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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 non-conforming 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 VAR analysis implies that shocks to credit conditions have quantitatively important dynamic causal effects on house price changes.

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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 an 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 and Sufi (2009); Mian and Sufi (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, and 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 wide-spread 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

[1] A growing body of theoretical work has addressed these questions in general equilbrium. See e.g., 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 bo as the "debt-to-income" limit in the mortgage industry even though the numerator

homebuyer who isn't 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.

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 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.

To measure beliefs, we study three separate 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* (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.

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 loan-to-value or payment-to-income limits, or more generally a greater expansion of credit to borrowers previously deemed unqualified according to a stricter set of lending 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 non-conforming

is the monthly debt payment rather than the debt itself. We therefore follow other academic literature and refer to it as the payment-to-income ratio, or PTI.

loans. The converse would be true of a reported net tightening of bank lending standards. By contrast, there is no reason to expect a belief-driven change in demand for mortgages to affect the composition of loans, since presumably the demand for all types of credit 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 beliefs were optimistic and decreasing when beliefs turned pessimistic. Under this hypothesis, a shift in the composition credit toward riskier non-conforming 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. If the two are correlated, but the true explanatory power for house prices lies more with one than the other, this should be revealed by a multivariate regression where both variables are included. So we ask whether bank credit supply contains information about current or 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.

It is important to consider whether beliefs have explanatory power for house prices beyond that contained in economic fundamentals. After all, beliefs about house prices evolve endogenously even in models where beliefs have no independent role to play in economic fluctuations, including models in which subjective expectations perfectly align with objective probability laws governing the behavior of economic fundamentals. An important question for the literature on behavioral biases is whether beliefs pushed house prices beyond what would be justified by fundamentals alone, in which case beliefs should contain information about house price growth that is independent of credit conditions and other economic fundamentals. This is straightforward to address with a multivariate analysis that employs data on beliefs, credit conditions, and economic fundamentals.

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 (e.g., Kaplan, Mitman, and Violante (2017)). If true, we would expect a shift toward more optimistic beliefs to predict an increase in future house price growth and to drive out credit conditions as a competing predictor variable. We therefore ask whether beliefs predict future house price changes, once other fundamentals and lagged house prices are controlled for.

The empirical analyses just described are silent on causality. Thus a final hypothesis we investigate 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. Causality might run entirely in the other direction, i.e., from rising home prices to greater credit extension in the boom, and from falling house prices to a constriction of credit during the bust. We address this question by estimating a bivariate structural vector autoregression (VAR) in our measure of credit supply and house price growth using the shock-restricted identification approach of Ludvigson, Ma, and Ng (2015) and Ludvigson, Ma, and Ng (2016). The approach permits set identification of exogenous variation in the VAR variables under assumptions that are typically weaker than those required for point identification. If credit conditions have no genuine causal effect, then shocks to credit conditions that are mutually uncorrelated with house price shocks should not have an impact on house prices. We use the shock-restricted structural VAR to address this question.

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 non-conforming 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 non-conforming 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. For example, it explains 31% of the variation in quarterly house price growth in the full sample from 1991:Q4-2017:Q4, and 54% in the GHC subsample. Several measures of beliefs also have statistically significant explanatory power for changes in home values, though they explain substantially 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. These are the Soo (2018) 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. Both of these measures add modestly to the fraction of variation explained in contemporaneous house price growth.

Third, in terms of predicting future house price changes, in every sample we consider 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 structural VAR analysis implies that shocks to 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 up to 1.4% on impact, or roughly 5.7% at an annual rate. At the lowest end of the range in the set, a one-standard deviation shock to ΔCS is found to increase real quarterly house price growth by roughly 0.8% on impact, or roughly 3.2% 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 structural VAR analysis of credit conditions shocks on house prices (Section 3.4). Section 4 concludes.

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 three 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 which 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 three 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 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 it is stationary. According to this measure, there was a notable easing of standards from 2002-2006, and a very sharp tightening afterwards. 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 show that standards were eased in every quarter. Recall that the survey asks banks about how their standards have changed *relative to the pervious three 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 GSE-backed conforming loans outstanding and non-conforming "asset backed securities" (ABS) outstanding, categories defined explicitly below. This estimate points to a quantitatively large easing of standards from 2002-2006, and a sharp tightening afterwards.

An important aspect of SLOOS survey is that it asks loan officers to explicitly distinguish between changes in mortgage credit supply as distinct from credit demand (ΔCD), on bank loans over the past three months. Thus in principle, answers to the appropriate questions are able to identify a movement in supply separately from a movement in demand. There could of course be some residual correlation between the two. As it turns out, there is very little such correlation. The results presented in the next sections are not sensitive to replacing ΔCS_t with the residual from a regression of ΔCS_t on ΔCD_t.

It's 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, 45, or 50 percent, 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 percent, which rose by 85% over this period, followed by the fraction that exceeded 45 percent, which rose 66%, and the fraction that exceeded

36 percent, which rose 28%. All three were sharply reduced in the bust, with the fraction exceeding 50% driven to zero shortly after 2010, in part the result of the Dodd-Frank act which explicitly limits PTI ratios on conforming loans. Because these data are available only annually since 2000, we don't 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) suggests that time-variation in these PTI constraints have an important influence on home prices in general equilibrium.[3]

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 buying conditions index (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 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 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.[4] The next two most important reasons given in the case of *good time to buy* are *current prices are low*, and *future prices will be higher*. Note that relatively few individuals cite an expectation of future price growth as a reason to

[3]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 payment-to-income standards has large effects on home prices and price-rent ratios in the model.

[4]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: 1. Lower down payment 2. Interest rates are low 3. Credit easy to get, easy money 4. Variable mortgage rate.

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, Mitman, and Violante (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 Δbci_t^{highFP}. This measure is available over the same time period as the overall buying conditions index.

The third measure available from the SOC asks households for a point forecast on house price changes over the next 12 months. This measures 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

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

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 $\Delta p_t^{e,avg}$.

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 U.S. 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 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., Piazzesi and Schneider (2009), Kaplan, Mitman, and Violante (2017)) 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 non-conforming 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 non-conforming 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 Δp_t.

3 Empirical Findings

This section reports the empirical findings. Output for all regressions include the coefficient estimates, adjusted R^2 statistic, and heteroskedasticity and serial correlation robust (HAC) t-statistics (Newey and 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 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 employs a parametric model of the serial dependence, while the second is a non-parametric 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 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 Government Sponsored Enterprises (GSEs) Fannie Mae and Freddie Mac. Conforming loans are considered less risky than non-conforming 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.[5] Second, the GSEs purchase these safer mortgages on the secondary market and guarantee them against default. *Non*-conforming 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, holding fixed aggregate credit demand. 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 non-price terms such as the maximum loan-to-value ratio, the maximum payment-to-income 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, there is no reason to expect an economy-wide change in demand for mortgages to be related to the composition of loans, since presumably the demand for all types of credit would change 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"

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

are Agency- and GSE-backed mortgage pools, comprised only of conforming mortgage loans. The line labeled "ABS" refers to issuers of asset backed securities, comprised entirely of non-conforming 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 2002-2007: 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 non-conforming 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 comprised of annual rather than quarterly observations. The analogy to the ABS category in the originations data 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 comprised entirely of non-conforming 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 non-conforming 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 2001-2006.

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 non-conforming 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 non-conforming debt during the housing boom. The $\overline{R}^2$ in this subsample is 47%, almost 5 times larger than that found in the the full sample, while the estimated regression coefficient is almost twice as large.

In contrast to changes in credit *supply*, there is little reason to expect a belief-driven change in *demand* for mortgages to be associated with a change in the composition of loans, since presumably demand for all types of loans would change in rough proportion. Columns two to six 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 non-conforming 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 non-conforming 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).

It's possible that a change in the beliefs of lenders about house prices over the housing cycle altered their willingness of 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 interpretation. But while shifts in the composition of mortgage credit are not associated with house price beliefs, they are associated with beliefs about economic fundamentals. The table 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 Survey of Professional Forecasters (SPF) median forecast of one-year-ahead GDP growth, denoted $E_t^{med}\Delta GDP_{t\rightarrow t+4}$. Like the percentage of banks reporting an easing of credit standards, survey expectations of positive economic growth are associated with a shift in the composition of loans, toward non-conforming loans and away from conforming loans.

Table 2 presents results for originations that are analogous to those just presented for debt outstanding. Because originations are only available annually, we relate the annual log difference in originations to the annual average of ΔCS_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, but they are broadly similar to those reported in Table 1. While ΔCS_t is positively related to changes in the ratio of PL/GSE; the three beliefs measures are statistically insignificant.

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 a structural vector-autoregression.

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:Q4-2017: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:Q1-2013:Q4, whereas in this sample ΔCS_t explains 37%. And 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 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 out-sized 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. In summary, the univariate regressions suggest that both credit conditions and beliefs are contemporaneously related to current house price growth, though credit conditions appear to explain much larger fractions 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 one-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 inflation forecast, denoted r_t^{10}. We refer to the sequence of observations on both $E_t^{med}\Delta GDP_{t\to t+4}$, and r_t^{10} simply as *fundamentals* hereafter.

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, so 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 twelve 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:Q1-2017:Q4 where neither ΔCS_t nor the belief measure $\Delta p_t^{e,avg}$ have any marginal predictive power. In this sample, the regressors appear 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, the bootstrap distribution of the t-statistic indicate significance for the coefficient on ΔCS_t only at the 10% level, however.

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 boostrapped distribution. Moreover, the incremental explanatory power of these beliefs measures is modest. In the sample from 1991:Q4-2017:Q4, including Δbci_t^{highFP} as an additional regressor allows the specification to explain an additional 4% of the variation in Δp_t, increasing the $\overline{R}^2$ from 0.34 to 0.38, while in the sample from 2000:Q1-2013:Q4, the inclusion of Δhmi_t also explains an additional 4% of the variation in Δp_t, increasing the $\overline{R}^2$ from 0.40 to 0.44.

