How Important Was Household Leverage in the Great Recession? Time Series versus Cross-Sectional Evidence

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Abstract

A dozen years later, economists have yet to reach a consensus on the role of household leverage in the Great Recession. A highly influential strand of literature uses cross-sectional data to suggest that the household balance sheet effects transformed a mild contraction into the Great Recession. Researchers have exploited variation in debt levels across households and regions to estimate how leverage affected consumer spending. Similarly, many studies suggested that the "forced" deleveraging after the 2008 crisis contributed to the economic slowdown. At the same time, using aggregate time series, researchers have found much weaker evidence. Bernanke (2018), for example, argues that the timing of the collapse is inconsistent with a central role for household balance sheets, and concludes that "the unusual severity of the Great Recession was due primarily to the panic in funding and securitization markets, which disrupted the supply of credit." This paper reviews the evidence and updates the cross-sectional and time series evidence for the period between the financial crisis and the most recent available data. In addition, the paper will discuss ongoing concerns and suggest potential policy responses going forward, especially in light of the recent changes in regulation and the Long-Term Monetary Policy Framework that suggests longer episodes of low interest rate periods.

1. Introduction

In the last two decades, the U.S. housing market has gone through an extended boom, bust, and recovery cycle. A number of papers have documented that the boom period was accompanied by a strong increase in debt-to-income (DTI) levels for mortgage borrowers across the income distribution, especially among middle-class borrowers, see Adelino, Schoar, and Severino (2016, 2018) and Foote, Loewenstein, and Willen (2021). At the same time the distribution of loan-to-value (LTV) levels did not change significantly, though of course the increase in overall house prices in the run up to the 2008 crisis meant households took on increasing levels of mortgage debt, see Adelino, McCartney, and Schoar (2020). An emerging consensus of the 2008 crisis is that rising house prices and optimistic expectations in the boom period played a key role in the rise of household debt levels and the ensuing defaults afterwards. Inflated house price expectation seems to have led households to take on larger loans relative to their income with the expectation of continued house price appreciations, while banks lent against increasing collateral values and seem to have underestimated the default risks.

In this paper, we study household leverage before and after the 2008 crisis. While the leverage buildup before the Great Recession has been extensively documented, the recovery phase has received less attention. We examine the time series and cross-sectional heterogeneity in household leverage and housing mortgages in the decade after the crisis in comparison to the 2008 housing cycle. Our main data sources are the 2005-2019 American Community Survey Public Use Microdata Sample (ACS PUMS) and the 2004-2020 Home Mortgage Disclosure Act (HMDA) mortgage datasets. The ACS data enable us to analyze the household-level homeownership and homeowner costs together with household characteristics. HMDA provides comprehensive loan-level data that cover the majority of originated home purchase mortgages in the U.S. market. House price indexes come from the FHFA House Price Index (HPI) and the Zillow Home Value Index (ZHVI). Throughout this paper, we focus on metropolitan statistical areas (MSAs) as the basic geographical unit in our analysis, which include cities and their adjacent functional communities.

We observe several distinct features of household leverage across these cycles in the mortgage market. First, overall homeownership rates were stable before 2008 but decreased quickly after the

financial crisis. While homeownership started increasing again in the decade after the crisis, as of 2020 overall rates are still below pre-crisis levels for many groups of households. There are also large and persistent differences in homeownership rates across income groups. In particular, homeownership rates among low-income households, the lowest tercile of the income distribution, started decreasing even before the 2008 crisis, and this divergence from the higher income groups further accelerated after 2008. However, interestingly, we find that low-income households have an earlier recovery in homeownership rates than higher income households (although, of course, the former group start from a much lower level). The decline in ownership for the lowest income groups see a steady increase in homeownership rates, but these are still well below pre-crisis levels as of 2020.

Second, while debt-to-income (DTI, measured as the size of mortgages as a proportion of borrower income) dropped off sharply in the aftermath of the 2008 crisis, over the decade following the crisis DTI ratios have risen steadily. As of 2020 these are at a level above pre-crisis times. The larger mortgage sizes as a proportion of income are, in part, explained by the persistence of very low interest rates over the decade after the financial crisis. In fact, the cost of owning a home as a fraction of income dropped significantly for all income groups after 2008 as house prices went down sharply. From the peak of the boom to the trough, we see that households who recently bought a house report spending about 34 percent of the income on housing before the crisis, but this ratio drops to 26 by 2012 and stays around that level until 2020. Here, again, we see significant differences across households. Conditional on owning a home, low-income households have much higher costs of owning a home as a percentage of household income than other income groups. The lowest income tercile spent up to 60 percent of income on housing pre-2008 in the highest house price areas, but they also saw a sharp drop in homeownership cost after the crisis.

Third, in contrast to the average drop in the cost of purchasing a house as a fraction of income, the ratio of rent to income did not change significantly during and after the financial crisis. In fact, especially in the 50 percent of MSAs with expensive housing (high median house prices), rental costs as a fraction of income never went down. This is quite surprising; it might reflect the fact that house prices prior to the 2008 crisis were divorced from rental yield but did not affect rental

prices too much. But it is also possible that the disruptions in the housing markets that tied up a significant fraction of homes in foreclosures, could have put pressure on the rental market (Gete and Reher, 2018).

Finally, we analyze how regional differences in the recovery affected different income groups. We first show that the post-crisis recovery of house prices varied widely across areas. While, on average, there was sizable growth in house prices from 2010 to 2019, many MSAs did not return to their pre-crisis HP levels or growth rates. There are many areas that had fast house price appreciation before the crisis but did not recover from the slump. In contrast, others had moderate growth before the crisis, but accelerated after 2010. These differences might reflect changing fundamentals either in the amenities or job opportunities of cities. Prominent example of places that were growing only moderately before 2008, but significantly accelerated after 2008 are Austin, Texas or Nashville, Tennessee. To capture these differences, we sort MSAs into quartiles based on their house price growth rates in the 2000-2006 boom period and the 2012-2019 recovery period. We form four groups depending on the house price growth in both the pre and post crisis period, (2) late boom, i.e. areas that had only above median HP growth after 2012 but not before, (3) early boom, and (4) never boom.

