House Prices and Consumption: A New Instrumental Variables Approach*

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Abstract

Fluctuations in house prices can lead to significant movements in household expenditures. However, empirical studies of this relationship must deal with the endogeneity of house prices. In this paper, we introduce a novel Bartik-like instrument for house prices that consists of the pre-existing local composition of housing characteristics interacted with broad-based changes in the marginal prices of these characteristics. In an application to household-level panel data, we estimate that the elasticity of non-durable consumption expenditures with respect to local house prices is between 0.09 to 0.11. These consumption effects are concentrated among the young and those most likely to be facing tight borrowing constraints. In a decomposition exercise, we show that the identifying variation in the instrument is largely associated with times and locations where house prices have varied the most: during the housing bust of the mid-2000s and in the Western US.

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

JEL Codes: E21; D12; C26; R30

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Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the authors and do not reflect the position of Zillow Group.

Researcher(s) own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

There is now a large literature studying the impact of fluctuations in house prices on the aggregate state of the economy. The response of household consumption to these fluctuations is of significant interest since price movements can have large effects on household balance sheets through both wealth and collateral channels.[1] However, empirically isolating these effects is challenging because house prices are endogenous equilibrium objects. Unobserved shocks to wealth or income, for example, will drive movements in both house prices and consumption, leading to inconsistent estimates of the effect of the former on the latter. The primary contribution of this paper is the development of a new Bartik-like instrument for house prices to address this endogeneity problem.

Much recent empirical work estimates the relationship between house prices and consumption using cross-section or panel data where household-level or geographically-aggregated consumption expenditures are linked to a measure of local house prices.[2] Following the seminal work of Mian et al. (2013), many studies adopt sophisticated instrumental variables strategies to isolate exogenous movements in house prices. For example, a popular approach exploits cross-sectional variation in housing supply elasticities to predict house price growth (Saiz, 2010; Gyourko et al., 2008). This rests on the assumption that housing supply elasticities are uncorrelated with unobserved factors driving consumption growth. However, the use of these measures as instruments poses several problems. First, several authors have argued that local housing supply elasticities are correlated with other determinants of household consumption such as local amenities, worker characteristics, and economic opportunities (Davidoff, 2016; Gyourko et al., 2013; Gyourko et al., 2021). Second, housing supply elasticities are typically only observed and measured for highly aggregated geographical areas, for a limited set of geographies, and at a single point in time.[3]

Our primary contribution to the literature is a novel Bartik-like instrument for house prices. We argue that the instrument is plausibly exogenous with respect to the most likely determinants of household consumption. We demonstrate that the instrument can be constructed for and applied top multiple levels of geography. And we illustrate how both cross-sectional and time-series variation int he instrument contributes to our estimates of the elasticity of consumption with respect to house prices.

[1] For an early discussion of wealth effects on consumption see Friedman (1957). For more recent theoretical work on the importance of credit constraints and collateral for consumption behavior, see Carroll et al. (1996), Carroll (2001), Kiyotaki et al. (1997), and Bernanke (2018).

[2] For example, see Campbell et al. (2007), Attanasio et al. (2009), Disney et al. (2010), Gan (2010), Carroll et al. (2011), Mian et al. (2013), Browning et al. (2013), Christelis et al. (2015), Aladangady (2017), Paiella et al. (2017), Angrisani et al. (2019), Kaplan et al. (2020), and Guren et al. (2020).

[3] Recently, Lutz et al. (2017) have extended the Saiz (2010) land availability measures to lower levels of geography, and Gyourko et al. (2021) have updated the Wharton Residential Land use index of Gyourko et al. (2008) using a survey from 2018.

To construct our instrument, we use detailed housing transaction data from the Zillow Transaction and Assessment Database (ZTRAX). We first measure cross-sectional variation in the composition of local (e.g. county-level) housing characteristics, such as age, number of bedrooms, and number of bathrooms. We combine this with time-series variation in the marginal prices of these housing characteristics, which we estimate through hedonic pricing regressions on housing transaction data grouped by US Census regions. Where geographic areas vary in the composition of housing characteristics, the instrument produces differential local exposures to regional changes in the prices of different house types. For example, if San Francisco consists mostly of two-bedroom houses built prior to the 1940s, while Las Vegas has mostly four-bedroom houses built in the early 2000s, then an increase in the price of larger and newer houses in the Western US would result in relatively faster house price appreciation in Las Vegas.

Our instrument builds on an emerging theoretical foundation for shift-share or Bartik-style instruments.[4] Following Goldsmith-Pinkham et al. (2020), our identifying assumptions rely on the exogeneity of local housing characteristics with respect to other determinants of household consumption. This is intuitively plausible for two reasons. First, local house characteristics are largely pre-determined at the time that consumption shocks are realized, since the composition of houses changes very slowly over time. We both show that this is the case in the data, and we follow the Bartik literature in measuring the composition of local housing characteristics prior to our estimation sample period. Second, while households may select into houses with particular characteristics within a geography, they are much less likely to select across geographies according to average house characteristics. This is supported by evidence that households move across broad geographies infrequently (Molloy et al., 2011; Bachmann et al., 2014), that long-distance moves are much more likely to be associated with employment than housing choice (Ihrke, 2014), and that most potential home-buyers search for houses in a limited geographic range (Piazzesi et al., 2020). Consistent with this intuition, we find weak correlations between the composition of county housing characteristics and household demographics.

With our Bartik-like instrument in hand, we estimate the elasticity of real non-durable household consumption expenditures with respect to changes in local house prices. We use household-level data from the Nielsen Consumer Panel covering the sample period 2005 to 2016. In our main specifications, we restrict attention to an inferred sample of homeowners, and link each of these households with real annual house price growth in their county. Conditioning on a range of potentially confounding controls at both the individual and geographic levels, we report precise 2SLS estimates of the consumption elasticity in the range of 0.09 to 0.11. This suggests that a 10 percent rise in house prices is associated with a 1 percent rise in non-durable expenditures.

[4]See, for example, Bartik (1991), Adão et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (Forthcoming).

Additionally, these estimates correspond to an approximate marginal propensity to consume (MPC) non-durables out of housing wealth of 0.78 to 0.92 cents in the dollar.

Our results are consistent with but at the lower end of those reported in the literature. Mian et al. (2013) estimate MPCs for food and grocery goods of 0.4 cents, for all non-durable goods of 1.6 cents, and for total consumption of 5.4 cents. Other studies have reported MPCs for total consumption of between 1 cent and 6 cents (Disney et al., 2010; Carroll et al., 2011; Guren et al., 2020; Paiella et al., 2017; Aladangady, 2017; Angrisani et al., 2019). Direct estimates of the elasticity of non-durables consumption to local house prices range from 0.17 (Gan, 2010), to 0.21 (Kaplan et al., 2020), to 0.38 (Campbell et al., 2007).

The use of household-level panel data allows us to explore several dimensions of heterogeneity in consumption responses to house prices. First, we find that young households are much more sensitive to to house price movements than older households, consistent with previous findings (Attanasio et al., 2009; Gan, 2010). This suggests that age-dependent wealth effects are less important than collateral effects that tend to be correlated with age (see also Cloyne et al., 2019). Second, because we lack household-level wealth data, we use zip code-level average loan-to-value (LTV) ratios of mortgages originated between 2004 to 2006 as a proxy for indebtedness over the period 2005 to 2016. We split households by zip codes with average LTVs above and below 0.8, which is a proxy for mortgage debt levels where collateral constraints are likely to bind. We find that households in more indebted zip codes have consumption elasticities that are about twice as large as those in less indebted zip codes, consistent with the recent literature (Mian et al., 2013; Aladangady, 2017). Third, we find no asymmetry in elasticities during the housing boom, suggesting little role for the cyclicality of consumption sensitivity (see also Aladangady, 2017; Guren et al., 2020).

To demonstrate the validity and broader applicability of our Bartik-like instrument for house prices, we conduct a series of robustness tests. First, using our household-level panel data we re-estimate the consumption elasticity using several alternative instruments from the literature (i.e. Saiz, 2010; Lutz et al., 2017; Guren et al., 2020). These estimates are of a similar magnitude to our benchmark results, but are less stable and less precise in the presence of controls for household characteristics, economic factors, industry composition, local demographics, and county and time fixed effects. Second, we estimate similar consumption elasticities using a version of the instrument constructed at the zip code- rather than county-level. Third, we show that an alternative version of the instrument using only house age characteristics produces nearly identical estimates to our benchmark specification, which allays concerns that housing size (i.e. bedrooms and bathrooms) may be correlated with local income or productivity shocks through variation in local land prices. Fourth, we demonstrate a version of the instrument that can be used when detailed housing transactions micro-data are unavailable. Since our identifying variation is entirely due to the composition of local housing characteristics, the housing quality prices simply act as a particular weighting matrix that provides time series variation in the instrument (see Goldsmith-Pinkham et al., 2020). In principle, any weighting matrix can be used, but with less relevant time-series variation producing weaker instruments. We show that a version of the instrument that replaces housing quality prices with year dummy variables produces remarkably similar estimates of the consumption elasticity, although this instrument is weaker than the benchmark, as expected.

Our Bartik-like instrument for house prices follows several popular instrumental variables strategies in the recent literature. Starting with Mian et al. (2011), Mian et al. (2013), and Mian et al. (2014), many papers have made use of cross-sectional variation in housing supply elasticities and land-use restrictions (see Saiz, 2010; Gyourko et al., 2008). However, these instruments cannot explain differences in house price fluctuations through time. To address this, Aladangady (2017) interacts local housing supply elasticities with time-series variation in real interest rates, which proxy for changes in national demand for housing through time. Following Palmer (2015), Guren et al. (2020) introduce a more general measure of local house price sensitivity to aggregate fluctuations in housing demand. To construct their instrument, they estimate historical sensitivities of local house prices to regional house price cycles, and interact these sensitivities with time-series variation in regional house price growth. Although these instruments are much more powerful than the cross-sectional housing supply elasticity instruments, they are less transparent. While Guren et al. (2020) suggest that these local sensitivities are proxies for various dimensions of local housing supply, there is no explicit link between the two concepts.

The benefit of our Bartik-like instrument is that it combines a transparent measure of local housing variation with the ability to predict time-series movements in local house prices. Rather than measuring the land available for future home construction, our local variation is due to the composition of the local housing stock across different house characteristics. Time-series variation in our instrument is provided by regional fluctuations in the marginal prices of these characteristics. When there is a broad-based increase in the price of certain types of houses, locations with large shares of houses with those characteristics are more exposed to the increase in prices since its housing stock is more concentrated in that house type. In this sense, our instrument draws on similar intuition to earlier Bartik instruments that measure local exposures to fluctuations in employment via the concentration of employment in different industries (Bartik, 1991).

A further benefit of our approach is that we can decompose the sources of identifying variation in the instrument. Goldsmith-Pinkham et al. (2020) describe a decomposition following Rotemberg (1983), in which IV regressions using shift-share instruments can be recast as over-identified GMM estimators where the local shares are treated as a set of individual instruments under a particular weighting matrix. In our case, these Rotemberg weights combine information from the housing characteristic shares and region-by-time variation in the housing quality prices. We show that the majority of the identifying variation in our instrument is concentrated in the housing age characteristics, in quality prices coming from the Western and Southern regions of the US, and in quality price movements during the housing bust years of 2008 to 2009 and the housing recovery years of 2013 to 2014.

The structure of the paper is as follows. Section 2 describes the data used in our empirical analysis. Section 3 describes our empirical approach and identification strategy. Section 4 provides details of the construction of our Bartik-like instrument for house prices. Section 5 documents our main results, robustness checks, and the instrument decomposition exercise. Section 6 concludes.

2 Data

2.1 Housing Data

We use transaction-level housing data 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. We exclude all observations with missing housing characteristics or where the sale price is less than $10,000. Data from several states have incomplete or missing information for large numbers of observations, so these states are dropped from the analysis. In a number of other states, a large proportion of observations are missing house price data due to non-mandatory disclosure rules and outright prohibitions on the reporting of transactions prices.[5] However, housing characteristics for properties in these states are still widely available. We use the house characteristic information in these states, but do not make use of the transaction price data.

Importantly, the detailed transaction-level data available in ZTRAX provides information about individual property characteristics and house prices. As discussed in Section 4, this information allows us to construct our Bartik-like instrument for local house prices. In Appendix B, we aggregate this information on individual house characteristics across geographies and show that it is largely consistent with housing data from the Census Bureau. Housing characteristics, such as the age of a home and the number of bedrooms it contains, in the ZTRAX data and the 2000 Decennial Census are highly correlated at the county level.

Our final sample contains 55 million observations on individual property transactions between

[5] States with incomplete or missing data: Rhode Island, Tennessee, and Vermont. States with missing house price data: Alaska, Idaho, Indiana, Kansas, Maine, Mississippi, Montana, New Mexico, Texas, Utah, and Wyoming. For details, see http://www.zillowgroup.com/news/chronicles-of-data-collection-ii-non-disclosure-states/.

1994 and 2016. Further details on the sample selection procedure are reported in Appendix A.2.

2.2 Consumption Data

Household-level consumption data come from the Nielsen Consumer Panel. Our summary statistics for this data are reported in Appendix A.3. We use the 2004 to 2016 waves of the panel, which contain between 40,000 and 60,000 households each year (see Table A.7). 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 expenditures. Nielsen reports on approximately 1.5 million unique goods, which account for approximately 30 percent of all household consumption categories (Nielsen, 2016). These goods 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.

