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Housing bubble scars

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Housing bubble scars*

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Abstract

We study scar formation and persistence after a house price bubble has burst using data on 3,089 US counties and county equivalents over the period 1980q1–2019q4. We date house price booms and busts for each county, and identify periods with explosive house price developments. Applying a sharp bubble definition to the data, we observe the regularities that the probability of a housing bubble increases when housing supply is inelastic and when access to credit is easy. We differentiate between non-bubble price accelerations and bubble price accelerations, and demonstrate that there is scar formation after the latter. Conditioning on a set of factors, including county-fixed effects, our results show that house price reductions are larger and macro aggregate responses are stronger in areas in which there was a house price bubble. In particular, areas that experience a housing bubble burst are areas in which, subsequently, there are stronger and longer increases in unemployment and decreases in household income.

Keywords: *Housing busts; Local housing cycles; Rational bubbles; Regional heterogeneity*

JEL classification: *E32; E44; R30; C33*

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1 Introduction

Housing markets go through boom-bust cycles (Agnello and Schuknecht, 2011). It is useful to understand this cyclicality because a housing bust may have severe impact on the real economy (Mian and Sufi, 2014). An understanding would encompass knowing why not all booms are followed by a strong bust and why some booms are characterized by a particularly strong growth in house prices. Moreover, while there are national trends, there are also substantial geographical deviations from these trends. In fact, housing markets are regional markets (Ferreira and Gyourko, 2012; DeFusco et al., 2018; Ferreira and Gyourko, 2021) to the point that it potentially is more useful to talk about thousands of housing markets instead of the housing market. This article seeks to bring these features together and asks whether a house price bust leaves economic scars and if so, how persistent these scars are.

Our answers are that certain types of price accelerations are associated with economic scars and these scars are surprisingly persistent.

In order to arrive at these answers, we start out by dating local housing cycles in 3,089 US counties and county-equivalents over the period 1980q1–2019q4. Our dating techniques of local housing cycles use the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm to detect turning points for each of the counties we consider. We discover major heterogeneities in timing, duration, and strength of the boom-bust cycle.[1] We then identify house price accelerations that are particularly strong, by testing for explosive house price developments using a version of the test for explosive roots by Phillips et al. (2015b,a). We classify such accelerations as bubble booms and we compare them to non-bubble booms.

Let us highlight a few striking patterns. A typical county has gone through 2-3 boom and bust phases since the 1980s. Booms typically last longer than busts. Cumulative real house price increases during the boom phase are considerably larger than the corre-

[1] These results corroborate the findings of Ferreira and Gyourko (2012), DeFusco et al. (2018) and Ferreira and Gyourko (2021), who show that there are large heterogeneities in how booms and busts play out across both metro areas and at the neighborhood-level in the US housing market.

sponding decreases in real house prices during the bust phase.

We observe that bubble booms are more common in counties in which housing supply is inelastic and in counties in which there is more competition over customers in the banking sector. We demonstrate that there is a clear association between bubble booms and subsequent decreases in house prices and construction activity. This finding is intact after controlling for several local factors, including county-fixed effects.[2] We find that bubble booms are associated with larger increases in unemployment and larger decreases in household income.

Our results show that periods with bubbles are rare, but that they typically are clustered in certain time-periods and in certain geographical areas. Using a logit-specification, we investigate how the probability of experiencing explosive house price developments is related to land unavailability. As our measure of land unavailability, we use the Lutz and Sand (2019) extension of the index of topographical constraints suggested by Saiz (2010). In a baseline model with this index as the only explanatory variable, we show that counties that score high on land unavailability are associated with a higher likelihood of experiencing a period of explosive house price developments. We augment the list of explanatory variables with growth in household income, log of population, the Herfindahl-Hirschman index of banking concentration from Acolin et al. (2021), the Rice and Strahan (2010) index of interstate branching deregulation, and year-by-quarter fixed effects. The result that more topographically restricted counties are associated with a higher probability of a house price bubble is maintained. We also find that the likelihood of a bubble increases when there is more competition in the banking sector and when the credit market is more deregulated.

Jordà et al. (2013) separate between normal recessions and financial recessions, and they show that financial recessions are both deeper and longer than normal recessions.

[2]Recent work by Chodorow-Reich et al. (2023) have also emphasized that areas with the strongest house price booms also experienced the largest busts. They also highlight that the same areas experienced the strongest recoveries and argue that the 2000s housing cycle is better viewed as a boom–bust–rebound period. The authors argue that the cycle was in part due to overoptimism about long-run fundamental growth at the city level.

Inspired by their empirical approach, we distinguish between non-bubble booms and bubble booms. Having classified area-by-time-periods, we use local-projection methods (Jordà, 2005) to calculate both unconditional and conditional paths of real house prices, house prices relative to income, housing starts, housing completions, income, and unemployment after the peak of non-bubble booms and bubble booms. The conditional paths controls for lags of house price growth, lags of growth in housing starts, lags of income growth, lags of the unemployment rate, lags of population growth, and the lagged value of the Herfindahl index of banking concentration. Finally, we control for the cumulative change in house prices in the preceding boom, as well as county-fixed effects. Both the unconditional and the conditional paths show that bubble booms are associated with deeper and longer housing busts, in which we subsequently observe larger decreases in construction activity, larger decreases in household income, and larger increases in the unemployment rate.

Our paper relates to several strands of the literature. First, we add to the literature on stylized facts about housing boom-bust cycles and regional heterogeniety (Glaeser and Gyourko, 2005; Ferreira and Gyourko, 2012; DeFusco et al., 2018; Ferreira and Gyourko, 2021). These papers focus on dating local housing cycles and how the housing cycle varies across regional markets. Glaeser and Gyourko (2005) study local variations over the national cycle in the US, and they define the phases of the national housing cycle based on periods with sufficient co-movements in house price growth across areas. They use data from 1982–2007 and define two booms; the 1982-1989 boom and the post-1996 boom, while the 1989-1996 is identified as a bust in the national cycle. When employing the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm to national house price data, we get remarkably similar results. Ferreira and Gyourko (2012) and Ferreira and Gyourko (2021) use detailed micro-level data, while DeFusco et al. (2018) use MSA level data, to find local housing cycles in US housing markets, by employing techniques to detect break-points in house price growth. For the overlapping period, our results corroborate their findings in that the timeline of the 2000-boom varies greatly across regional markets, and that it is misleading to talk about the boom at the beginning of the 2000s as a single national phenomenon. We contribute to these papers in two main ways. First, in addition to dating the phases of local housing cycles, we date sub-periods of booms with explosive house price movements, and study what factors increase the likelihood of such periods. Second, and more importantly, we study developments in house prices, construction activity, and local macro variables in the aftermath of booms, i.e., focusing on the implications of a housing bust. We seek to uncover the persistence of the ramifications, i.e. the scars.[3]

Another branch of the literature is concerned with the determinants of local house price variations. Several papers use US MSA data and find that local differences in housing supply elasticities are key drivers of variations in local house price developments (see e.g., Green et al. (2005); Gyourko et al. (2008); Saiz (2010); Huang and Tang (2012); Glaeser et al. (2014); Anundsen and Heebøll (2016); Aastveit et al. (2023)).[4] We add to this literature in two ways. First, we corroborate their findings by also by showing that land unavailability, as measured by the Lutz and Sand (2019) extension of the the index of topographical constraints suggested by Saiz (2007), is a key determinant for increasing the probability of explosive housing booms using county-level data. Second, we supplement to these papers by documenting what happens after the boom ends depends on the nature of the boom itself.

Many papers have focused attention on whether US house prices in the 2000s can be explained by economic fundamentals (see e.g., McCarthy and Peach (2004); Gallin (2006, 2008); Mikhed and Zemcik (2009a,b); Anundsen (2015); Kivedal (2013); Pavlidis et al. (2016)). Most of these papers take a national approach and focus on detecting and testing for housing bubbles in real time. We differ from these papers in two ways. First, we seek

[3]Charles et al. (2018) show that the housing boom and bust during the 2000s also affected college enrollment. They found that the boom decreased college enrollment. While most of the decline in enrollment was reversed during the bust, attainment have remained persistently low for particular cohorts.

[4]Aastveit and Anundsen (2022) also find that positive housing demand shocks, and in particular expansionary monetary policy shocks, have a greater impact on house prices in areas in which land is supplied in-elastically. The inelastic supply implies that these areas are vulnerable to strong responses to any demand shocks, not only monetary policy ones.

to emphasize the role played by geography so we use county-level granularity. Second, we are particularly interested in the sources of the heterogeneities and the implications of a bubble bust; the detection of a bubble is not our main concern.

