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Back to school when times are bad? The role of housing wealth

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Abstract

College enrolment 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 negative shocks to housing wealth significantly reduced college enrolment among homeowners relative to renters during this period. Up to 2% of the local college-age population did not pursue college enrolment at the height of the bust due to housing wealth destruction. The negative impact of homeownership on college education persists for a decade, contributing to persistently lower incomes among homeowners in the most affected areas.

JEL: I24, E32, J24

Keywords: Homeownership, Housing Wealth, College enrolment, Housing Boom-Bust Episodes.

Non-technical summary

For decades, college attendance in the U.S. kept increasing, reaching an all-time high in 2006 when 64% of those graduating from high school enroled in college. However, this trend was arrested in the wake of the housing bust of the late 2000s, with college enrolment stagnating and even declining. We hypothesis that the destruction of housing wealth during the bust played a role to play in the reversal of college attendance.

In theory, a decline in house prices can affect college attendance via two channels. The first one is the opportunity cost channel, whereby when the economy is in a recession and housing markets are in decline, college becomes relatively more attractive. The second one is related to changes in housing wealth whereby during a housing bust, home equity declines sharply, raising the effective cost of sending one's children to college. And while the former channel affects everyone, the latter affects homeowners but not renters. This makes it possible to identify the effect of the housing-leverage channel of fluctuations in house prices on college enrolment.

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 college enrolment 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 in areas that experienced a relatively larger decline in house prices were significantly less likely to be enroled in a higher education institution, as opposed to homeowners who experienced more modest declines in house prices. This effect is concentrated among homeowners with a mortgage, rather than among outright homeowners, strengthening the notion of the importance of credit constraints in determining college choice. Moreover, the effect is stronger when the parents themselves did not go to college, suggesting that family education history can affect the elasticity of the likelihood of college enrolment to housing shocks.

We also find that the housing leverage effect on college enrolment is meaningful in the aggregate: at the height of the housing bust, up to 2% of the local college-age population

did not enrol in college due to housing frictions. Importantly, it is observed long after the bust episode, and it translates into persistently lower income levels and lower likelihoods of working in an education-intensive industry for homeowners. This finding is consistent with other work that has recently documented long-lasting effects of the Great Recession.

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 enrolment. Our results shed new light on the long-lived adverse socioeconomic effects of housing busts and illuminates a potential trade-off between investment in real assets (housing) and investment in human capital (college education). Our evidence suggests that government policies aimed at reducing the cost of college should not be uniform, but should also take into account local housing price dynamics.

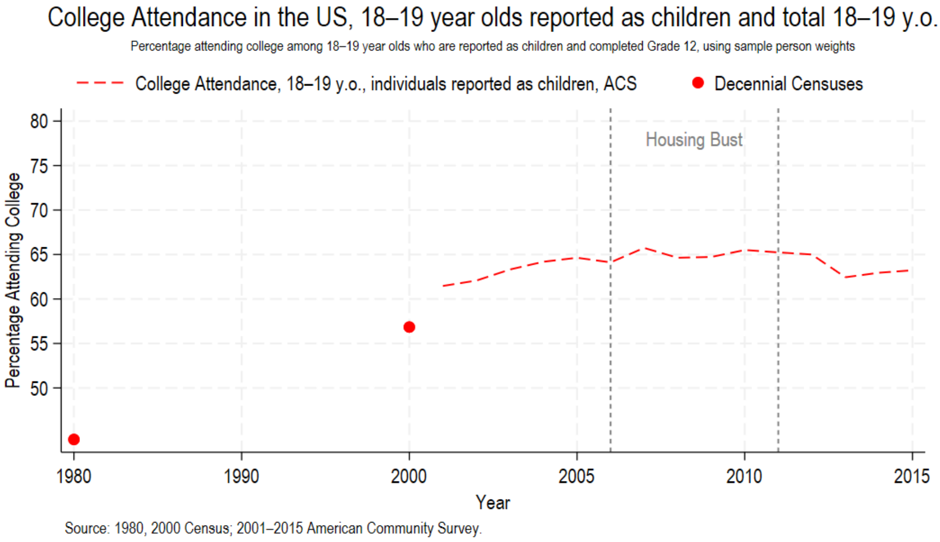
1 Introduction

Do housing busts have long-term economic consequences? We go to the heart of this question by studying the implications of the 2008-2011 U.S. housing boom on college enrolment. This question is important because 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. There is no reason to expect that the effect is not symmetric and therefore adverse shocks to home equity could significantly negatively affect college enrolment through a reduction in the housing wealth of families with college-age children. However, the empirical literature has not yet provided conclusive evidence to that end.

Figure 1 illustrates a significant slowdown in college attendance since the end of the housing boom. The percentage of 18- and 19-years-olds attending college increased between 1980 and 2006, from 44% to 64%. However, in the following decade this increase was not only arrested, but college attendance by that group even declined, to 63% in 2015. Figure 2 further emphasizes the important role that the homeownership status of college-age individuals' parents played in this development. While college attendance by homeowners' children increased by more than that of renters' children during the housing boom of the early-to-mid 2000s, attendance by renters' children continued increasing after 2006, while that of homeowners' children stagnated.

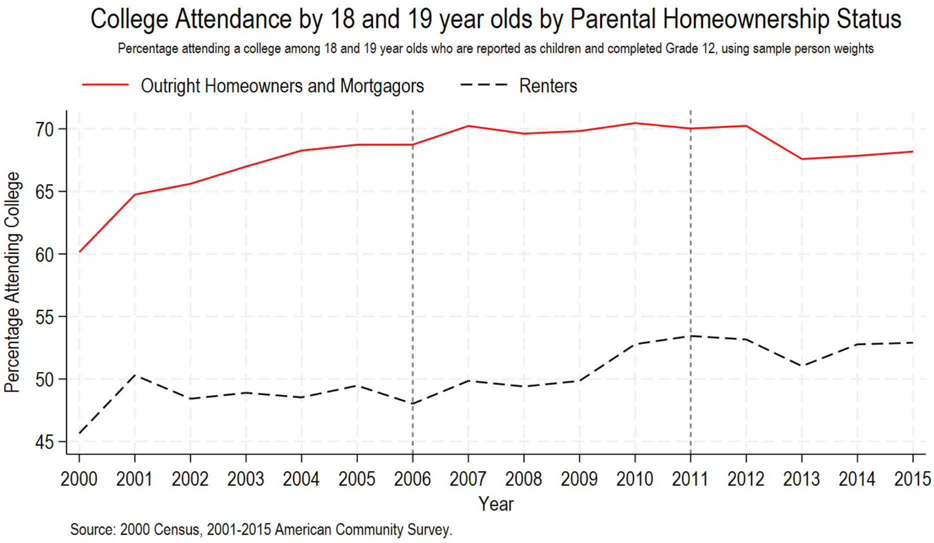
To explain this phenomenon, we study whether decreased affordability of college be-

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



Note: This figure reports college attendance in the past three months for 18-19 year old individuals who are reported in the ACS data as children, $RELATE = 3$. We restrict the sample to include individuals with at least Grade 12, $EDUC \geq 06$. We define recent college attendance as $GRADEATT = 6$. We exclude individuals with Grade 12 attending Grades 9 to 12 ($GRADEATTD = 54$ or $GRADEATTD = 50$). The housing bust period is marked by vertical dashed lines.

Figure 1. Long Term Evolution of College Attendance



Note: This figure reports college attendance in the past three months for 18-19 year old individuals who are reported in the ACS data as children, $RELATE = 3$. We restrict the sample to include individuals with at least Grade 12, $EDUC \geq 06$. We define recent college attendance as $GRADEATT = 6$. We exclude individuals with Grade 12 attending Grades 9 to 12 ($GRADEATTD = 54$ or $GRADEATTD = 50$). The housing bust period is marked by vertical dashed lines.

Figure 2. College Attendance of Homeowners and Renters

cause of housing wealth destruction during the housing bust altered 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 schooling over the business cycle are the primary reason why college enrolment 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 enrolment declined (Laeven and Popov, 2016; Charles et al., 2018). Importantly, fluctuations in the opportunity cost of college affect both homeowners and renters as long as they are not systematically sorted into different occupations with different sensitivity to the overall business and housing cycle.

The second channel is related to changes in housing wealth affecting primarily homeowners but not renters. 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. Note that renters are only affected by the opportunity cost channel,[2] while homeowners are affected by both, and for them, the two effects go in opposite directions.[3]

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 college enrolment 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 in areas that experienced a relatively larger decline in house prices were significantly less likely to be enroled in a higher education institution, as opposed to homeowners who experienced

[2]In principle, renters may be affected via changes in rental prices, but we show that this channel is not empirically relevant.

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

more modest declines in house prices. This effect is concentrated among homeowners with a mortgage, rather than among outright homeowners, strengthening the notion of the importance of credit constraints in determining college choice. Moreover, the effect is stronger when the parents themselves did not go to college, and is muted for Hispanics. This suggests that holding housing wealth constant, family educational history and cultural attitudes can affect the elasticity of the likelihood of college enrolment to housing shocks.

We also find that the housing leverage effect on college enrolment is meaningful in the aggregate. Importantly, it is observed long after the end of the Great Recession and translates into persistently lower income levels and likelihoods of working in an education-intensive industry for homeowners. This finding is consistent with other papers that have recently documented persistent effects of the Great Recession (see, e.g., Yagan, 2019 and Jones et al., 2022).

