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House Prices and Consumption: A New Instrumental Variables Approach[†]

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We introduce a novel Bartik-like instrument for house prices consisting of the local composition of housing characteristics interacted with aggregate changes in the marginal prices of these characteristics. Using household-level panel data, we estimate elasticities of nondurable consumption expenditures with respect to house prices of around 0.1. These consumption effects are concentrated among the young and those most likely to be facing tight borrowing constraints. A decomposition shows that identifying variation in the instrument is associated with times and locations where house prices have varied the most: during the housing bust of the mid-2000s and in the western United States. (*JEL* D12, E21, G51, R21, R31)

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.

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[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 and Kimball (1996); Carroll (2001); Kiyotaki and Moore (1997); and Bernanke (2018).

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, Rao, and Sufi (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 2010a; Gyourko, Saiz, and Summers 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, Mayer, and Sinai 2013; Gyourko, Hartley, and Krimmel 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 to multiple levels of geography. And we illustrate how both cross-sectional and time-series variation in the instrument contribute to our estimates of the elasticity of consumption with respect to house prices.

To construct our instrument, we use detailed housing transaction data from the Zillow Transaction and Assessment Database, or ZTRAX (Zillow 2020). 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 United States 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, Sorkin, and Swift (2020), our identifying assumptions rely on the exogeneity of local housing characteristics

[2]For example, see Campbell and Cocco (2007); Attanasio et al. (2009); Disney, Gathergood, and Henley (2010); Gan (2010); Carroll, Otsuka, and Slacalek (2011); Mian, Rao, and Sufi (2013); Browning, Gørtz, and Leth-Petersen (2013); Christelis, Georgarakos, and Jappelli (2015); Aladangady (2017); Paiella and Pistaferri (2017); Angrisani, Hurd, and Rohwedder (2019); Kaplan, Mitman, and Violante (2020); and Guren et al. (2021a).

[3]Recently, Lutz and Sand (2019a) have extended the Saiz (2010a) land availability measures to lower levels of geography, and Gyourko, Hartley, and Krimmel (2021) have updated the Wharton Residential Land use index of Gyourko, Saiz, and Summers (2008) using a survey from 2018.

[4]See, for example, Bartik (1991); Adão, Kolesár, and Morales (2019); Goldsmith-Pinkham, Sorkin, and Swift (2020); and Borusyak, Hull, and Jaravel (2022).

with respect to other determinants of household consumption. This is intuitively plausible for two reasons. First, local house characteristics are largely predetermined at the time that consumption shocks are realized since the composition of houses changes very slowly over time. We 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, Smith, and Wozniak, 2011; Bachmann and Cooper 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, Schneider, and Stroebel 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 nondurable 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 2005–2016. 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 nondurable expenditures. Additionally, these estimates correspond to an approximate marginal propensity to consume (MPC) nondurables 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, Rao, and Sufi (2013) estimate MPCs of 0.4 cents for food and grocery goods, 1.6 cents for all nondurable goods, and 5.4 cents for total consumption. Other studies have reported MPCs for total consumption of between one cent and six cents (Disney, Gathergood, and Henley 2010; Carroll, Otsuka, and Slacalek 2011; Guren et al. 2021a; Paiella and Pistaferri 2017; Aladangady 2017; Angrisani, Hurd, and Rohwedder 2019). Direct estimates of the elasticity of nondurables consumption to local house prices range from 0.17 (Gan 2010), to 0.21 (Kaplan, Mitman, and Violante 2020), to 0.38 (Campbell and Cocco 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 and 2006 as a proxy for indebtedness over the period 2005–2016. 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, Rao, and Sufi 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. 2021a).

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 2010a; Lutz and Sand 2019a; Guren et al. 2021a). 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 level rather than the 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 microdata 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, Sorkin, and Swift 2020). In principle, any weighting matrix can be used, but less relevant time-series variation produces 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-variable strategies in the recent literature. Starting with Mian and Sufi (2011); Mian, Rao, and Sufi (2013); and Mian and Sufi (2014) many papers have made use of cross-sectional variation in housing supply elasticities and land use restrictions (see Saiz 2010a; Gyourko, Saiz, and Summers 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. (2021a) 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. (2021a) 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 these characteristics are more exposed to the increase in prices since their housing stock is more concentrated in this house type. In this sense, our instrument draws on similar intuitions as 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, Sorkin, and Swift (2020) describe a decomposition following Rotemberg (1983) in which IV regressions using shift-share instruments can be recast as overidentified 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 United States, and in quality price movements during the housing bust years of 2008–2009 and the housing recovery years of 2013–2014.

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

I. Data

A. *Housing Data*

We use transaction-level housing data from the Zillow Transaction and Assessment Dataset (ZTRAX) made available by Zillow Research (Zillow 2020). The full ZTRAX dataset contains more than 370 million public records from across the United States 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, nonforeclosed 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 nonmandatory disclosure rules and outright prohibitions on the reporting of transaction prices.[5] However, housing characteristics for properties in these states are still widely available. We use the housing 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 III, this information allows us to construct our Bartik-like instrument for local house prices. In online 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 census are highly correlated at the county level.

Our final sample contains 55 million observations on individual property transactions between 1994 and 2016. Further details on the sample selection procedure are reported in online Appendix A.2.

B. *Consumption Data*

Household-level consumption data come from the Nielsen Consumer Panel (NielsenIQ 2021). Our summary statistics for this data are reported in online 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 and quantity of all goods purchased 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 nondurables from the following categories: health and beauty, dry grocery, frozen foods, dairy, deli, packaged, meat, fresh produce, nonfood grocery, alcohol, and general merchandise.

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

Table A.5 in the online Appendix shows that in the Consumer Panel the average age of a household head is 53, the average family size is 2.6 persons, the average annual income was $68,000, and the average annual expenditure is $7,489. Table A.6 in the online Appendix benchmarks demographic characteristics to their counterparts in the Current Population Survey (CPS) between 2004 and 2015 (Flood et al.