The real economic consequences of a house price bust were clearly shown during the Great Recession (see e.g., Ferreira et al. (2010); Mian et al. (2013); Mian and Sufi (2014); Brown and Matsa (2020), as well as in the excellent review in Duca et al. (2021)). We add to this literature by mapping how house prices, construction activity, and local macro variables evolve after the peak of both a non-bubble boom and a bubble boom. Inspired by Jordà et al. (2013), who show that financial recessions are both deeper and longer than normal recessions, we use local-projection methods (Jordà, 2005) and derive unconditional and conditional paths for house prices, construction activity, unemployment, and income after the peak of non-bubble booms and bubble booms. We find that a house boom bust has severe implications in both cases, but that both the housing and macro implications are more severe following a bubble boom.

The paper proceeds in the following way: The next section discusses the chronology of the national and regional housing cycle based on statistical tests for turning points. In Section 3, we explore whether there is evidence of explosive behavior in local US housing markets. In Section 4, we investigate how local housing market variables and macro aggregates evolve following a boom, and whether this depends on the type of boom. The paper concludes with summarizing remarks and a few words on policy direction.

2 Housing cycle chronology

Housing markets are cyclical, and in order to study the implications of a house price bust, a prerequisite is a set of dates of the chronology of housing cycles. We use the Bry and Boschan (1971); Harding and Pagan (2002) algorithm for quarterly data (BBQ) to detect turning points in real house prices.

The BBQ-algorithm starts by identifying potential peaks and troughs as local minima and local maxima. The method requires a choice on the minimum cycle length, a minimum length of each phase (boom and bust), and a window size over that determines the duration of the period within which to search for local minima and maxima. We set the minimum cycle length to 20 quarters and require that each phase lasts at least 4 quarters. The window size is set to 2 quarters. We start by dissecting the national cycle, before looking into regional housing cycles.

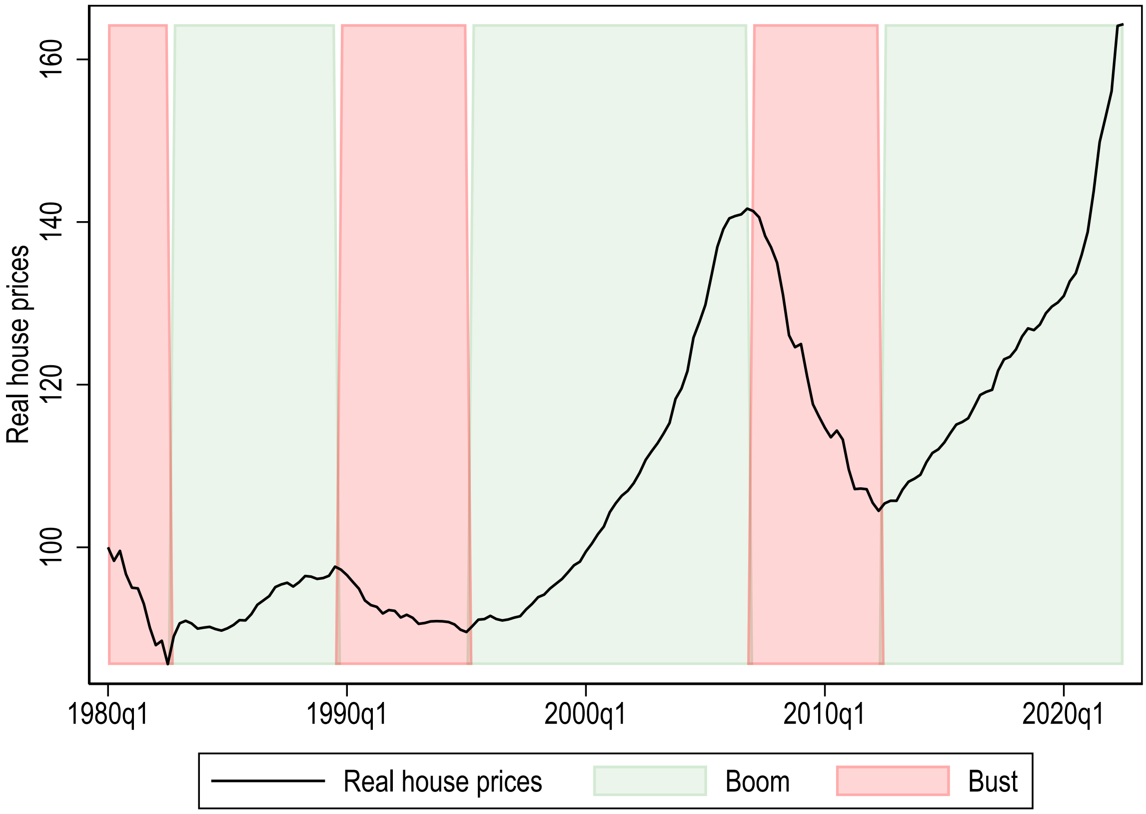
2.1 National cycle

We apply the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm to aggregate US data in order to define a national housing cycle. The results are displayed in Figure 1, in which the shaded green areas represent booms, while the shaded red areas represent busts in the national housing market.

By applying the BBQ-algorithm to the national data, we find that there are three boom phases over the sample period we consider; 1982q3-1989q3, 1995q1-2006q4, and one that commences in 2012q2. We also identify three busts: 1980q1-1982q3, 1989q3-1995q1, and 2006q4-2012q2. The first of these busts is imprecisely measured. This is due to the fact that we do not have the peak date since it precedes our sample period. The phases we identify using the BBQ-algorithm are very similar to the cycles identified by Glaeser et al. (2008), who use a different approach to date the national cycle.

Between 1995q1 and 2006q4, real house prices increased by 58 percent at the national level. Developments from 2012q2 to 2022q3 display a similar pattern, with a cumulative increase of 57 percent. By comparison, the total drop in real house prices in the wake of the subprime crisis was 26 percent. At a national level, it appears that housing booms lasts considerably longer than housing busts. Furthermore, the price increase in a boom is larger than the corresponding price reduction in a housing bust.

Figure 1: National housing cycle



Note: The figure shows booms (green) and busts (red) in the US housing market over the period 1980q1–2019q4. The cycle is dated by applying the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm for detecting turning points in the logarithm of real house prices at the national level. The black line shows the logarithm of real house prices, and it is normalized to 100 in 1980q1.

2.2 Regional heterogeneity

While it is important to date and understand the drivers of the national housing cycle, housing markets are regional and we observe different developments across regional markets. For this reason, we have collected data from 3,089 US counties and county equivalents over the period 1980Q1 to 2019Q4.

We use median sales prices to measure house prices. The data have been accessed through Moody's Analytics database economy.com, and the original source of the data is Zillow. To measure real house prices, we deflate the county-level house price series by the consumer price index in the MSA to which the county belongs. MSA-level data on CPI are also collected from Moody's Analytics database economy.com, which constructs the MSA-level data based on underlying data from BEA and BLS.[5]

To investigate the extent of regional heterogeneity as measured against the national cycle, we calculate the cumulative percentage real house price change for each county for each phase of the national cycle. The cross-county variations in cumulative house price growth for each phase of the national cycle are summarized in Table 1.

It is evident that there is major regional heterogeneity as measured against the national housing cycle. Although there are periods in which most of the counties follow the national pattern, there are also periods in which house prices in several counties have an opposite development relative to the national cycle. This observation suggests that it is not feasible, without strong assumptions and estimation constraints, to classify one common cycle across local housing markets. Even in periods in which most counties follow the same direction as the national cycle, there is substantial heterogeneity in house price growth. For instance, the fifth percentile of the cross-county cumulative real house price growth distribution was around 9 percent between 1995 and 2006. By comparison, the 95^{th} percentile was 93 percent.

[5]The BLS constructs CPI data only for a select group of MSAs. In our analysis, we use the estimates constructed by Moody's, which take the implicit price deflators of the BEA as a starting point. Monthly data are constructed using information on cost of living, population, and median household income, and backcasting techniques. We aggregate to quarterly data by computing the average of the monthly data within a quarter.