To gauge the external validity of our use of these non-durable goods, we compare the annual growth rate of per-capita consumption expenditures in the Consumer Panel to the growth rate of per-capita non-durable personal consumption expenditures in the National Income and Product Accounts. Figure A.7 shows that the growth rate of consumption as captured by the Nielsen data is consistent with the more complete measure of non-durable consumption reported in National Accounts data. Moreover, the Nielsen data has been used many times already in the literature; see, for example, Stroebel et al. (2019) and Kaplan et al. (2020) for applications of the data.

Table A.5 shows that in the Consumer Panel the average age of a household head is 53, average family size is 2.6 persons, average annual income was $68,000, and average annual expenditure is $7,489. Table A.6 benchmarks demographic characteristics to their counterparts in the Current Population Survey (CPS) between 2004 and 2015. In the Consumer Panel, the college-going rate is the same as in the general population at 42 percent. The fraction of non-employed household heads is 19 percent, compared to 24 percent of the general population.

Although the Consumer Panel reports demographic information associated with each household, home ownership status is not directly observed. To infer home ownership status, we follow Stroebel et al. (2019) who also use the Consumer Panel data. Households in the Consumer Panel 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, and that all remaining households are renters. The proportion of households living in single-family homes is 75 percent and does not change significantly across sample years. This compares to an average homeownership rate of 69 percent in the CPS data (see Table A.6). Figure A.6 shows the life-cycle pattern of homeownership implied by the data. We find similar inferred homeownership rates in the Consumer Panel to reported homeownership rates in the Survey of Consumer Finances for households aged 40 and older. However, the Consumer Panel produces higher rates of inferred homeownership than actual homeownership rates for younger households. This suggests the sample may select for wealthier households among younger age groups. This could attenuate our estimates of the consumption sensitivity to house prices for young households since the collateral effect is smaller for wealthier households (Mian et al., 2013).

In our main results, we restrict our panel to the sample of inferred homeowners for two reasons. First, we expect that only homeowners experience the wealth and collateral effects of house prices on consumption (Buiter, 2010). Second, the response of consumption to house prices may be affected by the decisions of renters to become homeowners.[6] For example, renters may be deterred from house purchases by rising prices, which leaves them with more to spend on other consumption goods. However, this would reflect a spurious correlation since renters experienced no change in their housing wealth. Thus, we drop renters and keep only households that remained homeowners throughout the sample.[7] In addition, Table A.6 shows that households are occasionally observed to move across geographies (2.1 percent per year), although this is less common than is observed in survey data from the CPS (7.8 percent). Because consumption patterns may differ for movers and non-movers, we further restrict our sample to those who never move.

Importantly, the Consumer Panel data reports the state, county, and zip code in which the households live. Each household can then be linked to a measure of local house prices, as well as other measure of local economic activity. This enables us to estimate the effect of changes in local house prices on the consumption expenditure patterns of our households.

2.3 Additional Data Sources

Although ZTRAX is a rich source of data for individual housing transactions, the varying availability of price data across geographies restricts our ability to construct consistent house price indexes for all locations. For this reason, we use published county-level house price indexes from the Federal Housing Finance Agency (FHFA). We use the CPI for all urban consumers to deflate all nominal variables. Average after-tax income at the county-level is computed from the IRS Statistics of Income (SOI) using the adjusted gross income variable less total tax payments. County unemployment data is collected from the BLS Local Area Unemployment statistics. County-level demographic information is provided by the 2000 Decennial Census. We use annual county employment by industry from Country Business Patterns data. We aggregate employment using the 6 digit NAICS codes into broad categories for construction (NAICS: 23), manufacturing (NAICS: 31, 32, 33), retail trade (NAICS: 44, 45), and finance/insurance/real estate (NAICS: 52, 53). A

[6] See also the discussions of selection into homeownership in Attanasio et al. (2009) and Campbell et al. (2007).

[7] In Section 5.3, we report a robustness exercise that re-estimates consumption elasticities using the sample of inferred renters.

detailed list of all data sources is reported in Appendix A.

3 Empirical Approach, Identification, and Inference

In order to assess the effects of changes in house price on household consumption, we estimate the elasticity of household-level non-durable consumption expenditures to local house price movements. Our benchmark regression specification takes the form

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

where i denotes an individual household, g denotes the geography of that household (e.g. county), and t denotes the year of observation. $\Delta c_{i,g,t}$ is the annual log-change in real household consumption expenditure, $\Delta p_{g,t}$ is the annual log-change in real local house prices in geography g. Our coefficient of interest is β_1, the elasticity of consumption with respect to local house prices.

Our regression specifications control for household demographics from the Consumer Panel, denoted $x_{i,t}$, including: real income growth, age of the household head, age squared, a dummy variable indicating the presence of children, annual growth in the size of the household, marital status, race, whether or not the household is of Hispanic origin, the occupation of the household head, and the education of the household head. We also control for local economic shocks, denoted $y_{g,t}$, including: annual real income growth, annual unemployment growth, and the annual shares of employment in the construction, manufacturing, retail trade, and finance/insurance/real estate industries. Finally, we follow the recommendation of Goldsmith-Pinkham et al. (2020) by controlling for local demographic characteristics measured at the beginning of the sample and interacted with year fixed effects. These characteristics taken from the 2000 Census and include: median age, mean household size, mean commute time, and the fractions of the population that are: black, Hispanic, foreign born, owner occupiers, college educated, employed in construction, employed in manufacturing, employed in retail, and employed in finance/insurance/real estate.

Finally, α_g and α_t are county and year fixed effects. The county fixed effects control for time-invariant cross-sectional dispersion in local amenities that could be correlated with both household consumption growth and local house prices. The year fixed effects control for common movements in house prices and consumption, such as the Great Recession period in which both national house prices and aggregate consumption declined significantly. Appendix A.4 provides a full description of all our control variables.

Our primary concern in estimating the elasticity of consumption from Equation 1 is that house prices $p_{g,t}$ are endogenous equilibrium objects. That is, house prices are determined by economic factors that almost certainly affect household consumption or that are themselves affected by changes in household consumption. Even after conditioning on a detailed set of household and local controls, our estimates of β_1 could be biased for at least three reasons. First, unobserved local productivity shocks or demand shocks could simultaneously increase consumption and house prices. This would generate an upwards bias in our estimates of β_1. Second, increases in consumption could generate an increase in employment growth, which then spills over into the housing market. This would also generate an upward bias in OLS estimates through reverse causality. Third, there may be measurement error if local house price growth is not a good proxy for the price growth of an individual's house. This would yield a downward bias in OLS estimates of β_1.

In order to address these endogeneity concerns, we develop a new Bartik-like instrument for house prices. Bartik instruments are often referred to as shift-share instruments since they consist of an aggregate shock (e.g. employment growth) that differentially affects groups according to the local share of some economic activity exposed to that shock (e.g. employment by industry).[8] Our instrument exploits plausibly exogenous variation in the composition of housing characteristics across locations—our shares. We then interact this local variation in house characteristics with estimated changes in the marginal value of those characteristics at the broader regional level—our shocks.

As discussed in detail in Section 4, we focus on characteristics of houses that reflect the quality of a home, such as the age and size of the structure. Since the valuation of these housing qualities varies over time, locations with a housing stock that is more concentrated in a particular house quality will experience larger house price fluctuations when that quality is in high demand throughout the region. For example, suppose San Francisco County in California consists of mainly two-bedroom homes built prior to the 1940s, whereas Clark County in Nevada consists of mostly four-bedroom homes built in the early 2000s. Then, an increase in demand for larger and newer homes would generate faster house price appreciation in Nevada, relative to San Francisco.

Before we discuss the details of the instrument construction in Section 4, we first state the identifying assumptions associated with our use of the instrument. Let $B_{g,t}$ denote our Bartik-like instrument for house price growth in location g at time t. We estimate Equation (1) via two-stage least-squares (2SLS) using $B_{g,t}$ as the instrument. The full model then consists of our second-stage equation from Equation (1), the first-stage regression, and the exclusion restrictions, as follows:

$$\Delta c_{i,g,t} = \beta_1 \Delta \widehat{p_{g,t}} + \beta_2 x_{i,t} + \beta_3 y_{g,t} + \alpha_g + \alpha_t + u_{i,g,t} \tag{2}$$

$$\Delta p_{g,t} = \gamma_1 B_{g,t} + \gamma_2 x_{i,t} + \gamma_3 y_{g,t} + \delta_g + \delta_t + v_{i,g,t} \tag{3}$$

$$0 = \text{cov}(B_{g,t}, u_{i,g,t} | x_{i,t}, y_{g,t}, \alpha_g, \alpha_t) \tag{4}$$

[8]For the first exposition of these instruments, see Bartik (1991). For recent discussions of identification and inference for shift-share instruments, see Borusyak et al. (Forthcoming), Adão et al. (2019), and Goldsmith-Pinkham et al. (2020).

The identifying assumption in Equation (4) is that, conditional on controls, the instrument $B_{g,t}$ does not affect consumption expenditure growth, except through its effects on local house price growth. That means the instrument has no correlation with the error term $u_{i,g,t}$ in Equation (2).

Following Goldsmith-Pinkham et al. (2020), our identification strategy relies on the assumption that the cross-sectional variation in housing characteristics embedded in the Bartik-like instrument is unrelated to $u_{i,g,t}$.[9] That is, unobserved shocks to household consumption are uncorrelated with the composition of the housing stock in the same location g of that household. The exclusion restrictions are intuitively plausible for two reasons. First, the average characteristics of local houses are pre-determined at the time of shocks to household consumption. Because construction is a small fraction of the total housing stock, the composition of houses changes very slowly and so it is largely insensitive to local income shocks, for example.

Second, while households may select into houses with particular characteristics within a given geography, they are much less likely to select across geographies according to their average house characteristics. While 12-15% of households move residence in a given year (Bachmann et al., 2014), only 6% move across counties (Molloy et al., 2011).[10] Conditional on moving across broad geographies, households are much more likely to do so for employment-related reasons than for housing-related reasons. In contrast, households that move within the same county tend to do so for housing related reasons, such as to improve the quality of their residence (Ihrke, 2014). Moreover, recent evidence on housing search behaviour suggests that most potential home-buyers search in a fairly limited geographic area. Piazzesi et al. (2020) find that a quarter of potential home-buyers consider only a single zip code when searching, that the average distance between all zip codes considered by multiple location searchers is just 3.2 miles, and that only 18% of these potential buyers search among non-contiguous zip codes. Thus, there is likely to be fairly weak household sorting across geographies according to local housing characteristics.

Nevertheless, we now consider the two primary threats to our identification assumption. First, the composition of the housing stock in a particular location may in fact be correlated with local economic shocks. This could occur, for example, if an increase in local incomes led to an increase in the quality of new houses being constructed in that location, which changed the composition of housing characteristics on the margin. In that case, cross-sectional variation in housing composition would be correlated with both house prices and unobserved local income shocks contained in the error term $u_{i,g,t}$.

Our construction of the Bartik-like instrument addresses this first concern directly. We measure

[9] Alternatively, Borusyak et al. (Forthcoming) discuss identification for shift-share instruments under the assumption that the aggregated shocks are exogenous, while the cross-sectional shares may be endogenous.

[10] In addition, renters are about twice as likely to move residence as homeowners (Bachmann et al., 2014), renters are nearly four times as likely to cross state lines as homeowners (Molloy et al., 2011), and less than a third of US natives move across state lines in their life time (Molloy et al., 2011).

the composition of housing characteristics using data observed prior to the beginning of the sample period used to estimate Equation (1). Since the cross-sectional variation in our housing characteristics are pre-determined at the time when consumption decisions are made, they are unlikely to be correlated with unobserved shocks that affect both house prices and consumption growth. In addition, we provide evidence that the composition of local housing stocks does indeed change very slowly over time. Figure 1 shows the fraction of houses in each county by age group—built before 1940, from 1940 to 1959, from 1960 to 1979, and 1980 to 1999—observed at two different points in time: the 2000 Decennial Census and the 2014-2018 five-year American Community Survey (ACS).[11] Across this 15 year period the age-composition of the housing stock is extremely persistent: we find within-county correlations of between 0.87 and 0.98 across housing age groups. Again, this suggests that the cross-sectional variation in housing composition embedded in our instrument is unlikely to respond to unobserved shocks that affect household consumption in those locations.

[INSERT FIGURE 1 HERE]

The second major threat to identification is that there may be household sorting on house types according to the characteristics of the households themselves. In that case, the consumption of households that tend to live in locations with particular house characteristics would be correlated with unobserved shocks to households with a particular demographic profile. For example, suppose young households live in smaller and older houses on average. In that case, both the consumption of households and the price of houses in these locations would be sensitive to income shocks that disproportionately affect young households. Thus, evidence of strong household sorting on housing characteristics would raise concerns about the exogeneity of the instrument.[12]

To investigate this possibility, Table 1 reports correlations between the county-level share of houses of different ages and a range of county-level demographic characteristics using data from the 2000 Census. Although these correlations are generally weak—no correlation is greater than 0.4 in absolute magnitude—we find that counties with a higher proportion of new houses have: higher home ownership rates, higher fractions of college-educated households, more white households, fewer black households, and fewer immigrant households. To alleviate concerns about potential household sorting, Section 5 shows that our estimates of Equation (1) are robust to the inclusion of both household-level and county-level demographic control variables. This suggests that to the extent that household sorting into locations by house characteristics does occur, it is largely uncorrelated with shocks to household consumption growth.

