Back to School When Times are Bad? The Role of Housing Frictions*

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Abstract

College enrollment typically rises during recessions. This paper demonstrates that housing wealth destruction dampened this countercyclical effect in areas most affected by the U.S. housing bust of 2008-2011. By combining household data with a mortgage credit register and housing price data, we reveal that rising household leverage significantly reduced college enrollment among homeowners relative to renters during this period. Up to 2% of the local college-age population did not pursue college enrollment at the height of the bust due to these housing frictions. The negative impact of homeownership on college education persists for a decade, ultimately contributing to lower incomes among homeowners in the most affected areas.

JEL: I24, E32, J24

Keywords: Homeownership, Household Leverage, College Enrollment, Housing Boom-Bust Episodes.

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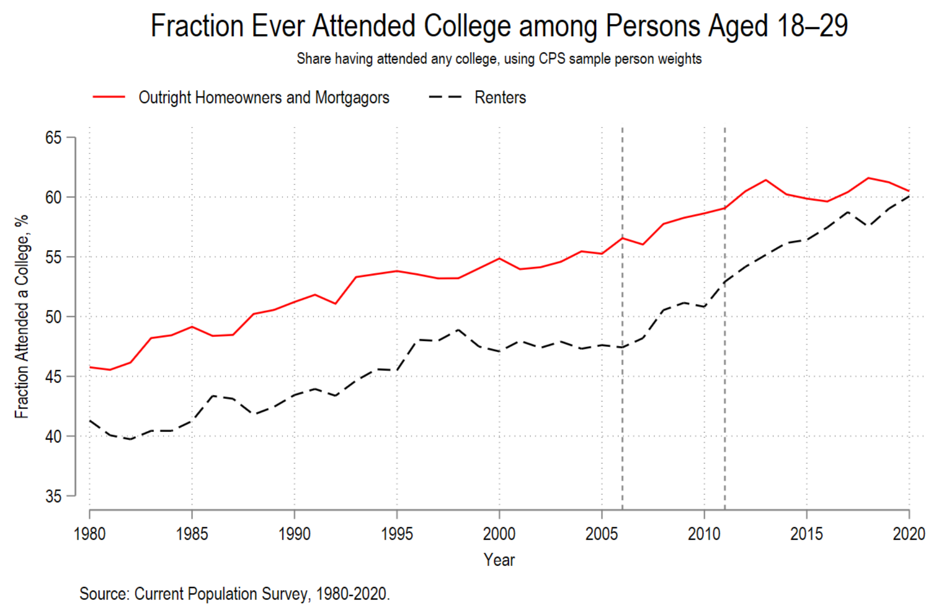
1 Introduction

How do financing conditions affect college enrollment? While the college premium has steadily increased since the 1970s (e.g., Goldin and Katz, 2008; Athreya and Eberly, 2021), so has the price of higher education in real terms (e.g., Dynarski et al., 2003), to the point where the rising cost of college has entered the debate about economic inequality and prompted government action.[1] It is therefore natural to hypothesize that households' ability to send their children to college is sensitive to shocks to their finances. Indeed, Lovenheim (2011) and Lovenheim and Reynolds (2013) show that rising home equity during the housing boom of the early-to-mid 2000s was associated with an increase in college attendance by the children of homeowners, and especially for lower-income ones, pointing to the importance of financing constraints in education decisions. However, while there is no reason to expect that the effect is not symmetric and therefore adverse shocks to home equity could significantly negatively affect college enrollment through a reduction in the housing wealth of families with college-age children, the empirical literature has not yet provided conclusive evidence to that end.

Figure 1 illustrates the striking differences in recent higher education trends across homeownership groups. While college enrollment by homeowners and renters moved in parallel between 1980 and the late 2000s, their college enrollment converged following the housing bust. While college attendance in the case of renters continuing to increase, college attendance in the case of homeowners stagnated.

In an attempt to explain this phenomenon, we study the role of household leverage in deterring educational choices. In theory, the housing price cycle can affect college attendance via two channels. The first is the opportunity cost channel. When the economy is booming and housing markets are hot, labor market opportunities are abundant, which raises the opportunity cost of going to college instead of joining the labor market. Conversely, when the economy is in a recession and housing markets are in decline, college becomes relatively more attractive. These fluctuations in the opportunity cost of school-

[1] For example, the Biden administration announced two rounds of student debt forgiveness between 2022 and 2024.



Note: This figure reports average college attendance defined as having at least 1 year of college (in the CPS data: $EDUC \geq 80$, $t \geq 1992$; $HIGRADE \geq 151$, $t \leq 1992$). The housing bust period is marked by vertical dashed lines.

Figure 1. College Attendance of Homeowners and Renters

ing over the business cycle are the primary reason why college enrollment tends to be countercyclical (e.g., Dellas and Sakellaris, 2003; Barr and Turner, 2013). They also explain why during the housing boom of the early-to-mid 2000s, college enrollment declined (Laeven and Popov, 2016; Charles et al., 2018).

The second channel is related to changes in housing wealth. During a housing boom, home equity increases, making it relatively easier for homeowners to cover the cost of their children's college. The opposite occurs during a housing bust, as homeowners' home equity declines sharply, with the impact being particularly severe for highly leveraged households, Mian and Sufi (2014a). The magnitude of the overall effect depends on the size of the boom-bust episode and on the relative size of mortgage debt and housing equity. However, it is clear that renters are only affected by the opportunity cost channel, while homeowners are affected by both, and for them the two effects go in opposite directions.[2]

We use micro-census data on around 104,300 households from the American Community Survey, for which we observe both parental homeownership status and children's

[2] Of course, fluctuations in home equity over the housing boom-bust cycle explains not only changes in the demand for schooling, but for other "normal" goods as well, such as nondurables (Kaplan et al., 2020).

college enrollment outcomes. We match these data with local indices on changes in house prices over time. Our main finding is that during the housing bust of 2008-2011, and compared with those of renters, the college-age children of homeowners were significantly less likely to be enrolled in a higher education institution in areas which experienced a relatively larger decline in house prices. This effect is concentrated among homeowners with a mortgage, rather than among full home owners. We also find that the housing leverage effect on college enrollment is meaningful in the aggregate. Moreover, it is observed long after the end of the Great Recession and translates into persistently lower incomes for homeowners.

The main result in the paper is remarkably robust to using different samples and model specifications. We continue documenting a statistically significant association between the extent of the housing bust and the likelihood of college enrollment for the children of homeowners once we use the housing supply elasticity as an instrumental variable for the decline in house prices in order to account for the potential endogeneity of college choice and house prices. We further demonstrate that our findings are not influenced by differences in the migrant status composition of homeowners and renters nor by homeowners displaced by the housing bust who subsequently became renters. This is because our main result holds when we restrict our sample to non-migrant households and when we focus exclusively on families who remained in the same housing units throughout the housing downturn. Our main result is also robust to using alternative proxies for the housing market shock: housing net worth destruction of Mian et al. (2013), and changes in foreclosure rates.

How persistent is this effect? And how important is it in the aggregate? To answer the first question, we compare owners and renters in the geographic localities more and less affected by the housing bust over the next decade. We find that differences in college attendance persist over time and translate into persistently lower incomes for homeowners compared to renters in more affected localities. Longer and more expensive college arrangements are affected more compared to shorter programs.

To answer the second question, we perform a back-of-the-envelope calculation based on the local decline in house prices during the bust, the number of college-eligible students, the share of homeowners in each geographic locality, and the elasticity of college enrollment to changes in house prices. Using this approach, we find that approximately 11,500 potential college students, or up to 2% of the local college-age population, did not enroll in college during the peak years of the housing bust due to housing frictions.

Our work contributes to the literature on financial frictions and education. Wealthy parents invest, on average, more in the human capital of their offspring than poorer ones (e.g., Becker et al., 2018; Chakrabarti et al., 2023). Consequently, easier access to external finance increases college enrollment for credit-constrained households. A number of papers have demonstrated this link by looking at the effect of exogenous changes in the availability of student loans on human capital accumulation (e.g., Lochner and Monge-Naranjo, 2011; Denning and Jones, 2021; Black et al., 2023). Others have demonstrated a similar effect by looking at the effect of banking deregulation on college enrollment which increased the availability and reduced the cost of bank credit (Sun and Yannelis, 2016), or of unexpected positive wealth shocks as a result of lottery wins (Bulman et al., 2021). Closest in spirit to our approach is the analysis in Lovenheim (2011) and Lovenheim and Reynolds (2013) who show that an increase in housing wealth increases significantly the likelihood of university enrollment, with the effect being strongest for lower-income families. Relative to this paper and to the rest of the empirical literature, we look at the effect of a *negative* wealth shock via the destruction of home equity.

Our paper also contributes to the literature on the socio-economic effects of fluctuations in house prices. One strand of this literature has linked the U.S. housing boom of the early-to-mid 2000s to household portfolio and labor choices, as well as to changes in the U.S. industrial structure. Mian and Sufi (2011) provide evidence on how home equity-based borrowing during the U.S. housing boom of the late 1990s and early-to-mid 2000s was responsible for the large observed increase in housing debt among U.S. households. Chetty et al. (2017) show that increases in home equity wealth tend to raise shareholdings by U.S. households. Charles et al. (2016) show that the housing boom allowed for a reallocation of unskilled workers from manufacturing to construction sectors, masking the overall unemployment effect of the U.S. manufacturing decline. Corradin and Popov (2015) show that the rise in homeowners' housing wealth brought about by rising house prices increased the rate of creation of business start-ups. Lovenheim and Reynolds (2013) and Dettling and Kearney (2014) document that an increase in housing wealth among homeowners increases significantly the probability of having a child. Daysal et al. (2021) show that housing price increases lead to better child health at birth. Farnham et al. (2011) show that fluctuations in house prices significantly affect the share of a cohort that is divorced. Laeven et al. (2024) document that an increase in local house prices is associated with a decrease in the time homeowners spend on religious activities compared to renters. Relative to these papers, we study the effect of house price declines on college enrollment, for children of homeowners compared with children of renters.

