The Impact of Housing Wealth on College Outcomes in the Housing Boom and Bust

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Abstract

Housing wealth constitutes the majority of family resources to support children's postsecondary education. In order to identify the causal effect of housing wealth on college outcomes, I take advantage of the recent housing boom and bust as an exogenous source of variation. I find that a $10,000 increase in home equity increases the probability of initial college enrollment by 0.19 percentage points. Housing wealth has a larger impact on college enrollment during the housing bust than during the housing boom. The asymmetry is only economically and statistically significant for families with lower annual incomes. According to my estimates, the decline in home equity during the housing bust would have caused a drop in college enrollment of 3.5 percentage points, or 9.6%, for families with income less than $70,000, other things equal. My results provide important implications for government financial aid policy. If the goal of the government is to maximize the college enrollment impact of a given level of financial assistance, it is useful for the government to implement a need-based counter-cyclical financial aid policy.

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1 Introduction

A large college enrollment gap across the family income distribution exists in the United States. The college enrollment rate of high school graduates at ages 17-19 from the highest income quartile is 83%, while the enrollment rate of those from the lowest income quartile is 51%[1]. Two main explanations for the large college enrollment gap have been proposed. First, students differ by skills and abilities. Skills and abilities are correlated with family income, and the skill differences, rather than income differences, affect college enrollment (Card 1999; Ellwood and Kane 2000; Dynarski 2002; Brown, Scholz and Seshadri 2011; Lovenheim 2011; Solis 2017). Second, students from low-income families are financially constrained, and cannot invest optimally in higher education (Cameron and Heckman 1998, 2001; Cameron and Taber 2004; Shea 2000; Keane and Wolpin 2001; Carneiro and Heckman 2002; Johnson 2013).

However, family income is a limited and incomplete measure of a family's ability to finance college attendance. Conceptually, family income is only loosely related to a family's ability to borrow. A low-income family may be able to pay for college if it can borrow against future income or use its assets as collateral. Several recent studies have shifted the focus of the discussion away from differences in college enrollment by family income and toward differences by family wealth and home equity in particular. The focus on home equity is motivated by the fact that home equity loans are typically both much easier to secure than loans against other assets, and have a lower interest rate. Two recent papers by Lovenheim (2011) and Johnson (2011) have investigated these issues[2].

Lovenheim (2011) investigates the effect of housing wealth on college enrollment during the housing boom (2000-2005). The author finds that a $10,000 increase in home equity raises college enrollment by 0.7 percentage points. The effect is mainly for lower-resources families. Johnson (2011) studies the impact of family wealth on college attainment. Johnson (2011) uses data from 2000 to 2009, and splits families into two groups, namely families that experienced a positive shock to housing wealth and families that experienced a negative

[1]The data comes from Current Population Survey (CPS) in 2015.

[2]Other related studies include Lovenheim and Reynolds (2012), Long (2013), Charles, Hurst, and Notowidigdo (2015). Lovenheim and Reynolds (2012) conclude that housing wealth positively affect school quality.

shock to housing wealth. The author separately estimates the effect of family wealth on college attainment for the two groups and concludes that family wealth has a larger impact on college attainment for families who experienced a negative shock in housing wealth.

Johnson's study raises an important issue: asymmetry in the effect of housing wealth on college enrollment across housing price cycles. The possible asymmetry is important due to at least two reasons. First, the asymmetry has significant implications for government financial aid policy. If there is an asymmetry in the impact of housing wealth on college enrollment across housing price cycles, it might be useful for the government to consider an asymmetric financial aid policy on higher education during the housing boom and bust[3]. Second, the asymmetry provides important guidance for families with college-age children to make home buying decisions. If housing wealth becomes a more important source of funding for college education during the housing bust, it might be useful for households to invest in home equity during the housing boom[4].

My paper studies the asymmetric impacts of housing wealth on college enrollment during the recent housing boom and bust. I make two main contributions compared to existing literature. First, I study the impact of home equity on college enrollment during both the recent housing boom (2005-2007) and the housing bust (2009-2013). Existing studies all focus on evaluating the impact of home equity on college enrollment during the housing boom, except Johnson (2011) who uses negative shocks in housing wealth to infer possible impacts in the housing bust. My paper differs from Johnson (2011) as I directly estimate the impact of home equity on college enrollment separately for the housing boom and bust. The data used in my study is the Panel Study of Income Dynamics (PSID) Transition to Adulthood (TA) 2005-2013 sample. The TA 2005-2013 sample allows me to study both the recent housing boom and the housing bust. Johnson (2011) combines the PSID 2000-2005 main study and TA 2005-2009 sample, which includes only one year covering the housing bust[5].

[3]For example, if housing wealth has a larger impact on college enrollment during the housing bust than during the housing boom, a counter-cyclical financial aid policy on higher education might be more useful to support college enrollment.

[4]Burnside, Eichenbaum, and Rebelo (2016) found that households are more likely to buy houses during the housing boom because of large expected capital gains. My paper provides another channel for home investment decisions during the housing boom.

[5]PSID TA is a biennial interview starting from 2005. Since 80% of the families already finished their

Second, my model specification controls for various types of family assets and detailed youth demographics, skills, and ability. I divide total family resources into home equity, liquid assets, illiquid assets other than home equity, and permanent family income[6]. Youth demographics include marital status, race, ethnicity, whether the youth has dependents, and the number of siblings. Lovenheim (2011) investigates the impact of home equity on college enrollment controlling for family income as the only alternative family resource and using household heads' information exclusively[7]. Since Lovenheim's model specification is nested wthin my model specification, I can test his specification. My test result shows that youths' characteristics and wealth variables are statistically significant. Moreover, I find that the estimate for home equity not only decreases in magnitude, but also becomes statistically insignificant after contorlling for additional variables. A possible reason is that all other family resources, such as liquid and illiquid assets, could positively correlate with college decisions, Lovenheim's estimates could overstate the true impact of home equity on college enrollment[8]. Johnson (2011) studies a different question by looking at the impact of total family wealth on college attainment. Since Johnson (2011) does not directly estimate the impact of home equity on college decisions, my model specification is not comparable to Johnson's.

My results show that home equity has a larger impact on college enrollment during the housing bust than during the housing boom[9]. The asymmetry is only economically and statistically significant for low-income families. According to my estimates, college enrollment for all families would have decreased by 1.6%, or 0.87 percentage points between 2009 and 2013, due to the observed decrease in home equity in the housing bust, all other

interview before the financial crisis (fourth quarter in 2007), the only year of housing bust in Johnson's (2011) data is 2009.

[6]Illiquid assets other than home equity include automobiles, jewelries, and net business value etc. Liquid assets include current family income, checking/saving account, and bonds/stocks etc. Permanent family income is defined as the expected long-term average income.

[7]Lovenheim only controls household head's demographic information, instead of individuals' own information. The reason is that the PSID main data used in Lovenheim (2011) is household head based.

[8]Detailed comparisons between my model specification and Lovenheim's model specification are presented in Section 4.2.

[9]I have also estimated the impact of home equity on other college outcomes, such as delayed entry to college, dropping out of college, total credits taken in college, and college completion. I find consistent results for other college outcomes, such that home equity has a larger impact on other college outcomes during the housing bust than during the housing boom. Estimation results for other college outcomes will be provided upon request.

things equal. This is a relatively small change in college enrollment given the large decrease in home equity ($43,728), with an implied elasticity of less than 0.1. However, for families with annual income less than $70,000, the college enrollment rate would have dropped by 9.6%, or 3.5 percentage points, due to the decline in home equity during the housing bust holding other things fixed. This indicates that home equity has a larger effect on college enrollment for low-income families during the housing bust, with an implied elasticity of 0.62. My results show that home equity has an economically small and statistically insignificant impact on college enrollment in the housing boom for both low-income and high-income families. This implies that a negative shock in the price of housing has a much larger impact on college enrollment than a positive shock in housing prices.

The magnitude of my estimate is comparable to Lovenheim's (2011) estimate if I use his specification during the housing boom[10]. A major conclusion in Lovenheim (2011) is that home equity has a positive and statistically significant effect on college enrollment during the housing boom. However, I find that after controlling for other family assets and youths' demographics, the positive effect is much smaller in magnitude and becomes statistically insignificant during the housing boom. My results are also consistent with Johnson (2011), as Johnson concludes that family wealth has a larger impact on college attainment for families who experienced negative shocks in housing wealth. However, the magnitude of Johnson's estimates are much larger than mine. A possible reason is that Johnson's study decomposes family groups by sign of housing price shocks, while I directly study the impact of home equity during the housing boom and bust. Individual-level changes in housing wealth are more likely to be endogenous, compared to the aggregate cyclical changes I study.

My finding that housing wealth has an asymmetric impact on college enrollment across house price cycles provides significant implications for government financial aid design. I simulate alternative policy designs and compare their impacts on college enrollment, holding the present discounted value (PDV) of assistance constant. I find that a counter-cyclical financial aid policy has a larger impact on college enrollment than constant financial aid policy holding the PDV of assistance constant[11]. If the goal of the government is to maximize

[10]Detailed comparisons between my study and Lovenheim (2011) are shown in Section 4.2.