[11] We used the Census and ACS, rather than ZTRAX, for this exercise as these data include all counties in the US for the 2000 and 2014-2018 periods.

[12] Similarly, Davidoff (2016) argues that household sorting across locations with differential housing supply elasticities threatens the exogeneity of instruments based on the housing supply measures of Saiz (2010).

[INSERT TABLE 1 HERE]

Finally, we consider statistical inference of our 2SLS estimates. Recent work by Adão et al. (2019) argues that standard inference procedures understate the true variation in 2SLS regression coefficients when using shift-share instruments. The primary concern is that if the shares or exposures used in constructing these instruments are correlated across locations, then the residuals in the second stage may also be correlated. This would be a problem if counties with similar shares of houses with particular characteristics attract similar households so that consumption patterns are correlated across these counties. In this case, standard errors clustered by geography are not helpful since the Bartik-like instrument shares may be correlated across spatially distant locations (e.g. in counties on the east and west coasts). Our main results in Section 5 present standard errors following Adão et al. (2019), which allows for correlation in regression residuals according to the similarity of housing characteristics across locations and clustered through time.[13]

4 Construction of the Bartik-Like House Price Instrument

We now describe the construction of our Bartik-like instrument for house prices. Following Goldsmith-Pinkham et al. (2020), we decompose house price growth $\Delta p_{g,t}$ in location g at time t as

$$\Delta p_{g,t} = \sum_{c} \lambda_{g,c,t} \Delta q_{g,c,t} \tag{5}$$

where $\lambda_{g,c,t}$ is the local share of houses with house characteristic c, and $\Delta q_{g,c,t}$ is the growth rate of the marginal price for houses with characteristic c. Since differences in house characteristics are associated with differences in house quality, we will alternatively refer to $q_{g,c,t}$ as the quality price for house characteristics c.

The decomposition in Equation (5) suggests that house price growth is given by changes in quality prices weighted by the proportion of those qualities in a particular location. Consider a simple example with one location, a single time period, and two housing types: small and large. In this case, the share of small houses is λ_s and price growth for each type is Δq_s and Δq_l. Then, overall house price growth is $\Delta p = \lambda_s \Delta q_s + (1 - \lambda_s)\Delta q_l$. The greater is the share of small houses, the more sensitive is overall price growth to changes in the marginal price of small houses. We further decompose housing quality prices as

$$q_{g,c,t} = q_g + q_{c,t} + \tilde{q}_{g,c,t}, \tag{6}$$

[13] We use the standard error formula in Adão et al. (2019) Equation (37), which is adapted for use in panel data contexts like ours.

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 a given housing quality depends on permanent location characteristics, time variation in the value of qualities, 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 aggregate income is high. But, since rural areas already have a lot of space there is 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.

Notice, however, that the location and idiosyncratic components of quality prices, q_g and $\tilde{q}_{g,c,t}$, are likely to be correlated with shocks to the consumption growth of households in these locations. Similarly, time variation in the shares of houses with different characteristics $\lambda_{g,c,t}$ is also likely to be related to the unobserved component of local household consumption growth. To avoid inducing endogeneity in our instrument, we use only the characteristic-time component of quality prices $\Delta q_{c,t}$, and we restrict the local housing shares to an initial period: $\lambda_{g,c} = \lambda_{g,c,0}$.

Our Bartik-like instrument can then be expressed as

$$B_{g,t} = \sum_{c} \lambda_{g,c} \Delta q_{c,t}. \tag{7}$$

Because housing quality consists of bundles of house characteristics (Rosen, 1974), we modify Equation (7) to allow for separate characteristics c with mutually exclusive categories i. We use characteristics for house age by decade of construction, number of bedrooms, and number of bathrooms. The share of houses in category i for characteristic c is denoted λ_{g,c_i}, where $\sum_i \lambda_{g,c_i} = 1$ for each characteristic in each location g. Equation (7) can then be rewritten as

$$B_{g,t} = \sum_{c} \sum_{i} \lambda_{g,c_i} \Delta q_{c_i,t}. \tag{8}$$

4.1 Local Housing Characteristic Shares

We compute the local shares of housing characteristics using ZTRAX housing transaction data. We pool data on all unique houses sold between 1994 and 2005, and compute the shares of house characteristics represented among these houses. We divide the data associated with each house characteristic into several categories. Building age is split into decadal bins: $\mathcal{D} \equiv$\{pre-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2005\}.[14] The number of bedrooms is split into the categories: $\mathcal{B} \equiv$\{1, 2, 3, 4, 5+\}. The number of bathrooms is split

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

into the categories: $\mathcal{H} \equiv \{0, 1, 2, 3, 4+\}$ where half-bathrooms are rounded down to the nearest whole-number category. Figure B.8 in Appendix B shows that the county-level housing shares computed using ZTRAX line up well with survey data from the 2005 ACS. In section 5.3, we conduct robustness checks for our use of the Bartik-like instrument, including one exercise where we construct a version of the instrument using only the housing age characteristic.

Figure 2 illustrates the distribution of housing 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. There is significant cross-county variation in house age. For example, counties in the North East and Midwest 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 large proportions 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 characteristics than the cities in the coastal states. Figure B.9 in Appendix B illustrates cross-zip code distributions of housing age, with significant variation at the sub-county level. This suggests that our instrument is likely to provide useful identifying variation in house prices at different levels of geography. In Section 5.3 we show that our estimates are robust to the use of our instrument when constructed at the zip code level.

[INSERT FIGURE 2 HERE]

We also show that our housing characteristic shares provide different identifying information about house prices than that provided by the housing supply elasticity instruments used in many other empirical applications. Table B.8 in Appendix B reports the population-weighted correlations between our housing characteristic shares and the housing supply elasticities from Saiz (2010) and the Wharton residential land use regulation indexes in Gyourko et al. (2008). Our shares are only weakly correlated with the two measures. Nevertheless, the share of houses built prior to (after) 1990 is weakly positively (negatively) correlated with housing supply elasticities, which is consistent with economic intuition that locations with high elasticities should have built relatively more houses during the 2000s house price boom.

4.2 Housing Quality Prices

We now estimate our housing quality prices using a standard hedonic pricing regression approach (Rosen, 1974). Our regression includes as explanatory variables the same housing characteristics used in constructing the local housing shares. The regression takes the form

$$p_{j,g,t} = \alpha_g + \sum_{d\in\mathcal{D}} q_{d,t}\mathbb{1}(d_j = d) + \sum_{b\in\mathcal{B}} q_{b,t}\mathbb{1}(b_j = b) + \sum_{h\in\mathcal{H}} q_{h,t}\mathbb{1}(h_j = h) + \beta_t^f f_j + \beta_t^l l_j + \eta_{j,g,t} \tag{9}$$

where $p_{j,g,t}$ is the log of the real house price for property j in location g and α_g is a county-specific fixed effect. The three sets of characteristics are the decades in which houses were built $\mathcal{D}$, the numbers of bedrooms $\mathcal{B}$, and the numbers of bathrooms $\mathcal{H}$. The dummy variables $\mathbb{1}(d_j = d)$, $\mathbb{1}(b_j = b)$, and $\mathbb{1}(h_j = h)$ are equal to one for property j in case of the relevant decade of construction, number of bedrooms, or number of bathrooms. The coefficients $q_{d,t}$, $q_{b,t}$, $q_{h,t}$ then represent the housing quality prices for the decade built, number of bedrooms, and number of bathrooms. These coefficients are time-varying to capture the characteristic-time component $q_{c,t}$ of quality prices discussed in Section 4. Finally, f_j and l_j are additional controls for the log of floor size and the log of property lot size for property j. We choose not to include these variables in the our benchmark instrument for two reasons. First, we are concerned that fluctuations in the marginal prices of floor size and lot size will be correlated with movements in the value of land, which is likely to be driven by other economic factors that affect household consumption. Indeed, in Section 5.3 we show that a modified version of our instrument that includes information about the marginal prices of floor size and lot size is sensitive to the inclusion of controls for local economic activity. Second, since these size characteristics are continuous measures, they do not have natural categorizations with which to compute local shares. Nevertheless, by controlling for these variables in our hedonic regression (9), the other regression coefficients can be interpreted as the marginal price of the relevant house characteristics holding house size constant.

We estimate Equation (9) separately for each Census region in the US: Mid-West, North-East, South, and West. This involves running a separate set of regressions for all houses sold in each region over the sample period, 2005 to 2016. In exploiting sub-national variation in house prices to construct our instrument, the time-series variation in our Bartik-like instrument is similar to that in Guren et al. (2020) who construct a sensitivity instrument that interacts regional house price growth with historical correlations between local house prices and regional house prices. The use of regional variation in house prices increases the informativeness of the instrument over one in which quality prices are estimated at the national level and allows us to include time fixed effects in our main regression specification. To avoid mechanical correlations between county-level house prices and our instrument, we use a leave-one-out procedure: we estimate Equation (9) for each location g separately by dropping all observations for houses in that location. In practice, counties are small relative to the surrounding region, so the leave-one-out procedure has no effect on our estimates of (9) or the estimated consumption elasticities. Additionally, our estimated hedonic regressions explain a significant proportion of the variation in house prices, with a median R-squared statistic of 0.6 across regions.

Figure 3 illustrates our estimated quality prices for houses constructed in different decades. The horizontal axis shows the decade in which a house was built and the vertical axis shows the three-year growth rate of the housing quality prices. We find significant variation in quality prices across regions and through time. For example, between 2006 and 2009, the price of houses of all ages increased in the North-East, but declined significantly in the South.

[INSERT FIGURE 3 HERE]

4.3 Strength of the Bartik-Like Instrument

Using the housing characteristics shares from Section 4.1 and the housing quality prices from Section 4.2, we construct the Bartik-like instrument for house prices using Equation (8). We now evaluate the relevance of our instrument for predicting house prices by reporting the results of the first-stage regression from Equation (3). Figure 4 presents a simple binned scatter plot of the residualized instrument against residualized house price growth. This residualization involves projecting out the additional control variables described in Section 3, including all household, local, industry, and demographic controls, together with the county 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.

[INSERT FIGURE 4 HERE]

5 Main Results, Heterogeneity, and Robustness

5.1 Main Results

We now turn to our estimates of the elasticity of non-durable household consumption expenditures with respect to local house price growth. Our sample covers the period 2005 to 2016, using the Nielsen Consumer Panel data and the Bartik-like house price instrument constructed with ZTRAX data. Our main results are reported in Tables 2, 3, and 4, while our robustness tests are reported in Section 5.3.

[INSERT TABLE 2 HERE]

Each column of Table 2 reports an estimate of the consumption elasticity under different sets of auxiliary controls, illustrating the sensitivity of our estimates to omitted and potentially endogenous variables. Columns (1) and (2) report elasticities estimated via OLS, with standard errors clustered at the county level. Column (1) includes no controls, while Column (2) introduces household-level controls as well as county and year fixed effects. Our OLS estimates are sensitive to the inclusion of these controls, as can be seen in the decline in the estimated elasticity from 0.118 to 0.030. This apparently endogenous relationship between house prices and consumption highlights the importance of our instrumental variables estimation strategy.

Columns (3)–(8) of Table 2 report 2SLS estimates using our Bartik-like instrument, with standard errors and F-statistics computed following Adão et al. (2019). Column (3) includes no controls while Column (4) includes household controls as well as county and year fixed effects. The elasticity in each column is 0.104 with no statistically significant difference between the two estimates. Columns (5)–(8) report 2SLS estimates conditional on additional controls for local economic activity, local industrial composition, and local demographic characteristics, as well as county and time fixed effects. In Column (5) we include controls for county-level real income growth and unemployment growth, but this has virtually no effect, again yielding an elasticity of 0.102. The controls introduced in Column (6) are the annual shares of employment in the construction, manufacturing, retail trade, and finance/insurance/real estate industries. This specification controls for shocks to local demand through non-tradable and tradable sector employment (Mian et al., 2014; Charles et al., 2016), as well as through those sectors most closely tied to the housing boom and bust of the mid-2000s. Our estimated elasticity falls slightly to 0.095, but remains statistically indistinguishable from our previous 2SLS estimates.

Column (7) of Table 2 includes the demographic controls suggested by Goldsmith-Pinkham et al. (2020). We use a range of demographic characteristics measured at the county-level from the 2000 Census with each characteristic interacted with year dummy variables.[15] Because of the large number of effective controls, this is an empirically demanding test of the possibility that the composition of local households is correlated with the composition of the local housing stock in a way that drives both consumption and house prices. We find little change in the estimated elasticity at 0.093, and again the estimate is not statistically different from our previous estimates. Finally, Column (8) includes all of the previously described controls. Our estimate rises slightly to 0.111, but is again statistically indistinguishable from each of our prior 2SLS estimates.

Overall, we find that a 10 percent increase in house prices is associated with a 0.93 to 1.11 percent increase in non-durable consumption expenditures. The estimates using our Bartik-like instrument for house prices are remarkably stable across regression specifications. Our instrument is not sensitive to controls for household characteristics, local economic factors, or local demographic composition.

