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Students in Distress: Labor Market Shocks, Student Loan Default, and Federal Insurance Programs
Holger M. Mueller and Constantine Yannelis
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ABSTRACT

The collapse in home prices during the Great Recession triggered a sharp drop in consumer demand by households, leading to massive employment losses. This paper examines the implications of these labor market shocks for the dramatic rise in student loan defaults, which originated during this time period. Linking administrative student loan data at the individual borrower level to de-identified tax records and exploiting Zip code level variation in home price changes, we show that the drop in home prices during the Great Recession accounts for approximately 24 to 32 percent of the increase in student loan defaults. Consistent with a labor market channel, we find a strong relationship between home prices, employment losses, and student loan defaults at the individual borrower level, which is concentrated among low income jobs. Comparing the default responses of home owners and renters, we find no evidence of a direct liquidity effect of home prices on student loan defaults. Lastly, we show that the Income Based Repayment (IBR) program introduced by the federal government in the wake of the Great Recession reduced both student loan defaults and their sensitivity to home price fluctuations, thus providing student loan borrowers with valuable insurance against adverse income shocks.

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1 Introduction

Student loans constitute the largest source of non-mortgage household debt in the United States, with an outstanding balance of $1.4 trillion. Given the significance of student loans for the financing of higher education, the recent surge in student loan defaults is alarming. Since the beginning of the Great Recession, student loan default rates have nearly doubled. Between 2007 and 2010 alone, two-year cohort default rates increased from 6.7 percent to 9.1 percent (U.S. Department of Education). The sharp rise in student loan defaults has important consequences not only for the federal budget—more than 92 percent of all student loans are federal loans—but also for the defaulting student loan borrowers.[1] Unlike other types of loans, student loans are not dischargeable in bankruptcy, and wages can be garnished for the rest of a borrower's lifetime. Thus, besides the usual stigma associated with loan defaults, such as tainted credit scores and limited future access to credit markets, the expectation of wages being garnished may affect borrowers' job search and incentives to work, while the fact that loan defaults can be observed by employers may affect their prospects of finding a job in the first place.[2]

As prior research has shown, the massive collapse in home prices during the Great Recession triggered a sharp drop in consumer spending by households (Mian, Rao and Sufi 2013; Stroebel and Vavra 2016; Kaplan, Mitman, and Violante 2016). This drop in consumer spending, in turn, led to a worsening of labor market outcomes: across different U.S. regions, those experiencing larger drops in home prices experienced significantly larger declines in employment (Mian and Sufi 2014; Giroud and Mueller 2017). Linking administrative student loan data from the U.S. Department of the Treasury to individual tax return data from IRS records, we examine the implications of these labor market

[1]Student loans are the largest financial asset held by the federal government, accounting for 45.6 percent of all federally owned financial assets (Financial Accounts of the United States, 2016 Q3).

[2]Using panel data from the NLSY97, Ji (2016) finds that student loan borrrowers spend 8.3 percent less time on their job search relative to non-borrowers. As a result, they earn 4.2 percent less annually in their first ten years after graduation. These findings are supported by survey evidence showing that 55 percent of student loan borrowers age 18 to 34 "accepted a job quicker to have income sooner" because of their student debt, while about 30 percent said that they "considered different industries or companies" (Earnest 2016). Other survey evidence shows that 47 percent of U.S. employers use credit checks to screen applicants, suggesting that loan defaults are likely to impact hiring decisions (SHRM 2010).

shocks for the rise in student loan defaults. Our student loan data represent a four percent random sample of all student loans that are either disbursed or guaranteed by the federal government. Our final sample consists of over one million annual observations of student borrowers who were in repayment during the Great Recession.

Our focus on the massive collapse in home prices and worsening of labor market outcomes informs the academic debate on the rise in student loan defaults. In that debate, a leading explanation is that the increase in defaults is largely driven by shifts in the composition of student borrowers toward "non-traditional" borrowers attending community colleges and, especially, for-profit institutions (Deming, Goldin, and Katz 2012; Looney and Yannelis 2015).[3] These borrowers tend to be older, come from less affluent family backgrounds, have lower completion rates, and experience weaker labor market outcomes. As Looney and Yannelis (2015) argue, all of these factors contribute to higher default rates. As the share of non-traditional borrowers increases over time, aggregate default rates have risen, mechanically, so to speak. Much recent research has been devoted to understanding better the for-profit education sector, reflecting its rising importance within the overall U.S. education system.[4]

Figure 1 provides suggestive evidence of a link between home prices and student loan defaults based on aggregated time series data. As home prices began to plummet at the onset of the Great Recession, student loan default rates began to rise. While the evidence in Figure 1 is suggestive, our empirical analysis exploits detailed variation in home price changes at the Zip code level during the Great Recession. Prior literature has argued that the massive collapse in home prices during the Great Recession has a causal effect on changes in consumer spending and local labor market outcomes (Mian, Rao and Sufi 2013; Mian and Sufi 2014; Stroebel and Vavra 2016; Kaplan, Mitman, and Violante 2016; Giroud and Mueller 2017). But even if the association between home price changes and local labor market outcomes were not causal, this would only mildly

[3] "Repayment outcomes tend to be worse among borrowers who attend for-profit or community colleges; those who are low-income or independent; those who attend part time; and, especially, those who do not complete their degrees. Many of these types of borrowers accounted for a disproportionate share of the increase in student borrowing during the Great Recession" (CEA 2016, pp. 4-5).

