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Large price movements in housing markets

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ABSTRACT

This paper examines large price run-ups with potential subsequent crashes and large price declines with potential subsequent rebounds in state-level and metropolitan-area-level housing markets in the U.S. over the past 40 years. We find that a sharper run-up in house prices predicts a higher probability of a crash, but a sharper decline does not necessarily predict a higher probability of a rebound. Changes in the effective interest rate in the local market can predict housing returns following large price run-ups, while it is harder to use the same factors to predict returns following large price declines. Such characteristics are robust to different thresholds of price movements.

1. Introduction

This paper documents and explains some regularities of large movements in house prices. More specifically, we search for (1) run-up episodes during which house prices increase by a large percentage within a short period of time that might end in crashes and (2) decline episodes during which house prices drop in a similar manner that might end in rebounds. In loose vernacular, we are identifying episodes of “bubbles developing” and “bubbles crashing” in the housing market, where the “bubbles” can be either positive or negative. Using a broad range of definitions, we find some common features among these episodes: changes in the effective interest rate in the local market can predict housing returns following price run-up episodes, but it is more difficult to use the same factors to predict returns following decline episodes. This finding is consistent with a model of self-reinforcing housing bubbles that features asymmetric search costs

We borrow ideas from similar exercises on the stock market. Fama (2014) states that the available research provides no reliable evidence that stock prices exhibit “bubbles”, which are defined as an irrational strong price increase that implies a predictable strong decline. In a recent study, Greenwood et al. (2019) revisit Fama’s statement by examining about 90 years of U.S. industry returns and 30 years of data on international sector returns. They find that, while Fama is mostly right in that a sharp stock price increase does not predict unusually low returns going forward, such an increase substantially heightens the probability of a crash. In another related work, Goetzmann and Kim (2018) study the opposite “negative bubbles” (i.e., rebounds after large price declines) and find that a sharp stock price decrease usually predicts positive returns and a higher probability of a rebound.

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Table 1
Predicting housing returns.

	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0046	−0.0102	−0.0111	−0.0079	−0.0046	−0.0102	−0.0111	−0.0079
	(0.0041)	(0.0078)	(0.0116)	(0.0161)	(0.0041)	(0.0078)	(0.0116)	(0.0162)
ΔTTM	−0.0165	−0.0668	−0.0960	−0.1214				
	(0.0209)	(0.0447)	(0.0711)	(0.0909)				
ΔLTV	−0.0002	−0.0000	−0.0005	−0.0006				
	(0.0005)	(0.0010)	(0.0015)	(0.0020)				
ΔRPI	0.2698	0.2702	0.1701	0.1445	0.2702	0.2735	0.1740	0.1494
	(0.1430)	(0.2281)	(0.3150)	(0.4166)	(0.1435)	(0.2310)	(0.3188)	(0.4195)
ΔUR	−0.0084**	−0.0122*	−0.0125	−0.0143	−0.0081**	−0.0115*	−0.0113	−0.0127
	(0.0028)	(0.0053)	(0.0079)	(0.0090)	(0.0029)	(0.0056)	(0.0083)	(0.0095)
Permits	$7.41e^{-7}$***	$1.52e^{-6}$***	$2.85e^{-6}$***	$4.38e^{-6}$***	$7.54e^{-7}$***	$1.55e^{-6}$***	$2.91e^{-6}$***	$4.45e^{-6}$***
	($7.37e^{-8}$)	($1.54e^{-7}$)	($2.18e^{-7}$)	($2.78e^{-7}$)	($7.59e^{-8}$)	($1.56e^{-7}$)	($2.25e^{-7}$)	($2.90e^{-7}$)
Current	0.3459**	0.6145**	0.7090**	0.5870	0.3472**	0.6151**	0.7123**	0.5912
Return	(0.1214)	(0.1936)	(0.2567)	(0.3054)	(0.1213)	(0.1943)	(0.2604)	(0.3106)
N	6928	6928	6928	6928	6928	6928	6928	6928
adj. R^2	0.242	0.229	0.148	0.074	0.242	0.227	0.145	0.072
par. R^2	0.050	0.036	0.020	0.014	0.049	0.034	0.017	0.011

The table reports the pooled ordinary least squares results with clustered standard errors of the multivariate regression $y = \mathbf{X}'\beta + u$, where y denotes the 1- to 4-year future housing return in each version, the regressor matrix $\mathbf{X}$ includes ΔEIR, ΔTTM, ΔLTV, ΔRPI, ΔUR, Permits, and Current Return, plus a constant for regressions (1) to (4) and the same regressors except for ΔTTM and ΔLTV for regressions (5) to (8). $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Constants are not reported. Standard errors in parentheses are clustered by year. The partial R^2 captures the decrease in R^2 that results from removing all predictor variables from the regression and keeping only the current housing return.

Both inside and outside the academia, the concept of "bubbles" has been applied to different asset markets. In particular, large fluctuations in stock and real estate markets have inspired numerous studies (see Allen and Gale, 2009; Reinhart and Rogoff, 2009; Shiller, 2005 among many others). Comparing to stock markets, large negative changes in house prices, although much less frequent, are found to be more disruptive and more likely to be associated with financial crisis recessions (see Jordà et al., 2015). Housing is also found to be one of the most important sectors over the business cycle and have large spillover effects on the broad economy (see Iacoviello and Neri, 2010; Leamer, 2007). Given that housing fluctuations have large effects for the economy as a whole, we would like to examine what tends to happen following large house price movements. Do the findings of Greenwood et al. (2019) and Goetzmann and Kim (2018) on stock markets apply to housing markets as well?

To answer this question, we examine the dynamics of house prices of 50 states (plus the District of Columbia) and 403 metropolitan statistical areas in the U.S. over the past 40 years. We first follow the method adopted by Greenwood et al. (2019) and identify episodes of price run-ups and crashes. A run-up episode is defined as an episode with a cumulative real housing return of 12% or more, in both raw and net-of-market terms, in the past year and a 20% or more raw return over the past four years (though our results are robust to alternative definitions). We have two major findings: (1) a sharp increase in real house prices usually predicts positive returns for about two years ahead and negative returns after. In other words, the first conclusion of Greenwood et al. (2019)'s, i.e., a sharp price increase does not predict unusually low returns going forward, is not applicable to housing markets; (2) a sharper increase in real house prices predicts a substantially higher probability of a crash, which means that their second conclusion goes in line with housing markets.

We then follow Goetzmann and Kim (2018) to examine the price decline episodes and rebounds, where an episode is analogously defined as a real housing return of negative 12% or worse, in both raw and net-of-market terms, in the past year and a negative 20% or worse raw return over the past four years. We find that sharp price declines are typically followed by negative returns for about three years ahead and positive returns after three years. In addition, the probability of a rebound following a price decline does not necessarily increase with the size of the decline. While there is a large body of work that focuses on whether (positive) housing "bubbles" exist or not (see, for example, Case and Shiller, 2003; Smith and Smith, 2006), this paper adds to the literature by examining housing returns following large price declines, or the negative equivalent of housing "bubbles".

It is well documented in the literature that stock returns are hard to predict. Does the predictability improve in housing markets? Generally speaking, the answer is no. Table 1 presents the forecasting results of future housing returns for 50 U.S. states and the District of Columbia over the 1975:Q1-2017:Q4 period using information on mortgage loans and a set of demand and supply factors as predictors. Housing returns are calculated as the percent change in the deflated house price index. The predictors include changes in the effective interest rate (ΔEIR), changes in the term to maturity (ΔTTM), changes in the loan to value ratio (ΔLTV), changes in real personal income (ΔRPI), changes in unemployment rate (ΔUR), and the number of new housing units authorized by building permits (in log).[1] In the forecasting regressions, we also control for the current housing return to capture the persistence in housing returns. In columns (1)–(4), we run multivariate forecasting regressions of 1- to 4-year ahead housing returns against all predictor variables and the current return. The adjusted R^2 varies from 7 to 24%, but most of the explained variation is due to the inertia of housing returns. The current housing return remains a significant predictor of future returns even after taking into account other predictor variables in the local market, results that are qualitatively similar to those of Campbell et al. (2009). The predictor variables jointly explain only 1–5% of the variation in future housing returns, as shown by the partial R^2, which captures the decrease in R^2 that results from removing all predictor variables from the regression and keeping only the current housing return. Since changes in the term to maturity and changes in the loan to value ratio are not statistically significant in any prediction regressions, we exclude them and show the results in columns (5)–(8). Our results are in line with the finding of Wheaton and Nechayev (2008) that the growth in fundamentals forecasts house price growth that is far below the actual growth.

While housing returns are hard to predict in general, we find important asymmetry in the predictability of returns following large price movements on the way up versus on the way down. To explore the properties of large price movements, or bubbles, in housing markets, we build asymmetric search costs into the model of Glaeser et al. (2008) for self-reinforcing housing bubbles. The augmented model implies that interest rate changes predict housing returns following large price movements and they are a stronger predictor during market upturns than downturns. The model also implies that demand and supply shocks predict housing returns but they are less reliable predictors compared to interest rate changes. Both model implications are supported by our empirical findings. Our results are also consistent with some behavioral explanations, e.g., feedback models and obstacles to smart money.

How is this paper different from other related studies on housing price bubbles or booms and busts? A large literature focuses on the driving forces of housing bubbles, especially the booming U.S. house prices in the 2000s. Leading explanations include declining interest rates (see Himmelberg et al., 2005, Hubbard and Mayer, 2009, Mayer and Sinai, 2009, Glaeser et al., 2012; Taylor, 2013), financial market liberalization (see Favilukis et al., 2017; Justiniano et al., 2015), easy credit and subprime lending (see Khandani et al., 2013, Favara and Imbs, 2015, Pavlov and Wachter, 2011, Mian and Sufi, 2009, Mayer and Sinai, 2009; Wheaton and Nechayev, 2008), foreign capital inflows (see Favilukis et al., 2017), and irrational exuberance and unrealistic expectations (see Shiller, 2005, Shiller, 2007, Angeletos and La'O, 2013; Case and Shiller, 2003). This paper does not aim at explaining what drives housing bubbles. Instead, we are interested in what tends to happen after large price movements are observed.

A few studies on housing price booms and busts are closely related to the present paper. Burnside et al. (2016) develop a matching model to explain the fact that some booms in house prices are followed by busts while others are not. Their model features optimistic and skeptical economic agents that form heterogenous expectations about long-run fundamentals. The model suggests that booms are typically followed by busts when skeptical agents happen to be correct and otherwise when optimistic agents happen to be correct. Since observed data do not suggest which agent is correct, their model implies that econometricians would not be able to predict whether a boom will turn into a bust or not. While we cannot make definite predictions about whether a boom will turn into a bust, our results suggest that changes in the effective interest rates significantly predict housing returns following large price run-ups.

Helbling (2005) examines housing price booms and busts and their relationship with interest rates across 14 industrial countries. The identification of booms and busts is also based on large price increases and decreases. The study suggests that monetary policy tightening tends to trigger housing price busts after booms because interest rates typically increase toward the end of a boom and remain high into the first year of a bust. Our approach is different. Instead of classifying booms and busts based on *ex-post* information, we identify price run-up episodes of certain sizes and try to rely on information that is available at the identification of these episodes to predict future housing returns. We also examine potential rebounds following house price busts and find it harder to predict housing returns following large price declines. To the best of our knowledge, this paper is the first study that documents the asymmetry in predictability of housing returns following large positive versus negative price movements. A model of self-reinforcing housing bubbles augmented with asymmetric search costs is consistent with such asymmetry.

The remainder of the paper is structured as follows: Section 2 identifies price run-up episodes with potential crashes and price decline episodes with potential rebounds. Section 3 provides a simple model for self-reinforcing (positive or negative) housing bubbles and finds empirical evidence that supports the model implications. Section 4 concludes the paper.

[1] These variables capture the condition of the regional mortgage market and the demand and supply conditions of the regional housing market. According to Hwang and Quigley (2006) and Jud and Winkler (2002), real price appreciation in local housing markets is influenced by changes in interest rates, income, and employment. Glaeser et al. (2008) argue that we must incorporate housing supply in order to understand boom-bust housing cycles. For each state, the effective interest rate, the term to maturity, and the loan to value ratio are collected from the Monthly Interest Rate Survey conducted by the Federal Housing Finance Agency, personal income data are collected from the Bureau of Economic Analysis, unemployment data are obtained from the Bureau and Labor Statistics, and the housing permits data are from the Building Permits Survey conducted by the Census Bureau. All predictor variables are available at annual frequency since 1978 and we use the observation in the previous year to make sure that the information is publicly available at the time of making predictions. More details on the data are provided in Sections 2 and 3.

2. Large price movements in housing markets

We examine large house price movements in this section. In particular, we study large price run-ups during market upturns with potential subsequent crashes and large price declines during market downturns with potential subsequent rebounds. We make use of quarterly house price data of 50 U.S. states, plus the District of Columbia, and 403 metropolitan statistical areas and divisions (MSAs) over the period 1975:Q1 to 2017:Q4. All-transactions indexes (estimated using sales prices and appraisal data) of single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac are obtained from the Federal Housing Finance Agency (FHFA). The FHFA house price index is a weighted, repeat sales index and it measures the average price changes in repeat sales or refinancing on the same properties. This measure of house price is used extensively in the literature (see Adelino et al., 2013; Adelino et al., 2015; Lovenheim and Mumford, 2013 among many others). We seasonally adjust the house price indexes and then deflate them with the national-level consumer price index (all items less shelter) obtained from the U.S. Bureau of Labor Statistics.[2]

2.1. Price run-ups and crashes

We rely on a four-year return to identify price run-ups and a four-year price path afterward to classify crashes, implying that we only pick up run-up episodes and crashes for the period 1979:Q1 to 2013:Q4. We identify one price run-up episode when a region, either a state or a MSA, experiences a real housing return (percent change in real house prices) of 12% or more in the past year, in both raw and net-of-market terms, and a 20% or more raw return over the past four years.[3] This definition requires high returns at both one-year and four-year horizons, and it avoids picking up temporary recoveries during periods of poor performance.[4] Indeed, annual price run-ups of 12% or more are quite rare and we observe only 17 episodes across 51 state-level regions and 128 episodes across 403 MSAs in almost four decades of data. The definition also imposes restrictions on net-of-market returns, calculated as the difference between real returns in a particular regional housing market and the national housing returns, so that our results are not biased toward the most recent housing boom-bust cycle.[5]

For each run-up episode, we track the path of house prices in the next four years and define a crash as a 20% or more drop in real house prices beginning at any point after we have first identified the episode. Among the 17 run-up episodes at the state level, this definition identifies 6 episodes that crash in the subsequent four years and 11 without subsequent crashes. The states that were hardest hit by the most recent housing crisis are successfully picked up by our criterion (Nevada, Arizona, California, and Florida).[6] By the same definition, 64 out of the 128 run-up episodes at the MSA level have subsequent crashes while the other half do not.

