soo measures housing sentiment through a textual analysis of content in newspaper articles from major publications in 34 cities of the United States spanning the period January 2000 to December 2013. Soo calculates sentiment by subtracting the number of negative words about housing from the number of positive words and dividing by the total number of words, where "negative" and "positive" refer to sentiment about current and future home values. Thus, this index rises when media housing sentiment is more "bullish" and falls when media sentiment turns more "bearish." Soo further shows that log changes in her index at the city level have important predictive power for house price changes in the corresponding city. Here, we employ log changes in the national version of her housing media index in our empirical analysis of national home prices. This variable is denoted by Δhmi_t.

Each of these four measures of beliefs are constructed so that an *increase* in the measure quantifies a general shift toward *optimism* about the housing market, while a *decrease* quantifies a corresponding shift toward *pessimism*. Models in which beliefs matter for home prices (e.g., Kaplan et al., 2017; Piazzesi & Schneider, 2009) predict that these measures should be positively related to home price growth.

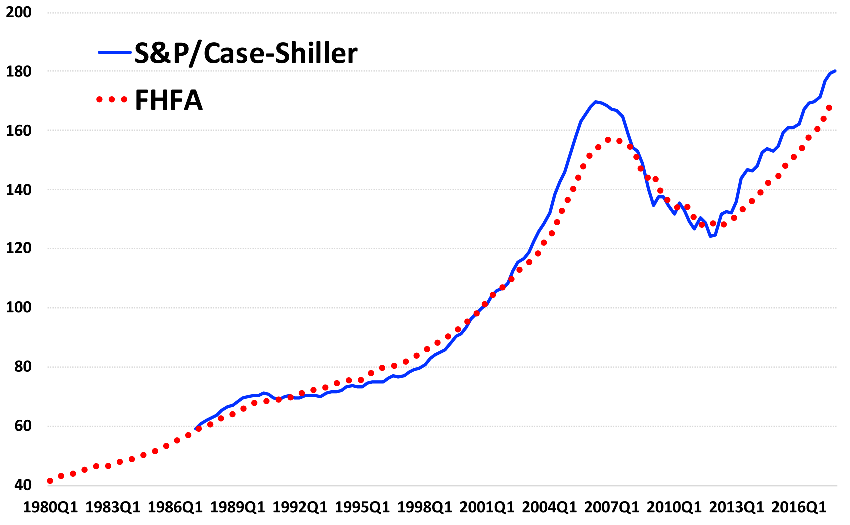
2.3 | Data on house prices

Two repeat-sales national home price indexes are commonly examined in the study of house price fluctuations at the aggregate level. The first is the S&P/Case-Shiller U.S. National Home Price Index (CSUS) and the second is the Federal Housing Finance Agency (FHFA) home price index. These series are divided by the Consumer Price Index (CPI) and plotted over time in Figure 5. The lower panel plots the same series relative to an aggregate measure of rents, a common specification of the fundamental dividend stream provided by the housing stock. The dramatic boom/bust cycle is clear in the figure for both series, but is much more pronounced in the CSUS than in the FHFA. The most significant difference between the two indexes is that FHFA collects data from mortgages that have been purchased or securitized by Fannie Mae or the Federal Home Loan Mortgage Corp. (Freddie Mac) only. (It also equal-weights house prices and includes refinances, while the CSUS does not.) The CSUS index includes all available transactions on single-family homes, including sales financed with nonconforming mortgages, such as jumbo, Alt-A and subprime. As a result, this index is broader than FHFA. Transactions are also value-weighted in the CSUS. Because of its breadth, and because nonconforming mortgage lending appears to have played an outsized role in the GHC, we use the CSUS index as our main measure of national home prices in the empirical work below. We employ log changes in the CPI-deflated value of this index in our empirical analysis. This variable is denoted by Δp_t.

3 | EMPIRICAL FINDINGS

This section reports the empirical findings. Output for all regressions includes the coefficient estimates, adjusted R^2 statistic, and heteroskedasticity and serial correlation robust (HAC) t-statistics (Newey & West, 1987). To assess potential finite sample biases, for each regression, we also undertake bootstrap procedures under the null that the explanatory variables have no marginal explanatory power. Following the prescription of Horowitz (2003), we use the bootstrap to estimate the probability distribution of

Panel A: Price Levels



Panel B: Price Rent Ratios

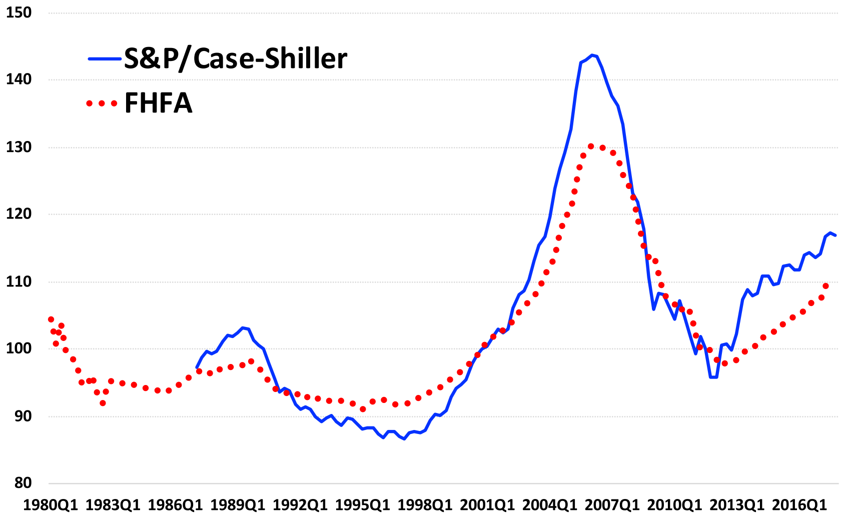


FIGURE 5 House prices [Color figure can be viewed at wileyonlinelibrary.com]

Notes: Panel A: The blue line refers to the S&P/Case-Shiller U.S. National Home Price Index (CSUS). The red line is the Federal Housing Finance Agency (FHFA) home price index. Both indices are divided by the Consumer Price Index (CPI) and rebased to 100 in the fourth quarter of 2000. Panel B: Price–rent ratios are constructed by dividing the real price index by the shelter CPI for all urban consumers. The blue line is the price ratio using the CSUS index and the red line the price ratio using the FHFA index. For both indices, the base is the fourth quarter of 2000.

Source: Federal House Finance Agency, S&P Dow Jones Indices LLC, and U.S. Bureau of Labor Statistics.

the t-statistic for each coefficient under this null, since such a statistic is asymptotically pivotal and can deliver bias reduction in finite samples. To account for the serial dependence of the data, we use two approaches. The first approach employs a parametric model of the serial dependence, while the second is a nonparametric model based on block bootstraps. We refer to these as the parametric and nonparametric bootstrap, respectively. Each regression table reports statistical significance on the basis of the two bootstrap distributions of the t-statistic, as well as the Newey–West HAC approximation to the asymptotic distribution of the t-statistic.

The samples used in each empirical analysis depend on data availability. Different measures of beliefs are available over different time periods. In addition, although the SLOOS survey begins in 1990:Q2, our measure of the real 10-year Treasury bond, used in several regressions, uses the Survey of Professional Forecasters (SPF) median 10-year inflation forecast to construct a real rate. This latter variable is available starting in 1991:Q4. Thus, our longest "full sample" spans the period 1991:Q4–2017:Q4. We begin by investigating mortgage credit extension and its relation to credit conditions and beliefs over time.

3.1 | Mortgages, credit conditions, and beliefs

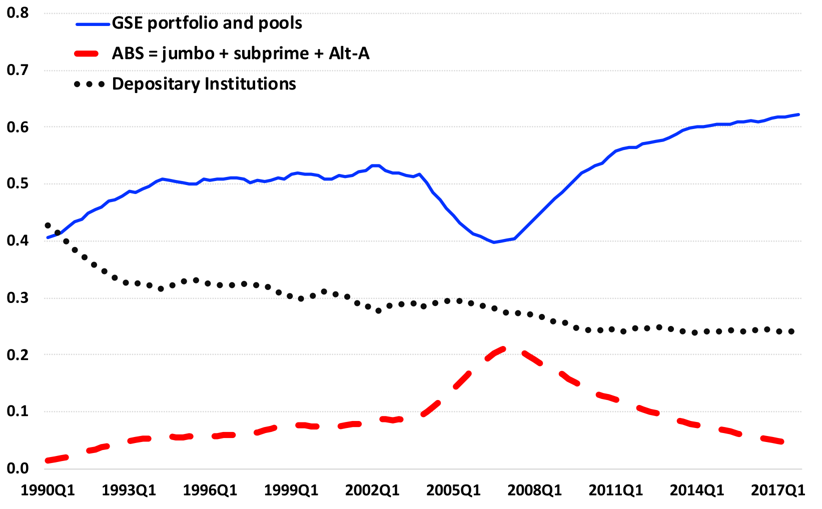
Mortgages vary in terms of the attributes that are considered to be closely related to the ex-ante riskiness of the loan. For the purposes of this paper, we shall define a *conforming* loan to be one that is eligible for purchase by the GSEs Fannie Mae and Freddie Mac. Conforming loans are considered less risky than nonconforming loans for two reasons. First, they must adhere to strict eligibility requirements that ostensibly limit the riskiness of the loan ex-ante. These include limits on the size of the loan, on the borrower's LTV ratio, on the borrower's PTI ratio, on the borrower's credit score, and the documentation requirements of the loan.[7] Second, the GSEs purchase these safer mortgages on the secondary market and guarantee them against default. *Nonconforming* loans, such as jumbo, subprime, and Alt-A mortgages, are considered riskier than conforming loans, since they need not adhere to these standards and they are ineligible for purchase and guarantee by the GSEs.