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 (e.g., Kaplan, Mitman, and Violante (2017)). 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, Mitman, and Violante (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, 6 and 7 display results of forecasting regressions of house price growth from the end of period t to the end of period $t+h$, denoted $\Delta p_{t+h,t}$. 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 bootrapped 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 ten-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 take-away from Tables 5, 6 and 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 same specification without Δbci_t exhibits an $\overline{R}^2$ that is just 2% lower than that including Δbci_t. The Δbci_t measure also has no predictive power for longer horizon house price changes, or for house price changes over any horizon in the GHC subsample

(Table 6). We also find that eliminating lagged house price growth as an additional predictor has little influence on the predictability results using beliefs.

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, i.e., 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 a structural VAR (SVAR). To identify exogenous variation, we employ the *shock-restricted* SVAR approach of Ludvigson, Ma, and Ng (2015) and Ludvigson, Ma, and Ng (2016) 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 these papers for details.

The structural shocks of interest are the mutually uncorrelated innovations in the SVAR variables ΔCS_t and Δp_t. In this paper we focus on identifying a shock to credit standards ΔCS_t and tracing out its affects on house price growth Δp_t.[6] The single identifying assumption we make is that changes in the composition of mortgages, i.e., toward non-conforming loans and away from conforming loans, should be informative about credit standard shocks. This is implemented by requiring that positive credit standard shocks (corresponding to an easing of standards) 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 correlation constraint*, where the parameter λ sets the lower bound of this constraint. Although this approach has the flavor of an external instrumental variable (IV) or proxy SVAR identification strategy (e.g., Stock and Watson (2008); Mertens and Ravn (2014)), unlike the external IV approach, the external variable in this methodology is *not* assumed to be

[6] We do not focus on identifying exogenous variation in house price growth to ask if affects ΔCS_t. Most paradigms, even those for which belief shocks play no role but exogenous movements in credit conditions have quantitatively important causal consquences for house prices (e.g., Favilukis, Ludvigson, and Van Nieuwerburgh (2017)), would imply this reverse causality. This is because credit conditions themeselves also have an endogenous component that moves with the economic state and home values. These values in turn shift collateralized borrowing capacity and alter financing constraints and credit conditions.

exogenous (uncorrelated with house price shocks) as would be required of a valid IV. Instead, we only require the weaker assumption that the composition of mortgages is relevant for credit standards. 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 and propagating mechanisms of a credit standards shock. Figure 7 shows, in shaded areas, the identified set of dynamic responses of quarterly real house price growth (in percent) to a one standard deviation *increase* in the credit standards shock, which constitutes an easing of lending standards. The Figure shows the results for two values of the lower bound on the correlation constraint between ΔCS shocks an $\Delta\ln\left(ABS_t/GSE_t\right)$: $\lambda = 0.07$ and $\lambda = 0.05$. That is, in the top panel 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. At the highest end of the range, the results for $\lambda = 0.07$ indicate that a one-standard deviation shock to ΔCS increases real quarterly house price growth by 1.4% on impact, or roughly 5.7% at an annual rate. At the lowest end of the range, a one-standard deviation shock to ΔCS increases real quarterly house price growth by roughly 0.8% on impact, or roughly 3.2% at an annual rate. These results are not highly sensitive to the value of λ, though the sets are invariably wider when the identifying restriction is slackened. In the bottom panel, the high end of the range is roughly the same as in the top panel, but the low end is lower than in the top panel. In this case, the low end shows that a one-standard deviation shock to ΔCS increases real quarterly house price growth by roughly 0.6% on impact, or roughly 2.4% at an annual rate. Though these magnitudes are substantial and well determined, the estimated persistence of the effects is less well determined. At least some solutions in the identified set imply that the effects die out after 3 quarters, while others suggest much more persistent effects.

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 in order 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 non-conforming 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, though 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. A structural VAR 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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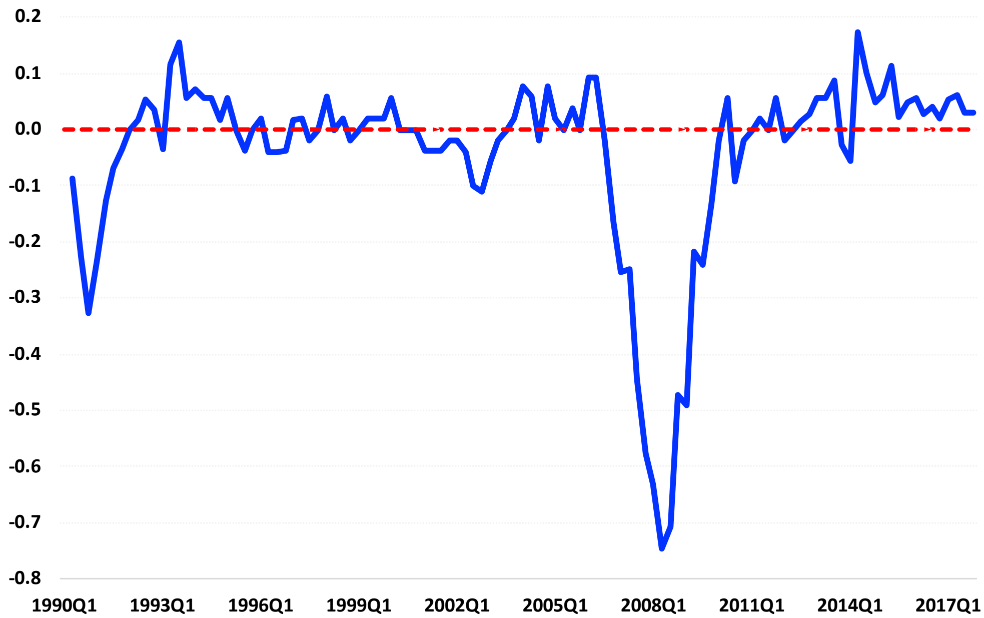
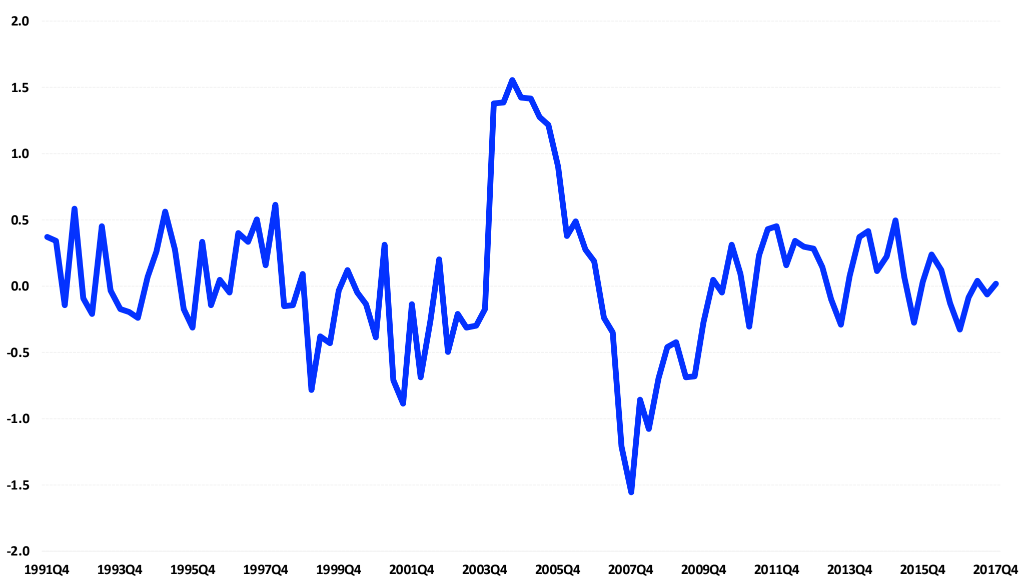
Figures and Tables

Figure 1: Credit Supply Measures

Panel A: Net Percentage of U.S. Banks Reporting Easier Credit Standards

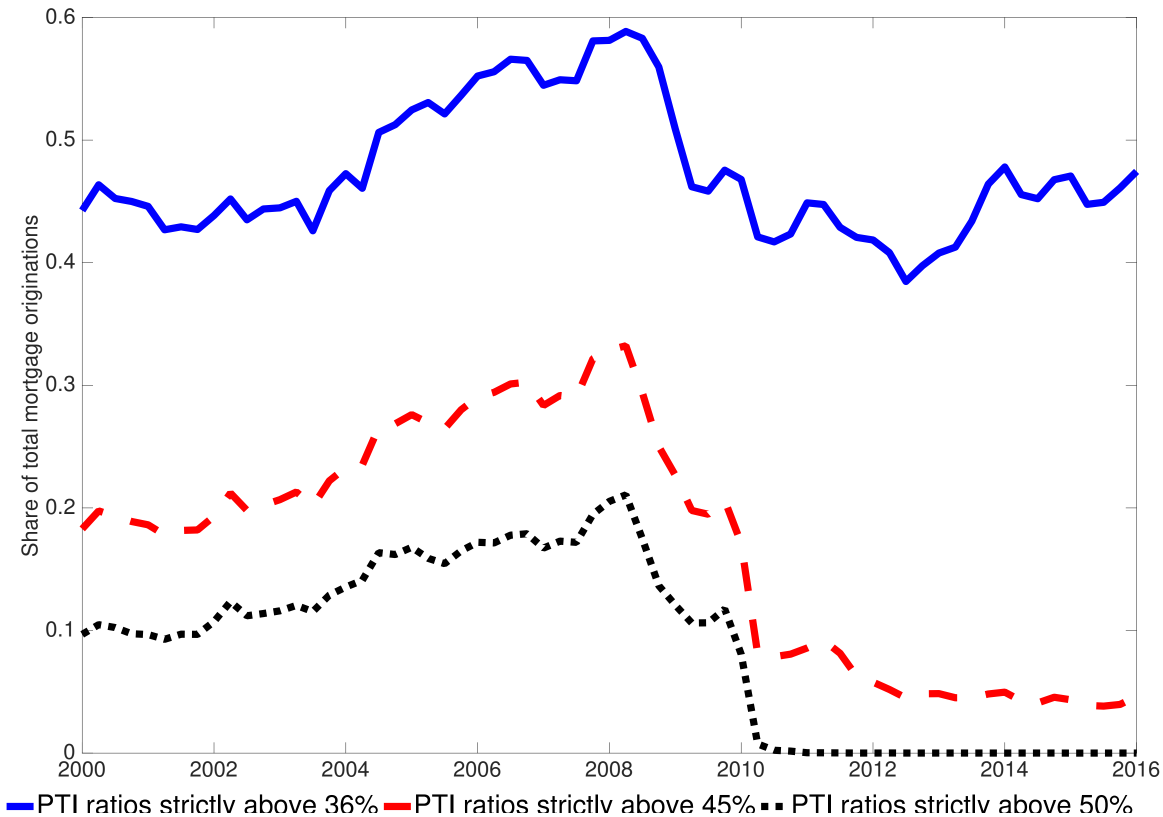


Panel B: Fitted Values $\Delta\widehat{CS}_t = \hat{\beta}_0 + \hat{\beta}_1 \Delta \log \text{GSE}_t + \hat{\beta}_2 \Delta \log \text{ABS}_t$



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.

