Housing Bust and Long-Term Human Capital Scarring in the U.S.*

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Abstract

We document persistent human capital scarring among the children of homeowners who reached college age during the 2008–2011 housing bust. Negative shocks to parental housing wealth substantially reduced college attendance among first-year college-age children of homeowners, relative to their counterparts from renter households. In regions experiencing the largest declines in housing wealth, the educational gap between the offspring of homeowners and renters persisted for at least a decade. The shortfall in human capital accumulation translated into lower long-run employability, particularly in education-intensive sectors, and resulted in lower earnings among the affected cohort.

(JEL: I24, E32, J24)

Keywords: Homeownership, housing wealth, human capital, housing boom-bust episodes

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1 Introduction

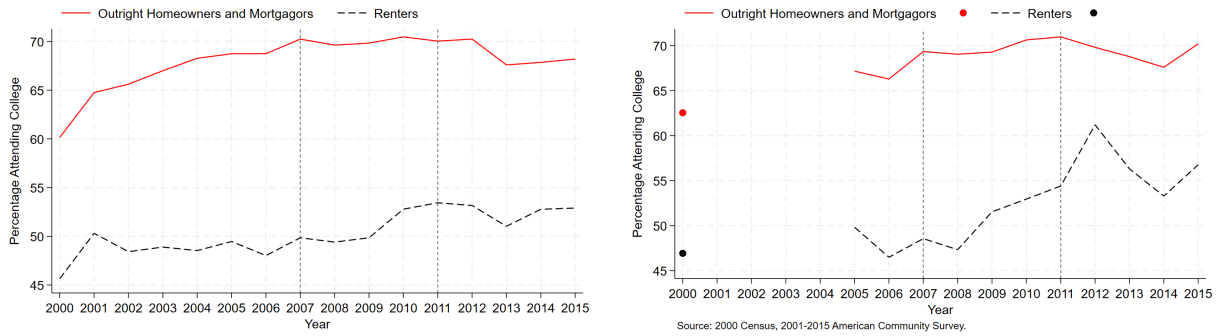
How does college attendance respond to adverse shocks to financial resources? To what extent do these effects persist over time, and how do they shape subsequent economic outcomes in adulthood? These questions are important because, after increasing for decades, undergraduate enrollment at degree-granting post-secondary U.S. institutions declined by 9% between 2010 and 2019 (NCES, 2023), despite the fact that the college premium has continued to rise (Athreya and Eberly, 2021). The decline in college enrollment has revived the interest of both academics and policy makers regarding the extent to which credit constraints shape households' ability to send their children to college in the context of rising higher-education costs (Lochner and Monge-Naranjo, 2011; Denning and Jones, 2021; Bulman et al., 2021). In contrast, housing wealth has received much less attention, despite the well-documented destruction of home equity during the housing bust of the late 2000s and the fact that residential property accounts for roughly 60% of all personal wealth in the United States (U.S. Census, 2010)

To contribute to this discussion, we use variations in home prices across around 2000 narrowly defined U.S. regions, together with demographic and mortgage credit register data to study the long-term impact of the loss of parental housing wealth between 2008 and 2011 on children's college attendance. Our methodology follows Lovenheim (2011), Chaney et al. (2012), Corradin and Popov (2015), and Schmalz et al. (2017) and is akin to a difference-in-differences strategy. Specifically, we compare college attendance among the children of homeowners and renters residing within the same region, and relate the resulting differential to cross-regional variation in house-price dynamics. Our identification strategy rests on the notion that declines in home prices reduce the value of homeowners' housing wealth, thereby limiting the resources they can draw upon to finance their children's college attendance. Renters in the same region provide an appropriate counterfactual, as they face identical returns to higher education and are exposed to the same local demand shocks as homeowners. Consequently, within-region comparisons of educational outcomes between homeowners and

renters allow us to difference out local economic shocks that might otherwise simultaneously affect home prices and college attendance.

Figure 1 illustrates the important role that the homeownership status of college-age individuals' parents played in shaping college education outcomes. Between 2000 and 2007, college attendance among homeowners' children increased by more than that of renters' children. In contrast, college attendance of homeowners' children stagnated after 2007, while that of renters' children continued to rise throughout the housing bust period, from less than 50% in 2007 to more than 53% in 2011. This effect is especially visible in areas with the most severe housing bust (i.e., 20% largest decline in home prices).

Figure 1. College Attendance Rate by Parental Homeownership Status



(a) All Areas (b) Areas Most Affected by the Housing Bust

Note: This figure reports college attendance in the prior three months for 18-19 year old individuals who are reported in the Americal Community Survey (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 $GRADEATT = 6$. Sample person weights provided in ACS are applied. Panel (a) presents the average college attendance rate across all Public Use Microdata Areas (PUMAs) in the U.S., whereas panel (b) reports the average college attendance rate in the areas most affected by the housing bust, defined as PUMAs in the first quartile of the home price growth distribution over 2006–2011 (peak to trough). For panel (b), data for 2001–2004 are not available because geographic identifiers smaller than states were not disclosed in the ACS for those years. Vertical dashed lines denote 2007 and 2011, the first and last years of the nationwide home price decline. Data sources: 2000 U.S. Census, American Community Survey (2001–2015), and Zillow.

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 increases 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 college enrollment tends to be countercyclical (e.g., Dellas and Sakellaris, 2003; Barr and Turner, 2013). They also explain why both college attendance and attainment declined during the housing boom of the early-to-mid 2000s (Laeven and Popov, 2016; Charles et al., 2018). Due to the opportunity cost channel, college attendance typically rises during recessions because labor market opportunities are scarce (Barr and Turner, 2013).[1]

The second channel is the housing-wealth channel, which is related to changes in home equity that primarily affect homeowners but not renters. U.S. college education is costly,[2] and parental contributions constitute up to 50% of college financing.[3] Housing wealth is the most important part of the total wealth portfolio for the bottom 90% of U.S. households (Kuhn et al., 2020), and therefore fluctuations in home prices greatly affect homeowners' balance sheets and perceived family wealth. During a housing boom, rising home equity can make it easier for homeowners to finance large education expenses, either through home-equity borrowing or through a broader wealth channel. 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). Note that renters are only affected by the opportunity cost channel,[4] while homeowners are affected by both, and for them the two effects go in opposite directions.[5]

We use a large-scale, nationally representative household survey of around 104,300 households from the American Community Survey, Ruggles et al. (2024), for which we observe

[1]For our identification approach, it is important that fluctuations in the opportunity cost of college affect homeowners and renters similarly. We show that, in terms of employment probability, children of homeowners and renters are similarly exposed to the housing cycle. We also perform many checks to ensure that our main results are not driven by any observed or unobserved differences between homeowners and renters.

[2]The average annual undergraduate budget (including tuition, room and board, and other expenses) in 2011-2012 (the peak of the housing bust) was $42,224 for a living-on-campus four-year program in a private nonprofit institution. Sources: Trends in College Pricing 2011; Baum and Ma (2011).

[3]These include a mix of parental savings and income plus parental borrowings. As of 2014, half of American families with children under the age of 18 were saving for college. Source: Sallie Mae. How America Pays for College, 2014.

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

[5]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).

both parental homeownership status and children's college attendance outcomes. We match these data with local indices on changes in home 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 home prices were significantly less likely to be attending a higher education institution, as opposed to homeowners who experienced more modest declines in home prices. To give a sense of these differences, our estimates suggest that children of homeowners were 2.25 p.p. less likely to be attending college in the top 20% geographies (Public Use Microdata Areas, PUMAs) in terms of home price declines, relative to the bottom 20%.

How important is this effect in the aggregate? How persistent is it? And how does it affect economic outcomes later in life? To answer the first question, we perform a back-of-the-envelope calculation based on local declines in home prices during the bust, the number of college-eligible students, the share of homeowners in each geographic locality, and the elasticity of college attendance to changes in home prices. Using this approach, we find that the effect is substantial in the aggregate: for example, in 2011 3.8% of the local college-age population did not attend college due to the destruction of their parents' housing wealth.

To answer the second question, we compare owners and renters in geographic localities that were 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 children of homeowners remaining significantly less likely to have attended college as of 2019. Longer and more expensive college arrangements were more affected than shorter programs.

Finally, we show that this persistent decline in human capital accumulation translates into persistently lower income levels. This is not driven by a decline in general employability, but by a significantly lower likelihood of being employed full-time, especially in education-intensive industries in which the college premium tends to be reflected in higher wages. These findings are consistent with other papers that have recently documented the persistent aggregate effects of the Great Recession (e.g., Yagan, 2019; Jones et al., 2022).

We address several potential threats to identification in our analysis. The main concern with our methodology is that renters are not an adequate control group because they are too different from owners. We address this concern in a number of ways. First, we show that the main effect still obtains when we account for time-invariant differences between owners and renters. Second, we document similar effects when we restrict the sample of owners to be observationally similar to the sample of renters. Third, we show that the main effect is not driven by renters and owners facing different labor market opportunities, nor by the differential evolution of rents in areas affected differently during the housing bust, nor by relative changes in the availability of student loans. Finally, we demonstrate that our findings are not influenced by differences in the migrant status composition of homeowners and renters; the main result of our study still obtains when we focus exclusively on families who remained in the same housing units throughout the housing downturn.

Another concern is related to the possibility that both the home price dynamics and the demand for college are driven by a common, unobservable factor, such as expectations about future growth. We show that a statistically significant association between the extent of the housing bust and the likelihood of college attendance for the children of homeowners still obtains when we use the housing supply elasticity from Saiz (2010) as an instrumental variable for the decline in home prices to account for the potential endogeneity of college choice and home prices.

Our main result is also robust to using alternative proxies for the housing market shock: direct measures of housing net worth decline based on Mian et al. (2013), and changes in foreclosure rates. The main result is still obtained when we control for tuition costs in the household's state of residence, which is a good proxy for the costs of college that students actually face, given that the vast majority (close to 90%) attend college in their state of residence. We also document, as an extension, that homeowners are more negatively affected in areas where in-state tuition is high relative to family house value.

Our work contributes to the literature on financial frictions and education, especially

in the context of the Great Recession.[6] Wealthy parents invest more, on average, in the human capital of their children than poorer parents (e.g., Becker et al., 2018; Chakrabarti et al., 2023). Consequently, easier access to external finance increases college attendance 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 examining the effect of banking deregulation on college enrollment, which increased the availability and reduced the cost of bank credit (Sun and Yannelis, 2016), or the effect 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 significantly increases the likelihood of college attendance for homeowners' children; in Laeven and Popov (2016) and Charles et al. (2018), who show that in areas with a steep housing price decline, college attendance was lower during the bust years; and in Johnson (2020), who shows that the college graduation rates of homeowners' children are significantly affected by changes in housing wealth. Relative to Lovenheim (2011) and Lovenheim and Reynolds (2013), we study the effect of a *negative* wealth shock on college attendance. Relative to Laeven and Popov (2016) and Charles et al. (2018), we identify the effect of fluctuations in home prices on human capital accumulation via the channel of decline in housing wealth. Finally, relative to Johnson (2020), we document that human capital losses are large at the local level, that they are not recovered in the wake of the housing bust, and that they lead to a persistent reduction in employability and income. This last point is important because Bárány et al. (2025) have recently shown that a significant share of those with a college education attain it later in life. Our analysis strongly suggests that this is not the case for those who came of college age at a time when their parents were experiencing large and persistent losses in

[6]For recent work on the effect of the Great Recession on education without accounting for financial frictions, see e.g. Barr and Turner (2013) and Bicakova et al. (2025).

housing wealth.

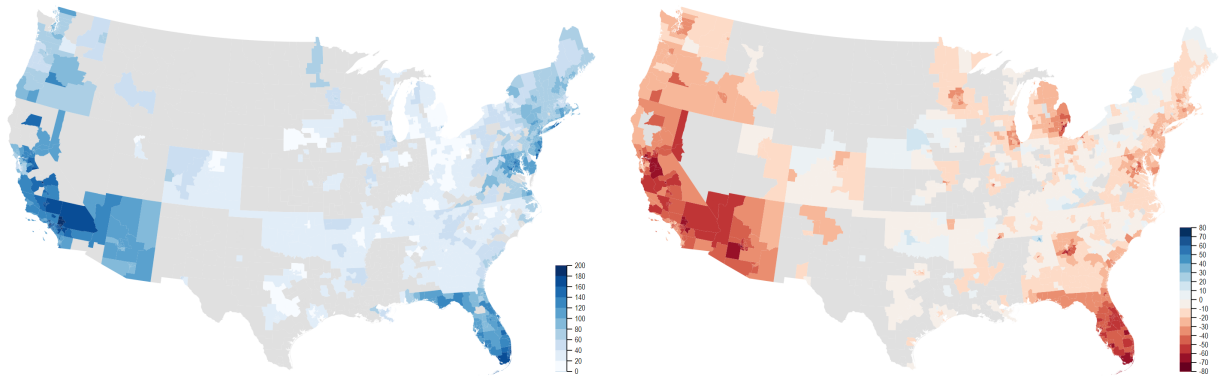
Our paper thus adds to previous work by demonstrating that large enough shocks to housing wealth can reduce the human capital of an "unlucky" cohort. More importantly, we also demonstrate that this effect is not undone during the boom phase of the cycle but persists over at least a decade. This is likely because household deleveraging is gradual and takes place over many years (Jones et al., 2022), driving a persistent wedge between the cost of and the return to higher education. Our paper also contributes to the literature on the socio-economic effects of fluctuations in home 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 the reallocation of many 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 the creation of business start-ups. Lovenheim and Reynolds (2013) and Dettling and Kearney (2014) document that an increase in housing wealth among homeowners significantly increases the probability of having a child. Daysal et al. (2021) show that housing price increases lead to better child health at birth. Furthermore, 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. By documenting a long-run decline in college attendance, employment, and income, we add to the literature suggestive evidence of a persistent negative effect of housing busts on human-capital-driven 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 was the severity of bust that followed it. Nationally, housing prices[7] rose by around 57% between the fourth quarter of 2000 and the fourth quarter of 2006,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 increased by 33% in Houston, TX Metropolital Statistical Area (MSA)[8]. Figure 2(a) illustrates this development at the detailed PUMA level.

