House Prices and Consumption: A New Instrumental Variables Approach *

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Abstract

While the elasticity of housing supply has served as a popular instrument for inferring the causal effect of housing price growth on economic outcomes, concerns about the exclusion restriction have emerged. We introduce a methodology for creating instruments using the pre-existing supply of local housing characteristics and either regional or national changes in the price of these characteristics. Unlike other common strategies for inferring the effects of housing price shocks, our Bartik-like instrument is a strong predictor of housing price growth in both the cross-section and over time even after controlling for county and time fixed effects, as well as a wide array of local demographic, business cycle, and industry characteristics. Using longitudinal household expenditure data, our instrument produces an elasticity of consumption with respect to local housing price growth of 0.12, corresponding to a marginal propensity to consume out of housing wealth equal to 1.2-1.8 cents on the dollar. These effects are concentrated among the young and those likely to be facing tight borrowing constraints.

Keywords: Consumption; House Prices; Marginal Propensity to Consume; Instrumental Variables; Bartik Instrument

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1 Introduction

There is now a large theoretical literature on the effects of housing price fluctuations on real economic activity (Bernanke and Gertler, 1989), specifically through a "balance sheet" channel where movements in housing prices generate wealth affects that influence consumption expenditures. Fluctuations in housing wealth are thought to have played an important role in explaining consumption activity through not only their direct effects (Mian and Sufi, 2011; Mian et al., 2013; Aladangady, 2017; Kaplan et al., 2017, 2020), but also their indirect effects as mediators of monetary policy (Di Maggio et al., 2017; Wong, 2020). However, empirically isolating these effects is challenging because both consumption and housing prices are equilibrium objects.

While traditional approaches have largely exploited variation in the elasticity of housing supply, these approaches face at least two limitations. First, there is increasing evidence that areas with more inelastic housing supplies also attract higher skilled workers and more immigrant workers (Davidoff, 2016), generating composition and income effects that confound movements in consumption. Second, the cross-sectional variation in the housing supply elasticity is only defined over the cross-section of a limited set of metropolitan areas, making it challenging to infer how changes in housing prices affect consumption over the business cycle across areas that vary in their home ownership rates, industrial composition, and more. The primary contribution of this paper is to introduce a new Bartik-like instrumental variables approach for estimating how changes in housing prices affect consumption, allowing for rich heterogeneity and within-location variation.

Building on an emerging theoretical foundation for Bartik instruments Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2018), the first part of the paper presents a new approach to identifying the effects of housing price growth on consumption by exploiting plausibly exogenous variation in a location's (county's) exposure to different types of housing structures. Using highly disaggregated micro-data from Zillow Transactions ("ZTRAX"), we begin by providing suggestive evidence that variation in housing shares is uncorrelated with location-specific shocks that could otherwise drive consumption decisions. Importantly, our identifying assumption relies on the fact that geographies vary in their exposure to different housing stocks, which can be traced back to policies following the Great Depression that led to a significant expansion of different types of housing units across space. We interact these cross-sectional housing shares with regional time-varying shocks to the price of housing quality for each structure type, allowing us to compare consumption among households in areas that are more exposed to certain aggregate shocks over others. Motivated by Goldsmith-Pinkham et al. (2018), we provide numerous diagnostics that suggest these local shares are exogenous with respect to contemporaneous shocks to consumption.

The second part of the paper uses the newly-formed instrument to obtain new estimates of the marginal propensity to consume out of housing wealth. Using household-level panel data, we compare our baseline two-stage least squares results with those obtained from a standard fixed effects estimator and from a cross-sectional Saiz (2010) elasticity instrument. We find that our baseline estimate is smaller, but in line with recent estimates (Aladangady, 2017; Guren et al., 2018): a one percentage point (pp) rise in housing price growth is associated with a 0.10-0.15pp rise in consumption growth. These consumption effects are concentrated among the young and those subject to borrowing constraints, consistent with literature on monetary policy shocks (Di Maggio et al., 2017; Kaplan et al., 2018; Wong, 2020) and housing wealth effects (Mian et al., 2013; Aladangady, 2017; Kaplan et al., 2014). However, we find no evidence of heterogeneity when we allow for differences in areas with high versus low shares of home owners or employment in the retail sector, suggesting that housing spillovers on consumption or employment do not spuriously account for our consumption growth effects (Anenberg and Kung, 2014; Mian and Sufi, 2014).

This paper contributes to two areas of the literature. The first is a growing empirical literature about the effects of housing price fluctuations on consumption. Motivated by early work from Bernanke and Gertler (1989), Mian and Sufi (2011) and Mian and Sufi (2014) estimate the effects of housing wealth declines on consumption and employment, respectively, leveraging variation in the housing supply elasticity as an instrument. Kaplan et al. (2020) replicate these results using publicly available and store-level scanner data, obtaining estimates of an MPC between 0.05 and 0.11. Aladangady (2017) produces similar results, highlighting the role of borrowing constraints. We follow these approaches, but add two major innovations: (a) a new identification strategy that provides within-location variation in housing prices, and (b) household-level panel data on consumption. While our approach and results are closely aligned with the housing price sensitivity instrument in Guren et al. (2018), ours includes two refinements. First, whereas they rely on residual variation in housing prices after controlling for local retail employment, we exploit locations' exposure to regional and/or national trends based on their pre-determined share of different housing structures. This helps us avoid the potential for other time-varying characteristics that are not captured by regional retail employment, but are still correlated with local housing prices. Second, we have household panel data with direct measurement of consumption, which allows us to embed rich heterogeneity. We view these features as a building block on the recent and important work of Aladangady (2017) and Guren et al. (2018).

We also provide additional microeconomic evidence on the collateral channel. Following Mian et al. (2013) and Aladangady (2017) who show that consumption is more elastic in zipcodes with high loan-to-vaue (LTV) ratios, we too validate these results and find that the elasticity is roughly twice as large in zipcodes with LTV ratios above 80%. We also document age-dependent elasticities, finding that individuals under the age of 40 have an elasticity that is roughly five times as large as those above the age of 60, consistent with recent evidence on the effects of monetary policy on consumption among the young and likely first-time home buyers (Wong, 2020).

This paper also contributes to a larger literature in urban economics that examines how housing price fluctuations affect local outcomes, including the labor market. For example, Gyourko et al. (2008) (updated by Gyourko et al. (2019)) and Glaeser et al. (2005) explore the quantitative effects of housing regulation on housing prices. Incorporating housing regulatory constraints and land availability, Saiz (2010) creates a measure of the elasticity of housing supply, which has been used in a wave of recent empirical contributions as an instrument for housing price growth.

The paper proceeds as follows. Section 2 presents the data sources and measurement strategy. Section 3 discusses the empirical strategy for estimating the effect of housing price growth on consumption. Section 4 introduces the new instrumental variables approach. Section 5 presents the main results, heterogeneity, and robustness. Section 6 concludes.

2 Data and Measurement

2.1 Housing Data

House price data come from the Zillow Transaction and Assessment Dataset (ZTRAX), made available by Zillow Research. The full ZTRAX dataset contains more than 370 million public records from across the US and includes information on deed transfers, mortgages, property characteristics, and geographic information for residential and commercial properties. We restrict the data to observations on arm's-length, non-foreclosed sales of residential properties made by owner-occupiers and exclude observations from Rhode Island, Tennessee, and Vermont due to missing data problems.[1] We also exclude all observations with missing data or where the sale price is less than $10,000. Nonetheless, even when the transaction price is missing, we retain information about the property characteristics, which we use in our construction of the Bartik instrument.

While we use the Zillow data because of the detailed heterogeneity that allow us to compute shares of housing structures by type and to estimate the price of housing quality for each type of structure, there are important similarities between the data and the Census Bureau data. Appendix A presents comparisons between the ZTRAX data and the 2000 Decennial Census. Housing characteristics (the age of a home, the number of bedrooms, and the number of bathrooms) between the two datasets are highly correlated. Our final data contains 55 million observations between 1994 and 2016. Further further details on the filtering are included in the Appendix.

2.2 Consumption Data

Household-level consumption data come from the Nielsen Consumer Panel data. The panel runs from 2004 to 2016 and contains between 40,000 and 60,000 households each year. Households report, via an in-home scanning device, the price paid for and quantity purchased of all goods bought during their time in the survey. We aggregate these purchases into household-level annual expenditure. The data reports on approximately 1.5 million unique goods, which account for approximately 30 percent of all household consumption categories (Nielsen, 2016). These goods

[1] Large numbers of observations are missing price data in Alaska, Idaho, Indiana, Kansas, Maine, Mississippi, Montana, New Mexico, Texas, Utah, and Wyoming due to either non-mandatory disclosure of or outright prohibitions on the reporting of transactions prices. See `http://www.zillowgroup.com/news/chronicles-of-data-collection-ii-non-disclosure-states/` for more details.

are largely non-durables from the following categories: health and beauty, dry grocery, frozen foods, dairy, deli, packaged, meat, fresh produce, non-food grocery, alcohol, general merchandise. Importantly, the data reports the state, county, and zip code in which each household lives. Each household can then be linked to a measure of local house prices.

Although the Consumer Panel reports demographic information associated with each household, home ownership status is not one of these variables. To infer home ownership status, we follow the procedure in Stroebel and Vavra (2014) who also use the Consumer Panel data. Households report whether they live in a one-, two-, or three-family dwelling, and also whether the house is a condo or co-op. We assume that single-family, non-condo/co-op residences are inhabited by homeowners, while remaining households are assumed to be renters. The average proportion of households living in single-family homes is 75 percent, and does not change significantly across sample years. For comparison, the national home ownership rate fell from 69 percent in 2004 to 64 percent in 2015.[2] Because only homeowners should experience the wealth and collateral effects of house prices on consumption (see Buiter, 2010), we restrict the empirical analysis to the sample of inferred homeowners. Households in the data are occasionally observed to move across geographies, although this is less common than is the case in the general population. Because consumption patterns are likely to differ for movers and non-movers, we restrict the sample to those households that never move during their time in the panel. Summary statistics for demographic groups and consumption patterns are reported in Appendix Section A.2.

[2]Home ownership rates for the United States are from FRED (code: USHOWN).

2.3 Additional Data Sources

County-level house price indexes come from the Federal Housing Finance Agency, city (MSA) and zip code house price indexes come from Zillow's publicly available ZHVI All Home price indexes.[3] To account for changes in the general level of prices, I use the CPI for all urban consumers from FRED. Average after tax income by zip code is computed from the IRS Statistics of Income (SOI), using the adjusted gross income variable less total tax payments. County-level unemployment data is collected from the BLS Local Area Unemployment statistics. Zipcode and county-level demographic information are computed from the 2000 Decennial Census. I also use annual county-level employment by industry from Country Business Patterns data. We aggregate employment using the 6 digit NAICS codes into broad categories for construction (NAICS: 23), retail trade (NAICS: 44, 45), and finance/insurance/real estate (NAICS: 52, 53). A detailed list of all data sources is reported in the Appendix.

3 Theory and Empirical Approach

Aggregate house prices and consumption are known to co-move over the business cycle. But, because house prices are endogenous equilibrium objects, it is difficult to distinguish the effect of price movements on consumption from the effect of underlying macroeconomic shocks. Nevertheless, economic theory suggests direct a relationship from house prices to household consumption through wealth and collateral effects on household balance sheets.

Owner occupied housing is a large component of household wealth and its market value rises

[3] Although the ZTRAX data is a rich source of individual housing transactions, zip code, county, and city data have varying degrees of completeness, which presents difficulties in constructing broad and consistent house price indexes. I instead rely on the published house price indexes of the FHFA and Zillow.

and falls with changes in house prices (Rognlie, 2015). Friedman's Permanent Income Hypothesis model of household consumption shows that an increase in permanent wealth leads to an increase in current expenditures (Friedman, 1957). However, housing wealth may be unlike other components of household wealth (Buiter, 2010). Owner-occupiers forgo rental income from leasing their homes, but also save on rental payments for housing services. If houses are priced according to the future stream of rental rates, then an increase in house prices reflects rising rental costs. Higher house values would mean that homeowners enjoy an increase in wealth on paper, but also face higher implicit housing service costs. These offsetting effects imply that changes in house prices may have no net wealth effect on consumption. Despite this, many empirical papers in the recent literature find some support for a general wealth effect channel (Case et al., 2005; Campbell and Cocco, 2007; Mian et al., 2013; Kaplan et al., 2020; Aladangady, 2017).

While wealth effects may be zero in infinite horizon models, life-cycle models suggest that they may differ according to age (Campbell and Cocco, 2007). For young households, future changes in income, family size, and preferences suggest a rising profile of housing consumption over their life time. In contrast, older households may expect to decrease housing consumption in the near future. Thus, rising house prices reflect a decrease in the present discounted value of wealth for young households since they expect to purchasing more housing in the future. For older households, an expected decline in housing consumption means that higher house prices reflect an increase in the present discounted value of wealth. Although Campbell and Cocco (2007) find empirical support for this age-dependent wealth channel, Attanasio et al. (2009) present contradictory evidence.[4]

The effect of a change in wealth on consumption can be non-linear. Consumption functions are concave in current wealth when households are faced with uncertainty and either convex marginal

[4] Mian and Sufi (2011) also find little evidence for differences across age in borrowing repsponses to house prices.

utility (Carroll and Kimball, 1996) or borrowing constraints (Carroll, 2001). Then, households can have very large marginal propensities to consume (MPCs) out of shocks to wealth.[5] Borrowing constraints are especially relevant in the context of housing wealth since houses act as collateral for mortgage borrowing. For example, rising house prices can relax borrowing constraints by reducing current loan-to-value ratios, which allows households to refinance mortgages or make use of home equity lines of credit (Chen et al., 2013). Households with little wealth or who are close to relevant borrowing constraints is especially sensitive to changes in house prices. Recent empirical work provides evidence that this collateral channel of house prices has a strong effect on borrowing (Mian and Sufi, 2011; Cloyne et al., 2017) and consumption (Mian et al., 2013; Aladangady, 2017).

The empirical literature has employed two reduced form model specifications for investigating the effect of house prices on consumption. One model estimates the elasticity of consumption with respect to house prices, and the other estimates the MPC out of housing wealth. While the former approach requires only data on consumption and house prices, the latter also requires information about the composition of wealth. Lacking information on balance sheets, we estimate the elasticity of consumption growth with respect to house price growth under arbitrary degrees of geographic disaggregation through regressions of the form:

$$\Delta c_{i,g,t} = \beta_1 \Delta p_{g,t} + \beta_2 x_{i,t} + \beta_3 y_{g,t} + \alpha_{cbsa} + \alpha_t + \varepsilon_{i,g,t}, \tag{1}$$

where i denotes an individual household, g denotes the location of that household (e.g. zip code, county, city), and t denotes the year of observation. $\Delta c_{i,g,t}$ is the annual log-change in real

[5] Large MPCs are even possible for high net-worth households if they are otherwise borrowing constrained. Consider, for example, the wealthy hand-to-mouth households in Kaplan et al. (2014).

household consumption expenditure, $\Delta p_{g,t}$ is the annual log-change in real local house prices, and β_1 is the elasticity of consumption with respect to local house prices. Household controls $x_{i,t}$ include a typical set of demographic characteristics, including real income growth. We also experimental with local controls, $y_{g,t}$, including employment and payroll growth. City-level (CBSA) fixed effects α_{cbsa} are included since county-level house prices tend to be strongly correlated within CBSAs. Time fixed effects α_t are included when controlling for common movements in house prices and consumption. See Appendix C for a full description of control variables.

Unfortunately, even with detailed household and local controls, we are still concerned that our estimates of Equation (1) may be biased for at least two reasons. On one hand, unobserved local productivity or demand shocks, like the opening of a new business that leads to greater income, could simultaneously raise consumption and housing price growth. This would generate upwards bias. On the other hand, increases in consumption could generate an increase in employment growth, spilling over into the housing market. This would generate downwards bias through reverse causality. Our inclusion of county labor market controls, such as the unemployment rate and growth in average payroll, and household controls, such as demographics and income, helps mitigate upwards bias, but does little to mitigate reverse causality.