The main result of the paper is remarkably robust to using different samples and model specifications. We find that the main effect is not driven by changes in rents or by renters and owners facing different labor market opportunities. We also continue documenting a statistically significant association between the extent of the housing bust and the likelihood of college enrolment for the children of homeowners once we use the housing supply elasticity as an instrumental variable for the decline in house prices 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: direct measure of the housing net worth destruction of Mian et al. (2013), and changes in foreclosure rates.

How important is this effect in the aggregate? And how persistent is it? To answer the first 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 enrolment to changes in house prices. Using this approach, we find that up to 2% of the local college-age population, did not enrol in college during the peak years of the housing bust due to housing wealth destruction.

To answer the second 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 beyond the housing bust, with owners still significantly less likely to be enroled in college as of 2019, one year before COVID-19 pandemic hitted. Longer and more expensive college arrangements are affected more compared to shorter programs. This persistent decline in human capital accumulation translates into persistently lower income levels for homeowners compared to renters in localities more affected during the housing busts. We show that this is not driven by different employment likelihood, but by a significantly lower likelihood of being employed in education-intensive industries in which the college premium tends to be reflected in higher wages.

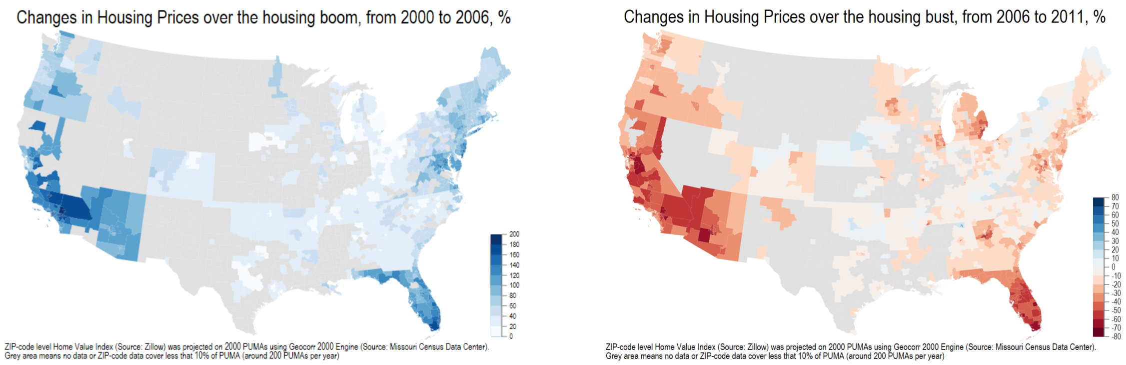
Our work contributes to the literature on financial frictions and education. Wealthy parents invest, on average, more in the human capital of their offspring than poorer ones (e.g., Becker et al., 2018; Chakrabarti et al., 2023). Consequently, easier access to external finance increases college enrolment 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 enrolment 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 enrolment, 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. We contribute to this literature by studying the effect of house price declines on college enrolment and by documenting their persistence, a question also important in the aggregate in the context of the high contribution of human capital to long-term growth .

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,[4] 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[5]. Figure 2, Panel (a) illustrates this development.



(a) Housing boom (b) Housing bust

Figure 3. Map of the U.S. housing boom and bust

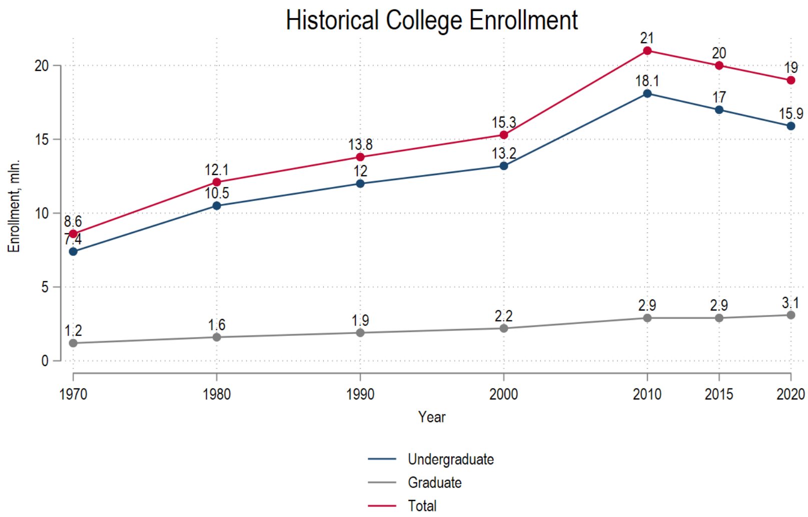
The housing bust, which started in 2007 and lasted until 2011, resulted in a 17% decline in house prices across the United States[6]. Similar to the boom phase, the bust was characterized by large heterogeneity in changes in house prices. For example, house prices declines by 45% in Miami, FL, but continued to grow and increased by 5% in Houston, TX. The patterns of large regional differences in house price adjustment after the US-wide peak are readily visible in Figure 3, Panel (b).

[4]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.

[5]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.

[6]From 2006:Q4 to 2011:Q4, U.S. Federal Housing Finance Agency, All-Transactions House Price Index. Here and below: same geographies as above.

2.2 The U.S. college enrolment trends



Source: National Center for Education Statistics (NCES).

Figure 4. Total undergraduate and graduate fall enrolment 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 enrolment until the Global Financial Crisis. Figure 4 shows that the number of undergraduate students increased from 7.4 million in 1970 to 18.1 million in 2010, 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 enrolment 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 private universities, rose 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.[7] This rules out a tuition-based explanation. Instead, given the differential trends in college attainment across homeownership groups reported in Figure 2, 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.

3 Data

Our goal is to assemble an individual-level dataset linking the timing and the status of the college enrolment decision to the severity of the local housing bust. To that end, we need geographical variation in the location of surveyed households and their detailed geography. 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

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

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.[8] 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.[9] Because of these selection criteria, we end up with a reliable link between the parents' homeownership status and the college enrolment status of the children for approximately 104,000 individuals.

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.[10] We use the ZIP code-to-PUMA crosswalk provided by the Missouri Census Data Center.[11] 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.[12] 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

[8] 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.

[9] 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 those aged 18-19 live in group quarters and their parents' homeownership status is not reported.

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

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

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

housing prices relative to the peak of the bust (2006 to 2007). We assume that the college enrolment 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 inclusive. 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 when using 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 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.[13]

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, the number of siblings, and parental education and parental age as controls. In Table 1, we present summary statistics for our sample.

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. 67% of this population are enroled in college.[14] On average, an individual is 18.6 years

[13]https://usa.ipums.org/usa/volii/00migpuma.shtml. We drop those Migration PUMAs which do not uniquely identify 2000 PUMAs (63%).

[14]Note that this number is slightly higher than 65%, the full sample weighted average college attendance in 2008-2011 reported earlier in Figure 1. This is because the full sample features 121,863 observations over 3 years whereas the sample we use for the econometric analysis is smaller. For 17,569 college-age individuals, we do not observe migration PUMA or other characteristics needed for the analysis.

old. We have almost equal proportion of male and female population. 70% of our sample are whites, 14% are blacks, and 5% are Asian. In terms of ethnicity, 21% are Hispanics. Average income per person amounts to around 16,500 USD (in 2010 prices). In our sample of families with children, homeownership rate is at 76% rate: 11% of parents are outright homeowners, and 65% are homeowners with a mortgage. 24% of the sampled population are renters.

Table 1. Summary Statistics

	Mean	Stand. Dev.	Min	Max	Number of obs.
Attends a College	0.67	0.47	0.0	1.0	104,294
PUMA Housing Price growth, to 2006	-0.13	0.16	-0.7	0.4	104,347
PUMA Unemployment Rate, 16-54	0.08	0.04	0.0	0.4	104,347
Age, years	18.62	0.49	18.0	19.0	104,347
Female	0.49	0.50	0.0	1.0	104,347
White	0.70	0.46	0.0	1.0	104,347
Black	0.14	0.35	0.0	1.0	104,347
Asian	0.05	0.22	0.0	1.0	104,347
Hispanic	0.21	0.41	0.0	1.0	104,347
Log Real Household Income Per Person	9.71	0.84	-1.6	13.0	104,007
Number of Siblings	1.28	1.18	0.0	9.0	104,347
Parental Years of Education	7.11	2.38	0.0	11.0	104,347
Parental Age	47.70	6.47	30.0	88.0	104,347
Homeowner (Outright + Mortgagor)	0.76	0.43	0.0	1.0	104,347
Outright Homeowner	0.11	0.31	0.0	1.0	104,347
Homeowner with a Mortgage	0.65	0.48	0.0	1.0	104,347
Renter	0.24	0.43	0.0	1.0	104,347

Note: Summery statistics are weighted using person probability weights provided in the ACS. Household income per person is transformed to 2010 prices using CPI.