Figure 2. Map of the U.S. Housing Boom and Bust



(a) Housing boom (b) Housing bust

Note: This figure depicts percent changes in home prices over the housing boom, from 2000 to 2006, Panel (a) and housing bust, from 2006 to 2011, Panel (b). ZIP-code level Home Value Index (sourced from Zillow) was projected on 2000 PUMAs using the Geocorr 2000 Engine (Source: Missouri Census Data Center). PUMAs are Public Use Microdata Areas. A gray area indicates that there are no data or that ZIP-code data cover less than 10% of PUMA (around 200 PUMAs per year).

The housing bust, which started in 2007 and lasted until 2011, resulted in a 17% decline

[7]In this section, we use *housing prices* based on single-family home values whereas in the main empirical analysis we use *home prices* based on Zillow Home Value Index which includes both single-family residences and condos. U.S. House Price Index: 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; fred.stlouisfed.org, Access date: October 30, 2024.

[8]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.

in house prices across the United States[9]. Similarly to the boom phase, the bust was characterized by large heterogeneity in house price changes. For example, house prices declined by 45% in Miami, FL, but increased by 5% in Houston, TX. The patterns of large regional differences in house price adjustments after the U.S.-wide peak are readily visible in Figure 2(b).

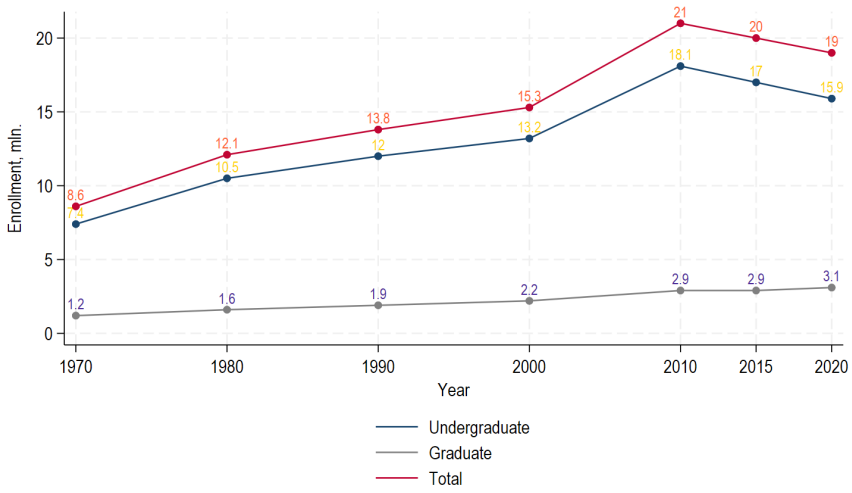
2.2 U.S. College Enrollment Trends

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

The most natural explanation is that tuition costs, particularly in private universities, rose faster than the return to college education (e.g., Delaney and Marcotte, 2024). This hypothesis, however, cannot directly account for the differential college attainment trends between homeowners and renters (see Figure 1). These could only be explained if homeowners and renters sorted into college programs of different lengths and cost. In particular, if renters sorted predominantly into shorter and cheaper programs while homeowners increasingly pursued longer and more expensive educational degrees, then a differential rise in tuition costs between short and long programs could help explain differences in college attainment. However, we do not observe differential trends in the fraction of homeowners and renters across

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

Figure 3. Total Undergraduate and Graduate Fall Enrollment in Degree-granting Postsecondary Institutions



Note: This figure depicts historical college enrollment in mln. of students. The data is sourced from the National Center for Education Statistics (NCES).

college attainment groups: some college vs. two and four years of college. This proportion is rather stable in time and equals 60% and 40%, respectively, among those aged 18-29.[10] This rules out a tuition-based explanation. Instead, given the differential trends in college attainment across homeownership groups reported in Figure 1, we conjecture that the ability of households to meet rising college tuition costs was 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 attendance 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 ACS data, that provides geographical identifiers of

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

the sampled population at the Public Use Microdata Area (PUMA) level. There are 2,057 distinct identified PUMAs 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 by the 2000 Census boundaries in the baseline analysis.

The combination of finely identified geography and large sample size makes the American Community Survey unique and the only appropriate public data source to study the question at hand. Other public datasets do not provide detailed geographical identifiers and/or have much smaller sample sizes (e.g., Current Population Survey, Panel Study of Income Dynamics, Survey of Income and Program Participation). By contrast, the American Community Survey 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 may have chosen to enter the workforce early and are ineligible for college because they have not completed high school.[11] We also restrict the sample to people who are identified in the survey as children who are related to the head of the household. This allows us to link first-year college-age individuals to their parents and thus to determine whether the household owns residential property or not.[12] Using these selection criteria, we establish a reliable link between parents' homeownership status and the college attendance status of their 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 home price growth relative to the peak of the housing boom, 2006

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

[12]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 parental homeownership status is not reported.

using Zillow ZIP code level home prices.[13] We use the ZIP code-to-PUMA crosswalk provided by the Missouri Census Data Center.[14] We convert ZIP code data to Census 2000 Geography to make home 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.[15] We use population data provided by the Missouri Census Data Center as the allocation factor of ZIP code data to PUMA-level data. We recalculate allocation factors proportionally if ZIP code-level home 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 home prices relative to the peak of the bust (2006 to 2007). We assume that the college attendance decision depends on the previous year's home 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 the ACS instead of PUMAs on 2000 boundaries, as was the case up to and including 2011. If we were to use a consistent PUMA variable to identify PUMAs pre- and post-2011, we would have only around 1,100 identified PUMAs, 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 the "migration PUMA" variable in the ACS. This is an individual's PUMA of residence 1 year prior to the survey year. We focus on U.S. geography and exclude migrants, i.e., those from non-U.S. destinations. Migration PUMAs are defined on Census 2000 Geography. We map 2000

[13] https://www.zillow.com/research/data/. Zillow Home Value Index (ZHVI).
[14] https://mcdc.missouri.edu/applications/geocorr2000.html.
[15] This way, we lose around 100 PUMAs.

PUMAs and "migration PUMAs" using the crosswalk provided by the IPUMS, Integrated Public Use Microdata Series [16]

To account for potential selection into college, we control for a rich set of individual- and family-level economic and demographic characteristics (in the following analysis we call them *Family controls*). In particular, in all specifications, we control for each individual's age, gender, race, ethnicity, real family income, number of siblings, and parental education and age. In all specifications, we also control for the local unemployment rate to account for the state of the local labor market.[17]

In Appendix Table A.I, we provide definitions of variables and data sources, and in Appendix Table A.II, we present summary statistics for our main sample. The main sample features around 104,300 observations on 18- and 19-year-old individuals who completed at least Grade 12 and are identified in the ACS as children over the 2008-2011 period. 67% are enrolled in college. On average, an individual is 18.6 years old. We have an almost equal proportion of males and females. 70% of the individuals in our sample are white, 14% are black, and 5% are Asian. In terms of ethnicity, 21% are Hispanics. The average income per person amounts to around 16,500 USD (in 2010 prices). In our sample of families with children, the homeownership rate is 76%: among all parents, 11% are outright homeowners and 65% are homeowners with a mortgage. 24% of parents are renters.

4 Methodology

Our identification strategy compares college attendance of college-age freshmen cohorts whose parents are either homeowners or renters, who reside in different U.S. geographic areas, and who reached college age in different years of the unfolding housing bust. We focus on the population who are 18- or 19-years-old because this is the age when most students complete

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

[17] This is important due to the well-documented variation in financial-frictions-driven changes in local unemployment during large macroeconomic contractions (Duygan-Bump et al., 2015; Benmelech et al., 2019).

high school and start college.[18] [19]

Our hypothesis is that all else being 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 the same age when home prices were rising, relative to the children of renters. There are several reasons why the children of homeowners may become less likely to go to college in geographic areas with a steeper home price collapse compared to the children of renters. First, college education is costly in the U.S. (Cai and Heathcote, 2022) and families tend to accumulate wealth in advance to send their children to college. In areas with a steeper home 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 the college attendance 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 home price collapse destroys family wealth, making homeowners feel poorer and decreasing the likelihood that they will send their children to college. Note that neither effect applies to the non-homeowner population: they are not locked into a home with collapsing value nor do they feel any wealth effect because the value of their home is declining. Therefore, and in line with prior work (e.g., Lovenheim, 2011; Laeven and Popov, 2017), 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 after home prices peaked in 2006 (see Figure

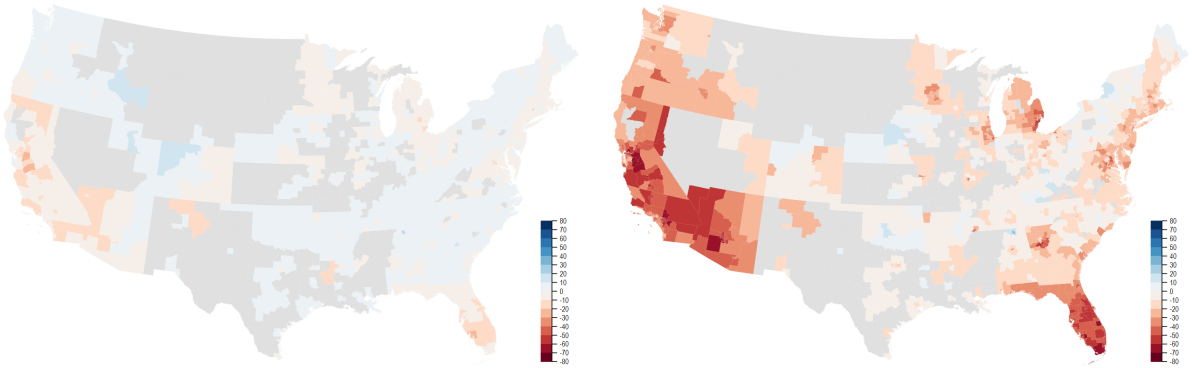
[18] According to the ACS, in 2000-2015, 91% of the 17 year old population were still attending high school and 2% of 17 year olds were college undergraduates, while among the 18 year old population, 47% were high school students and 33% college undergraduate students; among 19-years-olds: 9 and 56%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

[19] It has been previously documented in the literature that there is a business cycle variation in college attendance rate at ages older than 18-19 (Barr and Turner, 2013; Bicakova et al., 2025). Given that the highest attendance rate is observed at younger ages, 18-21 for 4-year college and 18-19 for 2-year college, as documented by Bicakova et al. (2025), we focus on the most important part of the variation in college attendance, in particular, on ages when individuals reach college age, 18-19. Our analysis could potentially be extended to older ages too.

1). During the boom phase of the home price cycle, the children of homeowners were enjoying significant progress in college attendance rates: from 60% in 2000 to 69% in 2006. 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 the 2007-2011 period, while children of renters increased their college attendance rate by 5 p.p., to 53%. Overall, the college attendance gap between homeowners and renters shrank by 4.1 p.p. between 2007 and 2011 and continued to decrease post-bust. Our hypothesis is that the destruction in homeowners' housing wealth during the housing bust played a role in the differential college attendance trends between the children of homeowners and renters.

To assess this hypothesis, we employ an empirical specification that takes advantage of differences in the timing and geographical variation in the impact of the housing bust. home prices started to collapse in 2007 when the average home price growth across PUMAs amounted to -1.6%, with 55% of PUMAs experiencing a negative home price growth rate. Over time and until 2012, the local home price dynamics progressively deteriorated: in 2011, 95% of PUMAs were in the "red zone" of negative home price growth, with an average home price decline of 23% from the peak of the housing boom (Figure 4). Note that the areas most affected by the housing bust are located on the east and west coasts of the U.S., particularly in Florida, Arizona, and California. Notably, these states contain some of the least elastic areas in terms of housing supply elasticity with respect to demand shocks, a factor that predicts the strength of the local housing booms and busts well (Saiz, 2010; Griffin et al., 2021).

Figure 4. Housing Bust Across Time and Space



(a) Start of the Housing Bust (b) Peak of the Housing Bust

Note: This figure depicts percent changes in home prices over the housing bust, from 2006 to 2007, Panel (a), and from 2006 to 2011, Panel (b). ZIP-code level Home Value Index (sourced from Zillow) was projected on 2000 PUMAs using Geocorr 2000 Engine (Source: Missouri Census Data Center). A gray area indicates that there are no data or that ZIP-code data cover less than 10% of PUMA (around 200 PUMAs per year)

We estimate an individual's college attendance sensitivity to changes in home prices depending on the parents' homeownership status. Our baseline econometric model is as follows:

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

The dependent variable $College_{i,p,t,b}$ is an indicator variable that equals one if a college entry-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 home 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), as well as the state of the local business cycle measured by the local (PUMA) unemployment rate.

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 demographic characteristics and family resources, present in $\mathbf{X}_{i,p,t,b}$. In Equation (1), we control for unobserved differences by including birth-year fixed effects α_b that capture variation common to all individuals in the same cohort; local time-invariant differences that are common to owners and renters in the same PUMA by including locality fixed effects α_p; and for aggregate shocks that are common to all individuals during the same year by including time fixed effects α_t. The specification thus allows us to identify the effect of changes in local home prices, $\Delta_{2006,t-1} \ln HPI_p$, on individual college attendance decisions.

Next, we saturate the model further and instead of accounting separately for time-invariant local differences and for 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 home price changes, $\Delta_{2006,t-1} \ln HPI_p$. Including the interaction PUMA $\times$ Year FEs is crucial: it controls for the local business cycle shocks that affect the college attendance decisions made by the children of homeowners and renters .

Additionally, in robustness checks, we account for differences between homeowners and non-homeowners 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 the ACS-provided individual 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 attendance to the housing bust between homeowners' and renters' children across regions differently affected by the bust.

5 College Attendance of the Children of Homeowners and Renters over the Housing Bust: Empirical Results

5.1 Baseline Estimation Results

The point estimates of Equation (1) are presented in Table 1. 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.V 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 column (6) of Table 1.