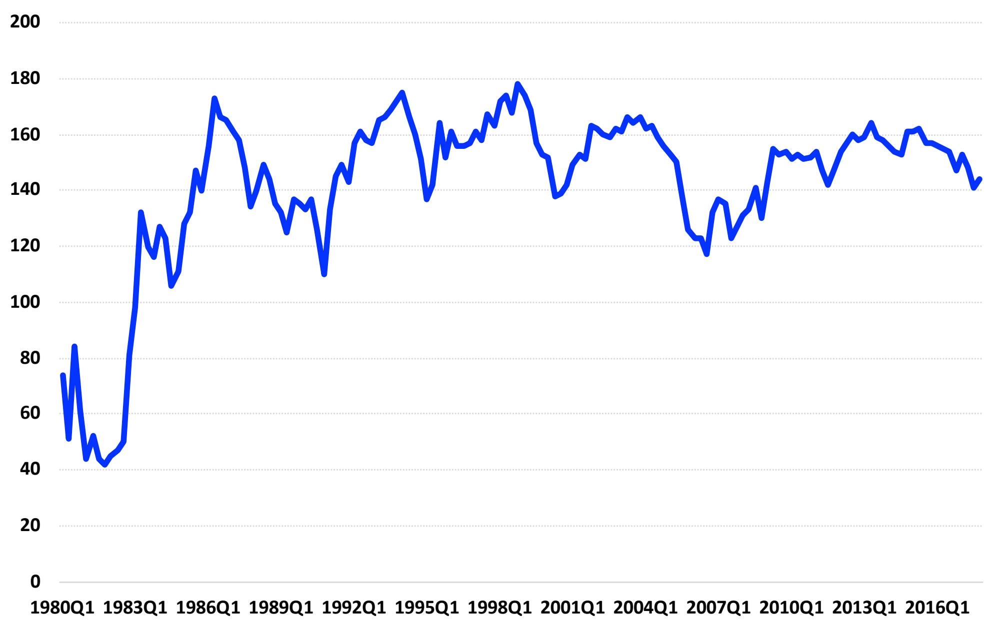
Figure 2: Share of Originations with Minimum Payment to Income Ratio (PTI)



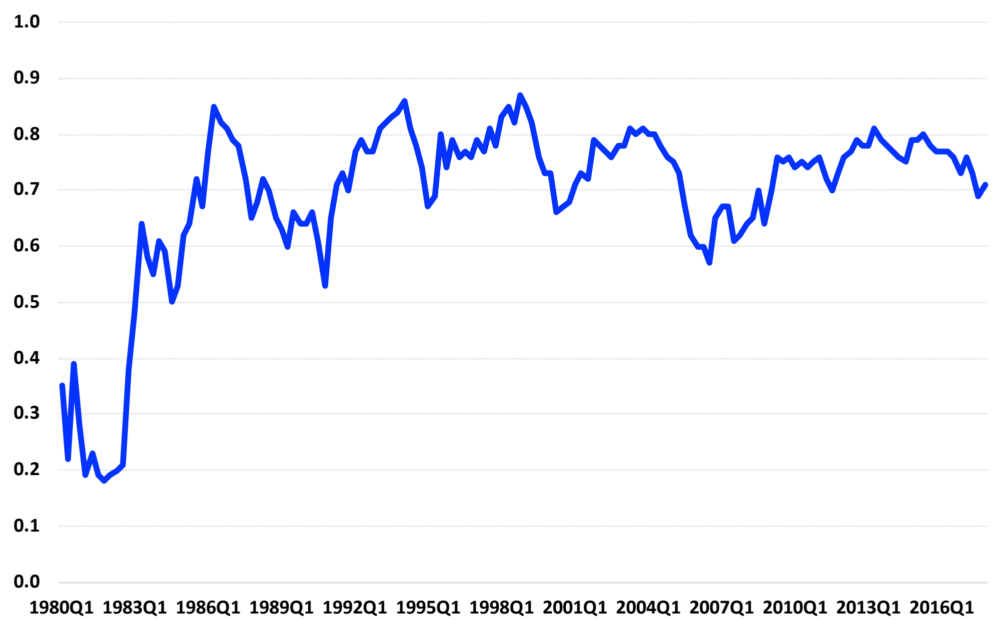
Notes: The figure displays the fraction, over time, of mortgage originations purchased by Fannie Mae with PTI ratios greater than 36, 45, and 50%, weighted by loan balance. The sample spans the period 2000:Q1 - 2016:Q1. *Source:* Fannie Mae Single Family Dataset.

Figure 3: Buying Condition for Houses

Panel A: Buying Condition Index

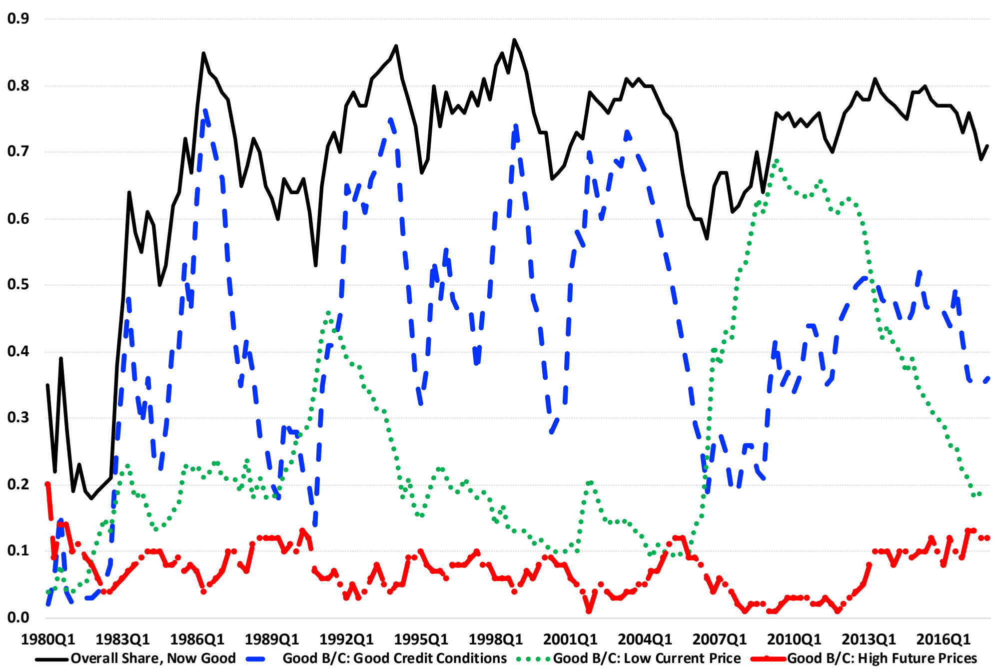


Panel B: Share of Respondents who "Answer Good Time"



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 respodents who answer that now is a "good time "to buy a house. *Source:* Survey of Consumers, University of Michigan.

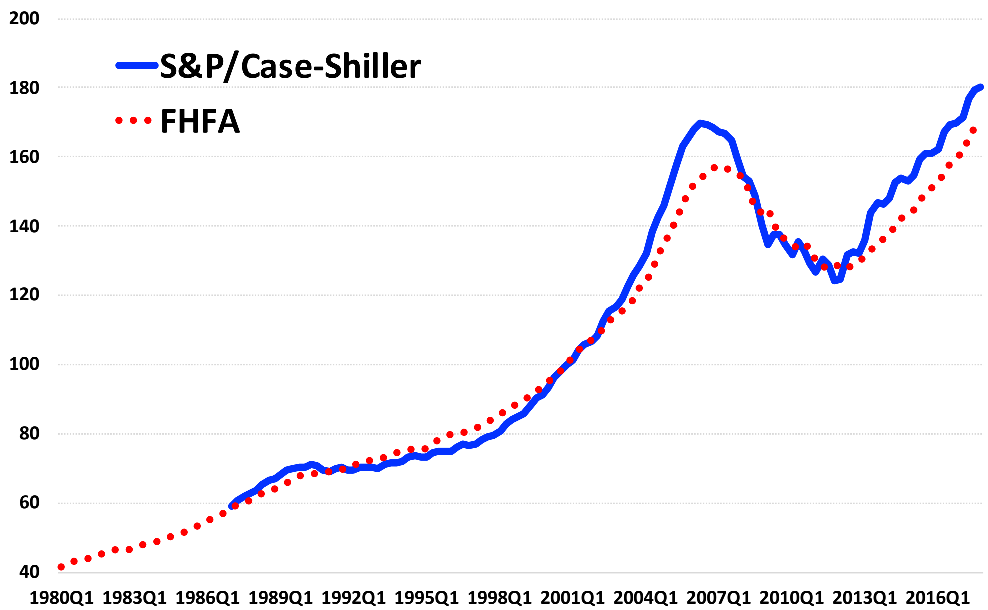
Figure 4: Reasons for Which it is a Good Time to Buy a House