2 Background

2.1 The U.S. housing boom and bust

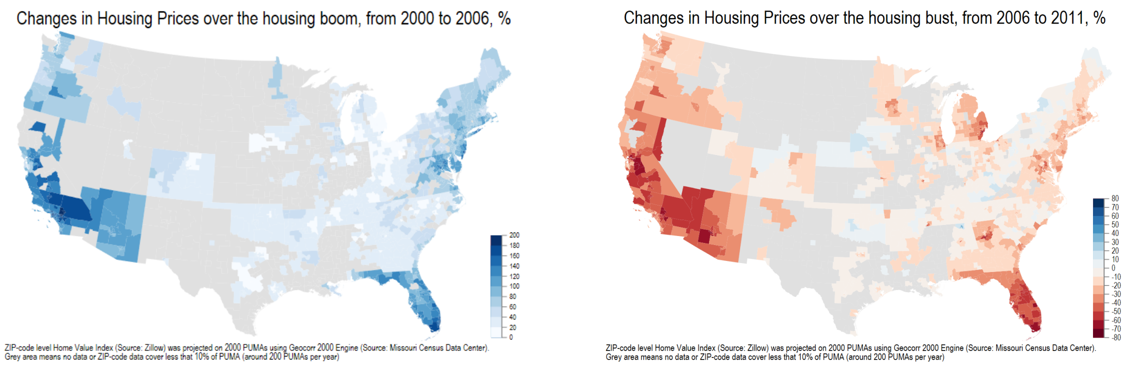
The housing boom of the early-to-mid 2000s was unprecedented in size, as well as in the severity of bust that followed it. Nationally, housing prices rose by around 57% between the fourth quarter of 2000 and the fourth quarter of 2006[3] but there were large regional differences. For example, over this period home prices grew by 2.6 times in the metropolitan area around Miami, FL, but they increased by 33% in Houston, TX MSA[4]. Figure 2, Panel (a) illustrates this development.

The housing bust, which started in 2007 and lasted until 2011, resulted in a 17% decline in house prices across the United States[5]. Similar to the boom phase, the bust was characterized by large heterogeneity in changes in house prices. For example, house prices declines by 45% in Miami, FL, but continued to grow and increased by 5% in

[3]U.S. Federal Housing Finance Agency, All-Transactions House Price Index for the United States [USSTHPI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USSTHPI, October 30, 2024.

[4]All-Transactions House Price Index for Houston-The Woodlands-Sugar Land, TX (MSA) and for Miami-Miami Beach-Kendall, FL (MSAD). [ATNHPIUS26420Q], [ATNHPIUS33124Q]. retrieved from FRED, Federal Reserve Bank of St. Louis; October 30, 2024.

[5]From 4Q2006 to 4Q2011, U.S. Federal Housing Finance Agency, All-Transactions House Price Index. Here and below: same geographies as above.

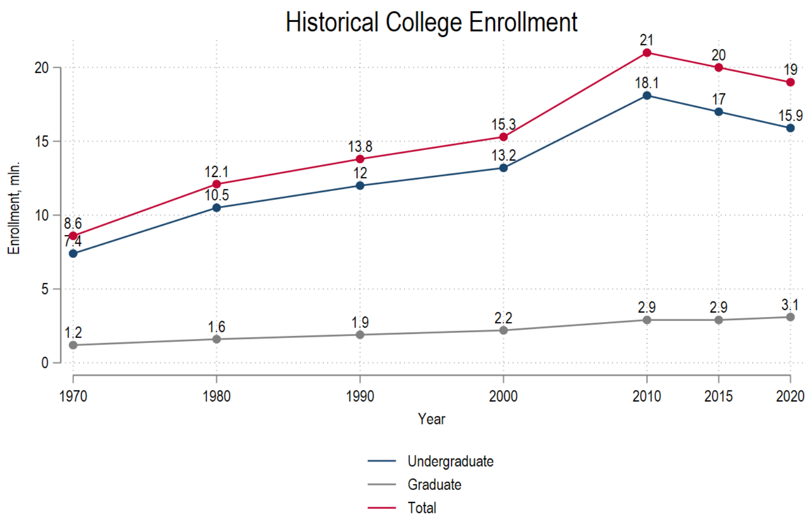


(a) Housing boom (b) Housing bust

Figure 2. Map of the U.S. housing boom and bust

Houston, TX. The patterns of large regional differences in house price adjustment after the US-wide peak are readily visible in Figure 2, Panel (b).

2.2 The U.S. college enrollment trends



Source: National Center for Education Statistics (NCES).

Figure 3. Total undergraduate and graduate fall enrollment in degree-granting postsecondary institutions

There have broadly been two phases in higher education attendance in the U.S in the past 50 years. The first was of a gradual increase in college enrollment until the Global Financial Crisis. Figure 3 shows that the number of undergraduate students increased from 7.4 million in 1970 to 18.1 million in 2010, by far outpacing population growth. At the same time, 2010 marks the peak of college attendance, after which the U.S. undergraduate population started to decline, to about 15.9 million in 2020. The undergraduate population thus declined by about 2.2 million during this period, making the 2010s the first decade with a negative college population growth. This negative trend in college enrollment contrasts with a continued steady increase in the number of graduate students in the U.S. which was not interrupted by the Global Financial Crisis and reached a historical peak of 3.1 million in 2020.

The most natural explanation is that tuition costs, particularly in public universities, have been rising faster than the return to college education (e.g., Delaney and Marcotte, 2024). This hypothesis however does not directly help explaining the differential college attainment trends between homeowners and renters. This hypothesis might work if homeowners and renters would sort differentially into college programs of different length and presumably, cost. In particular, if renters would sort more in time into shorter and less expensive programs while homeowners would increasingly pursue longer and more expensive educational degrees then a differential rise in tuition costs in short and long programs may help explaining differences in college attainment. However, we do not observe differential trends in the fraction of homeowners and renters across college attainment groups: some college, two- and four-years of college. This proportion is rather stable in time and equals to 60 and 40% among population aged 18-29.[6] This rules out a tuition-based explanation. Instead, given the differential trends in college attainment across homeownership groups reported in Figure 1, we conjecture that the ability of households to meet rising college tuition costs has been reduced in those cases where the housing bust of the late 2000s and early 2010s destroyed a substantial amount of home equity that could otherwise have been used to pay for college.

[6] ACS data. 2005-2020, excluding group quarter population, and restricting to those living in their states of birth.

3 Data

Our goal is to assemble an individual-level dataset linking the timing and the status of the college enrollment decision to the severity of the local housing bust. For that, we need geographical variation in the location of surveyed households and their detailed geographical identifiers. We use the American Community Survey data which provides geographical identifiers of sampled population at the Public Use Microdata Area (PUMA) level. There are more than 2,000 distinct PUMAs identified in the ACS. PUMAs do not cross state borders and cover areas with a population of approximately 100,000 people. PUMAs are the smallest geographic units for which the ACS provides public microeconomic data. We use PUMAs defined on 2000 boundaries in the baseline analysis.

The combination of finely identified geography and large sample size makes American Community Survey unique and the only appropriate public data source to study the question at hand. Other public datasets do not provide detailed geographical identifiers and/or have much smaller sample sizes (e.g., Current Population Survey, Panel Study of Income Dynamics, Survey of Income and Program Participation). The American Community Survey in turn, features about 1 million households surveyed each year. Among them, we select first-year college-age individuals aged 18-19 which yields 35,000-45,000 observations per year.

We restrict our sample to the population aged 18-19 who completed high school, i.e. whose reported education level is at least Grade 12. In this way, we include only those who make a *college choice* at the age of 18-19. We intentionally remove from the sample high-school drop-outs who could choose to go to work early and who are not eligible to go to college because of unfinished high school.[7] We also restrict the sample to people who are identified in the survey as children in relationship to the household head. This allows us to link college-age individuals to their parents and thus determine whether the household owns residential property or not.[8] Because of these selection criteria, we end up

[7]We also drop individuals who report having attained Grade 12 but continue attending any level of education less than Grade 12 because of reporting inconsistencies.

[8]We drop individuals residing in group quarters (e.g., military, college dormitories, mental institutions) because there is no information on parents' homeownership. Around 40% of the population aged 18-19 live in group quarters and their parents' homeownership status is not reported.

with a reliable link between the parents' homeownership status and the college enrollment status of the children.

We focus on the housing bust period which in our sample spans 2008-2011. We assemble a PUMA-level dataset on housing price growth relative to peak of the housing boom, 2006. For that, we use Zillow ZIP code level housing prices.[9] We use the ZIP code-to-PUMA crosswalk provided by the Missouri Census Data Center.[10] We convert ZIP code data to Census 2000 Geography to make housing prices data compatible with the ACS. We drop those PUMAs for which ZIP code-level housing-price data covers less than 10 percent of the PUMA.[11] We use population data provided by the Missouri Census Data Center as allocation factor of ZIP code data to PUMA-level data. We recalculate allocation factors proportionally if ZIP code-level housing prices are missing.

Our sample spans 2008-2011 for two reasons. First, we start in 2008 because it is the first year of the housing bust for which we have one full preceding year of declining housing prices relative to the peak of the bust (2006 to 2007). We assume that the college enrollment decision depends on the previous year housing price change relative to the peak. Second, in the main analysis, we stop in 2011 because starting from 2012, the ACS PUMA data is no longer compatible with the pre-2011 data. This is because the PUMA boundaries were redrawn in 2010 and starting in 2012, PUMAs on 2010 boundaries are used in ACS instead of PUMAs on 2000 boundaries as was the case before 2011. If we would use a consistent PUMA variable instead of PUMA to identify PUMAs pre- and post-2011. we would have only around 1,100 PUMAs identified which is half of what is available if used PUMA 2000 boundaries. Therefore, to maximize geographical variation, we use PUMA 2000 boundaries and stop in 2011 in the baseline analysis. However, when we later examine post-bust long-run education trends, we use the sample of consistent PUMAs. We further use "PUMA" to denote PUMAs on 2000 boundaries.

We link each individual observation to its previous-year geography using "migration PUMA" variable in the ACS. This is an individual's PUMA of residence 1 year ago. We

[9]https://www.zillow.com/research/data/.

[10]https://mcdc.missouri.edu/applications/geocorr2000.html.

[11]In this way, we lose around 100 PUMAs.

focus on the U.S. geography and we exclude migrants, i.e. those coming from non-US destinations. Migration PUMAs are defined on Census 2000 Geography. We map 2000 PUMAs and "migration PUMAs" using the crosswalk provided by the IPUMS.[12]

To account for potential selection into college, we control for a rich set of economic and demographic characteristics. We use local unemployment rate, as well as the individual's age, gender, race, ethnicity, real family income per capita, and the number of siblings as controls. Below, we present summary statistics for our sample (Table 1).

Our sample features around 104,300 observations on 18- and 19-year-old individuals who completed at least Grade 12 and identified in the ACS as children over 2008-2011. 68% of this population are enrolled in college. On average, an individual is 18.6 years old. We have almost equal proportion of male and female population. 74% of our sample are whites, 11% are blacks, 5% are Asian, and 19% are Hispanics. Average income per person amounts to around 17,200 USD (in 2010 prices). In our sample of families with children, homeownership rate is at 79% rate: 13% of parents are outright homeowners, and 67% are homeowners with a mortgage. 21% of the sampled population are renters.