We present the distribution of run-up episodes and crashes in Fig. 1. The horizontal axis represents the year in which we first identify a price run-up. We use vertical bars to denote the number of run-up episodes with shaded areas for those episodes that crash in the subsequent four years. The price run-ups tend to be concentrated during two particular periods, over the 1980–90 decade and around the year 2004. While only 5 out of the 17 run-up episodes at the state level are identified after 2000, most of the MSA-level run-ups occurred around 2004 and 2005. This inconsistency is due to the uneven distribution of MSAs across states in the data. For example, while a lot of states have only a few MSAs, California, Texas, and Florida have more than 20 each in our dataset. Both California and Florida have a lot of MSAs that experienced large price appreciation around 2004 and 2005.

Fig. 2 summarizes the average return for the price run-up episodes, either end in crashes or not. On average, state-level housing markets that experience a price run-up continue to go up over the next two years, by 13% during the first and another 2% during the second. After that, markets gradually go down by 27% over the following six years. A similar pattern can be detected in the MSA-level data as well. Upon the identification of price run-ups, markets continue to go up by 13% during the following year and another 2% during the second, and then they gradually go down by 35% over the

[2] We obtain a balanced panel of indexes at the state level except for two missing values, in 1976:Q1 for Vermont and in 1982:Q1 for West Virginia. We replace these missing values with the average of house prices in the previous and subsequent quarters. This extrapolation does not affect our results as price run-ups are not identified in either of these two states with missing observations. At the MSA level, however, available data start at different points in time. We discard all observations before any periods with two or more consecutive missing values and fill any periods with a single missing observation with the average house price in the previous and subsequent quarters.

[3] This definition focuses on a single specific aspect of price run-ups – rapidly rising real prices – as in Baker (2002). It does not involve the comparison of actual house prices with the value of houses as an investment calculated from fundamentals as in Smith and Smith (2006). For our purpose, we choose not to take into account the fundamental value of houses when defining price run-ups. The main advantage of focusing merely on the movement of house price itself is that one avoids choosing how to estimate the fundamental value. As Mayer (2011) points out, it is challenging to determine the reasonable expectations of changes in fundamentals such as population, income, interest rates, and rents.

[4] Among many overlapping one-year intervals in consecutive quarters, we choose the first instance of identifying a price run-up and do not allow a new run-up to be identified until a year later.

[5] With regard to the definition of price run-ups and crashes, we try to follow Greenwood et al. (2019) as closely as possible. That, of course, does not mean that we should use exactly the same horizons and thresholds as in Greenwood et al. (2019) because housing and stock markets are fundamentally different. We pick up the one-year and four-year horizons and 12% and 20% thresholds based on comparative statistics of housing and stock markets' cyclicalities. A detailed analysis can be found in the online Appendix.

[6] The 6 state-level run-up episodes that crash in the subsequent four years include Arizona (2005:Q2), California (2004:Q3), District of Columbia (1979:Q1), Florida (2005:Q3), Hawaii (1979:Q3), and Nevada (2004:Q2).

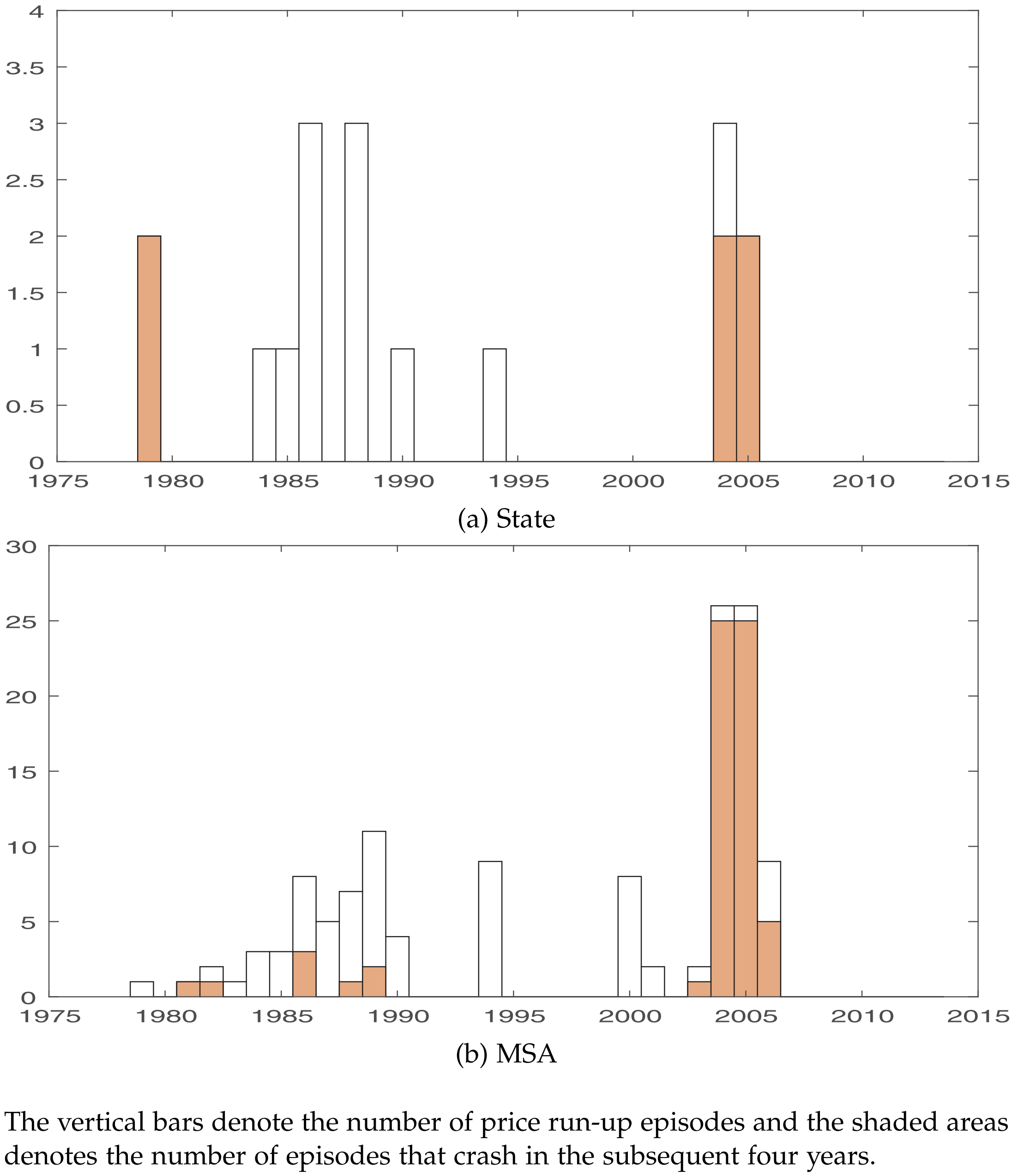
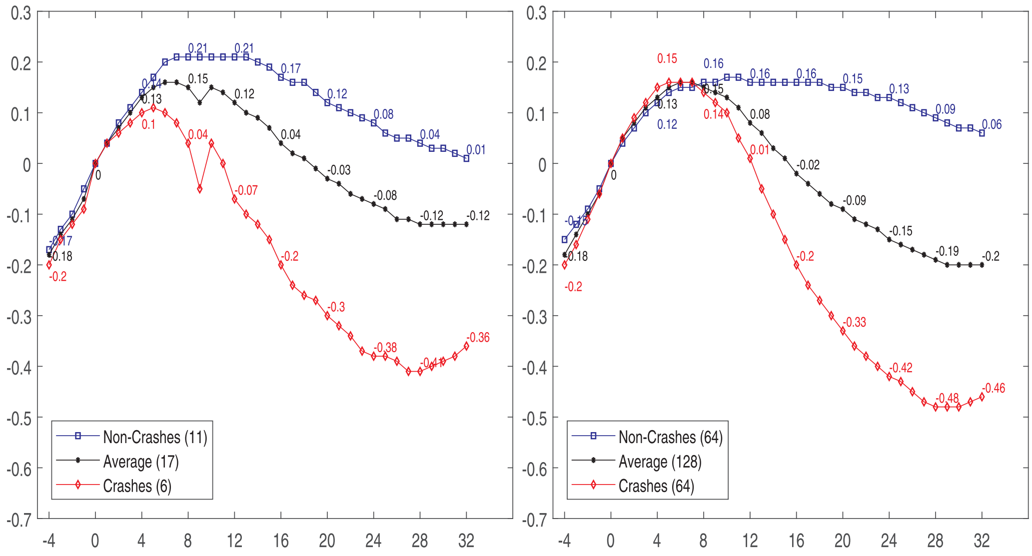


Fig. 1. Distribution of run-ups and crashes.

next six years. In other words, house price run-ups are persistent for up to two years and reverse over longer horizons. Significant momentum and mean reversion have been well documented in housing markets; see Case and Shiller (1989), Cutler et al. (1991) and Glaeser et al. (2014).

Not all run-up episodes are created equal. Some of them end in crashes and some others do not. Fig. 2 also separately plots the average return for each case. We do not observe much difference between crashing and non-crashing markets within the first year of identifying price run-ups. House prices start to drop in markets that will end in crashes right after the first year, whereas in markets that will not crash prices keep going up for another year. Eventually, prices fall in both



(a) State (b) MSA

On the horizontal axis, period zero denotes the quarter in which a price run-up is identified. The numbers along the curves denote the cumulative housing return, normalized to zero at the first identification of price run-ups. The numbers in the legends denote the count of run-up episodes.

Fig. 2. Returns following price run-ups.

types of markets, to a greater degree in crashing than non-crashing markets. There is no obvious difference between the state-level and MSA-level data.[7]

Two conclusions can be drawn from the data and be compared with those in stock markets: (1) Greenwood et al. (2019) find that a sharp stock price increase does not, on average, predict unusually low returns going forward, but it does not apply to housing markets. An average housing market experiences a loss of 27% at the state level and 35% at the MSA level in six years starting two years after the first identification of a run-up. Strong house price increases do predict strong declines. (2) Housing returns are more predictable compared to stock returns. Upon the identification of a price run-up, housing returns tend to be positive over the next year and negative after two years, no matter the market ends in a crash or not.

Now we show that the probability of a crash is strongly associated with the size of the price run-up. We fix the threshold on the four-year raw return at 20% and vary the annual return threshold, in both raw and net-of-market terms, from 4% to 20% using an increment of 4%. The top panel of Table 2 summarizes the probability of a crash as a function of the past annual price change. At the state level, the probability of a crash following a 4% annual price run-up is only 13%, but then rises rapidly to 35% at past annual run-up of 12%, and the probability increases further to 50% at past annual run-up of 20%. A similar pattern can also be identified in the MSA-level data. In particular, almost 80% of the episodes at 20% annual run-up experience a crash in the subsequent four years. This clearly suggests that the crash probability increases with the size of the price run-up, which is consistent with Greenwood et al. (2019)'s finding on stock markets where a sharper stock price increase predicts a substantially heightened probability of a crash.

Table 2 also presents the drawdown, defined as the largest decrease between any two time points within the subsequent four years of identifying a price run-up. In general, the mean or median magnitude of the drawdown increases with the size of the run-up. The average drawdown following a 4% annual price run-up is only 11% at the state level and 10% at the MSA level, but it increases to 21% and 24% at past annual run-up of 12% and further increases to 28% and 33% at past annual run-up of 20%.

In the bottom panel of Table 2, we list both the mean and the median of 1- to 4-year real housing returns after price run-ups under alternative annual return thresholds. Real housing returns at the state level are positive within two years after the identification of price run-ups at all thresholds. At higher cutoffs, e.g., 8% to 20%, cumulative returns start to fall since the third year while positive returns last longer at the low cutoff 4%. A similar pattern holds in the MSA-level data.

[7] In our benchmark analysis, we define a crash as a 20% or more drop in real house prices beginning at any point within four years of first identifying a price run-up. As a robustness check, we use two other cutoffs, 10% and 30%, to define crashes; see Figs. A1 and A2. Housing returns following price run-ups exhibit a similar pattern under alternative crash thresholds.

Table 2
Summary statistics of price run-ups and crashes.