Surprisingly, we find very different home purchase patterns across these four quartiles. When we look at "always boom" areas and measure the change in the likelihood that a household in one of the three income terciles buys in such an MSA, we see that there was overall a strong drop in purchase activity between 2008 and 2012 but then a quick recovery after 2012. These patterns were parallel across the three different income groups. Similarly, for "never boom" areas, while we do not see a drop-off in house purchase transactions post-2008, we again see quite similar behavior across income groups over time. However, there is a marked difference in home purchase behavior for low versus high income groups in areas that are either "late boom" or "early boom" places. Low-income households seem to accelerate their purchase behavior after the crisis primarily in "early boom" areas, those that had high house price growth in the period before 2008 but not after 2012. In contrast, they significantly reduce purchases in areas that had more recent high house price appreciation. And high-income households show exactly the opposite location

choices. These findings suggest that high- and low-income groups sort into different geographic areas during the recovery. Low-income households might reduce their purchases in recently booming cities, likely because they become unaffordable to them. But it is also possible that the changing composition of amenities or labor market opportunities is less favorable for low-income groups. More research is needed to understand the reasons for this differential sorting by income groups.

In sum, our results suggest that there has been significant heterogeneity in how the recovery has affected households across income levels and geographic locations. Housing affordability has improved for all households, especially for lower income households after the crisis and has stayed lower relative to 2008. But affordability in the rental market did not see the same relief.

2. Literature Review

The financial crisis and its aftermath spurred several strands of literature, starting with a focus on the role of securitization and the expansion of the supply of credit. Keys et al (2010) and Keys, Seru, and Vig (2012) argue that securitization led to lower screening standards in the context of subprime mortgage loans. The authors use a specific rule-of-thumb in the lending market that induces a higher number of securitized loans and find that greater ease of securitization leads to higher defaults. This is consistent with the underwriting characteristics of loans backing mortgage-backed securities declining steadily between 2001 and 2007 (Demyanyk and Van Hemert, 2011). Bubb and Kaufman (2014) question the role of securitization played in reducing screening and argue instead that the cutoff rules can be traced back to underwriting guidelines for originators.

Bernanke (2007) discusses how the global "savings glut", i.e. higher desired saving and investment in emerging markets, may have let to lower long-term real interest rates and, consequently, investment behavior in the US and the housing cycle. A number of papers have argued that changes in the supply of credit, as well as changes in origination practices, led to the increase in mortgage credit that preceded the financial crisis. Using different definitions of subprime, Mayer and Pence (2008) pointed out the high levels of subprime foreclosures took place during the bust. Mian and Sufi (2009) argue that credit expansion, particularly in subprime zip codes, lies at the heart of the default crisis of 2007-2008. They find a negative correlation between income and mortgage credit growth, which rules out fundamentals as the main driver of the increase in credit. Dell'Ariccia, Igan, and Laeven (2012) similarly find a connection between credit booms and the reduction in credit standards, and Griffin, Kruger, and Maturana (2021) find that credit supply variables have strong predictive power for the magnitude of the housing boom.

Agarwal et al (2014) argue that predatory lending helped to trigger the 2008-2010 mortgage crisis by contributing to high default rates. These authors analyze the effects of an anti-predatory program in Chicago that reduced the number of active lenders and the average default rate on mortgages through a decline in subprime borrowers. Corbae and Quintin (2015) provide a heterogeneous household model where high leverage (in the form of high LTV) loans can explain a large increase in foreclosure rates.

Establishing the causal relation between the increase in mortgage lending, house prices, and the foreclosure crisis remains a challenge. Coleman, LaCour-Little, and Vandell (2008) argue that the growth in subprime market was a product rather than the cause of the housing boom. Similarly, a long literature has pointed to the role of house price expectation, rather than innovations in origination practices and securitization, as the more important driver of the boom. Burnside, Eichenbaum, and Rebelo (2016) feature a model of housing booms and busts in which agents have heterogeneous expectations about long-run fundamentals and can change their views because of social dynamics. They show that the "shape" of the boom-bust cycle depends on which types of agents happen to be correct about fundamentals. Glaeser, Gottlieb, and Gyourko (2013) show that different measures of credit market conditions do affect house prices causally, but that they can only account for a small fraction of the boom. Adelino, Schoar, and Severino (2012) measure a housing price elasticity to mortgage rates ranging from 1.2 to 9.1, insufficient to account for a significant fraction of the housing boom.

A substantial literature argues that the 2007-2010 mortgage crisis was not primarily a subprime crisis and was, to a large extent, a middle-class phenomenon. Mortgage originations during the pre-crisis period increased for borrowers across the whole income distribution and, in the crisis, middle-income and high-income (and prime) borrowers dramatically increase as a fraction of

delinquencies, see for example, Ferreira and Gyourko (2015), Adelino, Schoar, and Severino (2016, 2018), and Albanesi, De Giorgi, and Nosal (2017). These papers also show that the connection between income growth and mortgage growth is stronger than previous literature had suggested (in line with Ferreira and Gyourko, 2015). Foote, Loewenstein, and Willen (2021) show that the increase in loan originations is offset by a relative increase in loan terminations in low-income areas.

Another strand of the literature has emphasized the role of investors in driving up prices and defaults. Bhutta (2015) underscores the role of real estate investors in the housing boom by showing that inflows from real estate investors grew more sharply than first-time homebuyers. After the crisis, first-time borrowing contracted much more sharply among low credit score individuals compared to high credit score, suggesting that tightened credit standards played an important role in limiting debt growth in recent years. Chinco and Mayer (2016) show that the demand from out-of-town second-house buyers predicts house price appreciation and that out-of-town second-house buyers behaved like misinformed speculators, earning lower capital gains.

Finally, there has been substantial work done on the drivers of defaults during the crisis. Palmer (2015) investigates the relative importance of house price declines and compositional changes in borrowers and mortgages as the underlying cause of the subprime default crisis, and shows that impact of property values explains at least 60% of the rapid rise in default rates across subprime borrower cohorts. Foote and Willen (2018) take stock of the existing evidence on mortgage default and argue that, while negative equity is a necessary condition for the magnitude of the foreclosure crisis, the existing evidence is more consistent with the double trigger theory of defaults (Foote, Gerardi, and Willen 2008; Fuster and Willen 2017; Gerardi et al 2018; Ganong and Noel, 2020). Guiso, Sapienza, and Zingales (2013) directly use survey data to show that, while the willingness to default increases in size of the home-equity shortfall, the vast majority of households considers it morally wrong to strategically default, i.e. to default only based on negative equity.

The increase in house prices led to higher household leverage through the home equity-based borrowing channel and the increase in leverage is linked to increased consumption, particularly for home improvements (Mian and Sufi, 2011). Similarly, the drop in house prices led to a slowdown in consumption and increase in unemployment (Mian and Sufi, 2014). Campbell and Cocco (2007) use UK micro level data to estimate the response of household consumption to house prices, considering different age groups, regional heterogeneity, and the response to predictable and unpredictable changes in house prices. Berger et al (2018) use a workhorse model of consumption with incomplete markets that produces large aggregate consumption responses to house price changes.