Table 1. Summary Statistics

	Mean	Stand. Dev.	Min	Max	Number of obs.
Attends a College	0.68	0.46	0.0	1.0	104,294
PUMA Housing Price growth, relative to 2006	-0.13	0.16	-0.7	0.4	104,347
PUMA Unemployment Rate, age 16-54	0.08	0.04	0.0	0.4	104,347
Age, years	18.63	0.48	18.0	19.0	104,347
Female	0.48	0.50	0.0	1.0	104,347
White	0.74	0.44	0.0	1.0	104,347
Black	0.11	0.31	0.0	1.0	104,347
Asian	0.05	0.23	0.0	1.0	104,347
Hispanic	0.19	0.39	0.0	1.0	104,347
Log Real Household Income Per Person	9.75	0.83	-1.6	13.0	104,007
Number of Siblings	1.26	1.17	0.0	9.0	104,347
Homeowner	0.79	0.40	0.0	1.0	104,347
Outright Homeowner	0.13	0.33	0.0	1.0	104,347
Homeowner with a Mortgage	0.67	0.47	0.0	1.0	104,347
Renter	0.21	0.40	0.0	1.0	104,347

Note: Household income per person is transformed to 2010 prices using CPI.

[12] https://usa.ipums.org/usa/volii/00migpuma.shtml. We drop those Migration PUMAs which do not uniquely identify 2000 PUMAs (70%).

4 Methodology

Our identification is based on comparing college attendance of college-age freshmen cohorts whose parents are either homeowners or renters, who reside in different geographic areas, and who reached college age in different years of the unfolding housing bust. We focus on the population of those who are 18- or 19-years-old because this is exactly the age when students complete high school and start college.[13]

Our hypothesis is that all else equal, those who reached college age *during the trough of the housing boom-bust cycle* and whose parents were homeowners were worse off in terms of college access compared to those who reached same age later when housing prices were rising. There are several reasons why children of homeowners may become less likely to go to college in geographic areas with a steeper housing price collapse compared to non-homeowners. First, college education is costly in the U.S. (Cai and Heathcote, 2022) and families accumulate wealth in advance to send their children to college. In areas with a steeper housing price decline, parents may find it harder to convert their home equity into cash so that they can pay for their children's college education. This explanation highlights the role of the timing of college enrollment decision and its relation to the timing and geography of the housing bust. Second, education choice *per se* is known to depend on family wealth (Lovenheim, 2011; Bulman et al., 2021), and housing assets make up the bulk of the U.S. middle class assets and wealth (Kuhn et al., 2020). A steep housing price collapse destroys family wealth making homeowners feel poorer and decreasing the likelihood of sending their children to college. Note that neither effect applies to non-homeowner population: they are neither locked in an underwater house nor do they feel any wealth effect because of home value depreciation. Therefore, we use renters as a comparison group in our analysis.

Our hypothesis is motivated by a shrinking college attendance gap between first-year college-age children of homeowners and renters over the housing bust, 2006-2011 (see Figure 4). Pre-bust, children of homeowners were enjoying a significant progress in college

[13] According to ACS, in 2000-2015, 91% of 17 year old population were still attending high school and 2% of 17 year olds were college undergraduates, while among 18 year old population, 47% were high school students and 33% college undergraduate students; among 19-years-olds: 9 and 56% correspondingly.

attendance rate: from 60% in 2000 to 69% in 2006, prior to the bust. In contrast, renters saw slow progress in college attendance over the same period: the same indicator rose from 46% in 2000 to 48% in 2006. These trends turned around during the bust when homeowners' college attendance stalled at 70% over 2007-2011 while children of renters increased college attendance rate by 5 p.p., to 53%. Overall, the college attendance gap between homeowners and renters shrunk by 4.1 p.p. over 2006-2011 and continued to decrease post-bust. Our hypothesis is that housing frictions, in particular homeownership and associated housing leverage, played a role in the differential college enrollment trends between homeowners and renters over the housing bust.

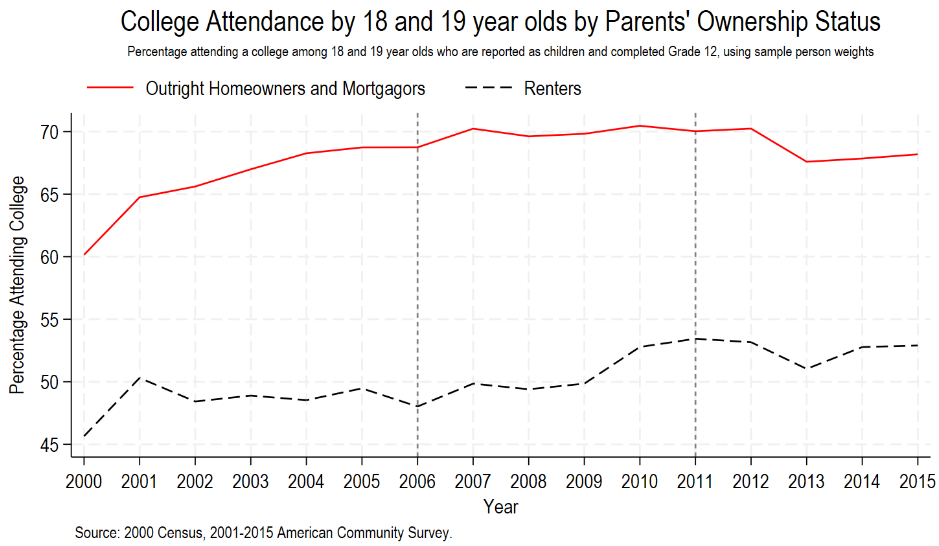
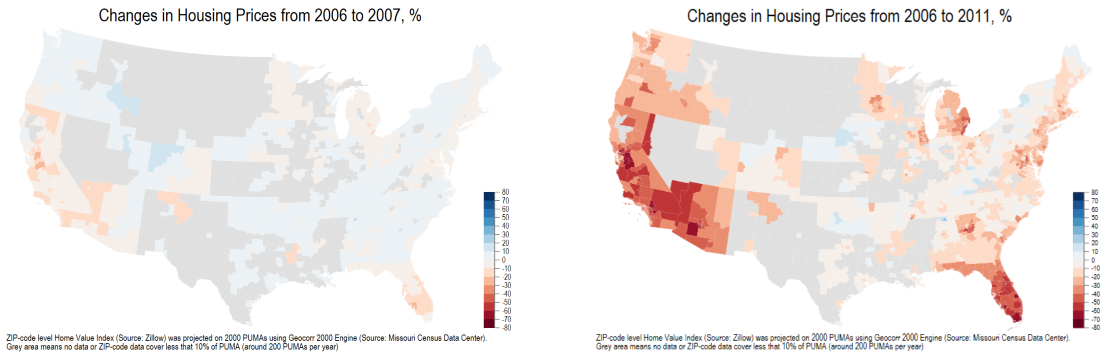


Figure 4. Decreasing College Attendance Gap between Homeowners and Renters over the Housing Bust

To assess this hypothesis, we employ an empirical specification taking advantage of differences in the timing and geographical variation in the strength of the housing bust. Housing prices started to collapse in 2007 when an average house price growth across PUMAs amounted to -1.6% and 55% of PUMAs encountering negative housing price growth rate in this year. Over time and up to 2011, the local housing price dynamics progressively deteriorated: in 2011, 95% of PUMAs were in the "red zone" of negative house price growth with an average housing price decline of 23% (Figure 5). Note that the most affected by the housing bust areas are located on both the East and the West coasts and in such states as Florida, Arizona, and California. Notably, these states contain some of the most inelastic areas in terms of housing supply elasticity with respect to demand shocks, Saiz (2010), a factor which predicts well the strength of the local housing booms and busts Mian et al. (2013).



(a) Start of the Housing Bust

(b) Peak of the Housing Bust

Figure 5. Housing Bust across Time and Space

We estimate an individual's college enrollment sensitivity to changes in house prices depending on the parents' homeownership status. Our econometric specification is as follows:

$$\begin{aligned} College_{i,p,t,b} = \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \\ + \beta_2 \cdot \Delta_{2006,t-1} \ln HPI_p + \beta_3 \cdot Owner_{i,p,t,b} \\ + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_p + \alpha_t + \varepsilon_{i,p,t,b} \end{aligned} \tag{1}$$

The dependent variable $College_{i,p,t,b}$ is an indicator variable which equals to one if individual i in geography p (PUMA) observed in year t born in year b is attending college.

The key explanatory variables are:

- $\Delta_{2006,t-1} \ln HPI_p$ stands for the percentage change in the local housing price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. It proxies both for changes in house prices and in the local business cycle.

- $Owner_{i,p,t,b}$ is an indicator variable capturing whether the parents of individual i are homeowners (=1) or renters (=0).

- $\mathbf{X}_{i,p,t,b}$ is a set of demographic and family-level controls (age, sex, race, ethnicity, number of siblings, and family real income per person).

We account for potential differences in college attendance rates by controlling for observed and unobserved heterogeneity. Observed differences are captured by differences in demographics and family resources. In equation (1), we capture unobserved differences by controlling for birth-year fixed effects α_b that capture variation common to all individuals in the same cohort; for local time-invariant differences α_p that are common to owners and renters in the same PUMA; and for aggregate shocks α_t that are common to all individuals during the same year. The specification allows to identify the effect of local housing price changes, $\Delta_{2006,t-1} \ln HPI_p$ on individual college decisions.

Next, instead of accounting for time-invariant local differences and time-varying aggregate shocks, α_p and α_t, we control for local time-varying shocks (PUMA $\times$ Year FEs, $\alpha_{p,t}$), and we treat this model as the baseline specification. In this model, we are no longer able to identify local housing price change effect, $\Delta_{2006,t-1} \ln HPI_p$.

Additionally, in the robustness check, we account for differences between owners and non-owners across geographies and time and further saturate the model with either PUMA $\times$ Owner FEs, $\alpha_{p,o}$) or Owner $\times$ Year FEs, $\alpha_{o,t}$. We apply person weights to all regression estimates which yields total population representativeness.

Our key coefficient of interest is β_1 which captures the effect of the interaction term, $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ and provides an estimate of differences in the sensitivity of college enrollment to housing bust across children of homeowners and renters.

5 College enrollment response to the housing bust of children of homeowners and renters

5.1 Baseline estimates

The point estimates of the equation (1) are presented in Table 2. We gradually saturate the model with the demographic controls and fixed effects in columns (1) to (5) of the

Table. We report coefficient estimates at demographic characteristics and other control variables in Table A.I in the Appendix. In column (6), we report the preferred specification with the most restrictive set of fixed effects and demographic controls. In the subsequent description, we focus on estimates presented in columns (5) and (6) of Table 2.