[11]Counter-cyclical financial aid policy refers to offering students more assistance during the financial bust and less assistance during the financial boom.

the college enrollment impact of a given amount of financial aid, it is useful for government to implement a need-based counter-cyclical financial aid policy[12].

This paper is organized as follows. Section II lays out the empirical approach. Section III presents data and summary statistics. Section IV discusses the results, and Section V concludes the paper.

2 Empirical Approach

My study intends to identify the causal impact of housing wealth on college enrollment decisions. However, housing wealth is a limited and incomplete measure of a family's ability to finance college attendance. Conceptually, families may rely on three major sources of funds to pay for college. First, families may use their liquid assets to directly pay for college. Second, families may borrow unsecured student loans provided by public or private programs[13]. Third, families may borrow against their illiquid assets, such as home equity, to support higher education. Since the different source of funding may have a varying effect on college decision, I control for various types of family assets and separately estimate their impacts on college enrollment. Moreover, I take advantage of the variation in housing wealth across time and geographic areas. The baseline empirical specification is as follows:

$$\begin{gathered} Y_{imt} = \beta_0 + \beta_1 Equity_{imt} + \beta_2 Own_{imt} + \beta_3 LiquidAssets_{imt} \\ +\beta_4 OthIlliqAssets_{imt} + \beta_5 PermInc_{imt} + \beta_6 X_{imt} + m_i + t_i + \varepsilon_{imt} \end{gathered} \tag{1}$$

Y_{imt} is the dependent variable of interest for individual i living in MSA m and year t. $Equity_{imt}$ represents the real value of home equity. Home equity is defined as the difference of home market value and remaining mortgage balance. Own_{imt} is an indicator of home-ownership. $LiquidAssets_{imt}$ is the real value of liquid assets. Liquid assets include current family income, checking/savings account, money market funds, bonds, treasury bills, stocks, annuities, and Individual Retirement Accounts (IRAs)[14]. $OthIlliqAssets_{imt}$ denote the real

[12]Need-based financial aid policy is denoted as subsidizing students from low-income families only.

[13]Public programs include federal, state, and local student loan programs. Private programs refers to student loan borrowing from banks, credit unions, state agency, or a school.

[14]I have also checked the estimates when annuities and IRAs are counted as illiquid assets. The results

value of illiquid assets other than home equity, such as automobiles, jewelry, and net business value etc. The sum of home equity, liquid assets, and illiquid assets other than home equity equals total net assets. $PermInc_{imt}$ is defined as the expected long-term average income. Since the EPDV of future incomes is unobserved, I use the average family income in the previous 20 years as a proxy for future expected incomes. X_{imt} includes individual and family demographics, as well as local labor market controls. m_i and t_i represent MSA and year fixed effects respectively[15].

Identification of β_1, the main parameter of interest, comes from the housing wealth variation across geographic areas and variation within geographic areas over time. A key identification issue is that home equity could be endogenous. For example, housing wealth could be correlated with children's unobserved ability and college preparation. I address this problem by controlling for individuals' childhood ability measure and high school achievements[16]. The second identification concern is that college outcomes may be correlated with local labor market conditions[17]. I deal with this concern by controlling for unemployment rates, real income per capita, and the size of the college-age population at the state-year level. These control variables take into account the local labor market demand.

Although the rich set of control variables addresses some of the potential identification problems, home equity nevertheless could be endogenous. If home equity is correlated with unobserved individual characteristics or endogenous for other reasons[18], the OLS estimate of β_1 would be biased. In order to address the endogeneity of home equity, I follow Lovenheim and Reynolds (2012) and Lovenheim and Mumford (2013) by constructing an Instrumental Variable (IV) given by the hypothetical 4-year change in the price of a family's house assuming that each family in an MSA experienced the same MSA-average price increase according

turn out to be unaffected.

[15]My baseline specification is more general than Lovenheim (2011). Lovenheim does not control for liquid assets, illiquid assets other than home equity, permanent family income, and individual characteristics. I replicate Lovenheim's (2011) specification and compare with my specification in the Results section. Johnson's (2011) specification is not directly comparable to my specification due to different explanatory variables.

[16]High school achievements include high school GPA, SAT score and ACT score. I shall elaborate more on the childhood ability measure and high school achievements in the Data section.

[17]This estimation challenge is discussed by Lovenheim (2011). I follow Lovenheim's strategies to overcome this concern.

[18]For example, families with higher home equity could be more likely to support children's higher education; or students from families with higher equity values could have higher preference to enroll in college.

to the variation in Housing Price Index (HPI) at the MSA level[19].

$$
\begin{aligned}
IV_{imt} &= P_{imt} - \widehat{P_{imt-4}} \qquad (2)\\
\widehat{P_{imt-4}} &= P_{imt}\frac{HPI_{mt-4}}{HPI_{mt}} \qquad (3)
\end{aligned}
$$

P_{imt} is the self-reported real house value for individual i living in MSA m and year t. $\widehat{P_{imt-4}}$ is the hypothetical house value at year $t-4$ by assuming that each household experienced the same HPI growth rate within an MSA in a given year. HPI_{mt} is the Housing Price Index in MSA m and year t. The IV is constructed as the hypothetical 4-year change in the value of the house. More specifically, the IV does not use variation in home price growth rates across households within MSA in a given year. All variation in the IV comes from HPI growth rate changes across MSAs and within MSAs over years[20].

A valid instrument must satisfy three assumptions, namely validity (uncorrelated with ε_{imt}), strong first stage, and exclusion restriction. The first stage estimates shown below indicate that the weak instrument hypothesis is soundly rejected. There are at least three potential identification concerns to the validity of exclusion restriction. The first identification concern is that family migration patterns could be correlated with college outcomes (Lovenheim and Mumford 2013). For instance, if families that are more likely to send their children to college move disproportionately into MSAs that experience a higher housing price growth, the IV estimate of β_1 will be upward biased. To check the possible endogeneity in migration patterns, I follow Lovenheim and Mumford (2013) to date back to use the MSA of residence for the first generation of the PSID who were interviewed in 1968. The robustness check is shown in Appendix Table 3, and it shows no evidence of endogeneity from migration patterns.

The second identification concern is that the housing price measures in the PSID come

[19] Lovenheim (2011) used the actual 4-year individual change in equity value as IV. However, home equity changes could be endogenous if families tap their equity to pay for college. Therefore, I stick to the short-run hypothetical change in housing values as the IV. I have also constructed the IV by using 3-year and 5-year changes in MSA-level HPI in Appendix Table 2, and the results are consistent.

[20] Another possible IV is the hypothetical 4-year change in HPI at MSA level, such as HPI_{mt-4}/HPI_{mt}. However, the first-stage F-statistics for the IV is lower than 7, which fails to reject the weak instrument hypothesis. One limitation of the study is that the IV estimates of home equity on college enrollment could be biased if the self-reported house value P_{imt} is endogenous. The sign and magnitude of the possible bias depends on the correlation between P_{imt} and $Equtiy_{imt}$.

from self-reported housing values. If families systematically underreport or overreport their housing values, the IV estimate of β_1 will be biased[21]. Lovenheim (2011) compares the HPI constructed from self-reported PSID home prices to the HPI published by Federal Housing Finance Agency. It is shown that the aggregate median and mean of the reported housing values in the PSID are very close to the national index, indicating that such systematic misreport of housing value is unlikely to be a concern.

The third identification concern in my research design is that homeownership, liquid assets, illiquid assets other than home equity, and permanent family income could be endogenous. If these control variables are endogenous and correlated with home equity, the IV estimate of β_1 would be biased (Angrist 2006; Wooldridge 2015). In order to examine how large the possible bias of β_1 is, I conduct several Monte Carlo experiments. In the Monte Carlo experiments, I generate artificial samples that are as close as possible to my TA sample through matching the mean and standard deviation of the observed variables. I also simulate correlation between home equity and control variables through matching the correlation in my sample. In the Monte Carlo experiments, I simulated different degrees of endogeneity in control variables. The results are shown in the Appendix. They indicate that even if the degree of endogeneity for control variables is high[22], the possible bias for the IV estimate β_1 would be less than 10% of the magnitude of the true parameter.

3 Data and Descriptive Statistics

The data used in my paper comes from the Panel Study of Income Dynamics (PSID) Transition into Adulthood (TA) supplement study. The TA sample included up to two children per household who were born between 1985 and 1997. Individuals in the TA sample are interviewed when they reach age 18 or move out of their family home. The TA supplement study began in 2005, and has interviewed respondents biennially afterwards. Up to the

[21]Households may not be able to precisely predict their housing values due to changes in liquidity premium. Therefore, it is possible for households to systematically underreport or overreport their housing values (Armantier, Bruine, Topa et. al 2015; Armona, Fuster, Zafar 2016). The IV estimates resolves the potential bias from classical measurement error problem.

[22]In the Monte Carlo experiments, I present estimates when the correlation between other family resources and unobserved variable to be as high as 0.6.

most recent survey in 2013, the TA has interviewed 2,570 individuals and contains 7,125 person-year observations. The TA contains rich information on education, employment, and demographics. Additionally, I use the restricted access county-level data, and I aggregate counties to MSA levels[23].