We deal with these identification concerns involves developing a Bartik-like instrument in the tradition of (Bartik, 1991). Rather than exploiting industrial or occupational composition in employment shares and interacting exposure from a pre-period with national employment or wage growth, we exploit plausibly exogenous variation in the composition of housing structures within a location–namely the age and size of the structure–and interact these shares with national housing price growth. These housing characteristics reflect the quality of a home, which vary in their price due to demand-side fluctuations in the national housing market. In this sense, if if San Francisco consists of mainly two-bedroom homes prior to the 1940s, whereas Nevada consists of mostly four-bedroom homes in the early 2000s, then an increase in demand for larger and newer homes would generate faster housing price appreciation in Nevada, relative to San Francisco.

Thanks to increasing research on the econometric assumptions behind Bartik-like instruments (Borusyak et al., 2018; Goldsmith-Pinkham et al., 2018), we now know that our exclusion restriction requires that unobserved shocks to consumption growth are uncorrelated with dispersion in the local shares of housing structures in our age $\times$ size categories. This condition would be satisfied if shocks to household consumption are idiosyncratic and uncorrelated across households within the same location–that is, if households in the same location make different consumption decisions for reasons that are uncorrelated with their location $\times$ group housing price shock.[6]

We produce these size $\times$ age local housing shares from 1994 to 2005, making them predetermined relative to 2005 and 2016. Moreover, these shares change very slowly over time. Figure 1 documents these results by comparing the fraction of houses in different age bins–built before 1940, from 1940 to 1959, from 1960 to 1979, and 1980 to 1999–across two snapshots: the 2000 Decennial Census and the 2014-2018 five-year American Community Survey. We find significant degrees of persistence: except between 1960 and 1979 where the correlation is 0.87, the correlation is at least 0.95. This means that the composition of the housing stock is unlikely to respond to shocks that affect household consumption in those locations.

Table 1 provides additional evidence that demographic characteristics are largely demonstrate no systematic correlation with the housing stock. Although no correlation is greater than 0.5 in absolute magnitude and the mean correlation across all house characteristics and demographics is 0.015, we find that counties with a higher proportion of new houses have: higher home ownership

[6]This assumption is similar to the conditions for Guren et al. (2018) and, to some extent, Palmer (2015).

rates, higher rates of college educated households, more white households, fewer black households, and fewer immigrant households. These results assuage concerns that more educated workers locate in larger and more urban cities that also exhibit a lower housing supply elasticity (Davidoff, 2016). Nonetheless, given the presence of some correlation between demographics and housing structures, we nonetheless control for these characteristics as robustness and show that they do not alter our elasticities from the baseline.

[INSERT FIGURE 1 HERE]

[INSERT TABLE 1 HERE]

4 Construction of the Bartik Instrument

Following the discussion in Goldsmith-Pinkham et al. (2018), we take the inner product of the growth in house prices $\Delta p_{g,t}$ decomposed into the interaction between local housing shares and local quality price growth rates $\Delta q_{g,c,t}$:

$$\Delta p_{g,t} = \sum_{c} \lambda_{g,c,t} \Delta q_{g,c,t}, \tag{2}$$

where $\lambda_{g,c,t}$ is the share of houses in location g with characteristic c at time t, and $\Delta q_{g,c,t}$ is quality price growth for houses with characteristic c in location g at time t. House price growth is then given by changes in quality prices weighted by the proportion of those qualities in a particular location. For instance, in a simplified setting where there is one location and a single time period with only two housing types (small and large), then the share of small houses in a location is λ_S and price growth for each type is $\Delta q_{g,S}$ and $\Delta q_{g,L}$. Then, overall house price growth is $\Delta p_g = \lambda_S \Delta q_{g,S} + (1-\lambda_S)\Delta q_{g,L}$. We further decompose the price of quality as follows:

$$q_{g,c,t} = q_g + q_{c,t} + \tilde{q}_{g,c,t}, \tag{3}$$

where q_g is a location fixed effect, $q_{c,t}$ is a characteristic-time component, and $\tilde{q}_{g,c,t}$ is an idiosyncratic location-characteristic-time component. Willingness to pay for housing qualities over time depends on location, the qualities themselves, and interactions between the two. For example, poor rural areas are less able to pay for any given characteristic yielding a low value of q_g. Large houses are relative luxuries, meaning that $q_{c,t}$ is high for large houses when income is high. But, since rural areas already have space, they put less of a premium on large houses so that $\tilde{q}_{g,c,t}$ is relatively low for large houses in rural areas when income is high.

However, the location and idiosyncratic components of quality prices may be correlated with local shocks to household consumption growth. To overcome this sendogeneity, we construct the Bartik instrument using only the characteristic-time component $\Delta q_{c,t}$ of quality prices.[7] We also restrict the local shares to an initial period: $\lambda_{g,c} = \lambda_{g,c,0}$. The instrument is then expressed as:

$$B_{g,t} = \sum_c \lambda_{g,c} \Delta q_{c,t}, \tag{4}$$

where $B_{g,t}$ denotes the Bartik instrument for house prices. In practice, we modify Equation (4) to allow for separate house characteristics c, each with mutually exclusive categories i because housing consists of bundles of characteristics (Rosen, 1974), such as house age and number of

[7]the local house characteristic shares $\lambda_{g,c}$ are measured in an initial period rather than in every period, to avoid endogeneity of the shares. To give an example, suppose productivity growth is associated with increases in demand for higher quality houses. If productivity growth is serially correlated, and new construction responds to changes in quality demand, then future local shares of high quality houses will be higher, and so these shares will be endogenous.

bedrooms. Much like the canonical applications of Bartik instruments that use industry as the categorical variable, and thus the industry shares sum to one in each location, we adhere to a similar practice: the share of houses in category i with characteristic c is denoted $\lambda^i_{g,c}$, where $\sum_i \lambda^i_{g,c} = 1$ for each c in each location. Equation (4) can be rewritten as:

$$B_{g,t} = \sum_c \sum_i \lambda^i_{g,c} \Delta q^i_{c,t}, \tag{5}$$

where $\lambda^i_{g,c}$ are the shares of houses in category i for characteristic c in each location g.[8]

4.1 Local Housing Characteristic Shares

We compute the local shares of housing characteristics using ZTRAX data on unique houses sold between 1994 and 2005. We divide the data associated with each house characteristic into several categories. Building age is split into decadal bins: {pre-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2005}.[9] The number of bedrooms is split into the categories {1, 2, 3, 4, 5+}. The number of bathrooms is split into the categories {0, 1, 2, 3, 4+}, where half-bathrooms are rounded down to the nearest whole-number category. The Appendix tests for the reliability of the local housing shares computed from ZTRAX data.[10].

Because the local housing shares provide identifying information for the instrument, there must be sufficient cross-sectional variation in these shares. Figure 2 presents the distribution of housing

[8]Equation (7) seems to suggest that the various characteristics are unweighted in the relation to house prices: since the category shares for each characteristic sum to 1, then house age is no more or less important than house size. However, the relative importance of each characteristic is embodied in the quality prices $\Delta q^i_{c,t}$. Equivalently, we could normalize the quality prices and apply a characteristic-specific weighting factor to each of them.

[9]This categorization broadly corresponds to the categories reported in the 2000 Census and subsequent American Community Surveys.

[10]We find that building age is well-measured relative to data in the American Community Survey, although data on the number of bedrooms may be less reliable. Section **??** considers a version of the Bartik instrument using only the local shares for housing age

age across counties in the US. For ease of presentation, we report the proportion of houses in each county built prior to 1960, between 1960 and 1990, and between 1990 and 2005. The figure suggests that there is significant cross-county variation in house age. For example, counties in the North East and Mid West have particularly high proportions of houses built prior to 1960. Counties in the South (e.g. Texas) and also in parts of the West (e.g. Nevada and Arizona) have a relatively large proportion of houses built in the latter half of the twentieth century. Importantly, there is variation in the housing age distribution even within regions, notably in the Western US where inland counties have much newer housing stocks than the cities in the coastal states. Figures A.4 and A.3 in the Appendix present the cross-city (CBSA) and cross-zip code distributions of housing age. Across each aggregation, we find substantial variation: for example, as of 2018, the standard deviations across counties in the proportion of homes built prior to 1960, between 1960 to 1990, and after 1990 are 0.15, 0.08, and 0.13, compared with their means of 0.29, 0.39, 0.31.

[INSERT FIGURE 2 HERE]

4.2 Housing Quality Prices

We estimate the price of housing quality using a standard hedonic regression (Rosen, 1974), controlling for the same housing characteristics used in constructing the local housing shares:

$$
\begin{aligned}
p_{i,g,t} = {} & \alpha_g + q'_{b,t}\mathbb{1}(b \in B) + q'_{h,t}\mathbb{1}(h \in H) + q'_{d,t}\mathbb{1}(d \in D) \\
& + \beta_t^f f_i + \beta_t^l l_i + \eta_{i,g,t}
\end{aligned}
\tag{6}
$$

where $p_{i,g,t}$ is the log of the real house price for property i in location g, α_g is a county-specific fixed effect, $\mathbb{1}(b \in B)$ is a dummy variable for the number of bedrooms, $\mathbb{1}(h \in H)$ is a dummy variable for the number of bathrooms, $\mathbb{1}(d \in D)$ is a dummy variable for the decade in which the house was built.[11] We allow for time-varying coefficients in these regressions so as to capture the characteristic-time component $q_{c,t}$ of quality prices in Equation (3). The additional variables f_i and l_i are the log of floor size in square feet and the log of property lot size in square feet.[12]

Similar to Guren et al. (2018) who exploit variation in regional housing price fluctuations, we estimate Equation (6) separately for each Census region in the US—Mid-West, North-East, South, and West—although results are similar at the national level (see Section **??**). Our hedonic regressions explain a significant proportion of cross-sectional variation in house prices—with a median R-squared statistic of 0.6—which is important since failure to effectively measure quality differences across locations could lead to a weak instrument.

Figure 3 shows quality price growth for houses constructed in different decades, normalized to houses built prior to 1940 with one bedroom and zero bathrooms. The horizontal axis plots the decade in which a house was built and the vertical axis reports housing quality price growth. We see, for example, that in the South between 2006 and 2009, houses built in the 1950s experienced a relative fall in price of more than 20 percent. And yet, houses in the Mid West built in the 1980s

[11] In keeping with the construction of Bartik instruments in the literature, the hedonic pricing regressions are estimated using a leave-one-out procedure. For the instrument in location g, we drop all of the observations for that location and then estimate the coefficients in (6). This ensures that housing market movements in a particular location do not dominate the variation in its own instrument. In practice, counties are small relative to the surrounding region so the leave-one-out procedure has virtually no effect on either the instruments or the estimated consumption elasticities.

[12] These house size variables are not included in the Bartik instrument, since size is a continuous variable and does not have an obvious natural categorization from which to compute local shares. However, conditioning on these variables means that the other regression coefficients can be interpreted as the marginal price of characteristics holding size constant. For example, we find that the coefficients on the number of bedrooms are typically negative and monotonically decreasing, suggesting an additional bedroom crowds out other living space in a house of otherwise fixed size.

experienced relative appreciation of roughly 12 percent during these same years. In sum, these descriptive statistics point towards substantial variation in the price of quality changes, which will benefit counties with larger proportions of those houses more than their counterpart counties.

[INSERT FIGURE 3 HERE]

We now evaluate the strength of the Bartik instrument. Figure 4 presents a simple binned scatter plot of the residualized instrument against residualized house price growth, after projecting out the exogenous variables, including all household, local, industry, and demographic controls, together with CBSA and time fixed effects. Despite the inclusion of a large number of control variables, there remains a tight relationship between the instrument and house prices with an F-statistic of 44 in the strictest specification (and R-squared of 0.76).

[INSERT FIGURE 4 HERE]

4.3 Economic Intuition for the Bartik Instrument

Beyond understanding the statistical sources of variation in the Bartik instrument, it is also useful to consider potential economic mechanisms underlying this variation. In particular, why might the marginal prices of certain property characteristics rise and fall relative to others?

We argue that the dispersion in housing structures that exists across counties is largely a function of significant investment that took place following the Great Depression. Because of the surge in foreclosures following unemployment with roughly 50% of mortgages in delinquency as of 1934 (Emmons, 2008), Roosevelt introduced the Federal Housing Act (FHA) in 1934, encouraging home ownership among the middle class with new protections for private mortgage companies.

While it was not until the end of World War II that many of the longer-term government-backed mortgages became pervasive, roughly 30 million new housing units were constructed over the next two decades, leading to a 60% home ownership rate (up from 40%) (Stone, 2006). Among other federal policy that encouraged home ownership, such as the Housing Act of 1968 and the Emergency Home Finance Act of 1970, the result was a large secondary mortgage market that continued stimulating home ownership. In this sense, historical differences in demographics, coupled with federal policy, created substantial dispersion in the types of housing structures across space.

Turning towards variation in the national price of housing quality, we argue that there are two possible explanations. First, given that housing markets are segmented (Piazzesi et al., 2015), buyers do not consider all houses currently on the market. Instead, buyers search along several dimensions, ranging from geography to price to size, which can generate different price dynamics for each type of house. For example, Landvoigt et al. (2015) show that initially low priced (quality) houses in San Diego appreciated much faster during the 2000s housing boom than initially high priced houses. In particular, they argue that lower income households were more affected by the increase in credit supply during the housing boom, thereby creating greater demand for houses where low income households were marginal buyers.

We compute the median prices in each tier for houses that were initially sold in 2000 and the re-sold in each year after that. Consistent with Landvoigt et al. (2015), the upper left panel of Figure 5 shows house price appreciation for houses that were in the bottom, middle, and top third of San Diego houses by sale price in 2000 using data from ZTRAX. House prices in the lowest tier were much more volatile price dynamics than in the other tiers. The remaining three panels of the figure report the distribution of housing characteristics across these house price tiers. We find that the lowest tier of houses are older and smaller, according to building size and number of bedrooms. Following Landvoigt et al. (2015), as low income households bid up the price of low quality houses during the housing boom, older and smaller houses should have appreciated more quickly since these house characteristics are disproportionately represented amongst the lowest quality houses. This is consistent with our results from Table 6 in Appendix Section **??** that the smallest and oldest houses drove much of the variation in the instrument.

[INSERT FIGURE 5 HERE]

Second, variation in the Bartik instrument may also be driven by changes in the purchasing power of other types of marginal house buyers, such as residential property investors. Several recent papers suggest that investors were especially active in housing markets with the largest swings in house prices (Haughwout et al., 2011; Mian and Sufi, 2018). These investors appear to have been especially sensitive to the availability of mortgage credit, and may have contributed to both the rise and fall in house prices. If these buyers invest in houses with particular features, they will influence the price dynamics of those houses for which they act as marginal buyers. It is also possible that the prices of particular houses in some housing markets are driven by variation in demand for luxury apartments or demand from out-of-town or foreign investors (Ait-Sahalia et al., 2004; Chinco and Mayer, 2015; Favilukis and Van Nieuwerburgh, 2017).

5 Main Results, Heterogeneity, and Robustness

5.1 Main Results

We estimate the elasticity of consumption with respect to house price growth using not only standard fixed effects and Saiz (2010) instrument approaches, but also our new Bartik-like approach between 2005 to 2016. While our Bartik-like instrument allows for regional, rather than national, time series variation in the price of quality changes, Table **??** in the Appendix presents estimates using *national* house price growth. This interaction between the Saiz instrument and a source of time series variation is similar to the approach in Chaney et al. (2012) and Aladangady (2017), who both use the cross-sectional elasticities interacted with national real interest rates.

Table 2 documents our main results under various specifications. Starting with column 1, which contains our baseline household controls and county fixed effects, we see that a 1pp rise in housing price growth is associated with a 0.11pp rise in consumption growth. However, there are many reasons that this could still be biased. In particular, we introduce time fixed effects in column 2, which reduces the estimate to a 0.032pp increase in consumption growth. This significant decline in the elasticity suggests that much of the variation in consumption growth over these years is linked with the aggregate shock resulting from the financial crisis.