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.[15]

[15] 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

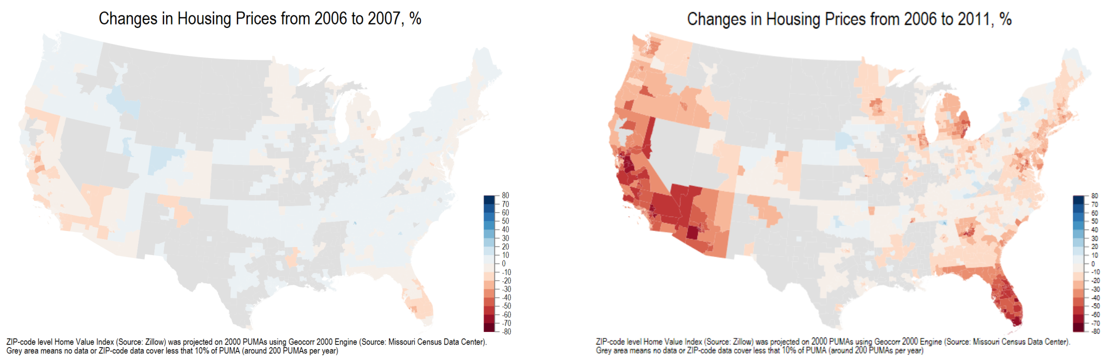
Our hypothesis is that all else equal, those who reached college age *during the trough of the housing boom-bust cycle* and whose parents were homeowners were worse off in terms of college access compared to those who reached same age later when housing prices were rising. There are several reasons why 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 enrolment 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 2). Pre-bust, children of homeowners were enjoying a significant progress in college 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 increasing

students and 33% college undergraduate students; among 19-years-olds: 9 and 56% correspondingly.

household leverage for homeowners, played a role in the differential college enrolment trends between homeowners and renters over the housing bust.

To assess this hypothesis, we employ an empirical specification that takes 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 particularly 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, as was shown in 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 enrolment 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 college-age 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.

- $Owner_{i,p,t,b}$ 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, for example, by variation 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 the independent effect of local housing price changes, $\Delta_{2006,t-1} \ln HPI_p$. The inclusion of the interaction PUMA $\times$ Year FEs is crucial: it controls for the local business cycle and therefore we do not need to include locality-specific time-varying variables such as the local unemployment rate.

Additionally, in robustness checks, 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, $\alpha_{o,t}$. In all regressions, we use ACS-provided person weights which ensure the representativeness of the sample with respect to the population.

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 thus provides an estimate of differences in the sensitivity of college enrolment to housing bust across children of homeowners and renters.

5 College attendance of children of homeowners and renters over 2008-2011

5.1 Baseline estimates

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

Our regressions yield three main findings. Firstly, independently of the local housing market conditions, children of homeowners are on average 14 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. Secondly, in areas with and during years of a steeper house price decline, the 18- and 19-year-olds were more likely to be enroled 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. Thirdly, there are significant differences across college-age children of homeowners and renters this push for college. This is demonstrated 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 enroled 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 enrolment 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 enrolment 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 the housing wealth effect (depreciated housing values causing an increase in housing leverage).[16]

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 encountered 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 enroled to college relative to children of renters in the highest housing-prices-decline PUMA-years relative to lowest housing-prices-decline PUMA-years.

[16]Note that 82% of homeowners have a mortgage over the analyzed period.

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)
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.038	0.053*	0.052*	0.083***	0.083***	0.086***
	(0.030)	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)
$\Delta_{2006,t-1} \ln HPI$	-0.132***	-0.168***	-0.162***	-0.122***	-0.134***	
	(0.027)	(0.027)	(0.028)	(0.034)	(0.036)	
Owner	0.188***	0.110***	0.110***	0.140***	0.140***	0.140***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Demographic controls		✓	✓	✓	✓	✓
Birth year FEs			✓	✓	✓	✓
PUMA FEs				✓	✓	
Year FEs					✓	
PUMA $\times$ Year FEs						✓
N obs	104,294	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA$\times$ Year)	7,544	7,542	7,542	7,490	7,490	7,425
R^2 *(adj.)*	0.028	0.101	0.101	0.136	0.136	0.163

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 $\times$ Year level.

5.2 Identification threats

5.2.1 Time-invariant differences between homeowners and renters

There are a number of threats to the identification of the causal mechanism we are after, namely, from changes in housing wealth to changes in the probability of college enrolment. The first is that owners and renters are different in unobservable ways that result in differential demand for college education. To address this concern, in Table A.II we report estimates from a version of Equation (1) where we also include homeowner fixed effects. In this way, we eliminate all time-invariant differences across homeowners and renters in their demand for tertiary education. The preferred specification in column (3) in Table A.II confirms that even when accounting for background forces that are common to all owners, relative to renters, the probability that children of homeowners are enroled in college during the housing bust declines with the extent of the bust, relative to the children of renters living in the same locality (PUMA). The coefficient of interest is still significant at the 5% statistical level, and about one-quarter smaller in magnitude relative to that in column (5) of Table 2.

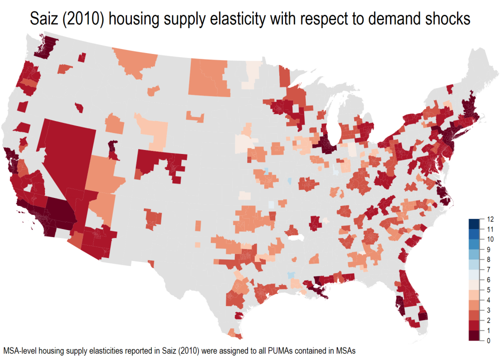
5.2.2 Endogeneity and IV estimation

In this section, we address the concern that changes in college enrolment 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 future. For example, negative shocks to 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 enrolment decisions, but we would interpret it as a causal effect. Our current identification strategy does not allow us to include PUMA × Owner × 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.

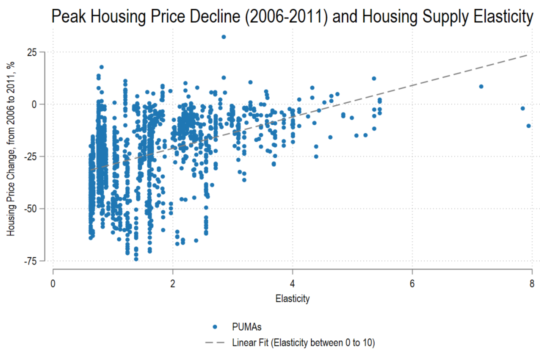
To overcome this limitation and draw a causal conclusion, we isolate the variation in the housing price decline which comes from *exogenously determined geographical reasons*. The idea is that if there is a U.S.-wide shock to the demand for housing, it will propagate differently into prices and quantities 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 relatively smaller 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.[17] 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 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 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 point estimates on the year dummies demonstrate that local housing supply elasticities are a significant predictor of changes in local house prices, and this effect increases over time with the severity of the bust. The value of the first-stage

[17] 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.

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 endogeneity of house prices may have induced a downward bias in the estimation.

The evidence in Table 3 thus confirms that owner-specific time-varying shocks do not drive our effect. Instead, we document that homeowners respond differently from renters to the housing bust even when the housing price decline is conditioned to be driven by exogenous forces, such as geography and housing regulation.

5.2.3 Differences in employment opportunities

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

There is, however, an alternative explanation of the observed differences in college responses that we need to rule out: that labor market opportunities change for children of renters and owners differently, for example due to differences in the structure of occupations children of homeowners and renters aspire to. Such differences in labor market opportunities could arise if, for example, the children of renters are more likely to accept 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 enrolment of about 14 p.p.,

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		0.189***	0.063**
		(0.052)	(0.030)
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.)*		0.083	0.158
First-stage F-stat	416.3		
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.

see Table 2). If so, and if low-skilled jobs (e.g., jobs in the non-tradable sector, Mian and Sufi, 2014b or jobs in the construction sector, Charles et al., 2018) were destroyed relatively more in areas with more pronounced housing price decline, then the lower increase in the probability of going to college for children of homeowners could be due to the stronger labor market effect influencing renters more than owners.

To rule out this alternative explanation, we consider changes in employment probabilities of *non-college* children: who are 18- and 19 years old and who are not in college. This measures how the opportunity cost of college reacts to local housing price change:

$$
\begin{aligned}
Employment_{i,p,t,b}|College = 0 = \\
&\beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \\
&+ \beta_2 \cdot \Delta_{2006,t-1} \ln HPI_p + \beta_3 \cdot Owner_{i,p,t,b} \\
&+ \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + + \varepsilon_{i,p,t,b} \qquad (2)
\end{aligned}
$$

The estimates of Equation (2) are presented in Table 4. As previously, we report coefficient estimates by gradually saturating the model with controls and fixed effects (columns (1)-(5)) until we reach the preferred specification in column (6). The point estimate of the regression coefficient on the interaction term $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ is insignificant throughout, including in the preferred specification. Based on the evidence in Table 4, we conclude that employment opportunities of homeowners and renters were equally sensitive to the housing bust.

The estimated employment response of homeowners and renters to the housing bust is thus 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. We therefore 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.

5.2.4 How important is renters savings on rent in most affected geographies?

One final possibility whereby our estimation strategy can be compromised is if rents declined by relatively more in areas that experienced a relatively stronger decline in house prices. This would imply that renters experienced a rise in financial resources that can be allocated to expenses such as college tuition. In this case, the differential response of college enrolment for children of renters and homeowners would be coming from changes in the circumstances of the former, as opposed to the latter. Put differently, renters would

Table 4. Employment of non-college children of homeowners and renters and the housing bust

	Dependent variable: $Employment \mid College = 0$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.054	0.047	0.044	0.065	0.063	0.076
	(0.052)	(0.051)	(0.051)	(0.050)	(0.050)	(0.058)
Demographic controls		✓	✓	✓	✓	✓
Birth year FEs			✓	✓	✓	✓
PUMA FEs				✓	✓	
Year FEs					✓	
PUMA × Year FEs						✓
N obs	25,032	24,983	24,983	24,934	24,934	23,726
N clusters (PUMA× Year)	6,751	6,744	6,744	6,695	6,695	5,487
R^2 (*adj.*)	0.015	0.064	0.065	0.113	0.114	0.180

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.

not be a proper control group.