Table 1: Heterogeneity over the national housing cycle

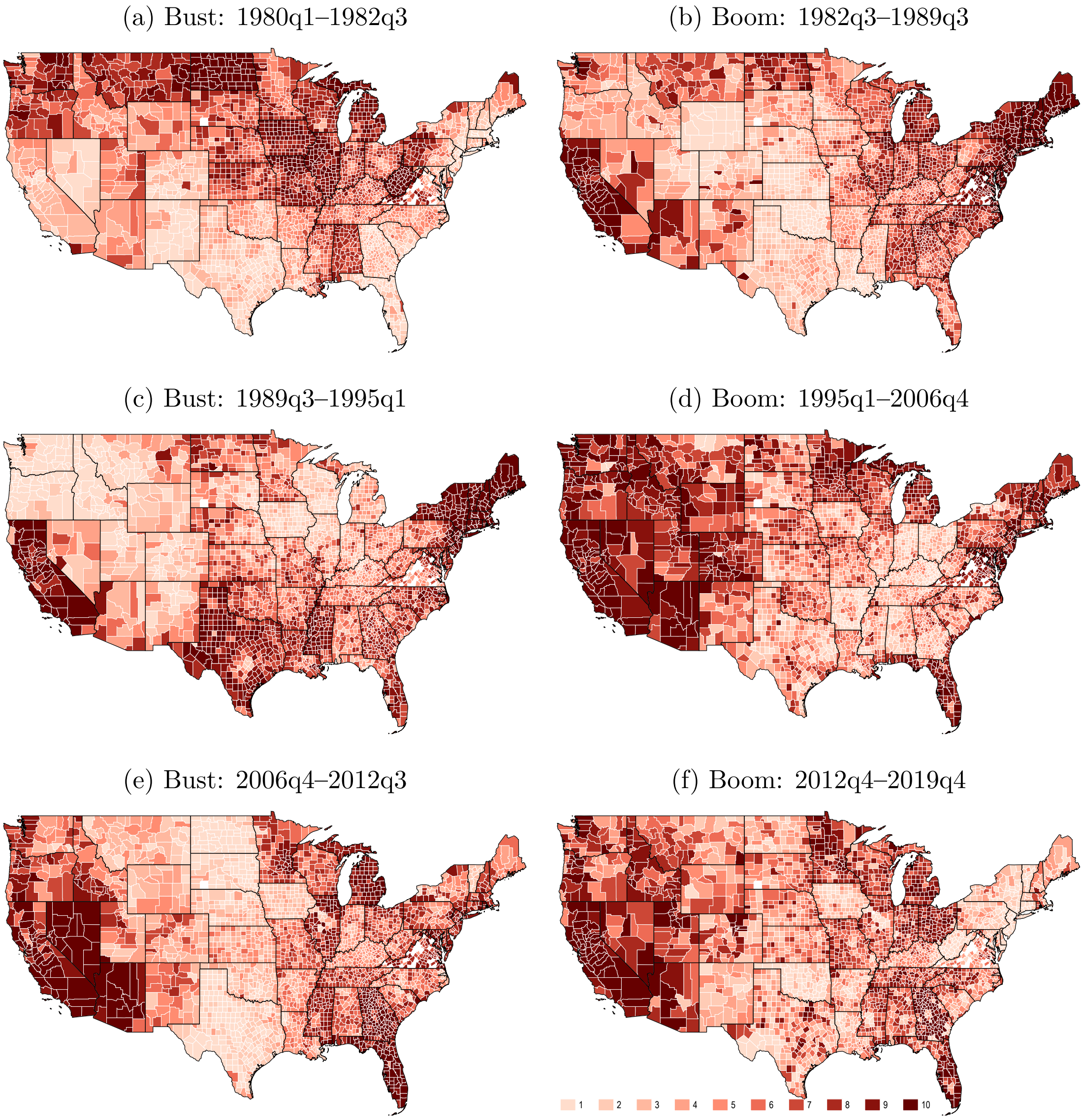
Period	Phase	5^{th} pct.	25^{th} pct.	50^{th} pct.	75^{th} pct.	95^{th} pct.	N	N >0
1980q1-1982q3	Bust	-25.71	-19.47	-14.87	-8.01	1.63	204	
1982q3-1989q3	Boom	-25.60	-11.18	1.01	10.65	41.22	1609	
1989q3-1995q1	Bust	-19.20	-4.93	3.32	11.55	28.91	1870	
1995q1-2006q4	Boom	9.36	22.17	35.99	55.71	93.33	3064	
2006q4-2012q2	Bust	-41.24	-26.17	-17.48	-8.24	5.59	343	
2012q2-2019q4	Boom	3.72	17.34	27.31	38.83	63.75	3010	

Note: The table summarizes the cross-county distribution of cumulative real house price growth as measured against the national US housing cycle. The national cycle is dated by applying the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm ton national real house prices. The second to last column shows the number of counties in our sample in a particular time period, whereas the final column shows the number of counties with a positive real house price growth over the period under consideration.

Figure 2 shows maps of cumulative real house price growth deciles for each county over the different phases of the national cycle. It is evident that there are clusters, in which counties on the east and west coasts have higher real house price growth in booms and larger real house price declines in a bust. The areas that experience the greatest price increase in a boom also see the largest price drop in a bust.[6]

[6] Recent work by Chodorow-Reich et al. (2023) have emphasized that areas with the strongest house price booms in the early 2000s not only experienced the largest busts in the late 2000s but also the strongest rebounds during the 2010s. They therefore argue that it is better to view the entire 1997-2019 period as a boom-bust-rebound period.

Figure 2: Regional variations in cumulative real house price growth over the national cycle.



Note: The figure shows maps of cumulative house price growth for each county as measured against the US housing cycle. The counties are grouped into deciles of the cumulative real house price growth over the different periods. The different phases of the cycle are calculated by applying the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm on national real house prices.

2.3 Regional housing cycles

Due to the heterogeneity in house price growth over time and across counties, we urge hesitance toward the notion of a common housing cycle across US counties. We share this position with Ferreira and Gyourko (2012), DeFusco et al. (2018) and Ferreira and

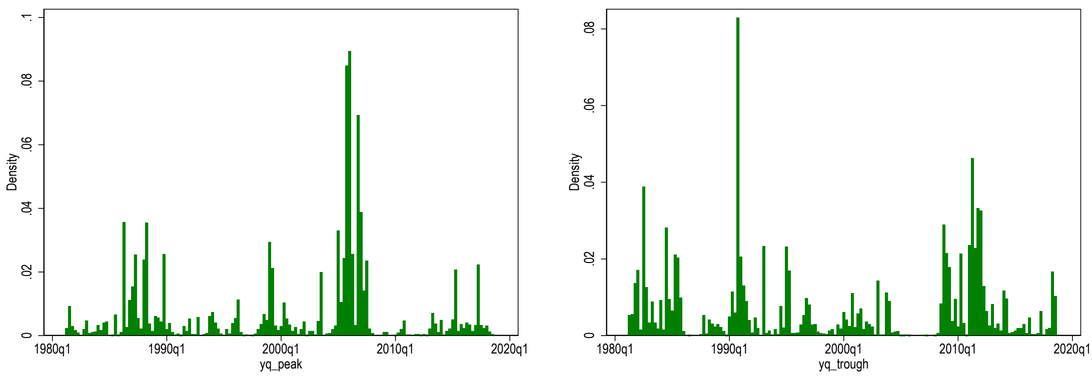
Gyourko (2021). For this reason, we apply the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm separately to the logarithm of real house prices in each of the 3,089 counties in our sample.

Figure 3 displays histograms of the cross-county distribution of starting points of peaks and troughs detected by the BBQ-algorithm. It is evident that the cycles are highly regional, although we do observe clusters over 2-3 year periods in terms of the timing of peaks and troughs.

Figure 3: Peaks and troughs in regional housing markets

(a) Peak

(b) Trough



Note: The figure shows histograms of the starting quarter for all peaks (Panel a) and troughs (Panel b) detected among 3,089 US counties over the period 1980q1–2019q4. Peaks and troughs are detected using the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm for detecting turning points.

Table 2 summarizes some key stylized facts about the regional US housing cycle chronology. Our results uncover that most of the counties have had two or three peaks and troughs since 1980. While the median bust phase (peak-to-trough) is 19 quarters, the median boom phase (trough-to-peak) is 29 quarters.

There is considerable regional heterogeneity in cumulative house price growth both in booms and in busts, with a significantly higher house price appreciation during the boom phase relative to the fall in house prices during a housing bust.

The total cycle length can be measured either as the number of quarters from peak-to-peak or trough-to-trough. In either case, we find that the typical cycle length is a bit more than 10 years.