Turning to column 3, we now present our IV estimates, finding that 1 pp rise in housing price growth is associated with a 0.096pp rise in consumption growth, controlling for county fixed effects and household demographics. Column 4 introduces year fixed effects, marginally raising our estimate. While we presented evidence earlier that our Bartik-like instrument isolates variation in the exposure of some counties to different regional housing price trends, one of our concerns, however, is that there are other time-varying county shocks that could be correlated with these shares and consumption fluctuations. Column 5, therefore, introduces several local controls, such as the unemployment rate and real per capita income. Consistent with the interpretation of our instrument isolating plausibly exogenous variation, our estimate is unaltered.[13]

Furthermore, to address the concern that local housing shares could be correlated with local

[13] See Section C in the Online Appendix for details on these variables.

industry shares, which account for fluctuations in local demand (Mian and Sufi, 2014; Charles et al., 2016), column 6 controls directly for time-varying changes in the industrial composition. While our estimate declines marginally, it is not statistically different from our baseline. Motivated by a similar concern that local housing shares are correlated with local demographic characteristics, which could also influence consumption growth and selection into sub-prime mortgages, column 7 controls for local demographic characteristics, ranging from race to education to the foreign-born population. Finally, column 8 incorporates each of these local business cycle, industry, and demographic controls, suggesting that a 1pp rise in housing price growth is associated with a 0.123pp rise in consumption growth. The robustness of our estimates amid these comprehensive and time-varying controls helps assuage concerns about omitted variables bias.

[INSERT TABLE 2 HERE]

We now compare these estimated elasticities with those obtained under alternative identification strategies introduced in recent literature. Table 3 documents these results. Column 1 begins with the baseline from our previous IV results, including local business cycle, demographic, and industry controls, together with county and year fixed effects and household demographic characteristics. Column 2 instruments for housing price growth using the Saiz (2010) housing supply elasticity, as in Mian and Sufi (2011). Similarly, Lutz and Sand (2017) instruments using their refined measure of land availability, which is an updated version of Saiz (2010) on a broader set of geographies. In both cases, however, their elasticity on housing price growth is nearly twice as large and statistically insignificant, except for Lutz and Sand (2017) at the 10% level. Consistent with an emerging literature about the underlying determinants of the financial crisis, these cross-sectional identification strategies can produce upwards biased estimates because they primarily exploit variation arising from aggregate fluctuations in consumption and housing prices. These fluctuations, however, are correlated with many other factors, including local shocks to economic activity and other aggregate factors.

Turning to column 4, we present the estimates obtained from the IV strategy introduced by Aladangady (2017), which interacts changes in the interest rate with the housing supply elasticity. Although this approach allows us to include county fixed effects, and it improves upon the standard Saiz (2010) approach, it still is subject to upwards bias since there are many other aggregate factors present that are correlated with movements in the real interest rate, particularly during the panic (Bernanke, 2018). Turning to column 5, we now interact regional housing price growth with the Lutz and Sand (2017) land availability instrument, allowing us to introduce both county and year fixed effects. Consistent with our concern that failure to include both county and year fixed effects biases the elasticity upwards, we find a much lower elasticity: a 1pp rise in housing price growth is associated with a 0.067pp increase in consumption growth, which is roughly 20% of the cross-sectional elasticity. The elasticity rises to 0.131pp when we introduce local business cycle, demographic, and industry controls, consistent with the presence of reverse causality, but the elasticity is now only statistically significant at the 10% level.

In column 7, we finally turn towards a novel IV strategy introduced in recent work by Guren et al. (2018) who exploit variation in regional housing price growth interacted with the housing supply elasticity. Unlike the standard approach, however, they control for the sensitivity of local retail employment to regional retail employment, which addresses some of the concerns by Davidoff (2016). Here, we find that a 1pp rise in housing price growth is associated with a 0.037pp rise in consumption growth. However, once we add our baseline local controls in column 8, the statistical and economic significance vanishes.

[INSERT TABLE 3 HERE]

It is also possible to express these elasticities in terms of marginal propensities to consume out of housing wealth.[14] The marginal propensity to consume non-durables out of housing wealth is 1.21 to 1.81 cents in the dollar. Note that this compares to other recent MPC estimates for non-durable consumption of 1.6 cents (Mian et al., 2013), and estimates for total consumption of 2.8 cents (Guren et al., 2018), 4.7 cents (Aladangady, 2017), and 5.4 (Mian et al., 2013).

5.2 Heterogeneous Treatment Effects

While we have identified an average treatment effect over the elasticity of consumption to housing price growth using plausibly exogenous variation in the exposure of counties to different national housing price shocks, we now turn towards potential heterogeneous treatment effects, allowing for differences in individual age, boom/bust periods, and zipcode borrowing constraints, home ownership, and retail employment. Table 4 documents our results.

We replicate our baseline estimate in column 1 for comparison. Column 2 allows for heterogeneity across the age distribution. We see that the elasticity is roughly five times as large for those under the age of 40 than those over the age of 60—that is, a 0.30pp increase in consumption growth versus a 0.06pp increase for a corresponding 1pp rise in housing price growth. While our larger consumption elasticity for the young contrasts with some prior literature on housing wealth effects (Campbell and Cocco, 2007; Buiter, 2010), it is consistent with age-dependent collateral effects. In particular, since younger have larger mortgages and higher LTV ratios, the value of

[14] We follow a convention in the literature that makes use of the fact that the MPC is equal to the elasticity of consumption multiplied by the consumption-to-housing wealth ratio. We take consumption to be aggregate expenditure on non-durable goods (FRED code: PCND) and housing wealth is the market value of owner-occupied real estate (FRED code: HOOREVLMHMV). The average ratio from 2000 to 2016 is 0.12. Note that the ratio for aggregate total expenditure (less housing and utilities) is 0.45.

their equity is more sensitive to movements in house prices. This is also consistent with recent evidence from Wong (2020) that younger households adjust their consumption more in response to monetary policy shocks likely because they are first-time home buyers.

Turning to column 3, we allow for heterogeneity in LTV ratios based on a large macroeconomic literature showing that housing prices and household responses are sensitive to the terms of financing mortgage debt—for example, whether the mortgage debt is collateralized against the value of their house (Mian et al., 2013; Aladangady, 2017). In these cases, increases in housing prices mean that households with previously high loan-to-value (LTV) ratios may borrow more, and perhaps borrow more cheaply (see Cloyne et al., 2017), at the new, lower LTV ratio. The increase in house prices can then relax borrowing constraints for the household, which induces larger changes in consumption expenditure than in comparison to households who are not constrained.

Unfortunately, the Consumer Panel does not report household asset or debt positions, so we cannot directly observe borrowing constraints. However, the transactions data in ZTRAX reports both house prices and mortgage sizes at origination, allowing us to compute average LTV ratios for mortgages at origination by zip code during the 2004 to 2006 housing boom. We assume that average LTV ratios at mortgage origination during this time are a good proxy for overall LTV ratios because many households bought houses or refinanced mortgages during the boom period. We split the sample of homeowner households into those living in zip codes with an average LTV at origination above 0.8 (high LTV) and below 0.8 (low LTV). New mortgages with LTV ratios above 0.8 have more stringent borrowing requirements if insured by GSEs and often required by lenders to have additional private mortgage insurance. This suggests that households with LTVs in this range are more likely to face borrowing constraints than their counterparts below 0.8.

We test this hypothesis by interacting housing price growth with a dummy variable for households in zip codes with average LTV ratios above 80 percent. Consistent with our age-dependent effects in column 2, we find that the consumption of households in zip codes with high LTV ratios is twice as sensitive as the consumption of households in zip codes with lower average LTV ratios. Moreover, our finding that consumption is more elastic to housing price fluctuations is in line with the results from Mian et al. (2013) and Aladangady (2017).

Do our results simply reflect aggregate fluctuations in the housing market and in consumption expenditures during the apex of the financial crisis? To investigate, column 4 interacts an indicator for the 2006 to 2009 time period. However, we find no evidence of heterogeneous treatment effects during these years—our estimate is slightly negative, but very statistically insignificant.

We were also concerned that our results could reflect the effects of spatial spillovers arising foreclosures, which could affect local economic activity directly through housing prices (Anenberg and Kung, 2014; Gupta, 2019) or through a spike in local uncertainty (Makridis and Ohlrogge, 2019). Although our sample is already restricted to a set of home owners, we furthermore allow for heterogeneity among zipcode that have above the median share of home owners, finding no evidence of heterogeneous treatment effects. Similarly, given the tight connection between employment in the non-tradables sector and housing market (Mian and Sufi, 2014), we also allow for heterogeneity in the employment share of retail. Again, we find no evidence of heterogeneous treatment effects. These results provide additional confidence that we are detecting a causal effect of housing price growth on consumption, rather than local spillovers or spatial externalities.

[INSERT TABLE 4 HERE]

5.3 Robustness

We have investigated a wide array of robustness exercises that give us confidence that our newly-formed instrument is not only relevant, but also valid from the perspective of its exclusion restriction. We summarize these exercises here. First, we begin with an alternative formulation of our instrument using variation in the sharing of different housing structures down to the zipcode-level. Table 4 in Section D of the Online Appendix documents these results. In addition to delivering almost identical elasticities, this formulation of the instrument also allows us to introduce county $\times$ year fixed effects. This specification isolates variation unique to the same zipcode over time, controlling for all shocks that are common to the county over time, eliminating the concern that labor market shocks are correlated with fluctuations in the housing market (Mian and Sufi, 2014).

Second, we present three alternative constructions of the Bartik instrument. One concern is that the number of bedrooms or bathrooms is endogenous to economic activity. If, for example, an unobserved productivity shock to a location raises the demand for renovation, then changes in the price of those houses could be linked with consumption growth in a location. We also consider a formulation of our instrument where we draw upon information about the size of the home, allowing for differences in square footage and the price associated with these types of homes. We re-estimate Equation 3 allowing for these additional dimensions of heterogeneity, combined the the county housing shares for these housing structures. Finally, we also investigate whether our results are sensitive to using regional versus national prices of housing quality from Equation 3.

Table 5 in Section D of the Online Appendix documents each of these results. We find nearly identical results when we construct the instrument using only variation in housing shares emerging from the age of the structure (i.e., excluding number of bedrooms and bathrooms). We also find a slightly larger elasticity of 0.14 when we allow for additional variation in the size of the home. Finally, while our baseline specification is qualitatively robust to using the national, rather than regional, price of housing quality, the elasticity declines to 0.046 and becomes statistically insignificant. This, however, is not surprising given that we are already controlling for demographic $\times$ year fixed effects in our preferred specification as suggested by Goldsmith-Pinkham et al. (2018), eliminating variation that is purely national (e.g., evident in a low F-statistic).

Finally, we follow Goldsmith-Pinkham et al. (2018) in recasting the Bartik instrument as an over-identified GMM estimator where the local shares are treated as a set of individual instruments under a particular weighting matrix. Goldsmith-Pinkham et al. (2018) refer to these as Rotemberg weights following Rotemberg (1983). Section E of the Online Appendix describes our construction of these weights and provides a detailed explanation of the results. In brief, we find that the bulk of the weight is concentrated in the West and between the bust years of 2008 to 2009 and the recovery years of 2013 to 2015.

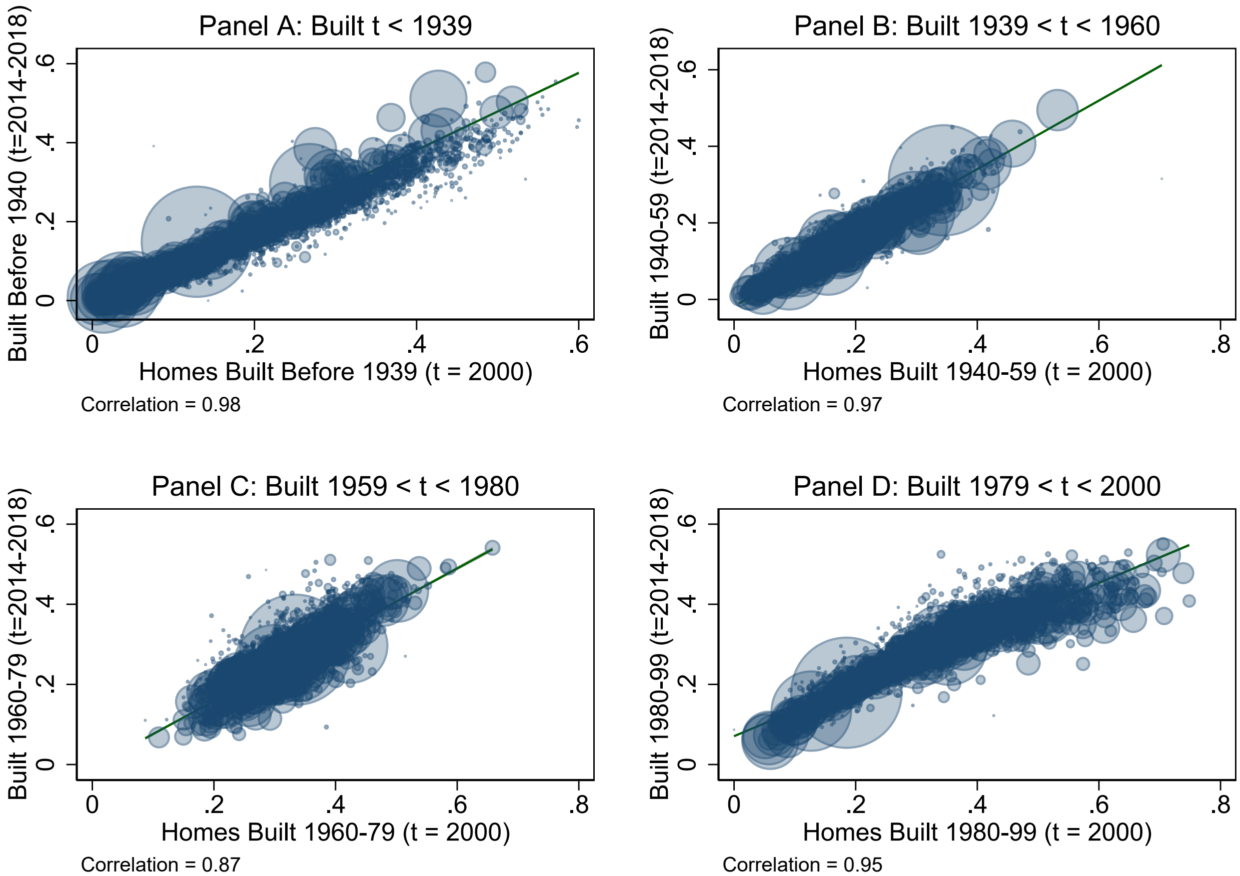
6 Conclusion

There is now a general understanding that housing price fluctuations have causal effects on consumption expenditures. However, these estimates have been tough to estimate because of time-varying shocks that jointly affect consumption and the housing market. We introduce a new Bartik-like instrument that exploits plausibly exogenous variation in the pre-existing housing stock, such as the age and number of bedrooms, within a location to time-varying aggregate trends in the price of these housing characteristics. Our results suggest that a one percentage point rise in housing price growth is associated with a 0.10-0.15 percentage point rise in consumption growth, implying a marginal propensity to consume of 1.2-1.8 cents on the dollar.

Our empirical approach offers two important advantages over existing methods that rely on, for example, the Saiz (2010) elasticity of housing supply. First, we have a larger sample of counties. Second, we obtain exogenous variation in housing price growth over time. Third, and most importantly, our exclusion restriction is more credible, especially in light of recent concerns about demand-side factors that are correlated with the housing supply elasticity (Davidoff, 2016). Our paper provides users with a new instrument for estimating the causal effect of housing price growth on a wide array of economic outcomes, ranging from household consumption to firm investment.

Tables and Figures

Figure 1: Investigating the Persistence of Housing Structure Types



Notes.—Source: Decennial Census (2000) and American Community Survey (2014-2018). The figure plots the relationship between the share of homes built before 1940, between 1940 and 1959, between 1959 and 1979, and between 1980 and 1999 based on an extraction of the 2000 Decennial Census and the 2014-2018 ACS.