In Figure 7, we plot average rents for the top quintile (in blue) and for the bottom quintile (in gray) of PUMAs in terms of house price declines, over the period 2008 to 2011. The chart clearly documents that rents did not increase more in the former, on the contrary, they were flat and even declined slightly in the PUMAs with the steepest house price decline. Rents increased slightly in the PUMAs with the most favorable house price development. The evidence is thus inconsistent with the hypothesis that the decline in relative college attendance for the children of homeowners during the housing bust was in fact driven by renters facing more beneficial financial conditions due to falling rents.[18]

[18] In unreported regressions, we re-run Equation (1) after controlling for disposable income (income net of mortgage or rental payments), and the results remain qualitatively and quantitatively unchanged.

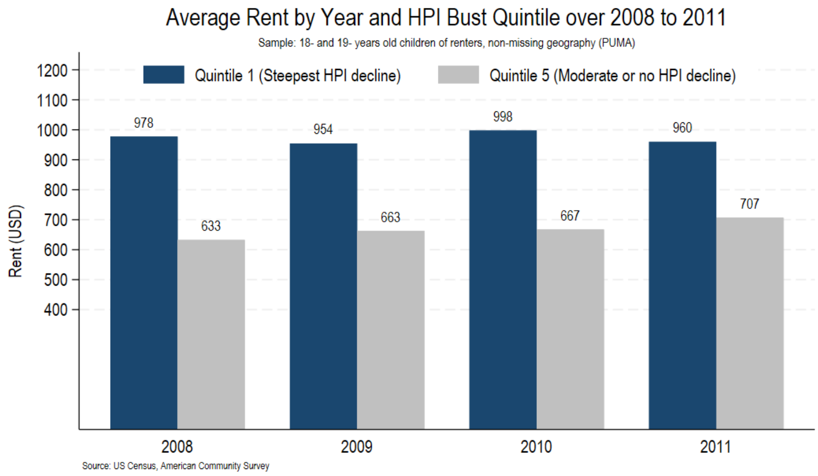


Figure 7. Average Rent over the Housing Bust

6 Mechanism

6.1 Tuition to house value gradient

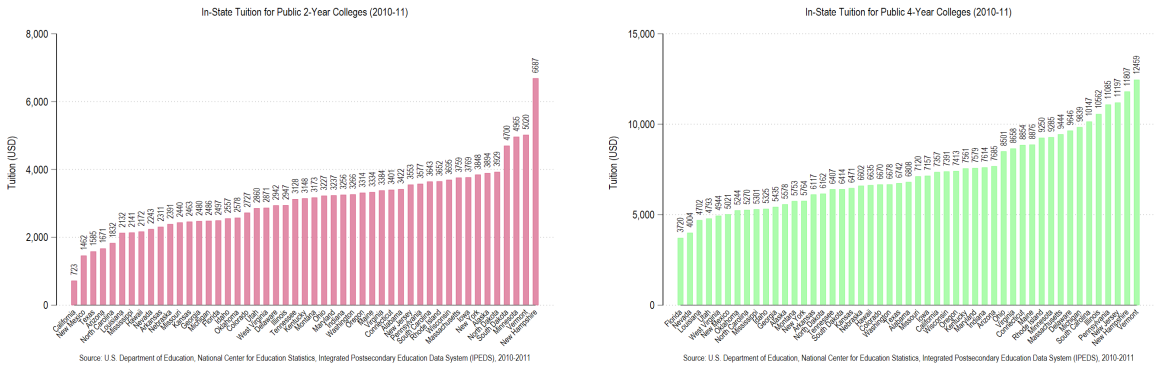
What role do tuition costs play in our estimates? On average, 82% of U.S. college students study in their states of residence which allows them to benefit from the in-state tuition rate.[19] In addition, there is a substantial variation in in-state college tuition across U.S. states (see Figure 8). This creates the possibility that college-age children who encounter higher in-state tuition-to-house-value ratio are less likely to attend college when their parents' housing wealth is destroyed than similar college-age children who face lower tuition costs.

To test for this possibility, we estimate the following model:

$$\begin{aligned} College_{i,p,t,b} = & \ \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \\ & + \beta_{\mathbf{2}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \times \frac{Tuition_s}{HouseValue_{i,p,t,b}} \\ & + \beta_3 \cdot Owner_{i,p,t,b} + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b} \end{aligned}$$

[19]Source: College Board. Trends in College Pricing, 2011.

We interact our term of interest, $\Delta_{2006,t-1} \ln HPI_p$ with $\frac{Tuition_s}{HouseValue_{i,p,t,b}}$. We calculate in-state average tuition $Tuition_s$ as of 2010-2011 as an average of public 2-year, public 4-year, and private 4-year college using the U.S. Department of Education IPEDS data.[20]



(a) Public 2-Year

(b) Public 4-Year

Source: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS)

Figure 8. In-state college tuition and required fees, 2010-2011 average

We report the resulting variation in the coefficient of interest in Figure 9. The figure captures a clear negative effect of tuition costs on the elasticity of college enrolment to changes in housing wealth. Relative to renters' children, the children of homeowners are three times less likely to enrol in college when their parents experience a decline in housing wealth if they reside in PUMAs at the 80th percentile, compared with PUMAs at the 20th percentile, of relative tuition costs.

[20] https://nces.ed.gov/programs/digest/d12/tables/dt12_382.asp.

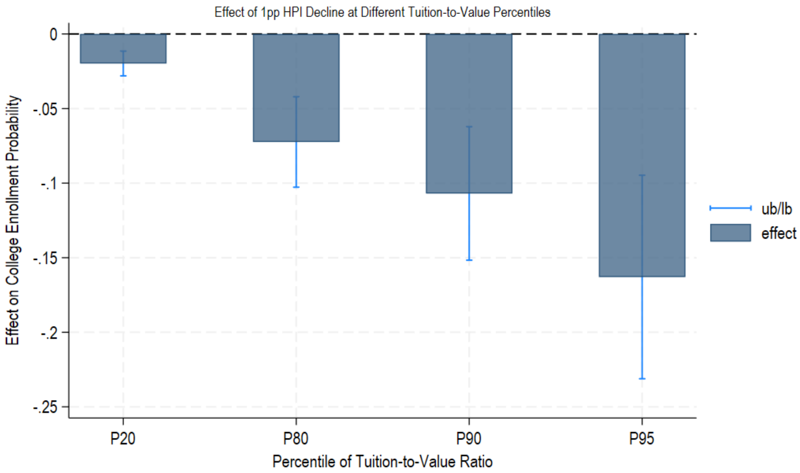


Figure 9. College enrolment response along tuition to house value gradient

6.2 Low- and high equity homeowners

In this section, we investigate if the dampening effect of homeownership on college attendance during the bust is concentrated among a particular type of homeowners. Controlling for the value of the house, homeowners with a mortgage experience a larger reduction in housing wealth than outright owners. Therefore, it is natural to hypothesize that the children of homeowners with a mortgage were less likely than the children of outright homeowners to enrol in college during the housing bust, especially in geographies that experienced 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 Equation (1) in which as before, we compare the sensitivity of children's college enrolment to housing bust of groups of owners to renters who form the baseline category:

$$\begin{aligned} College_{i,p,t,b} = \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Outright\ Owner_{i,p,t,b} \\ + \beta_{\mathbf{2}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Mortgagor_{i,p,t,b} \\ + \dots + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b} \end{aligned} \tag{3}$$

We employ the preferred econometric specification accounting for local time-varying shocks $\alpha_{p,t}$, PUMA-Year fixed effects. The estimates from Equation (3) are reported in column (2) of Table 5. For comparison, in column (1) of Table 5, 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 5, we conclude that the dampening effect of homeownership on college enrolment during the housing bust is driven primarily by homeowners with a mortgage: 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, analogous to the point estimate on the interaction variable of interest in column (1). 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, and so 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 enrolment 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 (empirical density of housing price changes splitted in quartiles is shown in Figure A.I in Appendix) and interact corresponding indicator variables with the homeownership status:

$$\begin{aligned} College_{i,p,t,b} = & \sum_{j=1}^{J} \theta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times Outright\ Owner_{i,p,t,b} \times 1_{\{Hetero_p=j\}} \\ & + \sum_{j=1}^{J} \delta j \cdot \Delta_{2006,t-1} \ln HPI_p \times Mortgagor_{i,p,t,b} \times 1_{\{Hetero_p=j\}} \\ & + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b}, \end{aligned} \tag{4}$$

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.

The results reported in columns (3) and (4) suggest that children of all homeowners (outright and mortgagors) were less likely to be enroled 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 3.1 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 $1_{\{\Delta_{2006,t-1} \ln HPI \leq median\}} \times$ Mortgagor in column (4) of Table 5 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. The 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 bottom quartile of the housing price growth distribution – those experiencing the most severe shock. This is illustrated by the negative (and the only significant) point estimate of the coefficient on the interaction term $1_{\{\Delta_{2006,t-1} \ln HPI \in Q_1\}} \times$ Mortgagor.

Overall, we conclude that the education gap between homeowners and renters is driven by mortgagors experiencing the highest housing wealth losses.