Table 2: Variations across regional housing cycles

Variable	5^{th} pct.	25^{th} pct.	50^{th} pct.	75^{th} pct.	95^{th} pct.
No. peaks	1	1	2	2	3
No. troughs	2	2	3	3	4
Peak-to-trough (qtrs.)	10	13	19	24	33
Trough-to-peak (qtrs.)	11	17	29	44	61
Peak-to-peak (qtrs.)	26	34	48	70	79
Trough-to-Trough (qtrs.)	29	35	50	75	94
Peak-to-trough (% growth)	-37.92	-28.12	-16.90	-8.50	-3.55
Trough-to-peak (% growth)	10.52	17.53	30.81	52.42	91.55
Peak-to-peak (% growth)	-9.48	1.88	15.83	33.68	60.17
Trough-to-Trough (% growth)	-13.87	-1.62	10.06	26.07	48.73

Note: This table summarizes key results from our mapping of regional cycles in the US housing market. The results are based on an analysis that applies the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm for detecting turning points to the logarithm of real house prices for 3,089 US counties. The table summarizes the cross-county distribution of some key variables over the different phases of the housing cycle.

3 Bubble detection

In testing for bubbles, we apply the recursive ADF-based framework suggested by Phillips et al. (2015b) and Phillips et al. (2015a) to explore whether we observe signs of real house prices switching from following an I(1)-process to following an explosive root process.[7]

For us to classify a bubble, it is a necessary, but not sufficient, condition that the Phillips et al. (2015b) and Phillips et al. (2015a) test signals explosive dynamics. We require that four more conditions are met. A bubble cannot occur if there is no boom, as detected by the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm. This condition rules out situations that are found due to negative explosive price developments. The housing market in question cannot enter and exit a bubble over a period of four quarters. The duration of the bubble needs to be at least four quarters. A bubble should be followed by a bust within two years. The latter condition is imposed to differentiate price accelerations that are non-permanent and price accelerations that constitute

[7]For a theoretical motivation and more details on the econometric approach, see Appendix A.

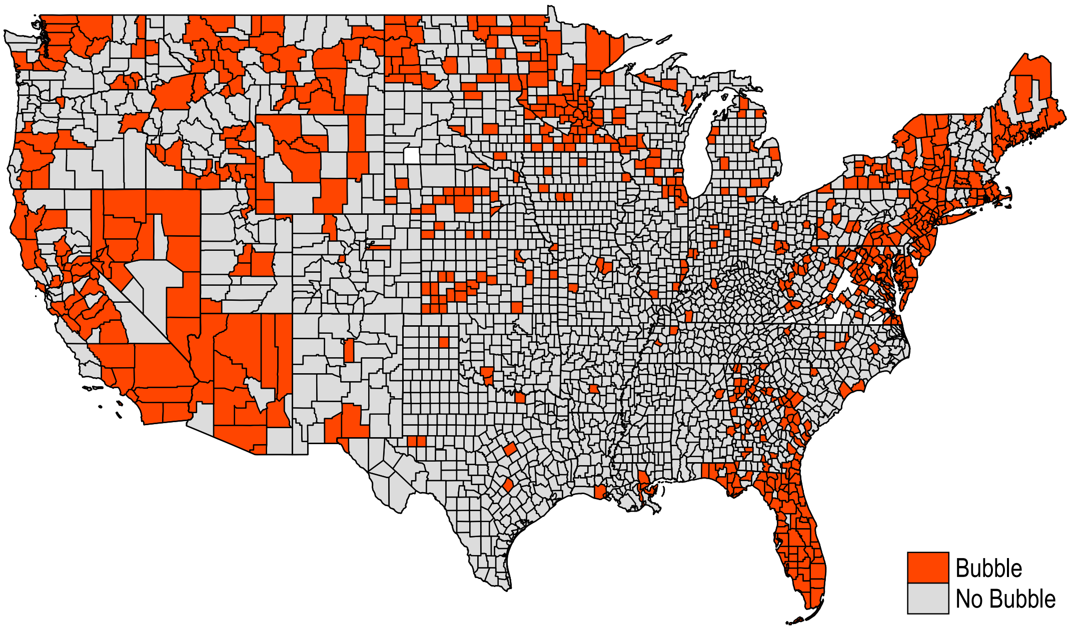
a permanent re-pricing of local areas.

We apply this approach to the logarithm of real house prices in each county over the period 1980Q1 to 2019Q4 separately.[8] Without imposing any additional constrains, i.e., just using the results from the Phillips et al. (2015b) and Phillips et al. (2015a) test directly, 63 percent of the counties in our sample have experienced a period in which we detect explosiveness. Ruling out negative bubbles by requiring that there is no bubble if there is no boom brings this number down to 59 percent. By requiring that a county cannot enter and exit a bubble over a period of one year, which we modify by imputation, there is no change in the fraction of counties that have experienced a bubble. This constraint only changes the duration and timing of bubbles. We find evidence of a bubble in 48 percent of the counties when we also require a minimum duration of four quarters. Finally, ruling out bubbles that are not succeeded by a bust within two years, we find that 24 percent of the counties in our sample have experienced at least one bubble over the sample period.

Figure 5 shows which counties have experienced a bubble, but suppresses information about the dating of the bubble. A larger share of the counties on the west coast and east coast have experienced at least one bubble over the sample period.

[8]We have data back to 1970Q1, but we require a minimum sample length of 40 observations. Therefore, our test-sample runs from 1980Q1–2019Q4.

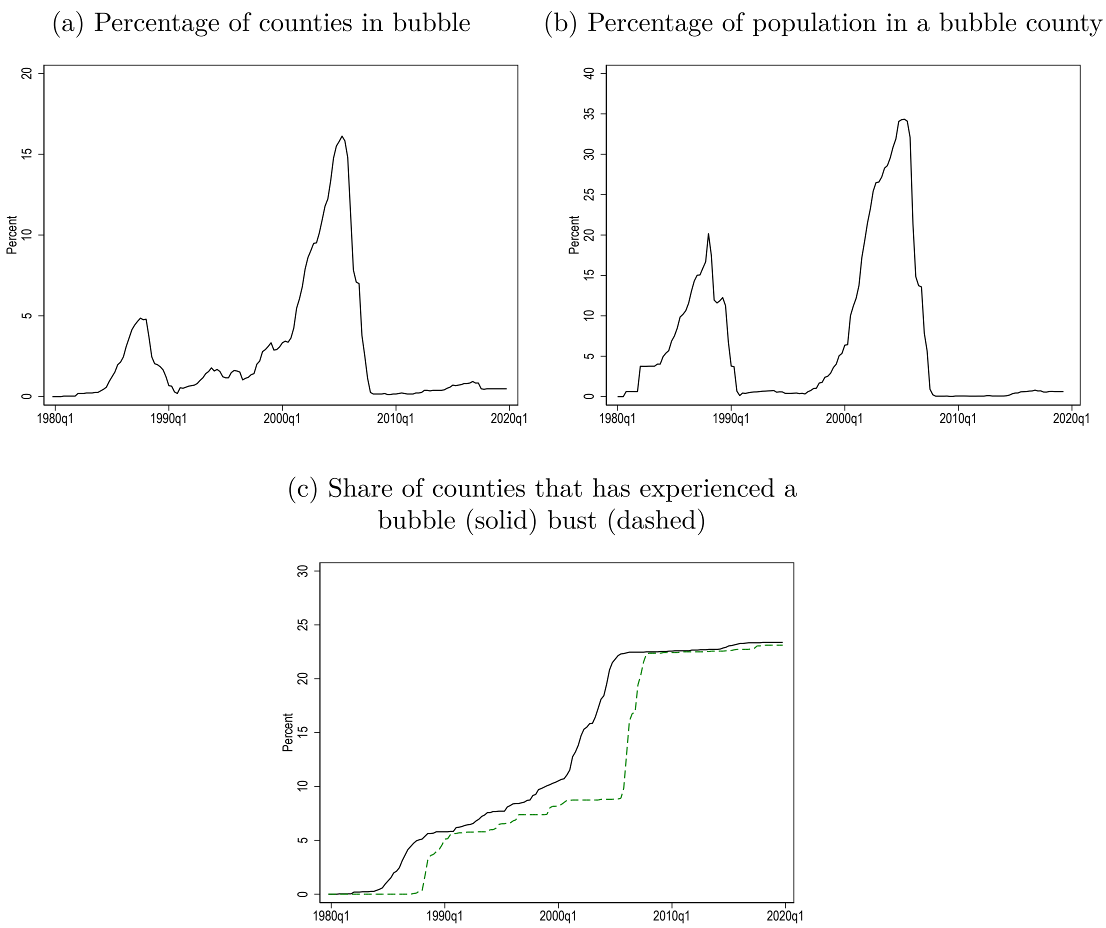
Figure 4: Counties that have experienced at least one bubble over the period 1980Q1–2019Q4.