Our estimates are consistent with but on the lower end of recent estimates from the literature. Previous authors that estimate the elasticity of non-durable consumption to local house prices

[15]See Section 3 and Appendix A.4 for a full description of these demographic variables.

via instrumental variables methods report values of 0.19 (Gan, 2010), 0.21 to 0.26 (Kaplan et al., 2020), and 0.38 (Campbell et al., 2007).[16] For comparison to other papers in the literature, we can express our estimates in terms of an approximate marginal propensity to consume (MPC) out of housing wealth.[17] We find MPCs for non-durables of 0.78 to 0.93 cents in the dollar. This is consistent with recent estimates of MPCs for groceries and non-durable goods, but on the lower end of estimates for total consumption. Mian et al., 2013 report an MPC for food and groceries of 0.4 cents, an MPC for all non-durables of 1.6 cents, and an MPC for total consumption of 5.4 cents. Other authors find MPCs for total consumption of 1 cent (Disney et al., 2010), 2 cents (Carroll et al., 2011), 2.8 cents (Guren et al., 2020), 3 cents (Paiella et al., 2017), 4.7 cents (Aladangady, 2017), and 6 cents (Angrisani et al., 2019).

[INSERT TABLE 3 HERE]

Our estimated elasticities may be low relative to the literature either because of our Bartik-like instrument for house prices, or because of our particular household-level panel data set. To explore this, we now compare estimates of the consumption elasticity in our data using three alternative instrumental variables proposed in the recent literature. Table 3 documents these results. Odd-numbered columns show estimates from regression specifications with no controls, while even-numbered columns report estimates from regression specifications with our full set of household, economic, industry, demographic, and fixed effects controls. For comparability of inference across different instruments, all standard errors are clustered at the county level.

Columns (1) and (2) repeat the results using our own instrument, as reported in Table 2. Columns (3) and (4) use an instrument for house prices constructed from the interaction between the Saiz (2010) housing supply elasticity and regional house price growth.[18] We use the interaction with regional house prices because this provides a similar source of price variation as the regionally-estimated housing quality prices used in our Bartik-like instrument. In the absence of controls, the Saiz (2010) instrument yields a statistically significant estimate of 0.178, which is 70% larger than our estimates using the Bartik-like instrument. However, the inclusion of the auxiliary

[16](Kaplan et al., 2020) use the Saiz (2010) housing supply elasticity instrument, and report cross-sectional (i.e. non-panel data) elasticities with respect to house prices for for samples from 2006-2009 and 2007-2011. Gan (2010) instruments for unexpected changes in housing wealth using household-level panel data from Hong Kong. Campbell et al. (2007) instrument for changes in local prices relative to national prices which is similar to a specification that includes time fixed effects, and use repeated cross section data from the UK with synthetic panel data methods.

[17]Following the literature, the MPC is equal to the elasticity of consumption divided 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.

[18]This use of cross-sectional and time-series variation is conceptually similar to the instrument employed by Aladangady (2017), which interacts the Saiz (2010) housing supply elasticity with national changes in real interest rates.

controls in Column (4) leads to a much weaker instrument so that the estimate falls to 0.125 and is insignificantly different from zero. The instrument in Columns (5) and (6) is from Lutz et al. (2017), which allows us to use a more refined measure of land availability at the county level, rather than the CBSA-level measure provided by Saiz (2010). We also interact this cross-county measure of land availability with regional house price growth. The Lutz et al. (2017) instrument yields statistically significant estimates of 0.132 to 0.146, although the inclusion of controls in Column (6) leads to a substantial reduction in the strength of the instrument, as evidenced by the decline in the F-statistic from 146 to 12. Nevertheless, these estimates are both close to and statistically indistinct from our benchmark estimates of around 0.104 to 0.111.

Finally, Columns (7) and (8) of Table 3 use the house price instrument introduced by Guren et al. (2020). This instrument is constructed from estimates of the historical sensitivity of CBSA-level house prices to regional house price growth, interacted with the growth rate of regional house prices. The Guren et al. (2020) instrument is similar to our own Bartik-like instrument in the sense that its identifying variation is due to the differential sensitivity of local housing markets to regional shocks. Column (7) reports an estimated elasticity of 0.129 in the absence of controls, which is very close to our own estimates. However, Column (8) shows a large drop in the estimated elasticity to very near zero when we include our set of control variables. We find that this is almost entirely driven by the inclusion of the year fixed effects, which absorb almost all of the variation in regional house price growth. Indeed, the minimum correlation between house price growth rates in our sample period across any two of the four regions is 0.88.[19]

Our comparison of estimates using the same consumption data set but with different instruments suggests that the Bartik-like instrument does not produce especially small consumption elasticities. Rather, our finding of smaller elasticities than the existing literature is likely due to the subset of non-durable consumption expenditures captured by the Nielsen Consumer Panel. The comparison of estimates under different instruments is also useful for demonstrating the robustness of our Bartik-like instrument in the face of a challenging set of additional control variables. While our estimates are largely invariant under different regression specifications, estimates using other popular instruments in the literature appear to be quite sensitive to the inclusion of these controls.

5.2 Heterogeneous Treatment Effects

Much of the empirical literature explores the possibility of heterogeneous treatment effects on consumption of house price movements. Recent papers have considered differences in housing wealth effects across household age (Campbell et al., 2007; Attanasio et al., 2009; Gan, 2010),

[19]Interestingly, the F-statistic in Column (8) remains very high suggesting that the Guren et al. (2020) instrument is a strong predictor of house prices, but that the controls absorb much of the variation that accounts for fluctuations in consumption.

the tightness of household borrowing constraints (Gan, 2010; Mian et al., 2013; Aladangady, 2017), and across housing booms and busts (Aladangady, 2017; Kaplan et al., 2020; Guren et al., 2020). Table 4 reports our tests for heterogeneity in consumption elasticities across household age, inferred borrowing constraints, and across the housing boom and bust period. All columns are estimated visa 2SLS using our Bartik-like instrument. Odd-numbered columns report results for specifications in the absence of any control variables, and even-numbered columns include our full set of household, economic, industry composition, demographic, and fixed effects controls.

[INSERT TABLE 4 HERE]

Columns (1) and (2) of Table 4 repeat our benchmark estimates of the consumption elasticity. Columns (3) and (4) tests for heterogeneity across the age distribution by including interaction terms for households aged 40 to 60 and greater than 60, with the excluded group being households under age 40. When including controls, our estimated elasticities for the youngest, middle, and oldest age groups are 0.273, 0.146, and 0.059. This implies that a 10 percent increase in house prices is associated with a 2.7 percent increase in young household consumption expenditures, but just a 0.6 percent increase in older household expenditures. These results contrast with those of Campbell et al. (2007), but are consistent with Attanasio et al. (2009) who find that the consumption expenditures of households aged 21 to 34 are nearly five times as sensitive to house price changes as are the expenditures of those aged 60 to 75. The results are also consistent with Gan (2010) who finds that non-durable consumption expenditures for households aged under 40 are nearly twice as sensitive as for those over 40.

Declining consumption sensitivity with household age contradicts theoretical predictions of rising housing wealth effects over the life-cycle (Buiter, 2010). However, the estimated age gradient is consistent with collateral effects that are likely correlated with age. Since young homeowners tend to have larger mortgages, changes in house prices are likely to have a larger effect on the value of their housing collateral and so their ability to borrow. An increase in house prices then relaxes borrowing constraints for indebted households, which induces larger changes in expenditure than for households who are not constrained. Cloyne et al. (2019) find empirical support for this hypothesis, estimating much larger changes in mortgage borrowing for more indebted households following house price shocks.

Columns (4) and (5) of Table 4 test for a collateral effect of house prices. Unfortunately, the Consumer Panel does not provide measures of household wealth, so we cannot directly observe household borrowing constraints. However, the transactions data in ZTRAX reports both house prices and mortgage sizes at origination. We use this data to compute average loan to value (LTV) ratios by zip code during the 2004 to 2006 boom, when household borrowing against housing was at its peak. We assume that average LTV ratios are a good proxy for LTV ratios at the household-level since many households bought houses or refinanced mortgages during this period (Adelino et al., 2016; Adelino et al., 2018). We split our sample of households into those living in zip codes with an average LTV at origination above and below 0.8. 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.[20] This suggests that households with LTV ratios in this range are more likely to face borrowing constraints than those with LTV ratios below 0.8.

Columns (5) and (6) include interactions between house price growth and a dummy variable for households in zip codes with average LTV ratios above 80 percent. Our results suggest that the consumption elasticity of households in high-LTV zip codes is almost twice as large as that for households in low-LTV zip codes. For our specification with controls, the point estimates imply that a 10 percent increase in house prices is associated with a 1.71 percent increase in consumption for households in high-LTV zip codes, but just a 0.97 percent increase in consumption for households in low-LTV zip codes. This result is consistent with Mian et al. (2013) who estimate MPCs that are twice as large for households with LTV ratios of 0.7 to 0.9 as for households with LTV ratios below 0.3. Similarly, Aladangady (2017) finds MPCs that are about twice as large for households with LTV ratios above 0.8 as they are for households with LTV ratios below 0.8.

Does the sensitivity of consumption to house prices vary over the housing cycle? Alternatively, do our results simply reflect aggregate fluctuations in the housing market and in consumption expenditures during the worst of the financial crisis? Columns (7) and (8) of Table 4 test whether the elasticity of consumption is different between 2006 and 2009. Column (7) suggests a statistically significant increase in the consumption elasticity during the bust, however the addition of controls in Column (8) flips the sign and removes the significance of the coefficient on the interaction between house price growth and the 2006 to 2009 period. We find that the change in sign is largely due to the inclusion of time fixed effects, which absorb much of the time series variation in house prices and consumption across the housing cycle. Similar tests for cyclical asymmetries by Aladangady (2017) and Guren et al. (2020) find no significant differences in consumption sensitivities during boom or bust periods.

In further exercises exploring heterogeneous effects, we test for differential consumption sensitivity among our excluded sample of inferred non-homeowner households (i.e. renters). While the consumption of renters should not be sensitive to house prices due to wealth or collateral effects, renters may expect house price changes to affect rental costs or their future home purchase decisions. Table C.9 in Appendix C documents our results. Column (1) reports our benchmark estimates for homeowners, while Column (2) reports estimates among the renter sample. We find

[20]Other recent studies, such as Aladangady (2017) and Barlett et al. (Forthcoming) have also used this cutoff from since 0.80 is the LTV threshold at which borrowers are exempt from purchasing mortgage loan insurance.

a renter consumption elasticity of 0.059, about half of the size of our estimates for homeowners, but the coefficient is not statistically significant from zero. In Columns (3) and (4) we test whether the consumption of owners and renters responds differently if they live in counties with high homeownership rates, since these areas are likely to have housing markets with more single family residences that are sensitive to the housing quality price changes captured by our instrument. However, we find no evidence of differential consumption sensitivities across high and low homeownership counties in either the owner or renter sample. Finally, in Columns (5) and (6) we test whether the consumption of owners and renters responds differently if they live in counties with a higher share of non-tradables employment, since these areas may be more sensitive to local economic demand shocks and since renters may be more likely to work in non-tradables employment. Again, however, we find no evidence of differential consumption sensitivities across counties with high and low non-tradables employment shares.

5.3 Robustness

We now investigate a range of robustness exercises to further test the validity of our Bartik-like instrument as well to demonstrate its broader applicability to future research. The results of these exercises are reported in Appendices C.

First, we show that the instrument can be constructed for different levels of geography. We use a version of the instrument with housing characteristic shares constructed at the zip code level (see Table C.10). Our 2SLS estimates instrument for zip code-level house prices taken from Zillow data, and our controls now include zip code fixed effects, zip code-level real income growth taken from the IRS SOI data, and zip code-level demographic controls taken from the 2000 Census. As in our benchmark results, we construct standard errors and F-statistics following Adão et al. (2019). Our results are remarkably similar across the zip code and county regression specifications. Table C.10 reports estimated elasticities of between 0.072 and 0.120, in comparison with our benchmark results using county-level data of between 0.093 and 0.111 (see Table 2).

Second, we present the results of three additional variations on the construction of our instrument in Table C.11. One concern about instrument validity is that in contrast to house age, the number of bedrooms or bathrooms is directly related to house size, which may be more likely to attract particular types of households, such as those with larger or wealthier families. Another concern is that because the number of bedrooms and bathrooms is closely tied to house size, these house characteristics may be correlated with local income or productivity shocks that affect both land prices and consumption. More generally, concerns about the relationship between house size and land prices are the main reason that we excluded floor size and lot size information from the construction of our Bartik-like instrument (see Section 4.2). Yet another concern is that the regional variation in housing quality prices that we use to construct our instrument may be too closely tied to unobserved local shocks to consumption demand.

Columns (1) and (2) of Table C.11 repeat our benchmark results with and without the full set of auxiliary controls. Columns (3) and (4) report elasticities estimated with a version of the Bartik-like instrument that uses information on housing age only, and drops bedroom and bathroom information from the instrument entirely. The results are virtually identical to those in Columns (1) and (2), suggesting that bedroom and bathroom information in the full instrument provide very little identifying information for house prices while housing age provides virtually all of the relevant information in the instrument. Columns (5) and (6) report elasticities estimated with a version of the instrument that includes the floor size and lot size quality prices estimated in Equation (9), which were excluded from the main specification of our instrument.[21] The elasticity reported in Column (5) is larger than and statistically significantly different from our benchmark results, at 0.157. However, the inclusion of our control variables in Column (6) causes the estimate to fall to 0.058 and it is no longer significantly different from zero. We interpret this result as suggesting that the information on house size is too closely tied to factors such as land prices that are likely to be correlated with local and aggregate economic activity, as captured by our controls. For this reason, we recommend that future researchers do not make use of direct measures of land size as inputs into Bartik-like instruments for house prices. Finally, Columns (7) and (8) report elasticities estimated with a version of the instrument that uses variation in housing quality prices estimated from national rather than regional data. The results are similar to those estimated with the benchmark instrument. However, the main drawback of this exercise is that we cannot use time fixed effects or demographic controls interacted with time dummies since they absorb too much of the time-series variation in the instrument.