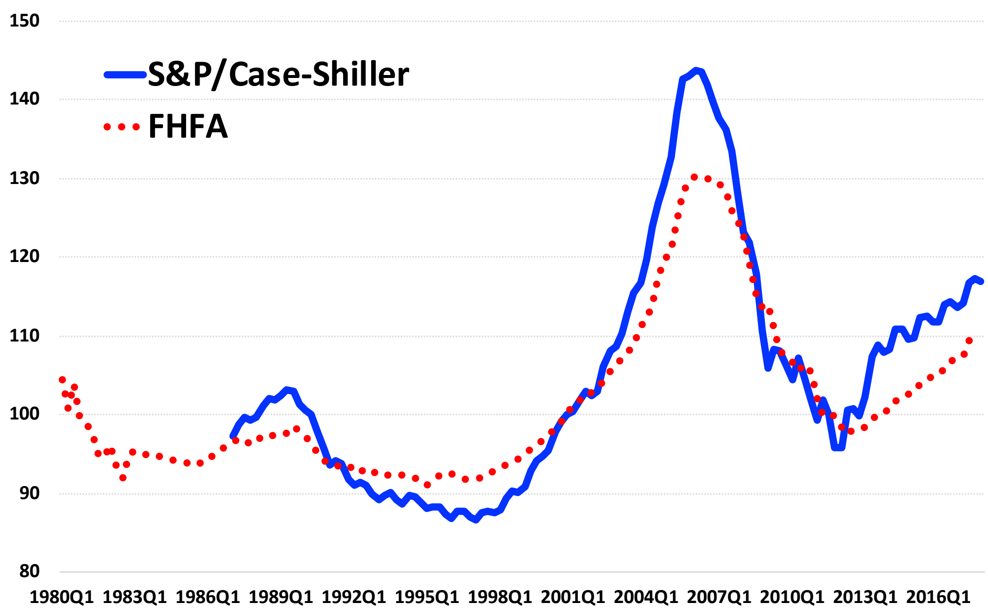
Notes: The black line presents the share of all respodents who answer that now is a "good time"to buy a house. We present the three most important reasons that respondents give when surveyed. The blue line presents the share of respondents who answer that it is a good time to buy a house because *credit 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 *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.

Figure 5: House Prices

Panel A: Price Levels



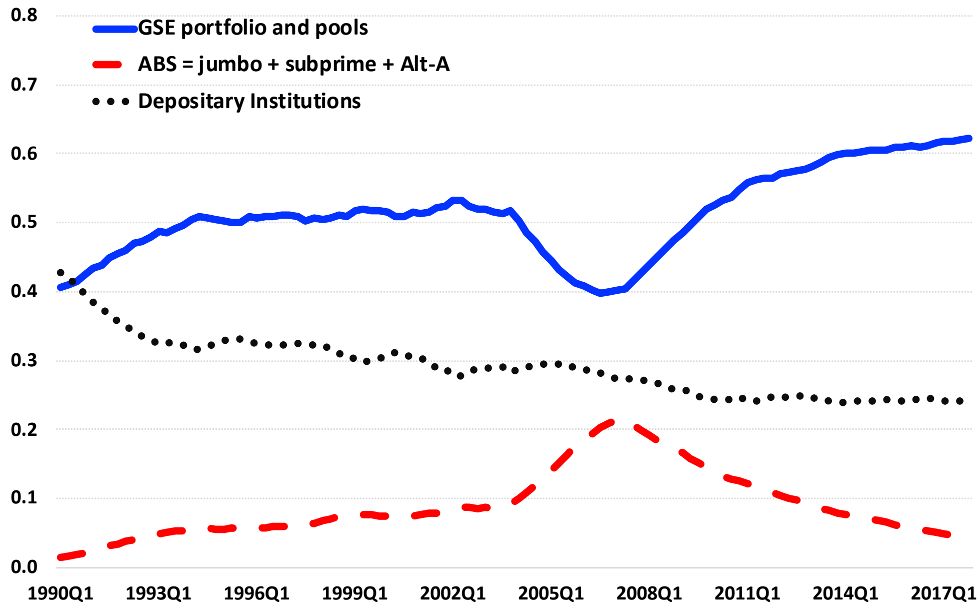
Panel B: Price Rent Ratios



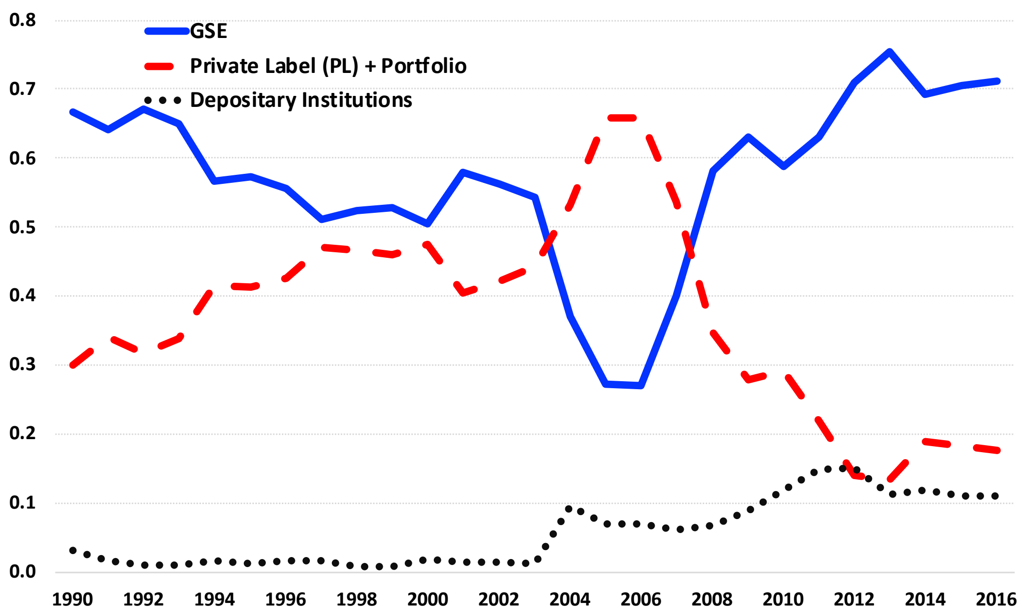
Notes: Panel A: The blue line refers to the S&P/Case-Shiller U.S. National Home Price Index (CSUS). The red line is the Federal Housing Finance Agency (FHFA) home price index. Both indices are divided by the Consumer Price Index (CPI) and rebased to 100 in the fourth quarter of 2000. Panel B: Price-rent 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.

Figure 6: Share of Mortgages by Mortgage Type

Panel A: Share of Mortgage Outstanding by Mortgage Type



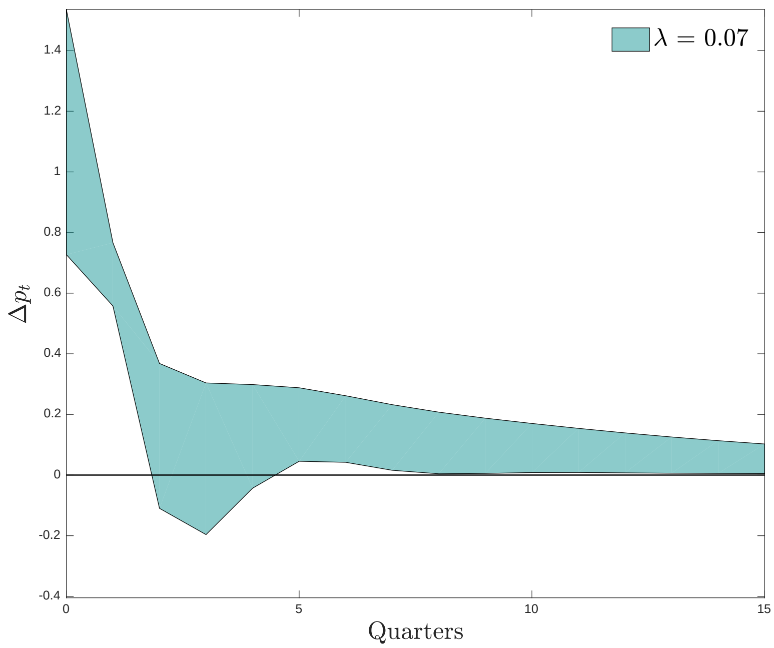
Panel B: Share of Mortgage Originations by Mortgage Type



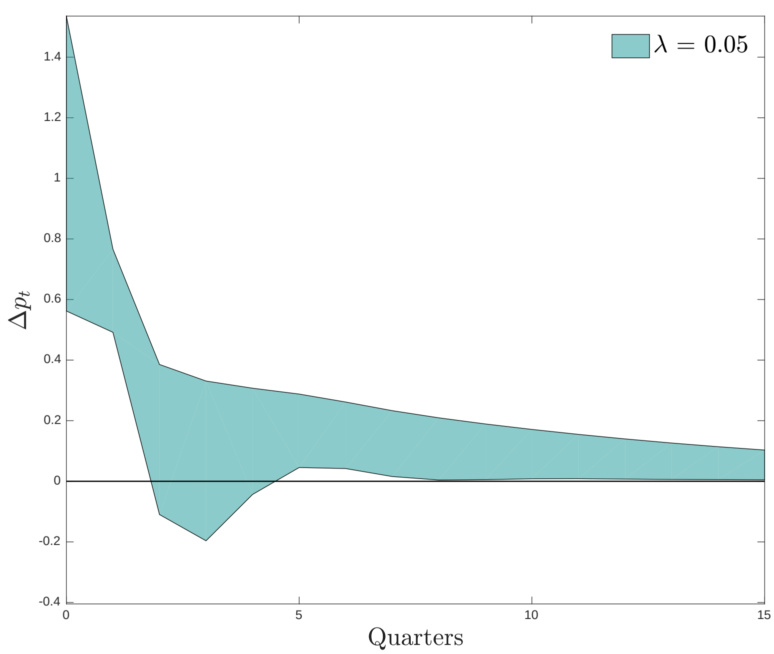
Notes: Panel A: The blue line reports the sum of GSE mortgage portfolio and Agency and GSE-backed mortgage pools. The red line shows mortgages of issuers of asset backed securities (ABS), calculated based on the sum of jumbo, subprime, and Alt-A mortgages. The black line reports the home mortgages held 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.