Few studies have considered the long-term consequences of the financial crisis, with a notable exception of Piskorski and Seru (2021), who document new facts about the long-term consequences of the Great Recession. They argue that regional variation in the extent and speed of recovery is strongly and persistently associated with frictions affecting the pass-through of lower interest rates and debt relief to households. They exploit heterogeneous regional differences in mortgage contract rigidity, refinancing constraints, and the organizational capacity of intermediaries to conduct loan renegotiations as potential factors driving the transmission of monetary policy to different geographic areas.

3. Data and Summary Statistics 3.1 Data

The household-level analysis in this paper relies on the American Community Survey (ACS public use microdata samples, or PUMS), an annual survey of U.S. households conducted by the Census. ACS allows us to jointly analyze a household's homeownership and housing costs, along with its location and moving status. Specifically, we use ACS 5-year PUMS samples from 2009, 2014, and 2019. Altogether they cover a 15-year sample period. By linking person records to household records, we rule out any vacant housing units and only focus on the occupied ones in ACS PUMS. We match ACS Public Use Microdata Areas (PUMAs) to Metropolitan Statistical Areas (MSAs) using IPUMS crosswalk files weighted by 2010 population¹. This is a many-to-many match, and we rely on 2010 population weights to assign each PUMA to at most three MSAs. This leaves us with about 91.60% of the ACS observations in the 15-year sample period. This percentage varies

¹ IPUMS crosswalk files are available at <u>usa.ipums.org/usa-action/variables/met2013#description_section</u>. We use both the "Crosswalk Between 2013 MSAs and 2000 PUMAs with 2010 Populations" and the "Crosswalk Between 2013 MSAs and 2010 PUMAs."

slightly across different years and is weighted by ACS household weights. After the PUMA-MSA match, at least 98.15% of each MSA's population in each year can be covered by the PUMA-MSA joint areas in our sample. In this paper, analysis on ACS data is always weighted by the household-level weights provided in ACS PUMS, and adjusted for population shares in the PUMA-MSA joint area as a fraction of the PUMA population.

The main ACS variables that we use in our analysis include: selected monthly owner costs as a percentage of household income during the past 12 months (OCPIP); gross rent as a percentage of household income during the past 12 months (GRPIP); housing tenure (TEN); and when moved into this house or apartment (MV). The housing unit weight (WGTP) and 80 housing record-replicate weights (WGTP1-WGTP80) are the weight variables we use. Public use microdata area (PUMA) codes are what we relied on to identify geographical areas. In order to adjust household incomes to 2020 dollars, we use the income adjustment factors (ADJINC) from ACS together with the all-item Consumer Price Index (CPI)². Our study on ACS spans from 2005 to 2019, because pre-2005 ACS PUMS do not identify PUMAs or any other geographic units more granular than states.

Analysis in this paper also uses data from the Home Mortgage Disclosure Act (HMDA) mortgage dataset between 2004 and 2020. The HMDA data contain all mortgage applications made to the vast majority of U.S. financial institutions.³ The variables of interest for our purposes are the loan amount, the applicant's gross annual income, the purpose of the loan (purchase, refinance, or remodel), the lien status, the occupancy type (owner occupied or not), the property type, the action type (granted or denied), the location of the property (state and county), and the year of origination. We match each county in HMDA data to an MSA, our main unit for the statistical analysis, using the county assignment from Census Bureau's Core Based Statistical Areas (CBSAs) delineation file⁴. All of the 381 MSAs can be found in the HMDA records, which account for approximately

² The yearly average data for All-item Consumer Price Index retroactive series using current methods (R-CPI-U-RS) are available at <u>www.bls.gov/cpi/research-series/r-cpi-u-rs-home.htm</u>.

³ Covered financial institutions include banks, savings associations, or credit unions subject to Regulation C 12 CFR 1003.2(g). This includes an asset size threshold, location and loan activity test, among others. See Summary of Requirements at www.fficc.gov/hmda/pdf/2020Guide.pdf.

⁴ Delineation files are available at <u>www.census.gov/programs-surveys/metro-micro/about/delineation-files.html</u>. We use the MSA delineation announced by the U.S. Office of Management and Budget (OMB) in February 2013, which is based on the 2010 standards and 2010 Census data.

91% (with minor differences across the years) of all home purchase loans in the HMDA data. We restrict our attention to originated first-lien home purchase mortgages for 1-4 family owner-occupied homes, and to observations with the loan amount and borrower's income both between 1 thousand and 5 million dollars.

House price changes are measured based on the FHFA House Price Index (HPI)⁵, a weighted, repeat-sales index that measures the movement of U.S. single-family house prices. We take annual average on the traditional, all-transactions, quarterly and not seasonally adjusted HPI at the MSA/MD level. To convert the 2020-version MSA/MD codes in FHFA data to the 2013-version MSA codes, we use county-level delineations released by the Census Bureau for both versions.⁶ House price levels are obtained from Zillow.⁷ The MSA-level house prices are estimated using the Zillow Home Value Index (ZHVI), a smoothed, seasonally adjusted measure of the typical value for all homes (single family residence, condo/co-op) in the mid-tier (35th to 65th percentile) range. We match the Metro Region IDs in the Zillow data to MSA codes with the Zillow/Commerce Data Service crosswalk⁸. We unify geographical units in all data samples we use into the 2013-version MSA codes, so that the boundaries of MSAs do not change throughout our analysis for different years.

3.2 Summary Statistics

Table 1 presents the summary statistics for our ACS sample, HMDA sample, and MSA-level housing prices. We report mean, standard deviation, 25th percentile, median, 75th percentile, and the total number of non-missing observations for each variable. All the ACS statistics we report in Table 1 Panel A are weighted by the product of the ACS household file weights and the percentage of PUMA population in the PUMA-MSA joint area. The ACS data sample represents 16,848,116 households in total for the 15-year (2005-2019) period. About 63.55% of households own their homes. Mover is defined as an indicator variable for households who moved into the current house or apartment within the last 12 months, regardless of whether they own it or not. Approximately

⁵ FHFA HPI is available at <u>www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx</u>.

 ⁶ The 2020 delineation is available at <u>www.census.gov/programs-surveys/metro-micro/about/delineation-files.html</u>.
⁷ Zillow house prices are available at <u>www.zillow.com/research/data/</u>.

⁸ Crosswalk file available for download at <u>files.zillowstatic.com/research/public/CountyCrossWalk_Zillow.csv</u>.

15.40% of the households are movers. The average household income in our sample is 89,102 dollars, while the median is \$64,066. These are not nationwide values because our ACS sample only consist of households who live in PUMAs that can be matched to at least one 2013-version MSA. Non-metropolitan households are excluded in all of our analysis.