	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of run-ups	60	37	17	9	2	324	221	128	70	19
No. of regions with run-ups	31	25	13	8	2	199	153	104	62	19
No. of crashes	8	12	6	4	1	51	73	64	42	15
No. of regions with crashes	8	12	6	4	1	49	71	61	41	15
Probability of crashes	13%	32%	35%	44%	50%	16%	33%	50%	60%	79%
Drawdown after run-ups										
Mean	−11%	−15%	−21%	−26%	−28%	−10%	−16%	−24%	−30%	−33%
Median	−7%	−9%	−15%	−13%	−28%	−8%	−13%	−21%	−23%	−27%
(Standard deviation)	(0.15)	(0.17)	(0.22)	(0.27)	(0.21)	(0.10)	(0.16)	(0.20)	(0.22)	(0.23)
1-year return after run-ups										
Mean	7%	10%	13%	13%	14%	9%	13%	13%	11%	7%
Median	8%	10%	15%	15%	14%	10%	13%	15%	12%	8%
(Standard deviation)	(0.09)	(0.11)	(0.07)	(0.06)	(0.03)	(0.08)	(0.08)	(0.09)	(0.08)	(0.12)
2-year return after run-ups										
Mean	12%	15%	15%	13%	16%	15%	18%	15%	9%	1%
Median	14%	20%	19%	16%	16%	16%	19%	15%	10%	1%
(Standard deviation)	(0.18)	(0.19)	(0.17)	(0.17)	(0.00)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)
3-year return after run-ups										
Mean	13%	14%	12%	10%	10%	17%	16%	8%	0%	−10%
Median	15%	14%	14%	8%	10%	14%	14%	9%	0%	−5%
(Standard deviation)	(0.22)	(0.22)	(0.21)	(0.18)	(0.04)	(0.18)	(0.18)	(0.19)	(0.21)	(0.21)
4-year return after run-ups										
Mean	12%	9%	4%	1%	−11%	15%	8%	−2%	−13%	−21%
Median	13%	10%	4%	8%	−11%	11%	8%	−2%	−13%	−17%
(Standard deviation)	(0.23)	(0.25)	(0.24)	(0.21)	(0.21)	(0.22)	(0.24)	(0.26)	(0.27)	(0.25)

Our main conclusion that house price run-ups exhibit persistence in the short run and reversal in the medium run holds across alternative choices of the run-up threshold.

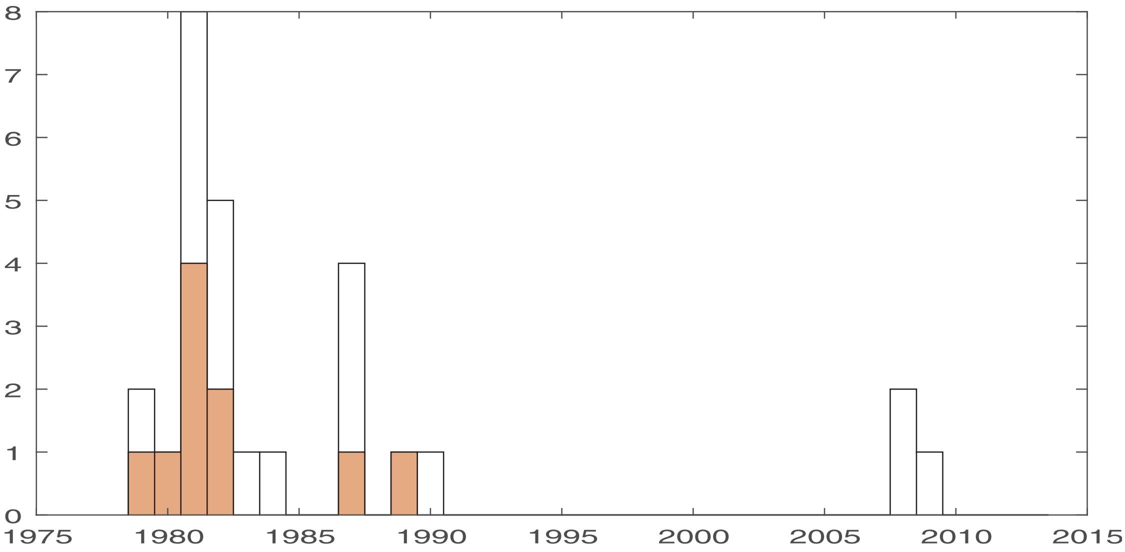
As a robustness check, we exclude the recent housing boom-bust cycle from the sample and present the summary statistics of price run-up and crashes over the period 1975:Q1 to 2000:Q4 in Table A1 in the Appendix A. Our findings, (1) the probability of a crash increases with the size of the price run-up and (2) price run-ups exhibit persistence before reversal, keep to hold in the subsample of both state-level and MSA-level data. We also use two other cutoffs, 10% and 30%, to define crashes and find that our findings are robust to alternative crash definitions; see Table A2.

2.2. Price declines and rebounds

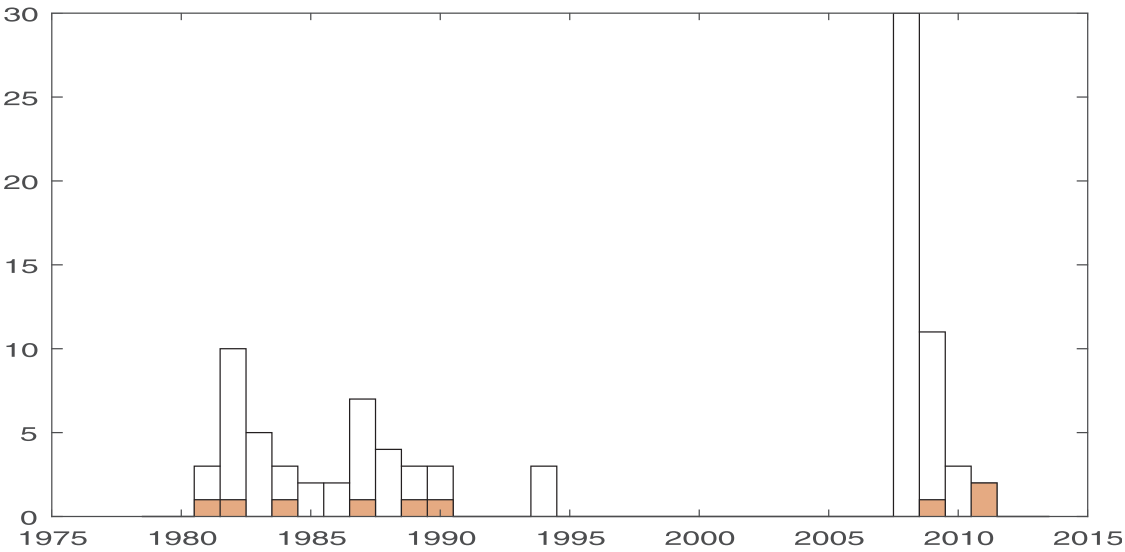
The previous subsection focuses on large price movements on the way up and potential subsequent crashes. In this subsection we examine large movements in house prices on the way down, i.e., declines, and potential rebounds following declines. The definition of a decline episode is analogous to that of a run-up episode. We define a price decline episode as a real housing return of negative 12% or worse in the past year, in both raw and net-of-market terms, and a negative 20% or worse raw return over the past four years. This definition gives 27 decline episodes at the state level and 91 at the MSA level over the 1979:Q1-2013:Q4 period. These declines occurred mostly in the 1980s and during the most recent recession. We then track house price changes in the next four years for each of these episodes and define a rebound as a 20% or more price increase at any point within four years of first identifying the price decline. Given this definition, 10 of the 27 state-level episodes and 9 of the 91 MSA-level episodes rebound in the subsequent four years. The distribution of price declines and rebounds is presented in Fig. 3. None of the 3 decline episodes at the state level identified during the recent crisis (Arizona, California, and Nevada) rebound in the next four years. Most of the MSA-level decline episodes do not rebound either.

Fig. 4 summarizes the average return following price declines, and results from the state-level and MSA-level data are broadly similar. The immediate upturn following price declines at the state level is mostly driven by two local markets of Hawaii and Vermont. The MSA-level data have more observations and are less affected by a few outliers. On average housing markets that have experienced a price decline continue to go down over the next three years by a total of 16% and then gradually go up by 24% during the following five years. In other words, price declines exhibit persistence for up to three years and reversal over longer horizons. Markets that rebound over the subsequent four years of identifying the decline remain stable during the first two years and then start to go up over the next four years. In contrast, non-rebounding markets do not start to recover until three years after the decline.[8]

[8] In our benchmark analysis, we define a rebound as a 20% or more increase in real house prices beginning at any point within four years of first identifying a price decline. As a robustness check, we use two other cutoffs, 10% and 30%, to define rebounds; see Figs. A3 and A4. Housing returns following price declines exhibit a similar pattern under alternative rebound thresholds.



(a) State

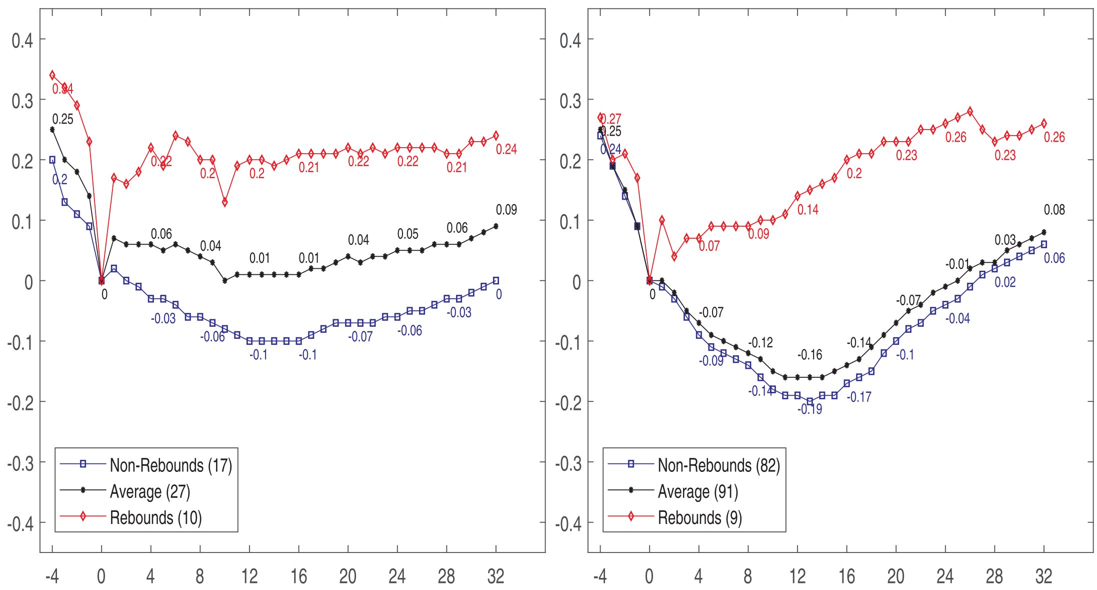


(b) MSA

The vertical bars denote the number of price decline episodes and the shaded areas denotes the number of episodes that rebound in the subsequent four years.

Fig. 3. Distribution of declines and rebounds.

We fix the threshold on the four-year raw return at negative 20% and vary the annual return threshold, in both raw and net-of-market terms, from negative 4% to 20%. The top panel of Table 3 summarizes the probability of a rebound as a function of the past negative price change. At the state level, the probability of a rebound following a 4% annualized price decline is only 24%, but it rises to 37% for a price decline of 12% and increases further to 67% for a price decline of 20%. The calculations suggest that the probability of a rebound increases with the size of the price decline at the state level. The MSA-level data, however, exhibit a different pattern. As we vary the threshold, the probability of a rebound following a price decline does not change much. This inconsistency between the two sources of data might be due to the uneven distribution of MSAs across states in the data. A large fraction of MSAs in California and Florida experienced large declines of 20% and more in 2008 and none of them rebounded in the subsequent four years. This causes a small probability of rebound in the MSA-level data. Since housing is an asset whose prime differentiator is location, we would like to draw conclusions based



(a) State (b) MSA

On the horizontal axis, period zero denotes the quarter in which a price decline is identified. The numbers along the curves denote the cumulative housing return, normalized to zero at the first identification of price declines. The numbers in the legends denote the count of decline episodes.

Fig. 4. Returns following price run-ups.

Table 3
Summary statistics of price declines and rebounds.

	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of declines	55	36	27	18	12	308	167	91	53	36
No. of regions with declines	34	26	21	15	9	206	130	80	50	34
No. of rebounds	13	11	10	9	8	28	13	9	6	3
No. of regions with rebounds	9	8	7	7	6	26	12	8	5	2
Probability of rebounds	24%	31%	37%	50%	67%	9%	8%	10%	11%	8%
Drawup after declines										
Mean	15%	18%	22%	25%	33%	9%	9%	9%	9%	9%
Median	10%	12%	13%	18%	28%	7%	7%	7%	5%	5%
(Standard deviation)	(0.17)	(0.20)	(0.21)	(0.22)	(0.23)	(0.09)	(0.09)	(0.10)	(0.12)	(0.13)
1-year return after declines										
Mean	1%	4%	6%	13%	20%	−5%	−6%	−7%	−8%	−8%
Median	−3%	2%	4%	10%	17%	−5%	−6%	−8%	−11%	−12%
(Standard deviation)	(0.15)	(0.17)	(0.19)	(0.21)	(0.21)	(0.08)	(0.09)	(0.11)	(0.13)	(0.14)
2-year return after declines										
Mean	−1%	1%	4%	11%	18%	−8%	−10%	−12%	−13%	−13%
Median	−2%	0%	2%	3%	13%	−7%	−11%	−14%	−17%	−17%
(Standard deviation)	(0.18)	(0.22)	(0.24)	(0.28)	(0.31)	(0.13)	(0.14)	(0.16)	(0.17)	(0.19)
3-year return after declines										
Mean	−2%	0%	1%	8%	16%	−9%	−12%	−16%	−18%	−19%
Median	−2%	−1%	−1%	3%	12%	−7%	−14%	−17%	−23%	−25%
(Standard deviation)	(0.19)	(0.23)	(0.26)	(0.29)	(0.33)	(0.17)	(0.18)	(0.20)	(0.22)	(0.23)
4-year return after declines										
Mean	0%	1%	1%	10%	18%	−6%	−10%	−14%	−16%	−17%
Median	−2%	0%	0%	5%	15%	−4%	−10%	−16%	−21%	−23%
(Standard deviation)	(0.21)	(0.24)	(0.27)	(0.31)	(0.34)	(0.18)	(0.20)	(0.22)	(0.23)	(0.25)

more on the MSA-level results. Unlike the sharper increase during market upturns that predicts a higher probability of a crash, a shaper decline during market downturns does not necessarily predict a higher probability of a rebound.