[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/.

2021). In the Consumer Panel the college-going rate is the same as in the general population, at 42 percent. The fraction of nonemployed 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 and Vavra (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 whether the house is a condo or co-op. We assume that single-family, noncondo/-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 in the online Appendix 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 age 40 and older (Board of Governors of the Federal Reserve System 2004, 2016). However, the Consumer Panel produces higher rates of inferred homeownership than actual homeownership rates for younger households. This suggests that 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, Rao, and Sufi 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 (3.0 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 nonmovers, we further restrict our sample to those who never move.

Importantly, the Consumer Panel data reports the state, county, and zip code in which households live. Each household can then be linked to a measure of local house prices as well as other measures 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.

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

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

C. *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 (US Federal Housing Finance Agency 2021). We use the CPI for all urban consumers to deflate all nominal variables (U.S. Bureau of Labor Statistics 2021). 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 (U.S. Internal Revenue Service 2017a, b). County unemployment data is collected from the BLS Local Area Unemployment statistics (US Bureau of Labor Statistics 2019). County-level demographic information is provided by the 2000 census (US Census Bureau 2001). We use annual county employment by industry from the County Business Patterns Survey data (US Census Bureau 2017). We aggregate employment using the six-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). To link data across geographies, we use crosswalk files between zip codes, counties, and CBSAs from the U.S. Department of Housing and Urban Development (2010) and the U.S. Census Bureau (2018). Finally, we compare our benchmark results to consumption elasticities estimated using alternative instruments for house prices from the existing literature (Saiz 2010a, b; Lutz and Sand 2019a, b; Guren et al. 2020a, b). A detailed list of all data sources is reported in online Appendix A.1.

II. 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 nondurable 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, Sorkin, and Swift (2020) by controlling for local demographic characteristics measured at the beginning of the sample and interacted with year fixed effects. These characteristics are 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, in which both national house prices and aggregate consumption declined significantly. Online 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 upward 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 affects groups differentially 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 III, 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

[8] For the first exposition of these instruments, see Bartik (1991). For recent discussions of identification and inference for shift-share instruments, see Borusyak, Hull, and Jaravel (2022); Adão, Kolesár, and Morales (2019); and Goldsmith-Pinkham, Sorkin, and Swift (2020).

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 III, 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:

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

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

$$0 = \mathrm{Cov}\big(B_{g,t}, u_{i,g,t} \,|\, x_{i,t}, y_{g,t}, \alpha_g, \alpha_t\big). \tag{4}$$

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, Sorkin, and Swift (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 predetermined 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 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 percent of households move residence in a given year (Bachmann and Cooper 2014), only 6 percent move across counties (Molloy, Smith, and Wozniak 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

[9] Alternatively, Borusyak, Hull, and Jaravel (2022) 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 and Cooper 2014), renters are nearly four times as likely to cross state lines as homeowners (Molloy, Smith, and Wozniak 2011), and less than one-third of US natives move across state lines in their lifetimes (Molloy, Smith, and Wozniak 2011).

evidence on housing-search behavior suggests that most potential home-buyers search in a fairly limited geographic area. Piazzesi, Schneider, and Stroebel (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 percent of these potential buyers search among noncontiguous 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 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 predetermined 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 stock 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 census and the 2014–2018 five-year American Community Survey (US Census Bureau 2019).[11] Across this 15-year period the age composition of the housing stock is extremely persistent: we find within-county correlations of between 0.91 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.

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]

[11] We use the census and ACS rather than ZTRAX for this exercise, as these data include all counties in the United States 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 (2010a).

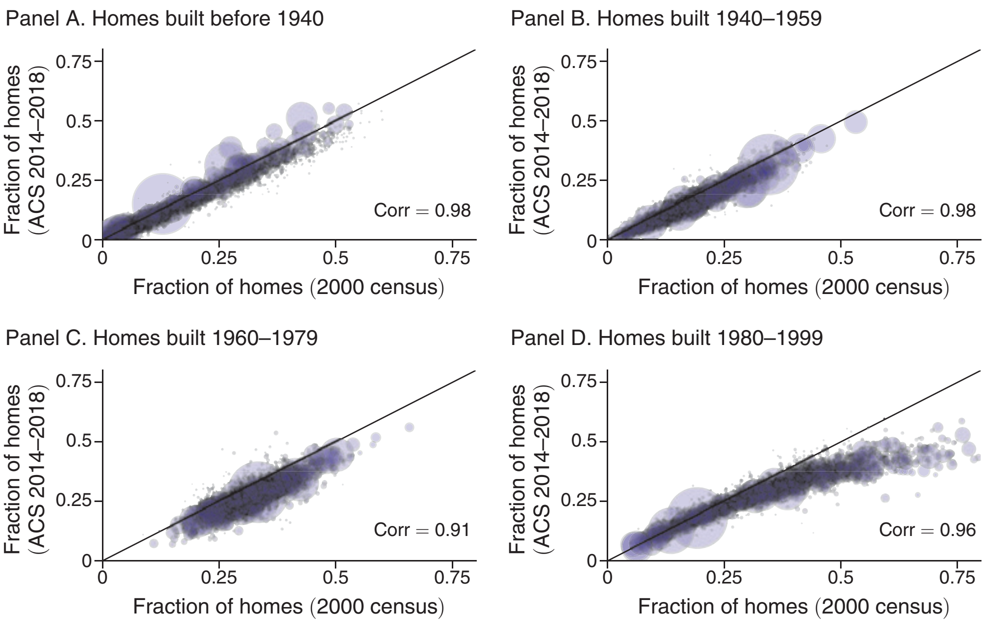

Figure 1. The Persistence of Housing Structure Types

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 census and the 2014–2018 ACS for a total of 3,212 counties. Observations are weighted by 2000 census populations.

Sources: Authors' calculations using 2000 census and American Community Survey (2014–2018) data.