In Panel B, we report summary statistics for our HMDA sample. There are over 49 million loan records after we impose the restrictions as described in the former section. The mean and median loan amount are around 286 and 232 thousand dollars respectively. The average borrower's gross annual income is about two-fifth of the average loan size. Both the mean and median borrowers' incomes are more than 20 thousand dollars higher than those statistics of household income in the ACS, implying a large disparity of income distribution between the households and the home buyers at metropolitan areas.

Panel C shows the summary statistics for the house price data. House price levels at 2015 for each MSA are obtained from the Zillow Home Value Index. In 2015, the average house price in all MSAs was 183199 dollars, and the median price was 157281 dollars. House price growth rates are calculated from the FHFA House Price Index. We present statistics for three periods of house price fluctuations corresponding to the boom, bust, and recovery. Between 2000 and 2006, house prices in MSAs surged by 56.13 percent on average. Even the median growth rate was as high as 40.25 percent for this boom stage. The second period 2006-2010 covers the crisis time. From 2006 to 2010, the median MSA fell by 3.03 percent in house price, and the average drop, 8.13 percent, was even larger than the median. The house price growth from 2010 to 2019 confirms a recovery of 23.91 percent for the median MSA, and a nearly 30 percent average price growth across all MSAs. The 75-percentile growth rate in the 2010-2019 recovery, 40.95 percent, came very close to the median growth rate during the 2000-2006 boom.

4. Homeownership across geographies and incomes

Even though summary statistics imply a sizable growth for house prices in 2010-2019, the recovery of house price was not uniform across U.S. metropolitan statistical areas (MSAs). By grouping MSAs into quartiles based on their house price growth in 2000-2006 and in 2012-2019, we show

a 4-by-4 quartile transition matrix in Table 2. The table shows the share of MSAs (across rows, i.e. the house price growth between 2000 and 2006) that end up in each quartile for each of the two periods. MSAs that experienced the same quartile of growth in the two periods are reflected in the entries on the principal diagonal. Each quartile contains 95 or 96 MSAs, so, for example, the top-left 20.8 percent in the matrix refers to 20 MSAs in the lowest quartile of house price growth in both periods.

We consider broadly four groups of MSAs: "Late boom" MSAs are those with below-median price growth between 2000 and 2006, followed by above-median growth in the recovery (2012-2019). "Early boom" areas are those with high house price growth in 2000-2006, but low growth post 2012. "Always boom" areas experienced high house price growth in both periods, and "Never boom" MSAs had low house price growth in both periods.

Table A4 lists the 12 largest MSAs for each of the four MSA groups. As an example of the kinds of areas included in each group, Los Angeles and Washington, DC are both in the "Always boom" category, Dallas and Houston, TX and Atlanta, GA are "Late boom" areas, whereas Cleveland, OH and Rochester, NY belong to the "Never boom" group. There is a significant number of MSAs falling in the off-diagonal categories, i.e. with different experiences during the boom and the recovery. The exception is the very highest quartile, where 62.1 percent of MSAs (59 MSAs) who were in the top in 2000-2006 are still in the highest quartile of growth in 2012-2019.

4.1. Homeownership across income groups

Given the imbalanced recovery across geographies, it is natural to ask whether home purchase and homeownership rates across income levels have deviated from the patterns as those documented in the 2000-2008 cycle literature, see for example Adelino, Schoar, and Severino (2016, 2018) and Foote, Loewenstein, and Willen (2021). We start with the volumes of home mortgage originations in the HMDA data. Figure 1 shows the total number of originated home purchase mortgages by income levels of the borrower, and is divided into two panels by MSAs with house price levels below or above the median of all MSAs in 2015. Large literature has pointed out the importance of location for the quality of amenities and upward mobility (for example, Kling, Liebman, and

Katz 2007; Chetty et al, 2018). To distinguish between expensive and cheaper cities, we use the difference in median house prices as of 2015. The income groups are defined by the nationwide tercile cut-offs obtained from ACS data for each year and shown in Table A1. We define income cutoffs on the whole population rather than directly on HMDA because the income distribution of HMDA home buyers is substantially skewed to higher incomes if compared to that of all U.S. households.

Figure 1 suggests that the aggregate volume of transactions across all time periods is much larger in expensive cities (i.e., the right panel) than in cheap cities (i.e., the left panel), but the difference is particularly driven by the high-income and middle-income groups. Both income groups saw a plunge of volume around 2007, followed by an extended upswing after 2011. The U-shape of crash and recovery looks more dramatic in expensive cities due to the larger scale of volumes. Figure 1 also shows that home mortgage volumes have recently risen above the pre-crisis peak volume for the middle-income group in both cheap and expensive cities, but the volume for the high-income group has not yet reached its pre-crisis level. Despite having a lower magnitude of volumes than the other two income groups, the lowest tercile in the population has had an evident rise in mortgage origination volumes post-2015.

HMDA provides information on the flow of new mortgages for home purchases, but not on the stock of people owning their home. We turn to the American Community Survey (ACS) for homeownership rates. We again classify income groups using the nationwide cut-offs for income terciles (see Table A1) derived from the whole ACS universe of U.S. households for each year. Table A3 shows the yearly average homeownership rates for the low-, the middle-, and the high-income households in our ACS sample from 2005 to 2019. The sample consists of ACS households who live in metropolitan areas (i.e., who live in PUMAs that can be matched to at least one 2013-version MSA).

Figure 2 shows the change in homeownership rates relative to the base year 2005. In Figure 2, the three income groups shared almost the same downward trajectory in the change of homeownership rates from 2005 to 2011. Average homeownership of all income groups was about 3.0-3.5 percent lower in 2011 than it was in 2005. However, homeownership rate for the low-income group became stable from 2012 to 2015 and rose after 2015, while the homeownership rates for the high-

and middle-income groups continued to decline until 2016. Surprisingly, the low-income group's homeownership rate had a 2 percent increase post-2015. This is larger than the 0.5 percent and 1.2 percent increase for the high- and the middle-income groups respectively, despite the fact that the low-income group's homeownership rate itself is far lower than the other two (see Table A3). Thus, the low-income group have a higher fraction of new homeownership recovery across incomes can be viewed as the net effect of mortgage flows documented in HMDA and shown in Figure 1, once we account for moves from one owner-occupied home to another. We find similar patterns of homeownership recovery by income with the Census CPS/HVS data in Figure A1.