Time variation in the composition of loans over time is of interest because of how it relates to lending standards. When loan officers at banks answer questions on whether their lending standards have eased or tightened, their answers presumably relate to the price terms of the mortgage contracts, such as interest rates, but also nonprice terms such as the maximum LTV ratio, the maximum PTI ratio, any requirements on private mortgage insurance, and the minimum credit score. If so, it is natural to expect a reported *easing* of bank lending standards to be associated with an increase in the share of credit extended to borrowers who do not meet the eligibility requirements of a conforming loan, and conversely for a reported tightening of standards. By contrast, the type of broadly shared optimism or pessimism about housing necessary to drive significant fluctuations in aggregate real estate prices would presumably change the demand for all types of credit in rough proportion.

The upper panel of Figure 6 shows the *share* of mortgages outstanding by mortgage type, over time, updating the same figure in FKLV. The line labeled "GSE portfolio and pools" are Agency- and GSE-backed mortgage pools, consisted only of conforming mortgage loans. The line labeled "ABS" refers to issuers of ABS, consisted entirely of nonconforming loans. The ABS mortgages are the sum of jumbo, subprime, and Alt-A mortgages discussed above. The figure shows a significant change in the composition of loans from 2002 to 2007: a sharp rise in the share of ABS during the housing boom, which mirrors a sharp fall in the share of GSE loans. From 2000 to 2006, the share of ABS in total mortgages outstanding almost tripled, increasing 178%. This indicates a shift in the composition of mortgage lending, away from conforming debt and toward nonconforming debt, a trend that was subsequently reversed after 2007 during the housing bust. The lower panel of Figure 6 shows a similar pattern in the share of mortgage *originations* over time, which comes from a different data source composed of annual rather than quarterly observations. The analogy to the ABS category in the originations data

[7]The eligibility matrix guidelines for conforming loans are given here https://www.fanniemae.com/content/eligibility_information/eligibility-matrix.pdf

Panel A: Share of Mortgage Outstanding by Mortgage Type



Panel B: Share of Mortgage Originations by Mortgage Type

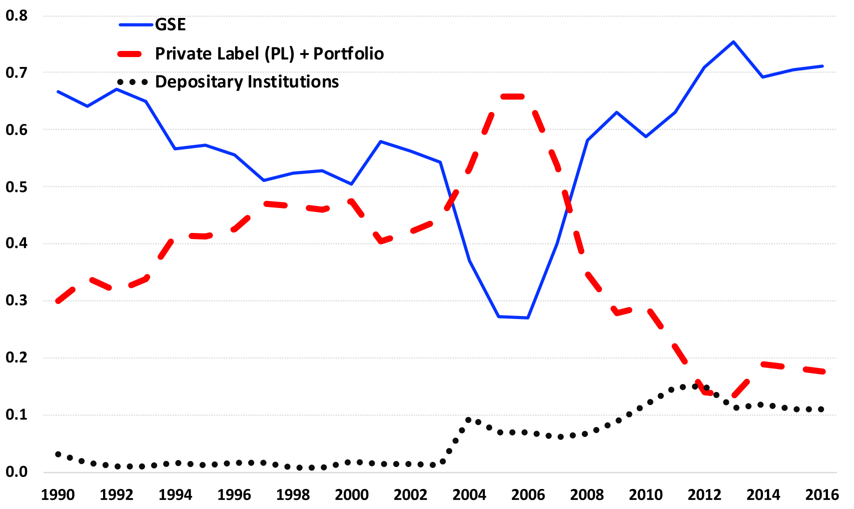


FIGURE 6 Share of mortgages by mortgage type [Color figure can be viewed at wileyonlinelibrary.com]
Notes: Panel A: The blue line reports the sum of GSE mortgage portfolio and agency and GSE-backed mortgage pools. The red line shows mortgages of issuers of asset-backed securities (ABS), calculated based on the sum of jumbo, subprime, and Alt-A mortgages. The black line reports the home mortgages held by U.S.-chartered depository institutions. Panel B: Private label (PL) and portfolio is the sum of private securitization, affiliate institutions, life insurance companies, credit unions, mortgage banks, and insurance firms.
Source: Flow of Funds and Federal Financial Institutions Examination Council.

is the "private label" PL+Portfolio category. Private label includes mortgages securitized by private institutions. Portfolio includes mortgages held in the asset portfolios of life insurance companies, credit unions, mortgage banks, and affiliate institutions. The sum of these two categories is composed entirely of nonconforming debt, since the conforming loans are all sold off to the GSEs and counted as part of the GSE category. Again, we see a significant change in the composition of originations over the boom period, with a sharp rise in the nonconforming PL loans relative to total originations, and a sharp reversal of this trend over the housing bust. Over the boom period 2000–2006, the share of PL+Portfolios loans in total originations increased by roughly 40%, but because the share falls in the intermediate aftermath of the 2000–2001 recession, it increased 63% from 2001 to 2006.

The first column of Table 1 shows that the short-term trends in ΔCS are related to these changes in the composition of lending. For the quarterly data on mortgages outstanding, we investigate the relation between the year-over-year growth in credit standards, measured as the four-quarter sum of the SLOOS net percentage easing indicator ΔCS shown in Figure 1, and year-over-year growth in mortgage credit outstanding, by mortgage type. The table reports results from a regression of the latter on the former. Changes in credit standards ΔCS are positively related to growth in ABS and negatively related to growth in mortgages held in GSE pools. The last column shows the results from a regression on the growth in the *ratio* of ABS to GSE pools. ΔCS is positively related to log changes in this ratio. The percentage of banks reporting an easing of credit standards is associated with a shift in the composition of loans, toward nonconforming loans and away from conforming loans. This result is more pronounced when looking only at the entire GHC period 2000–2010 (Panel B), underscoring the role of easier credit standards in the proliferation of nonconforming debt during the housing boom. The $\overline{R}^2$ in this subsample is 47%, almost five times larger than that found in the full sample, while the estimated regression coefficient is almost twice as large.

An important aspect of the SLOOS survey is that it asks banks to explicitly distinguish between changes in the *supply* of credit as distinct from the *demand* for credit. Thus, in principle, answers to the appropriate questions are able to identify a movement in supply separately from a movement in demand. We use the notation ΔCD to denote the SLOOS measure of change in demand for credit, where ΔCD measures the net percentage of banks reporting *greater* credit demand. The second row in Table 1 below presents the results for the same regressions as in the first row but instead of using the year-over-year growth in credit standards ΔCS as the regressor, we use the year-over-year growth in credit demand ΔCD. Although the percentage of banks reporting an easing of credit standards is associated with a shift in the composition of loans toward riskier debt, there is no such finding for the net percentage of banks reporting higher demand for mortgage credit, which is also statistically unrelated to changes in mortgages outstanding of any type. Year-to-year fluctuations in credit demand may simply have a negligible effect on changes in the total stock of mortgages outstanding, which includes many loans originated in years and decades prior. A more reasonable question is whether shifts in demand influence (contemporaneous) originations, a hypothesis we investigate below.