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 0.43 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 IV 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.

Finally, we consider statistical inference of our 2SLS estimates. Recent work by Adão, Kolesár, and Morales (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

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	−0.43	−0.22	−0.16	−0.07	0.23	0.07	0.39	0.32
Frac. college or more	−0.26	−0.12	−0.02	0.11	0.20	0.29	0.22	−0.04
Frac. White	−0.20	−0.28	−0.24	−0.16	0.13	0.00	0.29	0.28
Frac. Black	0.30	0.25	0.18	0.09	−0.29	−0.12	−0.27	−0.21
Frac. Hispanic	−0.13	0.04	0.10	0.05	0.09	0.15	−0.02	−0.01
Frac. foreign born	0.09	0.12	0.19	0.14	0.05	0.11	−0.20	−0.25
Median age	0.08	−0.03	−0.00	0.05	0.08	0.04	−0.11	−0.12
Mean household size	−0.26	−0.05	0.03	0.01	0.12	0.07	0.19	0.12
Mean commute time	0.20	0.02	0.01	−0.02	−0.13	0.05	−0.12	−0.12

Notes: The table shows the correlation between county shares for housing characteristics and county demographics from the 2000 census. Correlations are computed for 1,203 counties, weighted by census population counts.

Sources: Authors' calculations using 2000 census and ZTRAX data.

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 IV present standard errors following Adão, Kolesár, and Morales (2019), which allows for correlation in regression residuals according to the similarity of housing characteristics across locations and clustered through time.[13]

III. Construction of the Bartik-Like House Price Instrument

We now describe the construction of our Bartik-like instrument for house prices. Following Goldsmith-Pinkham, Sorkin, and Swift (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 characteristic c.

The decomposition in equation (5) suggests that house price growth is given by changes in quality prices weighted by the proportion of these 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 the share of small houses is,

[13] We use the standard error formula in Adão, Kolesár, and Morales (2019) equation (37), which is adapted for use in panel data contexts like ours.

the more sensitive overall price growth is to changes in the marginal price of small houses. We further decompose housing quality prices as

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

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

$$B_{g,t} = \sum_c \sum_i \lambda_{g,c_i} \Delta q_{c_i,t}. \tag{8}$$

A. *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

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

number of bedrooms is split into the categories $\mathcal{B} \equiv \{1,2,3,4,5+\}$. The number of bathrooms is split 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 the online Appendix shows that the county-level housing shares computed using ZTRAX line up well with survey data from the 2005 ACS. In Section IVC 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 United States. 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 housing age. For example, counties in the Northeast 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 United States, where inland counties have much newer housing characteristics than the cities in the coastal states. Figure B.9 in the online Appendix illustrates cross–zip code distributions of housing age with significant variation at the subcounty level. This suggests that our instrument is likely to provide useful identifying variation in house prices at different levels of geography. In Section IVC we show that our estimates are robust to the use of our instrument when constructed at the zip code level.

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 the online Appendix reports the population-weighted correlations between our housing characteristic shares and the housing supply elasticities from Saiz (2010a) and the Wharton residential land use regulation indexes in Gyourko, Saiz, and Summers (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.