I link the TA to the PSID main interview to obtain information on family income and wealth. The PSID is an ongoing family-based panel study of individuals and their descendants starting from 1968. The main interviews contain detailed information on family income, wealth, expenditures, and numerous other topics. The TA sample is also linked to the Child Development Supplement (CDS) study to obtain information on childhood assessment measures. CDS shares the same sample as TA. Families of the CDS children are interviewed three times starting from age 0 to age 17. CDS provides various childhood assessment tests on observations' cognitive and noncognitive skills. These test scores are used as proxies for abilities.

The Housing Price Index data used in my study comes from the Conventional Mortgage Home Price Index (CMHPI). The CMHPI is a housing price index created from repeated mortgage transactions for single-family homes. CMHPI is a widely used home price index in the housing literature and provides a consistent measure of average home price changes within and across MSAs in each year (Lovenheim and Reynolds 2012). For the local labor market control variables, I include state-level unemployment rate, real per capita income, and percentage of college-age population[24].

Table 1 displays the descriptive statistics of some key variables. The first two columns show the mean and standard deviation of my sample using the TA data (2005-2013). The last two columns show the mean and standard deviation of Lovenheim's (2011) sample using the PSID main data (2001-2005). Homeowner is an indicator of homeownership. The average homeownership in my sample is lower than in Lovenheim's sample due to the subprime

[23]The counties are aggregated to MSAs according to Census Bureau Delineation Flies 2010. For those unidentified counties, I aggregate them to state level. In my sample, more than 95% of the counties are identified.

[24]The unemployment rate data is collected from the Bureau of Labor Statistics. Real per capita income data comes from the U.S. Bureau of Economic Analysis. Percentage of college-age population is calculated as the ratio of 18-22-year-olds over the whole population, which is calculated from the 1980, 1990 and 2000 Public Use Microdata Sample (PUMS) of the U.S. Decennial Census. The choice of local labor market control variables follows Lovenheim (2011).

Table 1: **Mean and Standard Deviation of Some Key Variables**

Variable Name	PSID Transition to Adulthood (2005 - 2013) Mean (1)	SD (2)	Lovenheim's PSID Main Data (2001 - 2005) Mean (3)	SD (4)
1. Family Resources:				
Homeowner	0.73	0.43	0.83	0.37
Real home price ($10,000)	14.5	20.7	15.9	18.6
Real home equity ($10,000)	8.72	16.3	9.11	14.9
Real liquid assets ($10,000)	14.4	40.5	—	—
Real other illiquid assets ($10,000)	16.1	64.0	—	—
Real permanent family income ($10,000)	5.89	5.06	—	—
2. College Enrollment:				
Enrolled at age 18 or 19	0.51	0.49	0.52	0.50
Enrolled between ages 18 and 22	0.58	0.24	—	—
3. Instrumental Variable:				
Percentage of 4-yr change in HPI	-0.02	0.29	—	—
Instrumental variable (IV)	-0.21	8.34	—	—
4. Child Ability:				
GPA in high school	3.40	0.90	—	—
Childhood assessment test	61.4	26.8	—	—
5. Demographics:				
Male	0.50	0.50	—	—
White	0.70	0.44	0.77	0.42
Black	0.19	0.38	0.20	0.40
Single	0.88	0.23	—	—
Divorced	0.01	0.07	—	—
No. of siblings	1.82	1.25	—	—
Parents' year of education	10.3	4.71	—	—
No. of observations:	1,392	—	1,497	—

[*] All financial variables are CPI-deflated, the CPI base year is 2007. All statistics are weighted by TA sample weights. Real liquid assets include current family income, checking/savings account, money market funds, bonds, treasury bills, stocks, annuities, and IRAs. Real other illiquid assets denote the real value of illiquid assets other than home equity. The median of real home equity, liquid asset, asset other than home equity and liquid asset are 2.88, 7.38, and 1.74 respectively. The unit of observation is an individual.

mortgage crisis (Shiller 2012). The real home price and real home equity in my sample are slightly lower than Lovenheim's sample as my sample covers the housing bust. Since the real home equity, liquid assets, and other illiquid assets have relatively large standard deviations, I report the medians in the table note.

College enrollment is a binary indicator of enrollment in college. Half of the population enrolled in college at ages 18 and 19, and around 60% of the population enrolled in college between ages 18 and 22. Mean GPA in high school is 3.4 on a 4.0 scale. Childhood assessment measure is the percentile rank of the Woodcock-Johnson test scores. The Woodcock-Johnson test contains a battery of 20 questions on children's cognitive skills, including verbal comprehension, concept formation, and visual matching. Half of the sample are males. 72% of the sample are whites, 19% are blacks, and the rest of the sample are other races. Most of the individuals are single and only 1% of them got divorced. Each child has on average 1.82 siblings, and their parents have more than 10 years of education on weighted average.

Table 2: **Comparison of Mean of Some Key Variables by Family Income During the Housing Boom and Bust**

Variable Name	Family Income < \$70,000		Family Income ≥ \$70,000	
	Boom (1)	Bust (2)	Boom (3)	Bust (4)
Homeowner	0.59	0.50	0.94	0.87
Real home equity (\$10,000)	4.64	3.18	16.9	13.6
Real liquid assets (\$10,000)	4.75	4.49	37.8	23.6
Real other illiquid assets (\$10,000)	7.37	1.93	44.1	30.9
Real permanent family income (\$10,000)	3.15	3.18	7.68	7.79
Enrolled at age 18 or 19	0.38	0.40	0.66	0.70
Enrolled between ages 18 and 22	0.47	0.48	0.70	0.74
Childhood assessment test	59.5	54.9	73.5	70.9
No. of observations:	276	438	242	436

* All financial variables are CPI-deflated, the CPI base year is 2007. Sample means are weighted by TA sample weights. Units of observation is an individual.

Table 2 shows a comparison of means of some key variables by family income during the housing boom and bust. Columns (1) and (2) are for families with income less than

$70,000, and columns (3) and (4) are for families with income higher than $70,000. The homeownership rate for lower-income families was 59% during the boom period, while the homeownership rate for higher-income families was 94%. The homeownership rate is lower during the housing bust by 7 to 9 percentage points. Home equity, liquid assets, other illiquid assets, and permanent family income present similar patterns. The assets for families with lower income is less than families with higher income. Assets for both family groups are higher during the housing boom than during the housing bust. College enrollment during the housing bust is slightly higher than during the housing boom[25]. The childhood assessment test score for children from low income families are lower than children from high income families, and such difference is statistically significant.

4 Results

4.1 Housing Wealth and College Enrollment: Boom & Bust

In this subsection, I investigate the impact of housing wealth on college enrollment decisions. I further study whether home equity has asymmetric impacts on college enrollment during the housing boom (2005-2007)[26] and the housing bust (2009-2013).

Table 3 shows the OLS and IV estimates of the initial college enrollment decision during the housing boom and bust. The first two columns present estimates in the housing boom (2005-2007). For the IV estimation, a $10,000 increase in real home equity increases initial college enrollment by 0.15 percentage points. Neither the OLS nor the IV estimates of home equity in the housing boom are significantly different from zero or from each other. Columns (3) and (4) present estimates in the housing bust (2009-2013). For the IV estimation, a $10,000 increase in real home equity increases the overall college enrollment by 0.20 percentage points. For the IV regressions, the first-stage estimate of the effect of the IV on home equity is positive and precisely estimated. The first-stage F-statistics are high. One

[25] The counter-cyclical pattern of college enrollment is consistent with existing studies, as the opportunity cost of attending college is low during the financial bust (Long 2013; Charles, Hurst, and Notowidigdo 2015).

[26] According to Appendix Figure 1, Housing Price Index (HPI) starts to fall on the fourth quarter (Q4) of 2007. Since 80% of the families already finished their interview before the fourth quarter in 2007, I count 2007 as part of the housing boom.

Table 3: **OLS and IV Estimates of the Initial College Enrollment (Ages 18-19): Housing Boom and Housing Bust**

Independent Variable	Housing Boom (2005-2007) OLS (1)	Housing Boom (2005-2007) IV (2)	Housing Bust (2009-2013) OLS (3)	Housing Bust (2009-2013) IV (4)
Real home equity ($10,000)	.0009	.0015	.0012	.0020
	(.0013)	(.0018)	(.0008)	(.0009)
Homeowner	.0954	.1044	.1429	.1434
	(.1533)	(.0833)	(.0532)	(.0468)
Real liquid assets	-.0004	-.0003	-.0003	-.0003
($10,000)	(.0004)	(.0003)	(.0006)	(.0007)
Real illiquid assets other than	.0002	.0002	.0000	.0000
home equity ($10,000)	(.0004)	(.0004)	(.0001)	(.0001)
Real permanent family income	.0001	.0000	.0005	.0007
($10,000)	(.0007)	(.0005)	(.0003)	(.0003)
First-stage coefficient on		.5524		.6312
excluded instrument		(.1044)		(.0994)
First-stage F-statistics		18.83		26.37
No. of observations	518	518	874	874

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for 271 MSA clusters. Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects.

interesting phenomenon is that homeownership has a large effect on initial college decisions. Families that own a house are 10 percentage points more likely to send their children to college[27].