When we split the sample by cheap and expensive MSAs in Figure 3, we find that the low-income group's faster recovery of homeownership is driven by them buying in areas with higher 2015 house price levels. This might suggest that the low-income households have been able to afford houses at these places because of lower interest rates or lower prices. We return to the issue of affordability when we discuss owner costs below. The middle-income group show similar homeownership changes in cheap and expensive MSAs, consistent with the similar degree of recoveries in both the cheap and expensive MSAs for the middle-income group's mortgage volumes in Figure 1. For the high-income households, Figure 3 demonstrates that their homeownership decline is larger in magnitude in expensive MSAs.

4.2 Distribution of movers across locations

To integrate the cross-sectional variations of price recovery into our analysis of homeownership, we return to the four groups of MSAs by their house price growth discussed at the beginning of Section 2.1. We ask how the distribution of movers varies over time across these four groups of MSAs.

The sample includes ACS households who are homeowners and have moved within the last year (i.e., recent movers). For each income group, we compute the share of owners buying in each of the four groups of MSAs (such that this number adds up to 100% across the four panels in each year). Figure 4 plots the evolution of the changes in this share relative to the base year of 2005. Panel A ("Always boom") shows that around 5.9 percent fewer low-income owner-movers in 2008

moved in these MSAs relative to 2005. Specifically, in untabulated results, we find that 36.8 percent of low-income owner-movers bought in "Always boom" MSAs in 2005, then in 2008 that number went down to 30.9 percent, which results in the 5.9 percent drop for the low-income group in panel A for this set of MSAs.

Figure 4 shows that all income levels were more likely to buy in the "Always boom" MSAs right after the crisis, however the uptick was more pronounced for the low-income group. After 2012, low- and middle-income households were more likely to purchase in "Early boom" places, while a higher share of the high-income households were buying in "Late boom" areas. In Figure A2, we also show the change of the proportions for homeowners who moved recently living in MSAs that had above-median house prices in 2015. There was an extended increase in the percentage of low-income owners buying in expensive MSAs during 2008-2017.

5. Cost of Ownership

Homeownership recovery trends appear to suggest an improvement in housing affordability for low-income households, presumably due to lower homeownership costs relative to the period before the crisis. ACS provides data on a selected monthly owner cost,⁹ which measures how the cost of owning a home translates into monthly payments. In Figure 5, we show the average owner cost as a fraction of household income by income levels and in two separate panels – MSAs with above and below median house prices (i.e., relatively cheap and expensive MSAs. To focus on the owner cost faced by someone deciding to purchase in each year, we include only the homeowners who are recent movers.

We find substantially higher owner cost in expensive cities than in cheap cities for every income group, although that difference has narrowed after the crisis. In expensive MSAs, the cost of

⁹ The definition of the selected monthly owner cost can be found in the ACS Subject Definitions document at <u>https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2020_ACSSubjectDefinitions.pdf</u>.

[&]quot;Selected monthly owner costs are the sum of payments for mortgages, deeds of trust, contracts to purchase, or similar debts on the property (including payments for the first mortgage, second mortgages, home equity loans, and other junior mortgages); real estate taxes; fire, hazard, and flood insurance on the property; utilities (electricity, gas, and water and sewer); and fuels (oil, coal, kerosene, wood, etc.). It also includes, where appropriate, the monthly condominium fee for condominiums and mobile home costs (installment loan payments, personal property taxes, site rent, registration fees, and license fees)."

owning a home dropped sharply during 2007-2012 for all income groups, which might have shaped the income and geographic patterns of homeownership during the recovery. Still, even after this significant drop, the fraction of income spent on housing is above 50 percent for low-income borrowers in expensive cities. More recently, the costs remain flat at a lower level than pre-crisis levels, with moderate increases for the low-income and middle-income groups in expensive MSAs post-2012.

Contrary to the owner cost being lower than its pre-crisis level, our analysis on the HMDA home purchase loan amount relative to borrower income shows large upward trends from 2014. We define the loan-to-income (LTI) as the ratio of loan amount to borrower's gross annual income as reported in HMDA. Figure 6 shows that, after 2014, low- and middle-income people began to have much higher LTI ratios than before 2014, and the growth in LTI is higher in MSAs with high house price levels in 2015. The rising trends in LTI and the lower levels of owner cost are likely due to the low interest rate environment and stable combined loan-to-value ratios in recent years (Adelino, McCartney, and Schoar, 2020).

Besides the owner cost, ACS also provides data on monthly gross rent,¹⁰ which measures the cost of renting. We proceed in a similar fashion to the analysis of owner costs and focus on renters who are recent movers in order to show renter costs for the rental decision in each year. Figure 7 shows that low-income renters, on average, spend more than half of their household income on gross rents even in cheap cities, and there was a sudden increase in renter cost for these households right after 2008. For all income groups, gross rent as a percentage of household income has been relatively stable compared to the fluctuations of owner costs in Figure 5 and only slightly increasing after the crisis.

We show the cost of owning and renting split into the four MSA groups of house price growth in Figure A3 and Figure A4. For low-income households, owner cost dropped to lower levels in the

¹⁰ The definition of the monthly gross rent can be found in the ACS Subject Definitions document at <u>https://www2.census.gov/programs-surveys/acs/tech_docs/subject_definitions/2020_ACSSubjectDefinitions.pdf</u>. "Gross rent is the contract rent plus the estimated average monthly cost of utilities (electricity, gas, and water and sewer) and fuels (oil, coal, kerosene, wood, etc.) if these are paid by the renter (or paid for the renter by someone else)."

"Always boom" and "Early boom" MSAs than the other MSAs after 2012, which may help explain the low-income group's faster recovery in homeownership (Figure 2) and the increasing share buying in these two groups of MSAs (Figure 4).

6. Conclusion

This paper considers broad patterns in homeownership, cost of ownership, debt-to-income, and purchasing behavior across income groups over the last 15 years, spanning the last years of the runup to the financial crisis, the financial crisis and the recovery. Our analysis uncovers a few novel features of the post-crisis recovery: First, homeownership has not recovered to pre-crisis levels, and persistent differences in homeownership remain across groups. However, we see low-income households recovering earlier than higher income ones, although from much lower initial levels.

Second, we show that the size of mortgages relative to income have risen dramatically recently, without a corresponding increase in the cost of ownership. Persistently low interest rates likely help explain this pattern, but this raises the question of whether the current rhythm of home purchasing is sustainable once interest rates begin to rise.

Third, and finally, we show that MSAs experienced very heterogeneous recoveries, and this is visible in the purchase patterns of different households. Specifically, low-income households accelerated their purchasing behavior primarily in areas that had large runups in prices before the crisis, but lower house price growth in the recovery. In contrast, higher income households' purchasing behavior accelerated much more in areas with more recent house price booms. The drivers and implications of this sorting behavior is an interesting area for future research.