Third, we address a concern that our Bartik-like instrument may be difficult to use or update if researchers do not have access to detailed micro-data on housing transactions, such as that provided by ZTRAX. We show that it is still possible to make use of a Bartik-like instrument for house prices if the only information available to a researcher is the share of houses with different characteristics in each location.[22] As noted in Goldsmith-Pinkham et al. (2020), the identifying information for many shift-share instruments is contained in the local shares, while the aggregated shocks act like a weighting matrix that improves the ability of the instrument to predict the endogenous variable through time. This means that the Bartik-like shares can be used as instruments on their own, or

[21] To do this we interact the log of the median floor size and lot size in each county with the coefficients β_t^f and β_t^l from Equation (9). Note that this is not a standard Bartik-like instrument construction. However, a similar intuition is retained in that locations with larger houses experience faster house price appreciation when the marginal price of house size increases.

[22] This information can be gathered from the decennial Census, the American Community Survey, or the American Housing Survey.

in combination with any other time-varying weighting matrix, with the only drawback being a reduction in the strength of the instrument.

Table C.12 reports elasticities estimated with an instrument that interacts our local housing characteristics shares with time dummy variables. Columns (3)–(8) report estimates with different sets of control variables. We find statistically significant estimates in the range of 0.05 to 0.165. As expected, the use of year dummies in this version of the instrument produces much weaker time-series variation in house prices than our regionally estimated housing quality prices, especially when year fixed effects are included in the regression specification. Nevertheless, the instrument performs reasonably well even in regression specifications with a large number of auxiliary control variables such as Column (8). This suggests that the composition of the housing stock provides sufficient cross-sectional variation to be used as instruments for house prices on their own, which may be useful when data on the relative prices of these house characteristics is unavailable.[23]

5.4 A Decomposition of the Variation in the Bartik-Like Instrument

Finally, we provide a decomposition of the identifying variation in the Bartik-like instrument following Goldsmith-Pinkham et al. (2020). Goldsmith-Pinkham et al. (2020) show that IV regressions using shift-share instruments can be recast as over-identified GMM estimators where the local shares are treated as a set of individual instruments under a particular weighting matrix. These weights are known as Rotemberg weights following Rotemberg (1983) and, in our case, are a combination of information provided by the housing characteristic shares and region-by-time variation in the housing quality prices. The IV estimator can then be decomposed into a set of individual estimators each of which is associated with a Rotemberg weight. We use this decomposition to study the contribution of the housing characteristics shares toward the identifying variation of our Bartik-like instrument. Appendix D provides a detailed description of the decomposition and Table D.13 provides a summary of the decomposition statistics.

[INSERT FIGURE 5 HERE]

We find that the identifying variation in our instrument is concentrated in the housing age characteristics, in quality prices coming from the Western region of the US, and in quality price movements during the housing bust years of 2008 to 2009 and the housing recovery years of 2013 to 2014. Figure 5 illustrates these results graphically, by plotting the fraction of the total Rotemberg weights associated with different components of the instrument. Figure 5a combines Rotemberg

[23] To produce more time series variation in this version of the instrument, the housing characteristic shares could be interacted with regional house price growth as in the instrument from Guren et al. (2020).

weights across years and housing characteristic groups (i.e. housing age, number of bedrooms, and number of bathrooms). We also plot a national house price index for comparison, which shows that most of the variation in the Bartik-like instrument is provided in the years in which house prices fall or grow the fastest. Our results reinforce the results of Table C.11, which show that an instrument constructed using only housing age characteristics produces nearly identical results to an instrument containing all three housing characteristics. That housing age dominates variation in Bartik-like instrument is also consistent with our view that historical building patterns account for much of the exogenous cross-sectional variation in housing characteristics across the US.

Figure 5b combines Rotemberg weights across years and Census regions. Much of the variation in the instrument that explains the relationship between house prices and consumption is due to price fluctuations in the West and, to a lesser extent, the South of the US. This is consistent with the fact that Western and Southern states, such as California, Nevada, Arizona, and Florida, experienced some of the largest house price fluctuations in the country during the housing boom and bust of the mid-2000s. It should be unsurprising that the instrument places so much emphasis on times and places with rapid house price changes: this is precisely when and where house prices are most likely to affect household balance sheets, and thus to influence household consumption decisions.

6 Conclusion

It is widely believed that fluctuations in the price of housing leads to changes in household consumption expenditures. However, plausibly causal evidence for this effect has proven difficult to establish because of the endogenous nature of shocks that jointly affect both consumption and the housing market. To address this difficulty, this paper introduces a new Bartik-like instrument for house prices that exploits cross-sectional variation in pre-existing house characteristics and aggregated time-series variation in the marginal prices of these characteristics. Using this instrument, we estimate an elasticity of non-durable consumption expenditures with respect to house prices in the range of 0.09 to 0.11. This approximately corresponds to an average marginal propensity to consume out of housing wealth of 0.78 to 0.92 cents in the dollar.

Our empirical approach offers three advantages over existing instrumental variables methods discussed in the literature. First, in contrast to instruments that rely on local elasticities of housing supply (e.g. Saiz, 2010), our instrument can easily be constructed for virtually any level of geography, which expands the scope of future research applications of the instrument. In the paper we show that 2SLS estimates of consumption elasticities are very similar using instruments constructed at either the county or zip code level. Second, we improve on prior instruments that rely on empirically estimated historical price sensitivities of local housing markets to broader price movements (e.g. Palmer, 2015; Guren et al., 2020). Our instrument identifies a much more specific source of local housing market sensitivity. Historical differences in construction patterns across locations lead to spatial variation in the composition of housing characteristics, where these differences in the composition of the housing stock explain why, for example, the prices of houses in locations with newer houses rise more quickly when newer houses are in greater demand more generally. Third, the use of a Bartik-like instrument allows us to decompose the identifying variation in house prices that helps to estimate the effects of prices on consumption.

Our paper nonetheless opens several new and exciting areas for further research. In particular, now that we have a time-varying and plausibly exogenous source of variation for housing prices, researchers can evaluate the effects of local house price appreciation on many different outcome variables, ranging from consumption to employment to investment. Another interesting area for future research would be to better understand the source of the dispersion in housing structures that we see in urban environments today.

Tables and Figures

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.

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)
$\Delta p_{county,t}$	0.118***	0.030***	0.104*	0.104***	0.102***	0.095***	0.093***	0.111***
	(0.008)	(0.010)	(0.053)	(0.024)	(0.025)	(0.023)	(0.021)	(0.022)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	302,184	302,184	302,184	302,184	302,184	302,184	302,184	302,184
Households	66,394	66,394	66,394	66,394	66,394	66,394	66,394	66,394
Counties	1,202	1,202	1,202	1,202	1,202	1,202	1,202	1,202
Controls								
Household	N	Y	N	Y	N	N	N	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	N	Y	N	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	Y	Y	Y	Y
Standard Errors								
County Clusters	Y	Y	N	N	N	N	N	N
Adão et al. (2019)	N	N	Y	Y	Y	Y	Y	Y
F-statistic	–	–	56.84	33.23	32.39	31.40	114.27	115.19
Adjusted R-squared	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01

Notes: The table reports estimates of Equation (1) with 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. 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. (2020). Standard errors and F-statistics for 2SLS models are estimated following Adão et al. (2019), also allowing for correlation in housing characteristics through time.
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.

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)
$\Delta p_{county,t}$	0.104***	0.111**	0.178***	0.125	0.146***	0.132*	0.129***	0.005
	(0.014)	(0.047)	(0.017)	(0.193)	(0.015)	(0.078)	(0.011)	(0.022)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instrument	Bartik	Bartik	Saiz $\times \Delta p_r$	Saiz $\times \Delta p_r$	LS $\times \Delta p_r$	LS $\times \Delta p_r$	GMNS $\times \Delta p_r$	GMNS $\times \Delta p_r$
Observations								
Total	302,184	302,184	245,629	245,629	302,184	302,184	272,517	272,517
Households	66,394	66,394	54,187	54,187	66,394	66,394	60,026	60,026
Controls								
Household	N	Y	N	Y	N	Y	N	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	N	Y	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y	N	Y
Standard Errors								
County Clusters	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	238.14	55.76	153.16	1.79	146.07	11.64	1605.40	332.35
Adjusted R-squared	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01

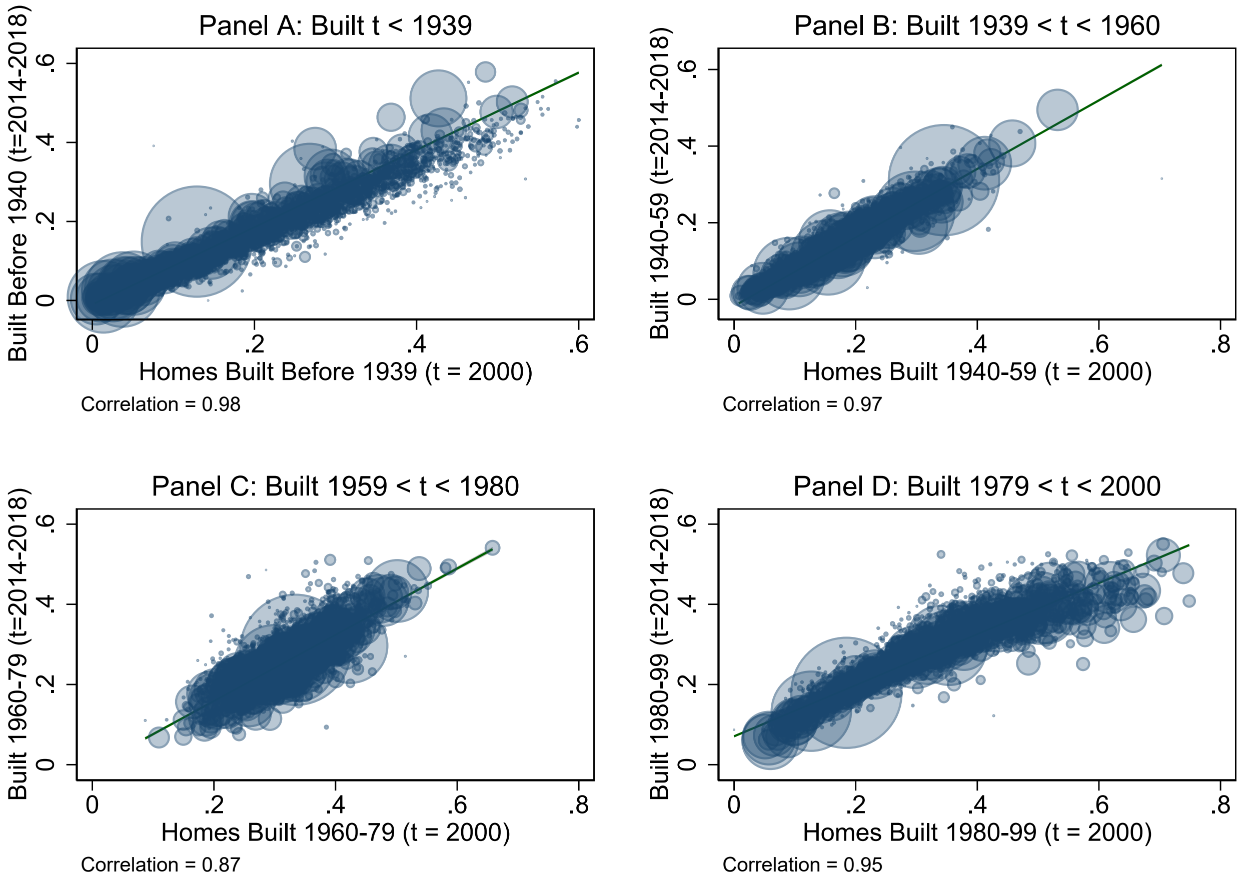
Notes: The table reports estimates of Equation (1) with household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects. Columns (1) and (2) use the baseline Bartik-like instrument discussed in the text. Columns (3) and (4) instrument for house prices using the Saiz (2010) housing supply elasticity interacted with the growth in regional house prices. Columns (5) and (6) instrument for house prices using the Lutz and Sand (2019) granular measure of land availability interacted with the growth in regional house prices. Columns (7) and (8) instrument for house prices using the Guren et al. (2020) measure of local house price sensitivity interacted with the growth in regional house prices. For comparability across instruments, standard errors and F-statistics are clustered at the county level. *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.