First, independently of the local housing market conditions, children of homeowners are on average 15.6-15.7 p.p. more likely to attend a college, which is captured by a positive and significant coefficient on the $Owner_{i,p,t,b}$ indicator variable. Second, in areas with and during years of a steeper house price decline, the 18- and 19-year-olds were more likely to be enrolled in a college. This is represented by the negative and statistically significant coefficient at $\Delta_{2006,t-1} \ln HPI_p$. A steeper decline in housing prices corresponds to a deeper local economic crisis (Mian et al., 2013; Mian and Sufi, 2014b) and a more pronounced decline in local housing-related low-skilled jobs (Charles et al., 2018). Both increase the college-age population's incentives to go to college due to vanishing labor market opportunities. Third, this push for college is different across college-age children of homeowners and renters. This is justified by the positive and significant coefficient at the interaction term, $\Delta_{2006,t-1} \ln HPI \times$ Owner. In particular, children of homeowners are on average 0.09 p.p. less likely to be enrolled in college compared to renters in response to the same local housing price decline of 1 p.p. (see the preferred specification reported in column 6 in Table 2). For the children of renters, the probability of college enrollment goes up by 0.13 p.p. in response to 1 p.p. housing price decrease whereas for children of owners, the probability of college enrollment goes up only by 0.05 p.p. in response to the same shock (see column 5 of Table 2 in which we can identify the sensitivity of renters to HPI growth). This dampened response of homeowners could be explained by housing frictions (depreciated housing values causing an increase in housing leverage). Note that 82% of homeowners have a mortgage over the analyzed period.

The estimated effect is economically significant. To get a sense of its size, we compare demeaned housing price growth relative to 2006 in the most affected geographies (housing prices on average declined by 11.3% in PUMAs which fall in the first quintile of housing prices growth distribution) and the least affected geographies (which on average encoun-

Table 2. Baseline estimation results: Homeowners' and renter' sensitivity to the housing bust

	Dependent variable: $College_{i,p,t,y}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.038	0.041	0.040	0.085***	0.084***	0.088***
	(0.030)	(0.030)	(0.030)	(0.028)	(0.028)	(0.029)
$\Delta_{2006,t-1} \ln HPI$	-0.132***	-0.190***	-0.180***	-0.126***	-0.131***	
	(0.027)	(0.028)	(0.029)	(0.034)	(0.037)	
Owner	0.188***	0.124***	0.124***	0.156***	0.156***	0.157***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Demographic controls		✓	✓	✓	✓	✓
Birth year FEs			✓	✓	✓	✓
PUMA FEs				✓	✓	
Year FEs					✓	
PUMA × Year FEs						✓
N obs	104,294	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA× Year)	7,544	7,542	7,542	7,490	7,490	7,425
R^2 (*adj.*)	0.028	0.071	0.071	0.113	0.113	0.141

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

tered a rise of housing prices by 13.8% relative to 2006 and which fall into the fifth quintile of the housing price growth distribution). This difference in housing price growth, -0.25, translates into $-0.25 \times 0.09 = -0.0225$ lower probability of college attendance. Our estimation suggests that children of homeowners were 2.25 p.p. less likely to be enrolled to college relative to children of renters in the highest housing-prices-decline PUMA-years relative to lowest housing-prices-decline PUMA-years.

5.2 IV estimation: Housing supply elasticity and the severity of housing bust

In this section, we address the concern that changes in college enrollment decisions are driven by a factor that is correlated with changes in house prices and that affects homeowners and renters differently, such as heterogeneous changes in expectations and beliefs about the futures. For example, changes in house prices, to which homeowners are more attuned, may be interpreted as a signal about the future prospects of the economy. Suppose that as a result, homeowners now expect human capital investment to yield lower returns on education. Renters, on the other hand, are not affected by such negative expectations shock because they are paying less or no attention to changes in house prices. Alternatively, an inward shift in the supply of credit which decelerates house price growth (see Mian and Sufi, 2009) may have also tightened constraints on education loans, more so for homeowners. In such cases, our econometric specification will pick up what is a simple correlation between house price dynamics and college enrollment decisions, but we would interpret it as a causal effect. Our current identification strategy does not allow us to include PUMA $\times$ Owner $\times$ Year FEs to control for local time-varying shocks specific for owners and renters, because these FEs would absorb our variation of interest and we would no longer be able to identify the coefficient of interest at the interaction term $\Delta_{2006,t-1} \ln HPI \times$ Owner.

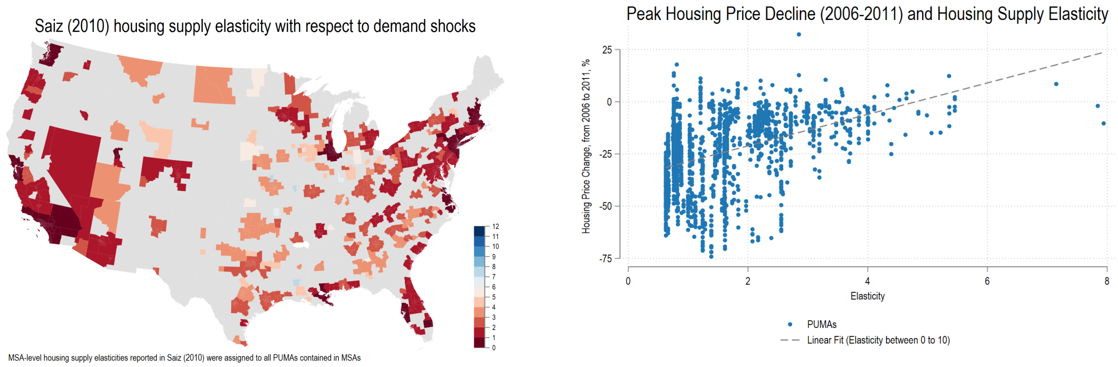
To overcome this limitation, we isolate the variation in the housing price decline which comes from *exogenously determined geographical reasons*. The idea is that if there is a U.S.-wide shock to the demand for housing, it will propagate differently into prices and quantities depending on the local geography. In areas in close proximity to water bodies and where the terrain is steeper and housing regulation more restrictive, the elasticity of the housing supply is lower, and so shocks to housing demand will mostly manifest themselves on the price margin. Conversely, in areas where land is flat and abundant and housing regulation is loose, the elasticity of the housing supply is higher, and so shocks to housing demand will primarily manifest themselves on the quantity margin, resulting in small house price movements.

As documented by Saiz (2010), there is a large geographical variation in housing supply elasticities across the U.S.: Figure 6, Panel A plots MSA-level Saiz (2010) housing supply elasticity projected on PUMAs on 2000 boundaries.[14] Areas with low housing supply elasticity (denoted in dark red) are subject to geographical restrictions to new construction such as uneven terrain, and proximity of oceans and other water bodies. These areas are

[14]Same elasticity was assigned to all metropolitan-type PUMAs constituting MSAs. We project MSA-level elasticity to metropolitan-type of PUMAs only. There are no corresponding MSAs to non-metropolitan PUMAs.

known to be prone to stronger housing price appreciation during the housing boom, Mian and Sufi (2011).

Because we are focused on the housing bust period, we need to check whether the housing supply elasticity also is a good predictor of the local severity of the housing bust. In Figure 6, Panel B, we show that less elastic areas are more likely to experience a stronger housing price decline, as the positively sloped linear fit line suggests.



(a) IV: Saiz (2010) Housing Supply Elasticity (b) Elasticity and the severity of the housing bust

Figure 6. Housing prices declined by more in inelastic areas

We next use the local housing supply elasticity as an instrument for local housing price changes, and then re-estimate the equation (1). The IV estimation is presented in columns (1) and (2) of Table 3. Column (1) demonstrates the estimates from the first stage of the 2SLS regression. The F-statistics demonstrates that local housing supply elasticities are a significant predictor of changes in local house prices. The value of the first-stage F-statistics is strictly higher than the critical value for the IV regression to have no more than 5% of the bias of the OLS estimate (see Stock and Yogo, 2005).

The point estimate from the second stage of the 2SLS estimation is reported in column (2). Under the instrumental variable strategy, our coefficient of interest reported in the first row of Table 3 is positive and significant at the 1-percent statistical level. In column (3), we also report a simple OLS estimate on the reduced sample dictated by the elasticity data availability (elasticity data is available at the MSA level and cover only metropolitan PUMAs which reduces the number of PUMAs from 2,057 to 1,612). We note that the point estimate from the IV-2SLS estimation is almost three times higher than that from the OLS estimation, suggesting the the endogeneity of house prices may have induced a downward bias in the estimation.

The evidence in Table 3 allows to confirm that owner-specific time-varying shocks do not drive our effect. Instead, we show that homeowners respond differently from renters to the housing bust when the housing price decline is driven by exogenously determined forces, such as geography and housing regulation.

Table 3. Instrumental variable estimation results: Saiz (2010) Housing Supply Elasticity as an instrument for the local HPI decline

Estimation:	IV-2SLS		OLS
Dependent variable:	HPI × (Owner)	College	College
	(1)	(2)	(3)
$\Delta_{2006,t-1} \ln HPI$ × Owner		0.193***	0.069**
		(0.052)	(0.031)
Elasticity × (Owner) × Year = 2008	0.023***		
	(0.002)		
Elasticity × (Owner) × Year = 2009	0.063***		
	(0.005)		
Elasticity × (Owner) × Year = 2010	0.082***		
	(0.006)		
Elasticity × (Owner) × Year = 2011	0.085***		
	(0.005)		
Demographic controls		✓	✓
Birth year FE		✓	✓
PUMA × Year FE		✓	✓
N obs	84,764	84,764	89,570
N clusters	6,063	6,063	6,468
R^2 (*adj.*)		0.059	0.137
First-stage F-stat	416.2		
Critical value at 5% (5% maximal IV relative bias)	19.86		

Note: *First-stage F-stat* is Kleibergen-Paap rk Wald F-statistic. *Critical value* is Stock-Yogo weak ID test critical value, the hypothesis that the maximum relative bias is at least 5%. Regression estimates are weighted using person probability weights provided in the ACS.
***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively.
Standard errors are clustered at the PUMA × Year level.

5.3 Dissecting the affected homeowners

In this section, we investigate if the dampening effect of homeownership on college attendance during the bust is concentrated among particular homeowners: whether homeowners with a mortgage or outright homeowners were more likely to reduce the education of their children in response to the housing bust and whether education is more sensitive to the housing bust in particular geographies, e.g., geographies experiencing the steepest housing price decline.