Home equity has a larger impact on college enrollment during the housing bust than during the housing boom, but the differences are small and not statistically significant. Between 2005 and 2007, the average home equity increased by $46,139, implying an increase in the initial college enrollment rate of 0.69 percentage points according to the IV estimates,

[27]The estimate of homeownership in in my model is comparable to Lovenheim's estimate, where Lovenheim predicts that owning a home increases college enrollment by 15 percentage points. The large estimate of homeownership can be explained by several reasons. One possible reason is that families owning a house are more likely to borrow student loan debt to support higher education (Baum and O'Malley 2003).

or 1.3%, other things equal. Between 2009 and 2013, the average home equity decreased by $43,728, implying that the college enrollment rate decreased by 0.87 percentage points, or 1.7% according to the IV estimates, slightly more than offsetting the increase during the bust.

Another question of interest is whether an asymmetric impact of home equity on college enrollment is more pronounced for low-income families. Since housing wealth comprises the majority of family resources for low-income families[28], a shock to housing prices directly affects their ability to borrow for college education. Table 3 compares the IV estimates of the initial college enrollment during the housing boom and bust by family income.

Columns (1) and (2) in Table 4 show the IV estimates in the housing boom and bust for families with annual income less than $70,000[29]. Home equity has a distinctly asymmetric impact on college enrollment for the low-income families. A $10,000 increase in home equity has essentially no impact on college enrollment during the housing boom, while a $10,000 decrease in home equity reduces college enrollment by one percentage point during the housing bust. The difference between the estimates is statistically significant at the 1% level.

Columns (3) and (4) show the IV estimates in the housing boom and bust for families with annual income more than $70,000. The IV estimates on home equity are small and very close to each other. Thus, the asymmetry of the effect of housing equity on college enrollment during the housing boom and bust is limited to low-income families. A negative shock in housing prices has a much larger impact on college enrollment than a positive shock in housing prices for low-income families.

In order to test the asymmetric effect of home equity on college enrollment across the family income distribution, I present IV estimates of the initial college enrollment decision in which home equity is interacted with family income quartiles. Table 5 differs from Table 4 by pooling families from different income groups into one sample and including interaction terms. Column (1) in Table 5 presents IV estimates in the housing boom. The first row

[28] A cross tabulation of family income, housing wealth and total assets is shown in Appendix Table 1. For homeowners with family income lower than $70,000, housing wealth comprises 60% of their total family wealth.

[29] Lovenheim (2011) uses family with annual income less than $70,000 as low income family. I follow Lovenheim's (2011) threshold to study asymmetric effects of low income and high income families. The results are robust to alternative income thresholds between $60,000 and $80,000.

Table 4: **IV Estimates of the Initial College Enrollment (Ages 18-19) by Current Family Income: Housing Boom and Housing Bust**

Independent Variable	Family Income < $70,000 Boom IV (1)	Family Income < $70,000 Bust IV (2)	Family Income > $70,000 Boom IV (3)	Family Income > $70,000 Bust IV (4)
Real home equity ($10,000)	.0001	.0104	.0015	.0011
	(.0017)	(.0023)	(.0035)	(.0010)
Homeowner	.0478	.1042	.1209	.0678
	(.1406)	(.0557)	(.1755)	(.0541)
Real liquid assets	.0060	.0085	-.0002	.0001
($10,000)	(.0088)	(.0078)	(.0002)	(.0004)
Real illiquid assets other than	.0019	-.0025	-.0001	.0001
home equity ($10,000)	(.0014)	(.0050)	(.0002)	(.0001)
Real permanent family income	-.0008	.0018	-.0014	.0004
($10,000)	(.0022)	(.0013)	(.0010)	(.0003)
First-stage coefficient on	.3983	.7431	.5311	.7469
excluded instrument	(.1914)	(.1559)	(.1987)	(.1528)
First-stage F-statistics	9.17	15.07	11.51	16.42
No. of observations	276	438	242	436

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for 271 MSA clusters. Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects.

provides baseline estimates of the impact of home equity on college enrollment decision for families in the highest family income quartile. For the IV estimate, a $10,000 increase in real home equity in the highest family income quartile raises the initial college enrollment by 0.12 percentage points. The interaction terms in the second through fourth rows present differences in the effect of home equity for the three lower income quartiles. In the housing boom, estimates of the interaction terms are generally small and not statistically significant, which indicates that home equity does not have an asymmetric effect on college enrollment across family income distribution.

Column (2) in Table 5 presents estimates in the housing bust. Estimates of the interaction

Table 5: **IV Estimates of the Initial College Enrollment (Ages 18-19) By Interacting Home Equity and Family Income Quartiles**

Independent Variable	Housing Boom (2005-2007)	Housing Bust (2009-2013)
	(1)	(2)
Real home equity ($10,000)	.0012	.0032
	(.0023)	(.0016)
Equity × FamIncQuartile3	.0013	.0002
	(.0029)	(.0017)
Equity × FamIncQuartile2	-.0020	.0031
	(.0014)	(.0017)
Equity × FamIncQuartile1	-.0007	.0075
	(.0024)	(.0031)
Homeowner	.0631	.1006
	(.1252)	(.0439)
Real liquid assets ($10,000)	.0005	.0002
	(.0003)	(.0006)
Real illiquid assets other than home equity ($10,000)	.0003	.0000
	(.0003)	(.0001)
Real permanent family income ($10,000)	-.0001	.0004
	(.0002)	(.0004)
First-stage coefficient on excluded instrument	.4752	.5628
	(.1002)	(.1082)
First-stage F-statistics	15.01	18.72
No. of observations	518	874

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for 271 MSA clusters. Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects. FamIncQuartile1 is an binary variable of 1 if current family income falls into the first quartile in the family income distribution.

term in the fourth row are economically large and statistically significant. Individuals from the lowest family income quartile are 0.75 percentage points more likely to enroll in college than individuals from the highest family income quartile if both of them experienced a $10,000 increase in home equity. Interaction terms from the second row to fourth row are positive and increasing, meaning that home equity has a larger impact on college enrollment for lower-income families. Table 5 shows that asymmetric effects of home equity across the family income distribution exist in the housing bust but not in the boom.

There are at least two possible explanations for the asymmetric impact of home equity on college enrollment. First, borrowing from home equity becomes a more important source of funding for higher education during the financial crisis (housing bust). Such effect is most prominent for low-income families as high-income families do not depend on home equity to pay for college. The PSID does not provide information on the amount of borrowing from alternative sources. However, data from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax shows that both student loans and Home Equity Lines of Credit (HELOC) constitute a larger proportion of family debt during the financial crisis (Brown, Stein, and Zafar 2013, Brown, Haughwout, Lee, and Van der Klaauw 2013)[30]. Second, students rely more on family support during the financial crisis, as their own earnings decreased. According to my data, students are 10 percentage points less likely to work in college during the housing bust than the housing boom[31]. The change in percentage of work in college largely differ by family income. For families with annual income less than \$70,000, probability of work in college dropped from 0.64 during the housing boom to 0.49 during the housing bust. However, for families with annual income higher than \$70,000, probability of work in college dropped from 0.86 during the housing boom to 0.81 during the housing bust. The results explain to some extent why the asymmetric effect of home equity across housing price cycles only exist for low-income families. My findings are consistent with existing literature (Chai et al. 2011, Oulton and Sebastia-Barriel 2016).

In my sample, the average home equity for families with income less than \$70,000 dropped by \$33,759 during the housing bust. Since the mean overall college enrollment for the low-income students was 0.37 in the housing bust, my estimates suggest that the college enrollment rate for low-income students would have dropped by 3.5 percentage points, or

[30]Home equity has a smaller effect on college enrollment during the housing bust, as family income is higher and borrowing from alternative sources is easier during the bust.

[31]In the housing boom (2005-2007), 77% of the college students work while in college. However, in the housing bust (2009-2013), only 67% work. Moreover, college students' total earnings from work dropped by 20% during the financial crisis. The decrease in work during college could be a result of the increase in unemployment rate during the 2007 financial crisis.

9.5% as a result of the decline in home equity, other things equal. My findings suggest that students from low-income families are more likely to be borrowing constrained in the housing bust.

Since families are more likely to be borrowing constrained during the financial bust, it might be useful for government to consider a counter-cyclical financial aid policy. In order to test which financial aid policy maximizes college enrollment, I simulate alternative policy experiments holding the same PDV of assistance constant. I compare the initital college enrollment rate by simulating four policy experiments, namely no assistance, constant assistance, counter-cyclical assistance, and counter-cyclical need-based assistance. Details of the simulation are shown in the Appendix. I find that a counter-cyclical financial aid policy increases college enrollment by more than a constant financial aid policy for a given PDV of assistance. Moreover, my simulation results show that a need-based counter-cyclical financial aid policy is the most efficient in increasing initial college enrollment. If the goal of the government is to maximize college enrollment, it is useful for government to implement a need-based counter-cyclical financial aid policy.

By a fortunate coincidence, the College Cost Reduction and Access Act (CCRAA) was passed into law in September 2007[32]. The CCRAA increased the maximum Pell Grant and alleviated burdens of student loan borrowers. Between 2007 and 2013, student loan borrowing increased by 36% and Pell Grants increased by 98%[33]. Thanks to the large increase in financial aid, the college enrollment rate for low income students remained almost constant during the housing bust (Trends in Student Aid 2016).