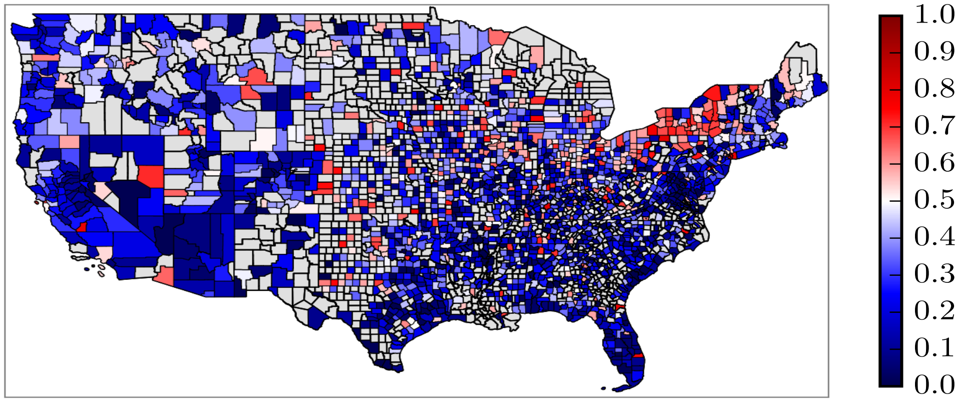
Table 1: Correlations of local characteristic shares and local demographics

	Years built							
	pre-1940	1940-1949	1950-1959	1960-1969	1970-1979	1980-1989	1990-1999	2000-2005
Frac. owner occupied	-0.4	-0.21	-0.15	-0.06	0.23	0.06	0.36	0.29
Frac. College or more	-0.24	-0.13	-0.03	0.08	0.16	0.26	0.23	0.0
Frac. white	-0.19	-0.27	-0.24	-0.16	0.14	0.0	0.28	0.27
Frac. black	0.27	0.24	0.17	0.09	-0.28	-0.11	-0.27	-0.21
Frac. Hispanic	-0.13	0.04	0.11	0.04	0.07	0.15	-0.02	-0.01
Frac. foreign born	0.08	0.12	0.19	0.13	0.04	0.11	-0.18	-0.24
Median age	0.05	-0.05	-0.04	0.03	0.1	0.06	-0.08	-0.1
Mean household size	-0.24	-0.01	0.08	0.05	0.13	0.09	0.14	0.07
Mean commute time	0.18	0.02	0.02	-0.02	-0.12	0.06	-0.11	-0.12

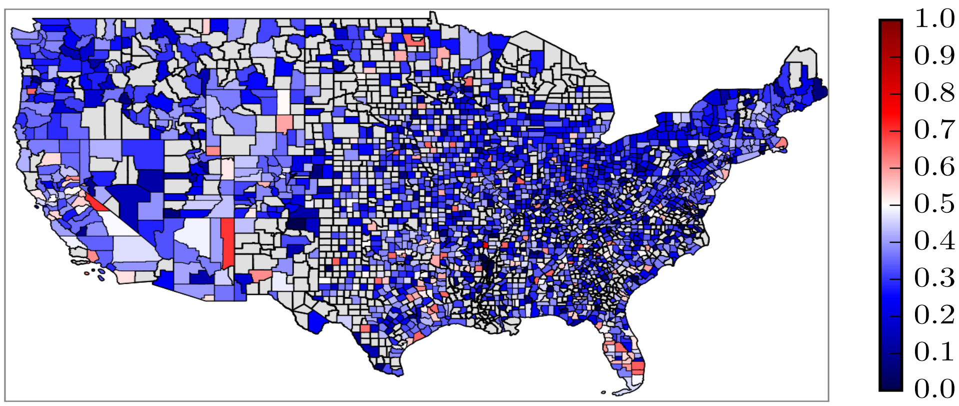
Notes: Correlation between county shares for housing characteristics and county demographics from the 2000 Census. Correlations computed for 1674 counties, weighted by Census population counts.
Sources: Author's calculations using 2000 Census, ZTRAX.

Figure 2: Distribution of Housing Age Across Counties

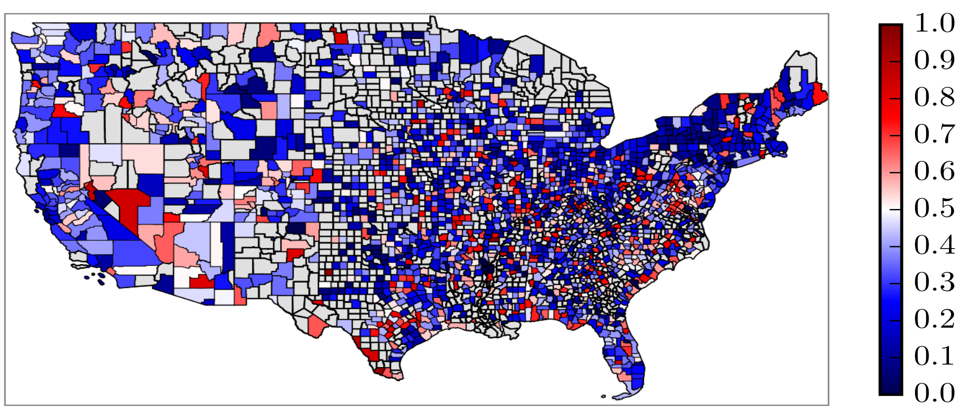
[Panel A: Proportion Built Prior to 1960]



[Panel B: Proportion Built 1960 to 1990]

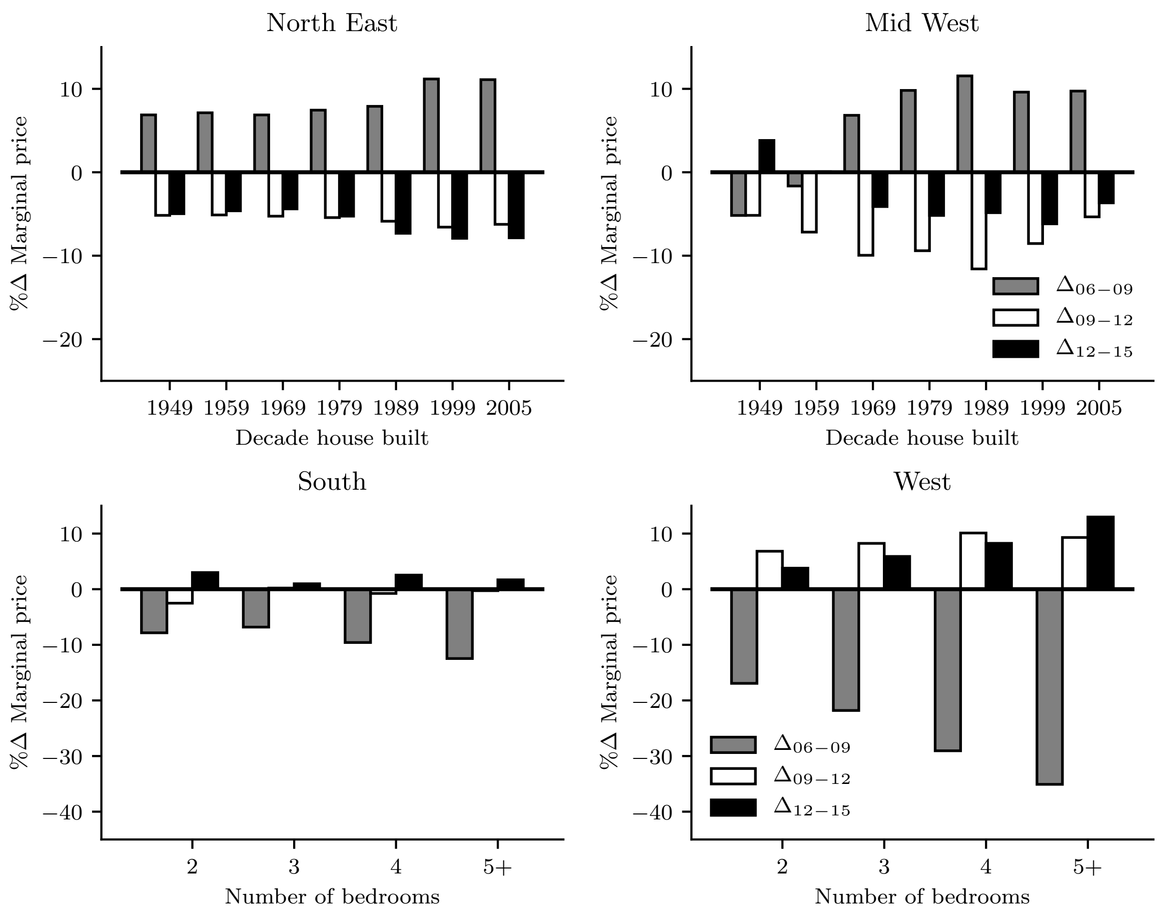


[Panel C: Proportion Built After 1990]



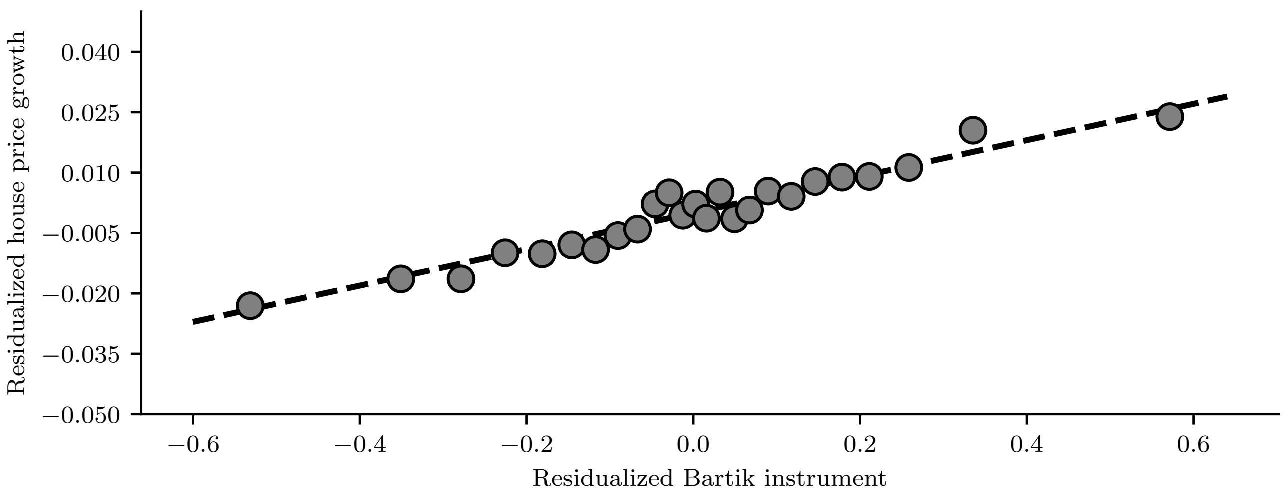
Notes.—Source: Zillow. The heat map shows the within-county proportion of all unique houses sold between 1994 and 2005 that were built before 1960, between 1960 and 1990, and between 1990 and 2005 for the 1283 counties that have at least 100 individual transactions of unique houses from 1994 to 2005.

Figure 3: Change in Marginal House Prices, By Housing Age



Notes.—Source: Zillow. The figure plots the change in marginal house prices corresponding with the decade of house construction. The coefficients are obtained from the regressions estimated in Equation 6. Growth rates are interpreted as the marginal price changes for a house with the given characteristic relative to a house built prior to 1939, with one bedroom, and zero bathrooms. Growth rates are calculated for 2006-2009, 2009-2012, and 2012-2015.

Figure 4: First Stage Effect of Bartik Instrument on House Price Growth



Notes.—Source: Zillow. The figure plots the residualized Bartik instrument and county house price growth, representing the first stage regression. The residualized variables are constructed using the same household-level data and include the full set of controls as in the IV estimation of the consumption elasticities. See Appendix C for a list of control variables. The value of the Bartik instrument is split into equal sized bins, where the mean of the instrument and house prices is computed for observations falling within each bin. The red dashed line plots the first stage regression coefficient on the Bartik instrument.

Table 2: Consumption Response to House Prices Using the Bartik Instrument

	Real annual non-durable household consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.109***	0.032***	0.096***	0.110***	0.115***	0.107***	0.112**	0.123***
	(0.007)	(0.009)	(0.014)	(0.029)	(0.032)	(0.028)	(0.044)	(0.047)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	296,787	296,787	296,787	296,787	296,403	296,746	296,699	296,274
Households	66,497	66,497	66,497	66,497	66,419	66,494	66,474	66,393
Counties	1,207	1,207	1,207	1,207	1,206	1,206	1,204	1,202
Controls								
Household	Y	Y	Y	Y	Y	Y	Y	Y
Local	N	N	N	N	Y	N	N	Y
Industry	N	N	N	N	N	Y	N	Y
Demographic	N	N	N	N	N	N	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	Y	Y	Y	Y
F-statistic	–	–	235.35	69.87	70.91	70.92	60.08	61.87
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Notes.—Sources: Bureau of Labor Statistics (BLS), County Business Patterns (CBP), Federal Housing Finance Agency (FHFA), Internal Revenue Service (IRS) Statistics of Income (SOI), Nielsen, Zillow ZTRAX. The table reports the coefficients associated with the household-level year-to-year growth in non-durable consumption expenditures (deflated using the CPI) on county year-to-year housing price growth from the FHFA index, conditional on household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects. Household controls come from the Nielsen Consumer Panel, including:Â real household income growth, a quadratic in age, the change in household size, the presence of children, marital status, race, Hispanic or Latino origin, occupation, and education. Household income is reported as for the year two years prior to the current panel date. While income is reported as a categorical variable, we record current income as the value assigned to the upper boundary of the current income category, subsequently deflating it by the CPI. Local business cycle controls include: county unemployment growth from the BLS and real per capita income from the IRS. Local industry composition controls include: the employment share of construction, manufacturing, retail trade, and finance/real estate/insurance (FIRE) from the CBP. Local demographic controls include population shares of: black, Hispanic, foreign-born, those with at least some college education, homeowners, median age, household size, mean travel time to work, and employment shares in construction, manufacturing, retail trade, and FIRE. Each of these local demographic variables are interacted with year-dummy variables as suggested by Goldsmith-Pinkham et al. (2019).