Our estimation results yield three main findings. Firstly, independently of the local housing market conditions, the children of homeowners are, on average, 14 p.p. more likely to attend 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 home price decline, 18- and 19-year-olds were more likely to attend a college. This is represented by the negative and statistically significant coefficient on $\Delta_{2006,t-1} \ln HPI_p$. A steeper decline in home 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 collapsing labor market opportunities. Thirdly, there are significant differences between the college-age children of homeowners and renters in this push for college, which is demonstrated by the positive and significant coefficient on the interaction term, $\Delta_{2006,t-1} \ln HPI \times$ Owner. The children

Table 1. Baseline Model: College Attendance of Children of Homeowners and Renters and 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)
Family controls		✓	✓	✓	✓	✓
Birth Year FE			✓	✓	✓	✓
PUMA FE				✓	✓	
Year FE					✓	
PUMA × Year FE						✓
N obs	104,294	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA × Year)	7,544	7,542	7,542	7,490	7,490	7,425
R^2 (*adj.*)	0.028	0.101	0.101	0.136	0.136	0.163

Note: This table reports the estimates of Equation (1), columns (1)-(5), and in column (6), of its appropriate modification in which we include PUMA×Year FEs instead of PUMA and Year FEs and do not identify a coefficient at $\Delta_{2006,t-1}HPI$. Here the dependent variable is an indicator variable which equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1}HPI$ is percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

of homeowners are, on average, 0.09 p.p. less likely to be enrolled in college compared to renters in response to the same local home price decline of 1 p.p. (see the preferred specification reported in column 6 in Table 1). This creates the heterogeneous total sensitivity of the children of homeowners and renters to the housing bust. In response to a 1 p.p. home price decrease, the probability of college attendance of the children of renters goes up by 0.13 p.p., whereas for the children of homeowners, the probability of college attendance goes up only by 0.05 p.p. in response to the same shock (see column 5 of Table 1 in which we identify the sensitivity of renters to HPI growth). This dampened response of children of

homeowners to the housing bust can be explained by a decline in parental housing wealth, a major component of family wealth that can be used as a source of college financing in the form of, e.g., home equity loans, mortgage refinancing, or realized housing wealth gains.

The estimated effect is economically significant. To get a sense of its size, we compare demeaned home price growth relative to 2006 in the most affected geographies (home prices, on average, declined by 11.3% in PUMAs that fall in the first quintile of the home price growth distribution) and the least affected geographies (which, on average, experienced a rise in home prices of 13.8% relative to 2006 and which fall into the fifth quintile of the home price growth distribution). This difference in home price growth, -0.25, translates into $-0.25 \times 0.09 = -0.0225$ lower probability of college attendance. Our estimation suggests that the children of homeowners were 2.25 p.p. less likely to be enrolled in college in the top-20% housing-price-decline PUMA-years, relative to the bottom-20%.

5.2 Identification Threats

5.2.1 Unobserved Differences Between Homeowners and Renters

To further address the notion that owners and renters are different in unobservable ways that may result in differential demand for college education, in Table A.VI we report estimates from a version of Equation (1) in which 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.VI confirms that even when we account for background forces that are common to all owners, relative to renters, the probability that the children of homeowners are enrolled 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 (6) of Table 1.

5.2.2 Observable Differences Between Homeowners and Renters: Matching

An important concern is that, if homeowners and renters are different along some characteristics, then any previously documented differences in homeowners' and renters' responses to the housing bust could be driven by differences in returns to college attendance stemming from their intrinsic differences rather than from homeowners' housing wealth decline driven by the housing bust. To address this concern, we first identify important characteristics in which the differences between homeowners and renters are the most profound. We then construct a matched sample in which we sample homeowners who are similar to renters in these identified characteristics using multivariate-distance nearest-neighbor matching. In this way, we ensure that our sampled homeowners and renters are as similar as possible. We then re-estimate Equation (1) on the matched sample.

We document important differences in observable characteristics between homeowners and renters in terms of race and ethnicity as well as on household income per person, parental education, and parental age (Table 2). Children of homeowners are less likely to be from racial and ethnic minority groups, and they come from higher-income families, and have better educated and older parents. Note that we use all of these variables as controls in all specifications throughout the paper. This way, all of our previous results are observed holding individual and family characteristics equal. Furthermore, we extend the previous analysis by sampling only those homeowners who are as close to renters as possible by observable characteristics.

We present all details on the matching of homeowners and renters in Appendix A.3. Overall, our matching procedure substantially reduces important differences between homeowners and renters – such as differences in race, ethnicity, geography, and year – and also reduces the differences on other characteristics (family income, parental education, and age; see Figure A.I in the Appendix). Our estimation results suggest that in the matched sample, the main result of the attenuated homeowners' response to the housing bust carries over, though it becomes somewhat less powerful: the coefficient on the interaction term $\Delta_{2006,t-1} \ln HPI \times Owner$

Table 2. Differences by Parental Homeownership: Homeowners vs. Renters, Raw Sample

	Homeowners	Renters	*Diff*
Attends a College	0.719	0.549	-0.170***
$\Delta_{2006,t-1} \ln HPI$	-0.122	-0.156	-0.035***
PUMA Unemployment Rate, 16-54	0.078	0.092	0.014***
Age	18.631	18.605	-0.026***
Female	0.480	0.499	0.019***
White	0.788	0.546	-0.242***
Black	0.076	0.233	0.157***
Asian	0.051	0.062	0.011***
Hispanic	0.158	0.299	0.141***
Log HH income per person (2010 USD)	9.903	9.156	-0.747***
Number of siblings	1.234	1.366	0.132***
Parental Years of Education	7.416	6.265	-1.151***
Parental Age	48.726	46.041	-2.686***
Housing Tenure, Years	13.197	7.066	-6.131***
Observations	82,942	21,405	

Note: This table reports mean-comparison t-tests of two samples: individuals aged 18-19 in 2008-2011 whose parents are homeowners and renters. Household income per person is transformed to 2010 prices using CPI. The data is sourced from ACS and Zillow.

is positive and significant at most at the 10-percent statistical level[20]; see Appendix Table A.VII. We interpret this as being partly driven by the smaller sample size in 1:1 matching, and therefore conclude that observable differences between homeowners and renters are unlikely to entirely drive our main result. There is still space for the differential response of homeowners and renters to the housing bust unrelated to their intrinsic differences.

5.2.3 Changing Renter Composition During the Housing Bust Period

Another concern is that our results are driven by the increased migration of renters during the housing bust. If this was the case, then the composition of renters would differ over time as the housing bust unfolded, which would invalidate the comparison between homeowners and renters. Another possibility is that renters disproportionately migrated away from areas most severely affected by the housing bust toward regions that experienced more limited housing market declines. Once again, this would make our baseline homeowner-renter comparison problematic.

[20] As before, the regressions control for demographics and fixed effects.

We rule out these possibilities using two simple tests. We compare the housing tenure of renters over time and space. First, we show that renting parents of children aged 18 and 19 have very similar housing tenures in 2008 and in 2011, as measured by the number of years since they moved into their current residence: 6.93 years in 2008 and 7.03 years in 2011. The difference between the two is statistically insignificant at conventional levels, according to a t-test. Simple averages thus speak against the argument that as the housing bust unfolded, migration by renters increased. Second, renting parents of first-year college-age children living in the areas most affected by the housing bust (i.e., those in the first quintile of the distribution of HPI changes, with average home price decline relative to 2006 of 43%) have the same housing tenure as similar parents living in the least affected PUMAs (-6% average HPI decline): both moved in 7.09 years ago. Once again, the difference between the two is not statistically significant.

We conclude that the composition of renters remained relatively stable over the course of the housing bust, and therefore selective renter migration is unlikely to drive our results.

5.2.4 Endogeneity in Home Price Dynamics during the Housing Bust: IV Estimation

In this section, we address the concern that changes in college attendance decisions are driven by a factor that is correlated with changes in home prices and that affects homeowners and renters differently for reasons unrelated to housing wealth, such as differences in expectations and beliefs about future revisions. If this is the case, then our econometric specification will pick up what is a simple correlation between home price dynamics and college attendance decisions, but we would interpret it as a causal effect.

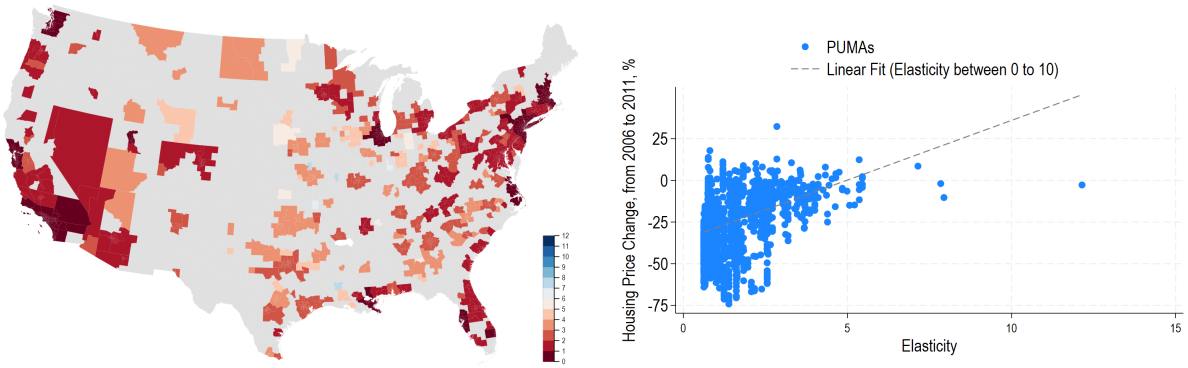
Moreover, the resulting bias can go in different directions. For example, negative shocks to home prices, to which homeowners are more attuned, may be interpreted as a signal about the future prospects of the economy. As a result, they now expect human capital investment to yield lower returns on education. Renters, in contrast, are not affected by such negative

expectations shocks because they are paying less or no attention to changes in home prices. This "pessimism channel" would imply an upward bias in the OLS coefficient, since larger price declines are correlated with lower college attendance. Alternatively, housing and human capital may be two separate items in homeowners' investment portfolios. With the return to housing going down, education may become a relatively more attractive investment. This "optimism channel" would imply a downward bias in the OLS coefficient, since larger price declines are correlated with higher college attendance.

Our current identification strategy does not allow us to include PUMA $\times$ Owner $\times$ Year FEs to control for local time-varying shocks specific to 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 on 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 home price decline that is due to *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 regulations 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 regulations are 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 home price movements.

Figure 5. Home Price Decline and Housing Supply Elasticity



(a) IV: Saiz (2010) Housing Supply Elasticity

(b) Elasticity and HPI change, 2006-2011

Note: This figure depicts the variation in housing supply elasticities across PUMAs, Panel (a), and the correlation between PUMA housing supply elasticity (x-axis) and the severity of the local housing bust, peak to trough, 2006 to 2011 (y-axis), Panel (b). Metropolitan Statistical Area (MSA) housing supply elasticities reported in Saiz (2010) were assigned to all PUMAs contained in corresponding MSAs. There are 362 MSAs based on 2000 Census boundaries definitions, and Saiz (2010) reports housing-supply elasticity in 269 of them.

As documented by Saiz (2010), there is a large geographical variation in housing supply elasticities across the U.S.: Figure 5, Panel (a) plots the Metropolitan Statistical Area (MSA)-level Saiz (2010) housing-supply elasticity adapted to PUMAs on 2000 boundaries.[21] 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 home price appreciation during a housing boom (see, e.g., Mian and Sufi, 2011).

Because we are focused on the housing bust period, we need to check whether the housing supply elasticity is a good predictor of the local severity of the housing bust. In Figure 5, Panel (b), we show that less elastic areas are more likely to experience a stronger home price decline, as the positively sloped linear fit line suggests.

We next use the local housing supply elasticity as an instrumental variable for local home

[21] We assign the same elasticity to all metropolitan-type PUMAs constituting the same MSA. We project MSA-level elasticity to metropolitan-type PUMAs only. There are no corresponding MSAs to non-metropolitan PUMAs.

Table 3. Instrumental Variable Estimation Results: Housing Supply Elasticity as an IV for the Local HPI Decline

Estimation:	IV-2SLS		OLS
Dependent variable:	$HPI \times$ (Owner)	$College_{i,p,t,y}$	$College_{i,p,t,y}$
	(1)	(2)	(3)
$\Delta_{2006,t-1} \ln HPI \times$ Owner		0.189***	0.063**
		(0.052)	(0.030)
Elasticity $\times$ (Owner) $\times$ Year = 2008	0.023***		
	(0.002)		
Elasticity $\times$ (Owner) $\times$ Year = 2009	0.063***		
	(0.005)		
Elasticity $\times$ (Owner) $\times$ Year = 2010	0.082***		
	(0.006)		
Elasticity $\times$ (Owner) $\times$ Year = 2011	0.085***		
	(0.005)		
Family controls		✓	✓
Birth Year FE		✓	✓
PUMA $\times$ 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: This table reports the IV-2SLS estimation of the regression of an individual's college attendance on the interaction term, $\Delta_{2006,t-1} \ln HPI \times$ Owner. Column (1) reports estimates of the first stage regression in which we regress $\Delta_{2006,t-1} \ln HPI \times$ Owner on local Housing Supply Elasticity $\times$ Owner $\times$ Year indicator variables and all relevant cross-products (not shown). Column (2) reports second stage estimation results, and Column (3) reports OLS estimates of the main Equation (1) but here instead of the baseline sample as previously used in Column (6) of Table 1, we restrict the sample to only metropolitan-type PUMAs constituting MSAs for which we have information on hosign supply elasticities from Saiz (2010). The dependent variable $College_{i,p,t,y}$ is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1} HPI$ is the percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether the parents of individual i are homeowners (=1) or renters (=0). *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. *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. The data is sourced from ACS, Zillow, and Saiz (2010).

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA $\times$ Year level.

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 indicator variables demonstrate that local housing supply elasticities are good predictors of changes in local home prices, and that this effect increases over time with the severity of the bust. The value of the first-stage F-statistics is strictly higher than the critical value for the IV regression (see Stock and Yogo, 2005).

The point estimate from the second stage of the 2SLS estimation is reported in column (2) of Table 3. 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 availability of data on local housing-supply elasticities (these data are 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 that the endogeneity of home 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 to the housing bust differently from renters even when the home price decline is conditioned to be impacted by exogenous forces, such as geography and housing regulations.