Figure 7: Impulse Response of Δp_t to a One Standard Deviation CS Shock

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



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



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.

Table 1: Regressions of Mortgage Growth Outstanding by Holder Type

Regressor	Left-hand-side Variable			
	$\Delta_4 \log \text{All}$	$\Delta_4 \log \text{ABS}$	$\Delta_4 \log \text{GSE}$	$\Delta_4 \log \left(\frac{\text{ABS}}{\text{GSE}}\right)$
	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]
$\Delta_4 bci$	-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	$-0.030^{***\dagger\dagger\diamond}$	-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]
$\Delta_4 bci$	-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	$-0.030^{***\dagger\dagger}$	0.064
t-stat	(0.039)	(0.418)	(-3.372)	(0.742)
$\bar{R}^2$	[-0.024]	[-0.013]	[0.250]	[0.012]
$E_t^{med} \Delta GDP_{t \to t+4}$	$0.059^{***\dagger\dagger\diamond\diamond\diamond}$	$0.205^{***\diamond\diamond}$	-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 annual log change of the buying condition index, i.e. $\ln bci_t - \ln bci_{t-4}$ ($\Delta_4 bci$), 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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. at 1%. Full sample spans all the available data in each case. The GHC sample spans the period 2000:Q1 - 2010:Q4.

Table 2: Regressions of Mortgage Origination Growth by Holder Type

	Left-hand-side Variable			
Regressor	$\Delta_4 \log \text{All}$	$\Delta_4 \log \text{PL + Potfolio}$	$\Delta_4 \log \text{GSE}$	$\Delta_4 \log \left(\frac{\text{PL + Potfolio}}{\text{GSE}}\right)$
$\Delta_4 CS$	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]
$\Delta_4 bci$	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]
$E_t^{med}\Delta GDP_{t\to t+4}$	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 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 $t+4$ ($E_t^{med}\Delta GDP_{t\to t+4}$), 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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. at 1%. The sample spans 1991 - 2016 for the first four row blocks and the period 2000 - 2013 in the last row block.

Table 3: Univariate Regressions of Δp_t on Contemporaneous ΔCS_t and Beliefs

Panel A

Regressor	1991:Q4 - 2017:Q4			2000:Q1 - 2013:Q4		2007:Q1 - 2017:Q4		
	(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]

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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. 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

Regressor	1991:Q4 - 2017:Q4			2000:Q1 - 2013:Q4		2007:Q1 - 2017:Q4		
	(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]

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)					
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]	–	–	–	–

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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. 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 5: Predicting House Price Growth $\Delta p_{t+h,t}$: Full Sample Period

Regressor	Panel A: 1991:Q4 - 2017:Q4				
	Forecast horizon				
	$h=1$	$h=1$	$h=2$	$h=3$	$h=4$
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]
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]
Regressor	**Panel B: 2000:Q1 - 2013:Q4**				
	Forecast horizon				
	$h=1$	$h=1$	$h=2$	$h=3$	$h=4$
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]

t-statistics in parentheses (Newey-West, 4 lags).
*** p<0.01, ** p<0.05, * p<0.1

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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. at 1%. 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***††	0.554*†††	1.072**†††	2.198***††
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**††	0.532*†††	1.051**†††	2.167***††
t-stat		(2.543)	(1.750)	(2.352)	(4.076)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.493]	[0.466]	[0.480]	[0.565]
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***††	0.568*†††	1.089**†††	2.219***††
t-stat		(2.824)	(1.915)	(2.371)	(4.167)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.481]	[0.459]	[0.477]	[0.561]
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***††	0.571**†††	1.145***†††	2.267***††⋄
t-stat		(2.993)	(2.253)	(2.975)	(4.662)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.430]	[0.473]	[0.452]	[0.476]	[0.561]

t-statistics in parentheses (Newey-West, 4 lags).
*** p<0.01, ** p<0.05, * p<0.1

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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: ⋄sig. at 10%. ⋄⋄sig. at 5%. ⋄⋄⋄sig. at 1%. 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**††
t-stat		(1.203)	(-2.656)	(-2.289)	(2.478)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.319]	[0.293]	[0.542]	[0.750]	[0.835]
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**††
t-stat		(1.126)	(-3.237)	(-2.940)	(2.312)
Fundamentals	✓	✓	✓	✓	✓
$\bar{R}^2$	[0.319]	[0.297]	[0.561]	[0.769]	[0.823]

t-statistics in parentheses (Newey-West, 4 lags).
*** p<0.01, ** p<0.05, * p<0.1

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: *sig. at 10%. **sig. at 5%. ***sig. at 1%. Parametric Bootstrap: †sig. at 10%. ††sig. at 5%. †††sig. at 1%. Non-Parametric Bootstrap: $^{\diamond}$sig. at 10%. $^{\diamond\diamond}$sig. at 5%. $^{\diamond\diamond\diamond}$sig. at 1%.

Online Appendix

Data Appendix

This appendix discusses the data.

Credit Standards

The Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) provides qualitative and limited quantitative information on bank credit availability and loan demand, as well as on evolving developments and lending practices in the U.S. loan markets. The FED requires one or more senior loan officers at each respondent bank to complete the survey, up to six times a year; however, the survey has typically been conducted only four times a year since 1992. The current reporting panel consists of up to 80 large domestically chartered commercial banks and up to 24 large U.S. branches and agencies of foreign banks. The minimum asset size for panel institutions is $2 billions (this amount was reduced in 2012 from $3 billion). As of March 31, 2017, the panel of domestic respondents contained 80 banks, 47 of which had assets of $20 billion or more. The assets of the panel banks totaled $11.8 trillion and accounted for about 69 percent of the $17.0 trillion in total assets of all domestically chartered institutions.

The FED seeks to limit the difficulty and quantitative content of survey questions. When quantitative information is requested, respondents generally are asked to provide approximate or rough estimates, usually in terms of percentages rather than dollar amounts. A respondent may decline to answer a particular question when answering would entail excessive burden. The FED distributes two versions of the survey, one to domestically chartered institutions and one to U.S. branches and agencies of foreign banks.

Since 2012, the FED maintains a panel of 80 banks (from 1981 to 2012, the FED maintained a panel of 60 insured, domestically chartered commercial banks, before 1981 they were 120). To ensure adequate geographic coverage, the survey panel of domestic banks spans all Federal Reserve Districts, while balancing the need to keep it heavily weighted toward the largest banks. However, the panel also includes a fair number of large and medium-size regional banks, which allows for a greater diversity of responses and provides a broader view of the banking system.

In selecting the panel, the Fed generally imposes three constraints: (i) **size**: banks that have less than $2 billion of total assets or for which commercial and industrial (C&I) loans are less than 5 % of total assets are eliminated from consideration, with a few exceptions, (ii) **geographic diversity**: between two and ten banks are included from each district, (iii) **mutual independence**: with some exceptions, a bank is eliminated from consideration if it is a subsidiary of a bank holding company that is already represented in the panel, because its responses would likely not be independent of those of the related bank already providing responses.

The Fed tries to maintain a panel of U.S. branches and agencies of foreign banks. As of March 2017, the panel included 23 institutions, 21 of which are located in the New York District. In March 2017, the share of C&I loans held by respondent U.S. branches and agencies of foreign banks ($187.7 billion) relative to that held by the universe of such institutions ($274.8 billion) was 68%.

As of April 2007, the SLOOS asked one question about supply of residential mortgages and one about demand. From April 2007 until January 2015, it divided the supply and demand questions in three categories of residential mortgage loans: (i) prime residential mortgages, (ii) nontraditional residential mortgages, and (iii) subprime residential mortgages. As stated by SLOOS:

- The **prime** category of residential mortgages includes loans made to borrowers that typically had relatively strong, well-documented credit histories, relatively high credit scores, and relatively low debt-to-income ratios at the time of origination.

- The **nontraditional** category of residential mortgages includes, but is not limited to, adjustable-rate mortgages with multiple payment options, interest-only mortgages, and Alt-A.

- The **subprime** category of residential mortgages typically includes loans made to borrowers that displayed weakened credit histories that include payment delinquencies, charge-offs, judgments, and/or bankruptcies; reduced repayment capacity as measured by credit scores or debt-to-income ratios; or incomplete credit histories.

From January 2015, it divided this question further into seven categories:

- The **GSE-eligible** category of residential mortgages includes loans that meet the underwriting guidelines, including loan limit amounts of the GSEs - Fannie Mae and Freddie Mac.

- The **government** category of residential mortgages includes loans that are insured by the Federal Housing Administration, guaranteed by the Department of Veterans Affairs, or originated under government programs, including the U.S. Department of Agriculture home loan programs.

- The **QM non-jumbo, non-GSE-eligible** category of residential mortgages includes loans that satisfy the standards for a qualified mortgage and have loan balances that are below the loan limit amounts set by the GSEs but otherwise do not meet the GSE underwriting guidelines.

Table 8: Results for the prime category: January 2010

	All Respondents		Large Banks		Other Banks	
	Banks	**Percent**	**Banks**	**Percent**	**Banks**	**Percent**
Tightened considerably	1	1.9	0	0	1	4.2
Tightened somewhat	8	15.1	3	10.3	5	20.8
Remained basically unchanged	42	79.2	24	82.8	18	75
Eased somewhat	2	3.8	2	6.9	0	0
Eased considerably	0	0	0	0	0	0
Total	**53**	**100**	**29**	**100**	**24**	**100**

Source: The Fed - Senior Loan Officer Opinion Survey on Bank Lending Practices.