Table 3 also shows the drawup, the largest increase between any two time points within the subsequent four years, of price declines. The mean or median magnitude of the drawup increases with the size of the decline in the state-level data but remains relatively stable in the MSA-level data. The bottom panel of the table shows the mean and the median of 1- to 4-year real housing returns after price declines. The MSA-level summary statistics show that housing markets keep going down for another three years before starting to recover under all selected annual return thresholds. The robustness analysis on the subsample of 1975:Q1-2000:Q4 presented in Table A3 in the Appendix A gives similar results. In short, house price declines exhibit persistence in the short run and reversal in the medium run. We also use two other cutoffs, 10% and 30% to define rebounds and find that the probability of a rebound does not necessarily increase with the size of the decline at alternative rebound definitions; see Table A4.

2.3. How are housing markets different from stock markets?

Both Greenwood et al. (2019) and Goetzmann and Kim (2018) find that very large (positive and negative) changes in stock prices exhibit reversal right away but price changes of lesser magnitude exhibit persistence prior to reversal. Our investigation of housing markets shows that price changes of various magnitudes exhibit persistence before reversal during both upturns and downturns. Even at 20% annual run-up where only two episodes are identified in the state-level data, as Table 2 shows, house prices keep increasing for two years before reversion. Our finding is consistent with the observation of Reinhart and Rogoff (2009) that equity prices are far less inertial than house prices. Why are house price changes more persistent?

Houses and stocks are two different assets by nature. As mentioned in Malpezzi (1999) and Glaeser and Nathanson (2017), there are three major differences between the two asset markets. First, shortselling is almost impossible in the housing market, potentially allowing overvaluation to persist longer than the stock market. Second, buying large amounts of stocks is easier than a large number of houses or apartments. Third, unlike a share of stock, there is no single, posted price in housing markets for a particular house. Due to this heterogeneity, transactions in the housing market are costlier and time consuming. For empirical patterns, Glaeser and Nathanson (2017) also point out that house prices tend to have more positive short-term serial correlation and mean reversion in the long run.

A major difference between housing and stock markets lies in market frictions. Three frictions in housing markets, as reviewed by Mayer (2011), might explain why house price changes exhibit more persistence. First, borrowing constraints are tied to housing values (see Iacoviello, 2005). As prices rise, capital gains relax borrowing constraints and lead to expansion in demand and price momentum on the way up. As prices decline, borrowing constraints become tighter and further shrink the housing demand. Homeowners with “underwater” mortgages find it impossible to purchase a new home because they would not have enough money to make a reasonable down payment (see Stein, 1995). Second, the procyclical behavior of housing sales and prices motivates the application of search models in the labor market literature to housing; see Wheaton (1990). Due to the existence of imperfect information, search is an important feature of housing markets. During market upturns, there are more buyers and sellers that lead to better matches and higher prices with a given search cost. During market downturns, however, matches are much harder to take place and lower mobility rates exert downward pressure on house prices. Third, it is well documented in the literature that house prices exhibit excessive volatility in markets with supply constraints. Glaeser et al. (2008) find that supply inelasticity is a crucial determinant of the duration of a housing bubble. Housing supply regulations limit the ability of housing supply to adjust to demand shocks and lead prices to spike in a boom and fall faster in a bust.

In contrast, the stock market does not have the above frictions, or at least they are weaker. The presence of such frictions is probably why the housing and stock markets are so different, but incorporating all these features of the housing market is clearly beyond the scope of this paper. Instead, we show in the next section that a simple model with some unique features of the housing market is enough to make sense of our empirical findings.

3. Predicting returns following large price movements

We show in the introduction that information on mortgage loans and local demand and supply factors, in general, do not predict housing returns well. Are returns following large price movements more predictable? In order to explore the properties of large price movements, we first develop a model of self-reinforcing housing bubbles by introducing a simple form of asymmetric search costs into the theoretical framework of Glaeser et al. (2008). We then derive implications from the model that will be tested later in this section.

3.1. A simple model of housing bubbles

We mostly follow the notations in Glaeser et al. (2008). Consider a region (state or MSA) in which the house price is jointly determined by demand and supply. Demand comes from new homebuyers, whose willingness to pay depends on the utility gains from living in the region, expected maintenance cost, and expected house price appreciation. Supply comes from old homes sold by existing homeowners and new homes produced by developers. We assume that, to keep old homes physically identical to new homes, homeowners always maintain their homes.

The stock of houses at time t is denoted $H(t)$, and it depreciates at a constant rate $\delta > 0$. The production of new homes is the difference between housing construction $I(t)$ and the replacement of existing homes $\delta H(t)$. The supply of homes at time t combines the new production, $I(t) - \delta H(t)$, and the existing homes being put on the market for sale by homeowners. Each current homeowner receives a Poisson-distributed shock with probability λ in each period that forces the homeowner to sell, leave the region, and receive zero utility for the rest of the homeowner's life. Therefore, at time t, housing supply is defined as $S(t) = \lambda H(t) + I(t) - \delta H(t)$. The marginal cost of housing construction is assumed to be $c_0 + c_1 I(t)$ where $c_1 > 0$, i.e., the cost of production rises linearly with the size of construction.

A fixed number of buyers gain utility from living in the region, and the utility of buyer i, $u(i)$, is drawn from a uniform distribution with density $1/\nu_1$ on the interval $[\underline{u}, \nu_0]$ at all points of time. Let $u^*(t)$ denote the utility of the marginal buyer, then potential buyers will decide to move into the region as long as their utility gain is higher than $u^*(t)$ and the number of buyers equals $(\nu_0 - u^*(t))/\nu_1$. Therefore, at time t, the housing demand is $D(t) = (\nu_0 - u^*(t))/\nu_1$.

Let $P(t)$ denote the house price at time t and r be the interest rate in continuous time. The expected utility flow from a potential buyer i at time t who receives utility $u(i)$ from living in the region is written as

$$\frac{u(i)}{r+\lambda} + E_t\left(\int_{x=t}^{\infty} e^{-(r+\lambda)(x-t)}(\lambda - \delta)P(x)dx\right) - P(t),$$

where $E_t(\cdot)$ denotes expectations as of time t and $\delta P(x)$ captures the maintenance cost.[9] Potential buyers move into the region until this expected utility flow becomes zero. As long as there is construction, price must equal marginal cost of construction in equilibrium. We then have the following equilibrium conditions:

$$\text{Demand: } \frac{\nu_0 - \nu_1 D(t)}{r+\lambda} + E_t\left(\int_{x=t}^{\infty} e^{-(r+\lambda)(x-t)}(\lambda - \delta)P(x)dx\right) = P(t), \tag{1}$$

$$\text{Supply: } P(t) = c_0 + c_1(S(t) - \lambda H(t)), \tag{2}$$

where $D(t) = S(t)$.

We normalize the start date of the bubble to be zero and assume that the region has reached its long-run stable level of population as of time zero. So we have

$$I(0) = \frac{\delta[\nu_0 - (r+\delta)c_0]}{\delta(r+\delta)c_1 + \nu_1\lambda}, \tag{3}$$

$$P(0) = c_0 + c_1 I(0). \tag{4}$$

Individuals update their beliefs only at discrete intervals. We let ϵ denote the expected future growth rate of house prices at time zero, where $\epsilon > 0$ for a positive bubble and $\epsilon < 0$ for a negative bubble. During a period when beliefs about the future are held constant, the expected house price $P(x) = P(t) + \epsilon \cdot (x - t)$. Then the demand side of the model becomes

$$P(t) = \frac{\nu_0 - \nu_1 D(t)}{r+\lambda} + E_t\left(\int_{x=t}^{\infty} e^{-(r+\lambda)(x-t)}(\lambda - \delta)[P(t) + \epsilon \cdot (x-t)]dx\right), \tag{5}$$

throughout a positive bubble, i.e., $\epsilon > 0$. During a negative bubble, i.e., $\epsilon < 0$, individuals expect selling the house to be more difficult in the future. We change the demand side of the market by adding a positive ϕ that captures the additional search cost individuals expect to incur (or the loss individuals expect to suffer) in order to sell the house during a market downturn:

$$P(t) = \frac{\nu_0 - \nu_1 D(t)}{r+\lambda} + E_t\left(\int_{x=t}^{\infty} e^{-(r+\lambda)(x-t)}(\lambda - \delta)[P(t) + \epsilon \cdot (1+\phi) \cdot (x-t)]dx\right). \tag{6}$$

This equation with $\phi = 0$ also captures the demand side of the market that is on the rise. The inclusion of a positive ϕ during market downturns is motivated by the fact that houses sell quickly in a boom but tend to sit on the market for long periods of time in a bust; see Genesove and Mayer (2001) for the empirical evidence. As in Piazzesi and Schneider (2009), the buyer knows that once he has decided to move out he will not be able to sell it immediately but will have to incur search costs. As with most search models, search costs tend to be higher during market downturns with lower mobility rates. In Eq. (6) the search cost is captured by the magnitude of $\epsilon \cdot \phi$, which is zero during market upturns but positive during market downturns.

[9] The interest rate in this model is simply the discount rate that potential homebuyers use to discount future utilities and capital gains. The interest rate can be modeled as part of the borrowing constraint on households, but that will require a more complex model which is outside the scope of this paper. Having the interest rate as a discount factor already implies that the interest rate is the cost of buying. Given certain future utilities and capital gains, a higher cost of buying makes buying a house less attractive, and it will shrink the housing demand and affect the fate of positive bubbles.

Including the supply side of the market implies

$$I(1)=\frac{\delta[\nu_0-(r+\delta)c_0]}{\delta(r+\delta)c_1+\nu_1\lambda}+\frac{(1+\delta)(\lambda-\delta)(1+\phi)\epsilon}{(1+\delta)[(r+\delta)c_1+\nu_1](r+\lambda)+(\lambda-\delta)\nu_1(r+\lambda)}, \tag{7}$$

$$P(1)=c_0+c_1I(1), \tag{8}$$

where $\phi=0$ and $\epsilon>0$ during market upturns, $\phi>0$ and $\epsilon<0$ during market downturns.

The price change between time zero and time one is

$$\Delta P=\frac{c_1(1+\delta)(\lambda-\delta)(1+\phi)\epsilon}{(1+\delta)[(r+\delta)c_1+\nu_1](r+\lambda)+(\lambda-\delta)\nu_1(r+\lambda)}. \tag{9}$$

The (positive or negative) bubble will persist at time one if and only if the price change in Eq. (9) is greater than ϵ in magnitude. The absolute value of ΔP is a monotonically increasing function of c_1 as long as $\lambda>\delta$ and equals zero when $c_1=0$. As c_1 grows arbitrarily large, ΔP approaches $\frac{(\lambda-\delta)(1+\phi)\epsilon}{(r+\delta)(r+\lambda)}$.

Proposition 1. *If $\frac{(\lambda-\delta)(1+\phi)}{(r+\delta)(r+\lambda)}<1$ or $\lambda<\lambda^*\equiv\frac{\delta(1+\phi)+(r+\delta)r}{1+\phi-r-\delta}$, then the bubble can never persist at time one. If $\lambda>\lambda^*$, then the bubble can persist at time one if and only if c_1 is larger than $c_1^*\equiv\frac{(r+\lambda)(1+\lambda)\nu_1}{(1+\delta)[(\lambda-\delta)(1+\phi)-(r+\delta)(r+\lambda)]}$.*

In the above proposition, λ^* and c_1^* are the minimum values of λ and c_1 for the bubble to persist. Note that λ denotes the probability of receiving a shock that forces homeowners to sell in each period and it positively affects expected capital gains during market upturns and losses during market downturns. The parameter c_1 affects the marginal cost of housing construction in a positive manner and a higher value indicates a less elastic housing supply. The bubble persisting condition, $\lambda>\lambda^*$ and $c_1>c_1^*$, means that, in order for the positive (negative) bubble to persist, capital gains (losses) have to be big enough and the housing supply has to be relatively inelastic. When both δ and ϕ equal zero, i.e., there is no housing depreciation or search costs, λ^* simplifies to $\frac{r^2}{1-r}$, the threshold in the original model of Glaeser et al. (2008). The derivatives of λ^* and c_1^* with respect to the interest rate r are given by

$$\frac{d\lambda^*}{dr}=\frac{(2r+\delta)(1+\phi-r-\delta)+\delta(1+\phi)+(r+\delta)r}{(1+\phi-r-\delta)^2}>0, \tag{10}$$

$$\frac{dc_1^*}{dr}=\frac{(1+\lambda)\nu_1}{1+\delta}\frac{(\lambda-\delta)(1+\phi)+(r+\lambda)^2}{[(\lambda-\delta)(1+\phi)-(r+\delta)(r+\lambda)]^2}>0, \tag{11}$$

which suggests that, for given values of λ and c_1, the bubble is more likely to persist at time one when the interest rate r decreases.

Taking the derivatives of $d\lambda^*/dr$ and dc_1^*/dr with respect to ϕ gives

$$\frac{d(d\lambda^*/dr)}{d\phi}=-\frac{r(1+\phi-r-\delta)+\delta(1+\phi)+(r+\delta)r}{(1+\phi-r-\delta)^4}<0, \tag{12}$$

$$\frac{d(dc_1^*/dr)}{d\phi}=-\frac{(1+\lambda)\nu_1}{1+\delta}\frac{(\lambda-\delta)[(\lambda-\delta)(1+\phi)+(r+\delta)(r+\lambda)+2(r+\lambda)^2]}{[(\lambda-\delta)(1+\phi)-(r+\delta)(r+\lambda)]^3}<0, \tag{13}$$

which indicates that a decrease in the interest rate r results in a smaller decrease in λ^* and c_1^* during market downturns when $\phi>0$ than market upturns when $\phi=0$.

Testable implication 1. A decrease in the interest rate r results in a decrease in the thresholds λ^* and c_1^* and makes it easier for a bubble to persist for given values of λ and c_1. The impact is larger during market upturns when $\phi=0$ than market downturns when $\phi>0$.

These two results imply that interest rate changes predict housing returns following large price movements in an asymmetric way. When the market is going up, a decrease in the interest rate results in a higher probability for a positive bubble to persist. In other words, housing returns following a run-up tend to be higher when the interest rate decreases. When the market is going down, a decrease in the interest rate results in a higher probability for a negative bubble to persist and lower housing returns following a given decline, but the relationship is weaker.