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 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.[21] The point estimates reported in estimates presented in columns (2) and (3) of Table 6 show that the significant differences in education responses between homeowners and renters continue to obtain if we use these alternative measures of housing shock.[22]. The estimate of β_2 is positive in

[21]Details on the data construction of Mian et al. (2013)'s housing net worth change and foreclosure rate at the PUMA level are provided in Appendix A.4.

[22]In column (1) of Table 6, we replicate the point estimate from our preferred specification reported

Table 5. 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	0.086***		-0.030***	
	(0.029)		(0.010)	
Housing price × Outright owner		0.079*		-0.025*
		(0.042)		(0.013)
Housing price × Mortgagor		0.086***		-0.031***
		(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.*)	0.163	0.163	0.163	0.163

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.

column (2) and negative in column (3), suggesting that a larger destruction of local net worth and a larger increase in local foreclosure rates are associated with a significant drop in college enrolment by the children of homeowners, relative to those of renters in the same location. In both cases, the effect is significant at the 1% statistical level.

Homeownership status change. Next, we explore the robustness of our baseline estimates to eliminating from the sample those who changed their homeownership status during the housing bust. For this exercise, we restrict our sample to those households that have lived in the same housing units for at least 5 years as measured by the $MOVEDIN$ variable provided in the ACS. In this way, we fix the composition of homeowners as of before the start of the housing bust. After applying this restriction, the sample is reduced from approximately 104,000 individuals to approximately 79,000. The estimation results are presented in column (4) of Table 6. The coefficient estimate of interest remains positive and significant at the 1% statistical level. Numerically, it is about 1/2 larger than that in the preferred specification in column (1), suggesting that owners who moved into their

earlier in column (6) of Table 2.

houses of residence relatively long ago are less likely to invest in the human capital of their children relative once local house prices decline, plausibly because their housing wealth has declined more relative to initial expectations.

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 ≥ 5
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.086***			0.124***
	(0.029)			(0.042)
$\Delta_{2006,t-1} \ln HNW$ × Owner		0.062***		
		(0.024)		
$\Delta_{2006,t-1} \ln ForeclosureRate$× 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.*)	0.163	0.161	0.164	0.164

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.

Excluding large states. Next, we make sure that our main results are not driven by individuals in a few very influential states. Recall that the largest collapse in house prices during the housing bust was in Arizona, California, and Florida (see Figure 3, Panel (b)). While it would not necessarily compromise our estimation strategy if it turned out that our results are driven by a handful of states, it would nevertheless have implications for their external validity. However, when we exclude these states one by one and as a group (columns (2)-(5) of Table 7), we find that the main effect still obtains and is if anything larger than the one from the preferred specification, replicated in column (1).

HPI growth since household moved into a residence instead of HPI growth since 2006.

Lastly, we show that dampening effect of homeownership on college education of children is still observed once we calculate housing price changes since period a family moved in to the residence and restrict time sample post-2000 or post-2006. Recall that in our

Table 7. Robustness to excluding large states

	Baseline	Excl. CA	Excl. FL	Excl. AZ	Excl. AZ,FL,CA
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.086***	0.100**	0.103***	0.085***	0.152***
	(0.029)	(0.039)	(0.031)	(0.030)	(0.051)
Demographic controls	✓	✓	✓	✓	✓
Birth year FEs	✓	✓	✓	✓	✓
PUMA × Year FEs	✓	✓	✓	✓	✓
N obs	103,837	86,633	97,555	101,627	78,141
N clusters	7,425	6,500	6,917	7,281	5,848
R^2 (*adj.*)	0.163	0.169	0.163	0.163	0.170

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, except for specification in column (2) in which standard errors are clustered at the State × Year level.

baseline analysis, we use housing price changes since 2006 which was the peak of housing price level prior to the housing bust. The results are presented in Table 8. In column (1), we replicate the baseline analysis from Table 2. In columns (2)-(4), we use time since moved in to calculate housing wealth losses/gains. The dampening effect of homeownership on college attendance is about a quarter stronger (Column 4 in Table 8) if we restrict the sample to those moved in after 2006, most likely, because most of these families encountered housing price losses associated with their primary residence.

Table 8. Robustness of the main result to an alternative measure of the housing price change: HPI since moved in

	Dependent variable: $College_{i,p,t,y}$			
	T = 2006	T = Moved in	T = Moved in, T≥2000	T = Moved in, T≥2006
$\Delta_{T,t-1} \ln HPI \times$ Owner	0.086***	-0.001	0.028**	0.120*
	(0.029)	(0.002)	(0.012)	(0.067)
Demographic controls	✓	✓	✓	✓
Birth year FEs	✓	✓	✓	✓
PUMA × Year FEs	✓	✓	✓	✓
N obs	103,837	97,877	48,303	19,091
N clusters (PUMA× Year)	7,425	7,317	6,963	4,729
R^2 (*adj.*)	0.141	0.144	0.177	0.215

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 Heterogeneity of college attendance responses to the housing bust

To account for potential heterogeneity in difference between homeowners' and renters' responses to the housing bust, we estimate the following regression:

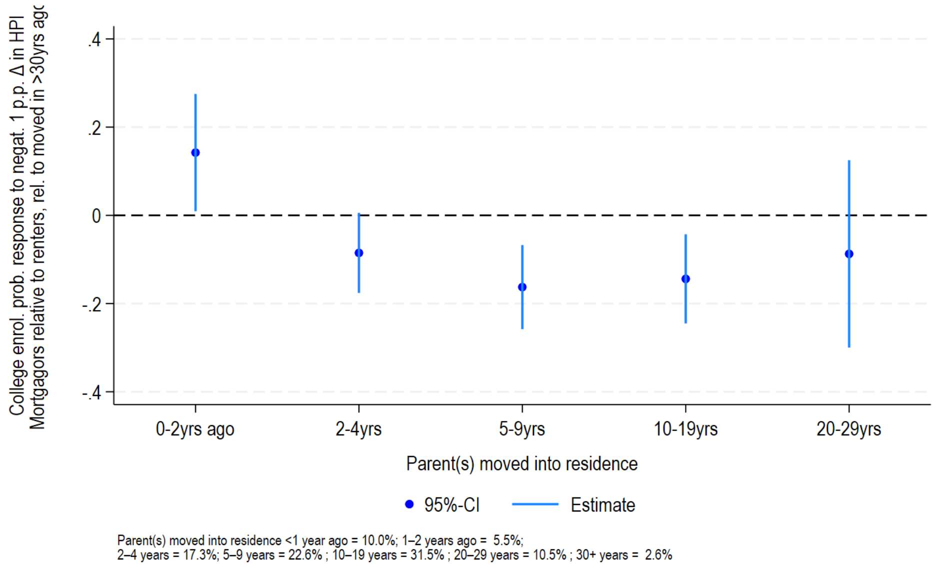
$$\begin{aligned} College_{i,p,t,b} = & \sum_{j=1}^{J} \theta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \times 1_{\{Hetero_{i,p,t,b}=j\}} \\ & + \sum_{j=1}^{J} \beta_j \cdot Owner_{i,p,t,b} \times 1_{\{Hetero_{i,p,t,b}=j\}} + \\ & + \sum_{j=1}^{J} \delta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times 1_{\{Hetero_{i,p,t,b}=j\}} + \\ & + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b}, \end{aligned} \tag{5}$$

where $1_{\{Hetero_{i,p,t,y}=j\}}$ is a heterogeneity parameter: indicator variable taking value 1 if an observation on individual i falls into category j. In what follows we look at a number of such categories that can plausibly induce heterogeneity in the response of college enrolment to changes in house prices, such as homeownership tenure, parental education, as well as gender, race and ethnicity.

8.1 Housing tenure heterogeneity

We compare parents of different housing tenure, parents having a mortgage and renting parents. We exclude outright homeowners because for them, there is no clear mapping between housing equity accumulation and housing tenure whereas it is the case for mortgagors. We interact the key term of interest $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ with an indicator variable that a head of the family moved into the residence some years ago. In the ACS, housing tenure is defined in intervals, therefore we use housing tenure bins corresponding to the reported intervals in the ACS. We combine recently moved households (i.e., those who moved in less than 1 year ago and those who moved in 1-2 years ago) and create a bin for those who moved in less than 2 years ago. We use those who moved in 30+ years ago as the baseline category and keep the other categories as reported in the

ACS.



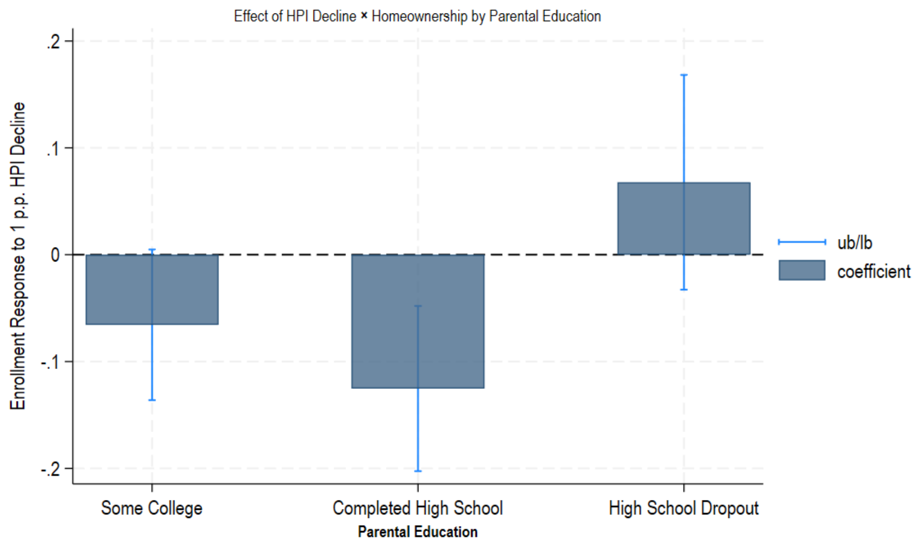
Note: This figure reports $-\theta_j$ for each moved in bin from the following regression: $College_{i,p,t,b} = \sum_{j=1}^{J} \theta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \times 1_{\{MOVEDIN_{i,p,t,y}=j\}} + \sum_{j=1}^{J} \beta_j \cdot Owner_{i,p,t,b} \times 1_{MOVEDIN_{i,p,t,y}=j\}} + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b}$, where $1_{\{MOVEDIN_{i,p,t,y}=j\}}$ is parents' income in a j-th bin of moving into the current residence.