Note: The figure shows which counties have experienced at least one bubble (red) over the period 1980Q1–2019Q4. Periods of bubble behavior are detected by applying the Phillips et al. (2015b,a) test for explosive roots to each of the 3,089 counties included in our data set and imposing additional constraints for bubble-like movements in house prices.

Panel a) in Figure 5 plots the share of counties that are in a bubble at a particular point in time. Most notable is the period before the global financial crisis, but it is also evident that several counties experienced a bubble in the late 1980s. Panel b) shows that a larger share of the population lives in counties that experience bubbles than the share of number of counties that have experienced a bubble. This finding indicates that bubbles tend to occur in counties with larger populations. Finally, Panel c) shows the cumulative share of counties that have experienced a bubble and a bubble bust over time. In the aftermath of the GFC, there have been nearly no bubbles.

Figure 5: Bubble presence over time.



Note: The figure shows time developments in bubble incidents in the US. Panel a) shows the percentage of counties that are in a bubble at a particular point in time. Panel b) shows the fraction of the population that resides in counties that are in a bubble at a particular point in time. Panel c) Shows the cumulative developments for bubbles and bubble busts. It shows the share of counties that up to a particular point in time has experienced at least one bubble (solid black) and at least one bubble bust (dashed red). All results are based on applying the Phillips et al. (2015a) test for explosive roots to real house prices in each county.

Table 3 compares some summary statistics for non-bubble booms versus bubble booms. In our sample of 3,089 counties, we observe 5,685 booms. The majority of these booms, 86 percent, are classified as non-bubble booms, while 14 percent are bubble booms. While the typical duration of a non-bubble boom is 29 quarters, bubble booms have a median duration of 35 quarters, among which the actual bubble-period lasts 13 quarters at the median. The median price growth in bubble-booms is much higher than in non-bubble booms, and more than 42 percent of the total price growth in a bubble-boom takes place

Table 3: Characteristics of non-bubble booms versus bubble booms. Median values.

Variable	All	Non-bubble boom	Bubble boom
Price growth	30.32	27.08	60.88
Boom duration	29.00	28.00	35.00
Price growth 1yr. aft.	-3.48	-3.32	-4.71
Price growth 5yrs. aft.	-11.90	-10.85	-21.97
Price growth 10yrs. aft.	-5.57	-3.94	-17.14
Price growth 15yrs. aft.	8.19	7.94	11.46
UNAVAL	0.21	0.20	0.28
Popu.	25.57	24.04	47.82
Obs.	5685.00	4901.00	784.00
Perc. obs.	100.00	86.21	13.79

Note: The table compares median real house price growth and boom duration for non-bubble booms versus bubble booms. It also shows the median cumulative real house price change from the peak of the boom to one year after the peak, five years after the peak, 10 years after the peak, and 15 years after the peak across the different boom types. The table also reports the median value of the UNAVAL measure, the median population size, number of observations, and the fraction of booms in each category.

during the bubble-phase.

We have also calculated the cumulative house price growth from the peak of the boom to one year after the peak, five years after the peak, 10 years after the peak, and 15 years after the peak. After 15 years, house prices are above their pre-peak level following both a non-bubble boom and a bubble boom. However, it is evident that the house price fall is deeper when it was preceded by a bubble boom. 10 years after the peak of a bubble boom, house prices are 17 percent lower than their peak-level. In comparison, the same number following a non-bubble boom is only four percent. We have also tabulated the median value of the unavailability measure and population size across the different booms. It is clear that counties that experience a bubble boom are larger in population size and that land is more restricted.

In a simple logit-regression (see Appendix B), we show that the probability of a house price bubble increases with land unavailability (Lutz and Sand (2019)) and a more deregulated credit market, (Rice and Strahan (2010)). We also show that bubbles are more frequent in counties with more competition in the banking sector (Acolin et al. (2021)), a larger population, and where income growth is higher. These results corroborate the literature that looks at variations in local house price developments over the boom-bust cycle (see e.g., Green et al. (2005); Gyourko et al. (2008); Saiz (2010); Huang and Tang (2012); Glaeser et al. (2014); Anundsen and Heebøll (2016)), by showing that the same determinants are important in explaining bubble behavior.

4 Consequences of a bubble bust

We have seen that some booms, which we classify as bubble booms, are characterized by an explosive house price growth. These booms tend to last longer and have a larger amplitude than the other category of booms, the non-bubble booms. In this section, we seek to understand what happens in the aftermath of a housing boom, and whether there are any differences between non-bubble and bubble booms. We follow Jordà et al. (2013) and calculate both unconditional and conditional paths for the cumulative response in house prices, construction activity, income, and the unemployment rate using local projection methods (Jordà, 2005).

4.1 Unconditional cumulative paths in housing busts

We start by comparing the evolution of real house prices, house prices relative to income, housing starts, housing completions, unemployment, and household income for each quarter in the five-year period after a housing market peak. We distinguish between the peak of a non-bubble boom and the peak of a bubble-boom. In particular, we estimate the following specification:

$$y_{i,t+h} - y_{i,t} = \alpha + \theta^{NBB} D_{i,t}^{\text{NBB}} + \theta^{BB} D_{i,t}^{\text{BB}} + \varepsilon_{i,t}$$

in which y is the variable of interest and is selected from the following list:

$$y \in \{\text{Real house prices}, \text{House prices-to-income}, \text{Housing starts}, \\ \text{Housing completions}, \text{Household income}, \text{Unemployment rate}\}$$

D^{NBB} is a dummy variable that equals one at the peak of a non-bubble boom, and zero otherwise. Likewise, D^{BB} is a dummy variable that equals one at the peak of a bubble-boom, and zero otherwise. We let i denote county, t is time (year-by-quarter), and h is the horizon for which we calculate the unconditional path of the variables in y.

Results for house prices and price-to-income ratios are shown in Panel a) and Panel b) in Figure 6. It is evident upon visual inspection that both real house prices and price-to-income ratios fall considerably more in a housing bust that is preceded by a bubble-boom than when the bust is preceded by a non-bubble boom. By inspecting Panel a) in Table 4, we observe that the drop in real house prices after one year is relatively similar and around 5-6 percent following both boom types. After this, there is a substantially larger drop in house prices in the aftermath of a bubble-boom. Four years after the peak, the cumulative drop following a non-bubble boom is around 18 percent, while it is 32 percent after a bubble-boom.

A similar pattern emerges if we instead look at quantity developments. Panel c) in Figure 6 shows the evolution of housing starts and Panel d) shows housing completions after the peak of a boom. Following both a non-bubble boom and a bubble boom, there is significant drop in construction activity, but the drop is substantially larger in a bust that is preceded by a bubble boom. Panel b) in Table 4 shows that the drop in housing starts is almost twice as large at all horizons after the peak of a bubble-boom. Four years after the peak of a bubble-boom, housing starts are 86 percent below its peak level, while it is 49 percent below its peak level following a non-bubble boom.