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Table 1: Summary Statistics

Panel A reports summary statistics for households in the ACS sample who live at PUMAs that can be matched to at least one 2013-version MSA. Homeownership and Mover are indicator variables. Owner Cost to Household Income and Gross Rent to Household Income are in percentage. All numbers in Panel A are weighted by the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a proportion of the PUMA population in 2010 (provided by the IPUMS crosswalk). Panel B reports summary statistics for the HMDA sample. Certain limits are placed on the HMDA data to get this sample: we only include observations of originated mortgages that are borrowed for the purpose of home purchase; the mortgages should be first-lien, borrowed for 1-4 family homes, and for owner-occupied principal dwellings; and both the loan amount and the borrower's income should to be between 1 and 5,000 thousand dollars. Home Purchase Loan is an indicator variable. Panel C reports summary statistics for the house price data. House Price Levels are from the Zillow Home Value Index. House Price Growth rates are from the FHFA House Price Index.

	Mean	Std. Dev.	p25	Median	p75	Ν
Homeownership (0-1)	0.64	0.48	0	1	1	16,848,116
Mover (0-1)	0.15	0.36	0	0	0	16,848,083
Household Income (adjusted to 2020 dollars; in thousand \$)	89.10	95.54	32.12	64.07	113.02	16,848,116
Owner Cost to Household Income (%)	25.91	21.77	12	20	31	11,833,073
Gross Rent to Household Income (%)	39.68	27.41	20	30	51	4,532,131

Panel A: Summary statistics for ACS

Panel B: Summary statistics for HMDA

¥	Mean	Std. Dev.	p25	Median	p75	Ν
Loan Size (adjusted to 2020 dollars; in thousand \$)	286.18	224.49	157.01	231.94	348.77	49,079,672
Borrower Income (adjusted to 2020 dollars; in thousand \$)	115.46	128.01	58.72	87.51	132.87	49,079,672

Panel C: Summary statistics for MSAs' house prices

¥	Mean	Std. Dev.	p25	Median	p75	Ν
House Price Levels (2015; ZHVI; typical \$ value for homes)	183,199	104,883	124,961	157,381	207,904	380
House Price Growth (2000-2006; FHFA HPI; in percentage)	56.13	37.75	28.45	40.25	74.13	381
House Price Growth (2006-2010; FHFA HPI; in percentage)	-8.13	16.07	-14.63	-3.03	2.98	381
House Price Growth (2010-2019; FHFA HPI; in percentage)	29.94	21.99	14.74	23.91	40.95	381

Table 2: Quartile Matrix for Boom and Recovery at the MSA Level

The table shows the quartile transition matrix for the house price growth rates of two periods (2000-2006 and 2012-2019) at the MSA level. Each number in the table is a conditional probability of which quartile the MSA's house price growth would end up in the column for 2012-2019, given that MSA was in the row quartile of price growth in 2000-2006. House price index is from FHFA HPI. Growth rates for each period are computed by taking the difference of index at the last year minus the index at the first year of that period, then dividing the difference by the first-year index. We use the annual average values of the MSA-level index throughout our calculations.

			HP Growth Qua	rtiles 2012-2019)	
		1	2	3	4	Total
	1	20.8	38.5	27.1	13.5	100
HP Growth Quartiles	2	34.7	26.3	29.5	9.5	100
2000-2006	3	30.5	23.2	31.6	14.7	100
	4	14.7	11.6	11.6	62.1	100

Figure 1: Volumes of Originated Home Purchase Mortgages by Income Levels and by MSAs' 2015 House Price Levels

This figure shows the total number of originated home purchase mortgages by income groups. Data are from HMDA. Panel A presents results for the subset of MSAs with below-median house price levels in 2015; panel B presents the subset of MSAs with above-median house price levels in 2015. The income terciles are defined by the nationwide cutoff values obtained from the ACS data for each year and shown in Table A1. Certain limits are placed on the HMDA data: we only include observations of originated mortgages that are borrowed for the purpose of home purchase; the mortgages should be first-lien, borrowed for 1-4 family homes, and for owner-occupied principal dwellings; and both the loan amount and the borrower's income should to be between 1 and 5,000 thousand dollars.



Panel B: MSAs with above-median HP levels in 2015



Figure 2: Change in Homeownership Rates by Household Income

This figure shows the change of average homeownership rates relative to homeownership rates in 2005 by household income. Data are from ACS. The annual average homeownership rates by household income are shown in Table A3. The sample consists of ACS households who live in PUMAs that can be matched to at least one 2013-version MSA. Homeownership rates are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk). The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1.



Figure 3: Change in Homeownership Rates by Household Income and by MSAs' 2015 House Price Levels

This figure shows the change of average homeownership rates relative to homeownership rates in 2005 by household income. Data are from ACS. Panel A presents results for the subset of MSAs with below-median house price levels in 2015; panel B presents the subset of MSAs with above-median house price levels in 2015. Homeownership rates are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk). The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1.



Panel B: MSAs with above-median house price level in 2015

Figure 4: Change in Location Choices of Recently Moved Homeowners by Income

This figure shows the change in homeowners' location choices relative to the proportion in 2005 by household income. Data are from ACS. The sample consists of ACS households who own their homes, have moved within 1 year (i.e., recent movers), and live in PUMAs that can be matched to at least one 2013-version MSA. Each panel presents the change of the proportion of owners buying in that group of MSAs. The proportions are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk). Panel A presents results for the group of MSAs that had high growth rates in house prices in both 2000-2006 and 2010-2019 ("always boom"); panel B is for the group of MSAs that had high growth rate in 2010-2019 but low growth rate in 2000-2006 ("late boom"); panel C is for the group of MSAs that had house growth rate in 2010-2019 but high growth rate in 2000-2006 ("early boom"); and panel D is for the group of MSAs that had low growth rate in house prices in both periods ("never boom").



Panel B: Late boom. High ΔHP 2010-2019 only

Panel C: Early boom. High AHP 2000-2006 only







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Figure 5: Average Owner Cost to Household Income for Recent Movers of Home Owners by Income Groups and by MSAs' 2015 House Price Levels

This figure shows annual average owner cost as a fraction of household income from 2005 to 2019 by income tercile groups and by house price levels in 2015. The sample consists of ACS households who are home owners, have moved within 1 year, and live in PUMAs that can be matched to at least one 2013-version MSA. The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1. Average values are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a proportion of the PUMA population in 2010 (provided by the IPUMS crosswalk). Panel A presents results for the subset of MSAs with below-median house price levels in 2015; panel B presents the subset of MSAs with above-median house price levels in 2015. The grey dashed line in both panels shows the average owner-cost-to-household-income ratio for the whole sample of recently moved homeowners for reference purpose.