Columns (3)–(7) in Table 1 show the relationship between the four beliefs measures and the composition of mortgage credit outstanding. We regress the year-over-year growth in mortgage credit outstanding, by mortgage type, on the year-over-year log change in beliefs. Using these measures, there is little evidence that shifts in the composition of mortgages toward riskier nonconforming debt during the housing boom were associated with optimism about the housing market. The only measure of beliefs that shows a statistically significant relationship to changes in ABS/GSE in a sample that includes the housing boom is the SOC measure Δbci_t in the GHC subsample, but this relationship has the wrong (negative) sign. This correlation should be positive if optimistic beliefs were a source of growth in the ratio of nonconforming to conforming debt during the boom, or pessimistic beliefs a source of decline in this ratio during the bust. The two other beliefs measures that are available in a sample that contains the GHC, Δhmi_t and Δbci_t^{highFP}, bear no relationship to this fraction. The one measure of beliefs that is statically significantly related to growth in the ratio ABS/GSE with the right (positive) sign is the survey average (but not the median) point forecast for housing growth $\Delta p_t^{e,avg}$, but this occurs in a sample that excludes the boom (2007:Q1–2017:Q4). These findings are consistent with the idea that the type of broadly shared optimism or pessimism about housing necessary to drive

TABLE 1 Regressions of mortgage growth outstanding by holder type

Regressor	Left-hand-side variable Δ_4 log All	Δ_4 log ABS	Δ_4 log GSE	$\Delta_4 \log(\frac{\text{ABS}}{\text{GSE}})$
		Sample: 1991:Q4–2017:Q4		
$\Delta_4 CS$	0.003	$0.013^{**\diamond}$	$-0.005^{***\diamond}$	$0.018^{***\diamond\diamond}$
t-Stat	(1.517)	(2.270)	(−3.362)	(3.587)
$\bar{R}^2$	[0.024]	[0.044]	[0.157]	[0.101]
$\Delta_4 CD$	−0.003	0.001	−0.001	0.002
t-Stat	(−1.046)	(0.116)	(−0.259)	(0.175)
$\bar{R}^2$	[0.016]	[−0.009]	[−0.008]	[−0.009]
$\Delta_4 bci$	−0.133	−0.037	0.131^{**}	−0.168
t-Stat	(−1.613)	(−0.072)	(2.363)	(−0.337)
$\bar{R}^2$	[0.043]	[−0.009]	[0.071]	[−0.004]
$\Delta_4 bci^{highFP}$	−0.013	−0.054	$-0.0030^{***\dagger\dagger\diamond}$	−0.025
t-Stat	(−0.994)	(−0.957)	(−3.942)	(−0.435)
$\bar{R}^2$	[0.013]	[0.013]	[0.165]	[−0.004]
$E_t^{med}\Delta GDP_{t\to t+4}$	$0.047^{***\diamond\diamond}$	$0.177^{***\diamond\diamond}$	0.000	$0.177^{***\diamond}$
t-Stat	(3.974)	(3.681)	(0.039)	(3.527)
$\bar{R}^2$	[0.217]	[0.185]	[−0.010]	[0.213]
		Sample: 2000:Q1−2013:Q4		
$\Delta_4 hmi$	−1.446	−6.313	−0.493	−5.819
t-Stat	(−1.167)	(−1.437)	(−0.460)	(−1.304)
$\bar{R}^2$	[0.029]	[0.059]	[−0.008]	[0.049]
		Sample: 2007:Q1–2017:Q4		
$\Delta p_t^{e,med}$	0.006	−0.002	−0.018	0.016
t-Stat	(0.582)	(−0.202)	(−1.232)	(1.597)
$\bar{R}^2$	[−0.004]	[−0.023]	[0.091]	[0.001]
$\Delta p_t^{e,avg}$	0.007	0.009	−0.009	$0.018^{**\diamond}$
t-Stat	(1.431)	(1.201)	(−1.209)	(2.539)
$\bar{R}^2$	[0.094]	[0.003]	[0.100]	[0.113]
		Sample: 2000:Q1–2010:Q4		
$\Delta_4 CS$	$0.007^{***\diamond\diamond\diamond}$	$0.028^{***\diamond\diamond\diamond}$	-0.003^{**}	$0.032^{***\diamond\diamond\diamond}$
t-Stat	(4.713)	(4.568)	(−2.215)	(4.700)
$\bar{R}^2$	[0.389]	[0.427]	[0.150]	[0.472]
$\Delta_4 CD$	0.000	−0.004	0.002	−0.005
t-Stat	(0.040)	(−0.249)	(0.479)	(−0.340)
$\bar{R}^2$	[−0.024]	[−0.021]	[−0.009]	[−0.019]
$\Delta_4 bci$	-0.239^{**}	-0.986^{**}	0.177^{***}	-1.162^{**}
t-Stat	(−2.285)	(−2.169)	(2.803)	(−2.508)
$\bar{R}^2$	[0.149]	[0.189]	[0.186]	[0.239]
$\Delta_4 bci^{highFP}$	0.001	0.034	$-0.0030^{***\dagger\dagger}$	0.064
t-Stat	(0.039)	(0.418)	(−3.372)	(0.742)
$\bar{R}^2$	[−0.024]	[−0.013]	[0.250]	[0.012]

(*Continued*)

TABLE 1 Continued

Regressor	Left-hand-side variable Δ_4 log All	Δ_4 log ABS	Δ_4 log GSE	$\Delta_4 \log(\frac{\text{ABS}}{\text{GSE}})$
$E_t^{med}\Delta GDP_{t\to t+4}$	0.059$^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	0.205$^{***\diamond\diamond}$	−0.012	0.216$^{***\diamond\diamond}$
t-Stat	(7.298)	(4.974)	(−1.128)	(4.476)
$\bar{R}^2$	[0.462]	[0.402]	[0.019]	[0.399]
$\Delta_4 hmi$	−0.545	−3.939	0.495	−4.434
t-Stat	(−0.397)	(−0.815)	(0.553)	(−0.881)
$\bar{R}^2$	[−0.017]	[0.009]	[−0.009]	[0.013]

Notes: Regressions of the log change of each mortgage type on the four quarter sum of credit supply ($\Delta_4 CS$), the four quarter sum of credit demand ($\Delta_4 CD$), the annual log change of the buying condition index, that is, ln bci_t − ln bci_{t-4} ($\Delta_4 bci$), and the annual log change in the share of respondents that answer that is "good time" to buy a house because prices will increase ($\Delta_4 bci^{highFP}$), the median SPF forecast of real GDP growth between t and $t+4$ ($E_t^{med}\Delta GDP_{t\to t+4}$), the annual log change in the House Media Index ($\Delta_4 hmi_t$), the expected median real house price change over the next 12 months ($\Delta p_t^{e,med}$), and the expected average real house price change over the next 12 months ($\Delta p_t^{e,avg}$). See Figure 6 for the definition of each mortgage type. For both panels, Newey–West corrected t-statistics in parentheses (lags = 4). Newey-West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: $^\diamond$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. Full sample spans all the available data in each case. The GHC sample spans the period 2000:Q1–2010:Q4.

significant fluctuations in aggregate real estate prices would presumably change the demand for all types of credit in rough proportion.

It is possible that a change in the beliefs of lenders about house prices over the housing cycle altered their willingness to bear mortgage credit risk, which resulted in the observed shift in the composition of credit. Lenders' beliefs would need to differ from those captured by the four house price beliefs measures considered here; however, otherwise the evidence in Panels A and B is not supportive of this hypothesis. It is worth pointing out, however, that while shifts in the composition of mortgage credit are not associated with shifts in beliefs about house prices, they are associated with measures of beliefs about *economic fundamentals*. To illustrate, Table 1 also reports the results of regressing changes in the composition of mortgages on the expected real gross domestic product (GDP) growth rate for the year ahead, as measured by the SPF median forecast of 1-year-ahead GDP growth, denoted as $E_t^{med}\Delta GDP_{t\to t+4}$. Unlike survey expectations of positive house price growth, survey expectations of positive economic growth are associated with a shift in the composition of loans, toward nonconforming loans and away from conforming loans. As we discuss below, survey expectations of positive economic growth are also positively related to ΔCS_t, our measure of growth in credit supply.