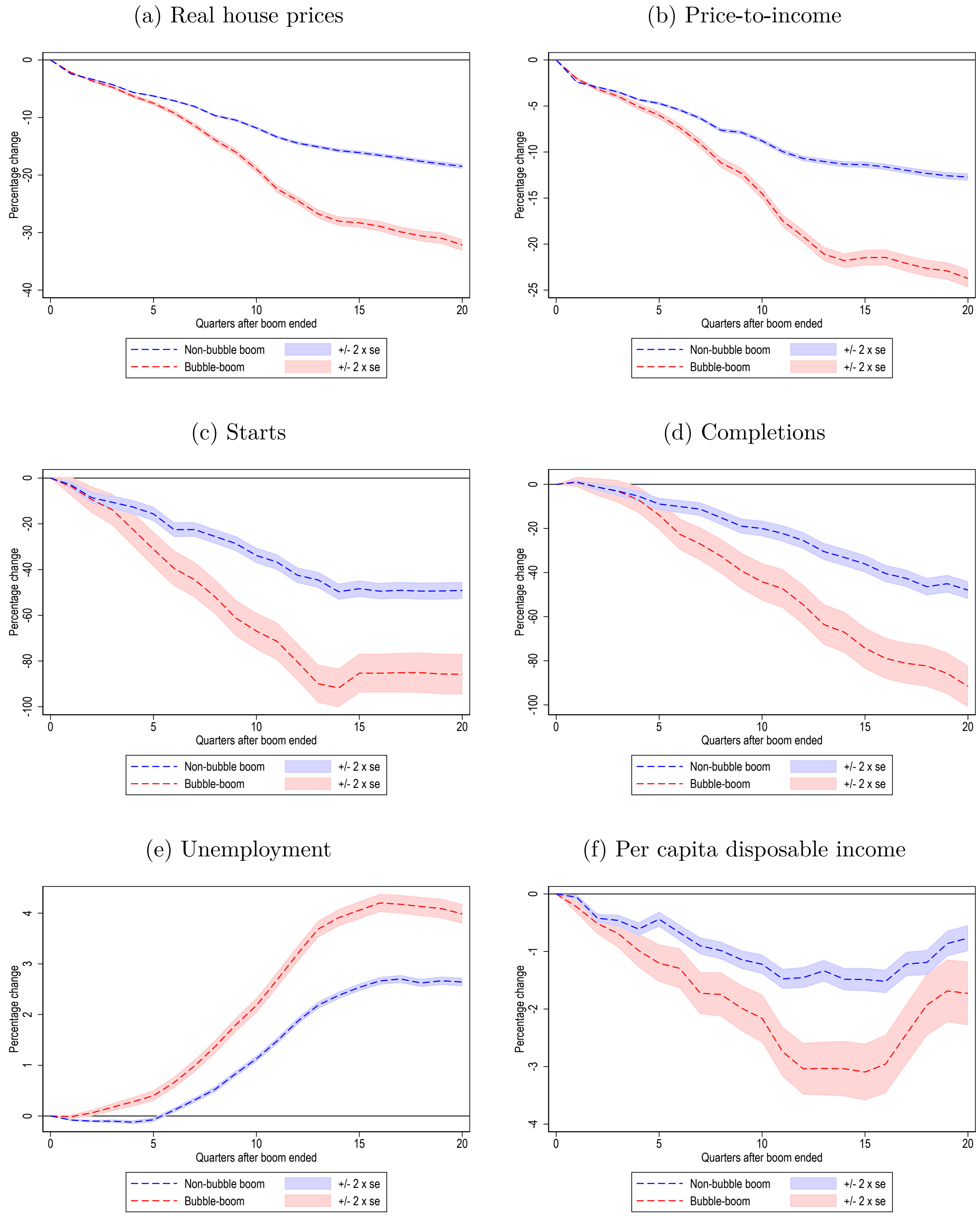
Finally, Panel e) in Figure 6 shows developments in the unemployment rate and Panel f) shows disposable income during a housing bust. The pattern that emerges is that unemployment rates increase during a bust, and that disposable income drops. Again, it is evident that a bubble boom is followed by a much sharper increase in unemployment and a larger drop in income than a non-bubble boom. In particular, as seen from Panel c) in Table 4, the unemployment rate is four percent higher than its peak level in the aftermath of a bubble-boom, while it is 2.6 percent above the peak level following a non-bubble boom.

Table 4: Unconditional responses at different horizons.

	Panel a: House prices				
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Bubble boom	-6.278***	-13.920***	-24.413***	-28.909***	-32.163***
	(0.206)	(0.332)	(0.442)	(0.539)	(0.616)
Non-bubble boom	-5.631***	-9.682***	-14.454***	-16.565***	-18.491***
	(0.082)	(0.132)	(0.177)	(0.216)	(0.251)
	Panel b: Housing starts:				
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Bubble boom	-22.439***	-52.006***	-80.480***	-85.329***	-85.800***
	(4.477)	(4.621)	(4.922)	(5.162)	(5.373)
Non-bubble boom	-12.626***	-25.569***	-42.500***	-49.471***	-49.139***
	(1.837)	(1.903)	(2.047)	(2.155)	(2.265)
	Panel c: Unemployment rate:				
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Bubble boom	0.281***	1.371***	3.197***	4.202***	3.985***
	(0.056)	(0.080)	(0.096)	(0.108)	(0.118)
Non-bubble boom	-0.122***	0.528***	1.866***	2.664***	2.642***
	(0.023)	(0.033)	(0.040)	(0.046)	(0.051)

Note: This table shows unconditional responses in real house prices (Panel a), housing starts (Panel b), and unemployment (Panel c) for some selected quarters following the peak of a non-bubble boom versus a bubble boom. The responses are normalized relative to the values the variables took at the peak of the boom. The asterisks denote significance levels: * = 10%, ** = 5% and *** = 1%. Standard errors in parenthesis below the point estimates.

Figure 6: Unconditional paths



Note: The figure shows unconditional responses in real house prices (upper left panel), price-to-income (upper right panel), housing starts (middle left panel), housing completions (middle right panel), unemployment (lower left panel), and per capita disposable income (lower right panel) in the quarters following the peak of a non-bubble boom (blue) versus a bubble-driven boom (red). The fans show 95% confidence intervals. The responses are normalized relative to the values the variables took at the peak of the boom.

4.2 Conditional cumulative paths in housing busts

Several factors may influence the housing market and the local macroeconomy in a housing bust. For this reason, we calculate conditional paths for the cumulative percentage change in housing and macro variables by controlling for key determinants. We consider the following conditional local-projection specification:

$$y_{i,t+h} - y_{i,t} = \alpha_i + \beta_{j,t} + \theta^{NBB} D_{i,t}^{\text{NBB}} + \theta^{BB} D_{i,t}^{\text{BB}} + \boldsymbol{\Gamma}' \boldsymbol{W}_{i,t} + \varepsilon_{i,t}$$

Again, y is a list of variables of interest:

$$\begin{aligned} y \in \{&\text{Real house prices}, \text{House prices-to-income}, \text{Housing starts}, \\ &\text{Housing completions}, \text{Household income}, \text{Unemployment rate}\} \end{aligned}$$

D^{NBB} is a dummy variable that equals one at the peak of a non-bubble boom, and zero otherwise, while D^{BB} is a dummy variable equal to one at the peak of a bubble boom, and zero otherwise. We let i denote county, t is time (year-by-quarter), and h is the horizon over which we calculate the conditional path of the variables in y. This specification controls for county-fixed effects, α_i, and a vector of lagged control variables $\boldsymbol{W}_{i,t}$, including four lags of house price growth,[9], four lags of the growth in housing starts,[10], four lags of growth in household income, four lags of the level of the unemployment rate, and four lags of population growth. In addition, we control for the lagged value of the Herfindahl index of banking concentration from Acolin et al. (2021), as well as the cumulative change in house prices over the boom under consideration.

The key parameters of interest are the estimated boom-type effects, θ^{BB} and θ^{NBB}, which represent the conditional path for the cumulative response of each variable in the

[9]In the model for the house price-to-income ratio, this is replaced by four lags of the growth on this ratio.

[10]In the specification for permits, this variable is replaced by four lags of growth in housing completions.

aftermath of a bubble boom and a non-bubble boom, respectively.

Figure 7 presents our conditional paths following the bust of a non-bubble boom versus a bubble boom. Similar to the unconditional path for the cumulative responses, the conditional responses reveal that a bubble boom is associated with a sharper decline in real house prices and in the price-to-income ratio (see Panel a) and Panel b). As seen from Panel a) in Table 5, the conditional response path suggests that real house prices are 22 percent below their peak-level five years after a bubble-boom. For a non-bubble boom, real house prices are 9.5 percent lower than their pre-preak level after a non-bubble boom.

Panel c) and Pancel d) in Figure 7 show that construction activity falls after the peak of a both boom types, but that there is a more marked fall in the aftermath of a bubble-driven boom. In particular, as can be seen from Panel b) in Table 5, the cumulative drop in housing starts relative to the peak-level after a bubble-boom is 43 percent. In comparison, the same number is 24 percent after a non-bubble boom.

