Changing supply elasticities and regional housing booms

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Abstract

Recent developments in US house prices mirror those of the 1996-2006 boom, but the recovery in construction activity has been rather weak. Using data for 254 US metropolitan areas, we estimate housing supply elasticities to have fallen markedly in recent years. Housing supply elasticities have declined more in areas that experienced the sharpest housing busts and in areas in which land-use regulation has tightened the most. A lowering of the housing supply elasticity implies a strengthened price responsiveness to a demand shock, whereas quantity should react less. We investigate this empirically through a monetary policy shock that raises housing demand. Our results show that the effect of a monetary policy shock on real house prices – after three years – has almost doubled relative to the previous boom. At the same time, we document that building permits respond less in response to a monetary policy shock today.

Keywords: House prices; Heterogeneity; Housing supply elasticities; Monetary policy

JEL classification: C23, E32, E52, R31

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1 Introduction

The recovery in the US housing market since the trough in 2011 has left nominal house prices in 2017 almost ten percent above the pre-recession peak. At the same time, construction activity has remained low and is considerably weaker than during the previous housing boom. This may be suggestive of a decline in the housing supply elasticity. Against this background, we ask whether local housing supply elasticities have changed since the previous housing boom. We document a substantial nation-wide decline in supply elasticities, although we find regional differences in the extent of the decline. This motivates us to further explore the following questions: (i) To what extent does the decline in housing supply elasticities impact house price volatility and the transmission of demand shocks?; and (ii) What factors have contributed to changing housing supply elasticities?

We consider a panel of 254 US Metropolitan Statistical Areas (MSAs). Our quarterly data set covers the previous boom (1996–2006) and the recent recovery period (2012–2017). For each of these sub-samples, we use panel data methods to estimate area-specific housing supply elasticities, taking housing permits as the dependent variable. The housing supply elasticity is computed as the coefficient on house prices, controlling for several other area-specific variables that may affect housing supply. This exercise is non-trivial for at least two reasons. First, there are large regional variations. Second, there is likely reverse causality between construction activity and house prices.

With respect to regional variations, theory suggests that local differences in topography and regulation should impact housing supply elasticities. We take this into account by interacting house prices with the index of topographical constraints calculated by Saiz (2010) and with the index of regulatory restrictions from Gyourko et al. (2008). To deal with reverse causality, we use an instrumental variable (IV) approach. Our identification problem requires separating housing demand from housing supply. We consider two instruments for house prices that we argue lead to shifts in housing demand, but that do not shift housing supply. The first instrument is the log of real personal disposable income. Income is one of the main determinants of housing and consumption demand in standard macro and housing models (Dougherty and Van Order 1982, Buckley and Ermisch 1983, Meen 1990, Muellbauer and Murphy 1997, Meen 2001, 2002, Duca et al. 2011), but typically does not affect housing supply directly. Thus, from a theoretical point of view, this instrument should satisfy both the relevance and the exogeneity conditions. The second instrument exploits variation in crime rates across MSAs and over time, compiled by
the Federal Bureau of Investigation (FBI). Given the significant negative impact that crime can have on society, crime can be viewed as a negative amenity (Pope and Pope 2012). Accordingly, crime rates should capture exogenous variations in (negative) amenities that drive house price changes both across and within MSAs over time.

Our IV estimates strongly suggest that housing supply elasticities are markedly lower today than during the previous housing boom. A direct implication of lower supply elasticities is that a given change in demand should have a stronger effect on house prices. For this reason, we proceed to estimate the effect of an exogenous monetary policy shock on house prices. To measure monetary policy shocks we follow a recent strand of the literature that resorts to high-frequency data to identify unexpected changes in the Fed policy rate (see, for instance, Gürkaynak et al. 2005, Gertler and Karadi 2015, Nakamura and Steinsson 2018). This high-frequency identified (HFI) approach isolates news about future policy actions that are orthogonal to changes in economic and financial variables. We take unexpected changes in interest rates for 3-month ahead contracts on Fed funds futures in a 30-minute window surrounding Federal Open Market Committee (FOMC) meetings. The identification assumption is that these surprises – changes in the futures rates – within that window can only arise from news about monetary policy, given that all publicly available information is priced into financial markets at the beginning of that narrow window. We estimate impulse responses with an instrumental variable local projection approach, in which the monetary policy shocks are used as instruments for the one-year Treasury bill yield (Jordà et al. 2015, Ramey 2016, Stock and Watson 2018).

Our results point to considerable heterogeneity in responses across local housing markets. We estimate a substantially larger response of house prices to a monetary policy shock in supply-inelastic markets than in areas with an elastic supply. This holds true for both boom periods. We also document a substantial increase in the responsiveness of house prices to a monetary policy shock in recent years. In particular, our results suggest that for a metro area with a median housing supply elasticity, an exogenous monetary policy shock that lowers the interest rate by one percentage point led to an increase in real house prices of about four percent after three years during the 1996-2006 boom. For the 2012-2017 recovery, the estimated response is seven percent. Consistent with this, we find that building permits today increase about two percentage points less in response to the monetary policy shock. Thus, our main finding of a decline in the supply elasticity implies that the sensitivity of house prices to housing demand shocks has increased considerably over the last years.
Moreover, we find that there are regional differences in how much elasticities have declined. Theoretically, there are several reasons why housing supply elasticities may change over time (Green et al. 2005), including changes in regulation, demographics, and in expectations about future demand and house prices. Herkenhoff et al. (2018) have shown that there have been substantial changes in land-use policy in most US states over time. Although they find the largest percentage increase in land-use regulation over 1970-1980, they also document a substantial tightening across states of around 18 percent between 1990 and 2014. Using their measure of time-varying land-use policy, we find that elasticities have declined the most in areas where regulation has tightened more. Our results also suggest a larger decline in elasticities in the areas that experienced the largest decline in house prices at the end of the previous decade. We interpret this as evidence that the fear of a new bust has led developers to be less price responsive than before. The irony of this behavior is that it may have paved the way for a new housing boom where house prices are more responsive to fluctuations in demand.

The results in this paper relate to several strands of the literature. First, a vast number of papers have emphasized local differences in housing supply elasticities as a central driver of cross-sectional variation in US 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). This literature has used time-invariant measures of housing supply elasticities to explore cross-sectional variation over the course of a boom-bust cycle, finding that supply-inelastic areas experience stronger house price booms than areas with an elastic housing supply. Our results are consistent with this view, but go a step further by showing that housing supply elasticities may change over time even within the same local market. Similarly to the cross-sectional studies, this entails greater house price volatility.

Second, there is a growing literature looking at the nexus between monetary policy and house prices (see e.g., Del Negro and Otron 2007, Iacoviello 2005, Jarocinski and Smets 2008, Jordà et al. 2015, Williams 2011, 2015). These papers, however, focus on the aggregate effects on house prices, therefore masking the substantial heterogeneity across regional US housing markets. We add to this literature by documenting non-trivial heterogeneous responses of regional house prices to a common monetary policy shock for both the 1996-2006 boom and for the 2012-2017 boom. Furthermore, we document sizeable time-variation in housing supply elasticities, which makes house prices even more responsive to monetary policy shocks today. In a related study, Paul (2018) focuses on the time-varying effects of monetary policy. He finds
that the transmission of monetary policy to financial variables, such as stock prices and house prices, has become stronger over time. Our work can provide an economic interpretation of these findings: an aggregate shock that raises housing demand is absorbed mostly by house prices rather than through an increase in quantity.

Our paper is also related to the more recent literature on changes in regulation over time. Herkenhoff et al. (2018) estimates land-use regulations at the state level to have generally tightened over 1950-2014. This is particularly true for states, such as California and New York, where house prices have edged up considerably. They argue that the stronger tightening in highly productive states has restricted the available land for housing and commercial use, raised house prices, reduced capital and labor reallocation, resulting in a substantial decrease in output and productivity. In a similar vein, Ganong and Shoag (2017) find that the decline in income convergence and migration rates across states since the 1980s can – at least partly – be attributed to tight land-use regulation and rising house prices in high-income states. Other papers, using cross-sectional data, point in the same direction of low supply-elasticity areas generating output costs. Hsieh and Moretti (2018) document that stringent housing restrictions in highly-productive areas, such as New York and San Francisco Bay Area, result in significant output costs in the form of spatial mis-allocation of labor across US cities. In addition, Glaeser and Gyourko (2018) posit that highly regulated areas are characterized by higher house prices and smaller population growth relative to the level of demand. Regulation of housing creates an implicit tax on development that is higher in several areas than any reasonable externalities associated with new construction. They suggest that this phenomenon, which leads to overall welfare losses, result from revealed preferences of existing homeowners. Our results relate to this literature by documenting that the tightening of land-use regulation has resulted in a lower supply elasticity, which in turn amplifies the responsiveness of house prices to demand shocks.

Our results are robust along several dimensions. In particular, we show that the decline in the housing supply elasticity is evident when (i) using total crime rates (sum of property crime and violent crime) as the crime variable instrument; (ii) controlling for mortgage originations to assess the impact on the housing supply response of subdued credit developments since the Great Recession; (iii) using permit intensity as the dependent variable to allow the dynamics in permits to differ according to the existing stock of houses; and (iv) replacing the measures of topographical and regulatory constraints with a summary measure of supply restrictions to account for the possibility that these two indicators might be correlated. We also show that the
finding of an increasing house price response to a monetary policy shock is robust along several dimensions of the high-frequency shock.