B. *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

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

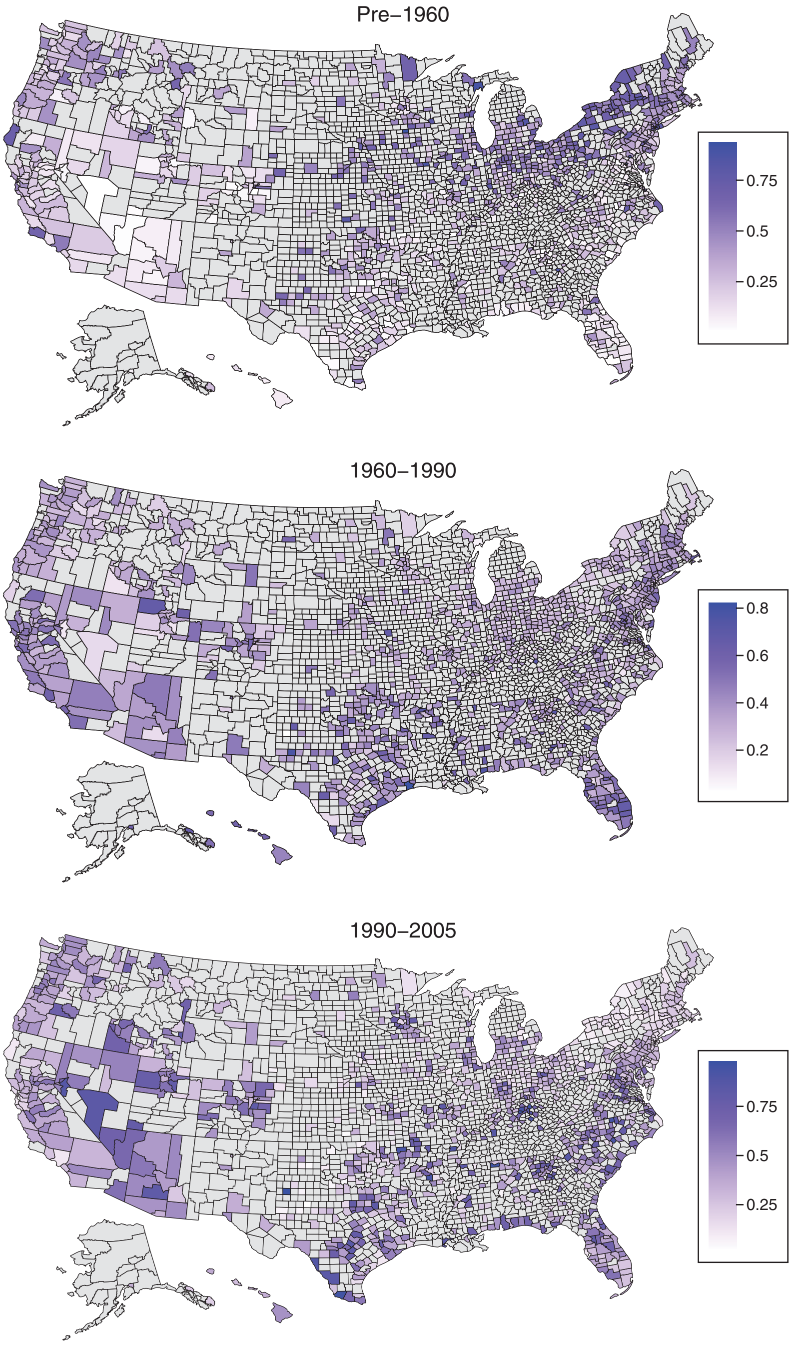

Figure 2. Distribution of Housing Age across Counties

Notes: The heat maps show the within-county shares of all unique houses sold between 1994 and 2005 across housing characteristics. The top panel shows the proportion that were built before 1960, the middle panel shows the proportion that were built between 1960 and 1990, and the lower panel shows the proportion that were built between 1990 and 2005. Figures illustrate counties that had at least 100 transactions involving unique houses between 1994 and 2005.

Source: Authors' calculations using ZTRAX data.

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 III. 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 IVC 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 United States: Midwest, Northeast, South, and West. This involves running a separate set of regressions for all houses sold in each region over the sample period 2005–2016. In exploiting subnational 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. (2021a), 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 regions, 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^2 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 2007 and 2010, the prices of houses of all ages increased in the Northeast but declined significantly in the West.

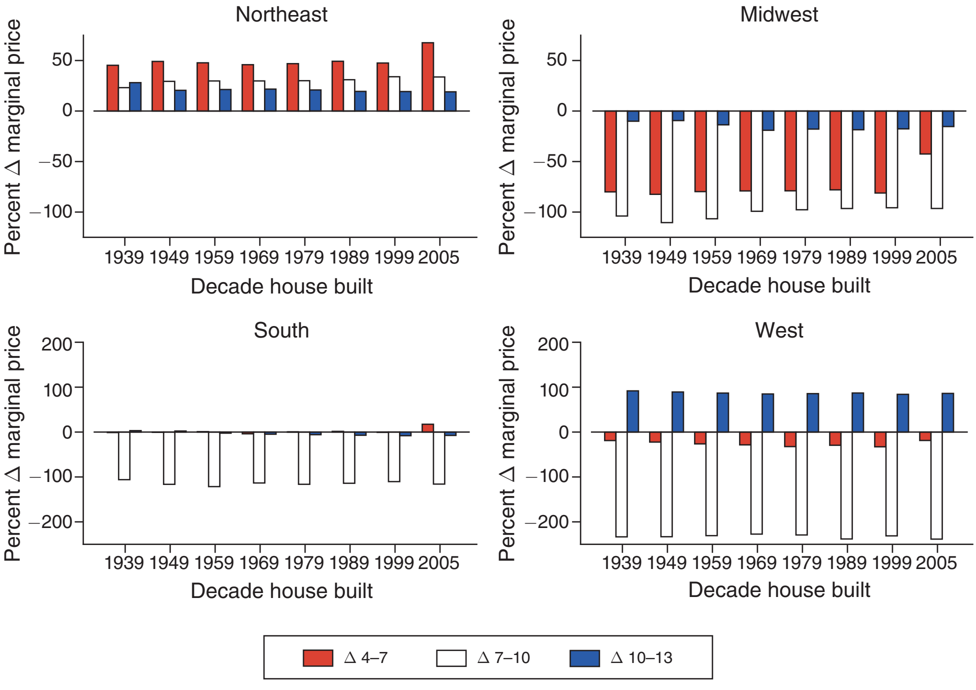

Figure 3. Change in Marginal House Prices By Housing Age

Notes: The figure plots the change in marginal house prices corresponding with the decades of houses' 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 data.

C. *Strength of the Bartik-Like Instrument*

Using the housing characteristic shares from Section IIIA and the housing quality prices from Section IIIB, 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 scatterplot of the residualized instrument against residualized house price growth. This residualization involves projecting out the additional control variables described in Section II, 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.

IV. Main Results, Heterogeneity, and Robustness

A. *Main Results*

We now turn to our estimates of the elasticity of nondurable household consumption expenditures with respect to local house price growth. Our sample covers the

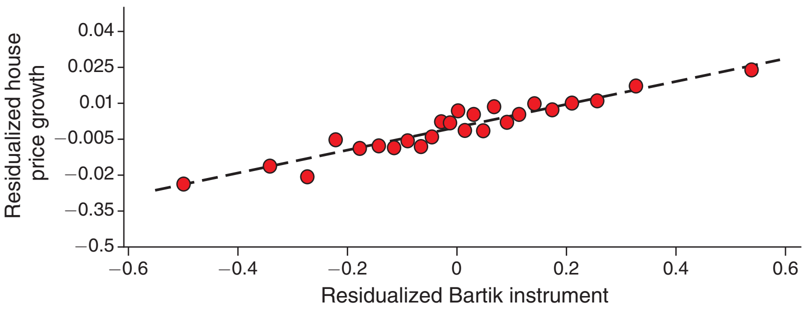

Figure 4. First-Stage Effect of Bartik-Like Instrument on House Price Growth

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. The value of the Bartik-like instrument is split into equally 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: Authors' calculations using Nielsen Consumer Panel and ZTRAX data.

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 IVC.

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 0.119 to 0.032. 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, Kolesár, and Morales (2019). Column 3 includes no controls, while column 4 includes household controls as well as county and year fixed effects. The elasticities are 0.102 and 0.107, respectively, 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 0.104. 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 nontradable and tradable sector employment (Mian and Sufi 2014; Charles, Hurst, and Notowidigdo 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 0.092, but remains statistically indistinguishable from our previous 2SLS estimates.