[4] See, e.g., Turner 2006; Deming, Goldin, and Katz 2012; Cellini and Goldin 2014.

change our interpretation. From our perspective, what matters is that changes in home prices constitute a first-order, and highly salient, source of cross sectional variation in local economic conditions during the Great Recession.

Cross sectional evidence based on variation in home price changes across Zip codes suggests that falling home prices during the Great Recession account for approximately 32 percent of the increase in student loan defaults. A potential concern with this cross sectional evidence is that Zip codes experiencing larger declines in home prices may be associated with larger shares of "non-traditional," or otherwise riskier, student borrowers, which could explain their higher default rates. To ensure that our estimates are not confounded by fundamental differences in borrower composition across Zip codes, we exploit the rich panel dimension of our data and include Zip code fixed effects in all our specifications. Our panel evidence suggests that declining home prices during the Great Recession account for approximately 24 percent of the increase in student loan defaults. While this is a lower magnitude than our cross sectional estimate, one must keep in mind that it reflects the relationship between home prices and student loan defaults based entirely on within Zip code level variation.

Another important concern is that the composition of student borrowers within a Zip code may have shifted over time. If such compositional shifts are correlated with home price changes, this could potentially confound our estimates. For example, if older repayment cohorts—which tend to have lower default rates—out-migrate in response to falling home prices, this could induce a negative correlation between home price changes and student loan defaults. To address this concern, we include Zip code $\times$ cohort year fixed effects. As it turns out, our estimates remain very similar. They also remain similar if we include individual borrower fixed effects, thereby absorbing any unobserved time invariant heterogeneity across student borrowers, such as schools attended, major choice, family background, and credit history, among others.

Consistent with a labor market channel, we find that the effect of home prices on student loan defaults is declining across income groups. In fact, for student borrowers with an annual income of $60,000 or more, there is no significant relationship between home prices and student loan defaults. We show that low income borrowers are more sensitive to home price changes for two reasons. First, low income jobs are more likely to be affected by a decline in home prices: while falling home prices are associated with substantial employment losses at the individual borrower level—defined as an earnings drop of 50 percent or more—this relationship is declining across income groups and only significant among low income borrowers.[5] Second, large earnings drops are more likely to trigger student loan defaults when student borrowers' income is low: while employment losses at the individual borrower level are highly predictive of subsequent student loan defaults, this relationship is monotonically declining across income groups, and it is only significant among low income borrowers. Intuitively, high income borrowers may have significant discretionary earnings even after facing a large earnings drop, or they may have accumulated savings in the past due to their higher earnings, allowing them to continue making repayments on their student loans.

The estimated effect of employment losses on student loan defaults is economically highly significant: student borrowers facing an earnings drop of 50 percent or more are 32 percent more likely to default in the following year. A potential concern with this estimate is that student borrowers facing a large earnings drop may be unobservably different from other student borrowers. To account for confounding factors, we conduct an event study around the date of the employment loss. If the relationship between employment losses and student loan defaults was driven by unobserved heterogeneity among student borrowers, we should see an "effect" already prior to the employment loss. We find no differences in pretrends, suggesting that employment losses play a major role in explaining student loan defaults in the Great Recession.

The drop in home prices during the Great Recession may have *directly* impacted student borrowers through a liquidity channel. Precisely, falling home prices may have impaired student borrowers' ability to borrow against home equity (Mian and Sufi 2011; Bhutta and Keys 2016), limiting their access to liquidity and consequently their ability

[5] This result both confirms and extends results in prior literature based on aggregated (establishment or county level) data (Mian and Sufi 2014; Giroud and Mueller 2017). In our case, the relationship between home prices and employment losses is based on within ZIP code level variation and observed at the individual borrower level. Importantly, we find that this relationship depends crucially on the level of borrower income: it is decreasing across income groups and only significant among low income borrowers.

to make student loan repayments. To test for a liquidity channel, we compare the default responses of home owners and renters to changes in home prices.[6] Intuitively, while a drop in home prices may have impaired home owners' ability to borrow against home equity, there should be no corresponding liquidity effect for renters. We find no significant differences in the default responses of home owners and renters to changes in home prices, suggesting that our results are primarily driven by a labor market channel, not a liquidity channel. We obtain similar results if we control for individual labor earnings and their interaction with home prices, or if we replace the Zip code fixed effects with individual borrower fixed effects.

We conclude our study by performing an evaluation of the Income Based Repayment (IBR) program rolled out by the federal government in 2009, in the wake of the Great Recession. Under this program, student loan repayments are capped at 15 percent of discretionary income, and repayment terms are extended to up to 25 years. Eligibility is based on a means test, which effectively requires that the student debt be sufficiently large relative to discretionary income. The purpose of income driven repayment plans, such as IBR, is to provide student borrowers with valuable insurance against income shocks by making their loan repayments contingent on discretionary income. To assess the efficacy of the IBR program, we conduct a triple difference analysis by examining the default responses of IBR eligible versus ineligible student borrowers to home price changes before and after the program's introduction. We find that the introduction of the IBR plan reduced both student loan defaults and their sensitivity to home price fluctuations, thus providing student borrowers with valuable insurance against adverse income shocks. Importantly, this effect is entirely driven by IBR eligible student borrowers who actually took up the IBR repayment option. In contrast, IBR eligible student borrowers who did not take up the IBR repayment option continue to exhibit high student loan default rates after 2009. Lastly, we find no differential trends between IBR eligible and ineligible student borrowers prior to the plan's introduction, strenghtening a key identifying assumption of our difference-in-differences analysis.