Table 4: Heterogeneity in Consumption Responses to House Prices

	Real annual household non-durable consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.104***	0.111**	0.349***	0.273***	0.078***	0.097**	0.064***	0.149*
	(0.014)	(0.047)	(0.059)	(0.076)	(0.016)	(0.046)	(0.020)	(0.088)
$\Delta p_{county,t} \times \mathbb{1}(40 < Age \leq 60)$			−0.213***	−0.127**				
			(0.058)	(0.057)				
$\Delta p_{county,t} \times \mathbb{1}(60 < Age)$			−0.315***	−0.214***				
			(0.060)	(0.057)				
$\Delta p_{county,t} \times \mathbb{1}(LTV > 0.80)$					0.074**	0.074**		
					(0.029)	(0.030)		
$\Delta p_{county,t} \times \mathbb{1}(2006 - 2009)$							0.072**	−0.067
							(0.029)	(0.131)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	302,184	302,184	302,184	302,184	302,184	302,184	302,184	302,184
Households	66,394	66,394	66,394	66,394	66,394	66,394	66,394	66,394
Counties	1,202	1,202	1,202	1,202	1,202	1,202	1,202	1,202
Adjusted R-squared	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01

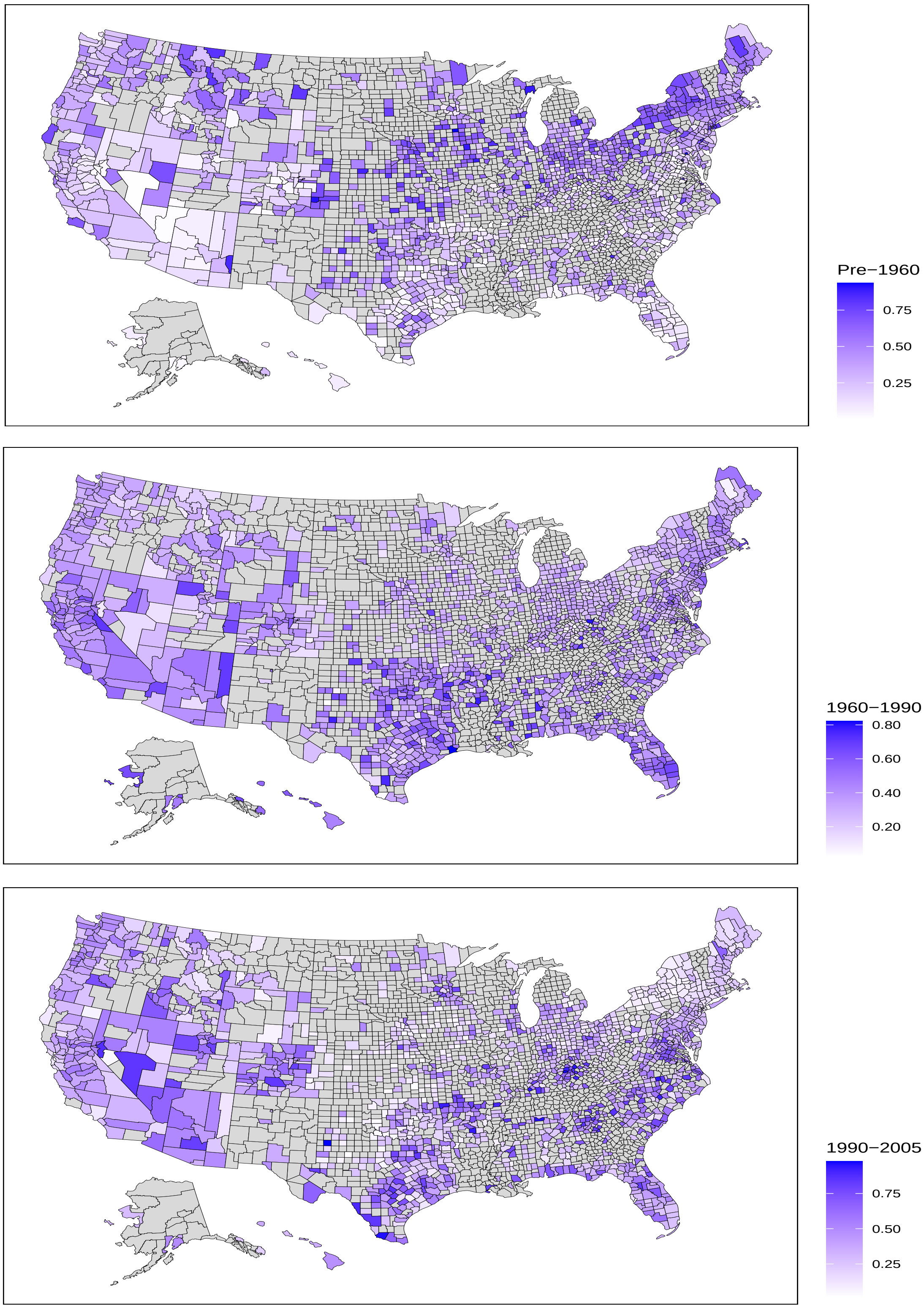
Notes: The table reports estimates of Equation (1) with household controls, county business cycle controls, county industry composition controls, county demographic controls, and county and year fixed effects. Columns (2)–(5) test for heterogeneity across: household age, zipcode-level loan-to-value ratios (average LTV at origination above 0.8), and the housing boom period (2006–2009). All columns are instrumented using the Bartik-like instrument discussed in the text. Standard errors are clustered at the county level.
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.

Figure 1: Investigating the Persistence of Housing Structure Types



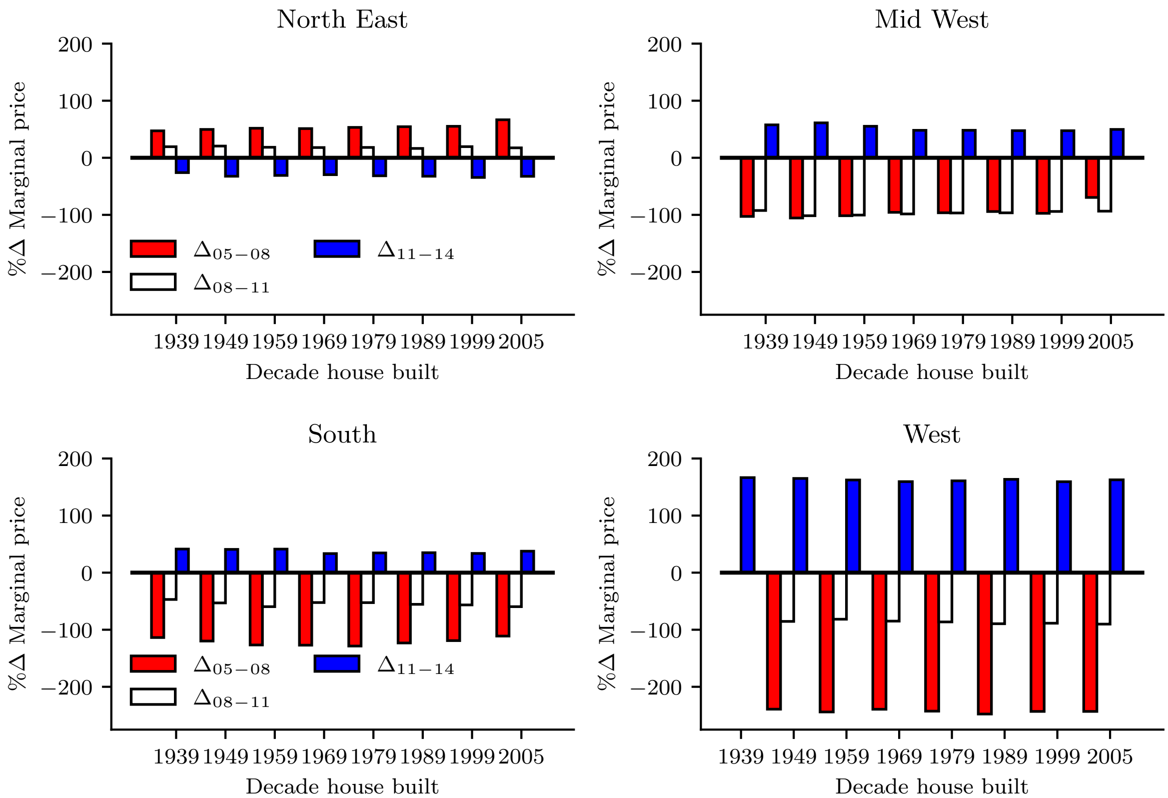
Notes: The figure plots the relationship between the share of homes built before 1940, between 1940 and 1959, between 1959 and 1979, and between 1980 and 1999 based on an extraction of the 2000 Decennial Census and the 2014-2018 ACS for a total of 3,212 counties. Observations are weighted by population in 2014-2018.
Sources: Authors' calculations using Decennial Census (2000) and American Community Survey (2014-2018).

Figure 2: Distribution of Housing Age Across Counties



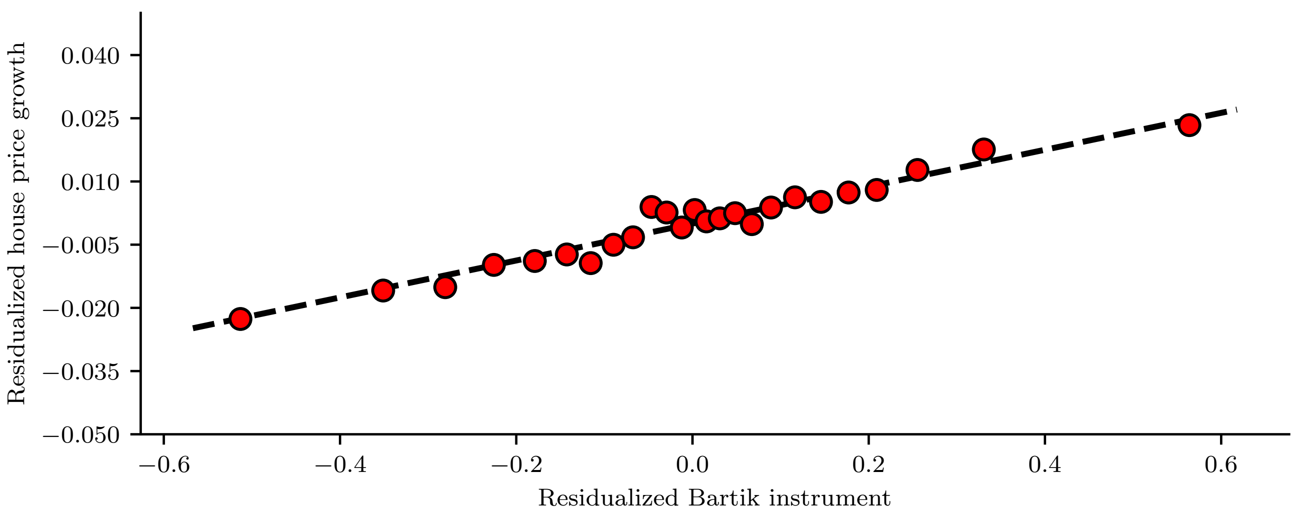
Notes: The heat map shows the within-county proportion of all unique houses sold between 1994 and 2005 that were built before 1960, between 1960 and 1990, and between 1990 and 2005 for the 1283 counties that have at least 100 individual transactions of unique houses from 1994 to 2005.
Source: Authors'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

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



Notes: 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 9. 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.
Source: Authors' calculations using ZTRAX.

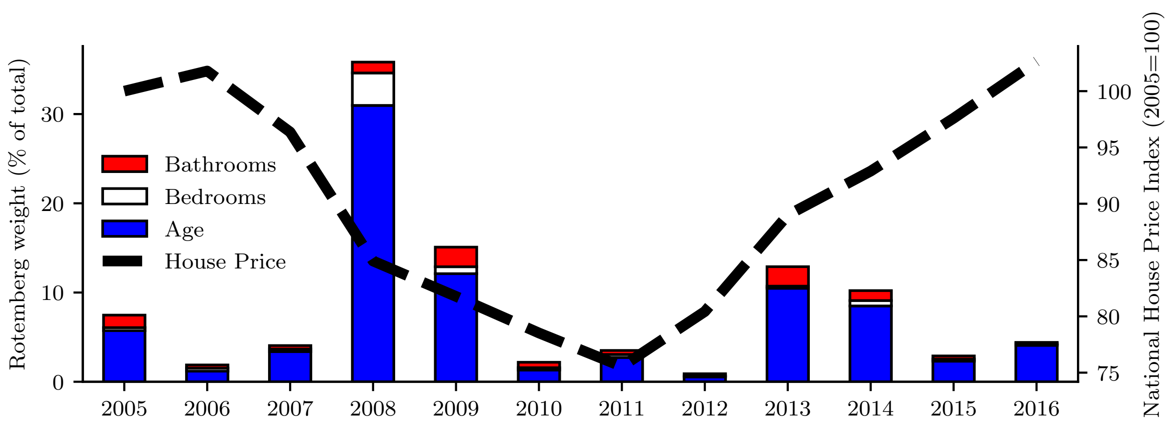
Figure 4: First Stage Effect of Bartik-like Instrument on House Price Growth



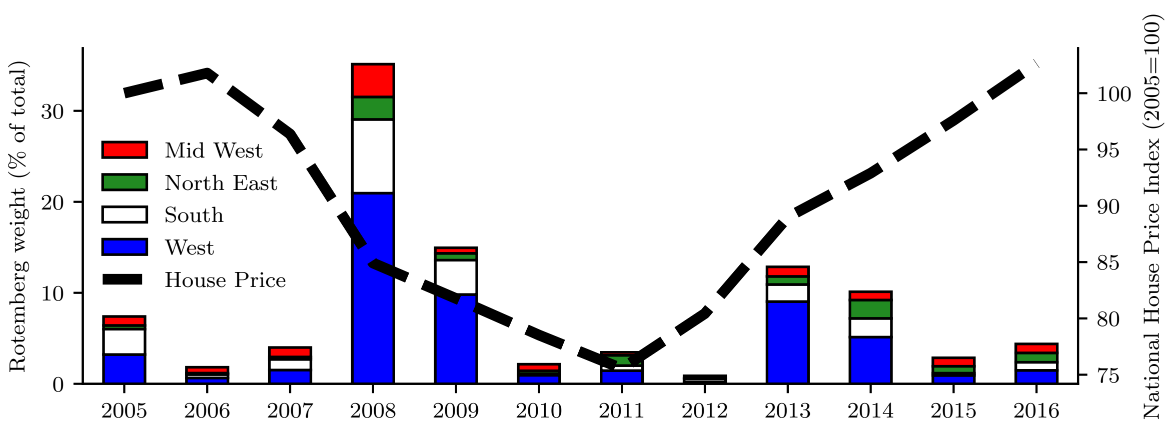
Notes: The figure plots the residualized Bartik-like instrument and county house price growth, representing the first stage regression. The residualized variables are constructed using the same household-level data and include the full set of controls as in the IV estimation of the consumption elasticities. See Appendix A.4 for a list of control variables. The value of the Bartik-like 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-like instrument.
Sources: Author's calculations, Nielsen Consumer Panel, ZTRAX.