Table 2 presents results for originations that are analogous to those for debt outstanding presented in Table 1. Because originations are only available annually, we relate the annual log difference in originations to the annual average of ΔCS_t and ΔCD_t over the four quarters of the year, and to the Q4-over-Q4 log difference in the three belief measures Δbci_t, Δhmi_t, and Δbci_t^{highFP}. Given the small number of observations, we do not use data on expected house price growth, Δp_t^e, which is only available since 2007. Even for the other measures, the samples are quite small, so these results can only be considered suggestive. Similar to the results reported for debt outstanding, we find that ΔCS_t is positively related to the composition of originations, as measured by changes in the ratio of (PL+Portfolio)/GSE, while the three beliefs measures are statistically insignificant. By contrast, the belief measures Δbci_t, Δhmi_t, as well as ΔCD_t, the net percentage of banks reporting greater demand for mortgages, are all found to be significantly related to shifts in mortgage originations across all mortgage types in a roughly proportional manner. Each of these measures is positively and statistically significantly related to changes in all originations, to changes in the PL+Portfolio originations, and to

TABLE 2 Regressions of mortgage origination growth by holder type

Regressor	Left-hand-side variable Δ_4 log All	Δ_4 log PL + $Portfolio$	Δ_4 log GSE	$\Delta_4 \log(\frac{\text{PL + Portfolio}}{\text{GSE}})$
$\Delta_4 CS$	0.014	0.041***	−0.014	0.056***††
t-Stat	(1.274)	(3.464)	(−1.374)	(7.879)
$\bar{R}^2$	[−0.020]	[0.135]	[−0.024]	[0.409]
$\Delta_4 CD$	0.087***	0.081***	0.087***	−0.006
t-Stat	(7.204)	(5.681)	(4.391)	(−0.278)
$\bar{R}^2$	[0.545]	[0.443]	[−0.432]	[−0.038]
$\Delta_4 bci$	2.059***	1.600**	2.565***	−0.965
t-Stat	(3.003)	(2.016)	(3.917)	(−1.567)
$\bar{R}^2$	[0.274]	[0.139]	[0.352]	[0.051]
$\Delta_4 bci^{highFP}$	−0.117	−0.108	−0.171	0.063
t-Stat	(−0.871)	(−1.064)	(−1.106)	(0.617)
$\bar{R}^2$	[0.011]	[0.001]	[0.048]	[−0.021]
$E_t^{med}\Delta GDP_{t\rightarrow t+4}$	0.019	0.197	−0.148	0.345***
t-Stat	(0.132)	(1.096)	(−1.273)	(3.789)
$\bar{R}^2$	[−0.041]	[0.052]	[0.003]	[0.363]
$\Delta_4 hmi$	17.986***	14.054**	17.066***	−3.012
t-Stat	(6.592)	(2.188)	(5.830)	(−0.407)
$\bar{R}^2$	[0.295]	[0.074]	[0.169]	[−0.083]

Notes: Regressions of the log change of each mortgage type on the annual sum of credit supply (ΔCS), the annual sum of credit demand (ΔCD), the annual log change of the buying condition index ($\Delta_4 bci$), the annual log change in the share of respondents that answer that is "good time" to buy a house because prices will increase ($\Delta_4 bci^{highFP}$), the median SPF forecast of real GDP growth between t and $t+4$ ($E_t^{med}\Delta GDP_{t\rightarrow t+4}$), and the annual log change in the House Media Index ($\Delta_4 hmi_t$). See Figure 6 for the definition of each mortgage type. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: ⋄significant at 10%. ⋄⋄significant at 5%. ⋄⋄⋄significant at 1%. The sample spans 1991–2016 for the first four row blocks and the period 2000–2013 in the last row block.

changes in the GSE originations. But neither the belief measures nor ΔCD_t is found to be related to the *composition* of originations as demonstrated by the last column, which shows the results when the ratio of the PL+Portfolio to GSE originations is regressed on each of Δbci_t, Δhmi_t, and $\Delta_4 CD_t$ individually. These findings are again consistent with the idea that waves of broadly shared optimism or pessimism about housing should change the demand for all types of credit in rough proportion, thereby creating a contrast with shifts in credit standards where changes in the composition of lending are found.

3.2 | Explaining contemporaneous house price changes

We begin our investigation of which variables, if any, are contemporaneously correlated with house price growth by analyzing univariate regressions of Δp_t on contemporaneous ΔCS_t and of Δp_t on contemporaneous beliefs. Throughout this section, we use the terminology "explain" when referring to the estimated empirical relations, with the proviso that we do not make claims about causality. The question of causality and the identification of exogenous variation in credit standards is addressed in the penultimate section of the paper using an SVAR.

Table 3 presents the results of the univariate regressions, where Panel A gives results over the full sample that is available given the data series being used, and Panel B presents results for the GHC subsample. Panel A shows that in the sample from 1991:Q4 to 2017:Q4, changes in credit standards as measured by ΔCS_t explain 31% of the variation in Δp_t, with the coefficient on ΔCS_t significant at the 1% or better level. To interpret the magnitudes of the coefficient on ΔCS_t, recall that this variable is standardized, so a one-unit increase in this measure implies a one-standard-deviation increase around its mean. Thus, a coefficient of 0.01 implies that a one-standard-deviation increase in ΔCS_t leads to a 100 basis point rise in quarterly real house price growth, or roughly a 4% rise at an annual rate. This increase represents about one-half of a one-standard-deviation change in quarterly U.S. real house price growth (1.9%).

Of the two measures of beliefs that are available over the same sample period, the overall buying conditions variable Δbci_t bears a negative empirical relation to contemporaneous house price growth, but the index created from the fraction of respondents who say buying conditions are good because future prices will be high, Δbci_t^{highFP}, is positively correlated with house price growth. This variable explains about 9% of current house price growth. Similarly, growth in Soo's housing media index Δhmi_t explains 8% of Δp_t and is strongly significant in a sample from 2000:Q1 to 2013:Q4, whereas in this sample, ΔCS_t explains 37%. Moreover, in the sample 2007:Q1–2017:Q4 for which the SOC point forecasts for housing growth are available, the median forecast $\Delta p_t^{e,med}$ and the average forecast $\Delta p_t^{e,avg}$ are both positively related to house price growth and strongly statistically significant, explaining 11% and 20%, respectively, of house price growth. By comparison, ΔCS_t explains 38% in this subsample. Since the average is more influenced by outliers than the median, the finding that the average point forecast explains a larger fraction of house price growth than the median forecast lends empirical support for the model in Piazzesi and Schneider (2009), which implies that a small number of optimists (or pessimists) can have an important effect on the relatively few repeat sales transactions observed in the data.

In the GHC subsample (Panel B), ΔCS_t explains a much larger fraction (54%) of the variation in Δp_t than in the full sample, reinforcing the notion that credit conditions played an outsized role in the housing boom and bust. Of the three beliefs measures that are available over this subsample, only the housing media index Δhmi_t is statistically related to Δp_t, explaining 6% of the variation compared to 8% when the sample is extended to 2013:Q4. By contrast, and unlike the full sample, growth in the share of optimistic households who said housing was a good investment because house prices would further appreciate, Δbci_t^{highFP}, bears no relation to house price growth in the GHC subsample. Thus, while the univariate regressions suggest that both credit conditions and beliefs are contemporaneously related to current house price growth, the credit conditions measure is found to explain much larger fractions than the beliefs measures of the variation in home values.

In most economic theories, both credit standards and beliefs evolve endogenously with the state of the economy and with expectations about future economic conditions. This is so even in fully rational models where beliefs have no independent role to play. Thus, an important question for the literature on behavioral biases is whether beliefs pushed house prices beyond what would be justified by economic fundamentals alone, in which case beliefs should contain information about house price growth that is independent of that in measures of economic fundamentals. Moreover, if beliefs but not credit standards are the driving force behind house price changes, the former should drive the latter out of the regression.

To address these questions, Table 4 presents results from multivariate regressions of Δp_t on contemporaneous ΔCS_t and contemporaneous beliefs (one at a time), controlling for two economic fundamentals other than credit conditions: the SPF median forecast of 1-year-ahead GDP growth, $E_t^{med} \Delta GDP_{t \to t+4}$, and the real 10-year Treasury-bond rate, as measured by the nominal 10-year Treasury bond rate minus the SPF median 10-year inflation forecast, denoted by r_t^{10}. We refer to the

TABLE 3 Univariate regressions of Δp_t on contemporaneous ΔCS_t and beliefs

Panel A								
	1991:Q4–2017:Q4			**2000:Q1–2013:Q4**		**2007:Q1–2017:Q4**		
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ΔCS_t	$0.011^{***\dagger\dagger\dagger\diamond\diamond\diamond}$			$0.012^{***\dagger\dagger\dagger\diamond\diamond\diamond}$		$0.011^{***\dagger\dagger\dagger\diamond\diamond\diamond}$		
t-Stat	(11.575)			(8.286)		(8.176)		
Δbci_t		$-0.043^{\dagger\dagger}$						
t-Stat		(−1.362)						
Δbci_t^{highFP}			0.017^{**}					
t-Stat			(2.551)					
Δhmi_t					1.212^{**}			
t-Stat					(2.666)			
$\Delta p_t^{e,med}$							$0.012^{***\dagger\dagger\diamond\diamond}$	
t-Stat							(3.935)	
$\Delta p_t^{e,avg}$								$0.007^{***\dagger\dagger\dagger\diamond\diamond}$
								(5.541)
$\bar{R}^2$	[0.307]	[0.000]	[0.087]	[0.370]	[0.079]	[0.380]	[0.107]	[0.201]

(*Continued*)

TABLE 3 Continued

Panel B: GHC sample								
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ΔCS_t	$0.013^{***\dagger\dagger\dagger\diamond\diamond\diamond}$				–	–	–	–
t-Stat	(9.704)				–	–	–	–
Δbci_t		−0.075						
t-Stat		(−1.562)						
Δbci_t^{highFP}			−0.004					
t-Stat			(−0.638)					
Δhmi_t				1.021^{**}				
t-Stat				(2.310)				
$\Delta p_t^{e,med}$							–	
t-Stat							–	
$\Delta p_t^{e,avg}$								–
t-Stat								–
$\bar{R}^2$	[0.535]	[−0.001]	[−0.014]	[0.061]	–	–	–	–

Notes: Regressions of Δp_t on ΔCS_t and beliefs. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: $^{\diamond}$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. Panel A: Full sample spans all the available data in each case. Panel B: The GHC sample spans the period 2000:Q1–2010:Q4.