- The **QM jumbo** category of residential mortgages includes loans that satisfy the standards for a qualified mortgage but have loan balances that are above the loan limit amount set by the GSEs.
- The **non-QM jumbo** category of residential mortgages includes loans that do not satisfy the standards for a qualified mortgage and have loan balances that are above the loan limit amount set by the GSEs.
- The **non-QM non-jumbo** category of residential mortgages includes loans that do not satisfy the standards for a qualified mortgage and have loan balances that are below the loan limit amount set by the GSEs.
- The **subprime** category of residential mortgages typically includes loans made to borrowers with weakened credit histories that include payment delinquencies, charge-offs, judgements, and/or bankruptcies; reduced repayment capacity as measured by credit scores or debt-to-income ratios; or incomplete credit histories.

For instance, in January 2010, the SLOOS asks about three categories of residential mortgage loans: (i) prime residential mortgages, (ii) nontraditional residential mortgages, and (iii) subprime residential mortgages. presents the results for the prime category in January 2010. The total of banks in the survey that answer this question during the particular time period was 53.

We use the net percentage of domestic respondents easing standards for mortgage loans. To construct this measure from the respondents' information, first sum all the banks that have eased (somewhat or considerably) their credit standards and subtract this from the number of banks that have tightened (considerably or somewhat) their credit standards. Using Table 8, the total number of banks easing their credit standards is 2 and the total number of banks tightening is 9. Therefore, the net percentage of domestic respondents easing standards for mortgage loans is $\frac{2-1-8}{53} = -13.2\%$.

Table 9: Number of Banks Reporting in 2015:Q1

	Number	Percentage	Weights
GSE-eligible	64	0.928	0.164
Government	60	0.870	0.154
QM non-jumbo, non-GSE-eligible	58	0.841	0.149
QM jumbo	65	0.942	0.167
Non-QM jumbo	57	0.826	0.146
Non-QM non-jumbo	57	0.826	0.146
Subprime	7	0.072	0.072
Total	**69**		**1.000**

Source: The Fed - Senior Loan Officer Opinion Survey on Bank Lending Practices.

Before 2007, the SLOOS reported one aggregated mesure of the net percentage of domestic respondents easing standards for mortgage loans. After 2007, and before 2015, it reported three different categories for the net percentage of domestic respondents easing standards for mortgage loans. Since 2015, it reports this variable for seven categories.

To aggregate these categories into one measure of credit supply, we create weights for each category. We take the total share of banks that report they have tightened/remained unchanged/eased subprime mortgage loans in each quarter. Then, we calculate the total share of banks that report they have tightened/remained unchanged/eased in the other categories (two before 2015 and six since 2015). For instance, in the first quarter of 2015, we have the following results: The share of banks answering for each category is in column Percentage. We fix the percentage of banks that answer for the subprime category and rebase the other percentages to make the weights sum up to 100%.

Beliefs measures

University of Michigan's Survey of Consumers - Price Expectations. The survey is conducted each month to a minimum of 500 households. It contains approximately 50 core questions, each of which tracks a different aspect of consumer attitudes and expectations. The samples for the Surveys of Consumers are statistically designed to be representative of all American households. We are interested in the Index of Consumer Expectations which focuses on: consumers' view of their own financial situation and their view of the general economy in the short and the long term

The method used to select monthly nationally representative samples of persons is generally referred to as random digit dialing (RDD) of cellular telephone numbers. However, any single monthly sample consists of two parts, an RDD sample of cell telephone subscribers selected in that month and a sample of RDD sample cell telephone subscribers who completed interviews six months previously. The latter is referred to as the re-contact sample, and the former the

RDD sample[7]. The questions we focus on are the following:

Question A24a: What do you think will happen to the prices of homes like yours in your community over the next 12 months? Will they

1. increase at a rapid rate?
2. increase at a moderate rate?
3. remain about the same?
4. decrease at a moderate rate? or
5. decrease at a rapid rate?

Question A24b: 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?
____________________ Percent

All responses are coded in an open-ended format, with any answers outside of the range -95% to +95% truncated to ±95%.

Some types of adjustments are made to the response distributions:

1. **Imputations for missing information:** There are three missing data codes that are used to document the type and extent of the missing information to the questions on price expectations. First, **NA** indicates that no information is available. In most cases, it reflects a respondent's refusal to answer the question. This type of missing data is relatively uncommon. Second, **DK IF** signifies that in response to the first question on the expected direction of change in prices, the respondent replied that they did not know whether prices would increase or decrease. This response reflects the respondent's lack of knowledge or understanding, and hence lacks any information content. This type of missing data has also been relatively uncommon. Third, **DK UP - DK DW** signify that only partial information was obtained. The respondents indicated the direction they expected prices to change but replied that they didn't know how much prices would increase/decline.

   Respondents coded as **NA** or **DK IF** were eliminated from the calculated estimates. By excluding these cases, the implicit assumption is that the overall sample mean or median is the best estimate of the missing information.

[7] See `https://data.sca.isr.umich.edu/fetchdoc.php?docid=57449`.

The partial information codes **DK UP** and **DK DW** provide important information about the direction of expected change in prices (but not the extent of expected change). The usual procedure is to impute the mean/median increase or decrease calculated among the complete data cases. Rather than imputing a *point estimate* of the mean or median, a distribution of responses is imputed whose mean/median is identical to the point estimate. This is done by distributing the DK UP and DK DW cases across all response codes in the same proportions as cases with complete information.

2. **Truncation of outliers:** At each step in the data collection process, all extreme values are verified: interviewers are instructed to probe all unusually large responses, asking respondents to confirm their answers; at each subsequent step in data processing all large values are subjected to special checking and editing procedures to verify that all responses were accurately transcribed. The remaining extreme values are assumed to accurately reflect the respondent' answers. The methodology favors the truncation rather than the elimination of extreme values.

University of Michigan's Survey of Consumers - Buying Condition Index. Because of the availability problem with the price expectations data, we use another measure provided by the SoC. This variables presents the share of households in the survey that reponds that it is a *good time to buy a house*. There are many reasons for which it is a good time to buy a house. The survey asks households to give up to two reasons. This is an open-ended question. SoC then groups the answers in six categories[8]. The questions we focus on are:

Question A16: Generally speaking, do you think now is a good time or a bad time to buy a house?

1. Good
2. Uncertain
3. Bad

Question A16a: Why do you say so? (Are there any other reasons?)

In their responses, households point to issues as either good or bad for buying a home. For instance, a response could be *credit is cheap* or *interest rate is going to increase*. Panel B of Figure 3 presents the share of respondents answering that it is a good time to buy a house. Panel A presents the buying condition index (BCI). We construct this index by summing the share of *good time answers* minus the share of *bad time answers* plus one hundred.

[8] See `https://data.sca.isr.umich.edu/data-archive/mine.php`

Table 10: **Classification of answers to Question A16a**

Good/Bad	Reason
Good time to buy	Prices are low; good buys available
Good time to buy	Prices won't come down; are going higher
Good time to buy	Interest rates low
Good time to buy	Borrow in advance of rising interest rates
Good time to buy	Good investment
Good time to buy	Times are good; prosperity
Bad time to buy	Prices low
Bad time to buy	Interest rates high; credit is tight
Bad time to buy	Times are bad; Can't afford
Bad time to buy	Bad times ahead; Uncertain future
Bad time to buy	Bad investment

Source: University of Michigan - Survey of Consumers.

The SoC classifies the answers to Question A16a in six groups in the case of a (1) good answer and in five groups if the answer is (3) bad.

Question A16a is open-ended. SOC classifies these answers into the categories in Table 10. For instance, category *Interest rates low* includes answers such as: lower down payment, Interest rates are low, credit easy to get, easy money, variable mortgage rate.

Figure 4 presents the most important three reasons that households give. These are *Good credit*, *current prices low*, and *future prices high*. In our regressions we use the log-growth of the BCI (Δbci_t). This variable goes back to 1978.

House Prices

We use the S&P/Case-Shiller U.S. National Home Price Index from S&P Dow Jones Indices LLC[9]. These data are on monthly basis, so we take last moth of each quarter. They are not seasonally adjusted. We rebase the index to 2005 = 100. We refer to this variable as P_t. We divide the house price index by the Consumer Price Index (All items in U.S. city average, all urban consumers, SA) rebased to 2005 = 100, from the Bureau of Labor and Statistics[10] to express it in real terms.

We use the log-growth of the real price in the contemporaneous regressions, that is $\Delta p_t = \log\left(P_t/CPI_t\right) - \log\left(P_{t-1}/CPI_{t-1}\right)$ and in the forecasting regressions we use the quarterly (denoted with h) forecasting price growth, $\Delta p_{t+h,t} = \log\left(P_{t+h}/CPI_{t+h}\right) - \log\left(P_t/CPI_t\right)$.

[9] S&P Dow Jones Indices LLC, S&P/Case-Shiller U.S. National Home Price Index (CSUSHPINSA), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CSUSHPINSA.

[10] All items in U.S. city average, all urban consumers, seasonally adjusted (CUSR0000SA0). See https://www.bls.gov/cpi/data.htm

To construct the price-rent ratio, we use the quarterly average of the Consumer Price Index for All Urban Consumers: Shelter from the U.S. Bureau of Labor Statistics[11]; that is, $pr_t = P_t/Rent_t$. Then we set the value of 2000:Q4 = 100 and apply the growth of pr_t to get the price-rent Panel B of Figure 5.

Fundamentals: 10-year real interest rates and GDP forecast

To construct the 10-year real interest rate (r_t^{10}), we use the 10-Year Treasury Constant Maturity Rate from the Board of Governors of the Federal Reserve System[12]. We take the last month of the each quarter (R_t^{10}). This variables is not seasonally adjusted. Then we use the mean response of the 10-Year CPI Inflation Rate (CPI10) from the Federal Reserve Bank of Philadelphia - Survey of Professional Forecasters[13] to express the interest rate in real terms; that is, $r_t^{10} = R_t^{10} - CPI10_t$

We create a measure of expected real GDP growth ($\Delta GDP^e_{t,t+4}$) using the annualized percent change of median responses of the real GDP from the Federal Reserve Bank of Philadelphia - Survey of Professional Forecasters[14]. The survey provides the annualized expected real GDP growth in the next four quarters ($\Delta GDP^f_{t+i,t}$) for $i = 1, \cdots 4$ which we use to construct our measure of real GDP growth:

$$\Delta GDP^e_{t,t+4} = \prod_{i=1}^{4} \left(1 + \frac{\Delta GDP^f_{t+i,t}}{100}\right)^{\frac{1}{4}} - 1$$

Mortgage Data

Mortgage outstanding Data for mortgage outstanding come from the Federal Reserve, Flow of Funds, Table L.218[15]. We use the *All sectors; home mortgages; asset* as total mortgage outstanding, the *U.S.-chartered depository institutions; home mortgages, including farm houses; asset* as mortgages held by depositary institutions. These are composed by U.S.-chartered commercial banks and savings institutions such as savings banks, federal savings banks, cooperative banks, and savings and loan associations.