Figure 5: Rotemberg Weights for Components of the Bartik-Like Instrument

(a) Rotemberg Weights by Housing Characteristic Type and Year



(b) Rotemberg Weights by Region and Year



Notes: Sums of the shares of absolute Rotemberg weights. Figure 5a reports weights within each housing characteristic group: age, bedrooms, and bathrooms. Figure 5b reports weights within each region. The dashed black line is the S&P/Case-Shiller National House Price Index.
Sources: Author's calculations, FRED, Nielsen Consumer Panel, ZTRAX.

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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-Datasets.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, we carry out the following cleaning procedure.

We 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 as long as they are not apartments or vacation homes. These property types include: Single Family Residences, Townhouses, Cluster Homes, Condominiums, Cooperatives, Row Houses, Bungalows, Patio Homes, Garden Homes, and Landominiums. This latter restriction includes 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, we remove any house sale that occurs within 180 days of a prior sale of the same house. Additionally, we 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.[24] For these states, property deeds and assessment records may still be reported to the ZTRAX database. We collect data on housing characteristics for these states, but we cannot use the transaction data on sales prices.[25] Instead, for these states we 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 A.5 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 A.6 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 et al. (2019) 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.[26] The second panel of Figure A.6 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

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

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

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

Table A.5: Household summary statistics, Nielsen 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 Nielsen Consumer Panel.

Table A.6: Demographics, Nielsen Consumer Panel

	College	Non-Employed	Home Owners	Moved Zip code	Moved County	Moved State
Nielsen	0.420	0.190	0.749	0.021	0.012	0.012
CPS	0.421	0.242	0.686	0.078	0.023	0.017

Notes: Computed using survey-weighted averages in the Consumer Panel and the Current Population Survey (CPS) for the period 2004-2015. In the Nielsen data: college is computed using the male household head, or the female household head if no male head is reported; non-employed is computed using only households with a male head aged between 18 and 65; homeownership is computed following Stroebel et al. (2019), where a household is considered a homeowner if they report living in either a one-family house or a one-family condo or co-op. In the CPS, college is computed for the whole population, and non-employed is computed for men aged between 18 and 65. The final three columns report average proportion of households moving across zip codes (within counties in the CPS), moving across counties, and across states.
Sources: Authors calculations using Nielsen Consumer Panel, CPS.

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 A.7 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.

Figure A.6 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.

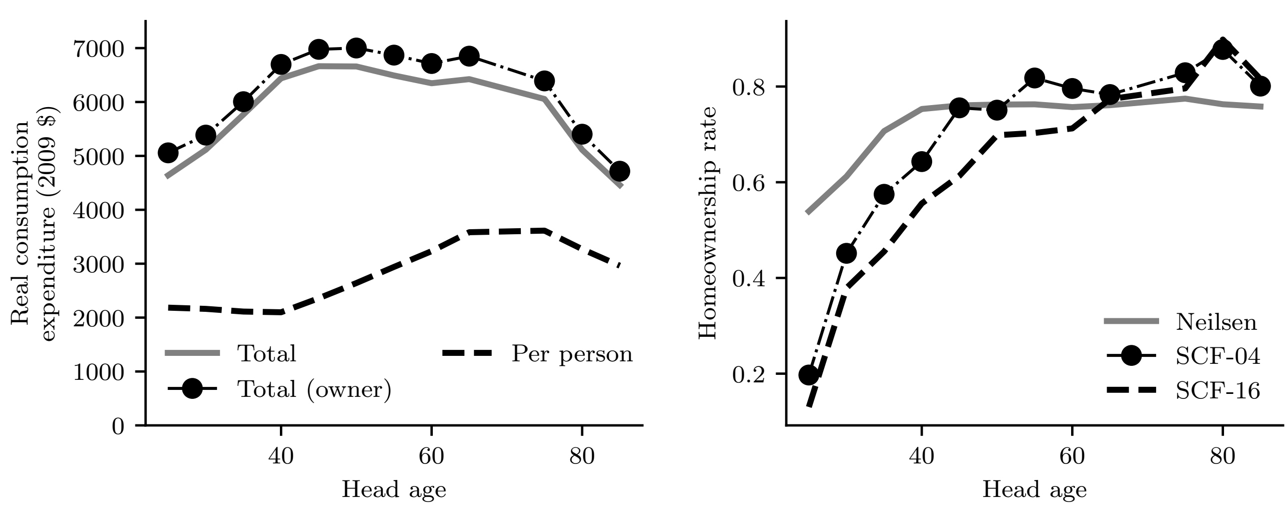
Figure A.7 shows the annual growth rate of nominal non-durable consumption per capita for the Nielsen data and for data taken from the personal consumption expenditures section of NIPA.

Table A.7: Number of panelists, Nielsen 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 Nielsen Consumer Panel.

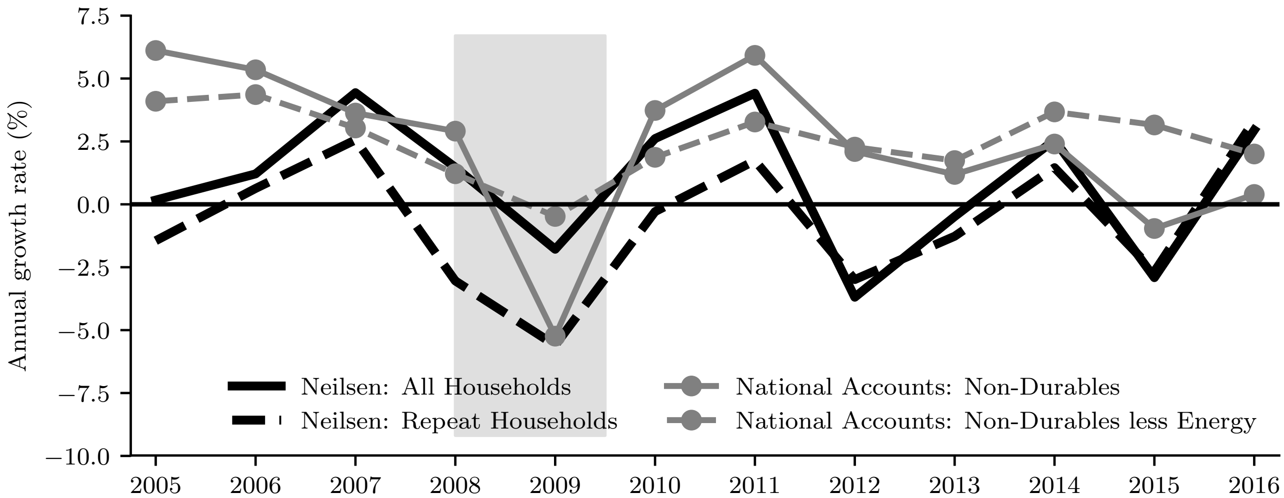
Figure A.6: Consumption and Homeownership Over the Life Cycle



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.

Growth rates are computed from the Consumer Panel data first by computing the growth rate in

Figure A.7: 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.

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.

A.4 Control Variables in 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: County fixed effects are included in all specifications. Some specifications include year fixed effects. We alternatively experimented with CBSA fixed effects, but this had no material effect on our results.

Local business cycle controls: County-level pre-tax 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: 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. (2020).

B Details of Bartik-like 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 B.8 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.[27] 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 B.8 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, we exclude houses reporting zero bedrooms from the analysis.[28] Additionally, Section C considers a version of the Bartik-like instrument using housing age as the only house characteristic.

Table B.8: Correlations of Local Characteristic Shares and Housing Supply

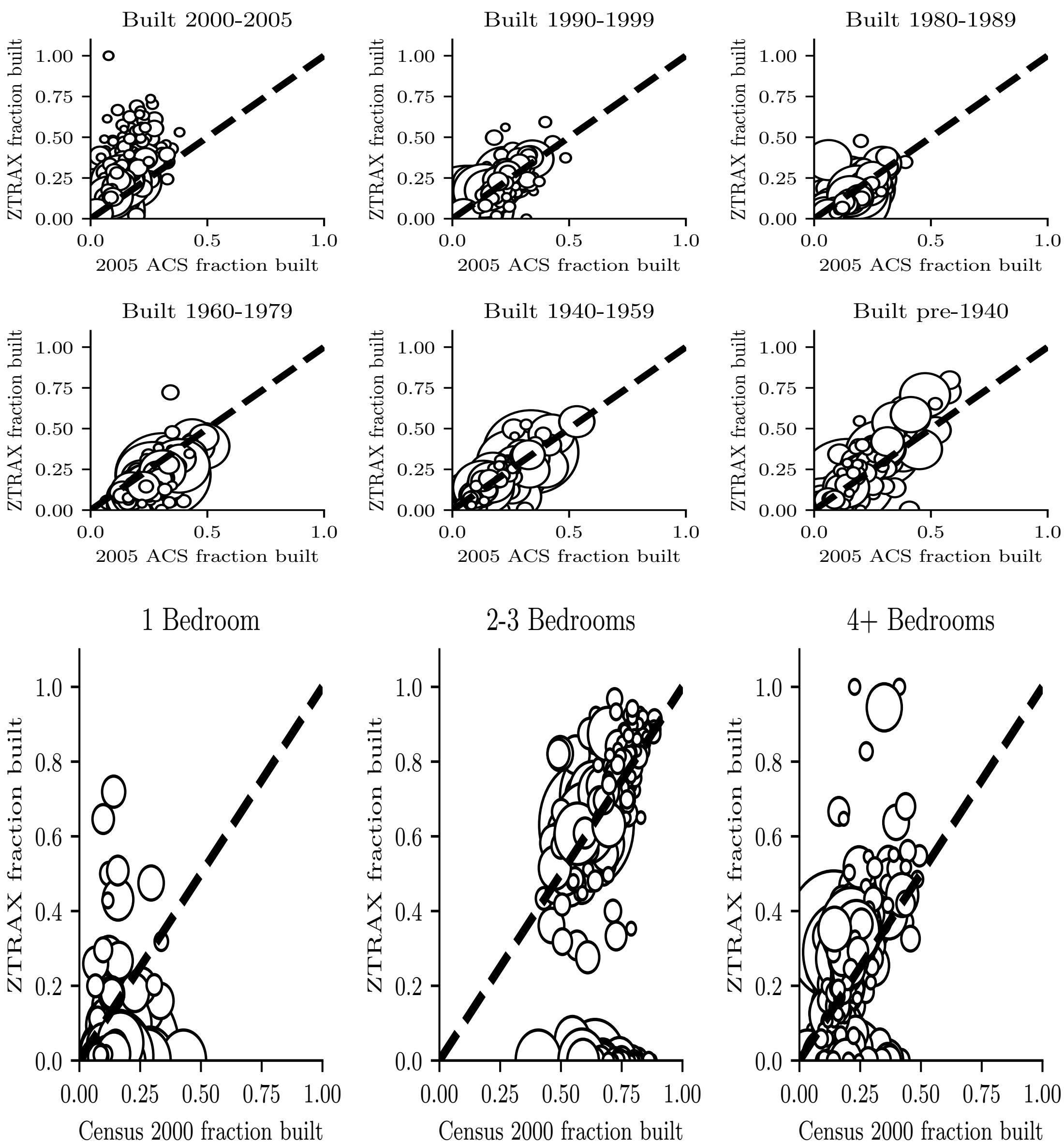
Built	Saiz	Wharton	Bedrooms	Saiz	Wharton	Bathrooms	Saiz	Wharton
pre-1940	−0.03	0.10	One	−0.16	0.16	Zero	0.06	−0.08
1940-1949	−0.15	0.08	Two	−0.20	0.24	One	−0.01	0.07
1950-1959	−0.27	0.12	Three	0.21	−0.14	Two	−0.10	0.09
1960-1969	−0.19	0.07	Four	−0.18	0.06	Three	−0.12	0.09
1970-1979	−0.22	0.08	Five+	−0.36	0.30	Four+	−0.20	0.04
1980-1989	−0.22	0.11						
1990-1999	0.22	−0.13						
2000-2005	0.37	−0.25						

Notes: Correlation between local shares for housing characteristics and measures of local housing supply. Correlation computed for cities (CBSAs), using 240 observations available for all three sets of instruments, weighted by population as at the 2000 Census.
Sources: Author's calculations using 2000 Census, Gyourko et al. (2008), Saiz (2010), ZTRAX.