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

	Real annual nondurable household consumption growth							
$\Delta p_{county,t}$	0.119	0.032	0.102	0.107	0.104	0.092	0.085	0.093
	(0.008)	(0.009)	(0.046)	(0.025)	(0.026)	(0.023)	(0.020)	(0.021)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	289,665	289,665	289,665	289,665	289,665	289,665	289,665	289,665
Households	64,898	64,898	64,898	64,898	64,898	64,898	64,898	64,898
Counties	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002
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 fixed effects	N	Y	N	Y	Y	Y	Y	Y
Year fixed effects	N	Y	N	Y	Y	Y	Y	Y
Standard errors								
County clusters	Y	Y	N	N	N	N	N	N
AKM (2019)	N	N	Y	Y	Y	Y	Y	Y
F-statistic	–	–	50.77	32.69	29.75	30.37	138.98	137.28
Adjusted R^2	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 and include 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 those who are Black, Hispanic, foreign born, have at least some college education, and are homeowners as well as 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, Sorkin, and Swift (2020). Standard errors and *F*-statistics for 2SLS models are estimated following Adão, Kolesár, and Morales (2019), also allowing for correlation in housing characteristics through time.

Sources: BLS, CBP, FHFA, IRS, Nielsen, Zillow, and ZTRAX.

Column 7 of Table 2 includes the demographic controls suggested by Goldsmith-Pinkham, Sorkin, and Swift (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 0.085 and, again, the estimate is not statistically different from our previous estimates. Finally, column 8 includes all of the previously described controls. Our estimate in this case is 0.093 but is again statistically indistinguishable from each of our prior 2SLS estimates.

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

TABLE 3—CONSUMPTION RESPONSE TO HOUSE PRICES USING THE BARTIK AND OTHER INSTRUMENTS

	Real annual nondurable household consumption growth							
$\Delta p_{county,t}$	0.102 (0.014)	0.093 (0.046)	0.223 (0.019)	0.050 (0.111)	0.182 (0.024)	0.113 (0.070)	0.157 (0.012)	0.060 (0.026)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instrument	Bartik	Bartik	Saiz × Δp_r	Saiz × Δp_r	LS × Δp_r	LS × Δp_r	GMNS × Δp_r	GMNS × Δp_r
Observations								
Total	289,665	289,665	198,333	198,333	216,105	216,105	215,072	215,072
Households	64,898	64,898	44,361	44,361	48,505	48,505	48,318	48,318
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 fixed effects	N	Y	N	Y	N	Y	N	Y
Year fixed effects	N	Y	N	Y	N	Y	N	Y
Standard errors								
County clusters	Y	Y	Y	Y	Y	Y	Y	Y
F-statistic	262.38	62.91	229.36	27.94	87.50	18.30	4,260.44	198.45
Adjusted R^2	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 (2010a) housing supply elasticity interacted with the growth in regional house prices. Columns 5 and 6 instrument for house prices using the Lutz and Sand (2019a) 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. (2021a) 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: BLS, CBP, FHFA, IRS, Nielsen, Zillow, and ZTRAX.

Overall, we find that a 10 percent increase in house prices is associated with a 0.9 to 1.1 percent increase in nondurable 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 nondurable consumption to local house prices via instrumental variables methods report values of 0.19 (Gan 2010), 0.21 to 0.26 (Kaplan, Mitman, and Violante 2020), and 0.38 (Campbell and Cocco 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 nondurables of 0.78 to 0.93 cents in the dollar. This is consistent with recent estimates of MPCs for groceries and nondurable

[16] Kaplan, Mitman, and Violante (2020) use the Saiz (2010a) housing supply elasticity instrument and report cross-sectional (i.e., nonpanel 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 and Cocco (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 United Kingdom 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 nondurable goods (FRED code: PCND)

Table 4—Heterogeneity in Consumption Responses to House Prices

	Real annual household nondurable consumption growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta p_{county,t}$	0.102	0.093	0.321	0.252	0.077	0.080	0.073	0.132
	(0.014)	(0.046)	(0.055)	(0.071)	(0.016)	(0.045)	(0.020)	(0.099)
$\Delta p_{county,t} \times \mathbb{1}(40 < Age \leq 60)$			−0.187	−0.123				
			(0.054)	(0.053)				
$\Delta p_{county,t} \times \mathbb{1}(60 < Age)$			−0.284	−0.213				
			(0.056)	(0.054)				
$\Delta p_{county,t} \times \mathbb{1}(LTV > 0.80)$					0.072	0.059		
					(0.029)	(0.029)		
$\Delta p_{county,t} \times \mathbb{1}(2006 - 2009)$							0.051	−0.069
							(0.030)	(0.146)
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations								
Total	289,665	289,665	289,665	289,665	289,665	289,665	289,665	289,665
Households	64,898	64,898	64,898	64,898	64,898	64,898	64,898	64,898
Counties	1,002	1,002	1,002	1,002	1,002	1,002	1,002	1,002
Controls	N	Y	N	Y	N	Y	N	Y
Adjusted R^2	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: BLS, CBP, FHFA, IRS, Nielsen, Zillow, and ZTRAX.

goods but on the lower end of estimates for total consumption. Mian, Rao, and Sufi (2013) report an MPC of 0.4 cents for food and groceries, an MPC of 1.6 cents for all nondurables, and an MPC of 5.4 cents for total consumption. Other authors find MPCs for total consumption of 1 cent (Disney, Gathergood, and Henley 2010), 2 cents (Carroll, Otsuka, and Slacalek 2011), 2.8 cents (Guren et al. 2021a), 3 cents (Paiella and Pistaferri 2017), 4.7 cents (Aladangady 2017), and 6 cents (Angrisani, Hurd, and Rohwedder 2019).

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 dataset. 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 (2010a) housing supply elasticity and regional house

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.