Panel B: MSAs with above-median HP levels in 2015

Figure 6: Median Loan-to-Income of Originated Home Purchase Mortgages by MSAs' 2015 **House Price Levels**

This figure shows the median loan-to-income ratio of originated home purchase mortgages by income. Data are from HMDA. Loan-to-income is defined as the ratio of loan amount to borrower's gross annual income as reported in HMDA. The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1. Panel A presents results for the subset of MSAs with below-median house price levels in 2015; panel B presents the subset of MSAs with above-median house price levels in 2015. The red dashed line in both panels shows the median loan-to-income ratio for the whole sample of all MSAs for reference purpose.



Panel B: MSAs with above-median HP levels in 2015

Figure 7: Average Gross Rent to Household Income for Recent Movers of Renters by Income Groups and by MSAs' 2015 House Price Levels

This figure shows annual averages gross rent as a fraction of household income from 2005 to 2019 by income tercile groups and by house price levels in 2015. The sample consists of ACS households who are home renters, have moved within 1 year, and live in PUMAs that can be matched to at least one 2013-version MSA. The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1. Average values are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a proportion of the PUMA population in 2010 (provided by the IPUMS crosswalk). Panel A presents results for the subset of MSAs with below-median house price levels in 2015; panel B presents the subset of MSAs with above-median house price levels in 2015. The grey dashed line in both panels shows the average owner-cost-to-household-income ratio for the whole sample of recently moved renters for reference purpose.







Appendix

Table A1: Upper Limits for the Low-Income Tercile and Middle-Income Tercile

This table shows upper limits for the low-income and middle-income groups. These nationwide cut-off values are calculated based on the whole ACS universe of U.S. households for each year. They are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk). The 2004 and 2020 limits shown in this table are computed by extending the 2005 and 2019 limits using the trends in the 30th and the 70th income percentile limits from the Current Population Survey (CPS)¹¹. These tercile limits are applied to our ACS analysis as well as our HMDA analysis for defining income groups.

Year	Low-Income Tercile's Upper Limit (adjusted to 2020 dollars)	Middle-Income Tercile's Upper Limit (adjusted to 2020 dollars)
2004	40269.52	87866.35
2005	40628.06	88298.31
2006	40901.37	89251.22
2007	41979.19	90827.70
2008	41716.51	90794.75
2009	39889.14	88239.63
2010	38319.58	86183.13
2011	37539.45	84463.76
2012	37621.56	85275.55
2013	38106.05	85290.32
2014	38628.79	86749.22
2015	39382.48	88610.59
2016	40648.16	91295.34
2017	41643.07	92789.30
2018	41773.12	93989.52
2019	43773.91	97161.73
2020	42307.83	94386.33

¹¹ CPS income percentile limits are available in Table A-4a at <u>www.census.gov/data/tables/time-</u> series/demo/income-poverty/historical-income-inequality.html.

Table A2: Volumes of Originated Home Purchase Mortgages by Income Levels and by MSAs'2015 House Price Levels

This table lists all of the data points plotted in Figure 1. It shows total number of originated home purchase mortgages by income groups. Data are from HMDA. Panel A presents results for the subset of MSAs with below-median house price levels in 2015, while panel B presents the subset of MSAs with above-median house price levels in 2015. The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year and shown in Table A1. Certain limits are placed on the HMDA data: we only include observations of originated mortgages that are borrowed for the purpose of home purchase; the mortgages should be first-lien, borrowed for 1-4 family homes, and for owner-occupied principal dwellings; and both the loan amount and the borrower's income should to be between 1 and 5,000 thousand dollars.

	Panel A: M	SAs with below-m	edian house	Panel B: M	SAs with above-m	edian house
	price le	evel in 2015 (cheap	o cities)	price leve	el in 2015 (expensi	ive cities)
Year	Low Income	Middle Income	High Income	Low Income	Middle Income	High Income
2004	126,068	469,761	356,385	148,072	1,158,732	1,828,441
2005	134,053	494,145	356,170	129,153	1,135,925	1,967,070
2006	131,560	467,595	329,493	106,155	942,427	1,720,380
2007	129,130	389,637	262,324	111,853	799,430	1,201,398
2008	98,351	307,124	194,596	105,518	689,120	820,854
2009	89,769	293,935	173,573	124,068	709,744	731,885
2010	79,182	246,019	171,804	116,974	602,619	707,511
2011	68,163	227,030	166,587	107,213	549,241	663,076
2012	78,256	257,133	188,856	119,378	617,461	767,027
2013	84,505	287,944	226,126	117,754	678,414	946,096
2014	88,916	307,852	228,571	119,849	732,236	971,812
2015	106,995	353,368	250,589	142,741	866,391	1,082,087
2016	124,304	400,333	263,173	160,396	996,851	1,167,301
2017	139,515	415,919	267,201	170,130	1,032,966	1,193,165
2018	142,826	432,694	258,283	166,405	1,046,488	1,148,297
2019	167,587	442,050	258,371	197,707	1,103,979	1,157,179
2020	168,010	491,795	291,473	184,893	1,205,314	1,311,673

Table A3: Annual Average Homeownership Rates by Income

This table shows average homeownership rates of U.S. households by income from 2005 to 2019. Data are from ACS. The sample consists of ACS households who live in PUMAs that can be matched to at least one 2013-version MSA. Homeownership rates are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk). The income terciles are defined by the nationwide cut-off values obtained from the ACS data for each year as shown in Table A1.

Year	Low Income	Middle Income	High Income
2005	46.2%	67.4%	86.4%
2006	46.0%	67.1%	86.1%
2007	45.7%	67.2%	86.1%
2008	45.3%	66.4%	85.2%
2009	44.4%	66.1%	84.8%
2010	43.6%	65.1%	84.1%
2011	43.0%	64.4%	83.4%
2012	42.7%	63.7%	82.4%
2013	42.7%	63.1%	81.9%
2014	42.6%	62.9%	81.4%
2015	42.5%	62.5%	81.3%
2016	43.1%	62.2%	81.0%
2017	44.2%	62.9%	81.5%
2018	44.6%	63.1%	81.5%
2019	44.5%	63.4%	81.5%

Table A4: List of the 12 Largest MSAs in the 4 Groups of MSAs

This table shows the 12 largest MSAs based on the estimated 2010 population (provided by the IPUMS crosswalk) in each of the four groups of MSAs that are categorized by the house price growth rates in 2000-2006 and 2010-2019.