4.2 Comparison With Lovenheim (2011)

My analysis follows Lovenheim (2011) in several respects, so a comparison of results is useful[34]. There are three major differences between my study and Lovenheim (2011). First,

[32] The CCRAA has four key provisions: (1) increase the maximum Pell Grants; (2) Income Based Repayment (IBR) plan; (3) Cut interest rate on subsidized Stafford loans; (4) Public Service Loan Forgiveness (PSLF) plan. The IBR and PSLF plans are reforms of the student loan repayment plans.

[33] Source of data comes from the National Center for Education Statistics.

[34] My results are not directly comparable to Johnson (2011) due to differences in model specification. Johnson (2011) studies the impact of family wealth on college attainment. However, Lovenheim (2011) and my paper study the impact of home equity on college enrollment.

my sample uses TA data (2005-2013) while Lovenheim (2011) uses PSID main interview (2001-2005). Second, The IV used in Lovenheim (2011) is the actual 4-year change in house values, while the IV used in my paper is the hypothetical 4-year change in house values according to variation in HPI at MSA level. Third, my model specification controls for more asset variables and individual characteristics.

Table 6: **OLS and IV Estimates of the Initial College Enrollment (Ages 18-19): Comparison Between My Sample and Lovenehim's Sample, Using Lovenheim's IV**

	PSID Transition to Adulthood (2005 - 2013)		Lovenheim's PSID Main Data (2000 - 2005)	
Independent Variable	OLS (1)	IV (2)	OLS (3)	IV (4)
Real home equity ($10,000)	.0018	.0042	.0014	.0056
	(.0009)	(.0019)	(.0018)	(.0030)
Homeowner	.1981	.1898	.1944	.1744
	(.0581)	(.0532)	(.0506)	(.0499)
Real current family income	.0027	.0017	.0031	.0020
($10,000)	(.0021)	(.0023)	(.0013)	(.0014)
First-stage coefficient on		.6229		.5940
excluded instrument		(.0781)		(.1297)
First-stage Adjusted R-square		.3739		
First-stage F-statistics		36.78		20.96
No. of observations	1,392	1,392	1,497	1,497

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for MSA clusters. The Instrumental Variable used in this table follows Lovenheim (2011). Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects. Results in columns (3) and (4) are from Table 2 in Lovenheim (2011).

Table 6 shows OLS and IV estimates using Lovenheim's IV and model specification. Columns (1) and (2) in Table 6 present estimates using my sample and columns (3) and (4) present Lovenheim's estimates. Both my sample and Lovenheim's sample present a positive relationship between home equity and initial college enrollment. The estimates are similar in magnitude, 0.42 versus 0.56. This indicates that differences in our results are due in part to different data covering different periods, since data source and time period is the only difference in Table 6.

Table 7: **IV Estimates of the Initial College Enrollment (Ages 18-19): Comparison Between My Specification and Lovenheim's Specification, Using My IV**

Independent Variable	PSID TA (2005-2013) Lovenheim's Specification	PSID TA (2005-2013) Middle Specification	PSID TA (2005-2013) My Specification
	(1)	(2)	(3)
Real home equity ($10,000)	.0035	.0026	.0019
	(.0016)	(.0011)	(.0008)
Homeowner	.1938	.1624	.1331
	(.0466)	(.0498)	(.0506)
Real current family income	.0022	.0017	—
($10,000)	(.0025)	(.0019)	—
Real liquid assets			-.0003
($10,000)			(.0001)
Real illiquid assets other than			-.0000
home equity ($10,000)			(.0001)
Real permanent family income			.0007
($10,000)			(.0004)
High school GPA		.0156	.0144
		(.0222)	(.0214)
Childhood assessment measure		.0041	.0040
		(.0006)	(.0006)
Youths' demographics		Yes	Yes
First-stage coefficient on	.5817	.6143	.6105
excluded instrument	(.0879)	(.0874)	(.0917)
First-stage F-statistics	30.19	35.76	32.40
No. of observations	1,392	1,392	1,392

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for 271 MSA clusters. Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects. **The real current family income is included in the real liquid assets**.

Table 7 compares estimates using different model specifications. The difference between Table 6 and Table 7 is that Table 6 uses Lovenheim's IV while Table 7 uses my IV. Column (1) in Table 7 presents estimates of Lovenheim's specification using the TA data and my instrument. Columns (2) presents estimates of a specification, in which youth demographics and ability measures are controlled in addition to Lovenheim's specification. Column (3) presents estimates of my specification. My specification is more general than Lovenheim's specification as I include additional control variables such as liquid assets, illiquid assets other than home equity, permanent family income, and youths' demographics. Youths' demographics include innate ability, high school GPA, marital status, race, ethnicity, whether have dependents, and the number of siblings[35].

The IV estimate in column (2) in Table 6 is similar to the estimate in column (1) of Table 7. This indicates that choice of instrument does not matter as the only difference in column (2) in Table 6 and column (1) in Table 7 is the instrument. Appendix Table 4 further compares different, and shows that choice of instrument has little impact on the results. Since Lovenheim's model specification is nested within my model specification, I test the overall significance of the additional variables. Comparing column (1) and column (2) in Table 7, the overall F-statistics for high school GPA, childhood assessment measure, and youths' demographics is 65.84, with a p-value 0.000. Comparing column (2) and column (3) in Table 7, the overall F-statistics for wealth variables is 168.02, with a p-value 0.000.

More importantly, the coefficient estimate is sensitive to specification, declining from 0.35 percentage points in column (1) to 0.26 percentage points in column (2) when youth demographics are controlled, to 0.19 percentage points in column (3) when other asset variables are controlled. This result implies that additional control variables are likely to be positively correlated with the error term. Ignoring these additional control variables generates an upward biased estimate on home equity. Real liquid assets and real illiquid assets other than home equity have small and negative effect on college enrollment, while real permanent family income has larger and positive effect on college enrollment. A $10,000 increase in real permanent family income increases initial college enrollment by 0.07 percentage points.

Table 8 summarizes IV estimates of the impact of home equity on initial college enrollment from Tables 6 and 7. Column (1) uses Lovenheim's sample and the estimate comes directly from Table 2 in Lovenheim (2011). Columns (2) to (5) use my sample to show the possible combinations of model specification and IV. The purpose of Table 8 is to examine whether the difference between my results and Lovenheim's results come from model speci-

[35] Due to data limitation, Lovenheim (2011) controls for household head's information, including race, ethnicity, and total number of children in the family.

Table 8: **IV Estimates of the Initial College Enrollment (Ages 18-19): Comparison Between My Model and Lovenheim's Model Specification and IV**

	Loven Sample	My PSID TA (2005-2013) Sample			
	Loven Spec Loven IV (1)	Loven Spec Loven IV (2)	Loven Spec My IV (3)	My Spec Loven IV (4)	My Spec My IV (5)
Real home equity	.0056 (.0030)	.0042 (.0019)	.0035 (.0016)	.0016 (.0012)	.0019 (.0008)
No. of observations	1,497	1,392	1,392	1,392	1,392

fication or choice of IV. Comparison between columns (2) and (3) and comparison between columns (4) and (5) show that the choice of instrument changes the estimate by 0.0007 and -0.0003 respectively, or around 17% of the magnitude. Comparison between columns (2) and (4) and comparison between columns (3) and (5) show that the change in model specification changes the estimate by 0.0026 and 0.0016 respectively, or more than 50% of the magnitude. Therefore, the difference between my results and Lovenheim's results mainly come from the difference in model specification. After controlling for asset variables and youth's demographics, the IV estimate of home equity drops by more than 50% in magnitude. Therefore, the additional control variables such as asset and youths' demographics are crucial in providing reliable estimates.

5 Conclusion

My paper adds to the vast existing literature on whether family resources affect the ability to optimally invest in human capital. I find that a $10,000 increase in home equity increases the likelihood of initial college enrollment by 0.19 percentage points. Housing wealth has a larger impact on college enrollment during the housing bust than during the boom, and this asymmetry is only economically and statistically significant for low-income families.

According to my estimates, college enrollment for families with income less than $70,000 dropped by 9.6%, or 3.5 percentage points, due to the decline in home equity during the housing bust holding other things fixed.

My findings provide significant implications for future financial aid policy designs. I use the estimates to simulate alternative policy designs and compare their impacts on college enrollment holding the PDV of assistance constant. My simulation results show that a counter-cyclical financial aid policy targeted on low-income families yields more college enrollment than other policy designs holding fixed financial assistance. If government plans to maximize college enrollment the most efficiently, they might consider implementing a need-based counter-cyclical financial aid policy.

Several limitations exist in this study. First, my policy implication relies on the assumption that financial assistance has a similar impact on college enrollment as housing wealth. If financial assistance affects college enrollment differently from housing wealth, the suggested counter-cyclical financial aid policy may not hold. For future studies, it would be interesting to directly estimate the asymmetric impact of financial assistance on college enrollment during the housing boom and bust.

Second, causes of the asymmetric impact of housing wealth on college enrollment across housing price cycles is unknown. Individuals are more affected by housing wealth during the financial bust either because they have asymmetric consumption behavior across business cycles or they are more borrowing constrained during the crisis. This question has significant implications for future financial aid policy designs. If the asymmetry mainly comes from a borrowing constraint, financial assistance would be useful to enhance college enrollment. For future studies, it is interesting to propose a structural model and investigate mechanisms of the asymmetric impacts on college enrollment across business cycles.