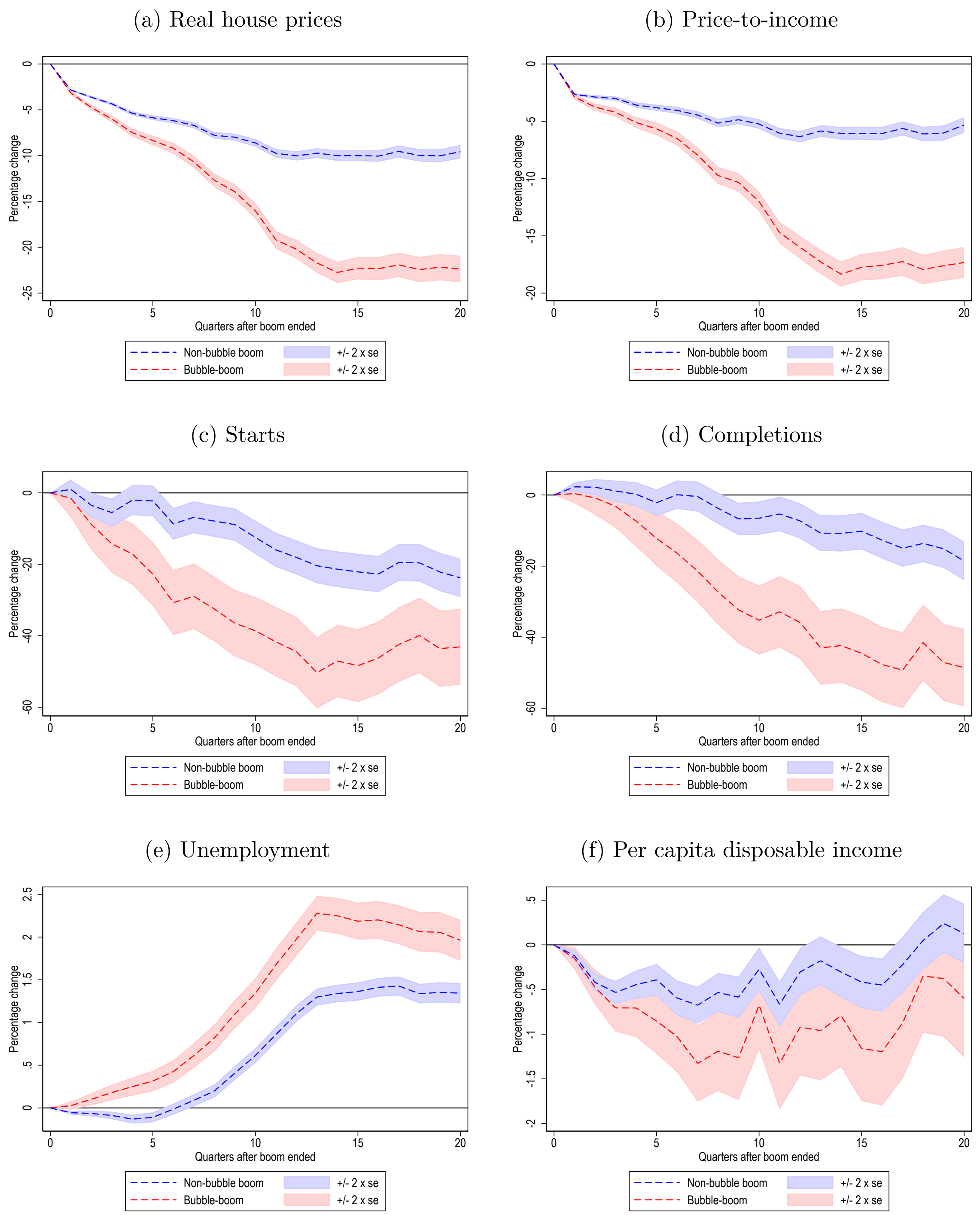
Finally, we find that the peak of a boom is associated with an increase in the unemployment rate (Panel e) in Figure 7) and a fall in income (Panel f) in Figure 7). Although the effects are less precisely estimated in the conditional paths – in particular for income – it is evident that the local macro variables respond more following a bubble boom than following a non-bubble boom. By inspecting Panel c) in Table 5, we see that, five years after the peak of a bubble boom, the unemployment rate is almost 2 percentage points higher than its peak level. Following a non-bubble boom, the unemployment rate is 1.3 percent higher than its peak level after five years.

Table 5: Conditional responses at different horizons.

	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Panel a: House prices					
Bubble boom	-7.493***	-12.684***	-20.213***	-22.324***	-22.375***
	(0.270)	(0.447)	(0.621)	(0.775)	(0.889)
Non-bubble boom	-5.382***	-7.779***	-10.028***	-10.049***	-9.567***
	(0.131)	(0.216)	(0.303)	(0.380)	(0.446)
Panel b: Housing starts:					
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Bubble boom	-17.103***	-32.505***	-44.438***	-46.231***	-43.106***
	(5.272)	(5.514)	(5.922)	(6.223)	(6.475)
Non-bubble boom	-2.029	-7.908***	-18.062***	-22.725***	-23.793***
	(2.556)	(2.683)	(2.913)	(3.074)	(3.266)
Panel c: Unemployment rate:					
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
Bubble boom	0.250***	0.818***	1.975***	2.201***	1.962***
	(0.065)	(0.095)	(0.119)	(0.135)	(0.146)
Non-bubble boom	-0.131***	0.198***	1.104***	1.412***	1.343***
	(0.031)	(0.046)	(0.058)	(0.066)	(0.073)

Note: This table shows conditional responses in real house prices (Panel a), housing starts (Panel b), and unemployment (Panel c) for some selected quarters following the peak of a non-bubble boom versus a bubble-driven boom. The responses are normalized relative to the values the variables took at the peak of the boom. The asterisks denote significance levels: * = 10%, ** = 5% and *** = 1%. Standard errors in parenthesis below the point estimates.

Figure 7: Conditional paths



Note: The figure shows conditional responses in real house prices (upper left panel), price-to-income (upper right panel), housing starts (middle left panel), housing completions (middle right panel), unemployment (lower left panel), and per capita disposable income (lower right panel) in the quarters following the peak of a non-bubble boom (blue) versus a bubble-driven boom (red). The fans show 95% confidence intervals. The responses are normalized relative to the values the variables took at the peak of the boom.

5 Conclusion and Policy Implications

In this paper we ask whether a house price bust leaves economic scars and if so, how persistent and significant these scars are. We start by dating local housing cycles in 3,089 US counties and county-equivalents over the period 1980q1–2019q4 using the Bry and Boschan (1971) and Harding and Pagan (2002) algorithm for detecting turning points. We then identify counties and time periods in which the house price growth was explosive, and classify these counties as being in bubble booms in certain time periods. In contrast, we use the term non-bubble booms for counties and time periods in which the house price growth was less strong.

We demonstrate that there is scar formation after the bust of a bubble boom. Conditioning on a set of factors, including county-fixed effects, our results show that house price reductions are larger and macro aggregate responses are stronger after the bust of a bubble boom. In particular, areas that experience a housing bubble bust are areas in which, subsequently, there are stronger and longer increases in unemployment and decreases in household income.

We find that busts are shorter and have a smaller price change in absolute terms than booms do. However, we document that there are substantial negative economic implications of busts, and show that the implications are more substantial after the bust of a bubble boom compared to the bust of a non-bubble boom.

Most booms, however, are non-bubble booms and they are less harmful in real economic terms. Unfortunately, the bubble booms are also often observed in areas with large populations, which implies that a large number of households nevertheless is affected by the economic consequences of a bubble.

We cannot prove causation so we are cautious in our policy implications. However, we do find a clear association between boom type and economic consequences, so a prudent approach would entail seeking to avoid the build-up of bubble booms. It is not altogether clear what recipe to follow in order to avoid having a non-bubble boom turn into a bubble boom, but we can philosophize over candidate ingredients. Since we observe that bubble booms occur more frequently when there is easy access to credit, we interpret this finding as offering supporting evidence for the notion that preventive action in the form of macroprudential regulation is a policy candidate. Moreover, we see an association between inelastic housing supply and bubble booms. Thus, intuition suggests that housing construction could help reduce the probability of a bubble boom and thus constitute a preemptive measure. Since we know that an increase in supply reduces house prices, a supply side policy would make home purchases more affordable. Construction could also help facilitate agglomeration effects. Policies focusing attention on making the supply side more elastic could thus have triple dividends.

Potentially, since scars involve loss of real output, the benefits might be large. We observe from Figure 7 that a conservative lower bound of the difference between bubble booms and non-bubble booms is at least half a percentage point of the unemployment rate over five years. Thus, making sure that a non-bubble boom does not turn into a bubble-boom could save a county from an accumulated loss of 2.5 percent of total number of hours worked. Figure 5 shows that almost 35 percent of the U.S. population has lived in a bubble. If that implies that 35 percent of the labor force was living in a bubble, a successful national policy designed to prevent a non-bubble boom from becoming a bubble boom would save the economy from a loss of 0.9 percent of total number of hours worked. Applying Okun's Law, using the national coefficient of -2.03 as estimated by Guisinger et al. (2018), this translates into saving a loss of 1.8 percent of GDP.

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A Bubble detection

A.1 Theoretical motivation

If we look at housing as any other asset, then standard asset pricing theory suggests that the current value of the asset (the house) should be equal to the expected discounted stream of dividends. This framework is similar to a standard present value model (see e.g. Gordon and Shapiro (1956) and Blanchard and Watson (1982)). Clayton (1996) argues that this valuation method applies for housing in a similar fashion.