TABLE 4 Multivariate regressions of Δp_t on contemporaneous ΔCS_t and beliefs

Panel A

	1991:Q4–2017:Q4			2000:Q1–2013:Q4		2007:Q1–2017:Q4		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCS_t	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.009^{***\dagger\dagger\diamond\diamond}$	$0.009^{***\dagger\dagger\diamond\diamond}$	$0.009^{***\dagger\dagger\diamond\diamond}$	0.008^{**}	0.006
t-Stat	(6.820)	(6.690)	(7.977)	(4.604)	(4.656)	(4.772)	(2.230)	(1.599)
Δbci_t		0.002						
t-Stat		(0.078)						
Δbci_t^{highFP}			0.012^{**}					
t-Stat			(2.026)					
Δhmi_t					0.930^{**}			
t-Stat					(2.383)			
$\Delta p_t^{e,med}$							0.002	
t-Stat							(0.360)	
$\Delta p_t^{e,avg}$								0.003
								(1.247)
Fundamentals	✓	✓	✓	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.341]	[0.334]	[0.384]	[0.395]	[0.443]	[0.360]	[0.345]	[0.372]
$R^2_{\Delta p, x_b \mid x_f}$	–	[0.000]	[0.075]	–	[0.098]	–	[0.003]	[0.043]

Panel B: GHC sample

Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCS_t	$0.008^{***\diamond}$	$0.008^{***\diamond}$	$0.008^{***\diamond}$	$0.008^{***\diamond}$	–	–	–	–
t-Stat	(3.292)	(3.401)	(3.611)	(3.542)	–	–	–	–
Δbci_t		$0.029^{\diamond}$						
t-Stat		(0.750)						
Δbci_t^{highFP}			0.007					
t-Stat			(1.166)					

(*Continued*)

TABLE 4 Continued

Panel B: GHC sample								
Regressor	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Δhmi_t				0.659*				
t-Stat				(1.914)				
$\Delta p_t^{e,med}$							–	
t-Stat							–	
$\Delta p_t^{e,avg}$								–
t-Stat								–
Fundamentals	✓	✓	✓	✓	–	–	–	–
$\bar{R}^2$	[0.581]	[0.573]	[0.585]	[0.607]	–	–	–	–
$R^2_{\Delta p,x_b\|x_f}$	–	[0.008]	[0.035]	[0.085]	–	–	–	–

Notes: Regressions of Δp_t on CS, beliefs. All regressions control for fundamentals, defined as the 10-year bond yield minus median SPF 10-year inflation forecast, and the median SPF forecast of real GDP growth between t and $t+4$. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: $^{\diamond}$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. The partial R^2 statistics, $R^2_{\Delta p,x_b|x_f}$, is a measure of the additional explanatory power afforded by $x_{b,t}$ for Δp_t when $x_{f,t}$ is already in the model, where $x_{f,t} = (\Delta CS_t, fundamentals_t)'$ and $x_{b,t}$ denote one of the beliefs measures consider in the regressions. Panel A: Full sample spans all the available data in each case. Panel B: The GHC sample spans the period 2000:Q1–2010:Q4.

sequence of observations on both $E_t^{med}\Delta GDP_{t\to t+4}$, and r_t^{10} simply as *fundamentals*. Collect observations on fundamentals along with ΔCS_t into a vector $x_{f,t} = (\Delta CS_t, fundamentals_t)'$, and also let $x_{b,t}$ denote one of the beliefs measures used in the multivariate regressions. Table 4 also reports partial R^2 statistics, denoted by $R^2_{\Delta p, x_b|x_f}$. This statistic is a measure of the additional explanatory power afforded by $x_{b,t}$ for Δp_t when $x_{f,t}$ is already in the model.

As a benchmark, the first column of Table 4 reports the explanatory power of ΔCS_t and fundamentals alone. Taken together, these variables explain 34% of the variation in Δp_t in the sample from 1991:Q4 to 2017:Q4 and 58% in the GHC sample 2000:Q1–2006:Q4. In the first sample, fundamentals alone account for a little less than half of the total. In the GHC subsample, fundamentals alone account for 49%, while ΔCS_t alone accounts for 54%. It is notable that ΔCS_t and $E_t^{med}\Delta GDP_{t\to t+4}$ are substantially collinear in the GHC period, implying that they contain much overlapping information. But credit standards remain statistically significant in the multivariate regression where both are included, whereas each fundamental variable, including $E_t^{med}\Delta GDP_{t\to t+4}$, is no longer individually statistically significant. (These latter results are not shown in the table.) This suggests that the information in ΔCS_t subsumes the information in fundamentals for house price growth.

For the regressions in Table 4, there are 12 different specifications covering four different sample periods. Of these, ΔCS_t remains strongly statistically related to contemporaneous house price growth in all specifications that control for beliefs and fundamentals except one, namely, the shorter sample from 2007:Q1 to 2017:Q4 where neither ΔCS_t nor the belief measure $\Delta p_t^{e,avg}$ has any marginal predictive power. In this sample, the changes in credit standards and beliefs are sufficiently collinear that the regression cannot distinguish their independent effects, as suggested by the finding that no regressor (including the fundamentals) is individually significant even though the adjusted R^2 is roughly the same as in column (1). In the GHC subsample, which also consists of fewer observations, regressions with ΔCS_t always explain large fractions of variation in house price growth, but the bootstrap distributions of the *t*-statistic indicate significance for the coefficient on ΔCS_t only at the 10% level. For beliefs, once fundamentals are controlled for, the only measures that have incremental explanatory power according to the asymptotic HAC *t* -statistics are the housing media index Δhmi_t and the growth in the share of optimistic households who said housing was a good investment because house prices would further appreciate, Δbci_t^{highFP}, though as above the latter is not related to Δp_t in the GHC subsample (Panel B). None of these measures are statistically significant according to either bootstrapped distribution. Moreover, the incremental explanatory power of these beliefs measures is modest. In the sample from 1991:Q4 to 2017:Q4, the partial $R^2_{\Delta p, x_b|x_f}$ statistic when $x_{b,t} = \Delta bci_t^{highFP}$ is 0.075, indicating that including this measure of beliefs allows the specification to explain an additional 8% of the variation in Δp_t above and beyond credit conditions and fundamentals. Similarly, in the sample from 2000:Q1 to 2013:Q4, the partial $R^2_{\Delta p, x_b|x_f}$ statistic when $x_{b,t} = \Delta hmi_t$ is 0.098, indicating that including this measure of beliefs allows the specification to explain an additional 10% of the variation in Δp_t above and beyond credit conditions and fundamentals.

3.3 | Predicting house price changes

The idea that beliefs may be an important independent driver of house price fluctuations often rests on the premise that it is beliefs about *future* house prices, or expectations, that are the key source of variation in home values. If true, we would expect a shift toward more optimistic beliefs to predict an increase in future house price growth. We now ask which measures, if any, help predict future house price growth, controlling for credit conditions and fundamentals. It is also of interest to ask whether credit conditions themselves predict home prices. In the model of Kaplan et al. (2017), credit conditions are predicted to have no forecasting power for house price growth once beliefs are controlled for, so the former should be driven out of the regression by beliefs.

Tables 5–7 display results of forecasting regressions of house price growth measured from the end of period t to the end of period $t+h$, denoted as $\Delta p_{t+h,t}$. Future house price growth is regressed on variables known at time t, including time t fundamentals, time t credit conditions, ΔCS_t, and time t beliefs (one at a time). Case and Shiller (1989) have pointed out that house price growth is correlated with its own lags; thus, we also include time t house price growth Δp_t as an additional control variable. The tables show results for horizons $h = 1, 2, 3$, and 4 quarters ahead. Several aspects of these results bear emphasis.