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 (2010a) instrument yields a statistically significant estimate of 0.22, which is twice as large as our estimates using the Bartik-like instrument. However, the inclusion of the auxiliary controls in column 4 leads to a much weaker instrument so that the estimate falls to 0.05 and is insignificantly different from zero. The instrument in columns 5 and 6 is from Lutz and Sand (2019a), 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 (2010a). We also interact this cross-county measure of land availability with regional house price growth. The Lutz and Sand (2019a) instrument yields estimates of 0.18 and 0.11, although the inclusion of controls in column 6 leads to a loss of statistical significance. Nevertheless, these estimates are close to our benchmark estimates of around 0.10.

Finally, columns 7 and 8 of Table 3 use the house price instrument introduced by Guren et al. (2021a). 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. (2021a) 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 0.16 in the absence of controls, which is about 50 percent larger than our own estimates. However, column 8 shows a large drop in the estimated elasticity, to 0.06, when we include our set of control variables.[19] 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.[20]

Our comparison of estimates using the same consumption dataset 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 nondurable 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 sensitive to the inclusion of these controls.

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

[19] Similar to the results presented here, Guren et al. (2021a) estimate an elasticity of 0.055, although they use CBSA-level consumption data over the 2000–2017 sample period.

[20] Interestingly, the *F*-statistic in column 8 remains high, suggesting that the Guren et al. (2021a) instrument is a strong predictor of house prices but that the controls absorb much of the variation that accounts for fluctuations in consumption.

B. *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 and Cocco 2007; Attanasio et al. 2009; Gan 2010), the tightness of household borrowing constraints (Gan 2010; Mian, Rao, and Sufi 2013; Aladangady 2017), and housing booms and busts (Aladangady 2017; Kaplan, Mitman, and Violante 2020; Guren et al. 2021a). Table 4 reports our tests for heterogeneity in consumption elasticities across household age, inferred borrowing constraints, and 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.

Columns 1 and 2 of Table 4 repeat our benchmark estimates of the consumption elasticity. Columns 3 and 4 test 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 0.32, 0.13, and 0.04. This implies that a 10 percent increase in house prices is associated with a 3.2 percent increase in young household consumption expenditures but just a 0.4 percent increase in older household expenditures. These results contrast with those of Campbell and Cocco (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 nondurable 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 expenditures 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 5 and 6 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 2004–2006 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, Schoar, and Severino 2016, 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 are often required by lenders to have additional private mortgage insurance.[21] 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 1.4 percent increase in consumption for households in high-LTV zip codes, but just a 0.8 percent increase in consumption for households in low-LTV zip codes. This result is consistent with Mian, Rao, and Sufi (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 2006–2009 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. (2021a) 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 nonhomeowner 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 the online Appendix documents our results. Column 1 reports our benchmark estimates for homeowners, while column 2 reports estimates among the renter sample. We find a renter consumption elasticity of 0.03, about one-third 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

[21] Other recent studies, such as Aladangady (2017) and Barlett et al. (2022) have also used this cutoff since 0.80 is the LTV threshold at which borrowers are exempt from purchasing mortgage loan insurance.

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 nontradables employment, since these areas may be more sensitive to local economic demand shocks and since renters may be more likely to work in nontradables employment. Again, however, we find no evidence of differential consumption sensitivities across counties with high and low nontradables employment shares.

C. *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 online Appendix 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 of the online Appendix). Our 2SLS estimates instrument for zip code–level house prices uses Zillow data (Zillow 2021), 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, Kolesár, and Morales (2019). Our results are remarkably similar across the zip code and county regression specifications. Table C.10 reports estimated elasticities of between 0.07 and 0.13, in comparison with our benchmark results using county-level data of between 0.085 and 0.107 (see Table 2).

Second, we present the results of three additional variations on the construction of our instrument in Table C.11 of the online Appendix. One concern about instrument validity is that in contrast to house age the numbers of bedrooms or bathrooms are 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 numbers of bedrooms and bathrooms are 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 IIIC). 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.[22] The elasticity reported in column 5 is larger than and statistically significantly different from our benchmark results at 0.16; however, the inclusion of our control variables in column 6 causes the estimate to fall to 0.07, 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.[23] As noted in Goldsmith-Pinkham, Sorkin, and Swift (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 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 of the online Appendix 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 0.06 to 0.17. 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

[22] 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.

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

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.[24]

D. *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, Sorkin, and Swift (2020). Goldsmith-Pinkham, Sorkin, and Swift (2020) show that IV regressions using shift-share instruments can be recast as overidentified 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. Online Appendix D provides a detailed description of the decomposition and Table D.13 provides a summary of the decomposition statistics.

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 United States, and in quality price movements during the housing bust years of 2008–2009 and the housing recovery years of 2013–2014. Figure 5 illustrates these results graphically by plotting the fraction of the total Rotemberg weights associated with different components of the instrument. The lower panel of Figure 5 combines Rotemberg 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 the 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 United States.

The upper panel of Figure 5 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 United States. 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

[24] 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. (2021a).