[6] Our sample includes all student borrowers *in repayment*, many of which are in their 30s, 40s, and even 50s. The average homeownership rate in our sample is 39 percent.

The surge in student loan volume and default rates since the beginning of the Great Recession has prompted an active debate in the media and academic circles (e.g., Avery and Turner 2012; Looney and Yannelis 2015).[7] A leading explanation for the dramatic rise in student loan defaults is that the composition of student borrowers has shifted toward "non-traditional" borrowers attending community colleges and, especially, for-profit institutions, which tend to have higher default rates. Our empirical study informs this debate by placing the focus on the massive collapse in home prices and worsening of labor market outcomes during the Great Recession, showing that it accounts for a significant fraction of the rise in student loan defaults.

More generally, our work is related to papers studying the effect of home prices on college enrollment and household debt, in particular, student loan debt. Mian and Sufi (2011) show that rising home equity values during the housing boom lead to a significant increase in household leverage. Brown, Stein, and Zafar (2015) extend these results to a larger sample period and analyze the effect of home prices on different categories of household debt, including home equity loans and student loans. The authors find no evidence of a substitution between home equity borrowing and student loan debt. Amromin, Eberly, and Mondragon (2016) examine the interaction between home prices, home equity loans, and student loans. Unlike Brown, Stein, and Zafar (2015), the authors find a significant substitution effect between home equity borrowing and student loan debt. Lovenheim (2011) finds a positive relation between home price growth and college enrollment, and Lovenheim and Reynolds (2013) find that home price growth is positively associated with attending a higher quality college. Charles, Hurst, and Notowidigo (2016) find that the housing boom leads to a decline in college enrollment. Similar to what we find in the context of student loans, the authors conclude that the effect of home prices on college enrollment operates primarily through a labor market channel.[8]

In light of these empirical studies, we should note that our results are orthogonal to

[7] Some commentators argue that student loan debt is "the most obvious candidate for the next bubble" (Chicago Tribune, August 24, 2016).

[8] Consistent with a substitution effect between labor market conditions and college enrollment, Barr and Turner (2013, 2015) find that the worsening of labor market outcomes during the Great Recession leads to an increase in college enrollment.

any variation in college enrollment or student borrowing induced by changes in home prices. Our sample consists of student borrowers who are already in repayment, meaning they have made their college enrollment and student borrowing decisions many years ago. Accordingly, while current home price changes may affect the default decisions of borrowers in our sample, they cannot, by construction, affect their college enrollment and student borrowing decisions. In addition, the inclusion of Zip code fixed effects accounts for any fixed compositional differences across Zip codes due to past home price changes (e.g., differences in college enrollment or student borrowing), while the inclusion of Zip code $\times$ cohort year fixed effects accounts for the possibility that past home price experiences may be "time varying" during our sample period due to the in- and out-migration of repayment cohorts across Zip codes. Finally, the inclusion of individual borrower fixed effects—in conjunction with the fact that borrowers in our sample are already in repayment—naturally accounts for any decisions made before entering the sample, such as college enrollment and student borrowing decisions.

Lastly, our paper contributes to a large existing literature which studies the risks and returns of financing higher education (see Avery and Turner (2012) for a review). On the return side, there is broad consensus that the returns to college education have increased over the past decades (e.g., Katz and Murphy 1992; Autor, Katz, and Kearney 2008; Goldin and Katz 2008). Our paper focuses on the risk side. Linking administrative student loan data to de-identified tax data and exploiting Zip code level variation in home price changes during the Great Recession, we document that home price fluctuations constitute an important source of student loan default risk, operating primarily through an aggregate labor market channel.[9]

The rest of this paper is organized as follows. Section 2 presents the data, variables, and summary statistics. Section 3 contains our main results. This section also examines the interaction between home prices, employment losses, and student loan defaults, and tests for a direct liquidity channel by comparing the default responses of home owners

[9]Another important source of student loan default risk is college dropout risk. Comparing cohorts from the high school classes of 1972 and 1992, Bound, Lovenheim, and Turner (2010) document that college completion rates have declined nationally, and this decline is most pronounced among students attending less selective public four-year colleges and community colleges.

and renters to home price changes. Section 4 performs an evaluation of the Income Based Repayment program introduced by the federal government in the wake of the Great Recession. Section 5 concludes.

2 Data, Variables, and Summary Statistics

2.1 Data

Our student loan data are from the National Student Loan Data System (NSLDS), which is the main data source used by the U.S. Department of Education to administer federal student loan programs. The NSLDS contains information on all federal student loans, accounting for more than 92 percent of the student loan market in the United States. Our analysis sample constitutes a four percent random sample of the NSLDS used by the U.S. Department of the Treasury for policy analysis and budgeting purposes, drawn using permutations of the last three digits of an individual's social security number. The sample is constructed as a panel, tracking individual student borrowers over time. For the purpose of our analysis, we focus on student borrowers who are in repayment. Student borrowers typically enter into repayment within six months after leaving their degree granting institution.