Table 3: Consumption Response to House Prices Using the Bartik Instrument

	Real annual non-durable household consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.127**	0.250	0.343*	0.260***	0.067**	0.131*	0.037***	0.016
	(0.050)	(0.357)	(0.194)	(0.033)	(0.032)	(0.075)	(0.014)	(0.020)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instrument	Bartik	Saiz	Lutz-Sand	Aladangady	Lutz-Sand $\times \Delta p_r$	Lutz-Sand $\times \Delta p_r$	GMNS $\times \Delta p_r$	GMNS $\times \Delta p_r$
Observations								
Total	310,109	255,895	310,622	255,895	310,622	310,109	281,908	281,438
Households	66,393	54,285	66,497	54,285	66,497	66,393	60,124	60,026
Controls								
Household	Y	Y	Y	Y	Y	Y	Y	Y
Local	Y	N	N	N	N	Y	N	Y
Industry	Y	N	N	N	N	Y	N	Y
Demographic	Y	N	N	N	N	Y	N	Y
County FE	Y	N	N	Y	Y	Y	Y	Y
Year FE	Y	N	N	N	Y	Y	Y	Y
F-statistic	63.14	2.10	6.22	142.25	42.20	11.30	902.29	345.47
Adjusted R-squared	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01

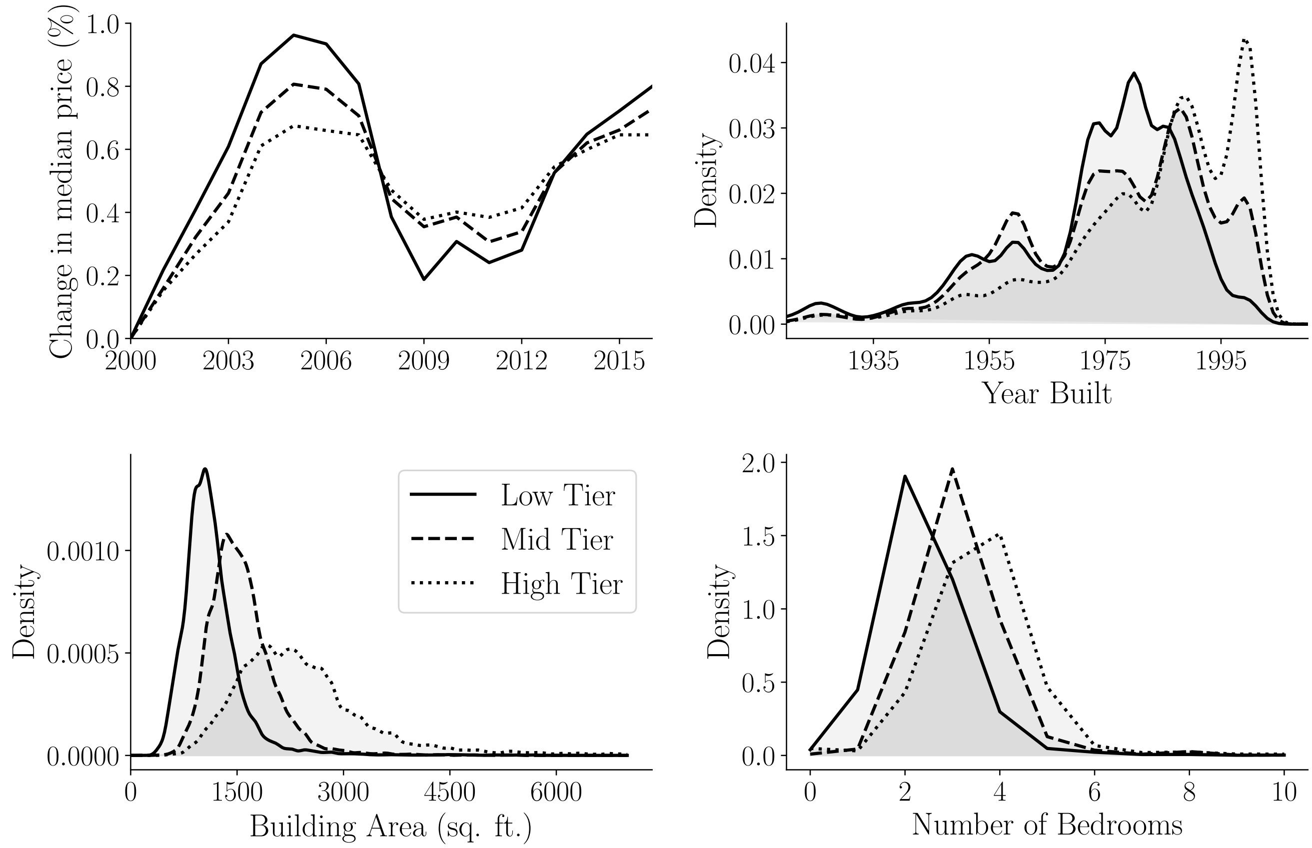
Notes.—Sources: Bureau of Labor Statistics (BLS), County Business Patterns (CBP), Federal Housing Finance Agency (FHFA), Internal Revenue Service (IRS) Statistics of Income (SOI), Nielsen, Zillow ZTRAX. The table reports the coefficients associated with the household-level year-to-year growth in non-durable consumption expenditures (deflated using the CPI) on county year-to-year housing price growth from the FHFA index under various instrumental variables specifications, conditional on household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects. In addition to the Bartik-like instrument that defines our baseline specification in column 1, we also use the instruments introduced by Saiz (2010) of the housing supply elasticity, Aladangady (2017) of an interaction between the housing supply elasticity and the interest rate, Lutz and Sand (2019) of a more granular measure of land availability, and Guren et al. (2020) of an interaction between the housing supply elasticity and regional housing prices. Household controls come from the Nielsen Consumer Panel, including: real household income growth, a quadratic in age, the change in household size, the presence of children, marital status, race, Hispanic or Latino origin, occupation, and education. Household income is reported as for the year two years prior to the current panel date. While income is reported as a categorical variable, we record current income as the value assigned to the upper boundary of the current income category, subsequently deflating it by the CPI. Local business cycle controls include: county unemployment growth from the BLS and real per capita income from the IRS. Local industry composition controls include: the employment share of construction, manufacturing, retail trade, and finance/real estate/insurance (FIRE) from the CBP. Local demographic controls include population shares of: black, Hispanic, foreign-born, those with at least some college education, homeowners, median age, household size, mean travel time to work, and employment shares in construction, manufacturing, retail trade, and FIRE. Each of these local demographic variables are interacted with year-dummy variables as suggested by Goldsmith-Pinkham et al. (2019).

Table 4: Heterogeneity in Consumption Responses to House Prices

	Real annual household non-durable consumption growth					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta p_{county,t}$	0.112***	0.298***	0.094***	0.140**	0.121***	0.112***
	(0.031)	(0.065)	(0.030)	(0.065)	(0.032)	(0.033)
$\Delta p_{county,t} \times \mathbb{1}(40 < Age \leq 60)$		-0.155***				
		(0.057)				
$\Delta p_{county,t} \times \mathbb{1}(60 < Age)$		-0.244***				
		(0.058)				
$\Delta p_{county,t} \times \mathbb{1}(LTV > 0.80)$			0.089***			
			(0.033)			
$\Delta p_{county,t} \times \mathbb{1}(2006 - 2009)$				-0.051		
				(0.102)		
$\Delta p_{county,t} \times \mathbb{1}(Homeownership > Median)$					-0.023	
					(0.023)	
$\Delta p_{county,t} \times \mathbb{1}(RetailTrade > Median)$						-0.0002
						(0.022)
Observations						
Total	296,362	296,362	296,362	296,362	296,362	296,362
Households	66,416	66,416	66,416	66,416	66,416	66,416
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Notes.—Sources: Bureau of Labor Statistics (BLS), County Business Patterns (CBP), Federal Housing Finance Agency (FHFA), Internal Revenue Service (IRS) Statistics of Income (SOI), Nielsen, Zillow ZTRAX. The table reports the coefficients associated with the household-level year-to-year growth in non-durable consumption expenditures (deflated using the CPI) on county year-to-year housing price growth from the FHFA index instrumented using the Bartik-like measure, conditional on household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects, allowing for heterogeneity across age (individual-level), a high loan-to-value ratio (LTV) at origination above 0.8 on average in the zipcode, time (2006-2009), zipcode homeownership (above the median), and the retail employment share (above the median). Household controls come from the Nielsen Consumer Panel, including: real household income growth, a quadratic in age, the change in household size, the presence of children, marital status, race, Hispanic or Latino origin, occupation, and education. Household income is reported as for the year two years prior to the current panel date. While income is reported as a categorical variable, we record current income as the value assigned to the upper boundary of the current income category, subsequently deflating it by the CPI. Local business cycle controls include: county unemployment growth from the BLS and real per capita income from the IRS. Local industry composition controls include: the employment share of construction, manufacturing, retail trade, and finance/real estate/insurance (FIRE) from the CBP. Local demographic controls include population shares of: black, Hispanic, foreign-born, those with at least some college education, homeowners, median age, household size, mean travel time to work, and employment shares in construction, manufacturing, retail trade, and FIRE. Each of these local demographic variables are interacted with year-dummy variables as suggested by Goldsmith-Pinkham et al. (2019).

Figure 5: Prices and Characteristics of Houses in San Diego by 2000 Price Tier



Notes.—Source: Zillow. The top left panel plots the median price for each tier based on houses sold repeatedly after 2000. The top right panel plots the distribution of housing structure ages for each of the three tiers. The bottom left panel plots the distribution of housing structure size (in square feet) for each of the three tiers. The bottom right panel plots the distribution of the number of bedrooms for each of the three tiers.

Online Appendix (Not for Print)

A Supplement to Data and Measurement

A.1 Data Dictionary

This section documents the sources of data used in the paper.

- Panel consumption data comes from the Nielsen Consumer Panel Data survey made available by the Kilts Center at Chicago Booth. This data is proprietary and is typically available only by institutional subscription. See the Kilts Center website for more information regarding access: https://research.chicagobooth.edu/nielsen/.

- The individual housing transaction data comes from Zillow's Assessment and Transaction Database (ZTRAX). This data is proprietary, but is available from Zillow by request. For information regarding access, contact see http://www.zillow.com/ztrax.

- Annual county house price indexes are publicly available from the Federal Housing and Finance Agency at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Dataset aspx.

- Additional house price indexes for zip codes, counties, and metropolitan areas (CBSA) are publicly available from Zillow at https://www.zillow.com/research/data/.

- The consumption price index is the monthly seasonally adjusted CPI-U for all items. This is available from FRED at https://fred.stlouisfed.org/, using code CPIAUCSL.

- Zip code level income is retrieved from the IRS Statement of Income (SOI) statistics at https://www.irs.gov/statistics/.
- County unemployment data is from the Bureau of Labor Statistics, available at https://www.bls.gov/lau/data.htm. Python code to clean this data is available at Github: https://github.com/jagman88/Clean-BLS-County-Level-Employment-Data.
- Zip code and county level demographic characteristics are retrieved from 2000 Census, available at https://factfinder.census.gov/.
- County employment by industry is in the County Business Patterns data, available at https://www.naics.com/business-lists/counts-by-naics-code/.
- Zip code, FIPS (county) code, and metropolitan area (CBSA) cross-walk information is retrieved from the Department of Housing and Urban Development at https://www.huduser.gov/portal/datasets/usps_crosswalk.html.
- Cartographic boundary files (i.e. TIGER shape files) used in the construction of maps are available from the Census Bureau at https://www.census.gov/geo/maps-data/.
- Additional figures use data from the Survey of Consumer Finances, available at https://www.federalreserve.gov/econres/scfindex.htm. Other data comes from the Current Population Survey, available via IPUMBS at https://cps.ipums.org/cps/.

A.2 ZTRAX House Price Data

Each transaction in ZTRAX contains information on the characteristics of the property and the sale including date of sale, property type, sale type, buyer type, and so on. We aim to work with a consistent data set containing typical property transactions conducted by residential owner-occupiers. To this end, I carry out the following cleaning procedure.

I restrict the data to housing transactions made at arm's-length and when not sold due to foreclosure. This removes all distressed sales, and all transactions with builders, developers, or real estate agents on either side of the transaction. We restrict properties to those that are are non-commercial, and that are either single family residences or owner-occupied properties. This latter restriction allows me to include properties that are apartments, as long as they are owner occupied (i.e. not sold by a landlord). This is important in cities like New York where a significant proportion of the owner-occupied housing stock consists of apartments. We also focus only on property transactions with non-zero sales prices, thereby removing all mortgages, mortgage refinancing, and transfers or gifts. We exclude transactions that may have been subject to 'house flipping', thereby distorting the market value of the house. To do this, I remove any house sale that occurs within 180 days of a prior sale of the same house. Additionally, I remove transactions with a sale price of less than \$10,000 as well as those with no reported transaction date. We exclude houses with no recorded build year (i.e. no known age of the building), no reported floor size, and no reported zip code.

The ZTRAX data is held in state-level files, each of which contains the entire set of property characteristics and transactions for that state. Three states – Rhode Island, Tennessee, and Vermont – have various missing data in the ZTRAX database, and are excluded from the analysis. For several other states, non-mandatory disclosure and outright prohibitions on the reporting of transactions prices mean that a very large proportion of transactions feature sales with prices reported as zero or missing.[15] For these states, property deeds and assessment records may still

[15] See http://www.zillowgroup.com/news/chronicles-of-data-collection-ii-non-disclosure-states/

be reported to the ZTRAX database. We collect data on housing characteristics for these states, but I cannot use the transaction data on sales prices.[16] Instead, for these states I use publicly available, geographically aggregated Zillow house price indexes. After data cleaning, there are 55 million individual transactions available between 1994 and 2016.

A.3 Consumer Panel Data

Table 1 reports household summary statistics from the Consumer Panel. Notice that average consumption is much lower than average income, which is because only non-durable expenditure is surveyed. Table **??** reports several demographic summary statistics. In comparison with data from the Current Population Survey (CPS) over the same sample period, the Consumer Panel has a similar proportion of households whose heads have attended college, are not in employment, and are homeowners. Additionally, we report the proportion of households that have moved in the past year across zip codes, counties, or states. Relative to the CPS, households are similarly likely to have moved across states, about half as likely to have moved across counties (not including cross-state moves), and less than a third as likely to have moved across zip codes (not including cross-county or cross-state moves). Since households are less likely to move than typical households in the population, they may experience greater consumption sensitivity with respect to house prices than the typical household in the population. For this reason, in the empirical analysis, we restrict households to those that do not move during the sample, and so all results should be interpreted as consumption responses to a house price change for non-moving households.

While home ownership is not directly reported in the Consumer Panel, we follow Stroebel and

for more details.

[16] The states with large numbers of missing transaction data are: Alaska, Idaho, Indiana, Kansas, Maine, Mississippi, Montana, New Mexico, Texas, Utah, and Wyoming

Table 1: Household summary statistics, Neilsen Consumer Panel

	Income	Expenditure	Age	Family Size
Mean	$ 68,141	$ 7,489	53	2.6
Median	$ 59,999	$ 6,317	52	2.0
StdDev	$ 42,330	$ 4,896	15	1.5

Notes: Means, medians, and standard deviations computed using Consumer Panel survey weights. Income is the households income two years prior to the panel year, and is recorded categorically. Income statistics are computed using the upper bound of each category. Expenditure is total nominal household consumption expenditure within the panel year. Age is computed using the male household head, or the female household head if no male head is reported. Family size is the number of family members reported to live in the household. *Sources:* Authors calculations using ZTRAX.

Vavra (2014) who infer ownership status household residence type. Households report whether they live in a one-, two-, or three-family dwelling, and also whether the house is a condo or co-op. Single-family, non-condo/co-op residences are assumed to be inhabited by homeowners, with remaining households assumed to be renters. The average sample weighted-proportion of households living in single-family homes is 0.75, and does not change significantly over the sample. From 2004 to 2015, the home ownership rate for the US as a whole fell from 69 percent to 64 percent.[17] The second panel of Figure A.1 in the Appendix reports the age profile of home ownership, which reveals that implied home ownership rates are overstated by between 15 and 30 percentage points for young households relative to data from the SCF. Implied home ownership rates for older households are very similar to those reported in the SCF. For most of the empirical results, we make use of the sample of implied home owners only.

Table 3 reports the number of panelists in each year, as well as the proportion of panelists remaining in the panel 2, 3 and 5 years after observing them in a given year. From 2006 to 2007 the size of the panel increases substantially, from 37,786 to 63,350. Attrition rates in both the short and medium term do not vary substantially over time and appear to be relatively low. The average proportion of panelists remaining after 2, 3, and 5 years is 0.81, 0.68, and 0.52, respectively.