The rest of the paper proceeds as follows. In the next section, we compare the 2000’s housing boom with the ongoing boom. In Section 3 we describe the data and some stylized facts about the US housing cycle over the past 20 years. We discuss our econometric approach and estimate the housing supply elasticities in Section 4. In Section 5 we present a simple supply-demand model with durable housing to illustrate the implications for housing market dynamics from having supply elasticities varying over time. We then proceed to analyze empirically the effects of monetary policy shocks on house prices over the two recent housing booms. In Section 6 we explore the factors that have led to the decline in the elasticities. In Section 7 we carry out several robustness checks, and offer alternative explanations of the disconnect between house prices and permits. Section 8 concludes the paper.

2 The 1996-2006 boom versus the 2012-2017 recovery

At the national level, real US house prices have increased more than 26 percent since the beginning of the housing recovery of mid-2012. The dynamics of real house prices during the recovery is similar to that of the previous housing boom. This is illustrated in the upper left panel of Figure 1, where we plot real house prices for both the 1996-2006 boom (red line) and the 2012-2017 recovery (blue line). We have scaled the price index such that it takes a value of 100 at the beginning of each period. The horizontal axis shows quarters around the beginning of the two booms, while the vertical line at zero is the starting point of both booms. In the upper right panel we perform the same exercise when deflating house prices by per capita income. Remarkably, the current boom looks far stronger relative to income than the previous boom.\footnote{The strong developments in house prices relative to income per capita can be partially attributed to the subdued income and consumption growth, as illustrated in Figure B.1 in Appendix B.}

Despite similar – or even stronger – developments in house prices, housing supply has grown substantially less during the current boom (lower panel of Figure 1). While the cumulative increases in building permits and housing starts were roughly 60 percent over the first 5-6 years of the previous boom, the cumulative increase between 2012 and 2017 has been around 16 percent.

Housing is characterized by important differences across regional markets (Ferreira and Gyourko 2012). Aggregate data may therefore mask significant heterogeneity at the local level.
We use MSA-level data and break the sample into quartiles of the cumulative house price change between 1996 and 2006. We define Low HPI MSAs as the areas belonging to the first quartile, while High HPI MSAs refers to the fourth quartile. We then compare the evolution of house prices relative to income and permits across the two booms (Figure 2). The red lines illustrate developments for the High HPI group, and green lines for the Low HPI group. To distinguish between the two periods, we use dotted lines for 1996-2006 and solid lines for 2012-2017.

Mirroring the aggregate picture, house prices relative to income per capita have been stronger during the current boom for both groups. At the same time, we notice that this ratio has been particularly strong for the High HPI MSAs. In contrast, permits have progressed at a very sluggish pace during the current recovery, with a slightly weaker expansion in High HPI MSAs.

Figure 1: House price developments across booms

Notes: The figure shows developments in real house prices, house prices relative to income per capita, building permits, and housing starts during 1996q4–2006q4 (red solid line) and 2012q3–2017q4 (blue line with markers). The series are scaled such that they take a value of 100 at the beginning of both periods. The horizontal axis shows quarters around the beginning of the two booms, and the vertical line at zero is the starting point of both booms.

One possible explanation for the apparent disconnect between house price developments and construction activity in the recent boom is that housing supply elasticities have declined over time. A lower housing supply elasticity is consistent with weaker developments in construction, and strong increases in house prices, even though demand shifters have been weak. This is because a larger part of the adjustment is absorbed by prices when supply is rigid. The marked differences in housing market developments across metropolitan areas highlight the importance
of studying regional markets. The use of disaggregated data follows the spirit of the most recent housing market literature, which tends to look at the housing market as a collection of several markets that differ not only by geography but also by other attributes – see Piazzesi and Schneider (2016) for a survey.

Figure 2: Housing indicators for MSA groups across housing booms

Notes: The figure shows developments in house prices relative to income per capita and permits for 1996q4–2006q4 (dotted lines) and 2012q3–2017q4 (solid lines). Low HPI MSAs (green) are the areas that recorded the smallest cumulative growth in house prices over 1996-2006, as measured by the first quartile, whereas High HPI MSAs (red) refers to the fourth quartile. The series are scaled such that they take a value of 100 at the beginning of each period. The horizontal axis shows quarters around the beginning of the two booms, and the vertical line at zero is the starting point of both booms.

3 Data and housing market cycles

3.1 Data

We use quarterly data for a panel of 254 MSAs between 1996 and 2017. The sample covers more than 80 percent of US income and population. Our MSA definitions follow the new delineations issued by the Office of Management and Budget (OMB), based on the 2010 Census.

The MSA data on housing supply encompass building permits, housing starts, as well as the housing stock. In addition, we have data on house prices, and controls for macroeconomic, financial and socio-demographic conditions: personal disposable income, unemployment rates, mortgage originations, population, crime rates, dependency ratio (ratio of people younger than 15 or older than 64 relative to those aged 15-64), and the fraction of Blacks and Hispanics relative to the total population. We also use wages and salaries in the construction sector to proxy builders’ costs, available only at the state level. We deflate all nominal macroeconomic series with MSA-level consumer price index (CPI). The MSA data have been provided by Moody’s Analytics, with the original sources of the data coming mainly from the Census Bureau, Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), and Federal Housing Finance Agency (FHFA). The exception is the crimes rates, which we compiled from publicly available
reports from the FBI. A full list of variables and sources are provided in Appendix A, and Table B.1 in Appendix B shows descriptive statistics.

We control for regional differences in supply restrictions with two indices. First, we measure topographical supply restrictions with the UNAVAL index by Saiz (2010), which measures MSA-level geographical land availability constraints. Saiz (2010) uses GIS and satellite information over 1970-2000 to calculate the share of land in a 50 kilometer radius of the MSA main city center that is covered by water, or where the land has a slope exceeding 15 degrees. These areas are seen as severely constrained for residential construction. Saiz (2010) finds that metropolitan areas that are more inelastic are typically more land constrained. Second, we measure regulatory constraints with the Wharton Regulatory Land Use Index (WRLURI) from Gyourko et al. (2008). WRLURI measures the stringency of local zoning laws, i.e. the time and financial cost of acquiring building permits and constructing a new home. It is based on a nation-wide survey in 2005, and on a separate study of state executive, legislative and judicial activity.\textsuperscript{2}

3.2 Housing market cycles

House prices have gone through a strong boom-bust cycle over the past 20 years. Although house prices tend to vary more locally than nationally, it is possible to identify periods when there is sufficient co-movement across MSAs to recognize a pattern in national house prices.

To date booms and busts over the housing cycle, we analyze peaks and troughs in real house prices at the median.\textsuperscript{3} For ease of illustration, we plot the national house price index, together with the median, the 10\textsuperscript{th} and 90\textsuperscript{th} percentiles of the house price distribution at the MSA level (Figure 3). Three phases of the housing cycle appear to show up quite clearly: a strong boom from 1996 until 2006, followed by a severe bust lasting until 2012. From 2012, a new boom (the ongoing recovery) has started. With our data set we cannot identify neither a boom nor a bust over 1986-1996, as in Glaeser et al. (2008). Instead, we observe significant heterogeneity across MSAs over this period; the MSAs at the bottom of the house price distribution recorded a steady increase in house prices, while the MSAs at the top saw the opposite dynamics. This

\textsuperscript{2}This index is based on 11 sub-indices measuring different types of complications and regulations in the process of getting a building permit. WRLURI is available at a town (or city) level, which we have aggregated to the MSA level using the sample probability weights of Gyourko et al. (2008).

\textsuperscript{3}Given that our sample of 254 MSAs includes some areas with large variations in prices, we look at the median, instead of the mean as in Glaeser et al. (2008). The median minimizes the effect that outliers have on dating the housing cycles. We track the evolution in the median real house price index over time, which does not mean necessarily that we track the same MSA over time. Alternative approaches to ours of defining a common housing cycle range from the identification of local house price booms and busts (Ferreira and Gyourko 2011) to clustering MSAs with similar cyclical patterns (Hernández-Murillo et al. 2017).
heterogeneity dissipates once we look at the median, or at the national index, with real house prices remaining relatively stable over that ten-year period. For this reason, we will abstract from this period throughout the rest of the paper.

Figure 3: Real house price cycles

All of the MSAs experienced increasing house prices during the 1996-2006 boom, but the dispersion was quite high; house prices increased by 17 percent, on average, for the MSAs belonging to the first decile, while they increased by 93 percent for the top decile (Table 1). During the 2006-2012 bust, house prices where falling in all, but one, MSA. By the end of 2017, house prices have increased in more than 90 percent of the MSAs since the trough of 2012.

Table 1: Local house price cycles

<table>
<thead>
<tr>
<th>Cycle</th>
<th>US</th>
<th>median</th>
<th>p10</th>
<th>p25</th>
<th>p75</th>
<th>p90</th>
<th>N</th>
<th>&gt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996-2006</td>
<td>51.5</td>
<td>32.7</td>
<td>16.6</td>
<td>22.0</td>
<td>64.4</td>
<td>93.1</td>
<td>254</td>
<td>254</td>
</tr>
<tr>
<td>2006-2012</td>
<td>-28.0</td>
<td>-21.2</td>
<td>-46.0</td>
<td>-31.7</td>
<td>-14.3</td>
<td>-10.0</td>
<td>254</td>
<td>1</td>
</tr>
<tr>
<td>2012-2017</td>
<td>23.3</td>
<td>13.3</td>
<td>1.3</td>
<td>6.2</td>
<td>27.4</td>
<td>52.2</td>
<td>254</td>
<td>237</td>
</tr>
</tbody>
</table>

Notes: Cumulative changes in real house prices for different phases of the housing cycle. The first column refers to the national index, and the following columns show points in the distribution for the MSA sample. N is the number of MSAs, while >0 counts the MSAs that recorded cumulative house price increases over each cycle.

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4In a sample of 79 MSAs, Glaeser et al. (2008) identify a national boom over 1982-1989, a subsequent bust until 1996, and a strong boom between 1996 and 2006. We get a different picture for 1986-1996, since we cover a substantially larger sample of MSAs.