First, in the full sample, ΔCS_t is a strong marginal predictor of house price growth at all horizons except $h = 4$ (where it is significant according to the HAC t-statistic but not the bootstrapped statistics), controlling for fundamentals, lagged house price growth, and beliefs. As a benchmark, the top panel of each table shows the results when no beliefs measures are included. In the sample 1991:Q4–2017:Q4 (Table 5), a specification using only ΔCS_t and fundamentals explains 26% of one-quarter-ahead house price growth, while adding lagged prices increases this value to 32%. In the sample for which the housing sentiment index is available (2000:Q1–2013:Q4, Panel B of Table 5), a specification using only ΔCS_t and fundamentals explains 31% of one-quarter-ahead house price growth, while adding lagged prices increases this to 34%. In the GHC sample (Table 6), a specification using only ΔCS_t and fundamentals explains 43% of one-quarter-ahead house price growth, while adding lagged prices increases this to 49%. In a sample covering the period when survey point forecasts are available (2007:Q1–2017:Q4, Table 7), a specification using only ΔCS_t and fundamentals explains 32% of one-quarter-ahead house price growth, while adding lagged prices decreases this to 29%. These results underscore the strong predictive power of credit conditions for aggregate home price fluctuations, especially in the GHC subsample. A caveat with the shorter GHC subsample results is that the coefficient on ΔCS_t, while significantly different from zero according to the HAC distribution of the t-statistic, is not significant according to the bootstrapped distributions.

It is worth noting that in each of the preceding results, the one-quarter-ahead forecasting regression using ΔCS_t as the *sole* predictor variable produces effectively the same $\overline{R}^2$ (if slightly greater) as does a regression using both ΔCS_t and fundamentals as predictor variables. The reason is the same as that given above for the contemporaneous regressions: credit standards contain information that subsumes the information in the real 10-year bond yield and expected economic growth, so that eliminating either or both of the latter has little effect on the fraction of variation explained in future house price growth.

A second takeaway from Tables 5–7 is that there is no evidence that beliefs have important predictive power for future house prices, once credit conditions, fundamentals, and lagged house price growth are controlled for. The single specification for which a belief measure is marginally significant is exhibited in Table 5 for the sample 1991:Q4–2017:Q4 where the buying conditions index Δbci_t is significant at the 5% level for predicting $h = 1$ quarter ahead house price growth using the HAC t -statistic (but not the bootstrapped statistics). But a comparison with the top panel of the same table shows that this measure adds little to the magnitude of predictability: the partial R^2 shows that the additional predictive power afforded by adding Δbci_t to a regression specification that already includes ΔCS_t, fundamentals, and lagged house price growth is a modest 4% when compared to the adjusted R^2 statistic of 34%. In addition, the Δbci_t measure has no predictive power for longer horizon house price changes, or for house price changes over any horizon in the GHC subsample (Table 6). Eliminating lagged house price growth as an additional predictor has little influence on these results.

TABLE 5 Predicting house price growth $\Delta p_{t+h,t}$: Full sample period

Panel A: 1991:Q4–2017:Q4	Forecast horizon				
Regressor	$h = 1$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
ΔCS_t	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.006^{***\dagger\dagger\diamond\diamond}$	$0.016^{***\diamond\diamond}$	$0.021^{***\diamond\diamond}$	0.021^{***}
t-Stat	(5.025)	(3.539)	(3.989)	(3.421)	(2.688)
Δp_t		$0.320^{***\dagger\dagger\dagger}$	$0.205^{\dagger\dagger\dagger}$	$0.539^{**\dagger\dagger\dagger}$	$1.386^{***\dagger\dagger\dagger}$
t-Stat		(4.352)	(1.091)	(2.000)	(4.234)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.262]	[0.323]	[0.308]	[0.380]	[0.505]
ΔCS_t	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.007^{***\dagger\dagger\diamond\diamond\diamond}$	$0.017^{***\diamond\diamond}$	$0.021^{***\diamond\diamond}$	$0.021^{***\diamond}$
t-Stat	(5.025)	(3.934)	(4.131)	(3.461)	(2.750)
Δbci_t		0.073^{**}	0.085	0.052	0.068
t-Stat		(2.067)	(1.398)	(0.774)	(0.800)
Δp_t		$0.319^{***\dagger\dagger}$	$0.203^{\dagger\dagger\dagger}$	$0.537^{**\dagger\dagger\dagger}$	$1.381^{***\dagger\dagger\dagger}$
t-Stat		(4.063)	(1.052)	(1.968)	(4.177)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.262]	[0.344]	[0.314]	[0.377]	[0.503]
$R^2_{\Delta p, x_b \mid x_f}$		[0.041]	[0.018]	[0.004]	[0.005]
ΔCS_t	$0.009^{***\dagger\dagger\dagger\diamond\diamond\diamond}$	$0.006^{***\dagger\dagger\diamond\diamond}$	$0.016^{***\diamond\diamond}$	$0.021^{***\diamond\diamond}$	0.021^{***}
t-Stat	(5.025)	(3.525)	(3.881)	(3.308)	(2.627)
Δbci_t^{highFP}		0.003	0.000	−0.004	−0.001
t-Stat		(0.559)	(0.016)	(−0.427)	(−0.086)
Δp_t		$0.301^{***\dagger\dagger}$	$0.204^{\dagger\dagger\dagger}$	$0.560^{*\dagger\dagger\dagger}$	$1.391^{***\dagger\dagger\dagger}$
t-Stat		(3.507)	(1.007)	(1.947)	(4.000)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.262]	[0.320]	[0.301]	[0.375]	[0.500]
$R^2_{\Delta p, x_b \mid x_f}$		[0.004]	[0.000]	[0.001]	[0.000]

(*Continued*)

TABLE 5 Continued

Panel B: 2000:Q1–2013:Q4	Forecast horizon				
Regressor	***h* = 1**	***h* = 1**	***h* = 2**	***h* = 3**	***h* = 4**
ΔCS_t	$0.010^{***\dagger\dagger\diamond\diamond}$	$0.008^{***\dagger\dagger\diamond\diamond}$	$0.020^{***\diamond}$	0.022^{***}	0.019^{*}
t-Stat	(4.742)	(3.472)	(3.750)	(2.742)	(1.955)
Δhmi_t		0.109	0.076	−0.112	0.253
t-Stat		(0.451)	(0.134)	(−0.148)	(0.319)
Δp_t		$0.282^{***\dagger\dagger}$	$0.171^{\dagger\dagger\dagger}$	$0.542^{\dagger\dagger\dagger}$	$1.320^{***\dagger\dagger}$
t-Stat		(2.983)	(0.762)	(1.570)	(3.033)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.309]	[0.337]	[0.340]	[0.400]	[0.506]
$R^2_{\Delta p, x_b \mid x_f}$		[0.001]	[0.000]	[0.000]	[0.001]

Notes: Regressions of the log change of CSUS real house price index for different forecast horizons in quarters (h) on CS, the buying condition index, the share of respondents that answer that is "good time" to buy a house because prices will increase, and the House Media Index. Regressions include fundamentals: the 10-year bond yield minus median SPF 10-year inflation forecast, and the median SPF forecast of real GDP growth between t and $t+4$. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: $^{\diamond}$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. The partial R^2 statistics, $R^2_{\Delta p, x_b \mid x_f}$, is a measure of the additional explanatory power afforded by $x_{b,t}$ for Δp_t when $x_{f,t}$ is already in the model, where $x_{f,t} = (\Delta CS_t, \Delta p_t, fundamentals_t)'$ and $x_{b,t}$ denote one of the beliefs measures consider in the regressions. The sample spans the period 1991:Q4–2017:Q4 for the first three blocks and the period 2000:Q1–2013:Q4 for the last block.