The NSLDS provides detailed information on student loan disbursements, balances, and repayment. It also contains information on the institutions where student borrowers enrolled, such as name and institutional control type. Private non-profit, public non-profit, and four-year for-profit institutions are included in our sample. In addition, the NSLDS contains demographic information on student borrowers and their parents from the Free Application for Federal Student Aid (FAFSA) form, which recipients of federal student loans are required to complete. The NSLDS has been linked to de-identified tax data from the IRS Compliance Data Warehouse (CDW). The CDW sources data from W-2s and other tax returns, such as Schedule C (Form 1040), which business owners and sole proprietors are required to file. Besides earnings and total income, the tax data also include information on marital status, mortgage interest deduction, and number of individuals in a household. The latter information is needed to calculate the poverty level of individuals when evaluating the Income Based Repayment program. Earnings are defined as Medicare wages plus self-employment earnings. Total income additionally includes non-labor income.

We match student borrowers to home prices at the Zip code level using home price data from Zillow.[10] Since our focus is on the Great Recession, we use (with few exceptions) home price data from 2006 to 2009. Changes in home prices from 2006 to 2009 based on Zillow data are highly correlated with the "housing net worth shock" in Mian, Rao and Sufi (2013) and Mian and Sufi (2014), "Δ Housing Net Worth, 2006–2009." The correlation at the MSA level is 86.3 percent. They are also highly correlated with changes in home prices from 2006 to 2009 using home price data from the Federal Housing Finance Agency (FHFA). The correlation at the MSA level is 96.4 percent. In line with prior research, we measure home prices in December unless otherwise noted.

2.2 Variables and Empirical Specification

The primary outcome variable is an indicator of whether a student borrower defaults on her student loan for the first time ("new default"). A student loan goes into default within 270 days of a payment being missed. When a student loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Hence, it takes about one year between when a payment is missed and when a default is recorded in administrative data. To account for this time lag, we always use student loan defaults in year $t+1$. Thus, our focus is on home prices from 2006 to 2009 and student loan defaults from 2007 to 2010. Our main empirical specification is:

$$\pi_{i,t+1} = \alpha_t + \alpha_z + \beta \text{ Home Price}_{z,t} + \gamma \mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $\pi_{i,t+1}$ is an indicator of whether individual i defaults in year $t+1$, $\text{HomePrice}_{z,t}$ is the home price (in logs) in Zip code z in year t, $\mathbf{X}_{i,t}$ is a vector of controls, which

[10] Zillow home price data have been used by, e.g., Keys et al. (2014), Kaplan, Mitman, and Violante (2016), Bailey et al. (2016), and Giroud and Mueller (2017).

includes loan balance, borrowing duration, family income, school type, and Pell grant aid, and α_t and α_z are year and Zip code fixed effects, respectively. The year fixed effect capture any economy wide factors, such as aggregate economic conditions. The Zip code fixed effects absorb any time invariant heterogeneity across Zip codes during the sample period, including any given differences in borrower composition, college enrollment, and student loan volume arising from different labor market outcomes during the preceding housing boom. In some of our specifications, we also include cohort year, Zip code $\times$ cohort year, or individual borrower fixed effects. Cohort year indicates the year in which the student borrower enters into repayment. Standard errors are clustered at the Zip code level. In robustness checks, we alternatively cluster standard errors at the county level. Observations are weighted by individual loan balances.

Two further variables that play an important role are employment losses and home ownership. Both variables are constructed from IRS tax data. Employment losses are defined as large earnings drops of 50 percent or more relative to the previous year's earnings. Home ownership is a dummy indicating whether an individual took the mortgage interest deduction. Individuals who are not home owners are classified as renters.

2.3 Summary Statistics

Table 1 presents basic summary statistics. All variables are measured over the 2006 to 2009 sample period. The only exception is student loan default, which is measured over the 2007 to 2010 period. There are 1,071,049 annual borrower-level observations associated with 298,003 individual student borrowers. The average student borrower has \$23,757 in student debt and earns \$44,930 during the sample period. Total income, which includes non-labor earnings, is \$62,369 on average. About eight percent of student borrowers experience a significant earnings drop of 50 percent or more in any given year ("employment loss"). By comparison, the average annual layoff rate during the Great Recession was about seven percent (Davis, Faberman, and Haltiwanger 2012). Student borrowers in our sample enter into repayment between 1970 and 2009. The average repayment cohort is 2002. In any given year, about four percent of student borrowers in repayment default on their student loans for the first time. When comparing this number to two- and three-year cohort default rates used by the U.S. Department of Education, one must keep in mind that these differ from our student loan default rates along two important dimensions. First, our student loan default rates measure the annual flow of student borrowers defaulting for the first time in any given year. Second, two- and three-year cohort default rates measure student loan defaults during the first two or three years after student borrowers enter into repayment—a time period during which a disproportionately large share of student borrowers tends to default. By contrast, our student loan default rates measure defaults across all repayment years.[11]

About 39 percent of student borrowers own a home, which is significantly less than the national average of 68 percent during the sample period. This discrepancy is likely because student borrowers are younger than the national average and earlier in their life-cycle, and also because they are often saddled with large amounts of student debt. The average Zip code level home price during the sample period is \$244,882. There is significant dispersion in home prices, though, ranging from \$26,800 in Youngstown, Ohio, to \$3,799,801 in Atherton, California. To reduce the sensitivity of our estimates to outliers, we use the natural logarithm of home prices in all our regressions.