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Appendices

Appendix Table 1: **Cross Tabulation of Family Income, Home Equity, Total Assets, and Fraction of Home Equity on Assets (PSID TA Sample)**

Current Family Income	Mean Equity (Homeowners)	Homeownership Percentage	Total Assets (Homeowners)	% Equity/Assets (Homeowners)
\$0-\$10,000	2.686	.2961	3.832	.7257
\$10,000-\$20,000	3.305	.3959	5.020	.6871
\$20,000-\$30,000	4.223	.4686	6.926	.6531
\$30,000-\$40,000	4.935	.5598	9.794	.5725
\$40,000-\$50,000	5.625	.6657	15.24	.4554
\$50,000-\$60,000	5.741	.7811	16.84	.4823
\$60,000-\$70,000	6.928	.7735	24.57	.4457
\$70,000-\$80,000	7.628	.8353	26.78	.3824
\$80,000-\$90,000	9.012	.8361	35.02	.3269
\$90,000-\$100,000	8.486	.8221	33.07	.2824
\$100,000-\$110,000	10.13	.8872	30.20	.2761
\$110,000-\$120,000	12.62	.9459	50.89	.2807
\$120,000-\$130,000	13.44	.9367	63.56	.2270
>\$130,000	22.95	.9567	123.2	.1971

[*] All financial variables are CPI-deflated, the CPI base year is 2007. The mean equity and total assets are in \$10,000. The sample size in the table is 2,570. Total assets contains the liquid assets, home equity, and illiquid assets other than home equity. The reported mean equity and mean assets are for home owners.

Appendix Table 2: **OLS and IV Estimates of the Initial College Enrollment (Ages 18-19): Comparison of IV**

Independent Variable	OLS (1)	IV1 (2)	IV2 (3)	IV3 (4)
Real home equity ($10,000)	.0018	.0035	.0038	.0032
	(.0009)	(.0016)	(.0018)	(.0015)
Homeowner	.2028	.1938	.1881	.1917
	(.0513)	(.0466)	(.0531)	(.0520)
Real current family income	.0035	.0022	.0021	.0023
($10,000)	(.0027)	(.0025)	(.0022)	(.0024)
Parents' demographics	Yes	Yes	Yes	Yes
Local labor market control	Yes	Yes	Yes	Yes
MSA & Year fixed effect	Yes	Yes	Yes	Yes
First-stage home equity estimates		.5817	.6289	.5437
		(.0879)	(.0893)	(.0914)
First-stage Adjusted R-square		.3774	.3826	.3819
First-stage F-statistics		30.19	36.71	27.80
No. of observations	1,392	1,392	1,392	1,392

[*] All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for MSA clusters. Lovenheim's IV refers to the actual change in housing values, while my IV uses the hypothetical change in housing values according to variation in HPI. IV1 is the simulated 4-year change in house value; IV2 is the simulated 3-year change in house value; and IV3 is the simulated 5-year change in house value.

Appendix Table 3: **OLS and IV Estimates of the Initial College Enrollment (Ages 18-19): Comparing MSA in PSID TA and Original PSID**

Independent Variable	PSID TA (2005-2013) (MSA in PSID TA)		PSID TA (2005-2013) (MSA in Original PSID)	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Real home equity ($10,000)	.0010	.0019	.0012	.0023
	(.0007)	(.0008)	(.0008)	(.0010)
Homeowner	.1369	.1331	.1353	.1298
	(.0574)	(.0506)	(.0554)	(.0597)
Real liquid assets	-.0002	-.0003	-.0002	-.0002
($10,000)	(.0001)	(.0001)	(.0001)	(.0001)
Real illiquid assets other than	-.0000	-.0000	.0000	.0000
home equity ($10,000)	(.0001)	(.0001)	(.0001)	(.0001)
Real permanent family income	.0009	.0007	.0011	.0008
($10,000)	(.0004)	(.0004)	(.0005)	(.0004)
Youths' demographics	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
First-stage home equity estimates		.6105		.5876
		(.0917)		(.0879)
First-stage F-statistics		32.40		33.28
No. of observations	1,392	1,392	1,392	1,392

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for 271 MSA clusters. Control variables include high school GPA, childhood assessment measure, youths' and parents' demographics, local labor market controls, and MSA and year fixed effects. Columns (1) and (2) use the MSA in the PSID TA sample. Columns (3) and (4) use the MSA in the original PSID sample.

Appendix Table 4: **OLS and IV Estimates of the Initial College Enrollment (Ages 18-19) Using My Specification: Comparison between Lovenheim's IV and my IV**

Independent Variable	PSID TA (2005-2013) Lovenheim's IV		PSID TA (2005-2013) My IV	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Real home equity ($10,000)	.0010	.0016	.0010	.0019
	(.0007)	(.0012)	(.0007)	(.0008)
Homeowner	.1369	.1355	.1369	.1331
	(.0574)	(.0516)	(.0574)	(.0506)
Real liquid assets ($10,000)	-.0002	-.0003	-.0002	-.0003
	(.0001)	(.0001)	(.0001)	(.0001)
Real illiquid assets other than home equity ($10,000)	-.0000	-.0001	-.0000	-.0000
	(.0001)	(.0001)	(.0001)	(.0001)
Real permanent family income ($10,000)	.0009	.0009	.0009	.0007
	(.0004)	(.0004)	(.0004)	(.0004)
Parents' demographics	Yes	Yes	Yes	Yes
Local labor market control	Yes	Yes	Yes	Yes
MSA & Year fixed effect	Yes	Yes	Yes	Yes
First-stage coefficient on excluded instrument		.7054		.6105
		(.1264)		(.0917)
First-stage F-statistics		21.33		32.40
No. of observations	1,392	1,392	1,392	1,392

* All financial variables are CPI-deflated, the CPI base year is 2007. All variables are adjusted by TA sample weights. Robust standard errors are adjusted for MSA clusters. Lovenheim's IV refers to the actual change in housing values, while my IV uses the hypothetical change in housing values according to variation in HPI.

Monte Carlo Experiments

Lovenheim (2011) used the exogenous change in equity values as an instrument to identify the causal effect of housing wealth on college enrollment. Lovenheim's identification strategy relies on the assumption that housing wealth correlates with unobserved attributes that would affect individuals' saving and education behaviors, such as child ability and preferences for schooling. However, Lovenheim (2011) treats the family income and the indicator of owning a house as exogenous control variables. This identification assumption is not only strong, but also invalid for most of the times. It is likely that both family income and indicator of owning a house suffer from endogeneity problems, with the same argument as the endogenous housing wealth. Moreover, another important channel of endogeneity comes from the relationship between family income and housing wealth. Families with higher income are more likely to own a house, and also more likely to buy a house with higher values.

In the next subsections, I shall set up Monte Carlo experiments to be as similar as possible to Lovenheim's (2011) settings. The data are generated to approximately replicate Lovenheim's (2011) key variables (mean, variance, and distribution) listed in Appendix Table 1. Although Lovenheim did not report the correlation between family income and equity value, I arbitrarily build in a correlation that higher income families are more likely to own a house with higher equity values. The Monte Carlo experiments aim to provide evidence on two questions: (1) Under the assumption that both family income and housing wealth are endogenous, would Lovenheim's estimates be unbiased and consistent? (2) If Lovenheim's estimates are biased or inconsistent, what would be the remedies to generate unbiased and consistent estimates?

Monte Carlo Setup

To set up the Monte Carlo experiment, I shall generate samples which are as close as possible to Lovenheim (2011). Table 1 compares the mean and standard deviation of some key variables drawn from the simulated sample and Lovenheim's sample. First, I define the number of observations in each Monte Carlo simulation to be 1,497, which equals the sample size in Lovenheim (2011). Second, I draw family income from the following functional form

$$Income = 2 + Y_{inc} + endo_{inc} + \varepsilon_{inc} \tag{4}$$

Y_{inc} is a combination of gamma and normal distribution to match the true family income. Since Lovenheim only reported the mean and variance of family income, I construct my simulated family income according to the distribution reported in NLSY79 between age 42 and 45[36]. $endo_{inc}$ is an endogenous component in income, and ε_{inc} is the i.i.d. income shock. Both $endo_{inc}$ and ε_{inc} are assumed to be standard normally distributed. Third, I generate the indicator of owning a house from the following probit model

$$\Pr(Own = 1|Income) = \Phi(0.8 + 0.3 \times Income) \tag{5}$$

[36]The family income distribution reported in NLSY79 between age 42 and 45 should be very similar to Lovenheim's sample. I will compare my simulated sample with Lovenheim's sample later.

Own is an indicator which equals 1 if family owns a house. Φ denotes the cdf of standard normal distribution. It is assumed that families with higher income are more likely to purchase a house. The coefficient 0.3 is arbitrarily defined, as the true relationship between family income and indicator of owning a house is not reported in Lovenheim (2011). Fourth, the equity value is randomly drawn from the following equation

$$Equity = Own \times (0.5 + Y_{equ} + 0.3 \times Income + endo_{equ} + \varepsilon_{equ}) \tag{6}$$

Equity denotes the equity value conditional on owning a house. Y_{equ} is a right-skewed normal distribution which matches the true distribution of equity values in U.S. in 2003. $endo_{equ}$ is an equity endogenous component, and ε_{equ} is the i.i.d equity shocks. Both $endo_{equ}$ and ε_{equ} are standard normally distributed. It is assumed that families with higher income are more likely to buy houses with higher equity values.