We start by splitting homeowners into two groups: outright homeowners and homeowners with a mortgage and re-estimate the accordingly modified version of the equation (1) in which as before, we compare the sensitivity of children's college enrollment to housing bust of groups of owners to renters who form the baseline category:

$$\begin{aligned} College_{i,p,t,b} = \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Outright\ Owner_{i,p,t,b} \\ + \beta_{\mathbf{2}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Mortgagor_{i,p,t,b} \\ + ... + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b} \end{aligned} \tag{2}$$

We employ the preferred econometric specification accounting for local time-varying shocks $\alpha_{p,t}$, PUMA-Year fixed effects. The estimation results of Equation (2) are reported in column (2) of Table 4. For comparison, in column (1) of Table 4, we report estimation results of the baseline specification in equation (1) with the same composition of fixed effects which was previously reported in column (6), Table 2.

Comparing columns (1) and (2) of Table 4, we conclude that homeowners with a mortgage drive the dampening effect of homeownership on college enrollment during the housing bust: the coefficient at the interaction term of $\Delta_{2006,t-1} \ln HPI_p \times Mortgagor_{i,p,t,b}$ is significant at 1% level, exactly as the main term $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ in column (1) is. This is intuitive given that the negative effect of the same housing price decline on mortgagors owning a house of a particular value is greater than on outright owners who own the same value house. This is because mortgagors are leveraged, their net housing equity (housing assets less outstanding debt) declines by more in response to the same housing price shock (Mian and Sufi, 2014a). The evidence presented provides additional support to the notion that house price declines suppress college enrollment by worsening households' financial position.

Next, we split geographies into those that experienced housing price change above and below the median and those experiencing housing price change falling in a particular quartile of its distribution and interact corresponding indicator variables with the homeownership status:

$$\begin{aligned} College_{i,p,t,b} &= \sum_{j=1}^{J} \theta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times Outright\ Owner_{i,p,t,b} \times 1_{\{Hetero_p=j\}} \\ &+ \sum_{j=1}^{J} \delta j \cdot \Delta_{2006,t-1} \ln HPI_p \times Mortgagor_{i,p,t,b} \times 1_{\{Hetero_p=j\}} \\ &+ \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b}, \end{aligned} \tag{3}$$

where $1_{\{Hetero_p=j\}}$ is a heterogeneity parameter: indicator variable taking value 1 if an individual resides in the geography p falling into category j.

In columns (3) and (4) of Table 4, we split all observations into those above and below median housing price growth. Estimation results suggest that children of all homeowners (outright and mortgagors) were less likely to be enrolled in college by 2.8 p.p. compared to renters in those localities that experienced housing price growth below the median compared to those localities that experienced housing price growth above the median. Again, this effect is driven by a 2.9 p.p. lower college attendance rate of children of homeowners with a mortgage compared to renters, as the negative and significant at 1 % level coefficient at the $1_{\{\Delta_{2006,t-1} \ln HPI \leq median\}}$ × Mortgagor in column (4) of Table 4 suggests.

Next, we further split all observations according to housing price growth quartiles and use the fourth quartile which pools the highest HPI growth observations as the baseline category. Estimation results are presented in Table A.III in the Appendix. It is again clear from the estimation results that the differences in college attendance between homeowners and renters are driven by mortgagors residing in localities falling into the lowers quartile of the housing price growth distribution – those experiencing the most severe shock. This is justified by the negative and the only significant coefficient at the interaction term $1_{\{\Delta_{2006,t-1} \ln HPI \in Q_1\}} \times$ Mortgagor in Table A.III in the Appendix.

Overall, we conclude that the education gap between homeowners and renters is driven by mortgagors experiencing highest housing wealth losses because they live in geographies facing the strongest housing price decline.

Table 4. Owner type and geographical variation of the dampening effect of homeownership on college attendance

	Dependent variable: $College_{i,p,t,y}$			
Housing price variable:	$\Delta_{2006,t-1} \ln HPI$		$1_{\{\Delta_{2006,t-1} \ln HPI \leq median\}}$	
	(1)	(2)	(3)	(4)
Housing price × Owner	0.088***		-0.028***	
	(0.029)		(0.010)	
Housing price × Outright owner		0.074*		-0.022
		(0.043)		(0.014)
Housing price × Mortgagor		0.089***		-0.029***
		(0.030)		(0.010)
Demographic controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
PUMA × Year FE	✓	✓	✓	✓
N obs	103,837	103,837	103,837	103,837
N clusters (PUMA× Year)	7,425	7,425	7,425	7,425
R^2 *(adj.)*	0.141	0.141	0.141	0.141

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

6 Did labor market opportunities collapse by more for renters compared to homeowners?

We have shown that children of homeowners are less responsive to the housing bust compared to children of renters: they are less likely to be enrolled in college relative to renters in response to the same local housing price decline. We interpret these differences as a housing wealth effect: homeowners suffer from housing net worth losses whereas renters do not.

In this section we rule out an alternative explanation of observed differences in college responses: that labor market opportunities change for renters and owners differently due to e,g, differences in the structure of occupations homeowners and renters take. Such differences in labor market opportunities could arise if, for example, children of renters are more likely to take low-skilled jobs while children of owners are more likely to chase after medium- and high-skilled jobs (a reasonable assumption given the gap in college enrollment of about 16 p.p., see Table 2). If under these conditions, a collapse in low-skilled jobs was stronger in the areas of more pronounced housing price decline (jobs in the non-tradable sector, Mian and Sufi, 2014b; jobs in the construction sector, Charles et al., 2018), then the lower increase in the probability of going to college for children of owners to local house price declines could be due to the stronger labor market effect influencing renters more that owners.

To rule out this alternative explanation of differences in college enrollment responses among individuals aged 18 and 19 whose parents are homeowners and renters, we relate changes in employment probabilities of *non-college* children, which measures an opportunity cost of college, to local housing price change:

$$\begin{aligned} Employment_{i,p,t,b} | College = 0 = \\ & \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \\ & + \beta_2 \cdot \Delta_{2006,t-1} \ln HPI_p + \beta_3 \cdot Owner_{i,p,t,b} \\ & + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + + \varepsilon_{i,p,t,b} \end{aligned} \tag{4}$$

The estimation of equation (4) is presented in Table 5, column (6). As previously, we also report coefficient estimates once we gradually saturate the model with controls and fixed effects: columns (1-5), Table 5. The coefficient estimate at the interaction term $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ is insignificant in the preferred specification as well as in all other specifications except for being positive and weakly significant in the specification without any controls or fixed effects.[15] Based on these estimations, we conclude that

[15] If we would trust this specification, then from the observation that in column (1) of Table 5, the coefficient is positive and significant at 10% level, we would conclude that the employment of children of homeowners is *more*, not *less* sensitive to the housing bust: the employment opportunities of non-college

employment opportunities of homeowners and renters were equally sensitive to the housing bust. We rule out the alternative explanation that the differential response of children of homeowners and renters to the housing bust is driven by different changes in employment opportunities across homeowners and renters.

Overall, the estimated employment response of homeowners and renters to the housing bust is consistent with the explanation that during the housing bust, renters went to college more intensively compared to homeowners because homeowners lost housing wealth and were stuck in devalued houses, not because renters' job market opportunities collapsed by more.

Table 5. Employment of non-college children of homeowners and renters and the housing bust

	Dependent variable: $Employment \vert College = 0$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.070*	0.048	0.046	0.047	0.041	0.059
	(0.038)	(0.038)	(0.038)	(0.036)	(0.036)	(0.038)
Demographic controls		✓	✓	✓	✓	✓
Birth year FEs			✓	✓	✓	✓
PUMA FEs				✓	✓	
Year FEs					✓	
PUMA × Year FEs						✓
N obs	59,847	59,698	59,698	59,645	59,645	59,393
N clusters (PUMA× Year)	7,442	7,440	7,440	7,387	7,387	7,135
R^2 *(adj.)*	0.029	0.083	0.084	0.110	0.111	0.155

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

7 Robustness

Alternative measures of the housing shock. In the baseline estimation presented in Table 2, we use local housing price change relative to the peak of the housing boom as a measure of the local severity of the housing bust. To assess the robustness of our baseline estimates, we use instead: (i) Mian et al. (2013)'s housing net worth change

children of homeowners if anything were destructed *by more* compared to children of renters in response to the same housing price decline. This is inconsistent with the employment explanation of differences in college enrollment responses and favors housing wealth explanation of those differences.

relative to 2006 measuring local housing wealth destruction and (ii) log change in the foreclosure rate, relative to 2006 measuring property losses during the bust. Details on data construction on PUMA-level Mian et al. (2013)'s housing net worth change and foreclosure rate are provided in Appendix A.4. The significant differences in education responses between homeowners and renters preserve if we use alternative measures of housing shock. This is evident when comparing coefficient estimates presented in column (1) of Table 6 to those in columns (2) and (3). Note that column (1) of Table 6 presents the estimation of our preferred specification reported earlier in column (6) of Table 2. In case we use alternative measures of the housing shock, homeowners college enrollment is still significantly less sensitive compared to that of renters to the shock. In particular, we observe a positive and significant coefficient at the interaction term $\Delta_{2006,t-1} \ln HNW \times$ Owner which suggests that college enrollment of children of homeowners is less sensitive in absolute value relative to renters to 1 p.p. decline in housing net worth. Similar evidence is observed in case a change of foreclosure rate is considered. In areas with larger increase in foreclosure rate, college enrollment of children of homeowners increase by less compared to renters as suggested by negative and significant coefficient at the interaction term $\Delta_{2006,t-1} \ln ForeclosureRate \times$ Owner reported in column (3) of Table 6.

Homeownership status change. Next, we explore the robustness of our baseline estimates to eliminating the population changing their homeownership status during the housing bust from our sample. For that, we restrict our sample to those households that live in the same housing units for at least 5 years as measured by the $MOVEDIN$ variable provided in the ACS. This way, we fix the composition of homeowners as they are in at least 2006, before the housing bust start. Applying this restriction leads to the sample reduction from 104,000 individuals to less than 80,000. The estimation results are presented in column (4) of Table 6, compared to column (1) of the same Table containing our baseline estimates. The coefficient estimate of interest at the interaction term $\Delta_{2006,t-1} \ln HPI \times$ Owner preserves its sign and significance and even becomes larger in magnitude suggesting that owners who moved into their houses of residence long ago are more likely to be stuck in their property and less likely to invest into human capital of their children relative to renters once the local housing prices decline.