The sum of *Government-sponsored enterprises; home mortgages; asset* and *Agency-and GSE-backed mortgage pools; home mortgages; asset* is denoted with GSE. GSE portfolio includes

[11] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: Shelter (CUSR0000SAH1), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CUSR0000SAH1.

[12] Board of Governors of the Federal Reserve System (US), 10-Year Treasury Constant Maturity Rate (GS10), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GS10.

[13] The CPI10 is the annual average inflation over the current and next nine years. See https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files

[14] Constructed from the RGDP in Billions of real dollars. Seasonally adjusted. Annual rate. Real GNP prior to 1992. Real GDP 1992-present. See https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files

[15] See https://www.federalreserve.gov/releases/z1/current/default.htm

home mortgages held by Fannie Mae, Freddie Mac, Federal Home Loan Banks, Farm Credit System (FCS) and farm mortgages held by the FCS excluding farm mortgages from the U.S. Department of Agriculture. Agency- and GSE-backed mortgage pools include home mortgages held in Ginnie Mae, Freddie Mac, Federal Farmers Home Administration, and Fannie Mae pools excluding the Federal Financing Bank pools. All these mortgages are known as conforming mortgage loans[16].

$$\begin{aligned} GSEportfolioandpools = {} & FannieMae + FreddieMac + FederalHomeLoanBanks \\ & + FarmCreditSystem + GinnieMae \\ & + FederalFarmersHomeAdministration \end{aligned}$$

We use the *Issuers of asset-backed securities; home mortgages; asset* as mortgages held by ABS. ABS is made up of home mortgages subtracting securitized home mortgages by real estate investment trusts (REITs). ABS is calculated based on the sum of jumbo[17], subprime, and Alt-A mortgages[18].

$$ABS = Jumbo + subprime + Alt - Amortgages$$

Panel A of Figure 6 presents these variables. For the regressions we use the annual log-growth of each series. For instance, in the case of ABS we have:

$$\Delta_4 \log \text{ABS}_t = \log \text{ABS}_t - \log \text{ABS}_{t-4}$$

Mortgage originations Panel B of Figure 6 presents the growth in mortgage origination by type of purchaser. In this case, GSE includes mortgages in Fannie Mae, Freddie Mac, Farmer Mac, and Ginnie Mae. Private label (PL) securitization includes private securitization and affiliate institutions. Portfolio includes depositary institutions, life insurance companies, credit unions, mortgage banks, and finance companies, and other type of purchasers. We get these data from the Federal Financial Institutions Examination Council.

Figure 2 presents the share of originations with minimum PTI.The population includes a subset of Fannie Mae's 30-year, fully amortizing, full documentation, single-family, conventional fixed-rate mortgages. This dataset does not include data on adjustable-rate mortgage

[16] A conforming loan is a mortgage that is eligible for purchase by the Federal National Mortgage Association and Federal Home Loan Mortgage Corporation. These agencies created standardized rules and guidelines that mortgages must conform to in order to be a conforming loan. Among these rules, one has the size of the loan (conforming limit), borrower's loan-to-value ratio (i.e. the size of down payment), debt-to-income ratio, credit score and history, documentation requirements, etc.

[17] A mortgage loan that is in an amount above conventional conforming loan limits. For 2018, the limit is $453,100. See https://www.fhfa.gov/Media/PublicAffairs/Pages/FHFA-Announces-Maximum-Conforming-Loan-Limits-for-2018.aspx

[18] An Alt-A mortgage is riskier than a prime but less risky than a subprime mortgage. Alt-A loans are not eligible for purchase by GSE. See https://www.federalreserve.gov/apps/fof/SeriesAnalyzer.aspx?s=FL673065105&t=L.218&suf=Q.

loans, balloon mortgage loans, interest-only mortgage loans, mortgage loans with prepayment penalties, government-insured mortgage loans, Home Affordable Refinance Program (HARP) mortgage loans, Refi Plus mortgage loans, and non-standard mortgage loans. Certain types of mortgage loans (e.g., mortgage loans with LTVs greater than 97 percent, Alt-A, other mortgage loans with reduced documentation and/or streamlined processing, and programs or variances that are ineligible today) have been excluded in order to make the dataset more reflective of current underwriting guidelines. Also excluded are mortgage loans originated prior to 1999, sold with lender recourse or subject to other third-party risk-sharing arrangements, or were acquired by Fannie Mae on a negotiated bulk basis. For manually underwritten loans, Fannie Mae's maximum total PTI ratio is 36% of the borrower's stable monthly income. The maximum can be exceeded up to 45% if the borrower meets the credit score and reserve requirements reflected in the Eligibility Matrix. For loan casefiles underwritten through Desktop Underwriter (DU), the maximum allowable PTI ratio is 50%. If the DTI on a loan casefile exceeds 50%, the loan casefile will receive an ineligible recommendation. We get these PTI ratios from the Fannie Mae Single Family Dataset.

Bootstrap Procedure

This appendix describes our bootstrap procedure. We employ two approaches that we refer to as the parametric and non-parametric bootstrap. The distinction refers to how serial dependence is modeled. In the first approach, serial dependence is specified using a parametric model. In the second approach, it is specified using a block bootstrap procedure. For both approaches, the general linear model we consider is the following:

$$y_t = \beta_0 + \boldsymbol{\beta}' \boldsymbol{x}_t + \epsilon_{yt} \tag{A1}$$

where $\boldsymbol{x}_t$ is a vector of regressors. In some specifications $\boldsymbol{x}_t$ will be a scalar; in other cases, it will be multidimensional. We are interested in the distribution of the t-statistic for each element of $\boldsymbol{\beta}$, under the null that $\boldsymbol{\beta} = 0$. We use "*" to denote statistics and data generated from the bootstrap procedure, while "hats" denote statistics estimated from historical data.

Algorithm 1: Parametric Bootstrap

This algorithm consists of the following steps:

1. Generate data under the null that $\boldsymbol{\beta} = 0$. Estimate the time series regression in (A2) and obtain the sample estimate $\widehat{\beta}_0$ of the parameter in

$$y_t = \beta_0 + \epsilon_{yt} \tag{A2}$$

2. Estimate the time series equations in (A3) separately and obtain the sample estimate of $\widehat{\boldsymbol{\alpha}}_0$, $\widehat{\boldsymbol{\alpha}}$

$$\boldsymbol{x}_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{kt} \end{bmatrix} = \underbrace{\begin{bmatrix} \alpha_1^0 \\ \alpha_2^0 \\ \vdots \\ \alpha_k^0 \end{bmatrix}}_{\boldsymbol{\alpha}_0} + \underbrace{\begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_k \end{bmatrix}}_{\boldsymbol{\alpha}} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \\ \vdots \\ x_{k,t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \epsilon_{xt}^1 \\ \epsilon_{xt}^2 \\ \vdots \\ \epsilon_{xt}^k \end{bmatrix}}_{\boldsymbol{\epsilon}_{xt}} \tag{A3}$$

3. Given these estimates, obtain the fitted residuals

$$\widehat{\epsilon}_{yt} = y_t - \widehat{\beta}_0 \tag{A4}$$

$$\widehat{\boldsymbol{\epsilon}}_{xt} = \boldsymbol{x}_t - \widehat{\boldsymbol{\alpha}}_0 - \widehat{\boldsymbol{\alpha}} \cdot \boldsymbol{x}_{t-1} \tag{A5}$$

   This leaves $T-1$ observations from (A5). We fill the first observation using the first observation in the sample, so that $\boldsymbol{x}_0 = \boldsymbol{x}_1$; hence, $\widehat{\boldsymbol{\epsilon}}_{x1} = \left(1 - \widehat{\boldsymbol{\alpha}}\right) \cdot \boldsymbol{x}_1 - \widehat{\boldsymbol{\alpha}}_0$.

4. Estimate an AR(1) process for the fitted residuals:

$$\widehat{\epsilon}_{yt} = \rho_y \widehat{\epsilon}_{y,t-1} + e_{yt} \tag{A6}$$

$$\widehat{\boldsymbol{\epsilon}}_{xt} = \boldsymbol{\rho}_x \widehat{\boldsymbol{\epsilon}}_{x,t-1} + \boldsymbol{e}_{xt} \tag{A7}$$

From the above estimation, we obtain the fitted residuals: $\left[\widehat{e}_{yt},\ \widehat{\boldsymbol{e}}_{xt}\right]_{t=2}^{T}$. Draw rows randomly with replacement from

$$\widehat{\boldsymbol{e}} = \begin{bmatrix} \widehat{e}_{y2} & \widehat{e}_{x_1 2} & \cdots & \widehat{e}_{x_k 2} \\ \widehat{e}_{y3} & \widehat{e}_{x_1 3} & \cdots & \widehat{e}_{x_k 3} \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{e}_{yT} & \widehat{e}_{x_1 T} & \cdots & \widehat{e}_{x_k T} \end{bmatrix} \tag{A8}$$

to obtain M bootstrap samples of these residuals:

$$\boldsymbol{e}^{*(i)} = \begin{bmatrix} e^{*(i)}_{y2} & e^{*(i)}_{x_1 2} & \cdots & e^{*(i)}_{x_k 2} \\ e^{*(i)}_{y3} & e^{*(i)}_{x_1 3} & \cdots & e^{*(i)}_{x_k 3} \\ \vdots & \vdots & \ddots & \vdots \\ e^{*(i)}_{yT} & e^{*(i)}_{x_1 T} & \cdots & e^{*(i)}_{x_k T} \end{bmatrix} \tag{A9}$$

for $i = 1, \cdots, M$.