5Figure B.2 in Appendix B shows Kernel densities of cumulative changes in house prices for each cycle.
4 Estimating housing supply elasticities in booms

4.1 Main specification

We now investigate whether there are signs that housing supply elasticities have changed over time in local housing markets. Our analysis is confined to the 1996-2006 housing boom and the ongoing recovery period that started in mid-2012. While housing busts are interesting to analyze, there are two main reasons why we focus on boom episodes. First, our main interest is to study the different dynamics across similar housing episodes. Second, the durability of housing entails that housing supply is rigid downwards (Glaeser and Gyourko 2005), implying that the elasticity should fall towards zero in a bust. Furthermore, since this should hold in all markets, local-specific factors, such as differences in topography and housing market regulation, should not matter for the responsiveness of housing supply during a bust.

Our point of departure to estimate local housing supply elasticities across the two housing booms is a single-equation approach in the spirit of Green et al. (2005). The authors estimate time-invariant housing supply elasticities for a sample of 45 MSA over 1979-1996, by regressing a proxy for the annual growth in the housing stock on lagged house price growth. We adjust their model in several ways. First, we use building permits as our housing supply variable to capture the immediate reaction of builders to a change in house prices. Second, given that building permits do not exhibit stochastic non-stationarities, we adopt a level specification. We follow Glaeser et al. (2008) and assume that permits depend on the price-to-cost ratio (Tobin’s Q). Due to data availability, we use wages and salaries in the construction sector as a proxy for total construction costs. Third, we directly account for geographical (Saiz 2010) and regulatory constraints (Gyourko et al. 2008) in the response of housing supply to a change in house prices.

We consider the following specification for each one of the booms:

\[
\log(H_{i,t}) = \beta \log(HPI_{i,t}) + \lambda [\log(HPI_{i,t}) \times UNAVAL_i] + \delta [\log(HPI_{i,t}) \times WRLURI_i] \\
+ \gamma X'_{i,t} + \eta_i + \zeta_t + \epsilon_{i,t}
\] (1)

where \( \log(H_{i,t}) \) denotes the log of building permits, \( \log(HPI_{i,t}) \) is the log of the FHFA house price index deflated by CPI, \( UNAVAL_i \) is the land unavailability index of Saiz (2010), \( WRLURI_i \) is the Wharton Land Use Regulatory Index (Gyourko et al. 2008), and \( X'_{i,t} \) is a vector of control

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**Footnote:** The process of building a housing unit first requires builders to apply for a permit to get their construction project approved, which can take a few months. After the approval is granted, the construction works start (housing starts). The process ends when the housing unit is occupied or available for occupancy (housing stock).
variables. We add $\eta_i$ to account for MSA-fixed effects, and $\zeta_t$ to capture time-fixed effects.

We expect $\beta$ to be positive, as builders apply for more building permits when house prices increase. In addition, the interaction terms in Eq. (1) imply that housing supply elasticities may differ across MSAs if there are differences in land availability or regulation. We expect the coefficients $\lambda$ and $\delta$ to be negative, as tighter geographical or regulatory restrictions should lead to a smaller expansion in building permits. It follows that the implied supply elasticity for a given MSA in housing boom $j$ is found by differentiating Eq. (1) with respect to house prices:

$$Elasticity_{i,j} = \beta_j + \lambda_j \times UNAVAL_i + \delta_j \times WRLURI_i$$

\[ (2) \]

### 4.2 IV identification

A potential concern with estimating Eq. (1) by OLS is the reverse causality between permits and house prices. To deal with this issue, we use an instrumental variable (IV) approach.

In particular, an instrument, $Z$, for house prices in the housing supply equation needs to shift housing demand (and thereby house prices), while at the same time be orthogonal to omitted supply factors. We thus need demand shift instruments to identify the parameters of the supply curve. More formally, the traditional IV conditions for all $i$ and $t$ need to be satisfied:

\[ Cov(Z_{i,t}, HPI_{i,t}) \neq 0 \]
\[ Cov(Z_{i,t}, \epsilon_{i,t}) = 0 \]

where Eq. 3 is the \textit{relevance} condition, stating that the external instrument $Z$ must be contemporaneously correlated with local house prices. The \textit{exogeneity} condition in Eq. 4 requires the instrument not to be contemporaneously correlated with the omitted supply factors in Eq. 1.

Our identification problem differs from other recent housing papers, where the interest is in determining how non-housing macro variables, such as labor market outcomes, respond to changes in house prices (Guren et al. 2018, Charles et al. 2018). In their context, both housing demand and housing supply shifters are relevant instruments for house prices.\footnote{In a study of the housing wealth effect on retail employment, Guren et al. (2018) instrument local house prices by taking the estimated house price sensitivity of each US city to regional house prices. The underlying assumption is that there must be substantial variation in house prices that is orthogonal to movements in local and regional retail employment. In turn, Charles et al. (2018) use an instrument for housing demand based on structural breaks in local house prices over 2000-06. Their instrument assumes that underlying fundamentals do not change abruptly, and therefore sharp breaks from the trend reflect variation that is the result of exogenous speculative activity or other housing specific forces, rather than unobserved changes in fundamental factors.}
supply shifters cannot be used as instruments, as they would not satisfy the orthogonality condition. In particular, we cannot resort to one of the most commonly used instruments for house prices, namely the housing supply elasticity calculated by Saiz (2010), see e.g., Mian et al. (2013), and Stroebel and Vavra (2018) – although not free of criticism (Davidoff 2016). The reason is that it enters the supply equation that we are interested in estimating, and because the housing supply elasticity is our main parameter of interest.

Against this background, we consider two instruments for house prices that we argue lead to shifts in housing demand (relevance), but that does not shift housing supply (exogeneity). The first instrument we use is the log of real personal disposable income. Income is one of the main determinants of housing and consumption demand in standard macro and housing models, but typically do not affect housing supply directly (Dougherty and Van Order 1982, Buckley and Ermisch 1983, Meen 1990, Muellbauer and Murphy 1997, Meen 2001, 2002, Duca et al. 2011). This instrument should thus satisfy both the relevance and exogeneity conditions.

The second instrument exploits variation in crime rates across MSAs and over time. We use data on crime rates (per 100,000 inhabitants) from the Uniform Crime Report Offenses Known to Law Enforcement data set, which is compiled by the FBI. These data provide counts of crimes reported to the police for each police agency (cities, towns, and villages), and broken down by two major types: violent crime (murder, forcible rape, robbery, and aggravated assault), and property crime (burglary, larceny theft, and motor vehicle theft). Given the significant negative impact that crime can have on society, either directly through destruction of life and of property, or indirectly through the creation of a sense of insecurity, fear and anxiety as a consequence of criminal acts, crime can be viewed as a negative amenity (Pope and Pope 2012). Accordingly, crime rates should capture the exogenous variation in (negative) amenities that drive house price changes both across and within MSAs.

The literature has found that high crime rates are strongly and negatively associated with property prices. The seminal paper by Thaler (1978) finds that an increase in property crime per capita reduces house prices in Rochester, New York. More recent papers have also found a detrimental effect of crime on property prices, such as Gibbons (2004) for London. In turn, Schwartz et al. (2003) estimates that falling crime rates were responsible for one-third of the increase in property values in New York over 1994-98. Along the same lines, but using zip code-level data, Pope and Pope (2012) estimates the elasticity of property values to the decline in crime rates over 1990-2000 to have been quite important (in the range of -0.15 to -0.35).
We choose property crime, which accounts for almost 90 percent of total crime, as our measure of crime since it is available for a larger sample of MSAs compared with violent crime. That said, we also show that none of our results are materially affected by instead using total crime as the instrument. We have an unbalanced sample over the two housing booms, although most MSAs have data for at least a handful of years within each housing boom.

To make it clear, we have three endogenous regressors, as house prices interacted with the supply restrictions \( UNAVAL \) and with \( WRLURI \) are also endogenous. To avoid falling into the ‘forbidden regression’ issue, as described in Wooldridge (2010), we also need to instrument the interaction terms with the logs of the property crime rate and disposable income interacted with the supply restrictions. We therefore have six instruments. For each boom, we estimate the following first- and second-stage regressions:

\[
W_{i,t} = \rho_1 \log(Crime_{i,t}) + \rho_2 [\log(Crime_{i,t}) \times UNAVAL_{i,t}] + \rho_3 [\log(Crime_{i,t}) \times WRLURI_{i,t}] \\
+ \omega_1 \log(Inc_{i,t}) + \omega_2 [\log(Inc_{i,t}) \times UNAVAL_{i,t}] + \omega_3 [\log(Inc_{i,t}) \times WRLURI_{i,t}] \\
+ \phi X'_{i,t} + \psi_i + \nu_t + \mu_{i,t}
\]

(5)

\[
\log(H_{i,t}) = \beta^{IV} \log(\hat{HPI}_{i,t}) + \lambda^{IV} [\log(HPI_{i,t}) \times UNAVAL_{i,t}] + \delta^{IV} [\log(HPI_{i,t}) \times WRLURI_{i,t}] \\
+ \gamma X'_{i,t} + \eta_i + \zeta_t + \epsilon_{i,t}
\]

(6)

where the dependent variable, \( W_{i,t} = \{HPI_{i,t}, HPI_{i,t} \times UNAVAL, HPI_{i,t} \times WRLURI\} \) in Eq. 5 refers to house prices, and house prices interacted with the supply restrictions. Eq. 6 is the second-stage IV regression of permits on the instrumented house price variables. To control for several possible confounders, we add a vector of local economic and socio-demographic variables, \( X'_{i,t} \), which includes the lagged dependent variable, the log of real construction wages, and its interaction with the supply restriction indices, log of population, unemployment rate, inflation rate, dependency ratio, and the fraction of Blacks and Hispanics in total population.