Figure 2 shows the age distribution of student borrowers. As is shown in Panel A, most student borrowers enter into repayment in their early to mid 20s. However, a large fraction of student borrowers enter into repayment in their late 20s, 30s, and even 40s, reflecting the prominent role of "non-traditional" borrowers—those attending for-profit and other non-selective institutions—in our administrative data. Panel B shows the age distribution of all student borrowers in repayment. The average student borrower in our sample is 37 years old. While the typical student debt repayment plan has a duration of ten years, student borrrowers often have the choice among alternative repayment options, which can significantly increase the duration of their loans (Avery and Turner 2012). For instance, by consolidating their loans, student borrowers can extend their repayment

[11] Cohort default rates have been historically used by the U.S. Department of Education at the cohort by school level to penalize schools with high student loan default rates. In contrast, our analysis focuses on student loan default at the individual borrower level, not at the cohort by school level.

term to up to 30 years, depending on the amount of their total indebtedness. This, in conjunction with the fact that many student borrowers enter into repayment in their 30s and even 40s, explains why the age distribution in Panel B has a big right tail.

3 Labor Market Shocks and Student Loan Defaults

3.1 Main Results

The time series evidence in Figure 1 based on aggregated data shows a strong inverse relationship between home prices and student loan defaults during the Great Recession. This relationship becomes even stronger if one accounts for the fact that there is a one-year time lag between when a payment is missed and when a loan default is recorded in administrative data. Figure 3 provides cross sectional evidence. Panel A shows the relationship between the percentage change in student loan defaults during the Great Recession, Δ Log Default$_{07-10}$, and the percentage change in home prices at the Zip code level, Δ Log Home Price$_{06-09}$. Zip codes are weighted by total student loan balances. For each percentile of Δ Log Home Price$_{06-09}$, the plot shows the mean values of Δ Log Home Price$_{06-09}$ and Δ Log Default$_{07-10}$, respectively. As can be seen, the inverse relationship between home prices and student loan defaults documented in the time series is also present in the cross section.

Table 2 shows results from a cross sectional regression in the spirit of Mian and Sufi (2014) and Mian, Rao, and Sufi (2013). Zip codes are weighted by total student loan balances. Standard errors are clustered at the Zip code level. In column (1), we regress the change in student loan defaults at the Zip code level from 2007 to 2010, Δ Default$_{07-10}$, on the percentage change in home prices at the Zip code level from 2006 to 2009, Δ Log Home Price$_{06-09}$. As can be seen, a one percent decline in home prices at the Zip code level is associated with a 0.009 percentage point increase in student loan defaults. This result is significant at the one percent level. In column (2), we measure the change in home prices from their peak in July 2006 to their trough in March 2009. As is shown, our estimates become slightly larger, and they remain highly significant. In column (3), home prices and student loan defaults are both measured in logs, implying that the coefficient associated with Δ Log Home Price$_{06-09}$ indicates the elasticity of student loan defaults with respect to home prices. This elasticity is -0.4179 and significant at the one percent level. To assess its economic significance, we note that new student loan defaults rose from 3.59 percent to 4.27 percent between 2007 and 2010, which represents an increase of 18.9 percent. Home prices at the Zip code level fell by 14.4 percent between 2006 and 2009.[12] Accordingly, the estimated relationship in column (3) accounts for approximately 31.8 percent ($= (14.4 \times (-0.4179))/18.9$) of the increase in new student loan defaults during the Great Recession.

A potential concern is that Zip codes experiencing larger declines in home prices during the Great Recession may be unobservably different from other Zip codes. For instance, they may be associated with a higher share of "non-traditional," or otherwise riskier, student borrowers. To address potentially confounding effects due to unobserved heterogeneity at the Zip code level, we exploit the panel dimension of our data and estimate the relationship between home prices and student loan defaults at the individual student borrower level, as described in equation (1), which includes year and Zip code fixed effects. The year fixed effects capture any economy wide factors, such as aggregate economic conditions. The Zip code fixed effects absorb any time invariant heterogeneity across Zip codes during the sample period, including any given differences in borrower composition, college enrollment, and student loan volume arising from different labor market outcomes during the preceding housing boom. Observations are weighted by individual loan balances. Standard errors are clustered at the Zip code level.

Table 3 presents the results. In column (1), which is our main specification, a one percent decline in home prices is associated with a 0.0113 percentage point increase in student loan defaults. This result, like all the results in Table 3, is significant at the one percent level. As previously in our cross sectional analysis, we can assess the economic significance of this relationship. Accordingly, the estimated relationship in column (1)

[12]The drop in home prices of 14.4 percent between December 2006 and December 2009 is similar to the 14.5 percent quoted in Giroud and Mueller (2017), also based on Zillow data, and the 14.9 percent quoted by the St. Louis Fed based on FHFA data (https://fred.stlouisfed.org/series/HPIPONM226S).

accounts for approximately 23.9 percent ($= (14.4 \times 0.0113)/(4.27 - 3.59)$) of the rise in new student loan defaults during the Great Recession. While this is a lower number than our cross sectional estimate, one must keep in mind that it reflects the relationship between home prices and student loan defaults based entirely on within Zip code level variation. In column (2), we cluster standard errors at the county level. Surprisingly, they become only slightly larger. In column (3), we include the full vector of controls $\mathbf{X}_{i,t}$ from equation (1), which includes loan balance, borrowing duration, family income, school type, and Pell grant aid. As can be seen, both the coefficient on home prices and the standard errors remains virtually unchanged. As it makes little difference whether these controls are included, we drop them from our further analysis.