5.2.5 Differences in Employment Opportunities

We have shown that, in terms of educational decisions, the children of homeowners are less responsive to the housing bust compared to those of renters: they are less likely to be enrolled in college relative to renters in response to the same decline in local home prices. We interpret these differences as driven by a housing-wealth effect: homeowners suffer from a decline in home equity, whereas renters do not.

There is, however, an alternative explanation of differences in college enrollment we observe

that need to be ruled out; i.e., that labor market opportunities change differently for the children of renters and owners . Such differences in labor market opportunities could arise if, for example, the children of renters are more likely to accept low-skilled jobs while the children of owners are more likely to aspire to medium- and high-skilled jobs (a reasonable assumption given the gap in college attendance of about 14 p.p.; see Table 1). Suppose that low-skilled jobs, such as 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 a more pronounced home price decline. If so, then the lower increase in the probability of going to college for the 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 – i.e., those who are 18 and 19 years old and are not in college at the time of the survey.[22] This measures how the opportunity cost of college reacts to the local home price change:

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

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 this evidence, we conclude that the employment opportunities of homeowners and renters were equally sensitive to the housing bust.

[22] We require that the *GRADEATT* variable provided in the ACS is not equal to either 6 or 7 (the level of recent schooling reported in the ACS is not college undergraduate or graduate or professional school).

Table 4. Employment of Non-College Children of Homeowners and Renters and the Housing Bust

	Dependent variable: $Employment \vert College = 0$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2006,t-1} \ln HPI \times$ 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)
Family 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: This table reports the estimates of Equation (2) (column 6, the most restrictive and preferred specification) and of its appropriate modifications, columns (1)-(5). Here the dependent variable is an indicator variable that equals one if a first year college-age individual i is employed and zero if unemployed (using *EMPSTAT* variable provided in ACS). We ensure an individual does not attend college by requiring that *GRADEATT* is not equal to either 6 or 7 (the level of recent schooling reported in the ACS is not college undergraduate or graduate or professional school). $\Delta_{2006,t-1} HPI$ is the percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether the parents of individual i are homeowners (=1) or renters (=0). *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from the ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

The estimated employment response of homeowners and renters to the housing bust is thus consistent with the explanation that, during the housing bust, children of renters went to college more intensively compared to those of homeowners because homeowners lost housing wealth, not because renters' job market opportunities declined more intensively. We therefore rule out the alternative explanation that the differential response of the children of homeowners and renters to the housing bust is driven by different changes in employment opportunities across homeowners and renters.

5.2.6 Rent Savings for Renters in Areas with with Declining Home Prices

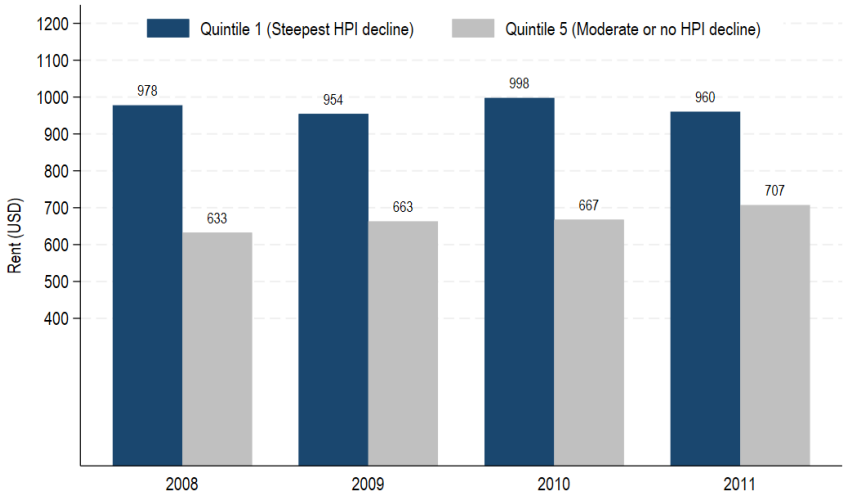
Another possibility whereby our estimation strategy can be compromised is if rents declined by relatively more in areas that experienced a relatively stronger decline in home prices. This would imply that renters experienced a rise in financial resources that can be allocated to expenses such as college tuition and student' living costs. In this case, the differential response of college attendance for the children of renters and homeowners would arise from changes in the circumstances of renters, as opposed to homeowners. Put differently, renters would not be a proper control group.

In Figure 6, we plot average rents for the top-quintile (in blue) and for the bottom-quintile (in gray) PUMAs in terms of home price declines in 2006-2011, over the period 2008 to 2011. The chart documents that rents were relatively flat over the housing bust, and moved in a similar fashion across PUMAs. If anything, rents increased by 20 USD between 2008 and 2010, while rents in the least affected areas increased by 34 USD. The difference of 14 USD a month, or 168 USD a year, represents less than 1% of the annual college budget of a commuting student enrolled in a public two-year college in 2011, or less than 0.3% of the annual budget of a student of a private nonprofit four-year college who lives on-campus.[23] This 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 substantially more beneficial financial conditions due to falling rents.[24]

[23] See Trends in College Pricing 2011. Baum and Ma (2011)

[24] 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 6. Average Rent by Year and Home Price Decline Quintile in 2006-2011



Note: This figure depicts nominal rents in the top-20% and the bottom-20% PUMAs in terms of home price decline in 2006-2011 (blue and gray, respectively). The sample consists of all 18- and 19- year old children of renters with non-missing geography (PUMA). Data is sourced from American Community Survey and Zillow.

5.2.7 Time-Varying Availability of Student Loans

One final possibility is that the decline in the college attendance of homeowners' children relative to renters is driven by relative changes in the availability of federal student loans. If federal student loans became less accessible to the children of homeowners during the housing bust (or more accessible to the children of renters), the effect we observe will partially be explained by the evolution of the student loan market, compromising our estimates.

We note, however, that this possibility is unlikely. Some types of student loans, like unsubsidized direct loans, are available regardless of student needs. Others, like subsidized direct loans or Pell Grants, use parental income and asset information, but exclude home equity. With declining parental home equity, the demand for federal student loans by the children of homeowners should, if anything, become higher during the bust. In fact, recent evidence suggests that for every dollar of home equity that parents did not draw upon, the student borrowed between 40 and 80 cents to replace it (Amromin, 2024). This suggests that the decline in the college attendance of homeowners' children that we document is observed

even though these households were able to make up for a large portion of the decline in their home-equity-borrowing potential by accessing the student loan market.

Another possibility is that renters' demand for federal student loans increased disproportionately. In this case, the observed differences between homeowners' and renters' college-age children could be driven by the changing financial situation of renters as opposed to that of owners. To rule out this possibility, we compare the fraction of owners' and renters' children attending college in terms of their student debt. To that end, we use data from the PSID Transition to Adulthood Supplement (TAS). The Supplement is a very short sample, which however, contains both parental homeownership status and children's outcomes, including student debt. We find no evidence of higher student loans by children of renters relative to homeowners. Both groups are equally likely to cover part of the cost of college with student loans, and this is the case both in 2009 (during the housing bust) and in 2013 (the post-bust period). In particular, among those who ever attended college and identified in the PSID as children, 45.9% of homeowners' children and 43.1% of renters' children had a student loan in 2009 (difference = 2.8, p-value = 0.719), and 43.0% and 44.1%, respectively, did in 2013 (difference = 1.1, p-value = 0.886, in both comparisons, TAS weights are applied). This allows us to rule out the possibility that our results are driven by any substantial increase in federal student loan borrowing among the children of renters.

6 Robustness of the Baseline Result

Alternative measures of the housing shock. In the baseline estimation presented in Table 1, we use local house-price changes 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) the log change in the foreclosure rate, relative to 2006, which measures property losses during the bust.[25] The point estimates

[25]Details on the data construction of Mian et al. (2013)'s housing net worth change and foreclosure rate

presented in columns (2) and (3) of Table 5 show that the significant differences in education responses between homeowners and renters continue to obtain when we use these alternative proxies for shocks to home equity.[26] The estimate of β_2 is positive in column (2) and negative in column (3), suggesting that a larger destruction of local net worth and a larger increase in local foreclosure rate are associated with a more sizable drop in college attendance by the children of homeowners, relative to those of renters in the same location. In both cases, the effect is statistically significant at the 1% level.

Homeownership status change. Next, we explore the robustness of our baseline estimates to eliminating those who changed their homeownership status during the housing bust from the sample. 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 it was before the start of the housing bust. This restriction reduces the sample from approximately 104,000 individuals to approximately 79,000. The estimation results are presented in column (4) of Table 5. The point estimate on the coefficient of interest remains positive and significant at the 1% level, and, numerically, it is about 50% larger than that in the preferred specification in column (1), suggesting that differential response of homeowners and renters is not driven by either migration during the housing bust or homeownership status change over the same period (e.g., homeowners losing their property and becoming renters).

Excluding large states. Next, we ensure that our main results are not driven by individuals in a few very influential states. Recall that the largest collapse in home prices during the housing bust was recorded in Arizona, California, and Florida (see Figure 2, Panel (b)). While it would not necessarily compromise our estimation strategy if it proved that our results are driven by a handful of states, this would nevertheless have implications for their external validity. However, when we exclude these states one by one and as a group

at the PUMA level are provided in Appendix A.5.

[26] In column (1) of Table 5, we replicate the point estimate from our preferred specification reported earlier in column (6) of Table 1.

Table 5. 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)	Moved In ≥ 5
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.086***			0.124***
	(0.029)			(0.042)
$\Delta_{2006,t-1} \ln HNW \times$ Owner		0.062***		
		(0.024)		
$\Delta_{2006,t-1} \ln ForeclosureRate \times$ Owner			-0.002***	
			(0.001)	
Family 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: This table reports the estimates of the following specification:

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

The dependent variable is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1} HPI$ is percentage change in the local home price index, $\Delta_{2006,t-1} \ln HNW$ is percentage change in the local housing net worth calculated following Mian et al. (2013)'s procedure; $\Delta_{2006,t-1} \ln ForeclosureRate$ in a change in local foreclosure rate; all in an individual's PUMA of residence in the previous year relative to 2006. Details on estimation of the last two measures of the *Housing Shock* are provided in Section A.5 in the Appendix. In column (4), we restrict the sample to those households who stayed in their residences from at least 2006 by requiring that they moved into the current housing unit 5 years ago or earlier. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). α_b and $\alpha_{p,t}$ capture Birth Year and PUMA-Year FEs. *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

(columns (2)-(5) of Table 6), we find that the main effect still obtains and is, if anything, larger than the results from the preferred specification, replicated in column (1).

Table 6. Robustness of the Main Result 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)
Family 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

This table reports the estimates of the baseline specification:

$$\begin{aligned} College_{i,p,t,b} = \alpha_b + \alpha_{p,t} + \beta_1 \cdot \Delta_{2006,t-1} HPI_p \times Owner_{i,p,t,b} \\ + \beta_2 \cdot \Delta_{2006,t-1} HPI_p + \beta_3 \cdot Owner_{i,p,t,b} \\ + \gamma' \mathbf{X}_{i,p,t,b} + + \varepsilon_{i,p,t,b} \end{aligned}$$

The dependent variable is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1} HPI$ is percentage change in the local home price index in an individual's PUMA of residence in the previous year relative to 2006. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). α_b and $\alpha_{p,t}$ capture Birth Year and PUMA-Year FEs. *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

7 Our Baseline Result Relative to Previous Work

Is homeowners' response to changes in home prices asymmetric between the housing bust and the housing boom? To answer this question, we compare our estimates of the response of college attendance to home price declines during the housing bust with previous work on the boom.

The only two comparable papers using the U.S. data are Lovenheim (2011) and Johnson (2020). The first studies only the boom period, while the second one covers the boom and bust periods. Given that both papers use housing wealth as a measure of shock, we employ the specification with the housing net worth shock estimated using Mian et al. (2013)'s procedure, presented in the robustness section in column (2) of Table 5.

In line with our estimates, a decrease in local housing net worth (HNW) of 1 p.p. decreases the probability of college attendance by homeowners' children by 0.062 p.p., relative to renters (column 2, Table 5). In 2006-2011, the average absolute decline in housing net worth per family was \$68,307 or –32.4%. This translates into a –2.0 p.p. lower probability of college attendance of the children of homeowners relative to renters. Overall, this magnitude accounts for around half of the overall reduction of the homeowner-renter gap in college attendance over the housing bust, which amounted to 4.1 p.p. in 2006-2011.

Lovenheim (2011) finds that a \$10,000 increase in home equity increases the probability of children of homeowners enrolling in college by 0.71 p.p. The average increase in home equity in 2001-2005 was \$57,965; therefore, homeowners saw an increase in the probability of college attendance by 4.1 p.p. Renters did not respond to changes in local home prices according to Lovenheim (2011)'s estimates.

Johnson (2020) estimates that a \$50,000 increase in home equity increased the probability of college enrollment of homeowners' children by 2.8-3.5 p.p. over 1992-2016, which includes several boom and bust periods in the U.S. housing market.

Our estimate is on the lower side of those in the literature, suggesting that during good times the college attendance response is, on average, stronger per unit increase in housing wealth. In bad times, in contrast, homeowners hesitate to limit college enrollment by their children to the same degree as they would increase it during boom times in response to the same unit home equity change. This could be rationalized by perceived high future yields of college education.

Overall, our finding of a *less strong* college attendance response during the housing bust compared to the boom points to a form of college attendance downward rigidity, similar to the downward nominal wage rigidity discussed in Schmitt-Grohé and Uribe (2016) and suggests that parents and children tend to turn to alternative ways to finance college when the housing boom turned into a bust, such as taking more student loans. Note that student debt started to rise exactly at the time of the housing bust, and there is already preliminary

evidence linking the housing crisis to the rise in student debt (e.g., Mondragon et al., 2017).

8 Missing College Students: Local Housing Bust and College Attendance

How much would local college attendance of first-year college-age individuals change if all homeowners responded to the housing bust the way renters did? Put differently, how many fewer individuals were actually enrolled in college because their parents were homeowners who faced home equity losses and, as a result, reduced their expenditures, including on college education?