5. Using the samples in (A9) and the estimated parameters in equations (A6)-(A7), we create M samples of the residuals by iterating on

$$\epsilon^{*(i)}_{yt} = \widehat{\rho}_y \epsilon^{*(i)}_{yt-1} + e^{*(i)}_{t} \tag{A10}$$

$$\boldsymbol{\epsilon}^{*(i)}_{xt} = \widehat{\boldsymbol{\rho}}_x \boldsymbol{\epsilon}^{*(i)}_{x,t-1} + \boldsymbol{e}^{*(i)}_{xt} \tag{A11}$$

for $i = 1, \cdots, M$, using the first observation in the sample to start the recursion (i.e. $\epsilon^{*(i)}_{y1} = \widehat{\epsilon}_{y1}$ and $\boldsymbol{\epsilon}^{*(i)}_{x1} = \widehat{\boldsymbol{\epsilon}}_{x1}$):

$$\boldsymbol{\epsilon}^{*} = \begin{bmatrix} \epsilon^{*(i)}_{y1} & \epsilon^{*(i)}_{x_1 1} & \cdots & \epsilon^{*(i)}_{x_k 1} \\ \epsilon^{*(i)}_{y2} & \epsilon^{*(i)}_{x_1 2} & \cdots & \epsilon^{*(i)}_{x_k 2} \\ \vdots & \vdots & \ddots & \vdots \\ \epsilon^{*(i)}_{yT} & \epsilon^{*(i)}_{x_1 T} & \cdots & \epsilon^{*(i)}_{x_k T} \end{bmatrix} \tag{A12}$$

for $i = 1, \cdots, M$.

6. Using the appropriate columns in (A12), $\widehat{\boldsymbol{\alpha}}_0$, and, $\widehat{\boldsymbol{\alpha}}$, use (A3) to create M samples of $\boldsymbol{x}$:

$$\boldsymbol{x}^{*(i)}_{t} = \widehat{\boldsymbol{\alpha}}_0 + \widehat{\boldsymbol{\alpha}} \cdot \boldsymbol{x}^{*(i)}_{t-1} + \boldsymbol{\epsilon}^{*(i)}_{xt}$$

for $i = 1, \cdots, M$ with $\boldsymbol{x}^{*(i)}_{1} = \boldsymbol{x}_1$.

7. Using the appropriate columns in (A12) and $\widehat{\beta}_0$, we construct M samples of y_t:

$$y_t^{*(i)} = \widehat{\beta}_0 + \epsilon_{yt}^{*(i)}$$

for $i = 1, \cdots, M$.

8. Given $\{y_t^{*(i)}\}_{t=1}^T$ and $\{\boldsymbol{x}_t^{*(i)}\}_{t=1}^T$ for $i = 1, \cdots, M$, we run regressions using bootstrapped data:

$$y_t^{*(i)} = \beta_0^{*(i)} + \boldsymbol{\beta}^{*(i)\prime}\boldsymbol{x}_t^{*(i)} + \epsilon_{yt}$$

to obtain M samples of parameters $\{\beta_0^{*(i)}, \boldsymbol{\beta}^{*(i)}\}_{i=1}^M$ and M samples of Newey-West HAC estimators t-statistic$\left\{t_{\beta_0^{*(i)}}, \boldsymbol{t}_{\boldsymbol{\beta}^{*(i)}}\right\}_{i=1}^M$.

9. We compute the 99%, 95%, and 90% bootstrap confidence intervals for $t_{\beta_0^{*(i)}}$. The coefficients $\hat{\boldsymbol{\beta}}$ are reported as statistically significant at the 1% († † †), 5% (††), or 10% (†) level if their t-statistics from historical data fall outside of the bootstrap confidence intervals.

Algorithm 2: Non-Parametric Bootstrap

This procedure uses block bootstrap sampling to capture serial dependence in the data. We choose the block length following the recommendation of Hall, Horowitz, and Jing (1995) who show that the asymptotically optimal block length for estimating a one-sided distribution function is $l \propto T^{1/4}$; also see Horowitz (2003). For the results reported in the text, we use a block length exactly equal to $T^{1/4} = 3$, but we check the robustness of our results to lengths of 2 and 5 and find little difference in the resulting distributions and confidence sets. This algorithm consists of the following steps:

1. Generate data under the null that $\boldsymbol{\beta} = 0$. Estimate the time series regression in (A13) and obtain the sample estimate of $\widehat{\beta}_0$.

$$y_t = \beta_0 + \epsilon_{yt} \tag{A13}$$

2. Estimate the time series equations in (A14) separately and obtain the sample estimate of $\widehat{\boldsymbol{\alpha}}_0$, $\widehat{\boldsymbol{\alpha}}$.

$$\boldsymbol{x}_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{kt} \end{bmatrix} = \underbrace{\begin{bmatrix} \alpha_1^0 \\ \alpha_2^0 \\ \vdots \\ \alpha_k^0 \end{bmatrix}}_{\boldsymbol{\alpha}_0} + \underbrace{\begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha_k \end{bmatrix}}_{\boldsymbol{\alpha}} \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \\ \vdots \\ x_{k,t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} \epsilon_{xt}^1 \\ \epsilon_{xt}^2 \\ \vdots \\ \epsilon_{xt}^k \end{bmatrix}}_{\boldsymbol{\epsilon}_{xt}} \tag{A14}$$

3. Given these estimates, obtain the fitted residuals

$$\widehat{\epsilon}_{yt} = y_t - \widehat{\beta}_0 \tag{A15}$$

$$\widehat{\boldsymbol{\epsilon}}_{xt} = \boldsymbol{x}_t - \widehat{\boldsymbol{\alpha}}_0 - \widehat{\boldsymbol{\alpha}} \cdot \boldsymbol{x}_{t-1} \tag{A16}$$

   This leaves $T - 1$ observations from (A16). We fill the first observation using the first observation in the sample, so that $\boldsymbol{x}_0 = \boldsymbol{x}_1$; hence, $\widehat{\boldsymbol{\epsilon}}_{x1} = \left(1 - \widehat{\boldsymbol{\alpha}}\right) \cdot \boldsymbol{x}_1 - \widehat{\boldsymbol{\alpha}}_0$.

$$\widehat{\boldsymbol{\epsilon}} = \begin{bmatrix} \widehat{\epsilon}_{y1} & \widehat{\epsilon}_{x_1 1} & \widehat{\epsilon}_{x_2 1} \\ \widehat{\epsilon}_{y2} & \widehat{\epsilon}_{x_1 2} & \widehat{\epsilon}_{x_2 2} \\ \vdots & \vdots & \vdots \\ \widehat{\epsilon}_{yT} & \widehat{\epsilon}_{x_1 T} & \widehat{\epsilon}_{x_2 T} \end{bmatrix} \tag{A17}$$

4. We create M bootstrap samples by sampling blocks from the data in (A17) randomly with replacement and laying them end-to-end in the order sampled until a new sample of observations of length equal to the data (T) is obtained. We consider a block length

equal to $L = [|T^{1/4}|]$

$$\boldsymbol{\epsilon}^{*(i)} = \begin{bmatrix} \epsilon_{y1}^{*(i)} & \epsilon_{x_1 1}^{*(i)} & \epsilon_{x_2 1}^{*(i)} \\ \epsilon_{y2}^{*(i)} & \epsilon_{x_1 2}^{*(i)} & \epsilon_{x_2 2}^{*(i)} \\ \vdots & \vdots & \vdots \\ \epsilon_{yT}^{*(i)} & \epsilon_{x_1 T}^{*(i)} & \epsilon_{x_2 T}^{*(i)} \end{bmatrix} \tag{A18}$$

for $i = 1, \cdots, M$.

5. Using the appropriate columns in (A18), $\widehat{\boldsymbol{\alpha}}_0$, and, $\widehat{\boldsymbol{\alpha}}$, use (A14) to create M samples of $\boldsymbol{x}$:

$$\boldsymbol{x}_t^{*(i)} = \widehat{\boldsymbol{\alpha}}_0 + \widehat{\boldsymbol{\alpha}} \cdot \boldsymbol{x}_{t-1}^{*(i)} + \boldsymbol{\epsilon}_{xt}^{*(i)} \tag{A19}$$

for $i = 1, \cdots, M$ with $\boldsymbol{x}_1^{*(i)} = \boldsymbol{x}_1$.

6. Using the appropriate columns in (A18) and $\widehat{\beta}_0$, we construct M samples of y_t:

$$y_t^{*(i)} = \widehat{\beta}_0 + \epsilon_{yt}^{*(i)} \tag{A20}$$

for $i = 1, \cdots, M$.

7. Given $\{y_t^{*(i)}\}_{t=1}^T$ and $\{\boldsymbol{x}_t^{*(i)}\}_{t=1}^T$ for $i = 1, \cdots, M$, we run regressions using bootstrap data:

$$y_t^{*(i)} = \beta_0^{*(i)} + \boldsymbol{\beta}^{*(i)\prime} \boldsymbol{x}_t^{*(i)} + \epsilon_{yt}$$

to obtain M samples of parameters $\{\beta_0^{*(i)}, \boldsymbol{\beta}^{*(i)}\}_{i=1}^M$ and M samples of Newey-West HAC estimators t-statistic$\left\{t_{\beta_0^{*(i)}}, \boldsymbol{t}_{\boldsymbol{\beta}^{*(i)}}\right\}_{i=1}^M$.

8. We compute the 99%, 95%, and 90% bootstrap confidence intervals for $t_{\beta_0^{*(i)}}$. The coefficients $\hat{\boldsymbol{\beta}}$ are reported as statistically significant at the 1% ($\diamond\diamond\diamond$), 5% ($\diamond\diamond$), or 10% ($\diamond$) level if their t-statistics from historical data fall outside of the bootstrap confidence intervals.