We assess the relevance and strength of the instruments with the weak identification F-test, including a version of the test that is robust to heteroskedasticity. We take Stock and Yogo (2005)’s critical value of 12.2 for the 5 percent relative bias to rule out the existence of a weak
IV regression results are reported in Table 2 for both the 1996-2006 boom – column (1) – and the 2012-17 boom – column (6). The first-stage F-test and robust F-test stand between 30 and 50, which is significantly above Stock and Yogo (2005)’s threshold value, suggesting that our instruments are valid and strong.8 The coefficient on house prices is highly statistically significant at conventional levels, and positive, for both housing booms. But there is a significant decline in the magnitude of the coefficient from the first to the second boom. This decline implies a weakening in the response of permits to a given change in house prices, which contrasts with the strong response during the 1996-2006 boom. Our estimates indicate that building permits increased by 2.8 percent over the short term (long-term response of 4.7 percent) for every 1 percent increase in house prices during the 1996-2006 boom, which is almost twice as large compared with the current housing recovery – a response of roughly 1.8 percent over the short term (long-term response of 2.2 percent).9

The interaction of house prices with the supply restriction variables yields the expected negative sign, i.e., the tighter the geographical and regulatory restrictions for a given house price, the smaller the expansion in building permits. The coefficient on the interaction term for UNAVAL is, however, not significant in the current boom.

We check the sensitivity of our preferred specification to: (i) using total crime rates (sum of property crime and violent crime) as the crime variable instrument; (ii) controlling for mortgage originations (the amount of new mortgage loans) to assess the impact on the housing supply response of subdued credit developments since the Great Recession; (iii) using permit intensity as the dependent variable to allow the dynamics in permits to differ according to the existing stock of houses; and (iv) replacing UNAVAL and WRLURI with a summary measure of supply restrictions, essentially the sum of these two variables standardized, to account for the possibility that these indicators might be correlated.10 Our estimated baseline coefficients remain overall

---

8 The first-stage coefficients on the instruments are highly statistically significant for both housing booms: for property crime rates we get coefficients within a range of -0.02 to -0.025 (t-stats above 2), and of around 0.3-0.4 (t-stats above 8) for income.

9 The long-term coefficient is the result of dividing its short-run coefficient by 1 minus the lagged coefficient on the dependent variable; for instance, for the 1996-2006 cycle: 4.7=2.774/(1-0.415).

10 We have run additional robustness checks by using housing starts and the housing stock as the dependent variables. Our baseline regression estimates remain qualitatively unchanged. Furthermore, in a previous version of the paper, we used the mean January temperature instead of crime rates as one of the instruments for house prices, based on the works of Glaeser and Gottlieb (2009), and Glaeser et al. (2012). January temperatures proxy housing demand as they capture the exogenous variation in amenities that lead house prices to change. We found qualitatively similar results as the baseline specification used throughout this paper. The drawback, however, is that the mean January temperature turned out to be a weaker instrument for house prices as it is only able to identify house prices in the cross-section; given the small variability over time, it is defined as monthly average temperatures in January calculated over 1941-1970. All results available upon request.
robust to the aforementioned alternative IV regressions (columns (2) to (5), and (7) to (10) of Table 2). Moreover, across all specifications we continue to observe a decline in the response of supply to house prices in the current boom.

When we add mortgage originations, our coefficient on house prices in the 2012-17 boom declines substantially and its statistical significance disappears – column (8). By contrast, the coefficient in the 1996-2006 boom remains the same as the baseline – column (3). We take this result as an indication that weak credit developments in the current boom have been an additional factor in making builders less responsive to a given change in house prices.\footnote{Although we would ideally like to control for changes in credit conditions of home builders, which can lead to a shift in the supply curve, data on credit to construction firms are not available at the MSA level. We use instead mortgage originations which should be correlated with the dynamics in credit to construction firms.}

Table 2: Regression estimates by housing boom

<table>
<thead>
<tr>
<th></th>
<th>1996-2006</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>2012-17</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
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<td>(3)</td>
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<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
<td>(10)</td>
</tr>
<tr>
<td></td>
<td>Base</td>
<td>Tot_crime</td>
<td>Mortg</td>
<td>Perm_int</td>
<td>SRI</td>
<td></td>
<td>Base</td>
<td>Tot_crime</td>
<td>Mortg</td>
<td>Perm_int</td>
</tr>
<tr>
<td>Log(HPI)</td>
<td>2.774***</td>
<td>2.261***</td>
<td>2.737***</td>
<td>2.671***</td>
<td>2.431***</td>
<td></td>
<td>1.780**</td>
<td>1.717***</td>
<td>1.065</td>
<td>1.707***</td>
</tr>
<tr>
<td></td>
<td>(0.428)</td>
<td>(0.376)</td>
<td>(0.417)</td>
<td>(0.425)</td>
<td>(0.367)</td>
<td></td>
<td>(0.855)</td>
<td>(0.862)</td>
<td>(0.890)</td>
<td>(0.856)</td>
</tr>
<tr>
<td>Log(HPI)×UNAVAL</td>
<td>-1.344***</td>
<td>-1.182***</td>
<td>-1.380***</td>
<td>-1.307***</td>
<td>-2.026</td>
<td></td>
<td>-0.890</td>
<td>-0.993</td>
<td>-2.026</td>
<td>-0.825</td>
</tr>
<tr>
<td></td>
<td>(0.340)</td>
<td>(0.316)</td>
<td>(0.325)</td>
<td>(0.336)</td>
<td>(1.192)</td>
<td></td>
<td>(1.192)</td>
<td>(1.238)</td>
<td>(1.259)</td>
<td>(1.191)</td>
</tr>
<tr>
<td>Log(HPI)×WRLURI</td>
<td>-0.718***</td>
<td>-0.604***</td>
<td>-0.672***</td>
<td>-0.705***</td>
<td>-0.364</td>
<td></td>
<td>-1.021**</td>
<td>-1.045**</td>
<td>-0.364</td>
<td>-0.985**</td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td>(0.095)</td>
<td>(0.091)</td>
<td>(0.096)</td>
<td>(0.428)</td>
<td></td>
<td>(0.428)</td>
<td>(0.433)</td>
<td>(0.401)</td>
<td>(0.428)</td>
</tr>
<tr>
<td>Log(HPI)×SRI</td>
<td>-0.432***</td>
<td>-0.404***</td>
<td>-0.488***</td>
<td>-0.424***</td>
<td>0.419***</td>
<td></td>
<td>0.180***</td>
<td>0.177***</td>
<td>0.182***</td>
<td>0.184***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td></td>
<td>(0.021)</td>
<td>(0.023)</td>
<td>(0.023)</td>
<td>(0.023)</td>
</tr>
</tbody>
</table>

Notes: IV estimates of Eq. 6, where the dependent variable is the log of building permits. Each column represents a separate regression: Base is the baseline specification, Tot_crime uses total crime (property crime plus violent crime) as the instrument, Mortg controls for mortgage originations, Perm_int uses permit intensity as the dependent variable, and SRI replaces UNAVAL and WRLURI with a supply restrictions index (the sum of those two variables standardized). The F-test and robust F-test assume that under the null the excluded instruments are not weakly correlated with the endogenous regressors. Additional control variables are not reported. Robust heteroskedastic standard errors shown in parentheses. Asterisks, *, **, and ***, denote statistical significance at the 10, 5, and 1% levels.

4.3 Estimated elasticities

We now compute the MSA-specific elasticities by inserting the relevant parameters of Eq. 6 into the expression of Eq. 2. Figure 4 shows the resulting estimated elasticities at the median, 10\textsuperscript{th} and 90\textsuperscript{th} percentiles for each housing boom. We estimate supply elasticities to have fallen across the whole distribution in the current boom. In addition, the dispersion in supply elasticities has increased during the current cycle, with a particularly strong decline in the lowest part of the distribution. Our baseline estimates are not materially affected by using the alternative specifications considered in Table 2 (Table B.2 in Appendix B).

We shed more light on the heterogeneity between MSAs by looking at the distribution of
the elasticities within the US territory across the two housing booms (Figure 5). Areas located in states such as California, Arizona, Florida, Oregon, and New York are characterized by the lowest elasticities in both booms. This is not surprising, given that geographical idiosyncrasies, such as steep ground and bodies of water, make it harder to build and limit the land available for construction in these areas, compared to the rest of the country (Saiz 2010). In addition, land-use regulation, which can also limit the expansion of supply, also tends to be more stringent in these areas (Gyourko et al. 2008). In fact, tighter regulation typically reduces the elasticity of housing supply, and thus raises house prices, reduces construction activity, and increases the volatility of house prices (see the review of the literature in Gyourko and Molloy 2015). By contrast, we estimate the highest elasticities to be located in several areas across the Midwest, where builders face relatively fewer restrictions to expand housing supply.

The maps also show that the rank ordering of the MSAs between the two booms is relatively stable. In other words, even if the elasticities have declined for each MSA over time, these changes are not large enough to affect significantly the relative ranking of the MSA over the past 20 years. The largest decline in elasticities between the two booms have taken place in the areas that had the lowest elasticities during the first housing boom (Figure 6). We will investigate this phenomenon in more detail in Section 6.
Figure 5: Estimated elasticities for the two housing booms

Notes: Estimated supply elasticities from Eq. 6 for the two housing booms. We split the elasticities for the MSAs into five groups, as represented by the different colors.