While the inclusion of Zip code fixed effects accounts for any fixed differences in borrower composition across Zip codes, it is conceivable that the composition of student borrowers within a Zip code may have shifted over time. If such compositional shifts are correlated with home price changes, this could potentially confound our estimates. For instance, student borrowers are more likely to default within the first few years after entering into repayment. If older repayment cohorts out-migrate in response to falling home prices, this could induce a negative correlation between home price changes and default likelihood. In columns (4) and (5), we rule out such confounding factors by including either cohort year or Zip code $\times$ cohort year fixed effects. As can be seen, our estimates remain ver similar. In column (6), we include individual borrower fixed effects, thereby absorbing any unobserved time invariant heterogeneity across student borrowers, such as schools attended, major choice, family background, and credit history, among others. Our estimates again remain similar.

Table 4 breaks down our main results by individual loan balances. Larger balances typically imply larger monthly repayments, and therefore a higher likelihood of non-repayment in response to any given income shock. On the other hand, however, larger balances are associated with *safer* student borrowers. During the 2006 to 2009 period, the median student borrower at for-profit institutions (two-year colleges) entered into repayment with $7,689 to $8,567 ($7,277 to $7,956) in student debt. By contrast, over the same time period, the median student borrower at selective four-year colleges entered into repayment with \$19,128 to \$20,494 in student debt (Looney and Yannelis 2015). As we have discussed earlier, student borrowers at for-profit institutions and two-year colleges exhibit significantly higher default rates than those at selective four-year colleges (Deming, Goldin, and Katz 2012; Looney and Yannelis 2015).

The results in Table 4 show that the relationship between home prices and student loan defaults is monotonically increasing across loan balances. For balances below the 25th percentile of the sample distribution, this relationship is insignificant, suggesting that students borrowers with small loan balances are able to avoid default in response to falling home prices during the Great Recession. That student borrowers with large loan balances are more sensitive to home price fluctuations underscores the important role of federal insurance programs, such as the Income Based Repayment (IBR) plan, which explicitly targets student borrowers with large loan balances relative to discretionary income. In Section 4, we show that the introduction of the IBR plan in 2009 reduced both student loan defaults and their sensitivity to home price fluctuations.

3.2 Labor Market Channel

One of the main narratives of the Great Recession is that the collapse in home prices triggered a sharp drop in consumer spending by households, leading to massive employment losses (Mian, Rao and Sufi 2013; Mian and Sufi 2014; Stroebel and Vavra 2016; Kaplan, Mitman, and Violante 2016; Giroud and Mueller 2017).[13] Layoffs and earnings declines, in turn, may have impaired student borrowers' ability to make loan repayments, especially if their labor earnings were low to begin with. In this section, we examine the implications of this labor market channel by studying the relationship between home prices, labor earnings, employment losses, and student loan defaults at the individual student borrower level.

Panel B of Figure 3 shows the relationship between changes in labor earnings during the Great Recession, Δ Log Earnings$_{06-09}$, and changes in home prices at the Zip code

[13] Mian, Rao, and Sufi (2013), Baker (2016), and Kaplan, Mitman, and Vilolante (2016) emphasize the role of household leverage in amplifying the consumption responses of households.

level, Δ Log Home Price$_{06-09}$. The figure is constructed analogously to that in Panel A. As is shown, labor earnings declined relatively more in Zip codes that experienced larger reductions in home prices. Labor earnings, in turn, strongly predict subsequent student loan defaults. Figure 4 depicts the relationship between individual labor earnings, in deciles of the earnings distribution, and student loan defaults in the following year. As can be seen, there is a negative and monotonic relationship between individual labor earnings and subsequent student loan defaults.

Tables 5 to 7 confirm these visual impressions. All regressions include year and Zip code fixed effects. Standard errors are clustered at the Zip code level. Table 5 examines the relationship between home prices and student loan defaults at the individual borrower level, stratified by borrower income. As can be seen, this relationship is monotonically declining across income groups and only significant among low income borrowers. Tables 6 and 7 show that low income borrowers are more sensitive to home price changes for two reasons. First, Table 6 shows that low income jobs are more likely to be affected by a decline in home prices. Specifically, we examine the relationship between home prices and employment losses—defined as an earnings drop of 50 percent or more—at the individual borrower level, stratified by borrower income. As is shown, this relationship is monotonically declining across income groups and only significant among low income jobs. This both confirms and extends results in prior literature based on aggregated (establishment or county level) data (Mian and Sufi 2014; Giroud and Mueller 2017). In our case, the relationship between home prices and employment losses is based on within Zip code level variation and observed at the individual level. Importantly, our results show that this relationship is primarily concentrated among low income jobs.

Second, Table 7 shows that low income borrowers are more likely to default on their student loans in response to a loss of employment. On average, student borrowers who experience a large earnings drop are 1.23 percentage points more likely to default in the following year. Given an average default rate of 3.87 percent, this implies a 31.8 percent higher default likelihood. That being said, there is substantial heterogeneity across student borrowers. As can be seen, the relationship between employment losses and student loan defaults at the individual borrower level is monotonically declining across income groups and only significant among low income borrowers. Intuitively, high income borrowers may have significant discretionary earnings even after facing a large earnings drop, or they may have accumulated savings in the past due to their higher earnings, allowing them to continue making repayments on their student loans.