Appendix Table 5: **Comparison Between Simulated and Lovenheim's Sample**

Variable	Simulated Sample		Lovenheim's Sample	
	Mean	SD	Mean	SD
Enroll	0.53	0.50	0.52	0.50
I(Homeowner)	0.82	0.37	0.83	0.37
Real home equity ($10,000)	9.38	13.28	9.11	14.88
Real family income ($10,000)	9.32	13.07	9.11	14.88
Real home equity change ($10,000)	3.77	6.61	3.92	9.28
First-stage Equity estimates	0.56	0.15	0.59	0.13
First-stage F-statistics	25.14	–	20.96	–

Note. All financial variables are in real 2007 $10,000. The simulated standard deviation for real home equity change is smaller than Lovenheim (2011), as the variation within state is smaller than variation within SMA.

The fifth step is to draw individual's state of birth. Since Lovenheim used a nationally representative sample, I draw the state of birth according to the population ratio of each state from the 2000 United States Census. For example, Ohio consists of 3.61% of the U.S. population. In my sample, I draw $3.61\% \times 1,497$ observations born in Ohio.

The sixth step is to generate the instrumental variable, which is the change in Housing Price Index (HPI) within each state. Although the geographic area used in Lovenheim

(2011) was MSA, changes in HPI within states are able to replicate the mean and variance of exogenous change in equity values.

The last step is to generate the binary college enrollment indicator. For certain assumed functional forms (e.g. linear, logit or probit), the binary enrollment variable is drawn from Bernoulli distribution with probability equal to the predicted value of a continuous enrollment value. Although the mean college enrollment varies across different functional forms, the constant terms can be used to set the mean college enrollment around 50 percent. After generating the comparable data set, I shall parameterize the equation and repeatedly draw random samples to generate mean and standard deviation of the parameter estimates.

Linear Relationship

In this subsection, I shall compare estimates of different model specifications under a linear data generating process of college enrollment. The binary college enrollment indicator is assumed to be a linear function of equity value, indicator of owning a house, family income, endogeneity components, and error term. The data generating process for college enrollment is displayed as below

$$Enroll = \delta_0 + \delta_1 Equity + \delta_2 Own + \delta_3 Income + \theta_1 endo_{equ} + \theta_2 endo_{inc} + (1 - \theta_1 - \theta_2)\varepsilon_{enroll} \quad (7)$$

Enroll is the binary enrollment indicator, which is drawn from Bernoulli distribution as demonstrated above. $endo_{equ}$ and $endo_{inc}$ are the endogeneity components from *Equity* and *Income* generating process. ε_{enroll} is an i.i.d. standard normal error term. The unobserved component for *Enroll* is $u = \theta_1 endo_{equ} + \theta_2 endo_{inc} + (1 - \theta_1 - \theta_2)\varepsilon_{enroll}$, which represents a weighted average of endogeneity and error term. θ_1 measures the fraction of endogeneity generated from equity values. θ_2 measures the fraction of endogeneity generated from family income. In order to cover different combinations of endogeneity

Table 2 shows the estimates of Monte Carlo experiments with 10,000 replications when linear data generating process is applied[37]. In order to study estimates of different models under various endogeneity problems, I propose four combinations of θ: (1) Neither *Equity* nor *Income* is endogenous ($\theta_1 = 0, \theta_2 = 0$); (2) Only *Equity* is endogenous ($\theta_1 = 2/3, \theta_2 = 0$); (3) Only *Income* is endogenous ($\theta_1 = 0, \theta_2 = 2/3$); (4) Both *Equity* and *Income* are endogenous ($\theta_1 = 1/3, \theta_2 = 1/3$)[38].

Under the setting of the linear data generating process, I test the consistency of estimates of four model specifications. The first model I test is the OLS which controls for *Equity*, *Own*, *Income*, $endo_{equ}$, and $endo_{inc}$. Although the endogenous components of equity and income are not observed in reality, controlling for them provides a baseline estimates which are unbiased and consistent. The second model I test is the OLS which only controls for *Equity*, *Own*, and *Income*. The third model I test is to use the change in HPI as an instrument for *Equity*, but not with *Own* and *Income* as instruments[39]. The fourth model

[37] The result hardly changes with higher number of replications. In other words, the estimates are convergent under 10,000 replications.

[38] Different combinations of endogeneities are presented from the 3^{rd} to 6^{th} columns in Table 2.

[39] In model three, the first stage regression is: $Equity = \alpha_0 + \alpha_1 \Delta HPI$. The second stage is: $Enroll =$

is to treat both *Own* and *Income* as exogenous control variables, and use change in HPI, *Own* and *Income* as instruments for *Equity*.

To follow the estimates presented in Lovenheim (2011), I assign the value of parameters as $\delta_1 = 0.004$, $\delta_2 = 0.1$, and $\delta_3 = 0.002$. The data generating process for college enrollment is

$$Enroll = 0.4 + 0.004 \times Equity + 0.1 \times Own + 0.002 \times Income + u \tag{8}$$

As shown in Table 2, model one always provides consistent estimators as the endogeneity components are controlled. Model two only provides consistent estimators under the case that both *Equity* and *Income* are exogenous. When *Equity* is correlated with the unobserved component, model two overestimates δ_1 as correlation between *Equity* and $endo_{equ}$ is positive. The same conclusion is drawn when *Income* is endogenous. If both of the endogeneity components exist, model two will overestimate δ_1 and δ_3.

Model 3 deals with the endogeneity of *Equity* by using the change in average equity value as the only instrumental variable. Results of the first stage is shown in Table 1, where the simulated first-stage estimates and F-statistics are very close to Lovenheim's reports. The change in short-run equity value should be a strong valid instrument, as the F-statistics is large and endogenous components are randomly drawn. However, the estimates of δ_1, δ_2, and δ_3 estimated in model 3 are all inconsistent. δ_1 is downward biased, while δ_2 and δ_3 are upward biased. One of the possible reasons for the inconsistency could be generated from the correlation between *Equity* and *Own*, as well as the correlation between *Equity* and *Income*. Since Lovenheim (2011) did not report the correlation between independent variables, I arbitrarily build in the relationship according to the generating process stated above. In my simulated sample, correlation between *Equity* and *Own* is 0.45 and correlation between *Equity* and *Income* is 0.29.

Model 4 differs from model 3 by including *Own* and *Income* in the first-stage regression. When both *Equity* and *Income* are exogenous, model 4 provides consistent estimates of all three parameters. Under the case when $\theta_1 = 2/3$ and $\theta_2 = 0$, model 4 consistently estimate δ_1 and δ_2 but under estimate δ_3. One possible reason is that *Income* is also correlated with $endo_{equ}$. When $\theta_2 = 2/3$ and $\theta_1 = 0$, model 4 under estimate δ_1 and over estimate δ_2. Lastly, when both endogenous components exist, IV strategy provides consistent estimates of δ_1 and δ_2 but inconsistent estimates of δ_3.

Probit Relationship

In this subsection, I shall draw college enrollment from a probit data generating process and test the consistency of different model specifications. The binary college enrollment indicator is assumed to be drawn from a probit function of equity value, indicator of owning a house, family income, endogeneity components, and error term. The specific functional form for the probit function is

$$Enroll^* = \gamma_0 + \gamma_1 Equity + \gamma_2 Own + \gamma_3 Income + \theta_1 endo_{equ} + \theta_2 endo_{inc} + (1 - \theta_1 - \theta_2)\varepsilon_{enroll} \tag{9}$$

$\beta_0 + \beta_1 \widehat{Equity} + \beta_3 Own + \beta_4 Income.$

$$Enroll = \begin{cases} 1 & Enroll^* = 0 \\ 0 & Ohterwise \end{cases} \tag{10}$$

Enroll is generated by drawing from Bernoulli distribution with probability $\Phi(Enroll^*)$. All the independent variables are the same as defined above, and $\varepsilon_{enroll} \sim i.i.d. N(0,1)$ is the key assumption for probit model. The combination of θ_1 and θ_2 follows the linear case. Table 3 shows the estimates of Monte Carlo experiments with 10,000 replications when probit generating process is applied. Since Lovenheim (2011) did not report results of probit estimation, I shall stick with the parameters assigned in the linear case. I set the value of parameters as $\gamma_1 = 0.004$, $\gamma_2 = 0.1$, and $\gamma_3 = 0.002$.

Under the setting of probit data generating process, I test the consistency of estimates of four model specifications. The first model I test is the OLS regression with independent variables *Equity*, *Own*, and *Income*. The second model is the baseline probit model, which regress college enrollment on *Equity*, *Own*, and *Income*. Model 3 uses the Maximum Likelihood Estimation (MLE) to check the consistency when endogeoneous variables occur in the porbit model. *Equity* is assumed to be endogenous, and the short-run change in equity value is treated as instruments. Model 4 uses Newey's (1987) minimum chi-squared estimator to estimate the probit model when *Equity* is endogenous. Model 4 is similar to model 3 in terms of the structural setting, but they differ in estimation methods. According to the inconsistent estimates of model 3 in the linear case, both *Own* and *Income* are treated as instrumental variables along with the change in equity value.