Figure 10. Housing tenure variation of the college attendance response to the housing bust

The estimates from this test are depicted in Figure 10. The evidence makes it clear that the largest effect, in terms of a decline in college attendance during the housing bust, is for the children of those parents who moved into their current residence not too recently and not too long ago. In the latter case, this is plausibly because for those who moved in more than 20 years ago, the mortgage has likely been close to paid off and so the decline in housing wealth is less dramatic. For the former group, it is possible that they are more likely to be optimistic and thus to perceive the decline in house prices as temporary.

8.2 Parental education heterogeneity

We consider the heterogeneity of children's responses to the housing bust with respect to parental education. As before, our key object of interest is the difference between the responses of homeowners and renters. To gauge how this difference varies parental education, we interact the key term of interest $\Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b}$ with an indicator variable equal to one if the household head's education falls in one of three categories: high school dropout, completed high school, and at least some college.



Note: This figure reports $-\theta_j$ for each moved in bin from the following regression: $College_{i,p,t,b} = \sum_{j=1}^{J} \theta_j \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \times 1_{\{EDUC_{i,p,t,y}=j\}} + \sum_{j=1}^{J} \beta_j \cdot Owner_{i,p,t,b} \times 1_{EDUC_{i,p,t,y}=j\}} + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b}$, where $1_{\{EDUC_{i,p,t,y}=j\}}$ is indicator variable of parental education falls into a j-th bin of education.

Figure 11. Parental education and college attendance response to the housing bust

The estimation results are depicted in Figure 11. The evidence shows that the overall decline in college attendance comes from the children of parents who have completed high school but have not been to college. While establishing the exact mechanism is not possible with our data, it is plausible that those without college education know that their labor income becomes more uncertain during a recession, or that they do not value college education as much.

8.3 Race, ethnicity, and gender heterogeneity

Next, we estimate Equation (5) after including interactions of the main variable of interest with dummy variables capturing gender, race and ethnicity. The estimation results are presented in Table 9. We find little or no evidence that these variables affect the sensitivity of homeowners to the housing bust, in terms of college attendance. All interaction terms of $\Delta_{2006,t-1} \ln HPI$ × Owner and gender and ethnic group indicator variables are insignificant except the one that captures Hispanic origin. In particular, Hispanic homeowners turn out to be less sensitive to the housing bust than non-Hispanic ones, as illustrated by the negative and significant coefficient at the interaction term $\Delta_{2006,t-1} \ln HPI$ × Owner × Hispanic. Once again, the exact mechanism is unclear, but one potential explanation may be that both the college enrolment rate and housing value of Hispanics are lower, leading to a lower sensitivity of college enrolment to the negative housing shock.

	Dependent variable: College				
	(1)	(2)	(3)	(4)	(5)
$\Delta_{2006,t-1} \ln HPI$ × Owner	0.072* (0.039)	0.027 (0.046)	0.086*** (0.032)	0.084*** (0.030)	0.122*** (0.037)
$\Delta_{2006,t-1} \ln HPI$ × Owner × Female	0.027 (0.052)				
$\Delta_{2006,t-1} \ln HPI$ × Owner × White		0.086 (0.059)			
$\Delta_{2006,t-1} \ln HPI$ × Owner × Black			-0.017 (0.077)		
$\Delta_{2006,t-1} \ln HPI$ × Owner × Asian				-0.079 (0.112)	
$\Delta_{2006,t-1} \ln HPI$ × Owner × Hispanic					-0.143** (0.060)
Demographic controls	✓	✓	✓	✓	✓
Birth year FE	✓	✓	✓	✓	✓
PUMA × Year FE	✓	✓	✓	✓	✓
N obs	103,837	103,837	103,837	103,837	103,837
N clusters (PUMA× Year)	7,425	7,425	7,425	7,425	7,425
R^2 (*adj.*)	0.163	0.163	0.163	0.163	0.163

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.
"–" denotes that the term is omitted because it is collinear with FEs.
Standard errors are clustered at the PUMA × Year level.

Table 9. The role of race, ethnicity, and gender in the variation of the college attendance response to the housing bust

9 Aggregate effect of homeownership and the housing bust on college enrolment

How sizable is the microeconomic effect we document when extrapolated to the aggregate? To estimate how many 18- and 19- years old did not go to college in the US 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 the estimated coefficient capturing the differential response to the housing bust across owners and renters (0.09; see first row, Table 2). At every PUMA, the estimated economic effect of housing frictions on college enrolment reads as follows:

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

Our calculations imply that up to 2% of the local college-age population, or 11,500 students in 2010-2011, did not pursue college enrolment at the height of the bust due housing frictions. The geographical distribution of college attendance losses is presented in Figure 12. 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 relatively high homeownership rates and relatively steep declines in housing prices (see Figure 13).

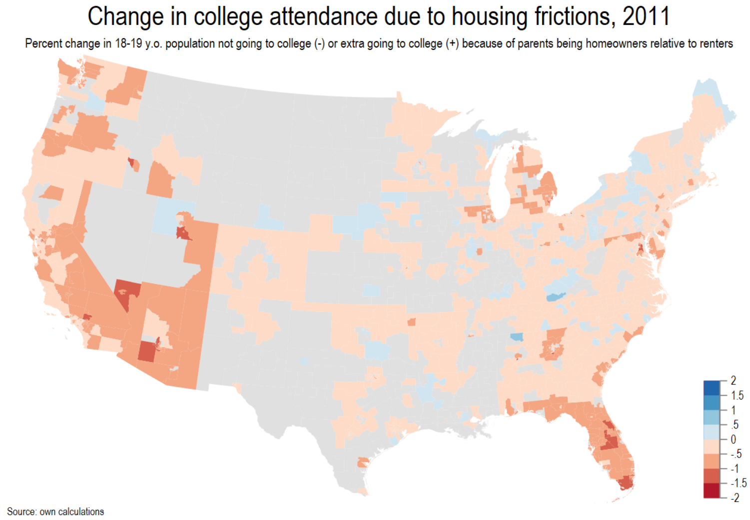
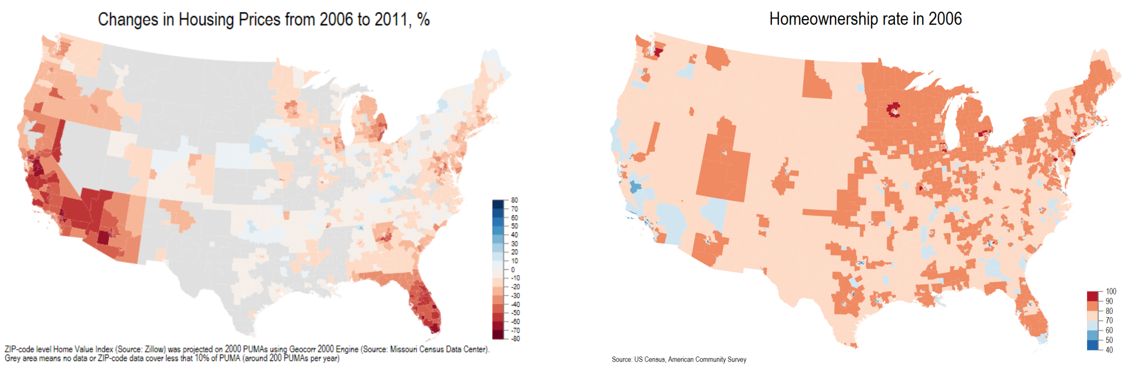


Figure 12. The Geographical Distribution of the Estimated Economic Effect of Housing Frictions on College Attendance

Note: Gray areas denote no data.



(a) Housing price decline

(b) Homeownership rate

Figure 13. Drivers of the Economic Effect of Housing Frictions on College Attendance: Housing Bust and Homeownership rate

Note: Gray areas denote no data.