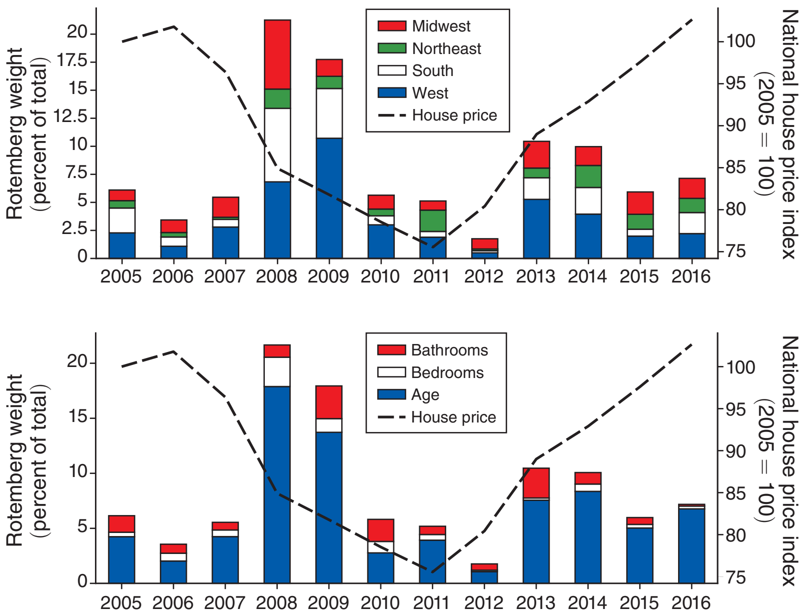

FIGURE 5. ROTEMBERG WEIGHTS FOR COMPONENTS OF THE BARTIK-LIKE INSTRUMENT

Notes: The figure shows sums of the shares of absolute Rotemberg weights. The upper panel reports weights within each housing characteristic group: age, bedrooms, and bathrooms. The lower panel reports weights within each region. The dashed black line is the S&P/Case-Shiller National House Price Index.

Sources: Author's calculations using FRED, Nielsen Consumer Panel, and ZTRAX data.

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.

V. Conclusion

It is widely believed that fluctuations in the price of housing lead 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 nondurable consumption expenditures with respect to house prices in the range of 0.09 to 0.11. This corresponds, approximately, 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 2010a), 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. 2021a). 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.

REFERENCES

Adão, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *Quarterly Journal of Economics* 134 (4): 1949–2010.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2016. "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class." *Review of Financial Studies* 29 (7): 1635–70.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2018. "Dynamics of Housing Debt in the Recent Boom and Great Recession." In *NBER Macroeconomics Annual*, Vol. 32, edited by Martin Eichenbaum and Jonathan A. Parker, 265–311. Chicago, IL: University of Chicago Press.

Aladangady, Aditya. 2017. "Housing Wealth and Consumption: Evidence from Geographically-Linked Microdata." *American Economic Review* 107 (11): 3415–46.

Angrisani, Marco, Michael D. Hurd, and Susann Rohwedder. 2019. "The Effect of Housing Wealth Losses on Spending in the Great Recession." *Economic Inquiry* 57 (2): 972–96.

Attanasio, Orazio P., Laura Blow, Robert Hamilton, and Andrew Leicester. 2009. "Booms and Busts: Consumption, House Prices and Expectations." *Economica* 76 (301): 20–50.

Bachmann, Rüdiger, and Daniel Cooper. 2014. "The Ins and Arounds in the U.S. Housing Market." Federal Reserve Bank of Boston Working Paper 14-3.

Barlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace. 2022. "Consumer-Lending Discrimination in the FinTech Era." *Journal of Financial Economics* 143 (1): 30–56.

Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute.

Bernanke, Ben S. 2018. "The Real Effects of Disrupted Credit: Evidence from the Global Financial Crisis." *Brookings Papers on Economic Activity* 49 (2): 251–322.

Board of Governors of the Federal Reserve System. 2004. "Survey of Consumer Finances [dataset]." Data retrieved from https://www.federalreserve.gov/econres/scf_2004.htm.

Board of Governors of the Federal Reserve System. 2016. "Survey of Consumer Finances [dataset]." Data retrieved from https://www.federalreserve.gov/econres/scf_2016.htm.

Board of Governors of the Federal Reserve System. 2021. "Households; Owner-Occupied Real Estate including Vacant Land and Mobile Homes at Market Value, Market Value Levels [dataset]." Data retrieved from FRED (Federal Reserve Bank of St. Louis): https://fred.stlouisfed.org/series/HOOREVLMHMV.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *Review of Economic Studies* 89 (1): 181–213.

Browning, Martin, Mette Gørtz, and Søren Leth-Petersen. 2013. "Housing Wealth and Consumption: A Micro Panel Study." *Economic Journal* 123 (568): 401–28.

Buiter, Willem H. 2010. "Housing Wealth Isn't Wealth." *Economics* 4 (1): 20100022.

Campbell, John Y., and João F. Cocco. 2007. "How do House Prices Affect Consumption? Evidence from Micro Data." *Journal of Monetary Economics* 54 (3): 591–621.

Carroll, Christopher D. 2001. "A Theory of the Consumption Function, With and Without Liquidity Constraints." *Journal of Economic Perspectives* 15 (3): 23–45.

Carroll, Christopher D., and Miles S. Kimball. 1996. "On the Concavity of the Consumption Function." *Econometrica* 64 (4): 981–92.

Carroll, Christopher D., Misuzu Otsuka, and Jiri Slacalek. 2011. "How Large are Housing and Financial Wealth Effects? A New Approach." *Journal of Money, Credit and Banking* 43 (1): 55–79.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2016. "The Masking of the Decline in Manufacturing Employment by the Housing Bubble." *Journal of Economic Perspectives* 30 (2): 179–200.

Christelis, Dimitris, Dimitris Georgarakos, and Tullio Jappelli. 2015. "Wealth Shocks, Unemployment Shocks and Consumption in the Wake of the Great Recession." *Journal of Monetary Economics* 72: 21–41.

Cloyne, James, Kilian Huber, Ethan Ilzetzki, and Henrik Kleven. 2019. "The Effect of House Prices on Household Borrowing: A New Approach." *American Economic Review* 109 (6): 2104–36.

Davidoff, Thomas. 2016. "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated with Many Demand Factors." *Critical Finance Review* 5 (2): 177–206.

Disney, Richard, John Gathergood, and Andrew Henley. 2010. "House Price Shocks, Negative Equity, and Household Consumption in the United Kingdom." *Journal of the European Economic Association* 8 (6): 1179–1207.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2021. "Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]." Data retrieved from IPUMS: https://doi.org/10.18128/D030.V9.0.

Friedman, Milton. 1957. *Theory of the Consumption Function*. Princeton, NJ: Princeton University Press.

Gan, Jie. 2010. "Housing Wealth and Consumption Growth: Evidence from a Large Panel of Households." *Review of Financial Studies* 23 (6): 2229–67.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110 (8): 2586–2624.