Table 6. Robustness of the main result to alternative measures of the housing shock and changes in homeownership status

	Dependent variable: $College_{i,p,t,y}$			
	(1)	(2)	(3)	MOVEDIN $\geq$ 5
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.088***			0.127***
	(0.029)			(0.043)
$\Delta_{2006,t-1} \ln HNW \times$ Owner		0.064***		
		(0.024)		
$\Delta_{2006,t-1} \ln ForeclosureRate \times$ Owner			-0.002***	
			(0.001)	
Demographic controls	✓	✓	✓	✓
Birth year FEs	✓	✓	✓	✓
PUMA × Year FEs	✓	✓	✓	✓
N obs	103,837	84,213	94,299	78,629
N clusters (PUMA× Year)	7,425	5,982	6,757	7,323
R^2 (*adj.*)	0.141	0.143	0.142	0.139

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

8 Aggregate effect of homeownership and the housing bust on college enrollment

To estimate how many 18- and 19- years old did not go to college because of the housing frictions, we perform the following back-of-the-envelope calculation. We multiply the size of the local housing bust by the local homeownership rate and by previously estimated coefficient governing differences in response to the housing bust between owners and renters (0.09; see first row, Table 2). At every PUMA, the estimated economic effect of housing frictions on college enrollment reads as follows:

$$\%\ not\ going\ to\ college_p = 100 \times \Delta_{2006,t-1} \ln HPI_p \times 0.09 \times \frac{Homeowners\ (Age = 18, 19\ )\ _p}{Total\ (Age = 18, 19\ )\ _p}$$

The geographical distribution of college attendance losses is presented in Figure 7. Up to 2% of the local college-age population, or 11,500 students in 2010-2011 did not pursue college enrollment at the height of the bust due housing frictions. The most affected areas lie within such states as Florida, Arizona, Nevada, California, and Michigan. The geographical distribution of the estimated effect is driven by two factors: the severity of the housing bust and the local homeownership rate. In particular, the highest losses in terms of college attendance are concentrated in areas with both high homeownership rate and steep decline in housing prices (see Figure 8).

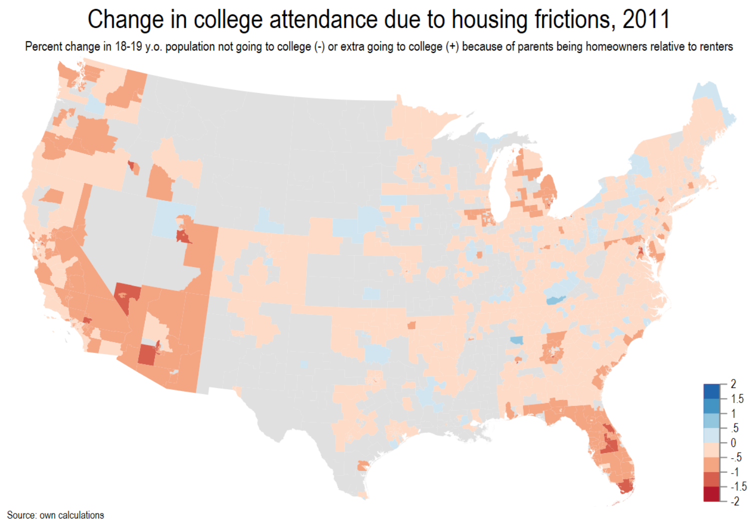
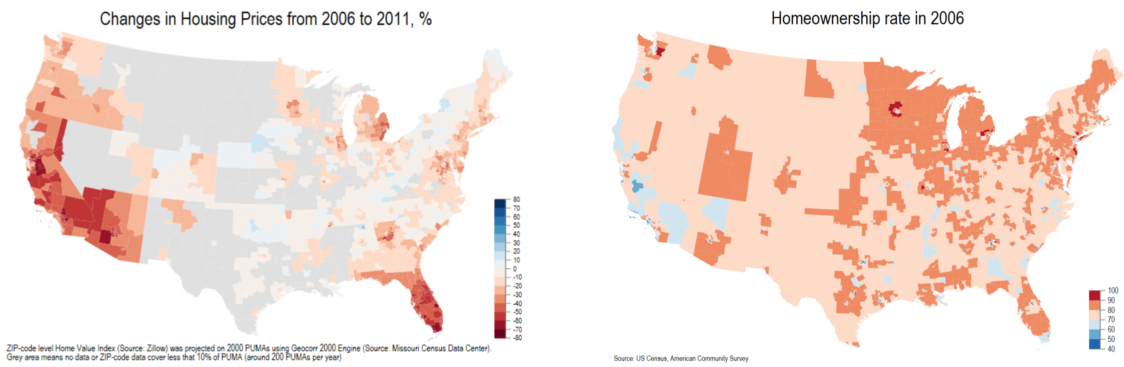


Figure 7. The Geographical Distribution of the Estimated Economic Effect of Housing Frictions on College Attendance

Note: Gray areas denote no data.



(a) Housing price decline

(b) Homeownership rate

Figure 8. Drivers of the Economic Effect of Housing Frictions on College Attendance: Housing Bust and Homeownership rate

Note: Gray areas denote no data.

9 Longer-term effect of the housing bust

Are the effect we document limited to the housing bust period, or do they persist in the longer run? For example, Jones et al. (2022) argue that areas with a bigger decline in house prices exited the recession more slowly, and Figure 3 shows that the decline in college enrollment after 2010 is not temporary. It is therefore possible that the increase in household leverage during the bust may have had a persistent effect on local outcomes, such as college attainment rates, employment level, and household income.

We now take this question to the data by comparing, during the post-bust period, homeowners and renters living in PUMAs with different severity of the housing bust in 2006-2011 measured by the local housing price decline. Our econometric model is as follows:

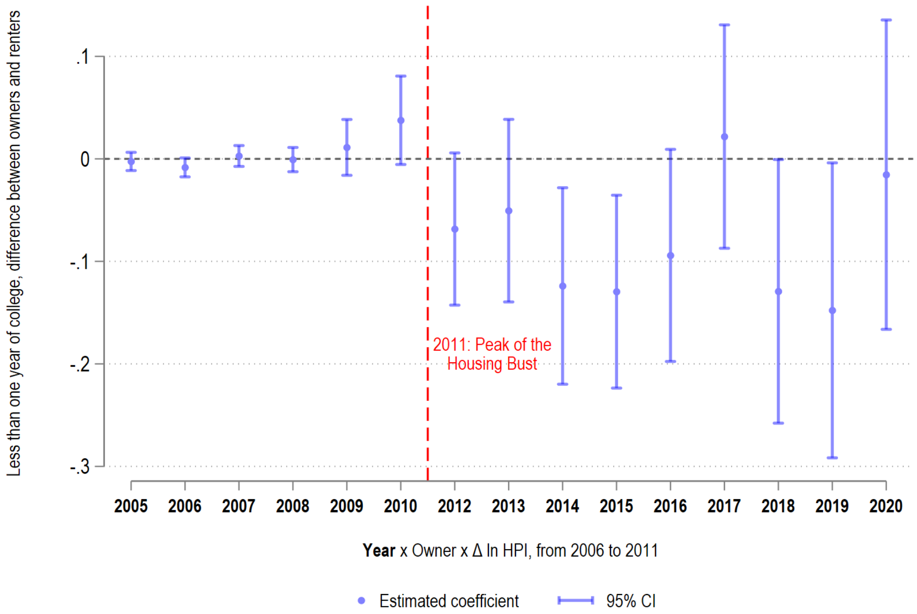
$$\begin{aligned} Y_{i,p,t,b} = & \sum_{k \neq 2011} \beta_k \cdot \mathbf{1}_{\{k=t\}} \cdot \Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b} \\ & + ... + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b} \end{aligned} \tag{5}$$

We interact year indicator variables $\mathbf{1}_{\{k=t\}}$ with the term of interest $\Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b}$ which allows us to trace the differences in outcome variables between homeowners and renters in time. We focus on the 2005-2020 period, and we look at those aged 18-19 during the trough of the housing cycle, 2010-2011 which yields birth cohorts of 1991-1993. As we have done so far, we control for an individual's demographic characteristics captured by $\mathbf{X}$, for the individual's cohort effect captured by birth-year FEs α_b, and for local time-varying shocks proxied by $\alpha_{p,t}$. The index p denotes consistent PUMAs. In this regression exercise, we cannot use PUMAs defined on 2000 boundaries as a unit of geography because starting in 2012, the ACS reports data in which individuals are attached to PUMAs on 2010 boundaries, and there is no one-to-one mapping between PUMA 2000 and PUMA 2010. To overcome this, we use consistent PUMAs 00-10 which did not change across the 2000s-2010s. This leaves us with 1,078 consistent PUMAs and we project PUMA 2000 housing price growth on consistent PUMAs 00-10 using PUMA

2000 - consistent PUMAs 00-10 crosswalk provided by the IPUMS.[16]

9.1 College attainment

We first run equation (5) with educational attainment as the dependent variable. Our estimation results suggest that there are persistent losses in college attainment as measured by having some college attainment: less than one year of college. Homeowners who were 18-19 years old in 2010-2011 were 0.13-0.15 p.p. less likely to have one year of college attainment compared to renters if they lived in PUMAs with a 1 p.p. stronger housing price decline (see Figure 9).

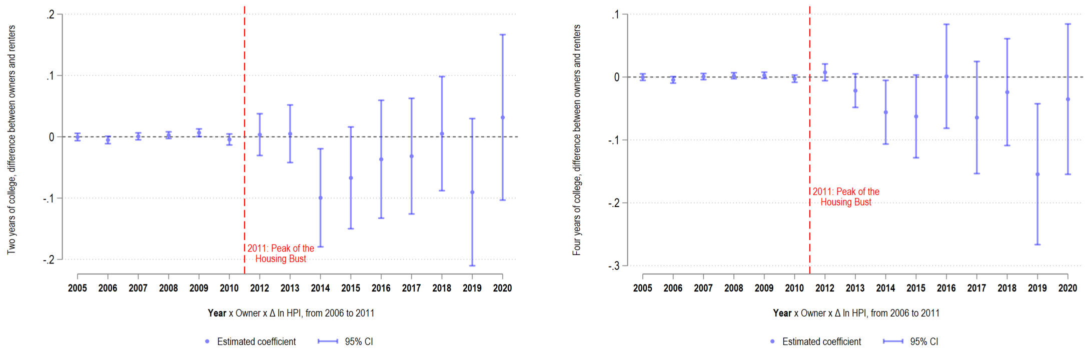


Note: The picture presents differences in college attainment probability between homeowners and renters in response to a 1 p.p. housing price decline in 2006-2011.

Figure 9. Housing bust and college attainment: some college, less than 1 year

The losses are short-lived in two-year college attainment and more persistent in four-year college attainment (see Figure 10).