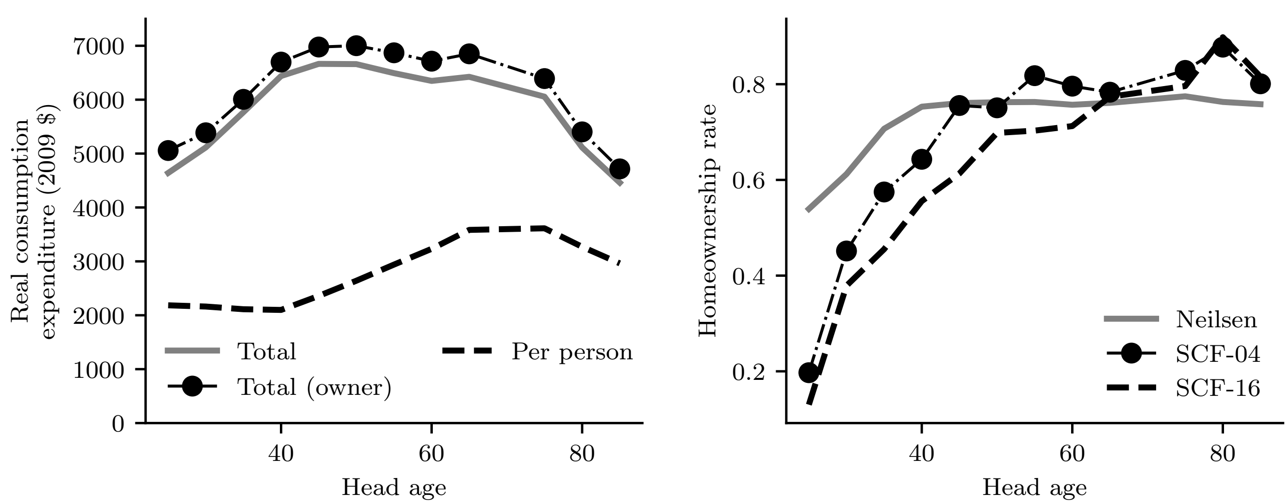
[17] Home ownership rates for the United States are from FRED (code: USHOWN).

Table 3: Number of panelists, Neilsen Consumer Panel

Year	Number Panelists	Remain, 2 years	Remain, 3 years	Remain, 5 years
2004	39577	0.79	0.64	0.51
2005	38863	0.78	0.69	0.53
2006	37786	0.85	0.73	0.55
2007	63350	0.79	0.66	0.47
2008	61440	0.80	0.65	0.48
2009	60506	0.77	0.64	0.50
2010	60658	0.78	0.67	0.52
2011	62092	0.82	0.71	0.55
2012	60538	0.82	0.70	0.55
2013	61097	0.82	0.70	–
2014	61557	0.82	0.71	–
2015	61380	0.83	–	–
2016	63150	–	–	–

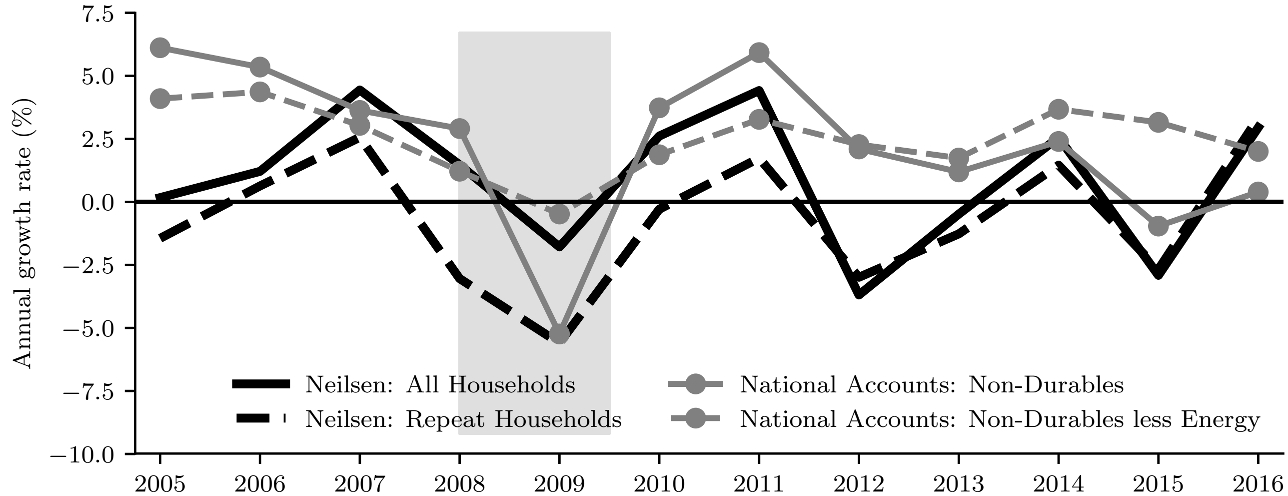
Notes: The first column reports the number of unique panelists per year. The remaining columns report the proportion of unique panelists remaining in the panel for 2, 3, and 5 years.
Sources: Authors calculations using Neilsen Consumer Panel.

Figure A.1: Consumption and Homeownership Over the Life Cycle



Notes: Consumption and homeownership rates in the Nielsen data are pooled across all years by age group. The left panel plots total household consumption for all households (blue, solid line), total household consumption for all (implied) homeowners (red, dash-circle), and total household consumption normalized by the household size (green, dashed line). Consumption values are reported in real, 2009 dollars. The right panel plots homeownership rates in the Nielsen data (blue, solid line), the 2004 SCF (red, dash-circle), and the 2016 SCF (green, dashed line).
Source: Author's calculations using Nielsen Consumer Panel, Survey of Consumer Finances.

Figure A.2: Per Capita Non-Durables Consumption Growth



Notes: Annual nominal non-durable consumption growth per capita in the Nielsen Consumer Panel and national accounts data. The solid blue line is the growth rate in the survey-weighted average of total consumption-to-household size. The dashed blue line is the growth rate in the survey-weighted average of total consumption-to-household size for households that remain in the panel for consecutive years. The solid red line is the growth rate in non-durable personal consumption expenditures-to-population. The dashed red line is the similar, but using non-durable personal consumption expenditure for all goods minus non-durable personal consumption expenditure for gasoline and other energy goods. Shaded area represents recession dates.
Source: Author's calculations using Nielsen Consumer Panel, NIPA via FRED.

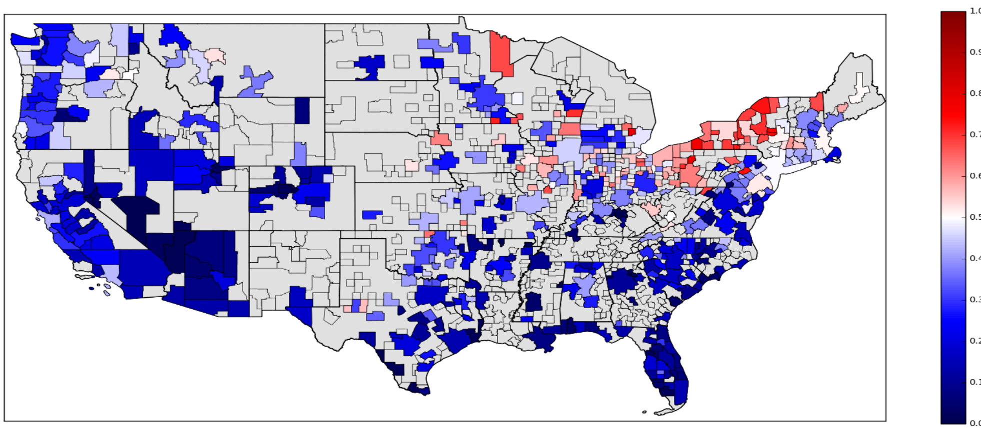
Figure A.1 presents the age profile of CPI-deflated consumption expenditure and the homeownership rate. Total household expenditure follows a well-known hump-shaped pattern over the life-cycle. Consumption expenditure for homeowners does not differ markedly from the average household. Household expenditure per person also follows a hump shape, although the initial rise in expenditure occurs later than for total household expenditures.

Figure A.2 shows the annual growth rate of nominal non-durable consumption per capita for the Nielsen data and for data taken from the personal consumption expenditures section of NIPA. Growth rates are computed from the Consumer Panel data first by computing the growth rate in the survey-weighted average of total consumption-to-household size for all households in the panel. Because of possible selection effects arising from panelist attrition, we also compute the growth rate in the survey-weighted average of total consumption-to-household size for households that remain in the panel for each pair of consecutive years. For national accounts data, growth rates are computed as non-durable personal consumption expenditures-to-population, and non-durable personal consumption less energy expenditures-to-population. The patterns of growth rates in non-durable consumption for the Consumer Panel and national accounts data are similar, with the notable exceptions of 2005 and 2012.

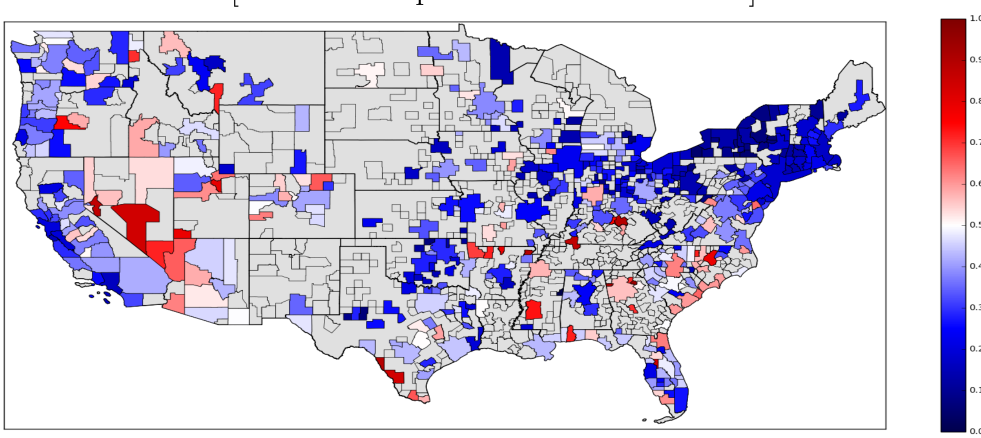
Bartik Instrument Characteristics and Quality Prices

Figure A.3: Distribution of Housing Age Across Cities

[Panel A: Proportion Built Prior to 1960]



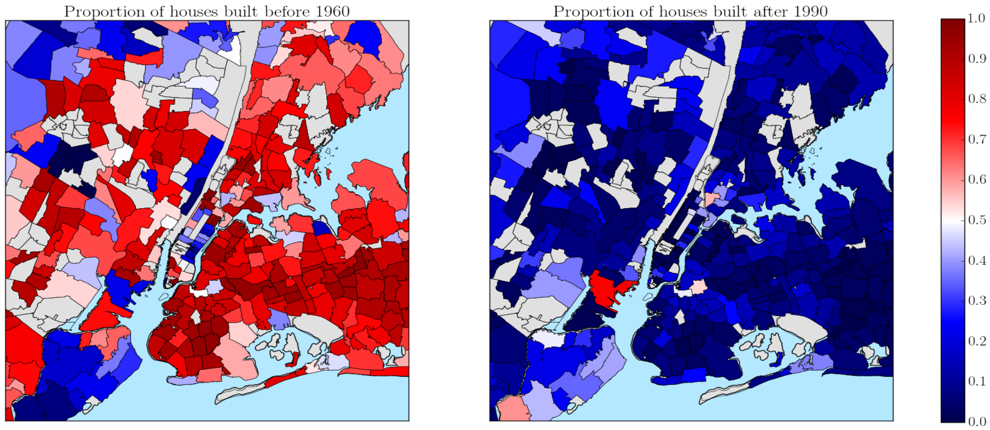
[Panel B: Proportion Built After 1990]



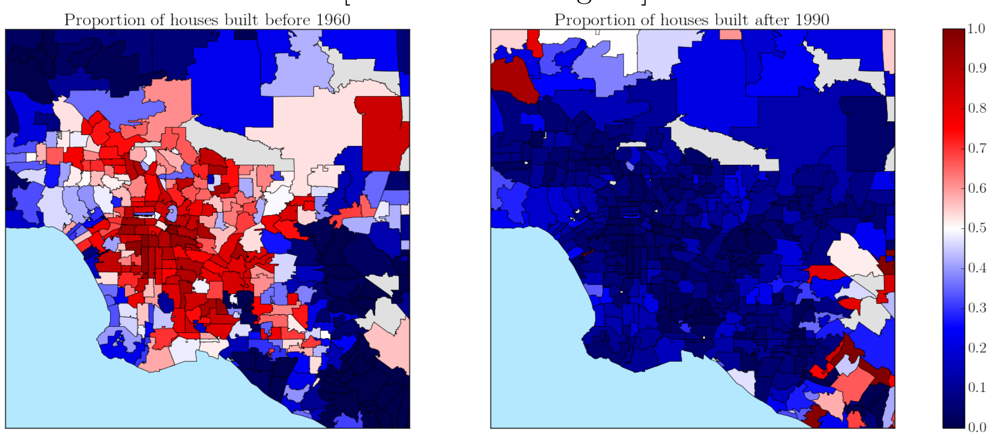
Notes: Maps show the proportion of houses built in three different year groups for each CBSA. Maps show 429 CBSAs for which there are at least 500 individual transactions of unique houses from 1994 to 2005. These CBSAs contained 80 percent of the US population in the 2000 Census.
Sources: Author's calculations using ZTRAX.

Figure A.4: Distribution of Housing Age Across Zip Codes

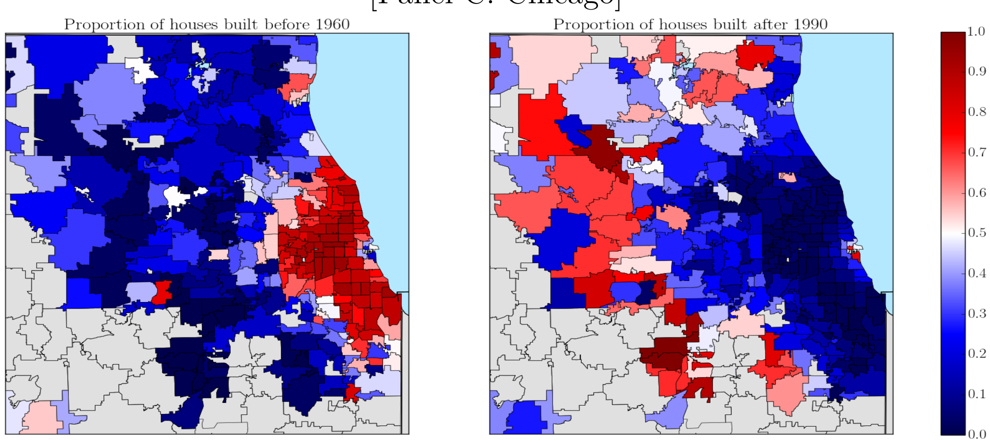
[Panel A: New York]



[Panel B: Los Angeles]



[Panel C: Chicago]



Notes: Maps show the proportion of houses built in two different year groups for each zip code within a city. Maps show zip codes for which there are at least 50 individual transactions of unique houses from 1994 to 2005.
Sources: Author's calculations using ZTRAX.

B Details of Bartik Instrument Construction

In order to compute the local housing characteristic shares, we use data on unique houses reported in ZTRAX. Because the sample period for the main empirical analysis is 2005-2016, we construct the local shares for a pre-sample period: 1994-2005. We include 2005, because housing data for some locations is not available in ZTRAX prior to 2005. However, the results of the analysis are not quantitatively affected by excluding these locations and ending the pre-period in 2004.

The set of housing characteristics used to construct instruments are: house age, building floor size, property lot size, number of bedrooms, and number of bathrooms. There are many other housing characteristics described in ZTRAX, however many of the fields containing this information are not broadly populated. Moreover, several important fields, such as total number of rooms, are not reported consistently across the data set. For example, in an unreported exercise, we found that the average number of rooms computed from ZTRAX was extremely inconsistent with the average number of rooms computed from the 2000 Census. One reason for this is that a 'room' is not easily defined, leading to variation in reports from assessors. Other variables, such as floor size, number of bedrooms, number of bathrooms, or property age are much better defined, and so likely to reflect higher quality data.

We assume that the houses transactions recorded in ZTRAX reflect a random sample of the existing housing stock. However, there could be a selection bias in this measure if, for example, lower quality houses tend to sell less often (i.e. a classic 'lemons' problem). In order to investigate whether selection bias is a problem, Panel A in Figure A.5 compares the proportion of the housing stock built during different periods of the 20th century for each county according to the data from the 2005 American Community Survey and the data derived from transactions in ZTRAX.[18] We present population weighted scatter plots against the 45-degree line reflecting perfect correlation between the two measures. For most year groups, the data like close to the 45-degree line, indicating that the ZTRAX data does not generally over- or under-sample housing age. Although the fraction of houses built in the 2000s is somewhat overstated in the ZTRAX data, this is likely attributable to the fact that a higher proportion of all new houses are sold at any given time than the proportion of old houses sold.