Graham, James, and Christos A. Makridis. 2023. "Replication Data for: House Prices and Consumption: A New Instrumental Variables Approach." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E154221V1.

Guren, Adam M., Alisdair McKay, Emi Nakamura, and Jón Steinsson. 2021a. "Housing Wealth Effects: The Long View." *Review of Economic Studies* 88 (2): 669–707.

Guren, Adam M., Alisdair McKay, Emi Nakamura, and Jon Steinsson. 2021b. "Housing Wealth Effects: The Long View; Local Sensitivity Instruments [dataset], 2020-01-31." Data retrieved from https://people.bu.edu/guren/gmns_gammas.zip (archived at http://web.archive.org/).

Gyourko, Joseph, Jonathan S. Hartley, and Jacob Krimmel. 2021. "The Local Residential Land Use Regulatory Environment Across U.S. Housing Markets: Evidence from a New Wharton Index." *Journal of Urban Economics* 124: 103337.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai. 2013. "Superstar Cities." *American Economic Journal: Economic Policy* 5 (4): 167–99.

Gyourko, Joseph, Albert Saiz, and Anita Summers. 2008. "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index." *Urban Studies* 45 (3): 693–729.

Ihrke, David. 2014. "Reason for Moving: 2012 to 2013." United States Census Bureau Report P20-574.

Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante. 2020. "Non-Durable Consumption and Housing Net Worth in the Great Recession: Evidence from Easily Accessible Data." *Journal of Public Economics* 189: 104176.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2): 211–48.

Lutz, Chandler, and Ben Sand. 2019a. "Highly Disaggregated Land Unavailability." Unpublished.

Lutz, Chandler, and Ben Sand. 2019b. "Highly Disaggregated Land Unavailability: Housing Unavailability Instruments [dataset], 2020-01-31." Data retrieved from https://github.com/ChandlerLutz/LandUnavailabilityData.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump." *Quarterly Journal of Economics* 128 (4): 1687–1726.

Mian, Atif, and Amir Sufi. 2011. "House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis." *American Economic Review* 101 (5): 2132–56.

Mian, Atif, and Amir Sufi. 2014. "What Explains the 2007–2009 Drop in Employment?" *Econometrica* 82 (6): 2197–2223.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2011. "Internal Migration in the United States." *Journal of Economic Perspectives* 25 (3): 173–96.

NielsenIQ. 2016. "Consumer Panel Dataset Manual." Chicago, IL: University of Chicago at Booth Kilts Center for Marketing.

NielsenIQ. 2021. "Nielsen Consumer Panel Dataset [dataset]." Data retrieved from Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business.

Paiella, Monica, and Luigi Pistaferri. 2017. "Decomposing the Wealth Effect on Consumption." *Review of Economics and Statistics* 99 (4): 710–21.

Palmer, Christopher. 2015. "Why Did So Many Subprime Borrowers Default during the Crisis: Loose Credit or Plummeting Prices?" Unpublished.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel. 2020. "Segmented Housing Search." *American Economic Review* 110 (3): 720–59.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy* 82 (1): 34–55.

Rotemberg, Julio J. 1983. "Instrument Variable Estimation of Misspecified Models." Sloan School of Management Working Paper 1508-83.

Saiz, Albert. 2010a. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics* 125 (3): 1253–96.

Saiz, Albert. 2010b. "The Geographic Determinants of Housing Supply: Housing Supply Elasticities [dataset], 2020-01-31." Data retrieved from http://real.wharton.upenn.edu/~saiz/SUPPLYDATA.zip. Archived at http://web.archive.org/.

Stroebel, Johannes, and Joseph Vavra. 2019. "House Prices, Local Demand, and Retail Prices." *Journal of Political Economy* 127 (3): 1391–1436.

U.S. Bureau of Economic Analysis. 2021. "Personal Consumption Expenditures: Nondurable Goods [dataset]." Data retrieved from FRED (Federal Reserve Bank of St. Louis): https://fred.stlouisfed.org/series/PCND.

U.S. Bureau of Labor Statistics. 2019. "2000–2019 Bureau of Labor Statistics Local Area Unemployment Statistics [dataset]." Data retrieved from https://download.bls.gov/pub/time.series/la/.

U.S. Bureau of Labor Statistics. 2021. "Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [dataset]." Data retrieved from FRED (Federal Reserve Bank of St. Louis): https://fred.stlouisfed.org/series/CPIAUCSL.

U.S. Census Bureau. 2001. "2000 Decennial Census [dataset]." Data retrieved from https://data.census.gov/.

U.S. Census Bureau. 2017. "County Business Patterns [dataset]." Data retrieved from https://www2.census.gov/programs-surveys/cbp/datasets/.

U.S. Census Bureau. 2018. "Population Estimates FIPS Codes [dataset]." Data retrieved from https://www.census.gov/geographies/reference-files/2018/demo/popest/2018-fips.html.

U.S. Census Bureau. 2019. "2014–2018 American Community Survey 5-Year Public Use Microdata Samples [dataset]." Data retrieved from https://data.census.gov/.

U.S. Department of Housing and Urban Development. 2010. "USPS ZIP Code Crosswalk Files [dataset]." Data retrieved from https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

U.S. Federal Housing Finance Agency. 2021. "Annual House Price Indexes [dataset]." Data retrieved from https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx.

U.S. Internal Revenue Service. 2017a. "Statistics of Income: County Data [dataset]." Data retrieved from https://www.irs.gov/statistics/soi-tax-stats-county-data.

U.S. Internal Revenue Service. 2017b. "Statistics of Income: ZIP Code Data [dataset]." Data retrieved from https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.

Zillow. 2020. "Zillow Transaction and Assessment Dataset [dataset]."

Zillow. 2021. "Zillow Home Value Index [dataset]." Data retrieved from https://www.zillow.com/research/data/.