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

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

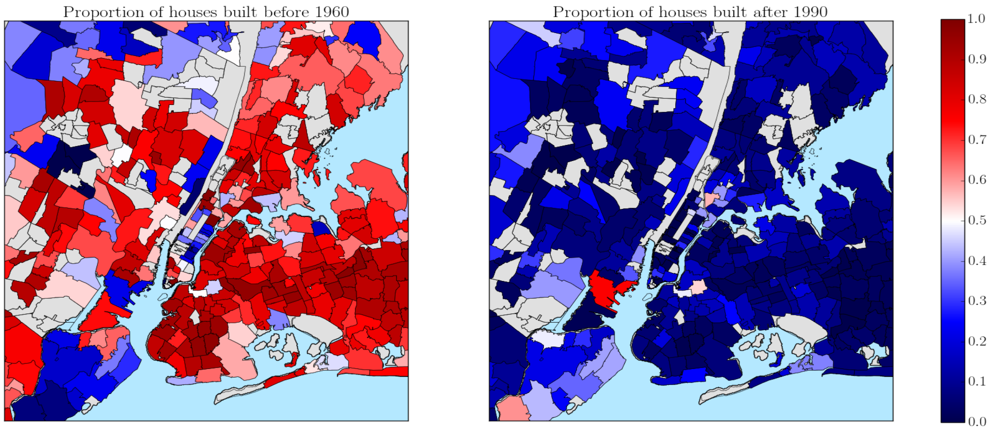
Figure B.8: Local House Characteristic Shares in ZTRAX and 2005 ACS



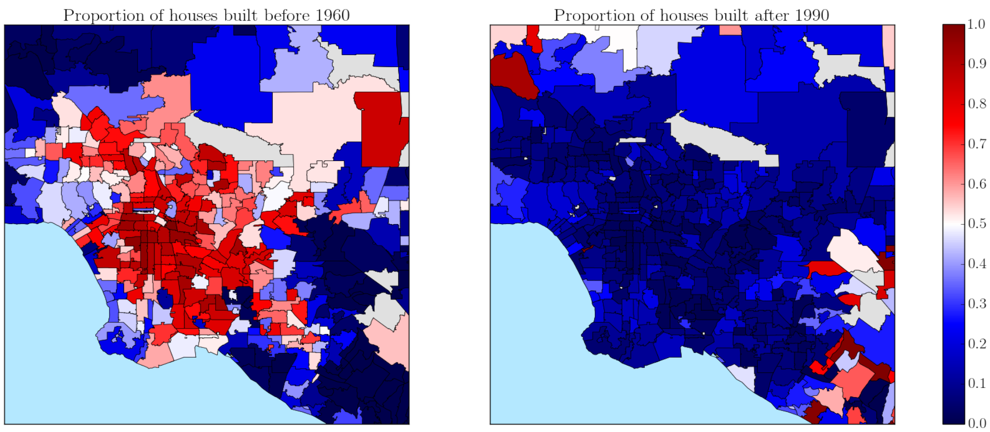
Notes: County share of housing stock by year built and number of bedrooms. Shares computed from the 2005 American Community Survey and ZTRAX data for unique houses sold between 1994 and 2005. Note that the ACS reports data for occupied houses only, while the ZTRAX data is drawn from all houses sold. 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

Figure B.9: Distribution of Housing Age Across Zip Codes

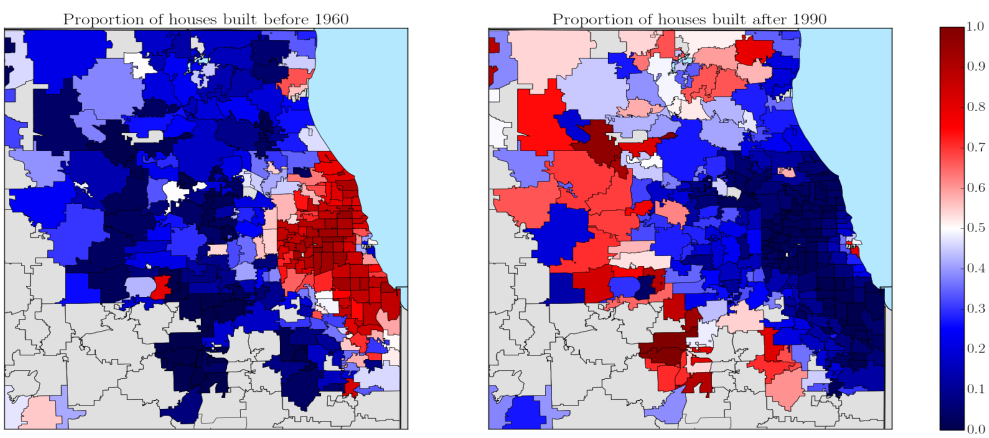
(a) New York



(b) Los Angeles



(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.

C Robustness of the Bartik-Like Instrument

Table C.9: Further Heterogeneity in Consumption Response to House Prices

	Real annual non-durable household consumption growth					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta p_{county,t}$	0.104***	0.059	0.105***	0.072	0.110***	0.075
	(0.031)	(0.060)	(0.030)	(0.059)	(0.035)	(0.068)
$\Delta p_{county,t} \times \mathbb{1}(Homeownership > Median)$			−0.002	−0.047		
			(0.030)	(0.050)		
$\Delta p_{county,t} \times \mathbb{1}(RetailTrade > Median)$					−0.010	−0.029
					(0.029)	(0.046)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	Owners	Renters	Owners	Renters	Owners	Renters
Observations						
Total	302,184	68,039	302,184	68,039	302,184	68,039
Households	66,394	18,284	66,394	18,284	66,394	18,284
Counties	1,202	1,065	1,202	1,065	1,202	1,065
Adjusted R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Notes: The table reports estimates of Equation (1) with household controls, county business cycle controls, county industry composition controls, and county and year fixed effects. Columns (1), (3), and (5) use the sample of inferred owner households, while Columns (2), (4) and (6) use the sample of inferred renter households. Columns (3) and (4) test for heterogeneity of consumption responses in counties with above-median homeownership rates. Columns (5) and (6) test for heterogeneity of consumption responses in counties with above-median retail trade employment sharaes. All columns are instrumented using the Bartik-like instrument discussed in the text. Standard errors are clustered at the county level.
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.

Table C.10: 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)
$\Delta p_{zipcode,t}$	0.063***	0.019**	0.072***	0.095***	0.099***	0.090***	0.106***	0.120***
	(0.006)	(0.008)	(0.023)	(0.015)	(0.017)	(0.015)	(0.016)	(0.019)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	220,265	220,265	220,265	220,265	220,265	220,265	220,265	220,265
Households	49,505	49,505	49,505	49,505	49,505	49,505	49,505	49,505
Zip Codes	7,617	7,617	7,617	7,617	7,617	7,617	7,617	7,617
Controls								
Household	N	Y	N	Y	N	N	N	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
Zip Code FE	N	Y	N	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	Y	Y	Y	Y
Standard Errors								
Zipcode Clusters	Y	Y	N	N	N	N	N	N
Adão et al. (2019)	N	N	Y	Y	Y	Y	Y	Y
F-statistic	–	–	162.00	231.92	259.02	229.37	386.93	350.92
Adjusted R-squared	-0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01

Notes: The table reports estimates of Equation (1) using zip code-level house price growth. The regressions include household controls, county and zip code business cycle controls, county industry composition controls, zip code demographic controls, and zip code 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. 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. (2020). Standard errors and F-statistics for 2SLS models are estimated following Adão et al. (2019), also allowing for correlation in housing characteristics through time.
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.

Table C.11: Consumption Response to House Prices Using Alternative Bartik Instruments

	Real annual non-durable household consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.104***	0.111**	0.105***	0.118**	0.157***	0.058	0.121***	0.327
	(0.014)	(0.047)	(0.014)	(0.046)	(0.015)	(0.066)	(0.015)	(0.270)
Instrument	Baseline	Baseline	Age Only	Age Only	Add Size	Add Size	National	National
Observations								
Total	302,184	302,184	302,184	302,184	302,184	302,184	302,184	302,184
Households	66,394	66,394	66,394	66,394	66,394	66,394	66,394	66,394
Counties	1,202	1,202	1,202	1,202	1,202	1,202	1,202	1,202
Controls								
Household	N	Y	N	Y	N	Y	N	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	N	Y	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y	N	N
Standard Errors								
County Clusters	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	238.14	55.76	262.87	52.39	271.40	33.08	166.05	2.35
Adjusted R-squared	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01

Notes: The table reports estimates of Equation (1) with 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. Column (7) uses a version of the Bartik instrument that makes use of national, rather than regional, variation in housing characteristic prices.
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.

Table C.12: Consumption Response to House Prices Using Housing Characteristic Share-Year Dummy Interaction Instrument

	Real annual non-durable household consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.118***	0.030***	0.165***	0.064***	0.052**	0.061***	0.094***	0.083**
	(0.008)	(0.010)	(0.012)	(0.020)	(0.021)	(0.020)	(0.036)	(0.036)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	302,184	302,184	302,184	302,184	302,184	302,184	302,184	302,184
Households	66,394	66,394	66,394	66,394	66,394	66,394	66,394	66,394
Counties	1,202	1,202	1,202	1,202	1,202	1,202	1,202	1,202
Controls								
Household	N	Y	N	Y	N	N	N	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	N	Y	N	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	Y	Y	Y	Y
Standard Errors								
County Clusters	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	–	–	246.71	33.95	45.99	34.54	11.94	10.79
Adjusted R-squared	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01

Notes: The table reports estimates of Equation (1) using as an instrument the interaction between the housing characteristic shares (see Section 4.1) with year dummies. The specifications include: 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. 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. (2020). Standard errors and F-statistics for 2SLS models are clustered at the county level.
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.

D Estimation of Rotemberg Weights

We follow the suggestion from Goldsmith-Pinkham et al. (2020) that shift-share 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-like 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-like instruments is $B = \Lambda Q$. The IV estimator of the consumption elasticity using the Bartik-like instrument has the familiar form:

$$\beta^{bartik} = \frac{B'C}{B'P} = \frac{Q'\Lambda'C}{Q'\Lambda'P} \tag{10}$$

Following Goldsmith-Pinkham et al. (2020), the Bartik-like estimate can then be decomposed into the just-identified estimates β_k^{bartik} and the associated Rotemberg weights α_k. Then the IV 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. (2020) notes that individual Rotemberg weights α_k may be negative, which means that the over-identified IV estimate using the full Bartik-like 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-like 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-like instrument for prediction.

Table D.13 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. The Rotemberg weights and housing quality price growth are negatively correlated, which suggests that more weight is placed observations in which housing quality prices are declining, as they are during the housing bust. The Rotemberg weights and the variance of the local housing shares are only weakly negatively correlated. Additionally, the variance of the local housing shares is only weakly negatively correlated with quality price movements. This is important, as it shows that the identifying variation in the instrument contained in the housing shares is not tied to the potentially endogenous time-series variation produced by the housing quality prices.

Panel C reports the components of the instrument with the largest share of absolute Rotemberg weights, decomposed into variation due to the house characteristics shares, region, and year. Strikingly, virtually all of the Rotemberg weight is associated with the Western region, with housing age characteristics, and is largely concentrated in the bust years of 2008 and 2009, but also the recovery years of 2013 and 2014. We graphically illustrate these results in Figure 5 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.

Table D.13: 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	0.106	1.087	0.037	-0.294	0.283	0.325
α_k	–	0.001	0	0	0.001	0.265

Panel B: Correlations

	α_k	Δq_k	β_k	var(λ_k)
α_k	1			
Δq_k	-0.384	1		
β_k	-0.014	0.003	1	
var(λ_k)	-0.047	0.024	0.061	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
Decade to 2005	2008	West	0.1	0.04	-1.74	0.19
Decade to 1989	2008	West	0.09	0.04	-1.74	0.1
Decade to 1999	2008	West	0.09	0.04	-1.68	0.18
Decade to 1979	2008	West	0.06	0.03	-1.68	0.13
Decade to 1999	2009	West	0.05	0.02	-0.8	0.02
Decade to 2005	2009	West	0.05	0.02	-0.82	0.01
Decade to 1999	2013	West	0.04	0.02	0.95	0.01
Decade to 2005	2013	West	0.04	0.02	0.97	-0.01
Decade to 2005	2008	South	-0.04	0.02	-0.77	0.02
Decade to 1989	2009	West	0.04	0.02	-0.84	-0.01
Decade to 1989	2013	West	0.04	0.02	0.97	0.09
Decade to 1959	2008	West	0.04	0.02	-1.73	0.14
Decade to 1969	2008	West	0.03	0.01	-1.68	0.13
Decade to 1999	2008	South	-0.03	0.01	-0.74	0.11
Decade to 1979	2013	West	0.03	0.01	0.95	0.08
Decade to 1979	2009	West	0.02	0.01	-0.79	0.04
Decade to 1999	2014	West	0.02	0.01	0.6	-0.04
Decade to 2005	2014	West	0.02	0.01	0.61	-0.1
Bathrooms: 2	2013	South	-0.02	0.01	0.26	0.06
Decade to 1989	2014	West	0.02	0.01	0.61	-0.12

Notes: Panel A reports summary statistics for the just-identified estimates β_k and Rotemberg weights α_k. Panel B reports correlations between these variables, housing quality price growth rates Δq_k and the cross-sectional variance of the local housing shares var(λ_k). Panel C reports the top 20 housing characteristics sorted by share of absolute Rotemberg weight associated with the just-identified estimates.