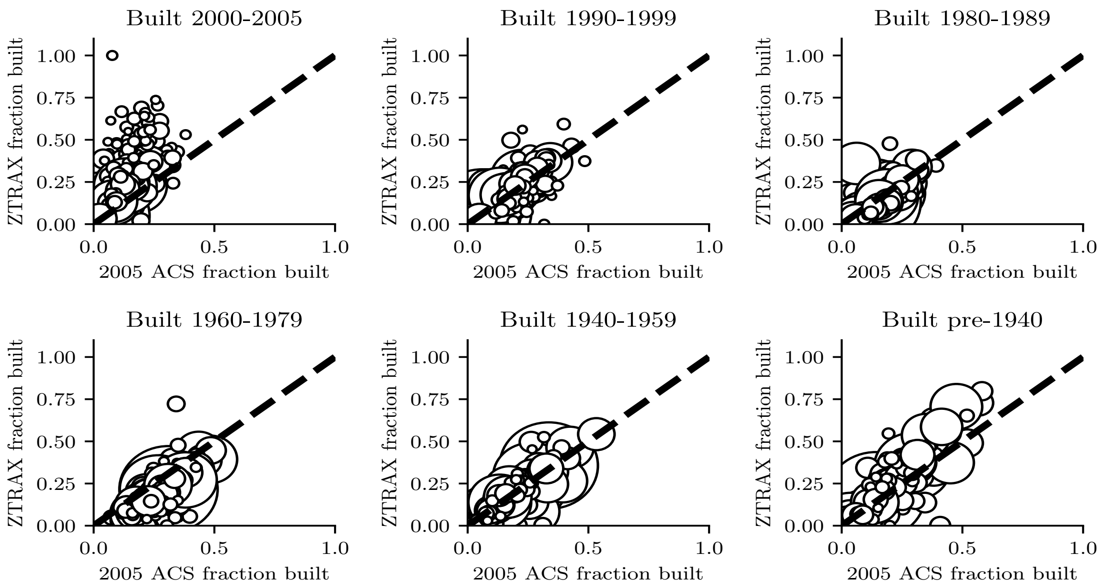
Panel B in Figure A.5 reports a similar exercise but for number of bedrooms. There appears to be systematic mis-reporting of the share of houses with zero bedrooms, although the proportion of houses with 2-3 or 4 or more bedrooms appears to reasonable. For this reason, I exclude houses reporting zero bedrooms from the analysis.[19] Additionally, Section **??** considers a version of the Bartik instrument using housing age as the only house characteristic.

[18] The year groups are selected to correspond to the categories reported in the ACS.

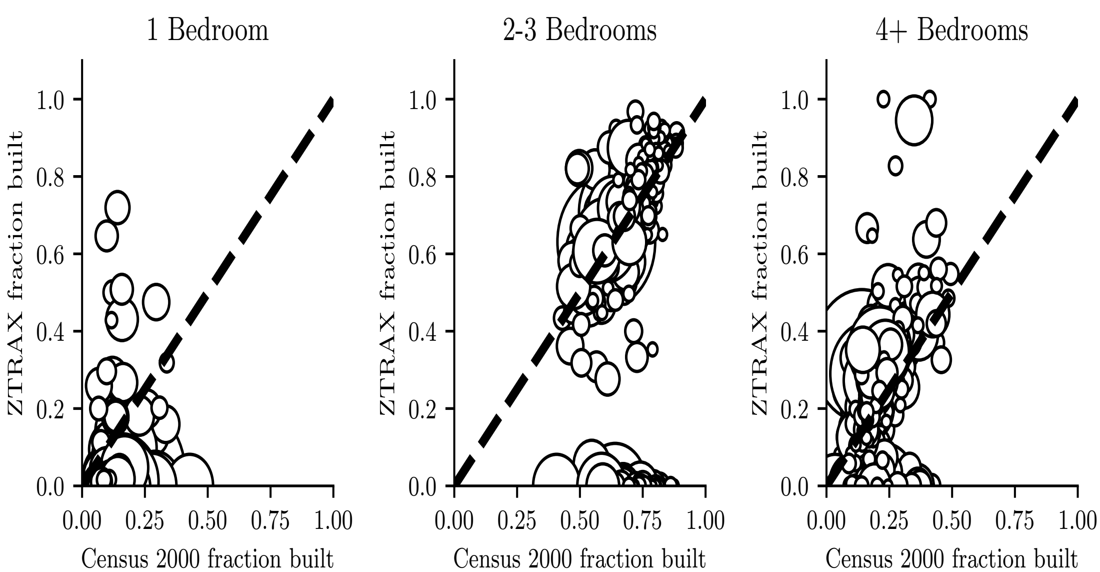
[19] This is approximately 16 percent of the sample. Despite the apparent measurement error, the main results are unaffected if include these zero bedroom houses.

Figure A.5: Local House Characteristic Shares in ZTRAX and 2005 ACS

[Panel A: Share of Houses by Year Built]



[Panel B: Share of Houses by Number of Bedrooms]



Notes: County share of housing stock by year built and number of bedrooms. Shares computed from the 2005 American Community Survey and ZTRAX data for unique houses sold between 1994 and 2005. Note that the ACS reports data for occupied houses only, while the ZTRAX data is drawn from all houses sold. Each blue circle is an observation for a county, weighted by the relative size of the housing stock as reported in the ACS. The black dashed line is the 45 degree line.
Sources: ACS, ZTRAX

C Control Variables Included in Various Regression Specifications

Household controls: All household controls are reported in the Consumer Panel. The controls refer either to the head of household, or apply to the household as a whole. When a household reports two household heads, we use information from the head male. Controls include: real household income growth, age, the square of age, the change in household size, an indicator variable for the presence of children, marital status, race, an indicator for Hispanic or Latino origin, occupation, education. Household income is reported as for the year two years prior to the current panel date. Income is reported as a categorical variable. In order to construct income growth, we record current income as the value assigned to the upper boundary of the current income category. Income is then deflated by the CPI, before the annual growth rate is computed.

Fixed effects: city-level (i.e. CBSA) fixed effects are included in all specifications. Some specifications include year-fixed effects.

Local business cycle controls: Zip code-level real income growth from the IRS SOI data, and county-level unemployment growth from BLS data. These data are reported annually.

Local industry composition controls: All industry controls are annual time series from the County Business Patterns survey. For each county, we take the total number of employees in a given industry, and divide by total employment in that county. We use employment shares for the following industries: agriculture, construction, manufacturing, retail trade, and finance/real estate/insurance (FIRE).

Local demographic controls: All demographic controls are county-level observations from the 2000 Census (i.e. a single cross-section of observations). The demographic controls reported as a proportion of the local population are: race=white, race=black, Hispanic ethnicity, foreign-born, those with at least some college education, homeowners. Other demographic controls are: median age, mean household size, mean travel time to work. Each demographic variable is interacted with year-dummy variables, as suggested by Goldsmith-Pinkham et al. (2018).

D Robustness to the Bartik Instrument

While the main text provides a summary of our robustness exercises, we now discuss them in greater detail. We begin by reporting the results associated with an alternative formulation of the Bartik instrument using variation in housing shares at the zipcode-level, rather than the county-level. Table 4 documents these results. Interestingly, we find nearly identical results. Our OLS estimates, like before, are marginally lower than the IV results. The fact that our IV estimates are slightly larger suggests that reverse causality is a larger concern than omitted variables, at least given the presence of our other controls. Under our preferred specification in column 8, we find that a 1pp rise in housing price growth is associated with a 0.11pp rise in consumption growth. This is robust to controlling for county $\times$ year fixed effects, which controls for potential time-varying labor market shocks to the same county that could be correlated with the housing market.

Table 4: Consumption Response to Zip Code House Prices Using the Bartik Instrument

	Real annual non-durable household consumption growth								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta p_{zipcode,t}$	0.053***	0.016**	0.071***	0.097***	0.105***	0.095***	0.113***	0.123***	0.090
	(0.006)	(0.008)	(0.010)	(0.030)	(0.033)	(0.030)	(0.043)	(0.047)	(0.130)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations									
Total	223,726	223,726	223,726	223,726	223,285	223,723	219,799	219,369	223,726
Households	50,446	50,446	50,446	50,446	50,359	50,446	49,335	49,251	50,446
Zip Codes	7,870	7,870	7,870	7,870	7,842	7,870	7,633	7,608	7,870
Controls									
Household	Y	Y	Y	Y	Y	Y	Y	Y	Y
Local	N	N	N	N	Y	N	N	Y	N
Industry	N	N	N	N	N	Y	N	Y	N
Demographic	N	N	N	N	N	N	Y	Y	N
Zip Code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	Y	Y	Y	Y	N
Year FE	N	N	N	N	N	N	N	N	Y
F-statistic	–	–	430.04	102.17	107.39	108.88	88.01	94.76	25.22
Adjusted R-squared	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01

Notes.—Sources: Bureau of Labor Statistics (BLS), County Business Patterns (CBP), Federal Housing Finance Agency (FHFA), Internal Revenue Service (IRS) Statistics of Income (SOI), Nielsen, Zillow ZTRAX. The table reports the coefficients associated with the household-level year-to-year growth in non-durable consumption expenditures (deflated using the CPI) on zip code year-to-year housing price growth from Zillow, conditional on household controls, county and zip code business cycle controls, county industry composition controls, zip code demographic controls, and county and year fixed effects. Household controls come from the Nielsen Consumer Panel, including:Â real household income growth, a quadratic in age, the change in household size, the presence of children, marital status, race, Hispanic or Latino origin, occupation, and education. Household income is reported as for the year two years prior to the current panel date. While income is reported as a categorical variable, we record current income as the value assigned to the upper boundary of the current income category, subsequently deflating it by the CPI. Local business cycle controls include: county unemployment growth from the BLS and zip code-level real per capita income from the IRS. Local industry composition controls include: the employment share of construction, manufacturing, retail trade, and finance/real estate/insurance (FIRE) from the CBP. Local demographic controls include population shares of: black, Hispanic, foreign-born, those with at least some college education, homeowners, median age, household size, mean travel time to work, and employment shares in construction, manufacturing, retail trade, and FIRE. Each of these local demographic variables are interacted with year-dummy variables as suggested by Goldsmith-Pinkham et al. (2019).

We now turn towards several additional alternative specifications of our Bartik instrument. In particular, one concern is that the number of bedrooms or bathrooms is endogenous to economic activity. If, for example, an unobserved productivity shock to a location raises the demand for renovation, then changes in the price of those houses could be linked with consumption growth in a location. We estimate the housing quality prices from the hedonic price regression (6) as before. This ensures that the estimated marginal prices of house age are conditional on the other house characteristics. However, we then construct the Bartik instrument using only the local shares and quality prices for house age.

We also consider a formulation of our instrument where we draw upon information about the size of the home, allowing for differences in square footage and the price associated with these types of homes. Since fluctuations in house prices might be driven by fluctuations in the value of land, the exclusion of these characteristics might needlessly tie our hands for causal inference.[20] To construct this version of the instrument, we first compute the median log-floor size and median log-lot size for each location. Like before, we estimate Equation (6) to form the quality prices. However, now the hedonic price regression coefficients on the house size variables enter the Bartik instrument. We rewrite the instrument as:

$$B_{g,t} = \sum_c \sum_i \lambda^i_{g,c} \Delta q^i_{c,t} + \mu_{g,f} \Delta q^i_{f,t} + \mu_{g,l} \Delta q^i_{l,t}, \tag{7}$$

where $\mu_{g,f}$ and $\mu_{g,l}$ are the local median log-floor size and log-lot size. This version of the instrument is not a standard Bartik instrument since the additional size variables do not reflect

[20]On the other hand, one reason not to include size variables in the instrument is due to a concern house price variation associated with fluctuations in land prices is likely to be correlated with both local and aggregate business cycle variation that drives household consumption. Including these variables in the instrument risks re-introducing endogenous variation in house prices.

the typical shift-share construction. However, a similar intuition is retained in that locations with larger houses on average should experience faster house price appreciation when the marginal price per square foot of floor or lot increases.

We also investigate whether our results are sensitive to using regional versus national prices of housing quality from Equation 3.

Table 5 documents all these results. In brief, we see large similarities with our baseline results (reported in columns 1 and 2 for convenience). For example, omitting bedrooms and bathrooms from our instrument does not alter our elasticity (see columns 3 and 4). Moreover, adding size only marginally increases our elasticity estimates from 0.12 to 0.14. We interpret these results as evidence that our measurement of the local housing structure shares captures plausibly exogenous variation in the exposure to regional housing price shocks. Finally, columns 7 and 8 present estimates using only national variation. Not surprisingly, our first-stage significance declines considerably and our statistical significance in the second-stage vanishes given that we already include demographic $\times$ year fixed effects. Moreover, since Guren et al. (2018) use regional housing price growth, we do not view these results as a disadvantage of our approach, but rather a feature of the rigorous specifications we are already subjecting on our data.

Table 5: Consumption Response to House Prices Using Alternative Bartik Instruments

	Real annual non-durable household consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.110***	0.123***	0.113***	0.126***	0.104***	0.138**	0.046	-0.078
	(0.029)	(0.047)	(0.029)	(0.046)	(0.030)	(0.065)	(0.170)	(0.335)
Instrument	Baseline	Baseline	Age Only	Age Only	Add Size	Add Size	National	National
Observations								
Total	296,787	296,274	296,787	296,274	296,787	296,274	296,787	296,274
Households	66,497	66,393	66,497	66,393	66,497	66,393	66,497	66,393
Counties	1,207	1,202	1,207	1,202	1,207	1,202	1,207	1,202
Controls								
Household	Y	Y	Y	Y	Y	Y	Y	Y
Local	N	Y	N	Y	N	Y	N	Y
Industry	N	Y	N	Y	N	Y	N	Y
Demographic	N	Y	N	Y	N	Y	N	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	–	–	73.72	58.07	46.91	37.75	1.68	0.73
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Notes.—Sources: Bureau of Labor Statistics (BLS), County Business Patterns (CBP), Federal Housing Finance Agency (FHFA), Internal Revenue Service (IRS) Statistics of Income (SOI), Nielsen, Zillow ZTRAX. The table reports the coefficients associated with the household-level year-to-year growth in non-durable consumption expenditures (deflated using the CPI) on county year-to-year housing price growth from the FHFA index, conditional on household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects. Columns (1) and (2) use the baseline Bartik instrument described in the text. Columns (3) and (4) use a restricted version of the Bartik instrument that only exploits the housing age characteristic. Columns (5) and (6) use an extended version of the Bartik instrument that adds continuous measures of floor size and lot size as housing characteristics. Columns (7) and (8) use a version of the Bartik instrument that makes use of national, rather than regional, variation in housing characteristic prices.

E Estimation of Rotemberg Weights

We follow the suggestion from Goldsmith-Pinkham et al. (2018) that Bartik instruments can be recast over-identified GMM estimators where the local shares are treated as a set of individual instruments under a particular weighting matrix. The IV estimator can then be decomposed into a set of estimators using each of the local shares, and a set of "Rotemberg" weights associated with each of these estimates (see also Rotemberg, 1983). Together with their Rotemberg weights, the local shares denote their contribution to the overall Bartik estimates. To see this, recall that a simplification of our two-stage least squares estimator is summarized by:

$$\Delta p_{l,t} = \gamma B_{l,t} + \eta_{l,t}$$

$$\Delta c_{l,t} = \beta \Delta \widehat{p_{l,t}} + \varepsilon_{l,t}.$$

where $B_{l,t}$ denotes our Bartik-like instrument and $\widehat{p_{l,t}}$ denotes the predicted values obtained from the instrument on housing price growth. Suppose only one household is observed in each location, that there is only one time period, and that the exclusion restriction holds.