TABLE 6 Predicting house price growth $\Delta p_{t+h,t}$: GHC period

Regressor	**Forecast horizon** $h=1$	$h=1$	$h=2$	$h=3$	$h=4$
ΔCS_t	0.010^{***}	0.006^{**}	0.015^{**}	0.016^{*}	0.009
t-Stat	(2.865)	(2.090)	(2.661)	(1.975)	(1.101)
Δp_t		$0.435^{***\dagger\dagger}$	$0.554^{*\dagger\dagger\dagger}$	$1.072^{**\dagger\dagger\dagger}$	$2.198^{***\dagger\dagger}$
t-Stat		(2.795)	(1.880)	(2.421)	(4.264)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.493]	[0.472]	[0.490]	[0.572]
ΔCS_t	0.010^{***}	0.006^{**}	0.016^{***}	0.016^{*}	0.010
t-Stat	(2.865)	(2.121)	(2.713)	(2.003)	(1.181)
Δbci_t		0.056	0.079	0.078	0.115
t-Stat		(1.222)	(0.947)	(0.600)	(0.617)
Δp_t		$0.420^{**\dagger\dagger}$	$0.532^{*\dagger\dagger\dagger}$	$1.051^{**\dagger\dagger\dagger}$	$2.167^{***\dagger\dagger}$
t-Stat		(2.543)	(1.750)	(2.352)	(4.076)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.493]	[0.466]	[0.480]	[0.565]
$R^2_{\Delta p,x_b\mid x_f}$		[0.024]	[0.014]	[0.007]	[0.011]
ΔCS_t	0.010^{***}	0.006^{**}	0.015^{**}	0.015^{*}	0.009
t-Stat	(2.865)	(2.063)	(2.625)	(1.928)	(1.043)
Δbci_t^{highFP}		−0.002	−0.003	−0.003	−0.004
t-Stat		(−0.283)	(−0.390)	(−0.397)	(−0.376)
Δp_t		$0.445^{***\dagger\dagger}$	$0.568^{*\dagger\dagger\dagger}$	$1.089^{**\dagger\dagger\dagger}$	$2.219^{***\dagger\dagger}$
t-Stat		(2.824)	(1.915)	(2.371)	(4.167)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.481]	[0.459]	[0.477]	[0.561]
$R^2_{\Delta p,x_b\mid x_f}$		[0.002]	[0.001]	[0.001]	[0.001]
ΔCS_t	0.010^{***}	0.006^{*}	0.015^{**}	0.014^{*}	0.008
t-stat	(2.865)	(1.925)	(2.613)	(1.839)	(0.958)
Δhmi_t		−0.123	−0.025	−0.378	−0.307
t-Stat		(−0.540)	(−0.039)	(−0.431)	(−0.313)
Δp_t		$0.461^{***\dagger\dagger}$	$0.571^{**\dagger\dagger\dagger}$	$1.145^{***\dagger\dagger\dagger}$	$2.267^{***\dagger\dagger\diamond}$
t-Stat		(2.993)	(2.253)	(2.975)	(4.662)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.473]	[0.452]	[0.476]	[0.561]
$R^2_{\Delta p,x_b\mid x_f}$		[0.002]	[0.000]	[0.003]	[0.001]

Notes: Regressions of the log change of CSUS real house price index for different forecast horizons in quarters (h) on CS, the buying condition index, the share of respondents that answer that is "good time" to buy a house because prices will increase, and the House Media Index. Regressions include fundamentals: the 10-year bond yield minus median SPF 10-year inflation forecast, and the median SPF forecast of real GDP growth between t and $t+4$. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Non-parametric bootstrap: $^{\diamond}$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. The partial R^2 statistics, $R^2_{\Delta p,x_b\mid x_f}$, is a measure of the additional explanatory power afforded by $x_{b,t}$ for Δp_t when $x_{f,t}$ is already in the model, where $x_{f,t}=(\Delta CS_t, \Delta p_t, fundamentals_t)'$ and $x_{b,t}$ denote one of the beliefs measures consider in the regressions. The sample spans the GHC period, 2000:Q1–2010:Q4.

TABLE 7 Predicting house price growth $\Delta p_{t+h,t}$: 2007:Q1–2017:Q4

Regressor	**Forecast horizon** $h = 1$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
ΔCS_t	$0.010^{***\dagger\dagger\diamond\diamond\diamond}$	$0.009^{**\diamond}$	$0.022^{***\diamond\diamond\diamond}$	$0.023^{***\diamond\diamond}$	$0.024^{***\diamond\diamond\diamond}$
t-Stat	(4.699)	(2.508)	(4.972)	(3.590)	(4.197)
$\Delta p_t^{e,med}$		0.001	0.002	0.001	$-0.014^{\diamond\diamond}$
t-Stat		(0.226)	(0.319)	(0.093)	(−1.488)
Δp_t		0.111	$-0.400^{***\diamond\diamond}$	$-0.359^{**\diamond\diamond}$	$0.410^{**\dagger\dagger}$
t-Stat		(1.203)	(−2.656)	(−2.289)	(2.478)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.319]	[0.293]	[0.542]	[0.750]	[0.835]
$R^2_{\Delta p, x_b \mid x_f}$		[0.001]	[0.002]	[0.000]	[0.067]
ΔCS_t	$0.010^{***\dagger\dagger\diamond\diamond\diamond}$	$0.008^{***\diamond\diamond}$	$0.020^{***\dagger\dagger\diamond\diamond\diamond}$	$0.018^{***\diamond\diamond}$	$0.017^{***\diamond}$
t-Stat	(4.699)	(2.848)	(6.176)	(3.451)	(2.654)
$\Delta p_t^{e,avg}$		0.001	0.005	0.006	0.000
t-Stat		(0.759)	(1.262)	(1.248)	(0.089)
Δp_t		0.095	$-0.463^{***\diamond\diamond\diamond}$	$-0.442^{***\diamond\diamond}$	$0.411^{**\dagger\dagger}$
t-Stat		(1.126)	(−3.237)	(−2.940)	(2.312)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.319]	[0.297]	[0.561]	[0.769]	[0.823]
$R^2_{\Delta p, x_b \mid x_f}$		[0.007]	[0.044]	[0.076]	[0.000]

Notes: Regressions of the log change of CSUS real house price index for different forecast horizons in quarters (h) on CS, expected real median house price change over the next 12 month, and expected real average house price growth. Regressions include fundamentals: the 10-year bond yield minus median SPF 10-year inflation forecast, and the median SPF forecast of real GDP growth between t and $t+4$. Newey–West corrected t-statistics in parentheses (lags = 4). Newey–West HAC: *significant at 10%. **significant at 5%. ***significant at 1%. Parametric bootstrap: †significant at 10%. ††significant at 5%. †††significant at 1%. Nonparametric bootstrap: $^{\diamond}$significant at 10%. $^{\diamond\diamond}$significant at 5%. $^{\diamond\diamond\diamond}$significant at 1%. The partial R^2 statistics, $R^2_{\Delta p, x_b \mid x_f}$, is a measure of the additional explanatory power afforded by $x_{b,t}$ for Δp_t when $x_{f,t}$ is already in the model, where $x_{f,t} = (\Delta CS_t, \Delta p_t, fundamentals_t)'$ and $x_{b,t}$ denote one of the beliefs measures consider in the regressions.

3.4 | Do credit standards cause changes in house prices?

In this section, we consider a final hypothesis, namely, that there was no genuine causality running from credit conditions to house price changes, despite the positive correlation between the two. Instead, the causality ran entirely in the other direction, that is, from rising home prices to greater credit extension in the boom, and conversely from falling house prices to a constriction of credit during the bust. This reverse causality story is often associated with models where beliefs play an important role. For example, exuberant expectations about future house prices might have been the singular driving force behind rising house prices and relaxed credit conditions. If so, shocks to credit conditions that are mutually uncorrelated with house price shocks should not have an impact on house prices.

To address this question, we identify exogenous variation in our measure of credit conditions, ΔCS_t, and relate it to home price growth Δp_t using an SVAR. To identify exogenous variation, we employ the shock-restricted SVAR approach of Ludvigson et al. (2019a, 2019b) that permits set identification of the structural shocks under assumptions that are typically weaker than those required for point identification. Here, we provide only a brief description of the identification strategy and refer the reader to those papers for details.

Consider an SVAR[8] with two variables our measure of credit standards and house price growth:

$$\mathbf{X}_t = \left(\Delta CS_t, \Delta p_t\right)', \tag{2}$$

where as above Δp_t measures quarterly real house price growth. Our objective is to identify a set of mutually uncorrelated structural shocks $\mathbf{e}_t = (e_{CS,t}, e_{p,t})'$, where $e_{CS,t}$ refers to the credit supply shock, and $e_{p,t}$ to the housing shock. Movements in $e_{CS,t}$ represent changes in credit supply that are not a response to changes in house prices. These shocks may be used to estimate the dynamic causal effects of an impulse to credit supply on house prices.

To identify these exogenous movements in credit supply measured by $e_{CS,t}$, we need to place restrictions on the system $\mathbf{X}_t$. The identifying restriction we make is that changes in the composition of mortgages, that is, toward nonconforming loans and away from conforming loans, should be informative about credit standard shocks. This is implemented by requiring that a $e_{CS,t}$ must exhibit a minimum (lower bound) correlation with the quarterly log difference in the ratio ABS/GSE, a variable that is external to the SVAR. We refer to this as a shock-based external variable constraint, where the parameter λ sets the lower bound of the correlation. An easing of credit standards corresponds to an increase in $e_{CS,t}$, so the constraint says that easier credit standards must be associated with at least a minimal shift toward riskier lending, where the lower bound on this association is dictated by λ. Note that this restriction in no way rules out the possibility that shifts in the ratio ABS/GSE could be correlated with $e_{p,t}$. In this sense, the identification strategy differs from the external instrumental variable or proxy-VAR approach (e.g., Mertens & Ravn, 2014; Stock & Watson, 2008) in which the external variable is assumed to be exogenous with respect to Δp_t (i.e., uncorrelated with $e_{p,t}$) as would be required of a valid instrument. Instead, we only require the weaker assumption that the composition of mortgages as measured by ABS/GSE is *relevant* for credit standards shocks. It is because these restrictions are weaker that we do not achieve point identification. The bounds of the identified set may still be informative, however, a possibility we now investigate.