To estimate how many 18- and 19- years old did not go to college in different U.S. regions because of homeowners' differential response to the bust, we perform the following back-of-the-envelope calculation. We multiply the size of the local housing bust by the local parental homeownership rate of the first year college-age cohort and multiply it by the estimated coefficient capturing the differential response to the housing bust across homeowners and renters (0.086; column (6) of Table 1).[27]

For every PUMA, we estimate the local economic effect of the housing bust on the college attendance of homeowners relative to renters as follows:

$$\%\ not\ going\ to\ college_p = 100 \times \Delta_{2006,t-1} \ln HPI_p \times 0.086 \times \frac{Homeowners\ (Age = 18, 19\ )_p}{Total\ (Age = 18, 19\ )_p}$$

The geographical distribution of lower college attendance is presented in Figure 7. Not surprisingly, given the geographical distribution of the home price collapse, the most affected areas (denoted in red and dark red) lie within Florida, Arizona, Nevada, and California.

Our calculations imply that, across 1,612 PUMAs that we have input data for,[28] on

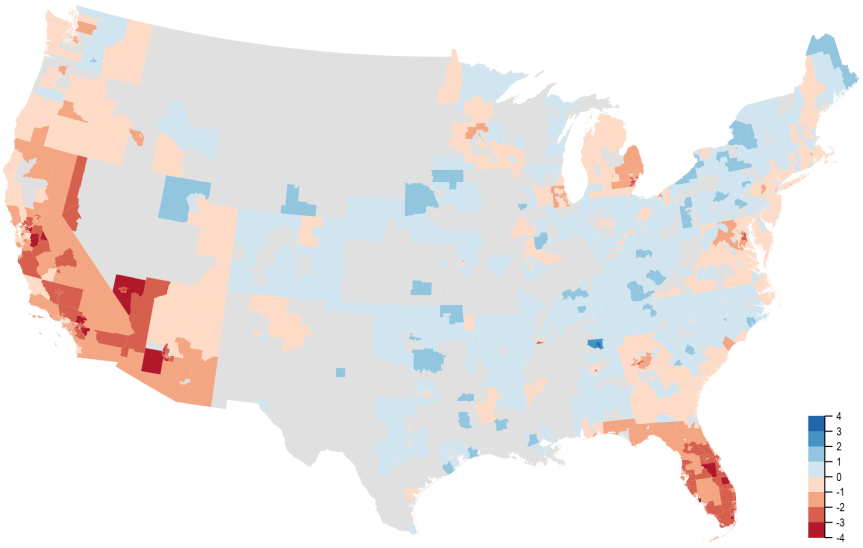
[27] Note that these estimates abstract from the general equilibrium effect, which could arise e.g., if colleges adjusted their selection criteria and pricing in response to decreased attendance.

[28] We lose another 260 PUMAs because there were no first-year college age individuals with Grade 12 identified as children surveyed.

average, 0.4 percent of 18 and 19 year old individuals did not go to college because their parents were homeowners, and home prices declined in their areas of residence. The maximum negative effect reaches 3.8 percent of the local college-age population who did not pursue college attendance at the height of the bust, in 2011, due to homeowners' differential response to the bust relative to renters. Note that there are many areas that saw no negative effect and even experienced an inflow of homeowners' children (depicted in blue in Figure 7). This is because in these areas, there was no or only a very moderate home price decline. In population count, red areas outweigh blue ones, suggesting that the aggregate effect was negative.

Overall, the geographical distribution of the estimated effect is driven by two factors: the severity of the housing bust and the local homeownership rate. The highest losses in terms of college attendance are concentrated in areas with both relatively high homeownership rates and relatively steep declines in home prices.

Figure 7. Geographical Distribution of the Estimated Economic Effect of the Housing Bust on the College Attendance of Homeowners' Children



Note: This figure depicts the percent change in the 18-19 y.o. population not going to college (-) or extra going to college (+) of homeowners relative to renters in 2011, which is the peak of the housing bust, in response to the local home price change. Missing attendance by homeowners' children is calculated as follows:

$$\%\ not\ going\ to\ college_p = 100 \times \Delta_{2006,t-1} \ln HPI_p \times 0.086 \times \frac{Homeowners\ (Age = 18,19)_p}{Total\ (Age = 18,19)_p}$$

Where $\Delta_{2006,t-1} HPI_p$ is the percentage change in the local home price index in PUMA in the previous year relative to 2006. $Homeowners\ (Age = 18,19)_p$ is the PUMA count of first-year college-age individuals whose parents were homeowners. $Total\ (Age = 18,19)_p$ is the PUMA count of all first-year college-age individuals independently of parental homeownership status. 0.086 is the coefficient of differential response of homeowners relative to renters reported in the preferred specification in column (6) of Table 1. A gray area indicates that there are no data on home prices or young individuals or that ZIP-code data cover less than 10% of PUMA (around 200 PUMAs per year).

9 The Scarring 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 larger decline in home prices exited the recession more slowly, and Figure 3 shows that the decline in college attendance after 2010 was not temporary. It is therefore possible that the decrease in housing wealth during the bust may have had a persistent effect on local outcomes through homeowners'

outcomes such as their children's lower college attainment rates, lower full-time employment rates, less uptake of skilled jobs, and lower income.

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

$$Y_{i,p,t,b} = \alpha_b + \alpha_{p,t} + \sum_{k \neq 2011} \beta_k \cdot \mathbf{1}_{\{k=t\}} \cdot \Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b} + \gamma' \mathbf{X}_{i,p,t,b} + \varepsilon_{i,p,t,b} \tag{3}$$

Here $Y_{i,p,t,b}$ denote outcome variables of interest, which include educational attainment, employment, and income. We interact year indicator variables $\mathbf{1}_{\{k=t\}}$ with the local severity of the housing bust, peak to trough, $\Delta_{2006,2011} \ln HPI_p \times Owner_{i,p,t,b}$. This event-study specification allows us to trace the differences in outcome variables between the children of homeowners and renters over time. We focus on the pre-COVID-19 pandemic period, 2005-2019, and we look at those individuals who were aged 18-19 during the trough of the housing cycle (2010-2011), which means birth cohorts 1991-1993. As we have done so far, we control for individual- and family-level demographic characteristics captured by $\mathbf{X}$, for cohort effects captured by birth-year FEs α_b, and for local time-varying shocks proxied by $\alpha_{p,t}$. As before, we retain individuals identified as children,$RELATE = 3$. We exclude those living in group quarters and keep individuals living in their state of birth (both restrictions are similar to Charles et al., 2018). The last one aims to remove those who migrated for college or for work from the sample, and thus were not exposed to the housing crisis in their current geography.

The index p denotes geography, which in this exercise, is *consistent PUMAs*, *CPUMA*. Here, we cannot use the PUMAs defined on 2000 boundaries as a unit of geography, as we have done so far, because starting in 2012, the ACS reports data on 2010 boundaries, and there is no one-to-one mapping between all PUMA 2000 and PUMA 2010. To overcome this, we use consistent PUMAs 00-10 reported in the ACS that did not change across the

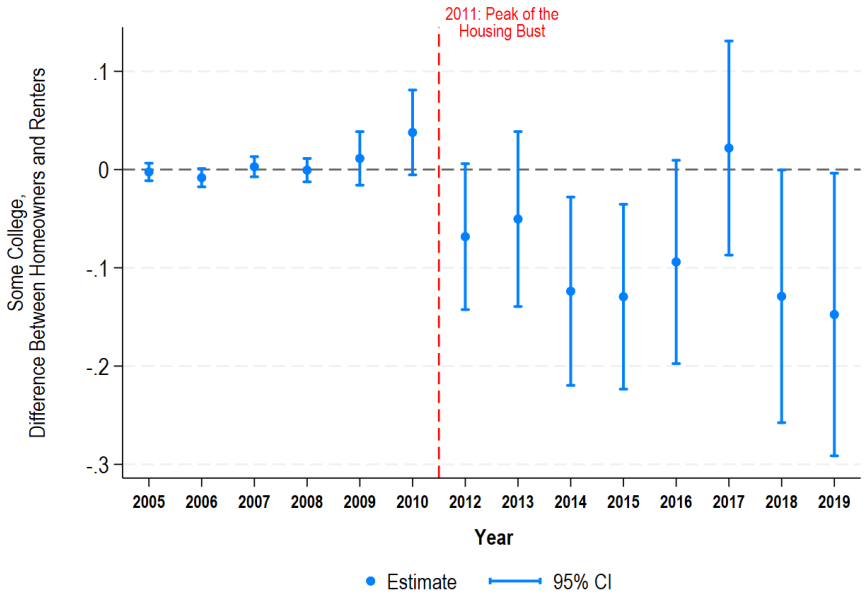
2000s-2010s. This leaves us with 1,078 consistent PUMAs, and we project PUMA 2000 home price growth on consistent PUMAs 00-10 using PUMA 2000 and the PUMA 00-10 crosswalk provided by the IPUMS.[29]

9.1 College Attainment

We first estimate Equation (3) with individual educational attainment as the dependent variable. In this section, we use educational attainment instead of current college attendance. We construct several proxies for having any college attainment using the detailed *EDUC* variable in the ACS, *EDUCD*. We construct an indicator variable "some college" equal to one if the individual has at least one year of college, $EDUCD \geq 065$. As additional college attainment outcomes, we also construct indicator variables for having an associate degree / two years of college, $EDUCD = 080$, and a bachelor's degree and higher / at least four years of college, $EDUCD \geq 101$.

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

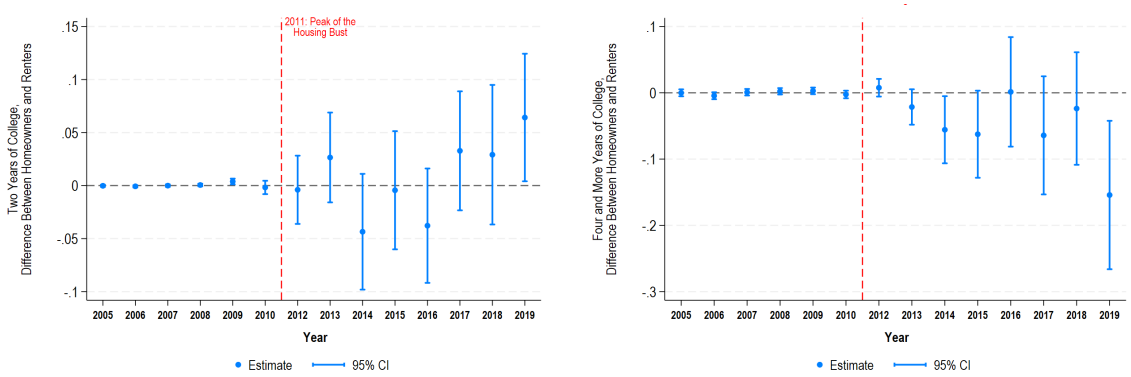
Figure 8. Housing Bust and College Attainment: Some College



Note: This picture reports coefficient estimates of β_k from Equation (3) re-normalized to a negative 1 p.p. home price change. Plotted coefficients represent differences between the children of homeowners and renters in areas with a 1 p.p. more sizable home price decline in 2006-2011. The dependent variable Y is "Some college". "Some college" includes less than one year of college; one or more years of college credit, no degree; two years of college, associate's degree; four years of college, bachelor's degree, and 5+ years of colleg, and zero otherwise. Narrow and close to zero estimated coefficients in 2005-2010 are due to the fact that surveyed individuals were mostly below college age at this time. Sample: ACS 1991-1993 birth cohorts, individuals identified as children, $RELATE = 3$, living in their states of birth, excluding group quarters.

Our estimation results point to persistent losses in college attainment as measured by having some college education (see Figure 8). Most of the estimated time coefficients are negative and half are statistically significant. We observe a one-year slightly positive rebound in 2017, which is insignificant and could possible arise because of the repeated cross-section nature of the data: a different sample of people is surveyed every year though all samples come from the same birth cohorts. As late as 2019, the end of our sample, children of homeowners who were 18 or 19 years old in 2010-2011 were 0.13-0.15 p.p. less likely to have some college education compared to renters if they lived in PUMAs with a 1 p.p. stronger home price decline.

Figure 9. Housing Bust and College Attainment: Substitution Between Programs



(a) Two Years of College, Associate's Degree

(b) Four-Years of College or More

Note: This picture reports coefficient estimates of β_k from Equation (3) re-normalized to a negative 1 p.p. home price change. Plotted coefficients represent differences between the children of homeowners and renters in areas with a 1 p.p. more sizable home price decline in 2006-2011. The dependent variable Y is "Two Years of College, Associate's Degree" (panel a) or Four-years of College or More (panel b). "Two Years of College, Associate's Degree" is defined to have exactly two years of college and associate's degree and zero otherwise. "Four-years of College or More" includes four years of college, bachelor's degree, and 5+ years of college, and zero otherwise. Note that narrow and close to zero estimated coefficients in 2005-2010 are due to the fact that surveyed individuals were mostly below college age at this time. Sample: ACS 1991-1993 birth cohorts, individuals identified as children, $RELATE = 3$, living in their states of birth, excluding group quarters.

We next look at different types of college attainment. We find some evidence of substitution between shorter and less expensive programs (2 years of college, associate degree) and more expensive and longer programs (at least 4 years of college, bachelor's degree or higher) (see Figure 9). In particular, there is some evidence (though quite imprecisely estimated as seen from many insignificant coefficients) of homeowners' offspring leaning towards 2-year programs instead of 4-year programs and longer. As of 2019 though, the end of our sample, this substitution effect becomes statistically significant as we observe a positive and significant coefficient on the estimated difference between homeowners and renters in more affected geographies in 2 years of college attainment (panel a, Figure 9) and negative and significant in 4 and longer years of college attainment (panel b, Figure 9). The negative coefficient in 2019 is larger in absolute value, suggesting that the net change in college attainment is still negative as of 2019.