Figure 6: Change in estimated elasticities between booms

Notes: Change in elasticities between the 1996-2006 boom and the 2012-17 boom. We split the elasticities for the MSAs into five groups, as represented by the different colors.
5 Supply elasticities and demand shocks across booms

5.1 Theoretical framework

We have shown that housing supply elasticities have declined over the past years, and that this decline has been a nation-wide phenomenon. We will make the case in this section that such a phenomenon may have implications for house price volatility in the context of a booming market. We take as a starting point a simple model with durable housing inspired by Glaeser et al. (2008), which is made up of an economy that contains a collection of several local housing markets that exhibit heterogeneity in economic, financial, and social dimensions, including in the supply elasticities. Abstracting from depreciation of the existing stock, the law of motion of capital accumulation for each area $i$ in each period $t$ is given by:

$$H_{i,t} = H_{i,t-1} + I_{i,t} \quad (7)$$

where $I_{i,t}$ is new investments in housing capital. We assume that the marginal cost of construction $MC_{i,t}$ is inversely proportional to the existing housing stock $H_{i,t-1}$, implicitly meaning that investment in new construction projects is more attractive in larger housing markets:

$$MC_{i,t} = C_{i,t} \times \left( \frac{I_{i,t}}{H_{i,t-1}} \right)^{\frac{1}{\varphi_{i,t}}}$$

where $C_{i,t}$ represents housing construction costs (land, labor, and building materials), which rise with investment to reflect the scarcity of the inputs used into housing production, and $\varphi_{i,t}$ is the local-specific housing supply elasticity that is allowed to vary over time. The assumption of a time-varying supply elasticity, consistent with our estimates in the previous section, is a new feature of our model compared with Glaeser et al. (2008). We apply Tobin’s Q theory to determine new investments, in that builders adjust supply based on the price of housing relative to the marginal cost of construction. The investment function is obtained by setting the price of housing $PH_{i,t}$ equal to $MC_{i,t}$:

$$I_{i,t} = H_{i,t-1} \times \max \left[ 0, \left( \frac{PH_{i,t}}{C_{i,t}} \right)^{\varphi_{i,t}} - 1 \right] \quad (8)$$

Assuming that the supply elasticity is always greater than zero, it follows from Eq. 8 that investment will only take place if the price of housing exceeds the costs of construction. By
inserting the expression of Eq. 8 into Eq. 7, and then taking logs, we get the housing supply function $S_{i,t}$:

$$
S_{i,t} = \begin{cases} 
H_{i,t-1} & \text{if } PH_{i,t} \leq C_{i,t} \\
H_{i,t-1} + \varphi_{i,t}(PH_{i,t} - C_{i,t}) & \text{if } PH_{i,t} > C_{i,t}
\end{cases}
$$

(9)

The supply curve is piecewise linear and kinked: if the price of housing is smaller or equal to construction costs, the supply of homes is simply equal to the existing housing stock. If the price of housing exceeds construction costs, builders will add a flow of new construction to the existing stock. In this framework, supply is assumed to be rigid downwards, as housing is typically not demolished or dismantled (Glaeser and Gyourko 2005). Note also that supply increases linearly with the supply elasticity $\varphi_{i,t}$, which we will show graphically later.

We specify housing demand as follows:

$$
D_{i,t} = v_0 r_t + v_1 Y'_{i,t} + v_2 PH_{i,t}
$$

(10)

where demand depends linearly on the interest rate $r_t$, assumed to be common across markets, on local house prices, and on area-specific factors captured by the vector $Y'_{i,t}$, such as household income and crime rates, as a proxy for local amenities – used before in the empirical analysis to identify a demand shift.

Consider a market where construction is greater than zero, with the equilibrium in the housing market being determined by the intersection of supply (Eq. 9) and demand (Eq. 10). It follows that in equilibrium, house prices and quantity of housing assume the following expressions:

$$
D_{i,t} = S_{i,t}
$$

$$
PH_{i,t} = \frac{1}{\varphi_{i,t} - v_2} (v_0 r_t + v_1 Y'_{i,t} - H_{i,t-1} + \varphi_{i,t} C_{i,t})
$$

(11)

$$
S_{i,t} = \frac{\varphi_{i,t}}{\varphi_{i,t} - v_2} (v_0 r_t + v_1 Y'_{i,t} + v_2 C_{i,t}) - \frac{v_2}{\varphi_{i,t} - v_2} H_{i,t-1}
$$

(12)

We now assume that the economy is in equilibrium at time $t=0$, and then is hit by a positive demand shock at time $t=1$, say, an expansionary monetary policy shock in which the central bank reduces the interest rate $r_t$. The marginal impact of an expansionary monetary policy
shock is given by the derivative of Eqs. 11 and 12 with respect to minus $r$:

\[-\frac{\partial PH_{i,t}}{\partial r_t} = -\frac{v_0}{\varphi_{i,t} - v_2} > 0\]  \hspace{1cm} (13)
\[-\frac{\partial S_{i,t}}{\partial r_t} = -\frac{\varphi_{i,t}v_0}{\varphi_{i,t} - v_2} > 0\]  \hspace{1cm} (14)

Our model predicts that both house prices and quantity would increase after an interest rate reduction, resulting from the combination of a negative numerator and positive denominator (multiplied by minus 1 as we have a reduction in the interest rate): housing demand is stimulated by declines in the interest rate (negative $v_0$), while supply elasticities are always equal to or greater than zero, and housing demand declines when house prices increase (negative $v_2$).

We illustrate the conjectures above in the left panel of Figure 7. After a reduction in the interest rate, the demand curve shifts from $D_0$ to $D_1$, implying a new equilibrium with both higher house prices $p_1h_1$ and quantity $h_1$ (point $B$). The dotted part of the housing supply curve illustrates that housing supply is rigid downwards, so that the supply curve kinks at A at time $t=0$ and at B after the shock. This exercise assumes that supply elasticities are constant over time as in Green et al. (2005), Gyourko et al. (2008), Huang and Tang (2012), Glaeser et al. (2014), Anundsen and Heebøll (2016), Aastveit and Anundsen (2017). The supply elasticities only play a role over the cross section. For instance, by exploring the variation in supply elasticities across a large sample of MSAs, Aastveit and Anundsen (2017) find that expansionary monetary policy shocks have a substantially greater impact on house prices in markets with an inelastic housing supply.

We move one step forward, and show in our model that the same logic applies within the same market: the impact of a given demand shock on house prices in the same area varies over time, if the slope of the supply curve changes between periods. When there is a reduction in the interest rate, the marginal effect of a decline in the supply elasticities on prices and quantities is given by the derivative of Eqs. 13 and 14 with respect to minus $\varphi_{i,t}$:

\[-\frac{\partial \left( -\frac{\partial PH_{i,t}}{\partial r_t} \right)}{\partial \varphi_{i,t}} = -\frac{v_0}{(\varphi_{i,t} - v_2)^2} > 0\]
\[-\frac{\partial \left( -\frac{\partial S_{i,t}}{\partial r_t} \right)}{\partial \varphi_{i,t}} = -\frac{v_0v_2}{(\varphi_{i,t} - v_2)^2} < 0\]

Our model suggests that if supply elasticities decline over time for the same area, a lower
interest rate would lead house prices to rise by more, and this would be reflected in a smaller expansion in supply. We illustrate this conjecture in the right panel of Figure 7. Assuming a decline in the supply elasticity for a given local housing market between period 0 and 1 – akin to what we have found in our empirical estimates – then a steeper supply curve implies that a demand shock moves the equilibrium to higher prices and lower quantity compared to a situation where the supply elasticity is constant (point C versus point B). In this new equilibrium, a steeper supply curve over time ($S_0 = S_1$ to $S_1'$) implies that a given demand shock can act as an amplification mechanism for house prices.

Figure 7: Impact of expansionary monetary policy shock on the housing market

![Figure 7: Impact of expansionary monetary policy shock on the housing market](image)

Market 1: Constant supply elasticity

Market 2: Steeper elasticity over time

Notes: Left panel: $D_0$ and $S_0$ are the original demand and supply curves, and point A is the initial equilibrium with house prices $p_{h0}$ and quantity $h_0$. After an expansionary monetary policy shock, demand shifts to $D_1$, and the new equilibrium is reached at point B, with both higher house prices $p_{h1}$ and quantity $h_1$, conditional on a time-invariant supply elasticity ($S_0 = S_1$). Right panel: If the supply elasticity declines between periods, i.e. the supply curve steepens from $S_0 = S_1$ to $S_1'$, the equilibrium moves to point C, with higher house prices $p_{h1}'$ and lower quantity $h_1'$.

5.2 High-frequency identification of monetary policy shocks

In a scenario of declining elasticities, our model with durable housing predicts an interest rate reduction to impact house prices more strongly, at the expense of a smaller expansion in housing supply. Since we estimate the supply curve for each MSA to have steepened since the 1996-2006 boom, it follows that an aggregate demand shock of the same magnitude should move the equilibrium of the economy to higher prices and lower quantity. We test empirically this theoretical conjecture by studying the sensitivity of house prices and housing supply to aggregate demand shocks, particularly monetary policy shocks, across the two housing booms.

Our main measure of monetary policy shocks is computed following a recent strand of
the literature that resorts to high-frequency data to identify unexpected changes in the Fed policy rate (see, for instance, Gürkaynak et al. 2005, Gertler and Karadi 2015, Nakamura and Steinsson 2018). This high-frequency identified (HFI) approach isolates news about future policy actions that is orthogonal to changes in economic and financial variables. We take the unexpected changes in interest rates for 3-month ahead contracts on Fed funds futures in a 30-minute window surrounding FOMC meetings. In total we cover 127 meetings over the two housing booms: 83 between 1997q1-2006q4 and 44 between 2012q3-2017q4. The identification assumption is that these surprises – changes in the futures rates – within that window can only arise from news about monetary policy, given that market participants incorporate all available public information into financial markets at the beginning of that narrow window.