10 Longer-term effect of the housing bust

Are the effects 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 enrolment 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:

$$\begin{aligned} Y_{i,p,t,b} = & \sum_{k \neq 2011} \beta_k \cdot \mathbf{1}_{\{k=t\}} \cdot \Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b} \\ & + ... + \gamma' \mathbf{X}_{i,p,t,b} + \alpha_b + \alpha_{p,t} + \varepsilon_{i,p,t,b} \end{aligned} \tag{6}$$

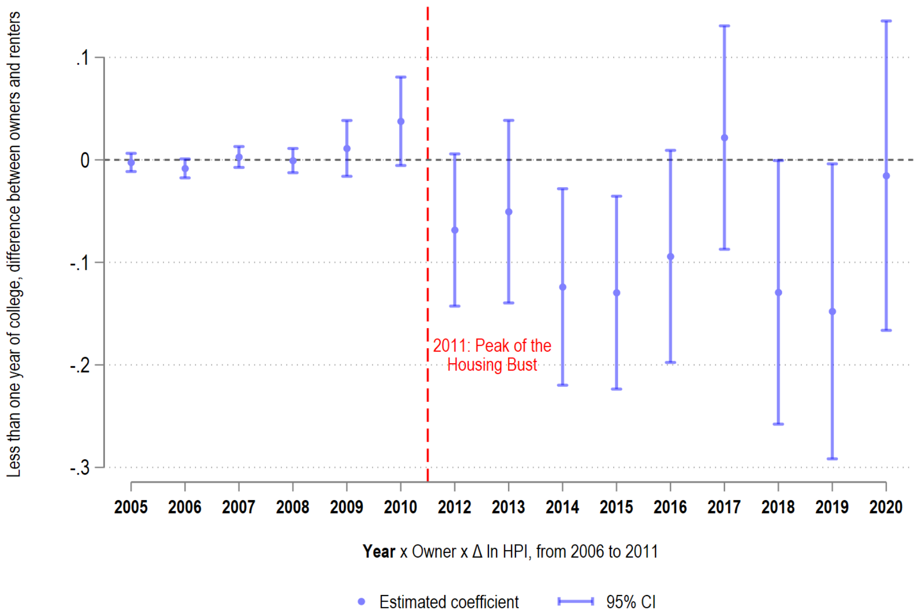
We interact year indicator variables $\mathbf{1}_{\{k=t\}}$ with the term of interest $\Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b}$ which allows us to trace the differences in outcome variables between homeowners and renters in time. We focus on the 2005-2020 period, and we look at those aged 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.[23]

10.1 College attainment

We first run Equation (6) with educational attainment as the dependent variable. Our estimation results suggest that there are persistent losses in college attainment as measured

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

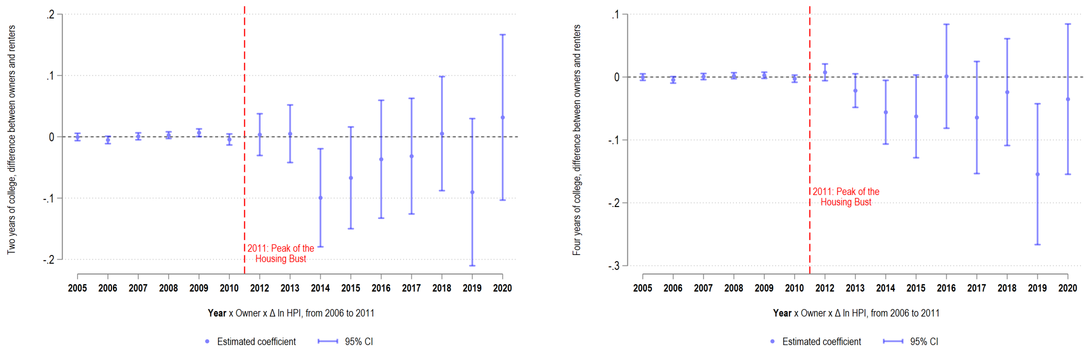
by having at least one year of college. As late as 2019, homeowners who were 18-19 years old in 2010-2011 were 0.13-0.15 p.p. less likely to have one year of college attainment compared to renters if they lived in PUMAs with a 1 p.p. stronger housing price decline (see Figure 14).



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 14. Housing bust and college attainment: some college, at least 1 year

We next look at different types of college attainment. We find that the education losses documented in the previous figure are short-lived in two-year college attainment and more persistent in four-year college attainment (see Figure 15).



(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 15. Housing bust and two- and four-year college attainment

10.2 Employment and income

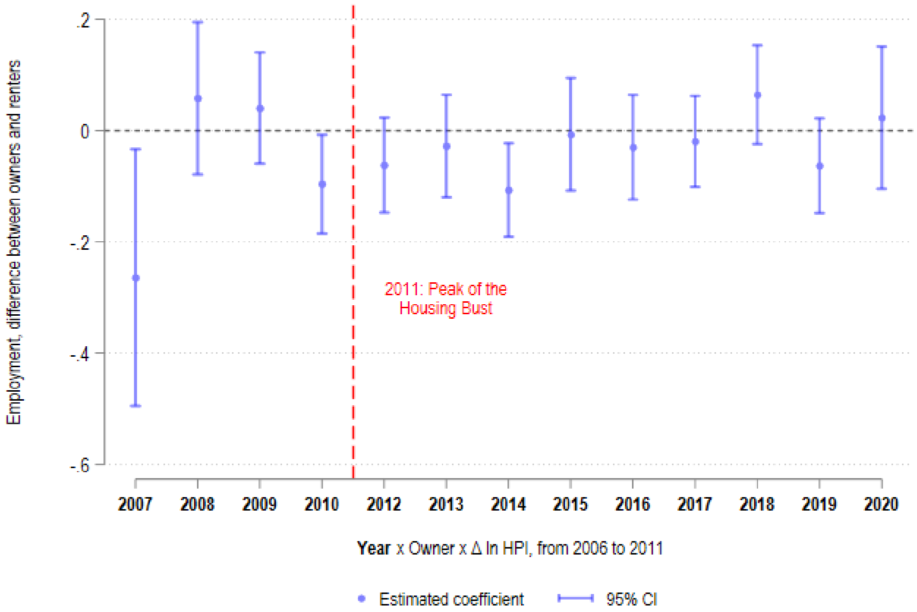
Next, we run Equation (6) with employment and real per-capita income as the dependent variable. We find no persistent employment differences across homeowners and renters on average, in localities more affected by the housing bust (see Figure 16). However, we document persistent differences in employment when we look at education-intensive sectors.[24] As late as 2017, homeowners living in areas that experienced the largest decline in house prices during the bust were up to 0.15 p.p. less likely to work in an education-intensive sector.

This reduction in employability in high-human-capital industries – which tend to be characterized by higher wages – result in persistent differences in per-capita real family incomes between homeowners and renters in more affected localities (see Figure 18). Even a decade 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.

The combined evidence thus suggests that in affected regions, homeowners experience a persistent loss of human capital. Rather than simply postponing college enrolment at

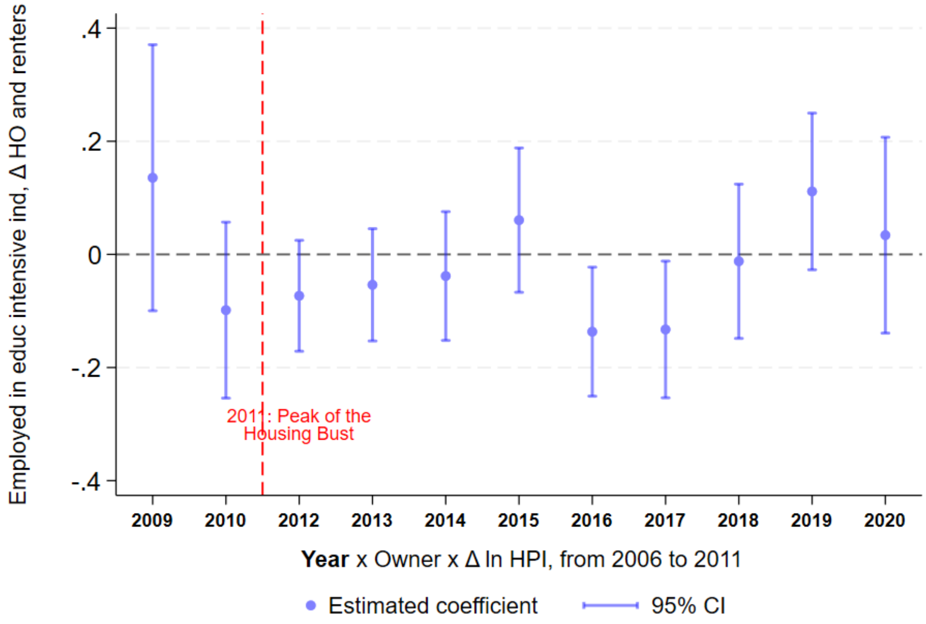
[24] We define these as the sectors in which over half of the respondents in the ACS who self-identify as working in them have at least some college education. For a similar strategy, see Ciccone and Papaioannou (2009).

the trough of the housing cycle and catching up later, they are less likely to have any college education as late as a decade after the bust. And while they not more likely to be unemployed in the years after the housing bust, they appear to be switching to more low-skill jobs and as a result, to experience a reduction in relative real income.