Let L denote the number of locations, and K the total number of house characteristics used in the instrument. Then C is the $L \times 1$ vector stacking $\Delta c_{l,t}$, P is the $L \times 1$ vector stacking $\Delta p_{l,t}$, and B is the $L \times 1$ vector stacking the instrument $B_{l,t}$. Recall that the instrument is constructed via $B_{l,t} = \sum_k \lambda_{l,k} \Delta q_{k,t}$, where $\lambda_{l,k}$ are the local housing characteristic shares for each location l and characteristic k, and $\Delta q_{k,t}$ is the growth in housing quality prices for characteristic k. Let Λ denote the $L \times K$ matrix of local housing characteristic shares, and Q is the $K \times 1$ vector of stacked quality price growth rates. Then the stacked vector of Bartik instruments is $B = \Lambda Q$. The IV estimator of the consumption elasticity using the Bartik instrument has the familiar form:

$$\beta^{bartik} = \frac{B'C}{B'P} = \frac{Q'\Lambda' C}{Q'\Lambda' P} \tag{8}$$

Following Goldsmith-Pinkham et al. (2018), the Bartik estimate can then be decomposed into the just-identified estimates β_k^{bartik} and the associated Rotemberg weights α_k. The Bartik estimate of the consumption elasticity is the Rotemberg-weighted average of the just-identified estimates: $\beta^{bartik} = \sum_k^{K=1} \alpha_k \beta_k^{bartik}$, where the Rotemberg weights α_k sum to one. Goldsmith-Pinkham et al. (2018) notes that individual Rotemberg weights α_k may be negative, which means that the overidentified IV estimate using the full Bartik instrument β^{bartik} can be outside of the range of the individual estimates β_k^{bartik}. The just-identified estimates are given by:

$$\beta_k^{bartik} = \frac{\Lambda_k' C}{\Lambda_k' P},$$

where Λ_k' is the k^{th} column of Λ. And the Rotemberg weights are given by:

$$\alpha_k = \frac{\Delta q_{k,t} \Lambda_k' P}{\sum_{k=1}^K \Delta q_{k,t} \Lambda_k' P} = \frac{\hat{\gamma} \Delta q_{k,t} \Lambda_k' P}{\hat{\gamma} B' P} = \frac{P_k^{bartik'} P}{P^{bartik'} P},$$

where the second equality follows from the definition of the Bartik instrument and $\hat{\gamma}$ is the estimated first stage coefficient used to predict house prices with the instrument. Then P^{bartik} are the fitted values for house price growth from the first stage, and P_k^{bartik} are the fitted values from the first stage but using only the k^{th} component of the Bartik instrument for prediction.

Table 6 Panel A summarizes the individual estimates and Rotemberg weights. Panel B explores the correlations between these, housing quality price growth, and the variance of the local housing characteristic shares. Panel C reports the house characteristics with the largest share of absolute Rotemberg weights, by region and year. The Rotemberg weights and housing quality price growth are negatively correlated, while the weights and the variance of the local housing shares are positively correlated. Because the over-identified GMM estimator places more weight on instruments that vary more, it is unsurprising that it draws heavily on the dramatic swings in housing quality prices that occur throughout the sample period.

Additionally, dispersion in the local housing shares implies variation in the cross-sectional exposure to quality price movements, which also helps generate variation in the instrument. Strikingly, virtually all of the Rotemberg weight is associated with the Western region, and is largely concentrated in the bust years of 2008 and 2009, but also the recovery years of 2013 to 2015.

We graphically document these results in Figure A.6 by overlaying the evolution of national house prices over this period. We see that much of the Rotemberg weight occurs in years featuring rapid house price movements: 2005 (end of the boom), 2008 and 2009 (deepest part of the bust), and 2013 and 2014 (fastest part of the recovery). Moreover, much of the variation is associated with price fluctuations occurring in the West of the US, which is perhaps unsurprising given that states such as Arizona, California, and Nevada had some of the largest house price fluctuations in the entire country during this period.

Panel C reports the house characteristics with the largest share of absolute Rotemberg weights, by region and year. The top five characteristics account for 25 percent of the Rotemberg weights, suggesting skewness in the influence of the just-identified estimates. The benchmark house (built prior to 1940 with one bedroom and zero bathrooms) is associated with much of the Rotemberg weight, while the next most influential characteristics are associated with two bathroom houses,

Table 6: Summary of Rotemberg Weights for the Bartik Instrument

Panel A: Summary of β_k and α_k

	Wgt. Mean	Mean	Median	25th Perc.	75th Perc.	Share Negative
β_k	0.155	-0.303	0.064	-0.348	0.304	0.306
α_k	–	0.001	0	-0.001	0.003	0.416

Panel B: Correlations

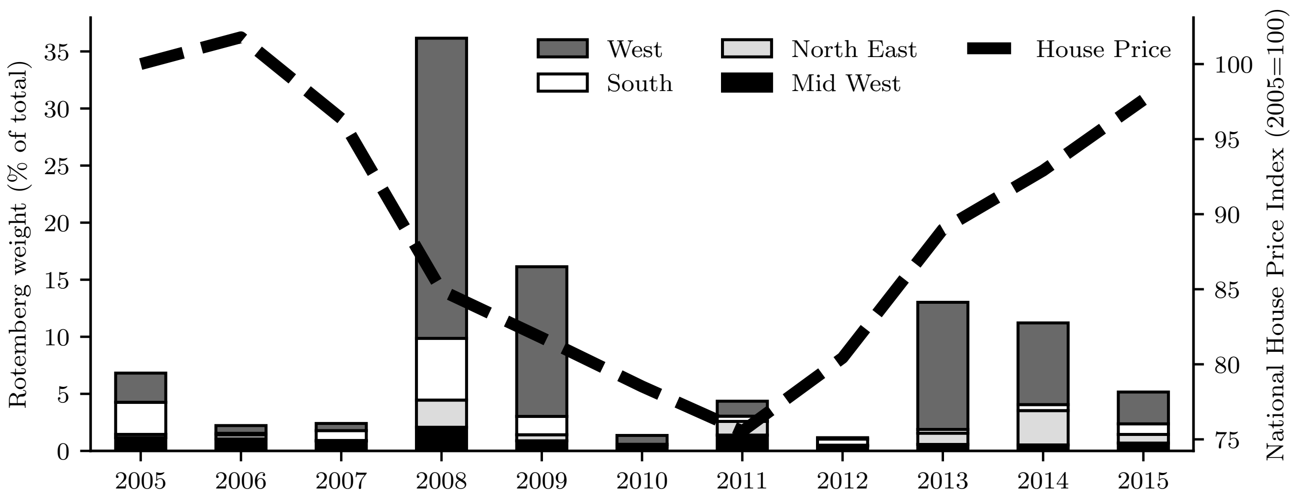
	α_k	Δq_k	β_k	$\text{var}(\lambda_k)$
α_k	1			
Δq_k	-0.248	1		
β_k	0.009	-0.007	1	
$\text{var}(\lambda_k)$	0.356	0.003	0.018	1

Panel C: Top 20 house characteristics by share of absolute Rotemberg weight

Characteristic	Year	Region	α_k	$\frac{\lvert\alpha_k\rvert}{\sum \lvert\alpha_k\rvert}$	Δq_k	β_k
Benchmark house	2008	West	-0.6	0.1	-1.68	0.13
Benchmark house	2009	West	-0.28	0.05	-0.87	0.16
Benchmark house	2013	West	-0.25	0.04	0.96	-0.05
Bathrooms: 2	2008	West	0.22	0.04	-1.69	0.08
Benchmark house	2014	West	-0.17	0.03	0.62	0.05
Bedrooms: 3	2008	West	0.14	0.02	-1.8	0.14
Bathrooms: 2	2009	West	0.11	0.02	-0.94	0.12
Benchmark house	2008	South	0.11	0.02	-0.72	-0.29
Decade to 2005	2008	West	0.1	0.02	-1.74	0.14
Decade to 1999	2008	West	0.09	0.01	-1.68	0.18
Bathrooms: 2	2013	West	0.09	0.01	0.93	-0.05
Bedrooms: 4	2008	West	0.09	0.01	-1.84	0.14
Decade to 1989	2008	West	0.07	0.01	-1.74	0.11
Benchmark house	2015	West	-0.07	0.01	0.53	0.16
Bedrooms: 3	2009	West	0.07	0.01	-0.86	0.15
Bathrooms: 1	2008	West	0.06	0.01	-1.71	0.19
Benchmark house	2014	NorthEast	-0.06	0.01	-0.29	0.21
Benchmark house	2005	South	0.06	0.01	0.35	-0.14
Decade to 1999	2009	West	0.06	0.01	-0.8	0.05
Bedrooms: 3	2013	West	0.06	0.01	0.96	-0.05

Notes: Throughout the table β_k are the characteristic-specific estimates, α_k are the Rotemberg weights, Δq_k are the housing quality price growth rates for characteristic k, and $\text{var}(\lambda_k)$ is the cross-sectional variance of the local housing characteric shares.

Figure A.6: Rotemberg Weights by Region and Year



Notes: Sums of the share of the absolute Rotemberg weights for each region and year. The dashed black line is the S&P/Case-Shiller National House Price Index.
Sources: Author's calculations, FRED.

three bedroom houses, and houses built in the 1990s and 2000s. Strikingly, virtually all of the weight is associated with the Western region, and is largely concentrated in the bust years of 2008 and 2009, but also the recovery years of 2013 to 2015. This is perhaps unsurprising given that Western parts of the country such as Arizona, California, and Nevada had some of the largest house price fluctuations in the entire country during this period. These results are emphasized in Figure A.6, which shows that much of the Rotemberg weight occurs in years featuring rapid house price movements: 2005 (end of the boom), 2008 and 2009 (deepest part of the bust), and 2013 and 2014 (fastest part of the recovery).

References

Ait-Sahalia, Y., Parker, J. A., and Yogo, M. (2004). Luxury goods and the equity premium. *The Journal of Finance*, 59(6):2959–3004.

Aladangady, A. (2017). Housing wealth and consumption: Evidence from geographically-linked microdata. *American Economic Review*, 107(11):3415–3446.

Anenberg, E. and Kung, E. (2014). Estimates of the size and source of price declines due to nearby foreclosures. *American Economic Review*, 104(8):2527–2551.

Attanasio, O. P., Blow, L., Hamilton, R., and Leicester, A. (2009). Booms and busts: Consumption, house prices and expectations. *Economica*, 76(301):20–50.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?

Bernanke, B. S. (2018). The real effects of the financial crisis. *Brookings Papers on Economic Activity*.

Bernanke, B. S. and Gertler, M. (1989). Agency costs, net worth and business fluctuations. *American Economic Review*, 79(1):14–31.

Borusyak, K., Hull, P., and Jaravel, X. (2018). Quasi-experimental shift-share research designs. Technical report, NBER Working Paper.

Buiter, W. H. (2010). Housing wealth isn't wealth. *Economics - The Open-Access, Open-Assessment E-Journal*, 4(22):1–29.

Campbell, J. Y. and Cocco, J. F. (2007). How do house prices affect consumption? evidence from micro data. *Journal of monetary Economics*, 54(3):591–621.

Carroll, C. D. (2001). A theory of the consumption function, with and without liquidity constraints. *Journal of Economic perspectives*, 15(3):23–45.

Carroll, C. D. and Kimball, M. S. (1996). On the concavity of the consumption function. *Econometrica: Journal of the Econometric Society*, pages 981–992.

Case, K. E., Quigley, J. M., and Shiller, R. J. (2005). Comparing wealth effects: the stock market versus the housing market. *Advances in macroeconomics*, 5(1).

Chaney, T., Sraer, D., and Thesmar, D. (2012). The collateral channel: How real estate shocks affect corporate investment. *American Economic Review*, 102(6):2381–2409.

Charles, K. K., Hurst, E., and Notowidigdo, M. J. (2016). The masking of the decline in manufacturing employment by the housing bubble. *Journal of Economic Perspectives*, 30(2):179–200.

Chen, H., Michaux, M., and Roussanov, N. (2013). Houses as atms? mortgage refinancing and macroeconomic uncertainty. Technical report, NBER Working Paper.

Chinco, A. and Mayer, C. (2015). Misinformed speculators and mispricing in the housing market. *The Review of Financial Studies*, 29(2):486–522.

Cloyne, J., Huber, K., Ilzetzki, E., and Kleven, H. (2017). The effect of house prices on household borrowing: A new approach. Technical report, NBER Working Paper.

Davidoff, T. (2016). Supply constraints are not valid instrumental variables for home prices because they are correlated with many demand factors. *Critical Finance Review*, 5(2):177–206.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., and Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–3588.

Emmons, W. R. (2008). The past, present and future of the U.S. mortgage market. *Federal Reserve Bank of St. Louis.*

Favilukis, J. Y. and Van Nieuwerburgh, S. (2017). Out-of-town home buyers and city welfare.

Friedman, M. (1957). *Theory of the consumption function*. Princeton university press.

Glaeser, E., Gyourko, J., and Saks, R. (2005). Why is Manhattan so expensive? Regulation and the rise in housing prices. *Journal of Law and Economics*, 48(2):331–370.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2018). Bartik instruments: What, when, why, and how. Technical report, NBER Working Paper.

Gupta, A. (2019). Foreclosure contagion and the neighborhood spillover effects of mortgage defaults. *Journal of Finance*, 74(5):2249–2301.

Guren, A. M., McKay, A., Nakamura, E., and Steinsson, J. (2018). Housing wealth effects: The long view. Technical report, NBER Working Paper.

Gyourko, J., Hartley, J., and Krimmel, J. (2019). The local residential land use regulatory environment across U.S. housing markets: Evidence from a new Wharton index. *NBER working paper*.

Gyourko, J., Saiz, A., and Summers, A. (2008). A new measure of the local regulatory environment for housing markets: The wharton residential land use regulatory index. *Urban Studies*, 45(3):693–729.

Haughwout, A., Lee, D., Tracy, J. S., and Van der Klaauw, W. (2011). Real estate investors, the leverage cycle, and the housing market crisis.

Kaplan, G., Mitman, K., and Violante, G. L. (2017). The housing boom and bust: Model meets evidence. Technical report, NBER Working Paper.

Kaplan, G., Mitman, K., and Violante, G. L. (2020). Non-durable consumption and housing net worth in the Great Recession: Evidence from easily accessible data. *Journal of Public Economics*.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary policy according to HANK. *American Economic Review*, 108(3):697–743.

Kaplan, G., Violante, G. L., and Weidner, J. (2014). The wealthy hand-to-mouth. Technical report, NBER Working Paper.

Landvoigt, T., Piazzesi, M., and Schneider, M. (2015). The housing market(s) of san diego. *The American Economic Review*, 105(4):1371–1407.

Lutz, C. and Sand, B. (2017). Highly disaggregated topological land unavailability. *Working paper*.

Makridis, C. and Ohlrogge, M. (2019). The local effects of foreclosures. *Working paper*.

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics*, 128(4).

Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review*, 101(5):2132–56.

Mian, A. and Sufi, A. (2014). What explains the 2007-2009 drop in employment? *Econometrica*, 82(6):2197–2223.

Mian, A. and Sufi, A. (2018). Credit supply and housing speculation. Technical report, NBER Working Paper.

Nielsen (2016). Consumer Panel Dataset Manual. *University of Chicago at Booth, Kilts Center for Marketing*.

Palmer, C. (2015). Why did so many subprime borrowers default during the crisis: Loose credit or plummeting prices. *Working paper*.

Piazzesi, M., Schneider, M., and Stroebel, J. (2015). Segmented housing search. Technical report, NBER Working Paper.

Rognlie, M. (2015). Deciphering the fall and rise in the net capital share: Accumulation or scarcity? *Brookings Papers on Economic Activity*, 46(1):1–69.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82:34–55.

Rotemberg, J. (1983). Instrument variable estimation of misspecified models.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3):1253–1296.

Stone, M. E. (2006). Pernicious problems of housing finance. *Philadelphia: Temple University Press*.

Stroebel, J. and Vavra, J. (2014). House prices, local demand, and retail prices. Technical report, NBER Working Paper.

Wong, A. (2020). Refinancing and the transmission of monetary policy to consumption. *American Economic Review, R&R.*