Panel .	anel A: Always boom		B: Late boom
31080	Los Angeles-Long Beach-Anaheim, CA	19100	Dallas-Fort Worth-Arlington, TX
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	26420	Houston-The Woodlands-Sugar Land, TX
33100	Miami-Fort Lauderdale-West Palm Beach, FL	12060	Atlanta-Sandy Springs-Roswell, GA
14460	Boston-Cambridge-Newton, MA-NH	19820	Detroit-Warren-Dearborn, MI
41860	San Francisco-Oakland-Hayward, CA	19740	Denver-Aurora-Lakewood, CO
40140	Riverside-San Bernardino-Ontario, CA	38300	Pittsburgh, PA
38060	Phoenix-Mesa-Scottsdale, AZ	16740	Charlotte-Concord-Gastonia, NC-SC
42660	Seattle-Tacoma-Bellevue, WA	41700	San Antonio-New Braunfels, TX
33460	Minneapolis-St. Paul-Bloomington, MN-WI	17140	Cincinnati, OH-KY-IN
41740	San Diego-Carlsbad, CA	28140	Kansas City, MO-KS
45300	Tampa-St. Petersburg-Clearwater, FL	18140	Columbus, OH
38900	Portland-Vancouver-Hillsboro, OR-WA	26900	Indianapolis-Carmel-Anderson, IN
Panel	C: Early boom	Panel	D: Never boom
Panel 35620	C: Early boom New York-Newark-Jersey City, NY-NJ-PA	Panel 17460	D: Never boom Cleveland-Elyria, OH
Panel 0 35620 16980	C : Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI	Panel 17460 13820	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL
Panel 0 35620 16980 37980	C: Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Panel 17460 13820 40380	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL Rochester, NY
Panel (35620 16980 37980 41180	C: Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI Philadelphia-Camden-Wilmington, PA-NJ-DE-MD St. Louis, MO-IL	Panel 17460 13820 40380 46140	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL Rochester, NY Tulsa, OK
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Panel 35620 16980 37980 41180 12580 47260 39300 33340 25540	C: Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI Philadelphia-Camden-Wilmington, PA-NJ-DE-MD St. Louis, MO-IL Baltimore-Columbia-Towson, MD Virginia Beach-Norfolk-Newport News, VA-NC Providence-Warwick, RI-MA Milwaukee-Waukesha-West Allis, WI Hartford-West Hartford-East Hartford, CT	Panel 17460 13820 40380 46140 12940 19380 32580 17900 24660	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL Rochester, NY Tulsa, OK Baton Rouge, LA Dayton, OH McAllen-Edinburg-Mission, TX Columbia, SC Greensboro-High Point, NC
Panel 35620 16980 37980 41180 12580 47260 39300 33340 25540 40060	C: Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI Philadelphia-Camden-Wilmington, PA-NJ-DE-MD St. Louis, MO-IL Baltimore-Columbia-Towson, MD Virginia Beach-Norfolk-Newport News, VA-NC Providence-Warwick, RI-MA Milwaukee-Waukesha-West Allis, WI Hartford-West Hartford-East Hartford, CT Richmond, VA	Panel 17460 13820 40380 46140 12940 19380 32580 17900 24660 10420	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL Rochester, NY Tulsa, OK Baton Rouge, LA Dayton, OH McAllen-Edinburg-Mission, TX Columbia, SC Greensboro-High Point, NC Akron, OH
Panel 35620 16980 37980 41180 12580 47260 39300 33340 25540 40060 49340	C: Early boom New York-Newark-Jersey City, NY-NJ-PA Chicago-Naperville-Elgin, IL-IN-WI Philadelphia-Camden-Wilmington, PA-NJ-DE-MD St. Louis, MO-IL Baltimore-Columbia-Towson, MD Virginia Beach-Norfolk-Newport News, VA-NC Providence-Warwick, RI-MA Milwaukee-Waukesha-West Allis, WI Hartford-West Hartford-East Hartford, CT Richmond, VA Worcester, MA-CT	Panel 17460 13820 40380 46140 12940 19380 32580 17900 24660 10420 30780	D: Never boom Cleveland-Elyria, OH Birmingham-Hoover, AL Rochester, NY Tulsa, OK Baton Rouge, LA Dayton, OH McAllen-Edinburg-Mission, TX Columbia, SC Greensboro-High Point, NC Akron, OH Little Rock-North Little Rock-Conway, AR

Figure A1: Homeownership in CPS/HVS

This figure shows the change of average homeownership rates by income, relative to the homeownership rates in April 2005. Data are from the Housing Vacancies and Homeownership (CPS/HVS)¹² by the Census.



¹² CPS/HVS data available at <u>www.census.gov/housing/hvs/index.html</u>.

Figure A2: Change in the Proportions of Recently Moved Homeowners Living in MSAs with Above-Median House Prices in 2015

This figure shows the change of proportions of recently moved homeowners living in expensive MSAs that had abovemedian house prices in 2015. Changes are computed relative to base year 2005. Data are from ACS. The sample consists of ACS households who own their homes, have moved within 1 year (i.e., recent movers), and live in PUMAs that can be matched to at least one 2013-version MSA. The proportions within each income group are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk).



Figure A3: Change of Owner Cost by Income and by Locations

This figure shows the change of annual average owner costs by household income and by locations of the four MSA growth-pattern groups. Changes are computed relative to base year 2005. Data are from ACS. The sample consists of ACS households who own their homes, have moved within 1 year (i.e., recent movers), and live in PUMAs that can be matched to at least one 2013-version MSA. Each panel presents the change of owner cost for homeowners buying in that group of MSAs. Average costs are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk).







Panel C: Early boom. High AHP 2000-2006 only



Panel D: Never boom. Low AHP 2000-2006 and 2010-2019



Figure A4: Change of Renter Cost by Income and by Locations

This figure shows the change of annual average gross rent by household income and by locations of the four MSA growth-pattern groups. Changes are computed relative to base year 2005. Data are from ACS. The sample consists of ACS households who rent their homes, have moved within 1 year (i.e., recent movers), and live in PUMAs that can be matched to at least one 2013-version MSA. Each panel presents the change of renter cost for recently moved renters living in that group of MSAs. Average costs are weighted by both the ACS household weight (provided in ACS PUMS) and the estimated population at PUMA-MSA intersection areas as a percentage of the PUMA population in 2010 (provided by the IPUMS crosswalk).



Panel A: Always boom. High ΔHP 2000-2006 and 2010-2019



Panel C: Early boom. High AHP 2000-2006 only



Panel D: Never boom. Low AHP 2000-2006 and 2010-2019