In the housing context, the alternative return is the imputed rent, i.e. what an owner-occupier foregoes when they live in the house instead of renting it out to a tenant. Asset pricing theory therefore suggests that the price of a house at time t is given by:

$$PH_t = \mathbb{E}_t \left(\frac{PH_{t+1} + R_{t+1}}{1+r} \right) \ , \tag{1}$$

in which $\mathbb{E}_t$ is an expectation operator, PH_t denotes house price, R_t is the imputed rent, and r is a risk-free discount rate. This equation simply states that the price of a house today is equal to the discounted sum of changes in the price of that house, i.e. the capital gains, and the value of living in the house (as measured by the alternative cost, i.e. the imputed rent). As shown in Campbell and Shiller (1987), adding an explosive bubble component and solving the infinite geometric sequence yields:

$$PH_t - \frac{1}{r}R_t = \frac{1+r}{r^2}\mu + B_t \ , \tag{2}$$

in which B_t is an explosive bubble component with $B_t = (1+r)^t c_t$ and $c_t = \mathbb{E}_t c_{t+1}$, as long as $r > 0$. This also demonstrated in greater detail below.

Thus, in the absence of explosivity ($B_t = 0$), the asset pricing model implies that house prices should have a unit root, and that house prices and rents are cointegrated.[11] That said, any explosive behavior in PH_t suggests that $B_t \neq 0$, i.e. that there is an explosive bubble component that affects house prices. This will also be the framework that we will use when testing for rational bubbles in disaggregated US housing markets. The implication is that a hypothesis of a rational bubble is rejected when house prices are integrated of the first order. However, if house prices has an explosive root, the asset pricing theory would suggest that there is a rational bubble (conditional on the rents following an I(1) process). Clearly, few markets are characterized by systematic bubble behavior, and we would expect bubbles to bust, and possible to re-arrive.

Equation (1) may easily be solved by forward recursive substitution to yield:

$$PH_t = \mathbb{E}_t\left[\sum_{i=1}^{j}\left(\frac{1}{1+r}\right)^i R_{t+i} + \left(\frac{1}{1+r}\right)^j PH_{t+j}\right] \tag{3}$$

The transversality condition (TVC) that rules out explosive behavior is given by:

$$\lim_{j\to\infty}\left(\frac{1}{1+r}\right)^j PH_{t+j} < \infty \tag{4}$$

[11] With time-varying risk-free rates, house prices, rents, and the risk-free rate should be cointegrated. That said, it seems relatively uncontroversial to assume that the risk-free rate follows an I(0)-process, which implies that it will not help for cointegration.

Imposing the TVC, the unique solution to the difference equation in (3) is given as:

$$PH_t = \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i R_{t+i} \right] \tag{5}$$

showing that the value of a house today, PH_t is equal to the expected discounted value of all future rents, i.e. the pay-off stream in the infinite future. The expression in (5) may be thought of as a fundamental housing price according to asset pricing theory. It is important to notice that the TVC rules out explosivity and ensures a unique solution to the difference equation.

If we relax the TVC, it can be shown that the solution to the difference equation in (3) is given by (see Sargent (1987) and LeRoy (2004)):

$$PH_t = \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i R_{t+i} \right] + B_t \tag{6}$$

in which B_t is an explosive bubble component with $B_t = (1+r)^t c_t$ and $c_t = \mathbb{E}_t c_{t+1}$, as long as $r > 0$. Campbell and Shiller (1987) have shown that (6) may alternatively be expressed as:

$$PH_t - \frac{1}{r} R_t = \frac{1+r}{r} \mathbb{E}_t \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i \Delta R_{t+i} \right] + B_t \tag{7}$$

If the fundamentals (the rents) follow a random walk process with drift with a mean of μ, then:

$$\Delta R_t = \mu + \varepsilon_t \tag{8}$$

with $\varepsilon_t \sim IIN(0, \sigma^2)$. Thus, $\mathbb{E}_t \Delta R_t = \mu$, which means that (7) may be written as:

$$PH_t - \frac{1}{r} R_t = \frac{1+r}{r} \left[\sum_{i=1}^{\infty} \left(\frac{1}{1+r} \right)^i \mu \right] + B_t \tag{9}$$

Solving the infinite geometric sequence, we find:

$$PH_t - \frac{1}{r}R_t = \frac{1+r}{r^2}\mu + B_t$$

A.2 Econometric approach

Consider the following generalized ADF-regression model:

$$\Delta X_t = \mu_{r_1,r_2} + \rho_{r_1,r_2} X_{t-1} + \sum_{j=1}^{p} \gamma_{r_1,r_2} \Delta X_{t-j} + \varepsilon_t,\ \varepsilon_t \sim IIN(0, \sigma^2_{r_1,r_2}) \tag{10}$$

in which $r_1 = \frac{T_1}{T}$ and $r_2 = \frac{T_2}{T}$, with T_1, T_2 and T denoting the sample starting point, end point and the total number of observations, respectively. When $T_1 = 0$ and $T_2 = T$, the model is similar to a standard ADF-regression model. What we are interested in testing is the hypothesis that $\rho_{r_1,r_2} = 0$, i.e., $X_t \sim I(1)$, against the alternative hypothesis that $\rho_{r_1,r_2} > 0$, i.e., X_t contains an explosive root.

We calculate the generalized sup-ADF statistic for each of the counties in our sample. The GSADF-statistic takes the following form:

$$GSADF = \underset{r_1 \in [0, r_2 - \tilde{r}], r_2 \in [\tilde{r}, 1]}{sup} ADF_{r_1}^{r_2}. \tag{11}$$

in which $ADF_{r_1}^{r_2} = \frac{\hat{\rho}_{i,r_1,r_2}}{se\left(\hat{\rho}_{i,r_1,r_2}\right)}$, and $\tilde{r} = \frac{\tilde{T}}{T}$ with $\tilde{T}$ denoting the minimum sample size. The GSADF statistic has a non-standard limiting distribution that is skewed to the left under the null of non-stationarity. Moreover, the distribution depends on both r_2 and nuisance parameters. Critical values may, however, be simulated using a Monte Carlo simulation.[12] A GSADF statistic that exceeds its critical value, for a given significance level, constitutes evidence of at least one bubble in the sample period.

[12] We use the Matlab program accompanying Phillips et al. (2015b) to simulate consistent finite sample critical values.

Conditional on the detection of explosive (i.e., bubble) behavior, we date-stamp the start and end point of the bubble(s). Consider the case in which we keep the sample end point fixed, i.e., $r_2 = \bar{r}_2 \geq \tilde{r}$, and consider the backward sup-ADF (BSADF) statistic (Phillips et al. (2015a)):

$$BSADF(r_2 = \bar{r}_2) = \underset{r_1 \in [0, \bar{r}_2 - \tilde{r}]}{sup} ADF_{r_1}^{r_2 = \bar{r}_2} \tag{12}$$

By (forward) recursively changing $\bar{r}_2$, we obtain a time series for the BSADF statistic. Comparing this to the relevant critical values, $CV\,(\alpha)_{r_1}^{r_2}$, we can determine for what periods there is evidence of explosive behavior.

The starting point of a bubble is defined as the first period for which the BSADF statistic exceeds the critical value, while the end point is defined as the first period after the start of the bubble for which the BSADF statistic is below the critical value.

B Bubble drivers

Table 6 reports results from a logit-specification in which the dependent variable is a binary variable that indicates whether a given county experiences a bubble in a given quarter. The set of explanatory variables include the county-level measure of land unavailability of Lutz and Sand (2019), which extends the index of Saiz (2010), the Herfindahl index of banking concentration in Acolin et al. (2021), log of population, income growth, and the Rice and Strahan (2010) index of interstate branching deregulation. We follow Favara and Imbs (2015) and reverse the index, so that a higher value implies a more deregulated banking sector.

Table 6: Logit regression. Bubble (=1) or no bubble as dependent variable

	I	II	III
Land unav.	0.691***	0.823***	0.810***
	(0.041)	(0.044)	(0.044)
Bank concentration		-2.859***	-2.330***
		(0.161)	(0.163)
Pop.sh 25-44			0.037***
			(0.003)
Income			1.618**
			(0.632)
Observations	354496	344464	338474
Year-by-quarter FE	NO	NO	YES

Note: The table shows results from different logit specifications. The dependent variable is a dummy variable taking the value one if there is evidence of a bubble, and a value of zero otherwise. The asterisks denote significance levels: * = 10%, ** = 5% and *** = 1%. Standard errors in parenthesis below the point estimates.