A potential concern with this evidence is that student borrowers who experience a large earnings drop may be unobservably different from other student borrowers. To further analyze the relationship between employment losses and student loan defaults, we present an event study in Figure 5. If this relationship was driven by unobserved differences between student borrowers who experience a large earnings drop and those who do not, we should see an "effect" on loan defaults already prior to the employment loss. Let T be the event date in which a student borrower experiences a 50 percent or more earnings drop. Figure 5 plots the coefficients β_j from the following specification:

$$\pi_{i,t+1} = \alpha_t + \alpha_z + \alpha_c + \sum_{j=T-4}^{T+4} \beta_j 1[t = j] + \gamma \mathbf{X}_{i,t} + \varepsilon_{i,t}, \qquad (2)$$

where $\pi_{i,t+1}$ is an indicator of whether individual i defaults in year $t+1$, $1[t = j]$ denotes the number of years before or after the employment loss event, $\mathbf{X}_{i,t}$ is a vector of controls, which includes labor earnings and school type, and α_t, α_z, and α_c are year, Zip code, and cohort year fixed effects. Standard errors are clustered at the Zip code level. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, the coefficient associated with a given year t is plotted in the following year, $t+1$. The dashed lines represent a 95 percent confidence interval.

As can be seen, there is a significant jump in student loan defaults one year after the event, consistent with there being a one-year time lag between when a payment is missed and when a loan default is recorded. The effect begins to attenuate three years after the event, suggesting that student borrowers who manage to avoid default in the first three years after losing their employment are increasingly able to also do so in subsequent years. Lastly, and most important, the coefficients are not significantly different from zero in the years prior to the event, mitigating concerns that the relationship between employment losses and student loan defaults may be driven by unobserved heterogeneity across student borrowers.

3.3 Direct Liquidity Channel

Under a labor market channel, the collapse in home prices during the Great Recession may have affected student loan defaults through its impact on aggregate labor market outcomes. We provided evidence for this channel in the previous section. Alternatively, falling home prices may have *directly* impacted student loan defaults through a liquidity channel. Precisely, they may have impaired student borrowers' ability to borrow against home equity (Mian and Sufi 2011; Bhutta and Keys 2016), limiting their access to liquidity and consequently their ability to make student loan repayments.

While the collapse in home prices may have directly affected mortgage defaults, it is not obvious whether it also should directly affect student loan defaults. Unlike mortgages, where underwater home owners have strong strategic incentives to default, there are no strategic default incentives in the student loan market. Further, unlike mortgages, student loans are not dischargeable in bankruptcy, and wages—even social security benefits—can be garnished for the rest of a borrower's lifetime. Indeed, Mian and Sufi (2011) find that rising home equity based borrowing during the housing boom is *not* used to pay down expensive credit card balances—even for households with a heavy dependence on credit card borrowing—suggesting that repayment spillovers toward other forms of household debt are not a priori obvious.

To test for a liquidity channel, we compare the default responses of home owners and renters to changes in home prices. Intuitively, while a drop in home prices may have impaired home owners' ability to borrow against home equity, there should be no corresponding liquidity effect for renters.[14] We measure home ownership through the mortgage interest deduction. The home ownership rate in our sample is 39 percent, which is considerably less than the national average of 68 percent during the sample

[14] Renters' liquidity may have *improved* if falling home prices are passed through to renters in the form of lower rents. However, this would only strenghten the argument that, under a liquidity channel, home owners should be more impaired than renters. See Rosen (1979) and Poterba (1984) for classic references.

period. While our sample includes all student loan borrowers in repayment—many of which are in their 30s, 40s, and even 50s (see Panel B of Figure 2)—they are still younger than the national average and hence earlier in their life-cycle.

Table 8 examines whether home owners respond more strongly to changes in home prices than renters, as predicted by the liquidity channel. As is shown, the coefficient associated with Home Price × Owner is always small and insignificant. This is true regardless of whether we add controls, how we cluster standard errors, or which fixed effects we include. On the other hand, with the exception of column (5), the direct effect of home ownership is significant and has the predicted sign: absent home price changes, home owners are significantly less likely to default than renters.[15] Hence, while home owners and renters may differ in their basic default likelihood, they respond similarly to changes in home prices. This is inconsistent with a direct liquidity channel of home prices on student loan defaults.

A potential concern is that home owners may have higher labor earnings, and this could mask liquidity effects. We address this concern in Table 9 by including labor earnings or total income and the respective interaction with home prices as additional controls. While these controls have the predicted sign—individuals with higher earnings or total income default less and are less sensitive to home price changes (see also Table 5)—the coefficient associated with Home Price × Owner remains highly insignificant. Another possible concern is that we do not measure home ownership directly but only through the mortgage interest deduction. Accordingy, home owners who have paid off their mortgage in full may be misclassified as renters. This could induce measurement error and attenuate the effect of home ownership in our regressions. To address this concern, we re-estimate the specification in column (1) of Table 8 separately for the pre 2000, 2000 to 2005, and post 2005 cohorts. The idea is that misclassification is unlikely to affect younger repayment cohorts, as these are unlikely to have paid off their mortgage in full. The results are shown in Table 10. Consistent with attenuation bias, the direct effect

[15] That the direct effect of home ownership becomes insignificant in column (5)—which includes Zip code × cohort year fixed effects—suggests that it may be driven by cohort and regional effects, e.g., home owners tend to be older and live in different neighborhoods than renters.

of home ownership is insignificant among the pre 2000 cohort. Importantly, however, the coefficient associated with Home Price $\times$ Owner is insignificant among all repayment cohorts, including younger cohorts.