Model 1 in Table 3 is the same as model 2 in Table 2. Since the actual generating process of the college enrollment is unobserved by econometrician, the Linear Probability Model (LPM) used in Lovenheim (2011) could be misspecified. OLS provides biased and inconsistent estimators under the probit generating process for enrollment. Although the signs of γ_1, γ_2, and γ_3 are positive, their magnitudes are largely underestimated. The mean of OLS estimates are 40% of the true parameters. Model 2 is the baseline probit model which does not control for endogenous components. Model 2 presents consistent estimators when *Equity* and *Income* are exogenous. Model 2 slightly overestimate γ_3 under the case when $\theta_1 = 0$ and $\theta_2 = 2/3$. The possible explanations for inconsistency follows model 2 in

Table 2.

Model 3 use MLE to deal with endogeneity problems in probit model. *Equity* is assumed to be endogenous, and it is instrumented by short-run change in equity value, *Own*, and *Income*. When $\theta_1 = 1/3$ and $\theta_2 = 1/3$, MLE overestimates γ_1 and underestimate γ_2. Model 4 check consistency of estimates using Newey's minimum chi-squared method. Newey's minimum chi-squared method use the same structural model as MLE, but different estimation methods. Surprisingly, model 4 underestimates γ_1 when $\theta_1 = 1/3$ and $\theta_2 = 1/3$. However, both model 3 and model 4 overestimate γ_3 when income is endogenous.

Appendix Table 6: **Estimates of Monte Carlo Experiments Assuming a Linear Model with 10,000 replications**

Model	Parameter	Neither Endogenous	Equity Endogenous	Income Endogenous	Both Endogenous
1. OLS (control for endo components)		0.00401	0.00399	0.00401	0.00399
		(0.0016)	(0.0015)	(0.0015)	(0.0015)
		0.09954	0.10061	0.10018	0.10060
		(0.0431)	(0.0396)	(0.0395)	(0.0412)
		0.00202	0.00200	0.00200	0.00197
		(0.0017)	(0.0015)	(0.0015)	(0.0016)
2. OLS (endo components not controlled)		0.00400	0.00414	0.00395	0.00409
		(0.0016)	(0.0016)	(0.0016)	(0.0016)
		0.10041	0.09912	0.10136	0.09954
		(0.0433)	(0.0431)	(0.0435)	(0.0433)
		0.00196	0.00191	0.00225	0.00207
		(0.0017)	(0.0017)	(0.0017)	(0.0017)
		0.00311	0.00308	0.00314	0.00321
		(0.0098)	(0.0096)	(0.0095)	(0.0096)
		0.14014	0.14118	0.14132	0.14135
		(0.0402)	(0.0397)	(0.0397)	(0.0400)
		0.00229	0.00223	0.00252	0.00240
		(0.0017)	(0.0017)	(0.0017)	(0.0017)
		0.00381	0.00414	0.00381	0.00410
		(0.0125)	(0.0124)	(0.0124)	(0.0124)
		0.10228	0.09791	0.10215	0.09927
		(0.1355)	(0.1336)	(0.1351)	(0.1346)
		0.00202	0.00195	0.00226	0.00212
		(0.0020)	(0.0019)	(0.0019)	(0.0019)

Note. All financial variables are in real 2007 \$10,000. The parameters used in the linear equation is set as $\delta_1 = 0.004, \delta_2 = 0.1$, and $\delta_3 = 0.002$. Model 1 is OLS regression which controls for endogenous components. Model 2 is OLS regression which does not control for endogenous components. Model 3 is the IV regression with $\Delta Equity$ the only instrument in first stage. Model 4 is the IV regression with $\Delta Equity$, Own, and Income as instruments in first stage.

Appendix Table 7: **Estimates of Monte Carlo Experiments Assuming a Probit Model with 10,000 replications**

Model	Parameter	Neither Endogenous	Equity Endogenous	Income Endogenous	Both Endogenous
1. OLS (endo components not controlled)		0.00158	0.00160	0.00156	0.00160
		(0.0016)	(0.0016)	(0.0016)	(0.0016)
		0.03891	0.03877	0.03949	0.03957
		(0.0443)	(0.0438)	(0.0435)	(0.0434)
		0.00078	0.00076	0.00090	0.00085
		(0.0017)	(0.0017)	(0.0017)	(0.0017)
2. Probit (endo components not controlled)		0.00397	0.00405	0.00392	0.00405
		(0.0041)	(0.0040)	(0.0040)	(0.0041)
		0.09903	0.09746	0.09800	0.09862
		(0.1120)	(0.1107)	(0.1109)	(0.1126)
		0.00195	0.00197	0.00229	0.00208
		(0.0043)	(0.0043)	(0.0043)	(0.0043)
		0.00397	0.00398	0.00398	0.00437
		(0.0290)	(0.0289)	(0.0290)	(0.0289)
		0.09682	0.09179	0.09576	0.09067
		(0.3167)	(0.3163)	(0.3164)	(0.3144)
		0.00183	0.00192	0.00210	0.00199
		(0.0048)	(0.0047)	(0.0048)	(0.0047)
		0.00417	0.00386	0.00396	0.00365
		(0.0316)	(0.0316)	(0.0317)	(0.0316)
		0.09553	0.10119	0.09769	0.10326
		(0.3405)	(0.3432)	(0.3453)	(0.3424)
		0.00197	0.00190	0.00228	0.00215
		(0.0050)	(0.0049)	(0.0049)	(0.0050)

Note. All financial variables are in real 2007 \$10,000. The parameters used in the probit function is set as $\gamma_1 = 0.004, \gamma_2 = 0.1$, and $\gamma_3 = 0.002$. Model 1 is OLS regression which does not controls for endogenous components. Model 2 is probit regression which does not control for endogenous components. Model 3 is the MLE with $\Delta Equity$, Own, and Income as instruments. Model 4 is the Newey's minimum χ^2 with instruments $\Delta Equity$, Own, and Income.

Simulation of Alternative Policy Design

In order to test whether counter-cyclical financial aid policy stimulates more college enrollment, I simulate alternative policy experiments with the same present discounted net costs to federal government. In a simplified model, I assume there are two periods, namely the housing boom period and the housing bust period. I assume the discounted factor of the two periods to be 1. I follow the descriptive statistics of the PSID TA 2005-2013 sample and parameter estimates from my results. The families are classified into low-income families (income<\$70,000) and high-income families (income>\$70,000).

In the simulation, I compare three alternative policy designs holding constant the present discounted value (PDV) of financial assistance. The first policy design is to offer students with the same amount of assistance across business cycles. This policy design is close to the current financial aid policy which is uncorrelated with business cycles. The second policy design is counter-cyclical which provide students with more assistance during the housing bust, and less assistance during the housing boom. The third policy design is need-based counter-cyclical which provide low-income students with more assistance during the housing bust than during the housing boom.

One difficulty of the simulation is that I don't directly estimate the impact of financial assistance on college enrollment. However, since the estimates of home equity and liquid assets present similar patterns, I assume that the impact of financial aid on college enrollment follows the pattern of home equity. In the TA sample, 56% of the individuals come from families with income less than \$70,000. I follow the estimates in Table 4 to show which policy experiment yields the highest initial college enrollment rate.

Appendix Table 8 shows the comparison of alternative student aid policy experiments. Column (1) shows the benchmark when there is no financial assistance. The initial college enrollment rate is assumed to be 50% if no Assistance is provided. Column (2) shows the experiment when there is a constant financial assistance across family income groups and business cycles. The average government spending in each period is assumed to be \$1,000. Column (3) shows the experiment when government applies counter-cyclical financial aid policy. The average government spending in the housing boom is \$500 and the average

Appendix Table 8: **Comparison of Alternative Student Aid Policy Experiments**

Variable	No Assistance (1)	Constant Assistance (2)	Counter-cyclical Assistance (3)	Counter-cyclical Need-Based Ass (4)
Initial College Enrollment	0.5000	0.5367	0.5518	0.5564
Assistance Low-Income Boom	\$0	\$10,000	\$5,000	\$8,000
Assistance Low-Income Bust	\$0	\$10,000	\$15,000	\$17,000
Assistance High-Income Boom	\$0	\$10,000	\$5,000	\$4,000
Assistance High-Income Bust	\$0	\$10,000	\$15,000	\$8,500
Total Cost to Government	\$0	\$20,000	\$20,000	\$20,000

Note. Assistance is the average assistance for each student. For example, assistance low-income boom means the average financial assistance for low-income families during the housing boom. Total cost to government refers to the average total cost of each student during both periods.

government spending in the housing bust is \$1,500. Column (4) shows the experiment when need-based financial aid policy is applied in addition to the counter-cyclical aid policy.

The results in Appendix Table 8 shows that financial aid policy does increase initial college enrollment. The three alternative policies all have the same net cost to federal government at \$20,000 per student. It is observed that the need-based counter-cyclical assistance policy is the most efficient in increasing initial college enrollment. The counter-cyclical assistance policy stimulates more college enrollment than the constant assistance policy. Therefore, if the goal of the government is to increase initial college enrollment, it is more efficient to implement the need-based counter-cyclical financial aid policy.