9.2 Employment and Income

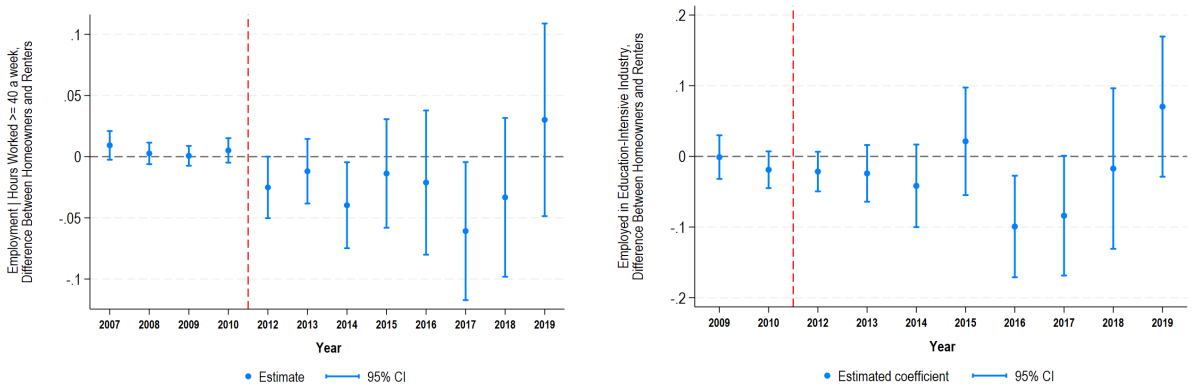
Next, we estimate Equation (6) with employment probability, as well as with real wage and salary income and real total personal income, as dependent variables.

We find some evidence of homeowners in more affected areas being less likely to have a full-time job. There are two statistically significant differences in full-time employment probability between homeowners and renters in response to a 1 p.p. deeper home price decline (Figure 10, panel a). These homeowners are also less likely to be employed in an education-intensive industry[30] (Figure 10, panel b). As late as 2017, homeowners living in areas that experienced the largest decline in home prices during the bust were up to 0.13 p.p. less likely to work in an education-intensive sector in areas that experienced a 1 p.p. steeper home price decline.

This reduction in employability – especially in high-human-capital industries, which tend to be characterized by higher wages – results in significant differences in real wage and salary income and real total personal income between homeowners and renters in more affected localities (see Figure 11). However, these differences tend to vanish in 3-4 years in our sample. The peak real income difference between homeowners and renters was about 1.5-2 p.p. lower incomes for every 1 p.p. home price decline over 2006-2011.

[30]We define these as 1990 basis industries in which the fraction of college-educated employment in total employment aged 16-54 is above the median, 2000-2020 average. For a similar strategy, see Ciccone and Papaioannou (2009).

Figure 10. Housing Bust and Employment



(a) Full-time Employment

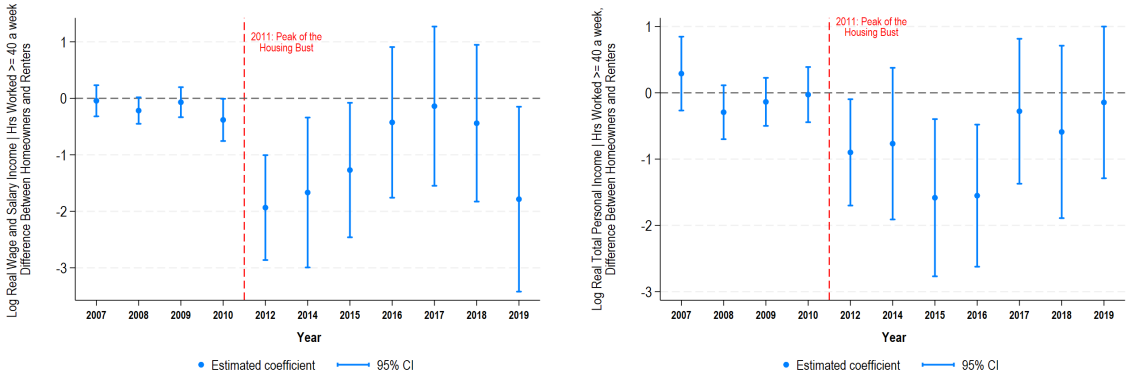
(b) Employment in Education-Intensive Industry

Note: This picture reports coefficient estimates of β_k from Equation (3) re-normalized to a negative 1 p.p. home price change. Plotted coefficients represent differences between the children of homeowners and renters in areas with a 1 p.p. more sizable home price decline in 2006-2011. The dependent variable Y is "Full-Time Employment Probability" defined as employment conditional on working hours being 40 hours a week or higher (panel a) and "Employment in Education-Intensive Industry" defined as being employed in an education-intensive sector, and zero otherwise (panel b). Education-intensive industry is defined as a 1990 basis industry with above median percent employees having at least four years of college, in total employment aged 16-54, 2000-2020 average. Top-3 education-intensive industries: Research, development, and testing services; Management and public relations services; Security, commodity brokerage, and investment companies. Note that in 2007-2008, coefficients are not identified and thus suppressed in panel (b) because too few surveyed individuals worked in education-intensive industries. Sample: ACS 1991-1993 birth cohorts, individuals identified as children, $RELATE = 3$, living in their states of birth, excluding group quarters.

The combined evidence thus suggests that, in affected regions, homeowners experience a persistent loss of human capital. Rather than simply postponing college attendance at 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. This is especially important in light of a recent analysis showing that obtaining education later in life has important individual and aggregate implications (see Bárány et al., 2025). Moreover, while children of homeowners were not persistently less likely to be employed 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. This points to a significantly more persistent effect of the housing bust on individual employability than earlier analysis by Laeven and Popov (2016) and Charles

et al. (2018) suggested.

Figure 11. Housing Bust and Individual's Income
Conditional on Full-time Employment



(a) Real Wage and Salary Income

(b) Real Total Personal Income

Note: This picture reports coefficient estimates of β_k from Equation (3) re-normalized to a negative 1 p.p. home price change. Plotted coefficients represent differences between the children of homeowners and renters in areas with a 1 p.p. more sizable home price decline in 2006-2011. The dependent variable Y is "Real Wage and Salary Income" which is total pre-tax wage and salary income: income received as an employee (panel a) and "Real Total Personal Income", which is total pre-tax personal income or losses from all sources (panel b). We deflate nominal values by the CPI adjustment factor available in the ACS. Both variables are defined conditional on working at least 40 hours a week. Sample: ACS 1991-1993 birth cohorts, individuals identified as children, $RELATE = 3$, living in their states of birth, excluding group quarters.

One important caveat is in order. In the long-run event study whose results we just reported, the estimated "scarring" effects pertain to co-residing adult children. This is because we keep the RELATE = 3 restriction, meaning the analyses is based only on those cohort members who still live with their parents in their mid-to-late twenties. In ACS, 38% of individuals aged 25 and 24% of individuals aged 29 who were 18-19 years old in 2011 live with parents (same numbers are 84% and 75% when individuals were 18 and 19 years old). The subgroup of individuals living with parents is unlikely to be representative of the cohort as a whole, and the propensity to remain in the parental home could itself vary with both the severity of the local housing bust and with parental homeownership status. For the sake of transparency, we need to acknowledge that any potential differences in co-residence might influence the results. At the same time, given that we do not observe data on parental

homeownership status for those young adults who moved out of parental homes, the current analysis provides a suggestive evidence of educational scarring on a subgroup of co-residing adult children.

10 Conclusion

The returns to investment in human capital are high both individually and socially: the college premium in lifetime income is substantial, and a more educated workforce is associated with a more productive economy. However, the cost of college in the U.S. has been rising in recent decades, pointing to the central role that credit constraints play in college attendance. 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 attendance in the U.S. has been declining since the housing bust of the late 2000s.

Using individual-level data from the ACS, we show that the children of homeowners are less likely to be enrolled in college, compared to the children of renters, in areas that experienced a relatively steeper home price collapse during the 2008-2011 period. Losses in educational attainment are concentrated in the South-West and South-East of the U.S. with up to 3.8% 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 reductions in the 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).

The rising cost of college has entered the debate about economic inequality and has prompted government action.[31] Our findings suggest that housing-wealth shocks trans-

[31]For example, the Biden administration announced two rounds of student debt forgiveness between 2022

mit into human-capital accumulation, implying that downturns in asset values have intergenerational costs that reduces college attendance over and above the rising costs of higher education. The evidence thus suggests that policy makers could think of a larger set of tools to increase the affordability of college, including counter-cyclical home-ownership-linked student-loan programs or more favorable conditions for housing-equity-based borrowing during housing busts.

and 2024.

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A Appendix

A.1 Variables Definition and Sources

Table A.I. Definitions of Variables and Data Sources, Main Sample, 2008-2011

Variable	Definition	Source	Variable	Unit
Outcome Variable				
Attends a College	Equals to 1 if an individual with at least Grade 12 attends a college	ACS	*GRADEATT*	0/1
PUMA Variables				
PUMA Home Price Growth, to 2006	Zillow Home Value Index, All homes, smoothed, seasonally adjusted. ZIP Code level data averaged over corresponding PUMAs using Geocorr 2000, Geographic Correspondence Engine. Growth relative to 2006	Zillow	*ZHVI*	%
PUMA Unemployment Rate, 16-54	Number of Unemployed in PUMA Divided by PUMA Labor Force (Employed + Unemployed), Aged 16-54	ACS	*EMPSTAT*	%
Individual and Family-Level Variables				
Individual's age	Person's age in years as of the last birthday	ACS	*AGE*	years
Female	Equals to 1 if an individual is female	ACS	*SEX*	0/1
White	Equals to 1 if an individual is white	ACS	*RACE*	0/1
Black	Equals to 1 if an individual is black	ACS	*RACE*	0/1
Asian	Equals to 1 if an individual is Asian (Chinese, Japanese, or other Asian)	ACS	*RACE*	0/1
Hispanic	Equals to 1 if an individual is Hispanic	ACS	*HISPAN*	0/1
Log Real Household Income Per Person	Total household income (standardized using *CPIU 2010*) divided by the number of individuals in the household, in natural log	ACS	*HHINCOME CPIU 2010*	log $US
Number of Siblings	Number of own siblings in household	ACS	*NSIBS*	-
Parental Education	Household's head education as tabulated in ACS	ACS	*EDUC*	-
Parental Age	Household's head age in years	ACS	*AGE*	years
Homeowner (Outright + Mortgagor)	Either Outright homeowner or Homeowner with a mortgage	ACS	*OWNERSHPD*	0/1
Outright Homeowner	Ownership of dwelling: Owned free and clear	ACS	*OWNERSHPD*	0/1
Homeowner with a mortgage	Ownership of dwelling: Owned with mortgage or loan	ACS	*OWNERSHPD*	0/1
Renter	Ownership of dwelling: Rented	ACS	*OWNERSHPD*	0/1
Additional Variables				
PUMA Housing Supply Elasticity	Housing Supply Elasticity, MSA averaged over PUMAs	Saiz (2010)	*ELASTICITY*	-
Employed, Not Attending College	Equals to 1 if an individual is employed, and 0 if unemployed conditional on not attending an undergraduate or graduate school	ACS	*EMPSTAT*	0/1
Monthly Rent	Monthly contract rent paid by renters	ACS	*RENT*	$US
PUMA HPI Growth Since Moved In	Change in PUMA home prices relative to year of moving in	ACS, Zillow	*MOVEDIN, ZHVI*	%
In-state College Tuition	In-state college tuition and required fees in public and private colleges, 2- and 4-year, 2010-2011 average	IPEDS	-	$US
House Value	Value of a housing unit	ACS	*VALUEH*	$US
Tuition to House Value	In-state college tuition divided by family's house value	IPEDS, ACS	*VALUEH*	-
PUMA Housing Net Worth change, to 2006	Previous year housing net worth growth relative to 2006	ACS, LLMA	-	%
PUMA Log Change Foreclos. Rate, to 2006	Previous year foreclosure rate growth relative to 2006	ACS, LLMA	-	%

Note: This table reports the variable constructions used in the main analysis. The sample includes individuals aged 18-19 in 2008-2011 identified as children, *RELATE=3* and who have education level of at least Grade 12, $EDUC \geq 06$. We exclude individuals who have Grade 12 according to *EDUC* variable but who attend Grade 9 to 12, $GRADEATTD = 54$ or $GRADEATTD = 50$.

Table A.II. Summary Statistics of the Main Sample, 2008-2011

	Mean	SD	Min	Max	N
Main Variables					
Attends a College	0.67	0.47	0.0	1.0	104,294
PUMA Home Price Growth, Relative 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
Individual's Age	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 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
Additional Variables					
PUMA Housing Supply Elasticity	1.59	0.99	0.6	12.1	85,147
Employed, Not Attending College Individuals	0.71	0.45	0.0	1.0	25,032
Monthly Rent	907.81	481.86	4.0	3,800	20,212
PUMA Home Price Growth Since Moved In	0.84	1.36	-0.6	18.4	98,435
In-state College Tuition	11,208	2,236	4,916	15,839	82,124
House Value	289,531	328,324	5,000	6,106,000	82,124
Tuition to House Value	0.08	0.10	0.0	1.1	82,124
PUMA Housing Net Worth Change, to 2006	-0.19	0.22	-1.8	0.6	84,713
PUMA Log Change Foreclosure Rate, to 2006	4.40	6.19	-0.9	67.6	94,796

Note: This table reports the summary statistics of our main sample of individuals aged 18-19 in 2008-2011 weighted using person weights provided in the ACS. The sample includes individuals identified as children, *RELATE=3* and who have education level of at least Grade 12, $EDUC \geq 06$. "Attends a College" is an indicator variable equal to 1 if an individual attends a college. "PUMA Home Price growth, to 2006" is the previous year PUMA-level home price growth relative to 2006. PUMA is migration PUMA of residence 1 year ago. "PUMA Unemployment Rate, 16-54" is the previous year PUMA-level unemployment rate among individuals aged 16-54. PUMA is migration PUMA of residence 1 year ago. "Age, years" is an individual's age in years. "Female" is an indicator variable equal to 1 if the individual is a female. "White" is an indicator variable equal to 1 if the individual is white. "Black" is an indicator variable equal to 1 if the individual is black. "Asian" is an indicator variable equal to 1 if the individual is Asian. "Hispanic" is an indicator variable equal to 1 if the individual is hispanic. "Log Real Household Income Per Person" is the logarithm of family per capita income transformed to 2010 prices using CPI provided in the ACS. "Number of Siblings" is the individual's number of own siblings residing with the individual. "Parental Education" is the household's head education level tabulated in ACS. "Parental Age" is the household's head age in years. "Homeowner (Outright + Mortgagor)" is an indicator variable equal to 1 if the housing unit is owned by its inhabitants. "Outright Homeowner" is an indicator variable equal to 1 if the housing unit is owned free and clear. "Homeowner with a Mortgage" is an indicator variable equal to 1 if the housing unit is owned with mortgage or loan. "Renter" is an indicator variable equal to 1 if the housing unit is rented. "PUMA Housing Supply Elasticity" is Saiz (2010) Housing Supply Elasticity projected to PUMAs. "Employment Status, Not Attending College Individuals" is an employed indicator variable among individuals not attending college. "Monthly Rent" is monthly contract rent paid by renters. "PUMA Home Price Growth Since Moved In" is PUMA home price growth relative to a year of moving in. "In-state College Tuition" is in-state college tuition and required fees in public and private institutions, 2- and 4-year, 2010-2011 average. "House Value" is house value in current dollars. "Tuition to House Value" is the ratio between previous two, trimmed at top 1%. "PUMA Housing Net Worth change, to 2006" is the previous year PUMA-level housing net worth growth relative to 2006. "PUMA Log Change Foreclosure Rate, to 2006" is the previous year PUMA-level foreclosure rate growth relative to 2006. The data is sourced from the American Community Survey, Zillow, Saiz (2010), IPEDS.