More specifically, let $f_{t+j}$ be the price of a Fed funds future in month $t$ that expires in $j$ months, and $S_{t+j}$ the unanticipated change in the expectation for the Fed funds rate $t+j$ months ahead. The monetary surprise is then constructed as the difference between the price of the $t+j$ month ahead Fed funds future contract 20 minutes after the FOMC announcement and the price of the same contract 10 minutes before the announcement:

$$S_{t+j} = f_{t+j} - f_{t+j,-1}$$

Given that our MSA dataset is of a quarterly frequency, we follow standard practice in transforming high frequency data into low frequency. In particular, we transform the daily shock series into a monthly series by first creating a cumulative daily surprise series, which corresponds to the sum of surprises during the last 31 days, and then take quarterly averages across each day of the three months of each quarter.

One of the issues with the HFI shocks is that they likely contain measurement error, thus may capture only part of the ‘true’ structural shock. For instance, some price changes within the 30-minute window around the policy announcements may reflect simply trading noise and volatility. In addition, the monthly (and quarterly) series of surprises contains some random zero observations, as a result of calendar months without FOMC meetings. Finally, the monthly (and quarterly) surprise series does not incorporate other monetary policy news released outside of the announcement window, such as speeches by FOMC members. In this context, we follow recent literature that has increasingly been treating these HFI surprise series not as the shock, but rather as instruments for the shock (Gertler and Karadi 2015, Ramey 2016, Nakamura and
Steinsson 2018, Stock and Watson 2018). We choose the one-year Treasury bill yield as the relevant monetary policy indicator, as in Gertler and Karadi (2015), as this risk-free asset with a longer maturity than the funds rate has the advantage of also incorporating shocks to forward guidance about the future path of interest rates, instead of just about the current rate.

5.3 Empirical results: LP-IV

Our empirical framework combines IV methods with Jordà (2005)’s Local Projection approach, similarly to Jordà et al. (2015), Ramey (2016), and Stock and Watson (2018). The Jordà method offers some advantages over Vector Auto Regressive (VAR) models, particularly that its impulse responses are less vulnerable to misspecification (Stock and Watson 2018). In addition, it easily accommodates non-linearities, allowing us to estimate simultaneously the dynamic causal effects of monetary policy shocks conditional on our housing supply elasticities. One of the drawbacks is that there is often some loss of efficiency, especially at longer horizons, resulting in less precise estimates than VARs, and sometimes in erratic patterns in the dynamic effects.

We estimate the LP-IV model over one unique sample, the two booms 1997q1-2006q4 and 2012q3-2017q4, by running a series of regressions for each horizon $h=1,2...,16$ quarters:

$$
\Delta_h Y_{i,t+h} = \beta^h \Delta MP_t + \gamma^h \Delta MP_t \times \text{Elast}_{i,t} + \sum_{j=1}^{4} \lambda^h_j \Delta X_{i,t-j} + \eta^h + \epsilon_{i,t+h}
$$

(15)

where the main dependent variables are the cumulative percentage change in real house prices or in building permits from period $t$ to $t+h$.\(^{12}\) $MP_t$ is the monetary policy indicator (the one-year Treasury bill yield), which is interacted with our supply elasticities $\text{Elast}_{i,t}$ for each boom, and $X_{i,t-j}$ refer to a vector of lagged control variables (four lags), namely the lagged dependent variables, the external instrument, the growth in real disposable income, population, and in real construction wages, the change in the unemployment rate, the inflation rate, and the dependency ratio. This large set of control variables helps minimize the omitted variable bias and reduce the variance of the error term (Stock and Watson 2018). In addition, Stock and Watson (2018) argue that the nature of the construction of the HFI monetary shocks induces a first-order moving average structure, which leads to correlation between the external instrument and past values of the policy indicator. We follow their suggestion and include lagged values of the external instrument as controls to make our IV valid.

\(^{12}\)Given the high volatility of permits, especially as $h$ increases, we transform the raw series into a 4-quarter centered moving average.
We add fixed effects $\eta_i^h$ to control for time-invariant idiosyncratic MSA characteristics, but we do not include time-fixed effects given that the monetary policy indicator is common across MSAs. The standard errors are MSA-specific cluster-robust which allow for fully flexible time series dependence in the errors within MSA. This adjustment tends to produce more conservative standard errors than a typical heteroskedasticity-and-autocorrelation (HAC) robust estimation (Jordà et al. 2015). Note that the standard errors are not distorted by the generated regressor issues, given that the high-frequency shock is used only as an instrument and not directly included in the model.

The parameters of interest in our model are $\beta^h$ and $\gamma^h$. Following the conjectures from the theoretical model, in the equation for house prices we expect an expansionary monetary policy shock to boost house prices ($\beta > 0$), but that this effect becomes smaller the higher the housing supply elasticity ($\gamma < 0$). In turn, in the housing supply equation (permits) we expect an expansionary shock to stimulate more construction ($\beta > 0$), and that this effect is reinforced by an higher elasticity ($\gamma > 0$).

The IV conditions for validity of the instrument, outlined in Section 4.2, require that the external instrument be contemporaneously correlated with the policy indicator (relevance condition), and contemporaneously uncorrelated with all other shocks (exogeneity condition). To be clear, we have two endogenous variables and two corresponding instruments in Eq. 15: the monetary policy indicator and its interaction with the estimated elasticities, instrumented with the HFI surprise series and with its interaction with the elasticities. The first-stage F-test and robust F-test we get turn out to be significantly above the Stock and Yogo (2005)’s threshold, suggesting that our instruments are valid and strong.

We find that an expansionary monetary policy shock that leads to a 100 basis point fall in the one-year Treasury bill yield raises both house prices and supply over the short to medium run in a statistically significant way for both housing booms (Figure 8). What is novel in our results is that we find that house prices rise by considerably more in the 2012-2017 boom compared with the 1996-2006 boom. While the price dynamics appear quite similar in the short term, after roughly 2 years house prices in the current boom start to increase at a statistically significant faster pace; for the same 100 basis points decline in government bond yields, real house prices in the current boom are almost 6 percentage points higher after four years (a cumulative 15 percent increase in the 2012-17 boom against 9 percent in the precedent boom).

By contrast, we estimate the opposite dynamics for supply: building permits react more
strongly to a monetary policy shock in the 1996-2006 boom. But the difference between the responses is of a relatively small magnitude given the scale of the increase in permits in both episodes (roughly 40 percent after four years). Moreover, the estimated housing supply responses are statistically different between booms more for shorter horizons, which contrasts with the profile of the responses for house prices. Overall, the differences in the responses are not driven by different magnitudes of the underlying shocks, as illustrated by a similar decline in the response of the policy indicator (Figure B.3 in Appendix B).

Figure 8: Responses to an expansionary monetary policy shock across booms

Notes: Cumulative impulse responses to a 100 basis point decline in the one-year Treasury bill yield, assessed at the sample median elasticity for each housing boom period. The right-hand charts depict the difference in the estimated response of house prices and building permits between the 2012-17 and the 1996-2006 booms. The grey area and the dashed red lines refer to 90 percent confidence bands.

We show that there is considerable heterogeneity in the responses across MSAs and within the same episodes. We replicate our results above but focus on individual MSAs, particularly by comparing the responses between selected low- and high-supply elasticity areas. We find that house prices in a typical low-elasticity MSA, such as San Francisco-Oakland-Hayward, California are hit harder by a given aggregate shock that raises housing demand, compared to a typical high-elasticity MSA, such as Kansas City, Missouri (Figure 9). While this result follows naturally from above, i.e. the lower the elasticity, the stronger the impact on house prices, we find some evidence that the differential effect between the two booms is larger in low-elasticity
areas than in high-elasticity areas.

Figure 9: Responses to an expansionary monetary policy shock for selected MSAs

Notes: Cumulative impulse responses to a 100 basis point decline in the one-year Treasury bill yield, assessed at the sample median elasticity for selected MSAs and for each housing boom. Kansas City, Missouri represents a high-supply elasticity MSA, while San Francisco-Oakland-Hayward, California a low-supply elasticity MSA.

Overall, our main finding of lower supply elasticities during the current housing boom point to the housing market being more susceptible now to stronger house price increases for a given increase in demand. Furthermore, we also shed some light on the possible amplification of asymmetries across regional markets; since low-supply elasticity metro areas have experienced a larger decline in elasticities between the two booms, the effect of a given shock on their housing market is larger in the current period than for high-supply elasticity areas.

6 Why have elasticities declined?

One of the questions that remains unanswered is about pinning down the reasons behind the generalized decline in supply elasticities between the two booms. In theory, several factors might change the slope of the housing supply curve, such as changes in regulatory conditions, demographics, and in expectations about future demand and house prices.

A recent paper by Herkenhoff et al. (2018) estimates a substantial tightening in land-use
policy in most US states since 1950. Although they find the largest percentage increase in land-use regulation over 1970-1980, Herkenhoff et al. (2018) also document a substantial tightening across states between 1990 and 2014, of around 18 percent. The tightening in regulation is particularly marked for high-house price states. Along the same lines, recent research has put forward the notion that the decline in construction productivity may be the result of increased costs stemming from tighter regulation over time (Davis and Palumbo 2008, Glaeser and Gyourko 2018). In this context, we conjecture that tighter regulation over time may play a central role in explaining the decline in the estimated housing supply elasticities, given that regulation makes it difficult to build and therefore leads to higher house prices (Glaeser et al. 2005).