The persistence of the bubble is also affected by two other parameters in the model, ν_1 and c_1, even though these parameters do not affect the threshold λ^*.

Testable implication 2. A decrease in ν_1 results in a decrease in the threshold c_1^*. Conditional on $\lambda>\lambda^*$, the bubble is more likely to persist when ν_1 decreases or when c_1 increases.

Table 4
Predicting housing returns following large price movements.

	Run-up episodes (State)				Decline episodes (State)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0339*	−0.0842***	−0.1394**	−0.1415*	0.0445*	0.0375	0.0400	0.0431
	(0.0116)	(0.0111)	(0.0311)	(0.0437)	(0.0144)	(0.0213)	(0.0202)	(0.0246)
ΔRPI	1.1025	3.1677*	4.5798*	5.8669**	−0.1661	−0.0935	−0.4649	−0.5946
	(0.8692)	(1.2964)	(1.4846)	(1.4837)	(0.6305)	(0.6821)	(0.6714)	(0.7180)
ΔUR	−0.0688	−0.0209	0.1137	0.1785	−0.0131	−0.0534	−0.0566	−0.0604
	(0.0487)	(0.0861)	(0.1680)	(0.1841)	(0.0275)	(0.0329)	(0.0351)	(0.0382)
Permits	−0.0043	−0.0304	−0.0595	−0.0826*	−0.0335	−0.0333	−0.0507	−0.0468
	(0.0153)	(0.0183)	(0.0340)	(0.0324)	(0.0272)	(0.0355)	(0.0422)	(0.0418)
Current	1.5735	1.4020	−0.5710	−2.9958	−0.7309***	−0.8712***	−0.8391***	−0.8824***
Return	(0.6669)	(0.9338)	(1.4595)	(1.7300)	(0.0809)	(0.0858)	(0.1342)	(0.1653)
N	15	15	15	15	24	24	24	24
adj. R^2	0.259	0.318	0.345	0.548	0.662	0.619	0.578	0.566
par. R^2	0.250	0.451	0.392	0.269	0.094	0.043	0.055	0.062
	Run-up episodes (MSA)				Decline episodes (MSA)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0479*	−0.0822**	−0.0850*	−0.0401	0.0275	0.0309	0.0289	0.0257
	(0.0175)	(0.0261)	(0.0356)	(0.0400)	(0.0172)	(0.0250)	(0.0327)	(0.0366)
ΔRPI	−0.7697	−1.7814	−3.5163	−1.6917	0.1585	0.5430	0.5256	−0.4643
	(0.5241)	(0.9412)	(1.7655)	(2.4304)	(0.5524)	(1.0415)	(1.2816)	(1.4026)
ΔUR	−0.0433*	−0.0444	−0.0461	−0.0676	−0.0311*	−0.0409*	−0.0365	−0.0358
	(0.0186)	(0.0386)	(0.0441)	(0.0444)	(0.0105)	(0.0173)	(0.0228)	(0.0239)
Permits	0.0176	0.0052	−0.0239	−0.0564*	−0.0224	−0.0398	−0.0700*	−0.0755*
	(0.0094)	(0.0159)	(0.0190)	(0.0207)	(0.0175)	(0.0238)	(0.0297)	(0.0320)
Current	0.5969*	0.3073	−1.4760*	−3.9240***	0.0848	−0.0074	0.2011	0.1982
Return	(0.2055)	(0.3545)	(0.6021)	(0.8099)	(0.3354)	(0.4236)	(0.4836)	(0.4935)
N	127	127	127	127	91	91	91	91
adj. R^2	0.377	0.275	0.294	0.392	0.267	0.241	0.289	0.277
par. R^2	0.203	0.258	0.189	0.022	0.049	0.028	0.016	0.016

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Constants are not reported. Standard errors in parentheses are clustered by year. The partial R^2 measures the proportion of variance in future housing returns not associated with any other predictors that is explained by changes in the effective interest rate.

Recall that housing demand is $D(t) = (\nu_0 - u^*(t))/\nu_1$ and the marginal cost of housing construction is $c_0 + c_1 I(t)$. A decrease in ν_1 can be interpreted as a positive housing demand shock, e.g., increases in personal income or decreases in unemployment rate. An increase in c_1 captures a negative supply shock that reduces housing production. The model implies that housing demand and supply shocks predict returns following large price movements, but they are less reliable predictors compared to interest rate changes as they only affect the persistence of the bubble through their impact on c_1^* given that $\lambda > \lambda^*$, while interest rate changes affect both λ^* and c_1^*.

3.2. Predicting housing returns

To test the above two implications, we now present cross-sectional forecasting regressions of future housing market returns on four variables that are observed when an episode is identified: changes in the effective interest rate (EIR) of conventional single-family mortgages, changes in real personal income (RPI), changes in unemployment rate (UR), and the number of new housing units authorized by building permits (in log). These variables capture the condition of the regional mortgage market and the demand and supply conditions of the regional housing market. For each state, effective interest rates are collected from the Monthly Interest Rate Survey conducted by the Federal Housing Finance Agency; personal income data are collected from the Bureau of Economic Analysis; unemployment data are obtained from the Bureau and Labor Statistics; and the housing permits data are from the Building Permits Survey conducted by the Census Bureau. All predictor variables are available at annual frequency since 1978 and we use the observation in the year prior to the identification of an episode to make sure that the information is publicly available at time zero. We have to emphasize that these data are only available at the state level. As a result, when predicting future housing returns in a MSA, we use its state-level characteristics as predictor variables. We can think of the predictor variables for the MSA-level regressions as measured with errors, and it is reasonable to assume that the coefficients are biased towards zero. Due to the persistence in house prices, we also control for the current annual return, i.e., the size of the price run-up.

Table 4 shows the results. In the top panel, we regress 1- to 4-year housing returns against the predictors and the current return using two samples, which include all run-up episodes and all decline episodes, respectively. It is worth noting that these are not panel but cross-sectional regressions and each observation denotes a run-up or decline episode. The table reports the parameter estimates, standard error estimates clustered by year, the number of observations, the adjusted R^2, and the partial R^2 due to changes in the effective interest rate of conventional single-family mortgages. Changes in the effective interest rate consistently predict housing returns at all selected horizons following run-up episodes. As expected, larger decreases in mortgage rate predict a higher probability for the positive bubble to persist and thus higher housing returns in the future. The partial R^2 suggests that interest rate changes explain 40% or more of the variation in 2-year and 3-year housing returns and about 25% of the variation in 1-year and 4-year housing returns after price run-ups have been identified. The same predictor becomes much less significant in the prediction of future housing returns following decline episodes. The partial R^2 also drops into the 4% to 9% range. Compared to interest rate changes, housing demand and supply shocks (i.e., ΔRPI, ΔUR, and housing permits) have much weaker predictive power. The bottom panel shows similar results at the MSA level. Changes in the effective interest rate significantly predict housing returns following price run-ups but not following price declines.

To check if the results are sensitive to the 12% criterion for price run-ups and declines, we consider two other cutoffs, 8% and 16%, and report the prediction regression results in Tables A5 and A6 in the Appendix A. We also report the prediction regression results using a subsample over the 1975:Q1-2000:Q4 period in Table A7. Our results are robust to alternative thresholds of price movements and the subsample that excludes the recent housing boom-bust cycle.

3.3. Housing market asymmetry

We find statistically and economically important predictability for large fluctuations in housing markets. After large price run-ups, a large fraction of the variation in future price changes is explained by interest rate changes. Housing returns following large price declines, however, are much less predictable. While the asymmetry is consistent with the implications of our model, we would like to mention other possible explanations in this section.

Feedback models and obstacles to "smart money" may be able to explain the asymmetry. For price run-ups, the feedback theory states that "when speculative prices go up, creating successes for some investors, this may attract public attention, promote word-of-mouth enthusiasm, and heighten expectations for further price increases" (Shiller, 2003).[10] Following the logic of De Long et al. (1990b) and more recently Barberis et al. (2018) and Glaeser and Nathanson (2017), when the housing market is on its way up, trend-following investors become optimistic and expect the market to keep going up in the future. The easing of credit availability, as captured by a decrease in the interest rate, further increases investment demand and leads to more positive price changes.

The efficient markets hypothesis (see Fama, 1970; Fama, 1991) implies that "smart money" sells when irrational optimists buy a financial asset and buys when irrational pessimists sell a financial asset, thereby eliminating the effect of the irrational traders on the market price. Based on the transaction data provided by Fidelity Investments, Goetzmann and Massa (2002) provide some direct evidence on the existence of both classes of investors: trend-following investors and the "smart money" that moves in the opposite direction. However, in the housing market, there exists an important obstacle to "smart money"'s offsetting the effects of irrational investors: the inelastic demand for shelter services.[11] According to the U.S. Census Bureau, about two-thirds of housing units are occupied by the unit's owner.[12] This reflects the fact that most homeowners own only one unit of housing, which restrains the size of the "smart money" in the housing market. Due to this relatively small role played by "smart money", predictability can persist in the housing market.

Shiller (2005) argues that the feedback theory may apply to price declines in addition to run-ups. Initial price declines may discourage investors from investing and encourage them to short the financial asset, causing further declines. When the housing market is on its way down, a significant fraction of homeowners might get trapped in "underwater" mortgages and it generates a "lock-in" effect due to loss aversion (Donovan and Senar, 2012; Engelhardt, 2003). More importantly, unlike stocks, it is intrinsically difficult to short sell in the housing market.

3.4. Housing market profitability

According to the findings above, large investors may time the housing market.[13] Hypothetically, investors may enter the market at time zero once a price run-up is observed and hold their housing stocks for a short period for the subsequent positive returns, due to the fact that house prices tend to keep going up for a short while no matter the market ends in a crash or not. It is, however, difficult to implement in practice because we have not accounted for a significant amount of transaction costs, maintenance costs, and taxes in housing markets. As a result, our analysis in this section is not meant to

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[10] There are a large number of models of feedback trading in the behavioral finance literature, for example see Shiller (1984), De Long et al. (1990a), Kirman (1993) and Campbell and Kyle (1993).

[11] We are not claiming that housing demand is perfectly inelastic, especially at state and MSA levels. Households can choose to migrate to other states or cities. In fact, house price differentials are important determinants of households' relocations; see Gabriel et al. (1992). However, many studies at the metropolitan level suggest that the price elasticity of housing demand is relatively low; see Polinsky (1977) and Tiwari and Parikh (1997).

[12] Statistics show that the homeownership rates vary between 63% and 70% and the homeowner vacancy rates vary between 1% and 3% over the period of 1996 to 2017.

[13] The returns in our discussion are for a portfolio of housing assets across a number of regions, which is not relevant for a typical investor who only owns one house in one region.

Table 5
Sharpe ratio of the portfolio conditional on price run-ups.

	Rental income	Transaction cost	Holding period			
			1 year	2 years	3 years	4 years
State	0%	0%	1.7497	0.6106	0.1898	−0.0551
	3%	9%	0.8298	0.4585	0.1898	0.0075
MSA	0%	0%	1.2863	0.5790	0.1105	−0.1191
	3%	9%	0.6531	0.4381	0.1105	−0.0661

Table 6
Sharpe ratio of the portfolio conditional on price run-ups with certain criteria.

	Rental income	Transaction cost	Selection criterion	Holding period			
				1 year	2 years	3 years	4 years
State	0%	0%	None (17)	1.7497	0.6106	0.1898	−0.0551
			ΔEIR < 0% (12)	2.4055	1.2432	0.5637	0.0891
			ΔEIR < −0.5% (10)	2.1925	1.0865	0.4791	0.0314
			ΔEIR < −1.0% (4)	5.6343	1.6595	0.6858	0.1923
	3%	9%	None (17)	0.8298	0.4585	0.1898	0.0075
			ΔEIR < 0% (12)	1.3328	1.0394	0.5637	0.1529
			ΔEIR < −0.5% (10)	1.2101	0.8962	0.4791	0.0926
			ΔEIR < −1.0% (4)	3.1626	1.4200	0.6858	0.2583
MSA	0%	0%	None (128)	1.2863	0.5790	0.1105	−0.1191
			ΔEIR < 0% (83)	1.9243	0.8753	0.2893	−0.0510
			ΔEIR < −0.5% (59)	2.1299	1.0117	0.3327	−0.0784
			ΔEIR < −1.0% (17)	1.4973	0.8011	0.3263	0.0458
	3%	9%	None (128)	0.6531	0.4381	0.1105	−0.0661
			ΔEIR < 0% (83)	1.1085	0.7184	0.2893	0.0005
			ΔEIR < −0.5% (59)	1.3132	0.8546	0.3327	−0.0306
			ΔEIR < −1.0% (17)	0.6893	0.6281	0.3263	0.1186

The number of run1up episodes picked up by the criterion is reported in parentheses.

compare the profitability of housing versus stock portfolios. Our goal is, instead, to show that the results on the predictability of housing returns from previous sections can be used to improve the profitability of a hypothetical housing portfolio.

Hendershott et al. (1980) estimate the real user cost for both owner-occupied and rental housing and they find a 2–3% difference between the rental user cost and the owner user cost each year. We take this gap as the net rental income to home owners. According to the statistics reported by the Global Property Guide, a "roundtrip" (i.e., buying and selling) transaction cost in the U.S. is, on average, about 9 percent of the property value, which is approximately equivalent to three to four years' worth of net rental income. In other words, if an investor purchases a property for rental purposes for three to four years and then sells it out, the rental income and the total cost more or less cancel out.[14]

To better assess the risk-adjusted housing returns following price run-ups, we calculate the ex-post (annualized) Sharpe ratio for the portfolio of housing assets conditional on the identification of price run-up episodes. We consider two cases. In the first case, we assume zero net rental income and zero transaction cost. In the second case, we assume a 3% annual net rental income and a 9% "roundtrip" transaction cost so that the rental income and the transaction cost cancel out when the portfolio is held for three years. The Sharpe ratio is reported in Table 5. For the state-level portfolio being held for three years, the Sharpe ratio is 0.19. The ratio is a bit lower for the MSA-level portfolio. The profitability of the portfolio decreases with the holding period, which is consistent with Fig. 2.