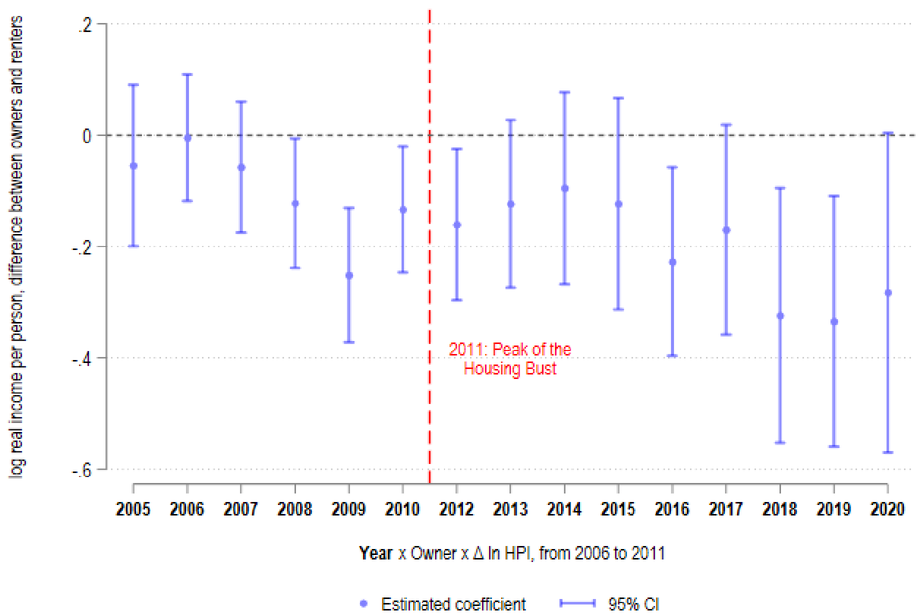
Note: The picture presents differences in employment probability between homeowners and renters in response to a 1 p.p. housing price decline in 2006-2011.

Figure 16. Housing bust and the likelihood of employment



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

Figure 17. Housing bust and the likelihood of employment in education-intensive industries



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 18. Housing bust and real income

11 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 enrolment. 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 enrolment 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 enroled 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.

More importantly, the education losses persist for at least a decade and translate into persistent lower employability in high-skill occupations and a reductions in relative household income of homeowners, compared with renters. Our paper thus sheds new light on the long-lived adverse socioeconomic effects of housing busts and illuminates a potential trade-off between investment in real assets (housing) and investment in human capital (college education). Our evidence suggests 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)
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.053*	0.052*	0.083***	0.083***	0.086***
	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)
$\Delta_{2006,t-1} \ln HPI$	-0.168***	-0.162***	-0.122***	-0.134***	
	(0.027)	(0.028)	(0.034)	(0.036)	
Owner	0.110***	0.110***	0.140***	0.140***	0.140***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PUMA Unemployment rate, age 16-54	-0.181**	-0.238***	0.014	0.048	0.014
	(0.071)	(0.078)	(0.118)	(0.142)	(0.587)
Female	0.111***	0.111***	0.109***	0.109***	0.106***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
White	-0.003	-0.003	0.006	0.006	0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Black	-0.006	-0.004	-0.015	-0.015	-0.017*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Asian	0.179***	0.179***	0.133***	0.132***	0.134***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Hispanic	0.048***	0.049***	0.007	0.008	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log (Real Family Income per person)	0.049***	0.049***	0.040***	0.040***	0.041***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of Siblings	0.007***	0.007***	0.003**	0.003**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Parental Years of Education	0.036***	0.036***	0.033***	0.033***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parental Age	0.005***	0.005***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Birth year FEs		Yes	Yes	Yes	Yes
PUMA FEs			Yes	Yes	
Year FEs				Yes	
PUMA $\times$ Year FEs					Yes
N obs	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA$\times$ Year)	7,542	7,542	7,490	7,490	7,425
R^2 (*adj.*)	0.101	0.101	0.136	0.136	0.163

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 $\times$ Year level.

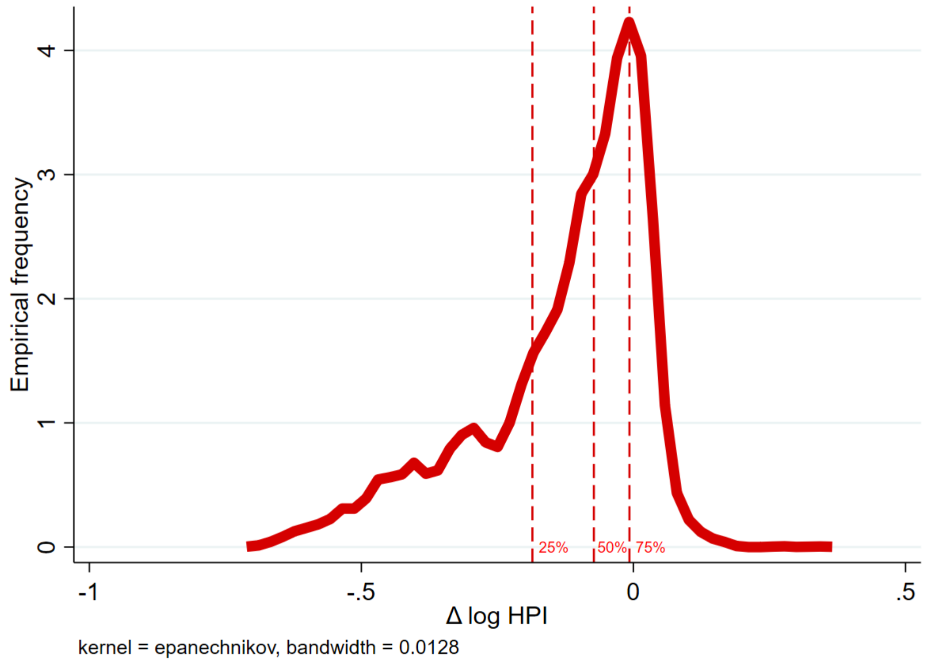
A.2 Accounting for homeowner-specific shocks

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	0.086***	0.116***	0.067**
	(0.029)	(0.044)	(0.032)
Owner	0.140***		
	(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.*)	0.163	0.160	0.163

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	-0.025	-0.028	-0.031*
	(0.020)	(0.019)	(0.019)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{25}\}}$ × Mortgagor	-0.031**	-0.036***	-0.032**
	(0.014)	(0.014)	(0.013)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{50}\}}$ × Outright owner	0.000	-0.006	-0.017
	(0.021)	(0.021)	(0.020)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{50}\}}$ × Mortgagor	-0.004	-0.020	-0.026*
	(0.016)	(0.016)	(0.015)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{75}\}}$ × Outright owner	0.010	-0.003	-0.007
	(0.021)	(0.020)	(0.019)
$1_{\{\Delta_{2006,t-1} \ln HPI \in Q_{75}\}}$ × Mortgagor	0.013	-0.003	-0.009
	(0.016)	(0.016)	(0.015)
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	0.163

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[25] 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)[26] 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 enrolment

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

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

[26] 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.

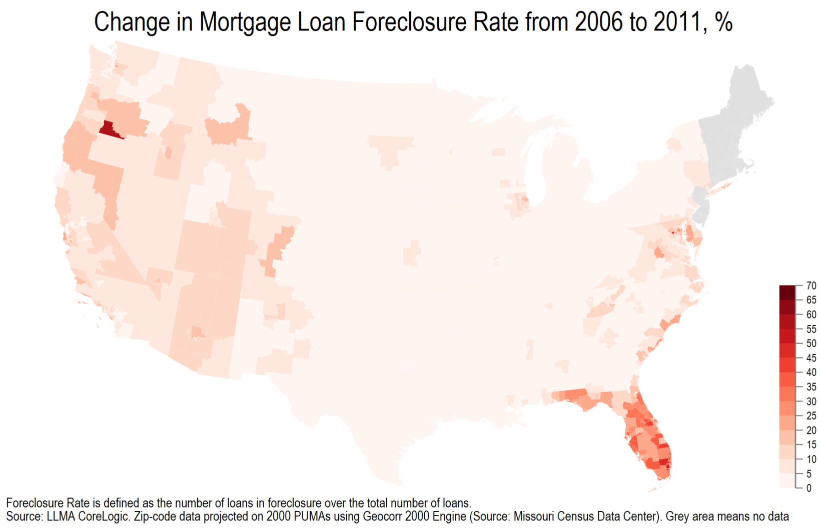
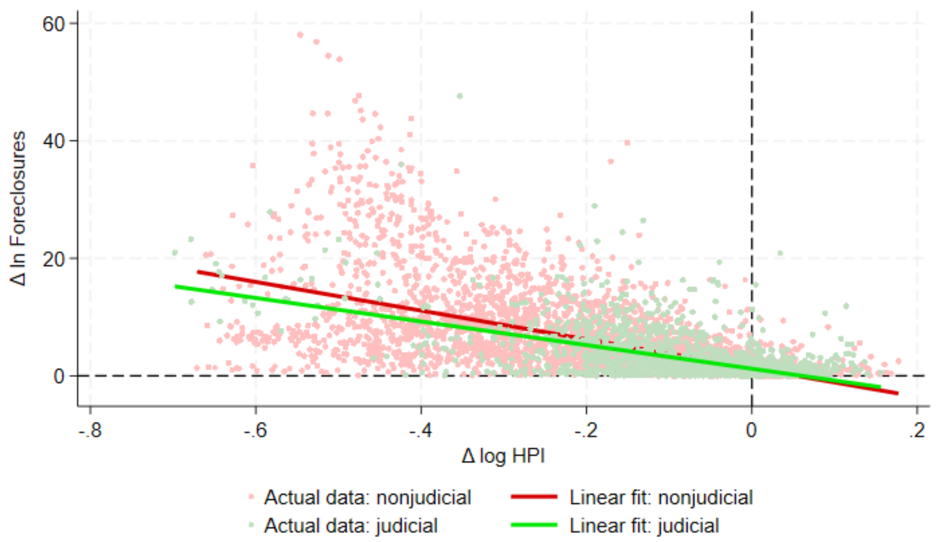


Figure A.II. Surge in foreclosures across PUMAs



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.

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