A simple correlation analysis between our estimated elasticities and Herkenhoff et al. (2018)’s land-use regulation index suggests that the tightening in regulation between 2000 and 2014 is associated with a decline in our estimated elasticities between the two housing boom episodes (correlation of -0.4).\footnote{Herkenhoff et al. (2018)’s land-use regulation indicator is available for 48 states, excluding Alaska and Hawaii, and for individual years: 1950, 1960, 1970, 1980, 1990, 2000, and 2014. We take the 2000 and 2014 values of that indicator as the data points relevant for respectively the 1996-2006 and 2012-2017 booms.} We show that this relationship holds in a multi-variate analysis, by estimating the following cross-sectional model:

$$\Delta \log (Elast_{17} - Elast_{06}) = \alpha_i + \beta_1 \Delta \log (X_{17} - X_{06}) + \beta_2 Z_i + \epsilon_i$$  \hspace{1cm} (16)

where the dependent variable is the log percentage change in the estimated elasticities between 2012-2017 (Elast$_{17}$) and 1996-2006 (Elast$_{06}$). We regress it on the log percentage change for the same period of a set of indicators $X_i$, namely the state-level Herkenhoff et al. (2018)’s land-use regulation, population density, construction wages, unemployment rate, and on initial conditions $Z_i$ that include the levels of house prices to income per capita and of population density. Finally, we also include the cumulative change in house price growth during the 2006-2012 bust.

Our results provide strong statistical evidence that tighter land-use regulation has been a strong predictor of the decline in elasticities across MSAs between the two booms (Table 3).\footnote{A decline in the land-use regulation index represents a tightening in regulation.} This concurres with the idea laid out in Herkenhoff et al. (2018) that stringer regulation has limited the expansion of supply in many parts of the country, and has thus led to a substantial increase in house prices. Our estimates also show that areas with stronger economic performance, as measured by the change in the unemployment rate, faster population density growth,
and higher initial levels of house prices relative to income and of population density at the beginning of the 2012-2017 boom, tend to be associated with larger declines in elasticities.

Finally, we find that areas that experienced the strongest bust in house prices over 2006-2012 ($\Delta HPI_{06-12}$) also recorded the largest declines in elasticities between the two booms. Our interpretation is that the Great Recession might have cast a long shadow on builders’ expectations, making them less price responsive than before. This fear of a new bust may have paved the way for a new housing boom where house prices are more responsive to fluctuations in demand, as we have shown in the previous section.

Table 3: $\Delta$Elasticity between booms

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
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<tr>
<td>$\Delta \log(\text{Land reg.})$</td>
<td>0.223***</td>
<td>0.204***</td>
<td>0.143***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.037)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>$\Delta HPI_{06-12}$</td>
<td>0.700***</td>
<td>0.679***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.132)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \log(\text{Pop density})$</td>
<td></td>
<td>-0.038</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.125)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \log(Wage)$</td>
<td></td>
<td>0.030</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.074)</td>
<td></td>
</tr>
<tr>
<td>$\Delta UR$</td>
<td></td>
<td>3.200**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.430)</td>
<td></td>
</tr>
<tr>
<td>$\text{Hpinc}_pc$</td>
<td></td>
<td>-0.377***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.127)</td>
<td></td>
</tr>
<tr>
<td>Pop density</td>
<td></td>
<td>-0.010**</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.004)</td>
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<tr>
<td>Observations</td>
<td>251</td>
<td>251</td>
<td>251</td>
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<tr>
<td>R-squared</td>
<td>0.107</td>
<td>0.319</td>
<td>0.391</td>
</tr>
</tbody>
</table>

Notes: Regression estimates of Eq. 16, where the dependent variable is the percentage change in the estimated supply elasticities between the 2012-2017 and the 1996-2006 housing booms. Robust heteroskedastic standard errors in parentheses. Asterisks, *, **, and ***, denote statistical significance at the 10, 5, and 1 percent levels.

7 Robustness and alternative explanations

7.1 Alternative explanations of the disconnect between house prices and permits

One potential alternative explanation for the disconnect between house price developments and construction activity in recent years is weaker aggregate demand, reflecting subdued wage
and income growth. In addition, although interest rates have been persistently low since the beginning of the Great Recession, and credit standards have loosened over the past years, credit growth to households has nonetheless been weak. This explanation cannot, however, account for why house prices at the same time are evolving along a similar trajectory as in the previous boom.

A second possibility is that the strong rise in construction activity during the 1996-2006 boom led to an oversupply of houses in the subsequent period, implying that there is less need for new homes to be built. To shed light on this, the left panel in Figure 10 compares developments in the housing stock per capita across the two booms. In the right panel, we show housing vacancy rates. It is evident that the housing stock per capita has been trending consistently downwards during the recovery period, whereas it increased over 1996-2006. In turn, housing vacancy rates have shown similar developments across the two booms. Based on these indicators, there seems to be little evidence of a supply overhang in the current recovery, suggesting that this cannot explain the low construction activity.

Figure 10: Housing supply indicators across booms

Notes: The figure shows developments in housing stock per capita and housing vacancy rates during 1996q4–2006q4 (red solid line) and 2012q3–2017q4 (blue line with markers). The housing stock per capita is scaled such that it takes a value of 100 at the beginning of each period, whereas the vacancy rate is displayed in percent of the total housing stock. The horizontal axis shows quarters around the beginning of the two booms, and the vertical line at zero is the starting point of both booms.

7.2 Alternative monetary policy shocks and specifications

As a robustness check, we compute an alternative monetary policy shock through a structural VAR (SVAR) along the lines of Christiano et al. (1996), using Wu and Xia (2016)’s shadow rate as the policy instrument to address the zero lower bound (ZLB) and unconventional policy after

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A similar picture is portrayed by the months’ supply of houses, which measures the ratio of houses for sale to houses sold. It indicates how long the current for-sale inventory would last given the current sales rate if no new houses were built. It is a commonly used indicator to assess the strength of the housing market, and it is only slightly above the levels recorded during the last housing boom (left panel of Figure B.4 in Appendix B).
We identify the shocks through a Cholesky identification scheme with the following order in our five-variable VAR: real GDP, GDP deflator, real oil prices, real house prices, and the shadow rate. All variables are expressed in logs, apart from the shadow rate which is in percent. As is standard in the VAR literature, the policy rate is ordered last, implying that monetary policy reacts contemporaneously to all the variables in the VAR, but is only allowed to influence macro and financial conditions with a lag of one quarter. We get similar results for the response of house prices compared to the benchmark shock, particularly of a stronger impact of monetary policy on the current boom (Figure B.5 in Appendix B). But the response of supply is also stronger compared to the previous boom, which is at odds with our benchmark results. Nevertheless, we suggest to take these latter results with a pinch of salt, as shock identification in the SVAR is more challenging in the context of the ZLB and unconventional measures, making the VAR more prone to misspecification (Ramey 2016).

We perform additional robustness checks by: (i) using surprises in the two-month ahead Fed funds futures to compute the high-frequency monetary shock; (ii) taking the two-year Treasury note rates as the policy indicator: (iii) controlling for Gilchrist and Zakrajšek (2012)’s excess bond premium (EBP) in the main specification, as Gertler and Karadi (2015) argue that the EBP has strong forecasting ability for economic activity, thus acting as a summary indicator of the potentially relevant information left out of the model to explain the dependent variable; and (iv) running the main model with only one lag. Figure B.6 in Appendix B shows that our main results remain qualitatively robust: irrespective of the specification used, house prices rise by considerable more in the 2012-2017 boom, at the expense of a slightly weaker supply response.

8 Conclusion

In this paper we have provided evidence of a substantial and synchronized decline in US local housing supply elasticities from the 1996-2006 housing boom to the ongoing recovery that started in mid-2012. In the current environment of very low supply elasticities, the implication of our

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16 We do not use the Romer and Romer (2004)’s narrative shocks given that the Greenbook projections are not available for the period covering the current recovery; they are released to the public with a lag of five years. 17 Wu and Xia (2016)’s shadow rate measures the effective policy rate in the economy during ZLB periods by translating changes in the Fed’s balance sheet into Fed funds rate equivalents. The shadow rate stayed in negative territory for more than six years, from 2009q2 to 2015q4, reaching a minimum of -2.9 percent in 2014q2. 18 The EBP is a measure of investor sentiment or risk appetite in the corporate bond market that is not directly attributable to expected default risk. More specifically, Gilchrist and Zakrajšek (2012) define it as the spread between the rate of return on corporate securities and a similar maturity government bond rate that is left after removing the default risk component.
finding is that the house price responsiveness to a given demand shock should be higher today, at the expense of a smaller increase in supply.

We have investigated this conjecture by estimating the effect of an exogenous monetary policy shock, identified with high-frequency data, on the housing market. We have found that monetary policy has a substantially greater impact on house prices during the current recovery than during the previous boom – estimated to be almost twice as large after three years. In contrast, we have found that the expansion in building permits is slightly smaller today. Furthermore, our results point to significant heterogeneity in the responses across local housing markets. In particular, we estimate a substantially larger response of house prices to a monetary policy shock in supply inelastic markets than in areas with an elastic supply.

We have also shed some light on the factors that may have contributed to the decline in supply elasticities between the two booms. Our results suggest that elasticities have declined the most in areas that experienced the largest bust in house prices during the Great Recession. We interpret this as evidence that the fear of a new bust has led developers to be less price-responsive than before. This behavior may have paved the way for a new housing boom where house prices are more responsive to fluctuations in demand.

Moreover, we also find that the elasticities have declined the most in areas where regulation has tightened more. We relate this finding to a recent strand of the literature studying the economic costs of tighter housing regulation. In the current environment of tighter regulation and declining elasticities, our findings cast some doubts about the view that the recent housing market recovery looks 'healthier' and more sustainable compared to the previous boom.
References


A Data

Building permits: number of permits issued by a local jurisdiction to proceed on a construction project. Source: Census Bureau, and Moody’s Analytics.

Housing starts: number of housing units in which construction work has started. The start of construction is when excavation begins for the footings or foundation of a building. Source: Census Bureau, and Moody’s Analytics.