Given that changes in the EIR play an important role in predicting housing returns following large price run-ups, we construct a hypothetical housing portfolio based on certain criteria on EIR changes. Table 6 reports the Sharpe ratio of the portfolio under different selection criteria, and the number of run-up episodes picked up by the criterion is reported in parentheses. We include the portfolio of all run-up episodes as the benchmark. When the portfolio includes run-up episodes with negative changes in the EIR only, the risk-adjusted price change is significantly increased at all holding periods. For a portfolio with negative interest rate changes being held for three years, the Sharpe ratio is 0.56 at the state level and 0.29 at the MSA level, not too far from the stock market's ratio of 0.39 (see Frazzini et al., 2013's calculation over the 1976–2011

[14] These numbers are quoted from the article "Housing Transaction Costs in the OECD" at the Global Property Guide by Prince Christian Cruz; see https://www.globalpropertyguide.com/investment-analysis/Housing-transaction-costs-in-the-OECD. Transaction costs include registration costs, real estate agent fees, legal fees, and transfer taxes. Registration costs are the fees and taxes incurred in registering the property with the competent land cadastre or registry. Real estate agent fees best capture various search costs. Legal fees are paid to lawyers or to the conveyancer in the preparation of sales and purchase agreement. Transfer taxes are imposed by local and national governments on the sale and purchase of real estate.

Table 7
Sharpe ratio of the portfolio conditional on price declines with certain criteria.

	Rental income	Transaction cost	Selection criterion	Holding period			
				1 year	2 years	3 years	4 years
State	0%	0%	None (27)	0.2352	−0.0415	−0.1821	−0.2094
			ΔEIR > −1.0% (20)	0.4180	0.0626	−0.0999	−0.1129
			ΔEIR > −0.5% (19)	0.4704	0.0864	−0.0762	−0.0908
			ΔEIR > 0% (16)	0.7130	0.2228	0.0382	−0.0200
	3%	9%	None (27)	−0.0786	−0.1353	−0.1821	−0.1480
			ΔEIR > −1.0% (20)	0.1192	−0.0228	−0.0999	−0.0564
			ΔEIR > −0.5% (19)	0.1714	0.0026	−0.0762	−0.0354
			ΔEIR > 0% (16)	0.3976	0.1408	0.0382	0.0341
MSA	0%	0%	None (91)	−0.7728	−0.8601	−0.7825	−0.5001
			ΔEIR > −1.0% (76)	−0.7395	−0.8453	−0.7678	−0.4740
			ΔEIR > −0.5% (69)	−0.6865	−0.7942	−0.7514	−0.4637
			ΔEIR > 0% (23)	0.0193	−0.2133	−0.2607	−0.2435
	3%	9%	None (91)	−1.3698	−1.0371	−0.7825	−0.4115
			ΔEIR > −1.0% (76)	−1.3068	−1.0147	−0.7678	−0.3895
			ΔEIR > −0.5% (69)	−1.2292	−0.9577	−0.7514	−0.3798
			ΔEIR > 0% (23)	−0.4399	−0.3522	−0.2607	−0.1526

The number of decline episodes picked up by the criterion is reported in parentheses.

period). When we choose run-up episodes with even larger decreases in the EIR, the Sharpe ratio is further improved. For example, under the selection criterion of $\Delta\text{EIR} < -1\%$, the Sharpe ratio is a remarkable 0.68 when the state-level portfolio is held for three years (as a comparison, Warren Buffett's ratio of 0.76 Frazzini et al., 2013). No matter which selection criterion we use, the Sharpe ratio decreases with the length of the holding period of the portfolio as house prices revert to their means.

We also calculate the Sharpe ratio for a housing portfolio conditional on the identification of price declines. Results are presented in Table 7. The Sharpe ratio is negative for most holding periods. By comparing Table 7 to Table 6, we can see that betting on a rebound is less profitable than betting on a continuing run-up in housing markets, which is not the case in stock markets. Goetzmann and Kim (2018)'s finding suggests that returns following a decline are on average significantly higher than those following a run-up. Since the predictive power of changes in the EIR is weaker during market downturns, varying the selection criterion based on interest rate changes does not improve the Sharpe ratio much.

4. Conclusion

We examine the characteristics of large price movements in housing markets. We find that a sharper increase in house prices predicts a higher probability of a crash but a sharper decrease does not necessarily predict a higher probability of a rebound. While housing returns are hard to predict in general, we find that changes in the effective interest rate significantly predict future housing returns following large price run-ups but it is more difficult to use the same factors to predict returns following large price declines. The asymmetry in predictability is consistent with the implications of the model for self-reinforcing housing bubbles of Glaeser et al. (2008) augmented with asymmetric search costs. We also mention how the asymmetry can be related to some behavioral explanations, including feedback models and obstacles to smart money.

This paper only looks at the U.S. housing markets over the past 40 years, and further research can verify if the empirical patterns we have identified are also present in other housing markets. Relating to the predictability of large fluctuations in house prices, it is also interesting to study the trading strategies implemented by REITs and other real estate mutual funds and see if and how they exploit such predictability.

Acknowledgment

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Appendix A. Robustness checks

Table A1
Summary statistics of price run-ups and crashes, 1975:Q1-2000:Q4.

	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of run-ups	36	22	12	7	1	127	78	55	32	12
No. of regions with run-ups	28	18	10	6	1	108	74	53	32	12
No. of crashes	6	4	2	2	0	8	5	8	8	8
No. of regions with crashes	6	4	2	2	0	8	5	8	8	8
Probability of crashes	17%	18%	17%	29%	0%	6%	6%	15%	25%	67%
Drawdown after run-ups										
Mean	−13%	−12%	−16%	−20%	−13%	−7%	−8%	−11%	−14%	−19%
Median	−7%	−7%	−8%	−11%	−13%	−5%	−7%	−11%	−16%	−23%
(Standard deviation)	(0.18)	(0.20)	(0.23)	(0.29)	(0.00)	(0.08)	(0.08)	(0.09)	(0.09)	(0.11)
1-year return after run-ups										
Mean	5%	8%	12%	13%	17%	7%	10%	10%	10%	5%
Median	5%	9%	14%	15%	17%	6%	10%	11%	12%	7%
(Standard deviation)	(0.10)	(0.12)	(0.08)	(0.07)	(0.00)	(0.09)	(0.09)	(0.11)	(0.11)	(0.14)
2-year return after run-ups										
Mean	7%	13%	14%	14%	16%	11%	15%	13%	10%	2%
Median	7%	13%	16%	19%	16%	8%	12%	12%	7%	2%
(Standard deviation)	(0.20)	(0.21)	(0.19)	(0.19)	(0.00)	(0.14)	(0.14)	(0.16)	(0.16)	(0.15)
3-year return after run-ups										
Mean	7%	13%	14%	14%	12%	11%	15%	12%	8%	−1%
Median	8%	11%	15%	15%	12%	9%	11%	10%	4%	−3%
(Standard deviation)	(0.24)	(0.25)	(0.22)	(0.16)	(0.00)	(0.17)	(0.17)	(0.18)	(0.18)	(0.14)
4-year return after run-ups										
Mean	7%	12%	12%	10%	4%	11%	14%	10%	4%	−6%
Median	9%	11%	7%	10%	4%	8%	11%	6%	−1%	−11%
(Standard deviation)	(0.23)	(0.25)	(0.21)	(0.14)	(0.00)	(0.18)	(0.18)	(0.19)	(0.20)	(0.15)

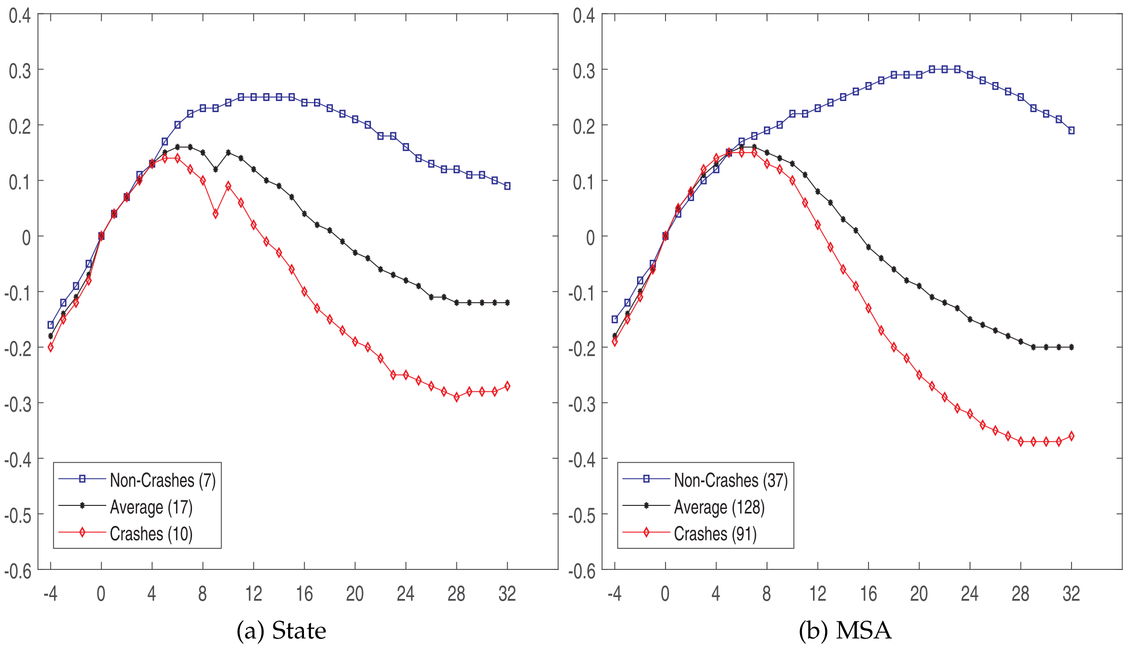


Fig. A1. Returns following price run-ups, 10% crash threshold.

Table A2
Summary statistics of price run-ups and crashes under alternative crash definitions.

Definition 1: Crash = 10% or more drop in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of run-ups	60	37	17	9	2	324	221	128	70	19
No. of regions with run-ups	31	25	13	8	2	199	153	104	62	19
No. of crashes	20	17	10	6	2	132	127	91	56	15
No. of regions with crashes	17	15	8	6	2	122	111	80	53	15
Probability of crashes	33%	46%	59%	67%	100%	41%	57%	71%	80%	79%
Definition 2: Crash = 20% or more drop in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of run-ups	60	37	17	9	2	324	221	128	70	19
No. of regions with run-ups	31	25	13	8	2	199	153	104	62	19
No. of crashes	8	12	6	4	1	51	73	64	42	15
No. of regions with crashes	8	12	6	4	1	49	71	61	41	15
Probability of crashes	13%	32%	35%	44%	50%	16%	33%	50%	60%	79%
Definition 3: Crash = 30% or more drop in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of run-ups	60	37	17	9	2	324	221	128	70	19
No. of regions with run-ups	31	25	13	8	2	199	153	104	62	19
No. of crashes	5	5	5	3	1	17	38	44	30	8
No. of regions with crashes	5	5	5	3	1	17	38	43	30	8
Probability of crashes	8%	14%	29%	33%	50%	5%	17%	34%	43%	42%

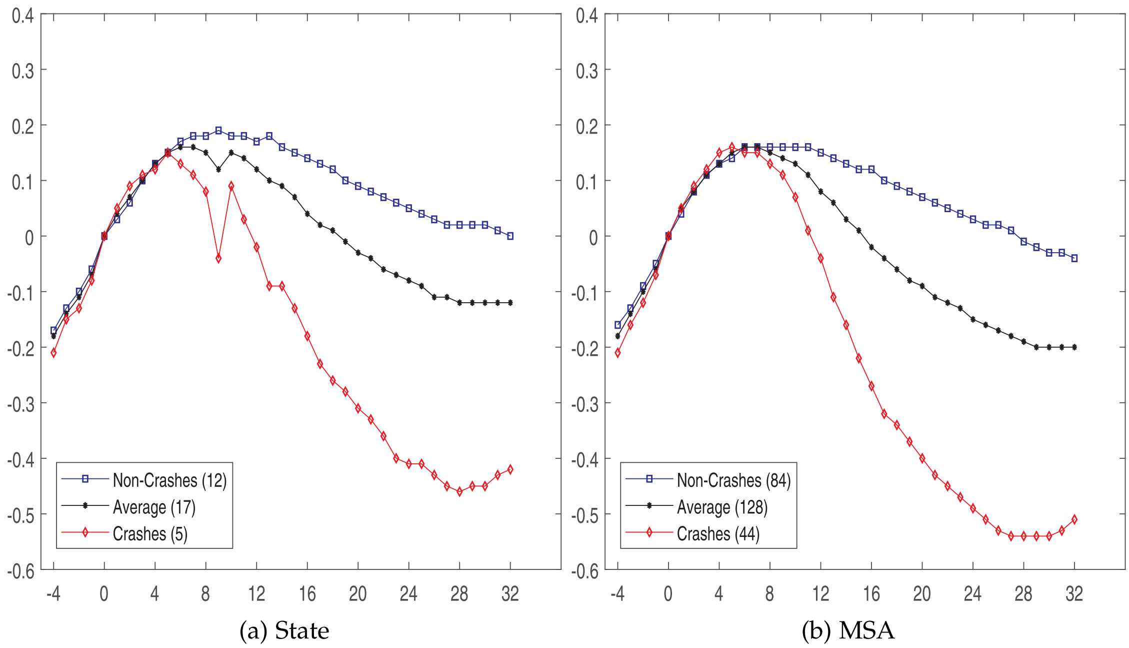


Fig. A2. Returns following price run-ups, 30% crash threshold.

Table A3
Summary statistics of price declines and rebounds, 1975:Q1-2000:Q4.