We use impulse response functions to understand the dynamic causal effects on house prices of a credit standards shock. Figure 7 shows, in shaded areas, the identified set of dynamic responses of Δp_t (in percent) to a one-standard-deviation *increase* in $e_{CS,t}$, which constitutes an easing of lending standards. The figure shows the results for two values of λ. The top panel shows that results obtained under the assumption that the credit standards shocks are required to have a correlation with $\Delta\ln(ABS_t/GSE_t)$ of at least 7%, while in the bottom panel, this requirement is slackened to 5%.

Given that we have a set of solutions, the impulse responses present a range of estimated magnitudes of the effect of credit standard shocks on house price growth. But the bounds of the set are sufficiently tight that they are still informative about the dynamic relationship of interest. The top panel of Figure 7

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[8]An SVAR may be summarized as follows. Let $\mathbf{X}_t$ denote an $n \times 1$ vector time series and suppose that $\mathbf{X}_t$ has a reduced-form finite-order autoregressive representation:

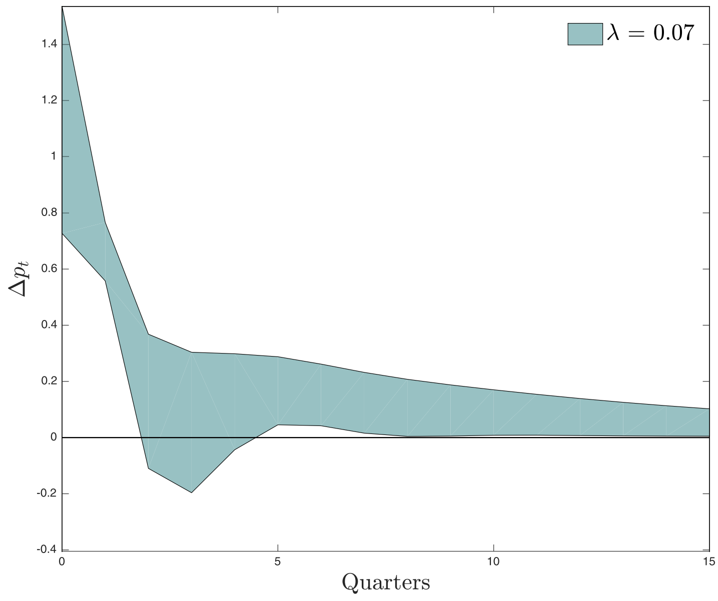
$$\mathbf{X}_t = \sum_{j=1}^{p} \mathbf{A}_j \mathbf{X}_{t-j} + \eta_t,$$

where $\eta_t \sim (0, \boldsymbol{\Omega})$. The reduced-form innovations η_t are mutually correlated but are related to the structural SVAR shocks $\mathbf{e}_t$ by an invertible matrix $\mathbf{H}$:

$$\eta_t = \mathbf{H}\boldsymbol{\Sigma}\mathbf{e}_t \equiv \mathbf{B}\mathbf{e}_t, \qquad \mathbf{e}_t \sim (0, \mathbf{I_K}), \qquad \mathrm{diag}(\mathbf{H}) = 1,$$

where $\mathbf{B} \equiv \mathbf{H}\boldsymbol{\Sigma}$, and $\boldsymbol{\Sigma}$ is a diagonal matrix with variance of the shocks in the diagonal entries. The structural shocks $\mathbf{e}_t$ are mean zero with unit variance, serially and mutually uncorrelated.

Panel A: Impulse Response of Δp_t with correlation constraint $\lambda = 7\%$



Panel B: Impulse Response of Δp_t with correlation constraint $\lambda = 5\%$

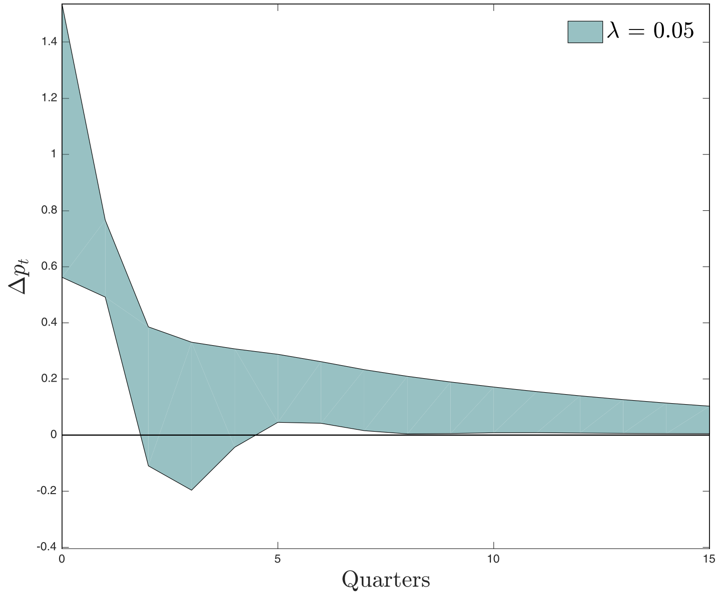


FIGURE 7 Impulse response of Δp_t to a one-standard-deviation CS shock [Color figure can be viewed at wileyonlinelibrary.com]

Notes: Dynamic responses of Δp_t to a positive one-standard-deviation ΔCS_t shock. Panel A reports the identified set of responses of Δp_t to a one-standard-deviation shock in ΔCS with a correlation constraint that sets the minimum correlation between ΔCS and $\Delta \ln(\frac{ABS}{GSE})$ at $\lambda = 7\%$. Panel B reports the set of responses when $\lambda = 5\%$. The sample spans the period 1991:Q4–2017:Q4.

shows the results obtained using $\lambda = 0.07$. The identified set of dynamic responses implies that a one-standard-deviation increase in $e_{CS,t}$ boosts real quarterly house price growth by anywhere from 1.4% on impact, or roughly 5.7% at an annual rate to 0.8% on impact, or roughly 3.2% at an annual rate. Although the sets are invariably wider when the identifying restriction is slackened, the overall results are not highly sensitive to the precise value of λ. The bottom panel of Figure 7 shows the results obtained using the weaker constraint with $\lambda = 0.05$. For this parameterization, we find that the high end of the range is roughly the same as that obtained using $\lambda = 0.07$, but the low end implies that a one-standard-deviation increase in $e_{CS,t}$ boosts real quarterly house price growth by 0.6% on impact, or roughly 2.4% at an annual rate. Thus, the magnitudes of these impact effects are substantial and well determined. The estimated persistence of the effects is less well determined, however. Some solutions in the identified sets imply that the effects die out after three quarters, while others imply that they persist much longer.

4 | CONCLUSION

We consider two potential driving forces of house price fluctuations, credit conditions, and beliefs, using direct measures of these variables. To measure credit conditions, we use the Senior Loan Officer Opinion Survey conducted by the Federal Reserve, which asks senior loan officers at banks to state whether their lending standards for purchase mortgages have eased or tightened relative to the previous quarter. To measure beliefs, we study three separate household-level survey measures from the University of Michigan's Survey of Consumers that ask specifically about the respondent's view on home prices and a fourth measure based on the index constructed by Soo (2018) that measures sentiment about housing using a textual analysis of major news publications. We combine these data with data on national house prices to compile a set of statistical facts on the empirical relationships among these variables at the aggregate level.

We find that a relaxation of credit standards is positively related to the fraction of riskier nonconforming debt in total mortgage lending, while beliefs bear little empirical relation to this fraction. Credit conditions have statistically significant and economically important explanatory power for contemporaneous house price changes as well as predictive power for future house price changes, even after lagged house price changes and economic fundamentals such as interest rates and expected economic growth are controlled for. Two measures of beliefs have statistically significant explanatory power for contemporaneous house price changes once fundamentals are controlled for, although these measures explain substantially smaller fractions of the variation in house price growth than do credit standards. These are the Soo national housing media sentiment index, and the growth in the share of households in the SOC who reported being optimistic about the housing market because they said house prices would further appreciate. We find little evidence that beliefs have important predictive power for future house price changes, once credit conditions, fundamentals, and lagged house price growth are controlled for. An SVAR analysis implies that shocks to credit conditions have quantitatively large dynamic causal effects on house price changes, especially in the short run, with positive shocks (an easing of credit) driving up home values and negative shocks driving them down.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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