Housing stock: a house, apartment, mobile home or trailer, a group of rooms, or a single room that is occupied or available for occupancy. Updated from 2010q3 onwards by accumulating housing completions. Source: Census Bureau, and Moody’s Analytics.

FHFA house price index: weighted, repeat-sales index, measuring average price changes in repeat sales or refinancings on the same single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac. Source: FHFA, and Moody’s Analytics.

UNAVAL: the land unavailability index captures housing supply geographical constraints. It is constructed using topographic maps measuring the proportion of land in a 50 km radius of the city center that is lost to steep slopes and water bodies, such as oceans, rivers, lakes and wetlands. Source: Saiz (2010).

WRLURI: the Wharton local land-use regulatory index captures regulatory restrictions in the housing market, i.e. measures the time and financial cost of acquiring building permits and constructing a new home. It refers to the principal component of 11 survey-based measures which is interpreted as the degree of stringency of local zoning laws. Source: Gyourko et al. (2008).

Crime rates: counts of crimes per 100,000 inhabitants reported to the police for each police agency (cities, towns, and villages). It is broken down into two major types: violent crime, which includes offences of murder, forcible rape, robbery, and aggravated assault, and property crime, which includes offences of burglary, larceny-theft, and motor vehicle theft. Source: Uniform Crime Report Offenses Known to Law Enforcement dataset of the FBI.

Population: resident population in each MSA. Source: Census Bureau, and Moody’s Analytics.

Population density: population per square mile. Annual data interpolated into quarterly. Data available since 2000. Source: Census Bureau, and Moody’s Analytics.

CPI: consumer price index for all urban consumers. Source: BLS, and Moody’s Analytics.

Disposable personal income: The income available to persons for spending or saving. It is equal to personal income less personal current taxes. Source: BEA, and Moody’s Analytics.

Construction wages: wages and salaries in the construction sector. Data available at the state level. The original quarterly series has been adjusted for seasonality using X-13-ARIMA from the Census Bureau. Source: BEA.

Unemployment rate: the number of unemployed as a % of total labour force. Source: BLS, and Moody’s Analytics.

Mortgage originations: dollar amount of new mortgage loans approved by the mortgage broker

Dependency ratio: ratio of people younger than 15 or older than 64 years old to the working age population (those aged 15-64). Source: Census Bureau, and Moody’s Analytics.

Black: fraction of black or African American relative to total population. Annual data interpolated into quarterly. Source: Census Bureau, and Moody’s Analytics.

Hispanic: fraction of people of Hispanic or Latino origin relative to total population. Annual data interpolated into quarterly. Source: Census Bureau, and Moody’s Analytics.

B Tables and figures

Table B.1: Descriptive statistics

<table>
<thead>
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<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<td>Real HPI (log)</td>
<td>21,336</td>
<td>4.8</td>
<td>0.2</td>
<td>4.1</td>
<td>5.5</td>
</tr>
<tr>
<td>Building permits (log)</td>
<td>21,336</td>
<td>7.3</td>
<td>1.5</td>
<td>2.1</td>
<td>12.1</td>
</tr>
<tr>
<td>Housing starts (log)</td>
<td>21,336</td>
<td>7.3</td>
<td>1.4</td>
<td>2.2</td>
<td>11.6</td>
</tr>
<tr>
<td>Housing stock (log)</td>
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<td>5.2</td>
<td>1.1</td>
<td>3.3</td>
<td>9.0</td>
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<td>UNAVAL</td>
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<td>0.3</td>
<td>0.2</td>
<td>0.0</td>
<td>0.9</td>
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<td>WRLURI</td>
<td>21,336</td>
<td>-0.1</td>
<td>0.8</td>
<td>-1.8</td>
<td>4.3</td>
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<td>Real personal income (log)</td>
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<td>1.2</td>
<td>14.2</td>
<td>20.7</td>
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<td>21,336</td>
<td>15.1</td>
<td>1.0</td>
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<td>17.0</td>
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<td>CPI (log)</td>
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<td>5.3</td>
<td>0.2</td>
<td>4.5</td>
<td>5.7</td>
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<td>Real mortgage originations (log)</td>
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<td>13.7</td>
<td>1.3</td>
<td>8.5</td>
<td>18.3</td>
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<td>Unemployment rate (%)</td>
<td>21,336</td>
<td>5.9</td>
<td>2.6</td>
<td>1.2</td>
<td>32.1</td>
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<tr>
<td>Population (log)</td>
<td>21,336</td>
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<td>1.1</td>
<td>4.0</td>
<td>9.9</td>
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<td>Population density</td>
<td>18,288</td>
<td>319.3</td>
<td>344.9</td>
<td>6.3</td>
<td>2754.3</td>
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<td>Dependency ratio (%)</td>
<td>21,336</td>
<td>50.7</td>
<td>6.2</td>
<td>31.5</td>
<td>85.2</td>
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<td>Black ratio (%)</td>
<td>21,272</td>
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<td>Hispanic ratio (%)</td>
<td>21,272</td>
<td>11.3</td>
<td>14.7</td>
<td>0.4</td>
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<td>Total crime rate (%)</td>
<td>17,000</td>
<td>3937.4</td>
<td>1291.2</td>
<td>1128.4</td>
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<td>Property crime rate (%)</td>
<td>17,360</td>
<td>3492.1</td>
<td>1159.3</td>
<td>3.1</td>
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<td>∆Real HPI (%)</td>
<td>21,336</td>
<td>0.3</td>
<td>1.9</td>
<td>-15.7</td>
<td>12.3</td>
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<td>∆Real personal income (%)</td>
<td>21,336</td>
<td>0.6</td>
<td>1.3</td>
<td>-8.9</td>
<td>11.9</td>
</tr>
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<td>∆Real construction wages (%)</td>
<td>21,336</td>
<td>0.5</td>
<td>3.0</td>
<td>-19.7</td>
<td>17.3</td>
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<td>∆CPI (%)</td>
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<td>0.5</td>
<td>0.6</td>
<td>-3.1</td>
<td>4.0</td>
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<td>∆Unemployment rate</td>
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<td>6.2</td>
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<td>∆Population (%)</td>
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<td>0.2</td>
<td>0.5</td>
<td>-44.3</td>
<td>10.2</td>
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Figure B.1: Demand fundamentals across booms

Notes: The figure tracks the evolution of real disposable income and real personal consumption at a quarterly frequency during the two house price booms. The zero on the x-axis marks the beginning of each housing boom. The solid line refers to the boom between 1996q4 and 2006q4, while the blue line with markers is from 2012q3 to 2017q4.

Figure B.2: Kernel densities

Notes: Kernel densities of the percentage cumulative change in real house prices for the local housing market cycles.
Table B.2: Estimated elasticities: alternative specifications

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<thead>
<tr>
<th></th>
<th>1996-2006</th>
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<th>2012-2017</th>
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<tr>
<td></td>
<td>p10</td>
<td>p50</td>
<td>p90</td>
<td>p10</td>
<td>p50</td>
<td>p90</td>
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<tr>
<td>Base</td>
<td>1.58</td>
<td>2.63</td>
<td>3.37</td>
<td>0.51</td>
<td>1.81</td>
<td>2.70</td>
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<td>Tot_crime</td>
<td>1.19</td>
<td>2.14</td>
<td>2.81</td>
<td>0.39</td>
<td>1.71</td>
<td>2.65</td>
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<td>Mortg</td>
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<td>2.54</td>
<td>3.29</td>
<td>0.21</td>
<td>0.69</td>
<td>1.29</td>
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<td>Perm_int</td>
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<td>2.53</td>
<td>3.25</td>
<td>0.49</td>
<td>1.76</td>
<td>2.60</td>
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<td>SRI</td>
<td>1.48</td>
<td>2.51</td>
<td>3.26</td>
<td>0.59</td>
<td>1.87</td>
<td>2.81</td>
</tr>
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</table>

Notes: Estimated elasticities from Eq. 6 for the median, 10th and 90th percentiles for each housing boom. **Base** is the baseline specification, **Tot_crime** uses total crime as the instrument, **Mortg** controls for mortgage originations, **Perm_int** uses permit intensity as the dependent variable, and **SRI** replaces UN-AVAL and WRLURI with a supply restrictions index.

Figure B.3: Responses of policy indicator to an expansionary monetary policy shock

Notes: Cumulative impulse responses to a 100 basis point decline in the one-year Treasury bill yield, assessed at the sample median elasticity for each housing boom period. The grey area and the dashed red lines refer to 90% confidence bands.

Figure B.4: Months’ supply of houses (in months)

Notes: The figure tracks the evolution of months’ supply of houses at a quarterly frequency during the two house price booms. The zero on the x-axis marks the beginning of each housing boom. The solid line refers to the boom between 1996q4 and 2006q4, while the blue line with markers is from 2012q3 to 2017q4.
Figure B.5: SVAR responses to an expansionary monetary policy shock across booms

Notes: Cumulative impulse responses to a 100 basis point decline in the one-year Treasury bill yield, assessed at the sample median elasticity for each housing boom period. The right-hand charts depict the difference in the estimated response of house prices and building permits between the 2012-17 and the 1996-2006 booms. The grey area and the dashed red lines refer to 90% confidence bands.
Figure B.6: Responses to an expansionary monetary policy shock: alternative specifications

Notes: Cumulative impulse responses to a 100 basis point decline in the one-year Treasury bill yield, assessed at the sample median elasticity for each housing boom. Base is the baseline specification, FF2 uses surprises in the two-month ahead Fed funds futures as the instrument for the monetary policy indicator, GS2 uses the two-year Treasury note yield as the policy indicator, EBP adds Gilchrist and Zakraješ (2012)’s EBP to the main specification, and 1 lag is the benchmark model with only 1 lag.