[16] https://usa.ipums.org/usa/volii/cpuma0010.shtml



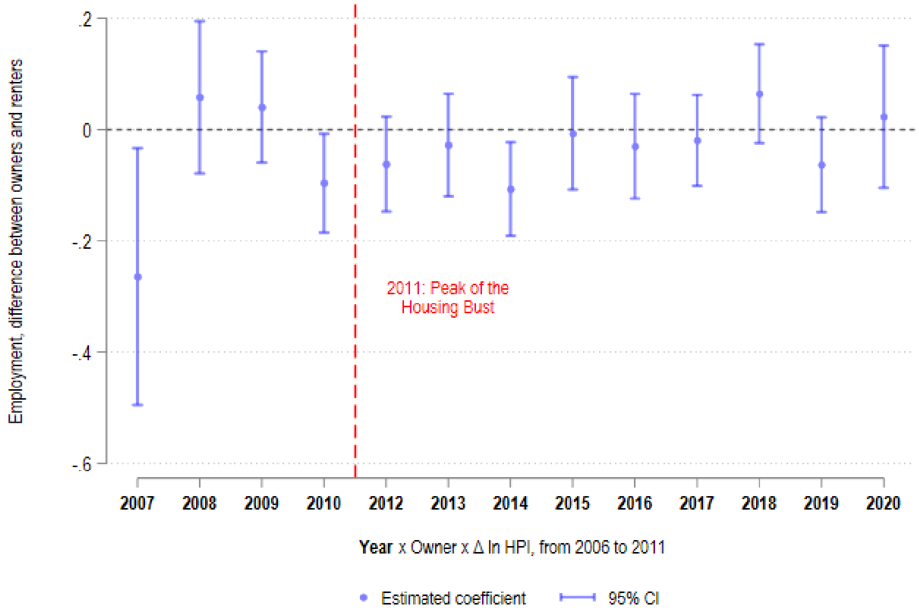
(a) Two-years of college (b) Four-years of college

Note: The picture presents differences in two-year and four-year college attainment probability between homeowners and renters in response to a 1 p.p. housing price decline in 2006-2011.

Figure 10. Housing bust and two- and four-year college attainment

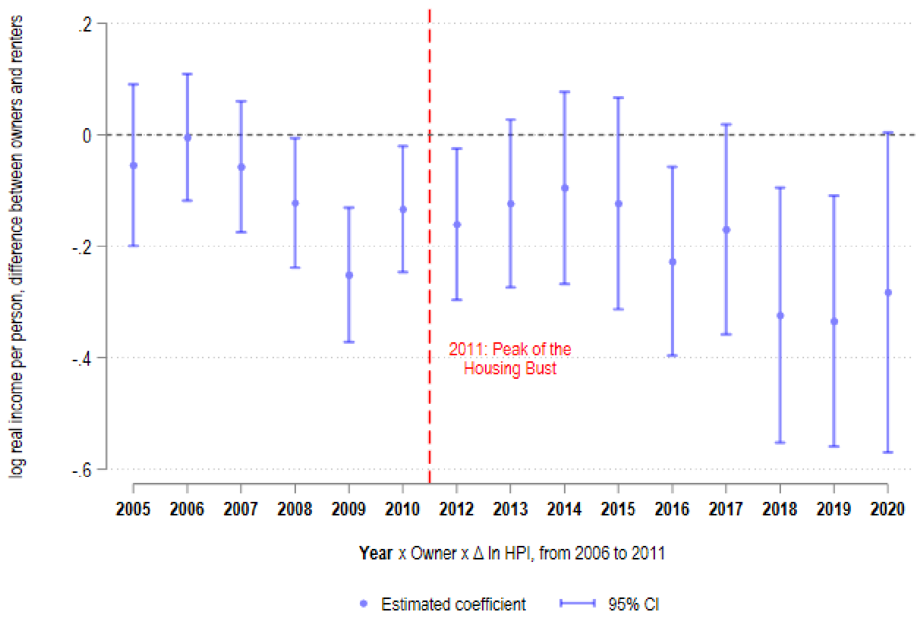
9.2 Employment and income

Next, we run equation (5) with employment and real per-capita income as the dependent variable. There are no persistent employment differences between homeowners and renters in localities more affected by the housing bust (see Figure 11). However, there are long-lived differences in per capita real family incomes between homeowners and renters in more affected localities (see Figure 12): 7-8 years after the housing bust, family incomes of homeowners are 0.35 p.p. lower for every 1 p.p. housing price decline over 2006-2011. This corresponds to a vanished college premium for the affected homeowners. Even though homeowners sustain their employment rate at a rate no lower than that of renters, their average income falls behind in areas more affected by the housing bust because homeowners were less likely to get a college education.



Note: The picture presents differences in employment probability between homeowners and renters in response to a 1 p.p. housing price decline in 2006-2011.

Figure 11. Housing bust and the likelihood of employment



Note: The picture presents differences in real household income per capita between homeowners and renters in response to a 1 p.p. housing price decline in 2006-2011

Figure 12. Housing bust and real income

10 Conclusion

The returns to investment in human capital are high both individually and socially: the college premium in lifetime income is substantial, and a more educated workforce is associated with a more productive economy. However, the cost of college in the U.S. has been rising in recent decades, pointing to the central role that credit constraints play in college enrollment. In this paper, we study whether financial frictions stemming from housing market dynamics play a meaningful role in shaping education choices. In asking this question, we are motivated by the empirical observation that after rising for decades, college enrollment in the U.S. has been declining ever since the housing bust of the late 2000s.

Using individual-level data from the ACS, we show that the children of homeowners are less likely to be enrolled in college, compared to children of renters, in areas that experienced a relatively steeper house price collapse during the period 2008-2011. Losses in educational attainment are concentrated in the South-West and South-East of the U.S. with up to 2% of the local college-age population affected. This corresponds to approximately 11,500 potential college students in the years of the trough of the housing cycle. The education losses persist for at least a decade and translate into decreased local household income of homeowners compared to renters. Our paper sheds new light on the socioeconomic effects of housing booms and busts and illuminates a potential trade-off between investment in real assets - housing, and investment into human capital - college education. Our results suggest that government policies aimed at reducing the cost of college should not be uniform, but they should also take into account local housing price dynamics.

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A Appendix

A.1 Individual characteristics and college attendance

Table A.I. Main model: College attendance sensitivity to demographic and family-level control variables

	Dependent variable: $College_{i,p,t,y}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.041	0.040	0.085***	0.084***	0.088***
	(0.030)	(0.030)	(0.028)	(0.028)	(0.029)
$\Delta_{2006,t-1} \ln HPI$	-0.190***	-0.180***	-0.126***	-0.131***	
	(0.028)	(0.029)	(0.034)	(0.037)	
Owner	0.124***	0.124***	0.156***	0.156***	0.157***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PUMA Unemployment rate, age 16-54	-0.364***	-0.487***	0.028	0.059	-0.179
	(0.073)	(0.081)	(0.119)	(0.142)	(0.588)
Female	0.111***	0.111***	0.109***	0.109***	0.106***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
White	0.005	0.004	0.013*	0.012*	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Black	0.002	0.005	-0.009	-0.010	-0.011
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Asian	0.199***	0.199***	0.143***	0.143***	0.144***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Hispanic	-0.005	-0.004	-0.041***	-0.041***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log (Real Family Income per person)	0.087***	0.087***	0.071***	0.071***	0.072***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of Siblings	0.005***	0.005***	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Birth year FEs		Yes	Yes	Yes	Yes
PUMA FEs			Yes	Yes	
Year FEs				Yes	
PUMA × Year FEs					Yes
N obs	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA× Year)	7,542	7,542	7,490	7,490	7,425
R^2 (*adj.*)	0.071	0.071	0.113	0.113	0.141

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

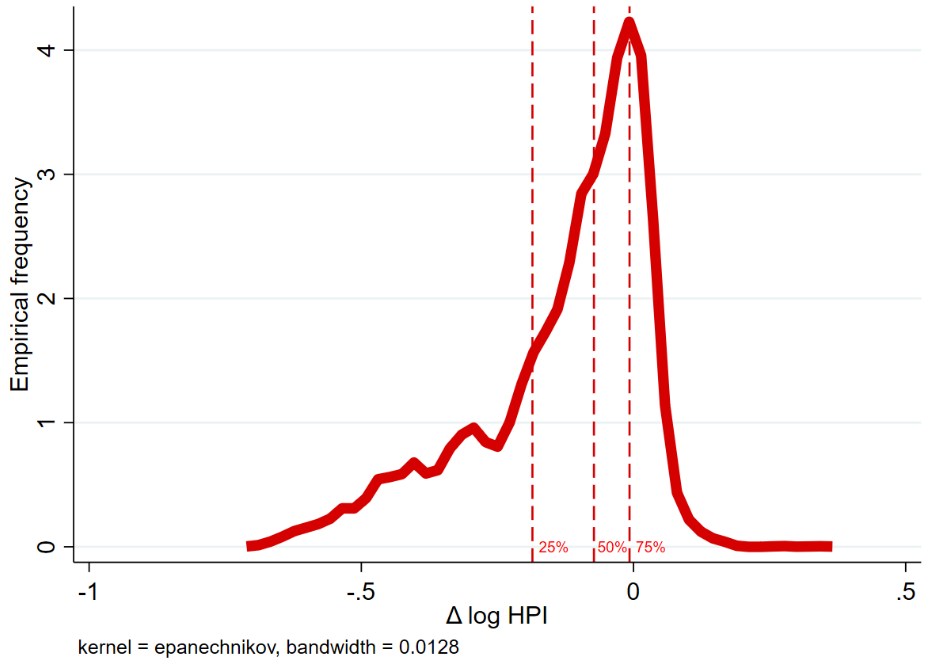
A.2 Accounting for homeowner-specific shocks

Table A.II. Extended main model: Homeowners' and renter' sensitivity to the housing bust with homeownership fixed effects

	Dependent variable: $College_{i,p,t,y}$		
	(1)	(2)	(3)
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.088***	0.109**	0.070**
	(0.029)	(0.045)	(0.033)
Owner	0.157***		
	(0.007)		
Demographic controls	Yes	Yes	Yes
Birth year FEs	Yes	Yes	Yes
PUMA × Year FEs	Yes	Yes	Yes
PUMA × Owner FEs		Yes	
Owner × Year FEs			Yes
N obs	103,837	103,814	103,837
N clusters (PUMA× Year)	7,425	7,422	7,425
R^2 (*adj.*)	0.141	0.139	0.141

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

A.3 Dissecting the affected homeowners: additional estimates



Note: This figure reports the density of housing price change relative to the housing cycle peak, 2006. Vertical dashed lines show borders of HPI growth quartiles.