Table A.III. Definitions of Variables and Data Sources, Extended Sample, 2005-2019

Variable	Definition	Source	Variable	Unit
Outcome Variable				
Some College	Equals to 1 if an individual has less than one year of college, or one or more years of college credit and no degree, or two years of college and associate's degree, or four years of college and bachelor's degree, or 5 and more years of college, and zero otherwise	ACS	*EDUCD*	0/1
Two Years of College, Associate's Degree	Equals to 1 if an individual has two years of college and associate's degree, and zero otherwise	ACS	*EDUCD*	0/1
Four-Years of College or More	Equals to 1 if an individual has four years of college and bachelor's degree, or 5 and more years of college, and zero otherwise	ACS	*EDUCD*	0/1
Full-time Employment ($\geq$ 40 Hours per Week)	Equals to 1 if an individual is employed with working hours at lease 40 hours per week, and 0 otherwise	ACS	*EMPSTAT, UHRSWORK*	0/1
Employment in Education-Intensive Industry	Equals to 1 if an individual is employed in an education-intensive industry defined as an 1990 basis industry with above median percent employees having at least four years of college, in total employment aged 16-54, 2000-2020 average, and 0 otherwise	ACS	*EMPSTAT, IND1990*	0/1
Log Real Wage and Salary Income, Full-time Employment	Total pre-tax wage and salary income received as an employee. Current dollar values transformed to constant prices using ACS CPI adjustment factor. Defined conditional on working at least 40 hours a week: missing is assigned otherwise	ACS	*INCWAGE, UHRSWORK*	log $US
Log Real Total Income, Full-time Employment	Total pre-tax personal income or losses from all sources. Current dollar values transformed to constant prices using ACS CPI adjustment factor. Defined conditional on working at least 40 hours a week: missing is assigned otherwise	ACS	*INCTOT, UHRSWORK*	log $US
PUMA Variables				
CPUMA HPI growth, 2011 to 2006	Zillow Home Value Index, All homes, smoothed, seasonally adjusted. ZIP Code level data averaged over corresponding PUMAs using Geocorr 2000, Geographic Correspondence Engine. 2011 relative to 2006	Zillow	*ZHVI*	%
CPUMA Unemployment Rate, 16-54	Number of unemployed in CPUMA 0010 divided by labor force (Employed + Unemployed), aged 16-54	ACS	*EMPSTAT*	%
Individual and Family-Level Variables				
Individual's age	Person's age in years as of the last birthday	ACS	*AGE*	years
Female	Equals to 1 if an individual is female	ACS	*SEX*	0/1
White	Equals to 1 if an individual is white	ACS	*RACE*	0/1
Black	Equals to 1 if an individual is black	ACS	*RACE*	0/1
Asian	Equals to 1 if an individual is Asian (Chinese, Japanese, or other Asian)	ACS	*RACE*	0/1
Hispanic	Equals to 1 if an individual is Hispanic	ACS	*HISPAN*	0/1
Log Real Household Income Per Person	Total household income (standardized using *CPIU 2010*) divided by the number of individuals in the household, in natural log	ACS	*HHINCOME CPIU 2010*	log $US
Number of Siblings	Number of own siblings in household	ACS	*NSIBS*	-
Homeowner (Outright + Mortgagor)	Either Outright homeowner or Homeowner with a mortgage	ACS	*OWNERSHPD*	0/1
Outright Homeowner	Ownership of dwelling: Owned free and clear	ACS	*OWNERSHPD*	0/1
Homeowner with a mortgage	Ownership of dwelling: Owned with mortgage or loan	ACS	*OWNERSHPD*	0/1
Renter	Ownership of dwelling: Rented	ACS	*OWNERSHPD*	0/1

Note: This table reports the variable constructions used in the longer-run analysis (Section 10). The sample includes individuals born in 1991-1993 who were 18-19 in 2010-2011 identified as children, *RELATE=3*, who live in their states of birth, excluding group quarter population. The sample covers 2005-2019.

Table A.IV. Summary Statistics of the Extended Sample, 2005-2019

	Mean	SD	Min	Max	N
Outcome Variables					
Some College	0.28	0.45	0.0	1.0	811,446
Two Years of College, Associate's Degree	0.03	0.17	0.0	1.0	811,446
Four-Years of College or More	0.07	0.25	0.0	1.0	811,446
Full-time Employment ($\geq$ 40 Hours per Week)	0.04	0.19	0.0	1.0	549,290
Employment in Education-Intensive Industry	0.18	0.38	0.0	1.0	549,290
Log Real Wage and Salary Income, Full-time Employment	3.35	4.53	0.0	11.2	322,678
Log Real Total Income, Full-time Employment	3.59	4.45	0.0	11.2	409,066
CPUMA Variables					
CPUMA Home Price Growth, 2011 to 2006	-0.23	0.17	-0.7	0.2	773,774
CPUMA Unemployment Rate, 16-54	0.08	0.03	0.0	0.3	811,446
Individual and Family-Level Variables					
Individual's Age	18.57	4.27	12.0	29.0	811,446
Female	0.47	0.50	0.0	1.0	811,446
White	0.70	0.46	0.0	1.0	811,446
Black	0.16	0.36	0.0	1.0	811,446
Asian	0.03	0.18	0.0	1.0	811,446
Hispanic	0.19	0.39	0.0	1.0	811,446
Log Real Household Income Per Person	9.69	0.92	-2.1	13.2	808,035
Number of Siblings	1.22	1.18	0.0	9.0	811,446
Homeowner (Outright + Mortgagor)	0.74	0.44	0.0	1.0	811,446
Outright Homeowner	0.14	0.35	0.0	1.0	811,446
Homeowner with a Mortgage	0.60	0.49	0.0	1.0	811,446
Renter	0.26	0.44	0.0	1.0	811,446

Note: This table reports the summary statistics of the extended sample of individuals born in 1991-1993 who were 18-19 years old in 2010-2011. The sample covers 2005-2019. The summary statistics is weighted using person weights provided in the ACS. The sample includes individuals identified as children, *RELATE=3* living in their states of birth, excluding group quarters. "Some College" is an indicator variable equal to 1 if an individual has less than one year of college, or one or more years of college credit and no degree, or two years of college and associate's degree, or four years of college and bachelor's degree, or 5 and more years of college, and zero otherwise. "Two Years of College, Associate's Degree" is an indicator variable equal to 1 if an individual has two years of college and associate's degree, and zero otherwise. "Four-Years of College or More" is an indicator equal to 1 if an individual has four years of college, or bachelor's degree, or 5 and more years of college, and zero otherwise. "Full-time Employment ($\geq$ 40 Hours per Week)" is an indicator variable equal to 1 if an individual is employed with working hours at lease 40 hours per week, and 0 otherwise. "Employment in Education-Intensive Industry" is an indicator variable equal to 1 if an individual is employed in an education-intensive industry (defined as an 1990 basis industry with above median percent employees having at least four years of college, in total employment aged 16-54, 2000-2020 average), and 0 otherwise. "Log Real Wage and Salary Income, Full-time Employment" is total pre-tax wage and salary income received as an employee. "Real Total Personal Income" is total pre-tax personal income or losses from all sources. For both variables, current dollar values were transformed to constant prices using ACS CPI adjustment factor. Both variables are defined conditional on working at least 40 hours a week: missing is assigned otherwise. "CPUMA Home Price growth, 2011 to 2006" is the Consistent PUMA 0010 home price growth over 2006-2011. PUMA is migration PUMA of residence 1 year ago. "CPUMA Unemployment Rate, 16-54" is the Consistent PUMA 0010 unemployment rate among individuals aged 16-54. PUMA is migration PUMA of residence 1 year ago. "Individual's age" is an individual's age in years. "Female" is an indicator variable equal to 1 if the individual is a female. "White" is an indicator variable equal to 1 if the individual is white. "Black" is an indicator variable equal to 1 if the individual is black. "Asian" is an indicator variable equal to 1 if the individual is Asian. "Hispanic" is an indicator variable equal to 1 if the individual is hispanic. "Log Real Household Income Per Person" is the logarithm of family per capita income transformed to 2010 prices using CPI provided in the ACS. "Number of Siblings" is the individual's number of own siblings residing with the individual. "Homeowner (Outright + Mortgagor)" is an indicator variable equal to 1 if the housing unit is owned by its inhabitants. "Outright Homeowner" is an indicator variable equal to 1 if the housing unit is owned free and clear. "Homeowner with a Mortgage" is an indicator variable equal to 1 if the housing unit is owned with mortgage or loan. "Renter" is an indicator variable equal to 1 if the housing unit is rented. The data is sourced from the American Community Survey and Zillow.

A.2 Baseline Model: Additional Estimates

Table A.V. Full Baseline Model with Demographic and Family-Level Controls: College Attendance and Housing Bust

	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 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		✓	✓	✓	✓
PUMA FEs			✓	✓	
Year FEs				✓	
PUMA × Year FEs					✓
N obs	103,954	103,954	103,902	103,902	103,837
N clusters (PUMA× Year)	7,542	7,542	7,490	7,490	7,425
R^2 (*adj.*)	0.101	0.101	0.136	0.136	0.163

Note: This table reports the full estimates of Equation (1), where the dependent variable is an indicator variable which equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1}HPI$ is percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). This Table presents coefficient estimates on individual- and family-level controls previously not reported to preserve space. Coefficients appearing in first three rows of this Table were previously reported in Table 1 in the main text. Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

Table A.VI. Extended Main Model with Homeowner Fixed Effects: College Attendance and the Housing Bust

	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)		
Family controls	✓	✓	✓
Birth year FEs	✓	✓	✓
PUMA × Year FEs	✓	✓	✓
PUMA × Owner FEs		✓	
Owner × Year FEs			✓
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: This table reports coefficient estimates of the Equation (1), column (1), and of its modified versions accounting for homeowner-specific shocks, columns (2)-(3). In Column (2), the table reports coefficient estimates of the following specification:

$$College_{i,p,t,b} = \alpha_b + \alpha_{p,t} + \alpha_{p,o} + \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} + \gamma' \mathbf{X}_{i,p,t,b} + \varepsilon_{i,p,t,b} \quad (4)$$

Here the dependent variable is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1} HPI$ is percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. α_b stands for Birth year FEs, $\alpha_{p,t}$ captures PUMA-specific time-varying shocks, and $\alpha_{p,o}$ are time-invariant PUMA-specific Homeowners' fixed effects, PUMA-Owner FEs.

In Column (3), we present coefficient estimates of the following Equation:

$$College_{i,p,t,b} = \alpha_b + \alpha_{p,t} + \alpha_{o,t} + \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} + \gamma' \mathbf{X}_{i,p,t,b} + \varepsilon_{i,p,t,b} \quad (5)$$

Here $\alpha_{o,t}$ captures PUMA-invariant owner-specific time-varying shocks.
Regression estimates are weighted using person probability weights provided in the ACS. The data is sourced from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

A.3 Details on Matching

We match homeowners to renters using multivariate-distance nearest-neighbor matching. We use matching variables corresponding to observable characteristics that are different between homeowners and renters (see Figure A.I, raw sample) and that we use as control variables throughout the paper. These are: race and ethnicity (dummies for white, black, Asian, and Hispanic), average real household income per person, parental education, and parental age. We require exact matching on geography and on year of observation to make sure that matched homeowners come from the same PUMA and were sampled in the same year as renters. We also require an exact match on racial and ethnic characteristics to reduce demographic imbalances between homeowners and renters.