	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of declines	46	32	24	16	11	138	85	45	23	16
No. of regions with declines	30	23	18	13	8	110	72	37	20	14
No. of rebounds	11	11	10	9	8	9	6	6	4	3
No. of regions with rebounds	8	8	7	7	6	8	5	5	3	2
Probability of rebounds	24%	34%	42%	56%	73%	7%	7%	13%	17%	19%
Drawup after declines										
Mean	16%	20%	24%	28%	36%	9%	10%	12%	15%	17%
Median	11%	12%	13%	22%	32%	7%	7%	9%	12%	14%
(Standard deviation)	(0.18)	(0.20)	(0.22)	(0.21)	(0.22)	(0.09)	(0.10)	(0.12)	(0.15)	(0.16)
1-year return after declines										
Mean	4%	6%	9%	16%	24%	−2%	−2%	−1%	1%	3%
Median	1%	2%	6%	11%	20%	−2%	−2%	−3%	−1%	0%
(Standard deviation)	(0.15)	(0.17)	(0.19)	(0.20)	(0.18)	(0.07)	(0.09)	(0.11)	(0.13)	(0.14)
2-year return after declines										
Mean	1%	5%	7%	15%	23%	−3%	−4%	−3%	−2%	0%
Median	−1%	2%	3%	7%	14%	−4%	−4%	−5%	−4%	−3%
(Standard deviation)	(0.18)	(0.21)	(0.23)	(0.27)	(0.28)	(0.11)	(0.13)	(0.16)	(0.19)	(0.21)
3-year return after declines										
Mean	1%	4%	6%	14%	22%	−4%	−4%	−3%	−2%	1%
Median	−1%	−1%	1%	7%	14%	−4%	−6%	−6%	−6%	−4%
(Standard deviation)	(0.18)	(0.21)	(0.23)	(0.26)	(0.26)	(0.12)	(0.14)	(0.18)	(0.21)	(0.20)
4-year return after declines										
Mean	1%	5%	6%	16%	25%	−2%	−3%	−2%	0%	3%
Median	−1%	1%	1%	10%	15%	−1%	−2%	−1%	−1%	−2%
(Standard deviation)	(0.20)	(0.23)	(0.25)	(0.26)	(0.27)	(0.14)	(0.16)	(0.19)	(0.22)	(0.21)

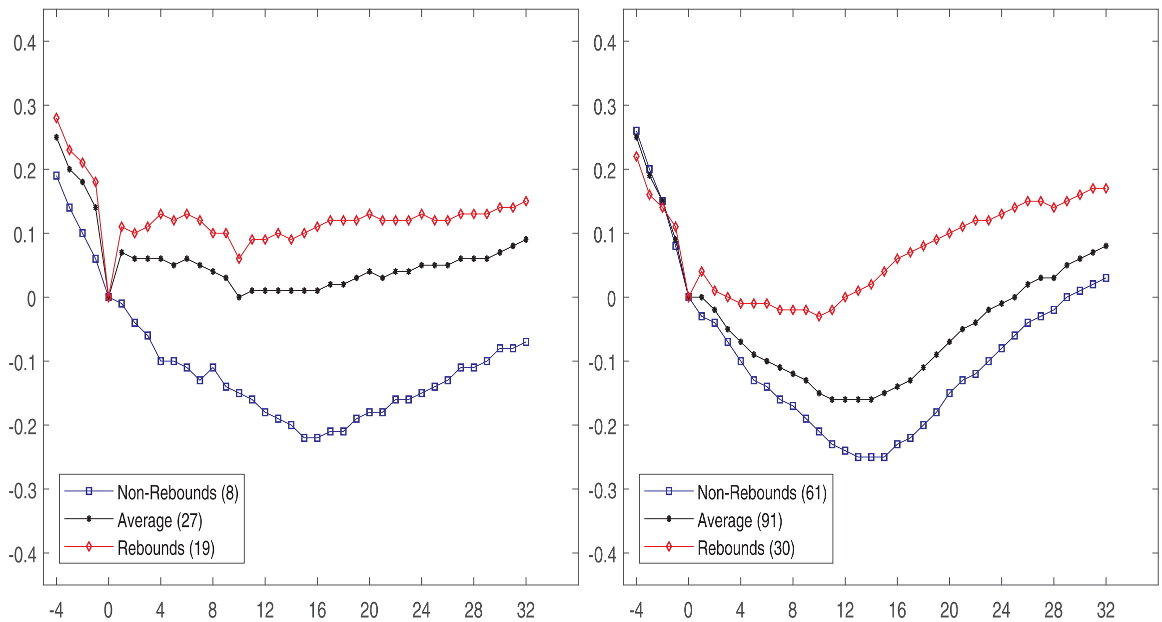
Table A4
Summary statistics of price declines and rebounds under alternative rebound definitions.

Definition 2: Rebound = 10% or more increase in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of declines	55	36	27	18	12	308	167	91	53	36
No. of regions with declines	34	26	21	15	9	206	130	80	50	34
No. of rebounds	28	22	19	14	11	96	57	30	17	13
No. of regions with rebounds	21	18	15	11	8	82	52	26	15	11
Probability of rebounds	51%	61%	70%	78%	92%	31%	34%	33%	32%	36%
Definition 2: Rebound = 20% or more increase in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of declines	55	36	27	18	12	308	167	91	53	36
No. of regions with declines	34	26	21	15	9	206	130	80	50	34
No. of rebounds	13	11	10	9	8	28	13	9	6	3
No. of regions with rebounds	9	8	7	7	6	26	12	8	5	2
Probability of rebounds	24%	31%	37%	50%	67%	9%	8%	10%	11%	8%
Definition 2: Rebound = 30% or more increase in real house prices within four years										
	State					MSA				
Pick-up threshold	4%	8%	12%	16%	20%	4%	8%	12%	16%	20%
No. of declines	55	36	27	18	12	308	167	91	53	36
No. of regions with declines	34	26	21	15	9	206	130	80	50	34
No. of rebounds	7	7	7	6	6	11	4	4	2	1
No. of regions with rebounds	6	6	6	6	6	11	4	4	2	1
Probability of rebounds	13%	19%	26%	33%	50%	4%	2%	4%	4%	3%

Table A5
Predicting housing returns following large price movements, 8% threshold.

	Run-up episodes (State)				Decline episodes (State)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0376*	−0.0869*	−0.1071*	−0.1191	0.0293	0.0163	0.0196	0.0243
	(0.0157)	(0.0314)	(0.0447)	(0.0573)	(0.0149)	(0.0228)	(0.0221)	(0.0209)
ΔRPI	−0.0049	0.6909	0.7718	1.7860	−0.2131	−0.0627	−0.4306	−0.5461
	(0.5187)	(1.0077)	(1.0351)	(1.4921)	(0.6521)	(0.6516)	(0.6437)	(0.6399)
ΔUR	−0.0527**	−0.0939*	−0.0976	−0.1201*	−0.0109	−0.0375	−0.0460	−0.0519
	(0.0171)	(0.0384)	(0.0463)	(0.0515)	(0.0233)	(0.0335)	(0.0331)	(0.0330)
Permits	−0.0007	−0.0139	−0.0322*	−0.0554*	−0.0249	−0.0371	−0.0500	−0.0477
	(0.0043)	(0.0075)	(0.0139)	(0.0215)	(0.0165)	(0.0227)	(0.0252)	(0.0258)
Current	2.0057**	3.2476**	3.4180**	2.6212	−0.7031***	−0.8371***	−0.7582**	−0.7586*
Return	(0.5123)	(0.8638)	(0.8561)	(1.2156)	(0.1152)	(0.1697)	(0.2362)	(0.2686)
N	33	33	33	33	33	33	33	33
adj. R^2	0.439	0.400	0.335	0.325	0.630	0.558	0.518	0.497
par. R^2	0.145	0.232	0.246	0.229	0.061	0.011	0.022	0.034
	Run-up episodes (MSA)				Decline episodes (MSA)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0499**	−0.0916**	−0.0972*	−0.0613	0.0249*	0.0301	0.0304	0.0306
	(0.0177)	(0.0304)	(0.0402)	(0.0502)	(0.0111)	(0.0164)	(0.0203)	(0.0233)
ΔRPI	−0.0769	0.0397	−0.0076	1.6159	0.6045	1.7052*	2.1658*	1.7318
	(0.4681)	(1.0466)	(1.4305)	(1.8137)	(0.3428)	(0.7204)	(0.9401)	(1.1395)
ΔUR	−0.0055	0.0203	0.0499	0.0566	−0.0159*	−0.0167	−0.0111	−0.0093
	(0.0185)	(0.0408)	(0.0527)	(0.0536)	(0.0059)	(0.0112)	(0.0157)	(0.0174)
Permits	0.0193**	0.0196	0.0091	−0.0146	−0.0192	−0.0350	−0.0586*	−0.0630*
	(0.0052)	(0.0103)	(0.0149)	(0.0207)	(0.0137)	(0.0195)	(0.0234)	(0.0251)
Current	0.6770*	0.4351	−0.7327	−2.9084**	0.1278	0.1289	0.3800	0.4061
Return	(0.2737)	(0.4124)	(0.5616)	(0.8737)	(0.2583)	(0.3318)	(0.4038)	(0.4238)
N	219	219	219	219	167	167	167	167
adj. R^2	0.309	0.234	0.172	0.181	0.252	0.235	0.285	0.246
par. R^2	0.198	0.220	0.145	0.044	0.059	0.065	0.056	0.036

* $p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Constants are not reported. Standard errors in parentheses are clustered by year. The partial R^2 measures the proportion of variance in future housing returns not associated with any other predictors that is explained by changes in the effective interest rate.



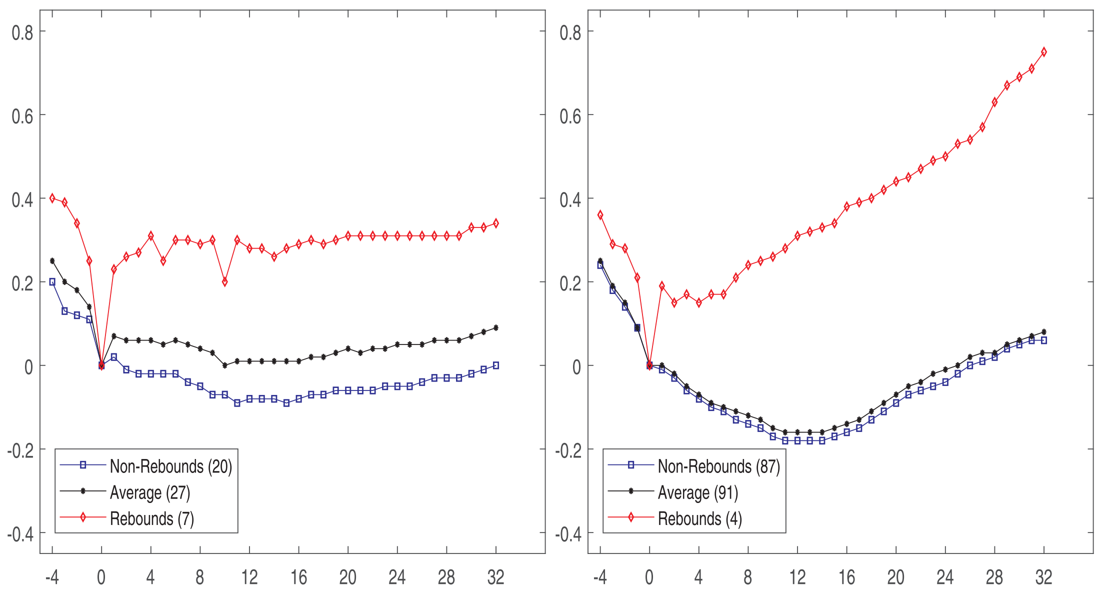
(a) State (b) MSA

Fig. A3. Returns following price declines, 10% rebound threshold.

Table A6
Predicting housing returns following large price movements, 16% threshold.

	Run-up episodes (State)				Decline episodes (State)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0761***	−0.0777	−0.0664	−0.0490	0.0407*	0.0471*	0.0484	0.0475
	(0.0062)	(0.0373)	(0.1165)	(0.0956)	(0.0142)	(0.0176)	(0.0213)	(0.0236)
ΔRPI	−2.9521***	−2.8515	−4.6800	−3.6473	0.2155	0.1405	−0.3716	−0.4351
	(0.2342)	(1.6153)	(4.0978)	(3.1787)	(0.6128)	(0.8947)	(0.9140)	(0.8657)
ΔUR	−0.1054***	−0.1584**	−0.2185	−0.1935	−0.0205	−0.0692	−0.0718	−0.0754
	(0.0053)	(0.0290)	(0.1053)	(0.0924)	(0.0339)	(0.0360)	(0.0393)	(0.0424)
Permits	0.0215*	−0.0032	−0.0518	−0.0690	−0.0498	−0.0543	−0.0791	−0.0836
	(0.0069)	(0.0491)	(0.1162)	(0.0838)	(0.0240)	(0.0318)	(0.0428)	(0.0477)
Current	−0.9746**	−1.2184	−1.9926	−4.1512	−0.7739***	−0.9509***	−0.9176***	−0.9561**
Return	(0.1903)	(1.3203)	(3.1461)	(2.1757)	(0.0717)	(0.1052)	(0.1535)	(0.1951)
N	8	8	8	8	18	18	18	18
adj. R^2	0.976	0.618	0.322	0.772	0.657	0.646	0.568	0.575
par. R^2	0.245	0.076	0.018	0.006	0.071	0.053	0.053	0.049
	Run-up episodes (MSA)				Decline episodes (MSA)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0477*	−0.0743*	−0.0959*	−0.0817*	0.0273	0.0299	0.0352	0.0446
	(0.0172)	(0.0314)	(0.0357)	(0.0288)	(0.0290)	(0.0385)	(0.0538)	(0.0589)
ΔRPI	1.0476	1.5505	0.7312	2.6710	−0.1692	−0.2327	−0.3616	−1.1456
	(0.5055)	(1.2424)	(1.9878)	(1.8438)	(0.7407)	(1.0156)	(1.2871)	(1.4658)
ΔUR	−0.0637	−0.0175	0.0399	0.0732	−0.0319*	−0.0413	−0.0322	−0.0199
	(0.0298)	(0.0584)	(0.0761)	(0.0655)	(0.0136)	(0.0202)	(0.0301)	(0.0330)
Permits	0.0069	−0.0244	−0.0657*	−0.0989***	−0.0305	−0.0493	−0.0774*	−0.0829*
	(0.0100)	(0.0175)	(0.0215)	(0.0186)	(0.0221)	(0.0276)	(0.0349)	(0.0369)
Current	0.3998	0.0384	−2.1447*	−4.7736***	−0.0457	−0.1847	−0.0263	−0.0127
Return	(0.2251)	(0.4733)	(0.7387)	(0.6863)	(0.4125)	(0.5193)	(0.5985)	(0.6208)
N	70	70	70	70	53	53	53	53
adj. R^2	0.429	0.298	0.398	0.585	0.224	0.247	0.276	0.294
par. R^2	0.230	0.225	0.150	0.067	0.035	0.023	0.021	0.039

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Constants are not reported. Standard errors in parentheses are clustered by year. The partial R^2 measures the proportion of variance in future housing returns not associated with any other predictors that is explained by changes in the effective interest rate.