Figure A.I. Empirical density of the Housing price growth in 2008-2011 relative to 2006

Table A.III. Owner type and geographical variation of the dampening effect of homeownership on college attendance

	Dependent variable: $College_{i,p,t,y}$		
Housing price variable:	$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_j\}}$		
	(1)	(2)	(3)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{25}\}}$ × Outright owner	-0.026	-0.029	-0.028
	(0.020)	(0.019)	(0.019)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{25}\}}$ × Mortgagor	-0.029**	-0.035**	-0.031**
	(0.014)	(0.014)	(0.014)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{50}\}}$ × Outright owner	0.001	-0.005	-0.013
	(0.021)	(0.021)	(0.020)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{50}\}}$ × Mortgagor	-0.002	-0.019	-0.024
	(0.016)	(0.016)	(0.015)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{75}\}}$ × Outright owner	0.012	-0.003	-0.008
	(0.021)	(0.020)	(0.020)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{75}\}}$ × Mortgagor	0.013	-0.003	-0.008
	(0.016)	(0.016)	(0.016)
Birth year FE		✓	✓
PUMA × Year FE		✓	✓
Demographic controls			✓
N obs	104,294	104,177	103,837
N clusters (PUMA×Year)	7,544	7,427	7,425
R^2 (*adj.*)	0.029	0.112	0.141

Note: Regression estimates are weighted using person probability weights provided in the ACS. ***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

A.4 Details on the housing net worth and foreclosure rate data construction

A.4.1 Mian et al. (2013)'s housing net worth

We follow Mian et al. (2013) and calculate PUMA-level housing net worth change relative to 2006, $\Delta_{2006,t} \ln HNW_p$ as follows:

$$\Delta_{2006,t} \ln HNW_p = \frac{\Delta_{2006,t} HPI_p \cdot H_{2006,p}}{HNW_{2006,p}},$$

where $H_{2006,p}$ is 2006 housing stock value.

We estimate 2006 housing stock value, $H_{2006,p}$ as the product of median housing value and the number of homeowners in 2006. To calculate median housing value in 2006, we take PUMA median housing value reported in 2000 decennial census data and multiply it by PUMA-level housing price growth over 2000-2006 estimated using Zillow ZIP code-level housing price data and ZIP code to PUMA crosswalk provided by the Missouri Census Data Center. We estimate the number of homeowners in PUMAs in 2006 by multiplying PUMA population in 2006 and PUMA homeownership rate in 2006. We estimate PUMA homeownership rate directly using the ACS household heads sample. To estimate PUMA population in 2006, we project PUMA population growth known from 2000 and 2010 decennial census data to 2006 assuming constant annual population growth.

We estimate PUMA-level housing net worth in 2006, $HNW_{2006,p}$ as the difference between housing assets in 2006 and housing debt in 2006. Housing assets in 2006 are equal to the value of the housing stock in 2006, $H_{2006,p}$ described above. We estimate PUMA-level housing debt similar to Mian et al. (2013). We use CoreLogic Loan-Level Market Analytics (LLMA) data to estimate PUMA structure of the housing debt. CoreLogic LLMA data is known to be representative of the overall sample of mortgage loans in the U.S., this data cover around 60% of the first liens originated, DeFusco and Mondragon (2020). We use current unpaid principal balance as of December 2006 and we exclude paid off, sold, and unknown status loans. We aggregate loan balances to ZIP code level. Next, we aggregate ZIP code level mortgage debt data to PUMAs using Missouri Census Data

Center crosswalk. We calculate PUMA-level structure of the total outstanding mortgage debt and allocate aggregate St.Louis FRED data[17] to PUMAs proportionally.

Overall, we use the same data and same assumptions as Mian et al. (2013) to estimate key components of $\Delta_{2006,t} \ln HNW_p$. The only difference is the housing debt, a component of housing net worth in 2006: Mian et al. (2013) use ZIP code Equifax household borrowing as an input while we use CoreLogic LLMA ZIP code outstanding mortgage debt. Both them and we use household debt estimates to distribute aggregate household debt to geographies: they use counties as the level of analysis, we use PUMAs. As long as we use same data for aggregate number, and our datasets agree on geographical distribution of mortgage debt, our estimates reproduce their analysis on the different level of aggregation.

A.4.2 Foreclosure rate

We calculate PUMA-level foreclosure rate using CoreLogic LLMA data. We use information on current unpaid principal balance as of December of each year in 2006-2011, loan delinquency status, and ZIP code of loan origination. We drop real estate owned (REO)[18] sold, and unknown status loans. We allocate all loans to corresponding PUMAs using Missouri Census Data Center ZIP code to PUMA crosswalk. We then estimate PUMA-level foreclosure rate as the proportion of loan balances in foreclosure status to the total loan balance. The total loan balance includes all delinquent loans, performing loans (delinquency status = current), and loans in foreclosure.

A.5 Foreclosure rule, foreclosure rate, and college enrollment

In this section, we are interested whether the intensity of local foreclosures dampen or exacerbate the homeownership effect on education and whether foreclosure rate is affected by state foreclosure rule.

For that, we instrument local change in foreclosure rate by the type of state foreclosure law provided in Mian et al. (2015): judicial or nonjudicial foreclosure law. We then interact

[17] Home mortgage liabilities, Household sector. https://fred.stlouisfed.org/release/tables?rid=52&eid=808266&od=2006-01-01#.

[18] Mian et al. (2015) also exclude REOs from foreclosure data.

our key term of interest $\Delta_{2006,t-1} \ln HPI \times$ Owner with changes in foreclosure rate driven by differences in the foreclosure law. This yields two-stage estimation results.

First, note that there is a substantial geographical variation in changes in foreclosure rate (Figure A.II), and the presence of the nonjudicial foreclosure law significantly increases local foreclosure rate under the same housing price decline (see suggestive evidence on Figure A.III; judicial foreclosure law is associated with a smaller increase in foreclosure rate, column 3, Table A.IV).

Second, the estimation results suggest that increased intensity of foreclosures *decrease* dampening effect of homeownership on education. This is evident from the negative and significant coefficient at the triple interaction term $\Delta_{2006,t-1} \ln HPI \times$ Owner $\times$ $\Delta_{2006,t-1} \ln Fcsr$ independently of whether we use $\Delta_{2006,t-1} \ln Fcsr$ as it is or instrument it with foreclosure law (columns 2 and 4 of Table A.IV). This suggests that a greater foreclosure rate reduces the dampening effect of homeownership on education as some homeowners may more easily walk away from underwater property, and discard mortgage debt. This may enable them to move geographically to better opportunities and / or to take student loan facilitating educational attainment.

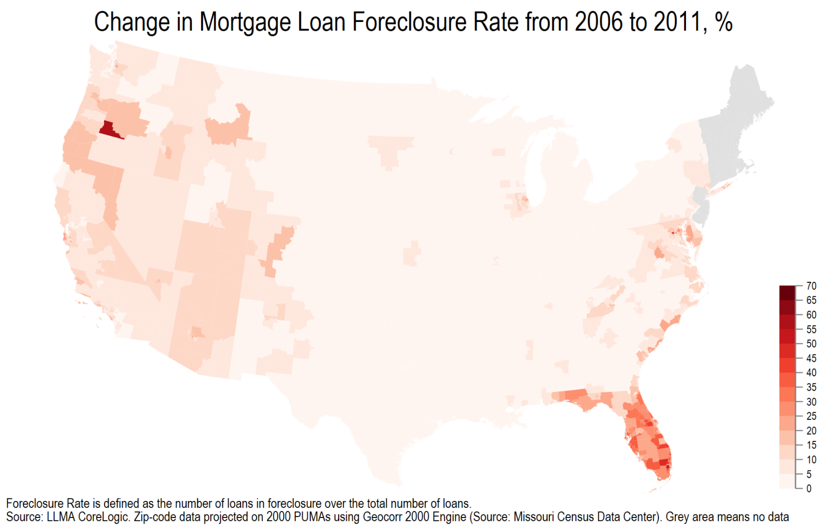
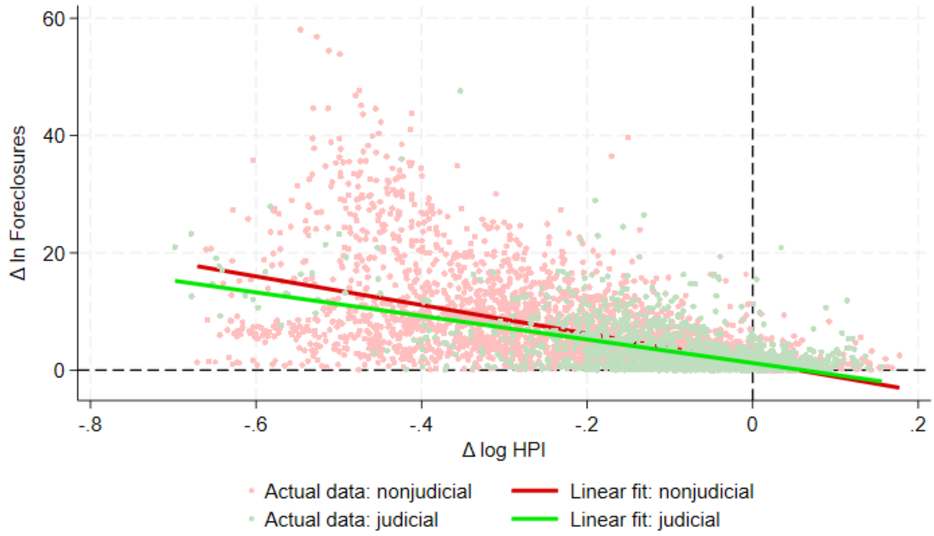


Figure A.II. Surge in foreclosures across PUMAs



Note: This figure reports changes in foreclosure rate depending on the judicial status of the foreclosure procedure. The pairwise correlation between HPI and local foreclosure rate change is -0.65

Figure A.III. Housing price decline and increase in foreclosure rate across PUMAs

Table A.IV. Homeowners and renters sensitivity to the housing bust and the rise of foreclosures

Dependent variable:	$College_{i,p,t,y}$		$\Delta_{2006,t-1} \ln Fcsr$	$College_{i,p,t,y}$
X:	Judicial	$\Delta_{2006,t-1} \ln Fcsr$		$\Delta_{2006,t-1} \ln \widehat{Fcsr}$
	(1)	(2)	(3)	(4)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.094***	0.120***		0.232**
	(0.033)	(0.043)		(0.108)
$\Delta_{2006,t-1} \ln HPI$ × Owner × **X**	0.106	-0.011**		-0.014*
	(0.090)	(0.005)		(0.008)
Judicial			-0.504***	
			(0.094)	
$\Delta_{2006,t-1} \ln HPI$			-24.198***	
			(0.760)	
Demographic controls	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
PUMA × Year FE	✓	✓		✓
N obs	90,749	82,231	82,413	90,749
N clusters (PUMA× Year)	7,395	6,727	6,869	7,395
R^2 (*adj.*)	0.145	0.146	0.463	0.145

Note: Regression estimates are weighted using person probability weights provided in the ACS. *Outright owners* have been dropped from regressions, because foreclosures do not apply in their case.
***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively.
Standard errors are clustered at the PUMA × Year level.