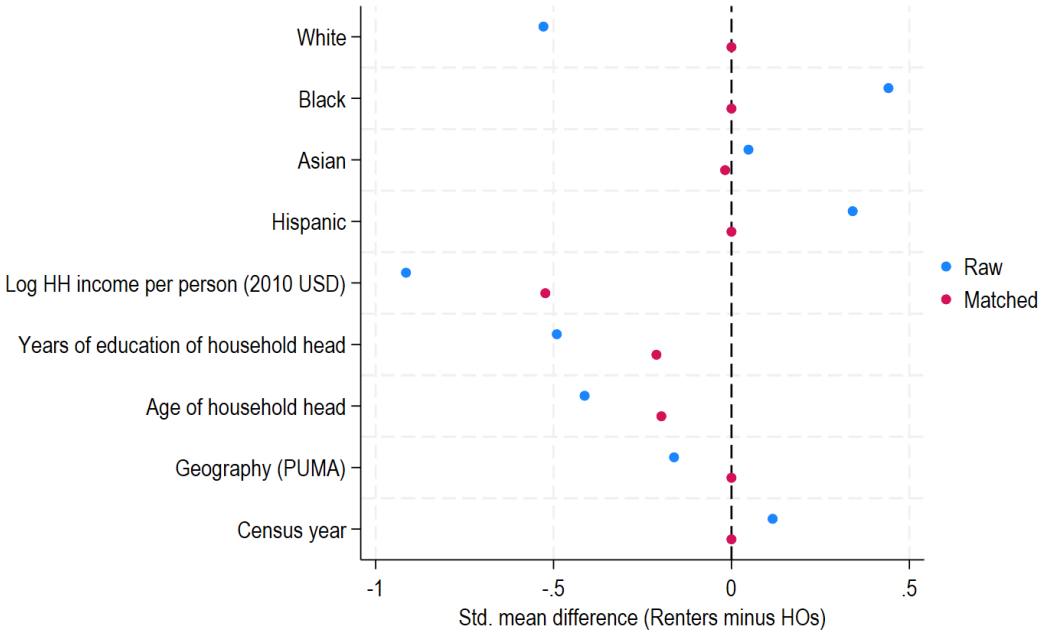
In the nearest-neighbor matching, we match one homeowner to one renter. This is because when using the 1:4 nearest-neighbor matching as in Abadie and Imbens (2011), we have difficulty finding 4 homeowners with similar demographic and economic characteristics for each renter in each geography and each year. Because of that, 1:4 matching yields over-sampling of low-income and minority homeowners and has many duplicate observations in the matched sample.

We present baseline matching balancing statistics on Figure A.I. Our matching procedure yields zero ethnic and racial imbalances between homeowners and renters because we require exact matching there. Matching also substantially reduces differences in incomes, education, and age, by around a factor of two, measured in standardized differences. Geography and year of observation are also exactly matched by construction. As we noted earlier, it is impossible to perfectly match on all observables, as well as on geography and year, because this type of match results in an oversampling of minority and low-income homeowners, who are relatively rare in the actual population. Therefore, with the current matching, we reach a point in which for every existing renter, we find one *existing* homeowner with the closest possible characteristics yielding a meaningful match. Given the limitation of the ACS sample, our matching does the best under constraints discussed above.

The estimation results of Equation (1) on the matched sample are presented in Table A.VII. The structure of the table follows the baseline of Table 1. Note that conclusions regarding coefficients signs and their significance are preserved when the estimation is performed on the matched sample instead of on the raw one. Importantly, our key coefficient of interest $\Delta_{2006,t-1} \ln HPI \times Owner$ is still positive and statistically significant, and its magnitude is around 15% smaller.

The fact that we obtain quantitatively and qualitatively similar results when using the matched sample suggests that the differential responses of homeowners and renters to the housing bust are unlikely to be solely driven by their differences in terms of observable char-

Figure A.I. Matching Balancing Statistics



Note: This graph reports differences in means in raw and matched samples. Method: multivariate-distance nearest-neighbor matching, 1:1. Matching renters and homeowners on the following characteristics: white, black, Asian, hispanic, real household income per person, parental education, parental age, geography (PUMA), and year of observation. Exact matching on the following variables: white, black, hispanic, geography (PUMA), and year of observation. The data is sourced from American Community Survey and Zillow.

acteristics. Instead, even when we sample only homeowners that are as comparable to renters on observable characteristics as possible, we still find a dampening effect of homeownership on college attendance during the housing bust, though the effect becomes somewhat less strong.

Table A.VII. Baseline Model Estimated on the Matched Renters-Homeowners Sample, 1 to 1 Matching: College Attendance and the Housing Bust

	Dependent variable: $College_{i,p,t,y}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2006,t-1} \ln HPI \times$ Owner	0.071	0.079*	0.077*	0.071*	0.071*	0.073*
	(0.047)	(0.045)	(0.045)	(0.043)	(0.043)	(0.042)
$\Delta_{2006,t-1} \ln HPI$	-0.163***	-0.204***	-0.185***	-0.106*	-0.121**	
	(0.029)	(0.033)	(0.034)	(0.056)	(0.061)	
Owner	0.169***	0.142***	0.142***	0.147***	0.147***	0.150***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Family controls		✓	✓	✓	✓	✓
Birth year FEs			✓	✓	✓	✓
PUMA FEs				✓	✓	
Year FEs					✓	
PUMA × Year FEs						✓
N obs	34,607	34,607	34,607	34,607	34,607	34,607
N clusters (PUMA× Year)	5,837	5,837	5,837	5,837	5,837	5,837
R^2 (*adj.*)	0.028	0.088	0.088	0.158	0.159	0.229

Note: This table reports the estimates of Equation (1), where the dependent variable is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1}HPI$ is the percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). *Family controls* include individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. The sample is constructed using multivariate-distance nearest-neighbor matching, 1:1, one homeowner is matched to each renter. Matching variables: White, Black, Asian, Hispanic, Real Household Income, Parental Education, Parental Age, Geography (PUMA), and Year of Observation. Exact matching on the following variables: White, Black, Hispanic, Geography (PUMA), and Year of Observation. The data is from ACS and Zillow.

***, **, * denotes significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the PUMA × Year level.

A.4 Extension: Cost of College – Tuition-to-House-Value Gradient

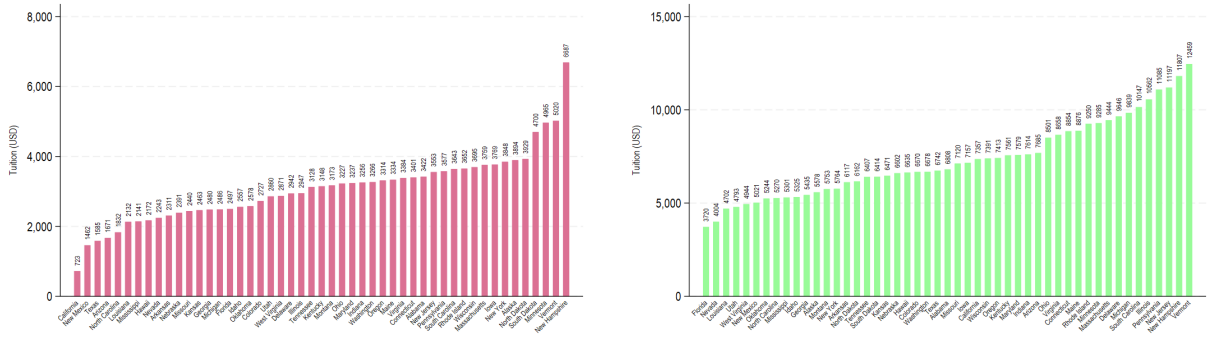
In a well-documented trend, tuition costs have risen steadily in recent decades (e.g., Dynarski et al., 2003). What role does this phenomenon play in our estimates? On average, close to 90% of U.S. college students study in their states of residence, which allows them to benefit from the in-state tuition rate.[32] There is a substantial variation in in-state college tuition across U.S. states (see Figure A.II). This creates the possibility that, under the same shock to local home prices, college-age children who experience higher in-state-tuition-to-house-value ratios are less likely to attend college when their parents' housing wealth is negatively affected, compared to similar college-age children who face lower tuition costs.

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

$$\begin{aligned} College_{i,p,t,b} = \alpha_b + \alpha_{p,t} + \beta_{\mathbf{1}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \\ + \beta_{\mathbf{2}} \cdot \Delta_{2006,t-1} \ln HPI_p \times Owner_{i,p,t,b} \times \frac{Tuition_s}{HouseValue_{i,p,t,b}} \\ + \beta_3 \cdot Owner_{i,p,t,b} + \gamma' \mathbf{X}_{i,p,t,b} + \varepsilon_{i,p,t,b} \end{aligned} \tag{6}$$

We interact our term of interest,$\Delta_{2006,t-1} \ln HPI_p$ with $\frac{Tuition_s}{HouseValue_{i,p,t,b}}$. We calculate the in-state average tuition $Tuition_s$ as of 2010-2011 as the average of public 2-year, public 4-year, and private 4-year college using U.S. Department of Education IPEDS data.[33]

Figure A.II. In-State College Tuition and Required Fees, 2010-2011



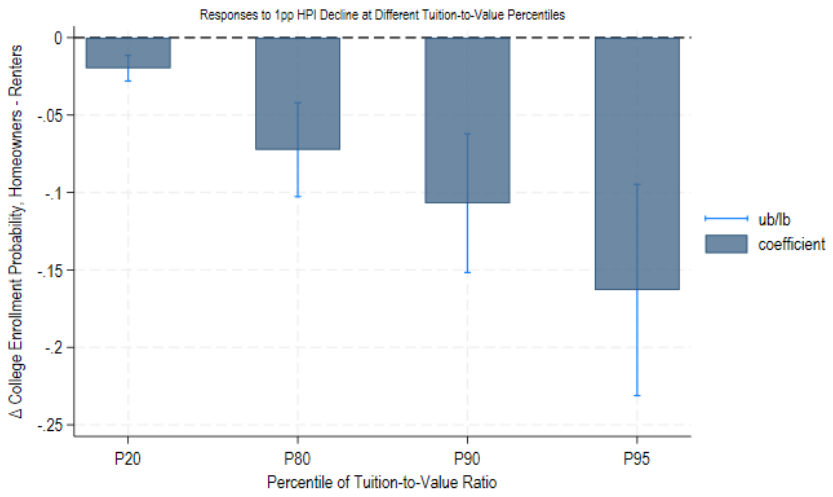
(a) Public 2-Year (b) Public 4-Year

Note. This picture shows variation in in-state college tuition and required fees. The data is sourced from the U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS).

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

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

Figure A.III. College Attendance Response at Tuition to House Value Percentiles



Note. This figure reports $-\beta_2 \times \frac{Tuition_s}{HouseValue_{i,p,t,b}}$ (renormalized to represent a response to a 1 p.p. home price *decline*) for several percentiles of $\frac{Tuition_s}{HouseValue_{i,p,t,b}}$, as estimated from equation (6). The dependent variable is an indicator variable that equals to one if a first-year college-age individual i is attending college and zero otherwise. $\Delta_{2006,t-1}HPI$ is percentage change in the local home price index relative to 2006 (the peak of the housing boom) in an individual's PUMA of residence in the previous year. *Owner* is an indicator variable capturing whether parents of individual i are homeowners (=1) or renters (=0). α_b and $\alpha_{p,t}$ capture Birth Year and PUMA-Year FEs. $\mathbf{X}$ include the following *family controls*: individual's age, gender, race, ethnicity, real family income per capita, the number of siblings, and parental education and parental age. We also control for the local unemployment rate. Regression estimates are weighted using person probability weights provided in the ACS. Standard errors are clustered at the PUMA × Year level. 95% confidence intervals are reported. The data is sourced from ACS and Zillow.

We report the resulting variation in the coefficient of interest in Figure A.III. The figure captures a clear negative gradient of the elasticity of college attendance to changes in home prices with respect to tuition cost that is statistically different from zero. Relative to the children of renters, the children of homeowners are three times less likely to enroll in college in response to a 1 p.p. home price decline when their parents experience a decline in housing wealth if they reside in PUMAs at the 80th percentile of college-tuition-to-house-value, compared to PUMAs at the 20th percentile of relative tuition costs. Importantly, this coefficient becomes even larger in absolute value when they approach the 90th and 95th percentiles of corresponding distribution (Figure A.III). The identified negative gradient supports the notion that the financial-cost mechanism is a significant driver of the differential responses of homeowners' and renters' children to the housing bust.

A.5 Details on the Housing Net Worth and Foreclosure Rate Data

A.5.1 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 the 2006 housing stock value, $H_{2006,p}$, as the product of the median housing value and the number of homeowners in 2006. To calculate median housing value in 2006, we take the median housing value reported in the 2000 decennial census data in each PUMA and multiply it by PUMA-level home price growth over 2000-2006 estimated using Zillow ZIP code-level home price data and ZIP code to PUMA crosswalk provided by the Missouri Census Data Center. We estimate the number of homeowners in each PUMA in 2006 by multiplying the PUMA population in 2006 and the PUMA homeownership rate in 2006. We estimate the PUMA homeownership rate directly using the ACS household heads sample. To estimate the PUMA population in 2006, we project the PUMA population growth calculated from the 2000 and the 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 the housing assets and the 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 the PUMA structure of the housing debt. This data cover around 60% of the first liens originated (DeFusco and Mondragon, 2020), making it representative of the overall sample of mortgage loans in the U.S. We use the current unpaid principal balance as of December 2006 and we exclude paid off, sold, and unknown status loans. The dataset does not contain information on second liens, home equity loans, and home equity lines of credit, and given that we use first lien data to allocate aggregate mortgage liabilities to geographies, we assume that the geographical structure of first lien liabilities is similar to total mortgage liabilities. We aggregate CoreLogic LLMA 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 the PUMA-level structure of mortgage debt and allocate aggregate St.Louis FRED data[34] to PUMAs proportionally.

[34]Home mortgage liabilities, Household sector. https://fred.stlouisfed.org/release/tables?rid=

Overall, we use the same data and same assumptions as Mian et al. (2013) to estimate the 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, first liens. Similar to Mian et al. (2013), we use household debt estimates to distribute aggregate household debt to geographies, but we use PUMAs as the geographic units instead of counties. As long as we use the same data for the aggregate number, and our datasets agree on geographical distribution of mortgage debt, our estimates reproduce the analysis in Mian et al. (2013) at a different geographic level.

A.5.2 Foreclosure Rate

We calculate PUMA-level foreclosure rates using CoreLogic LLMA data. We use information on the current unpaid principal balance as of December of each year during the period 2006-2011, loan delinquency status, and ZIP code of loan origination. We drop real estate owned (REO)[35] sold, and unknown status loans. We allocate all loans to corresponding PUMAs using the Missouri Census Data Center ZIP code to PUMA crosswalk. We then estimate the PUMA-level foreclosure rate as the proportion of loan balances in foreclosure status to total loan balances. The total loan balance includes all delinquent loans, performing loans (delinquency status = current), and loans in foreclosure.

52&eid=808266&od=2006-01-01#.

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