(a) State (b) MSA

Fig. A4. Returns following price declines, 30% rebound threshold.

Table A7
Predicting housing returns following large price movements, 1975:Q1-2000:Q4.

	Run-up episodes (State)				Decline episodes (State)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0236*	−0.0659*	−0.1029	−0.1067	0.0364	0.0233	0.0240	0.0291
	(0.0088)	(0.0221)	(0.0452)	(0.0626)	(0.0160)	(0.0200)	(0.0186)	(0.0212)
ΔRPI	1.3910	3.9946**	5.4810*	5.5717	−0.0827	0.0392	−0.2936	−0.4109
	(0.9082)	(0.8158)	(1.5762)	(2.7928)	(0.6426)	(0.6578)	(0.5956)	(0.6470)
ΔUR	−0.1628	−0.1950	−0.1658	−0.0600	−0.0218	−0.0653	−0.0761*	−0.0857*
	(0.0846)	(0.1370)	(0.1483)	(0.1949)	(0.0259)	(0.0280)	(0.0265)	(0.0292)
Permits	0.0093	−0.0099	−0.0154	−0.0282	−0.0044	0.0154	0.0070	0.0094
	(0.0182)	(0.0183)	(0.0174)	(0.0127)	(0.0226)	(0.0120)	(0.0071)	(0.0114)
Current	2.9579**	3.3851	2.4574	0.1277	−0.7676***	−0.9305***	−0.9171***	−0.9638***
Return	(0.6182)	(1.7927)	(2.4143)	(2.9623)	(0.0600)	(0.0592)	(0.0481)	(0.0748)
N	10	10	10	10	21	21	21	21
adj. R^2	0.600	0.445	0.306	0.082	0.718	0.759	0.797	0.783
par. R^2	0.190	0.458	0.524	0.448	0.068	0.019	0.027	0.035
	Run-up episodes (MSA)				Decline episodes (MSA)			
	(1) 1-year	(2) 2-year	(3) 3-year	(4) 4-year	(5) 1-year	(6) 2-year	(7) 3-year	(8) 4-year
ΔEIR	−0.0330*	−0.0412	−0.0354	−0.0155	0.0257	0.0211	0.0288	0.0317
	(0.0140)	(0.0221)	(0.0353)	(0.0442)	(0.0119)	(0.0207)	(0.0228)	(0.0261)
ΔRPI	−0.3843	0.0336	−0.3799	−1.3470	0.3872	−0.0008	0.3498	−0.6891
	(1.2884)	(2.2270)	(2.4711)	(3.1250)	(0.5921)	(1.1533)	(1.1579)	(1.2545)
ΔUR	−0.0866**	−0.1148**	−0.1153*	−0.1164	−0.0300**	−0.0335*	−0.0391	−0.0485
	(0.0228)	(0.0275)	(0.0394)	(0.0533)	(0.0079)	(0.0144)	(0.0213)	(0.0231)
Permits	0.0143	−0.0225	−0.0451	−0.0580	0.0144	0.0094	0.0010	0.0068
	(0.0122)	(0.0226)	(0.0304)	(0.0413)	(0.0074)	(0.0169)	(0.0147)	(0.0121)
Current	0.1357	−0.1850	−0.6096	−1.4017	−0.6466***	−0.9293***	−0.8780***	−0.8981***
Return	(0.6099)	(0.7502)	(0.8196)	(0.9128)	(0.1009)	(0.1116)	(0.1015)	(0.1019)
N	62	62	62	62	45	45	45	45
adj. R^2	0.447	0.424	0.312	0.185	0.585	0.479	0.435	0.437
par. R^2	0.085	0.065	0.034	0.007	0.067	0.026	0.036	0.062

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Constants are not reported. Standard errors in parentheses are clustered by year. The partial R^2 measures the proportion of variance in future housing returns not associated with any other predictors that is explained by changes in the effective interest rate.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2019.05.012.

References

Adelino, M., Gerardi, K., Willen, P.S., 2013. Why don't lenders renegotiate more home mortgages? Redefaults, self-cures and securitization. J. Monet. Econ. 60 (7), 835–853.
Adelino, M., Schoar, A., Severino, F., 2015. House prices, collateral, and self-employment. J. Financ. Econ. 117 (2), 288–306.
Allen, F., Gale, D., 2009. Understanding Financial Crises. Oxford University Press.
Angeletos, G.-M., La'O, J., 2013. Sentiments. Econometrica 81 (2), 739–779.
Baker, D., 2002. The run-up in home prices: a bubble. Challenge 45 (6), 93–119.
Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2018. Extrapolation and bubbles. J. Financ. Econ. 129 (2), 203–227.
Burnside, C., Eichenbaum, M., Rebelo, S., 2016. Understanding booms and busts in housing markets. J. Pol. Econ. 124 (4), 1088–1147.
Campbell, J.Y., Kyle, A.S., 1993. Smart money, noise trading and stock price behaviour. Rev. Econ. Stud. 60 (1), 1–34.
Campbell, S.D., Davis, M.A., Gallin, J., Martin, R.F., 2009. What moves housing markets: a variance decomposition of the rent–price ratio. J. Urban Econ. 66 (2), 90–102.
Case, K., Shiller, R., 1989. The efficiency of the market for single-family homes. Am. Econ. Rev. 79, 125–137.
Case, K.E., Shiller, R.J., 2003. Is there a bubble in the housing market? Brookings Pap. Econ. Act. 2003 (2), 299–342.
Cutler, D.M., Poterba, J.M., Summers, L.H., 1991. Speculative dynamics. Rev. Econ. Stud. 58 (3), 529–546.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990a. Noise trader risk in financial markets. J. Pol. Econ. 98 (4), 703–738.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990b. Positive feedback investment strategies and destabilizing rational speculation. J. Finance 45 (2), 379–395.
Donovan, C., Senar, P., 2012. Locked in the House: Do Underwater Mortgages Reduce Labor Market Mobility? eres2012-099. European Real Estate Society (ERES).

Engelhardt, G.V., 2003. Nominal loss aversion, housing equity constraints, and household mobility: evidence from the United States. J. Urban Econ. 53 (1), 171–195.
Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Finance 25 (2), 383–417.
Fama, E.F., 1991. Efficient capital markets: II. J. Finance 46 (5), 1575–1617.
Fama, E.F., 2014. Two pillars of asset pricing. Am. Econ. Rev. 104 (6), 1467–1485.
Favara, G., Imbs, J., 2015. Credit supply and the price of housing. Am. Econ. Rev. 105 (3), 958–992.
Favilukis, J., Ludvigson, S.C., Van Nieuwerburgh, S., 2017. The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. J. Pol. Econ. 125 (1), 140–223.
Frazzini, A., Kabiller, D., Pedersen, L.H., 2013. Buffett's Alpha. Technical Report. National Bureau of Economic Research.
Gabriel, S.A., Shack-Marquez, J., Wascher, W.L., 1992. Regional house-price dispersion and interregional migration. J. Hous. Econ. 2 (3), 235–256.
Genesove, D., Mayer, C., 2001. Loss aversion and seller behavior: evidence from the housing market. Q. J. Econ. 116 (4), 1233–1260.
Glaeser, E.L., Gottlieb, J.D., Gyourko, J., 2012. Can cheap credit explain the housing boom? In: Housing and the Financial Crisis. University of Chicago Press, pp. 301–359.
Glaeser, E.L., Gyourko, J., Morales, E., Nathanson, C.G., 2014. Housing dynamics: an urban approach. J. Urban Econ. 81, 45–56.
Glaeser, E.L., Gyourko, J., Saiz, A., 2008. Housing supply and housing bubbles. J. Urban Econ. 64, 198–217.
Glaeser, E.L., Nathanson, C.G., 2017. An extrapolative model of house price dynamics. J. Financ. Econ. 126 (1), 147–170.
Goetzmann, W.N., Kim, D., 2018. Negative bubbles: what happens after a crash. Eur. Financ. Manage. 24 (2), 171–191.
Goetzmann, W.N., Massa, M., 2002. Daily momentum and contrarian behavior of index fund investors. J. Financ. Quant. Anal. 37 (3), 375–389.
Greenwood, R., Shleifer, A., You, Y., 2019. Bubbles for Fama. J. Financ. Econ. 131 (1), 20–43.
Helbling, T.F., 2005. Housing price bubbles-a tale based on housing price booms and busts. BIS Papers 21, 30–41.
Hendershott, P.H., Bosworth, B.P., Jaffee, D.M., 1980. Real user costs and the demand for single-family housing. Brookings Pap. Econ. Act. 1980 (2), 401–452.
Himmelberg, C., Mayer, C., Sinai, T., 2005. Assessing high house prices: bubbles, fundamentals and misperceptions. J. Econ. Perspect. 19 (4), 67–92.
Hubbard, R.G., Mayer, C.J., 2009. The mortgage market meltdown and house prices. BE J. Econ. Anal. Policy 9 (3), 1935–1982.
Hwang, M., Quigley, J.M., 2006. Economic fundamentals in local housing markets: evidence from US metropolitan regions. J. Reg. Sci. 46 (3), 425–453.
Iacoviello, M., 2005. House prices, borrowing constraints, and monetary policy in the business cycle. Am. Econ. Rev. 95 (3), 739–764.
Iacoviello, M., Neri, S., 2010. Housing market spillovers: evidence from an estimated DSGE model. Am. Econ. J. 2 (2), 125–164.
Jordà, Ò., Schularick, M., Taylor, A.M., 2015. Leveraged bubbles. J. Monet. Econ. 76, S1–S20.
Jud, G.D., Winkler, D.T., 2002. The dynamics of metropolitan housing prices. J. Real Estate Res. 23 (1/2), 29–46.
Justiniano, A., Primiceri, G.E., Tambalotti, A., 2015. Credit Supply and the Housing Boom. Technical Report. National Bureau of Economic Research.
Khandani, A.E., Lo, A.W., Merton, R.C., 2013. Systemic risk and the refinancing ratchet effect. J. Financ. Econ. 108 (1), 29–45.
Kirman, A., 1993. Ants, rationality, and recruitment. Q. J. Econ. 108 (1), 137–156.
Leamer, E.E., 2007. Housing is the Business Cycle. Technical Report. National Bureau of Economic Research.
Lovenheim, M.F., Mumford, K.J., 2013. Do family wealth shocks affect fertility choices? Evidence from the housing market. Rev. Econ. Stat. 95 (2), 464–475.
Malpezzi, S., 1999. A simple error correction model of house prices. J. Hous. Econ. 8 (1), 27–62.
Mayer, C., 2011. Housing bubbles: a survey. Annu. Rev. Econ. 3 (1), 559–577.
Mayer, C., Sinai, T., 2009. US house price dynamics and behavioral finance. Policy Making Insights from Behavioral Economics. Federal Reserve Bank of Boston, Boston, Mass.
Mian, A., Sufi, A., 2009. The consequences of mortgage credit expansion: evidence from the US mortgage default crisis. Q. J. Econ. 124 (4), 1449–1496.
Pavlov, A., Wachter, S., 2011. Subprime lending and real estate prices. Real Estate Econ. 39 (1), 1–17.
Piazzesi, M., Schneider, M., 2009. Momentum traders in the housing market: survey evidence and a search model. Am. Econ. Rev. 99 (2), 406–411.
Polinsky, A.M., 1977. The demand for housing: a study in specification and grouping. Econometrica 45 (2), 447–461.
Reinhart, C.M., Rogoff, K.S., 2009. This Time is Different: Eight Centuries of Financial Folly. Princeton University Press.
Shiller, R.J., 1984. Stock prices and social dynamics. Brookings Pap. Econ. Act. 1984 (2), 457–510.
Shiller, R.J., 2003. From efficient markets theory to behavioral finance. J. Econ. Perspect. 17 (1), 83–104.
Shiller, R.J., 2005. Irrational Exuberance. Princeton University Press.
Shiller, R.J., 2007. Understanding Recent Trends in House Prices and Home Ownership. Technical Report. National Bureau of Economic Research.
Smith, M.H., Smith, G., 2006. Bubble, bubble, where's the housing bubble? Brookings Pap Econ Act 2006 (1), 1–67.
Stein, J.C., 1995. Prices and trading volume in the housing market: a model with down-payment effects. Q. J. Econ. 110 (2), 379–406.
Taylor, J.B., 2013. Getting Off Track: How Government Actions and Interventions Caused, Prolonged, and Worsened the Financial Crisis. Hoover Press.
Tiwari, P., Parikh, J., 1997. Demand for housing in the Bombay metropolitan region. J. Policy Model. 19 (3), 295–321.
Wheaton, W., Nechayev, G., 2008. The 1998-2005 housing "Bubble" and the current "Correction": what's different this time? J. Real Estate Res. 30 (1), 1–26.
Wheaton, W.C., 1990. Vacancy, search, and prices in a housing market matching model. J. Pol. Econ. 98 (6), 1270–1292.