4 Income Based Repayment Program

Our previous results show that low income borrowers and those with high loan balances are particulary affected by adverse labor market shocks. Under the standard ten-year repayment plan, student borrowers facing adverse income shocks can apply for a loan deferment (if they are unemployed) or a forbearance (if the amount owed exceeds 20 percent of their gross income). In addition, prior to 2009, student borrowers may have had the option to enroll in alternative repayment plans, but take-up rates have been historically low, in part due to lack of information, and in part because loan servicers may have had inadequate incentives to enroll students.

In the wake of the Great Recession, in 2009, the U.S. Department of Education rolled out the Income Based Repayment (IBR) program, accompanied by a significant push to enroll student borrowers.[16,17] The purpose of income driven repayment plans, such as IBR, is to provide student borrowers with valuable insurance against income shocks by making their loan repayments contingent on discretionary income. Under the IBR plan, repayments are capped at 15 percent of discretionary income, and repayment terms are extended to up to 25 years, after which all remaining student debt is forgiven.[18] Eligibility is based on a means test, which requires that 15 percent of the borrower's discretionary income be less than her payment under the standard ten-year repayment plan. Discretionary income is any income above 150 percent of the federal poverty level.

[16] "To achieve this increase, the Administration has used tools such as behavioral "nudges," improved loan servicer contract requirements, efforts associated with the President's Student Aid Bill of Rights, a student debt challenge to gather commitments from external stakeholders, and increased and improved targeted outreach to key borrower segments" (CEA 2016, pp. 63-64).

[17] Despite theoretical interest, income driven repayment plans have been relatively understudied by empirical researchers in the U.S. See Chapman (2014) for an overview of income contingent student loan schemes in an international context.

[18] The 15 percent cap was later reduced to 10 percent for new borrowers on or after July 1, 2014.

Essentially, student borrowers are eligible for the IBR repayment option if their student debt is sufficiently large relative to their discretionary income.

To assess the efficacy of the IBR program, we classify student borrowers as IBR eligible and ineligible based on the means test. That is, we do not assign treatment status based on whether an individual enrolled in the IBR program, which is an endogenous choice, but based on whether she was eligible for enrollment. We later provide graphical evidence showing that changes in student loan defaults attributed to the IBR program come from those (eligible) student borrowers that actually took up the IBR repayment option. We calculate IBR eligibility as $0.15 \times (E_{it} - \overline{E_{it}}) < P_{it}$, where E_{it} is individual i's earnings in year t, $\overline{E_{it}}$ is the federal poverty level—which varies from year to year and depends on household size—and P_{it} is the annual payment faced by individual i in year t under the standard ten-year repayment plan. Household size, including marital status and number of dependent children, is obtained from IRS records. Annual payments under the standard ten-year repayment plan, P_{it}, are computed using the amortization formula $P_{it} = L_{i0} \times (r_{it} + \frac{r_{it}}{(1+r_{it})^n - 1})$, where L_{i0} is the initial loan balance, r_{it} is the borrowing rate, and $n = 10$ is the number of years. Notice that IBR eligibility—which is based on the means test—is well defined for any given year, including years prior to the introduction of the IBR plan. Accordingly, we can compare student loan defaults by IBR eligible and ineligible student borrowers before and after the plan's introduction.

Given that the IBR program was introduced in 2009, we extend our sample period to include student loan defaults up until 2012.[19] Thus, we focus on home prices between 2006 and 2011 and student loan defaults between 2007 and 2012. Extending the sample period increases the number of annual observations to 1,556,296. To gauge the insurance value of the IBR plan, we conduct a triple difference analysis by examining the default responses of IBR eligible versus ineligible student borrowers to home price changes before and after the plan's introduction. We estimate the following specification:

[19] We choose 2012 as the ending date year since a new insurance program, the PAYE program, was introduced in December 2012.

$$
\begin{aligned}
\pi_{i,t+1} \quad = \quad & \alpha_t + \alpha_z + \beta_1 \text{ Home Price}_{z,t} + \beta_2 \text{ IBR Eligible}_{i,t} + \beta_3 \text{ Home Price}_{z,t} \times \text{Post} \\
& + \beta_4 \text{ IBR Eligible}_{i,t} \times \text{Post} + \beta_5 \text{ Home Price}_{z,t} \times \text{IBR Eligible}_{i,t} + \qquad (3) \\
& + \beta_6 \text{ Home Price}_{z,t} \times \text{IBR Eligible}_{i,t} \times \text{Post} + \varepsilon_{i,t},
\end{aligned}
$$

where $\pi_{i,t+1}$ is an indicator of whether individual i defaults in year $t+1$, Home Price$_{z,t}$ is the home price (in logs) in Zip code z in year t, IBR Eligible$_{i,t}$ is a dummy indicating whether individual i passes the means test $0.15 \times (E_{it} - \overline{E_{it}}) < P_{it}$ in year t, Post is a dummy that equals one beginning in 2009, and α_t and α_z are year and Zip code fixed effects, respectively. Standard errors are clustered at the Zip code level. Observations are weighted by individual loan balances.

The main coefficients of interest are β_2, β_4, β_5, and β_6. Given our previous results, we would expect β_2 to be positive: IBR eligible student borrowers—those with high ratios of student debt to income—are more likely to default on their student loans. The coefficient β_4 indicates the relative change in student loan defaults of IBR eligible versus ineligible student borrowers after the plan's introduction. If the IBR plan is effective at reducing student loan defaults, we would expect β_4 to be negative. The coefficient β_5 indicates whether student borrowers with high ratios of student debt to income are more sensitive to changes in home prices. Given our previous results, we would expect this coefficient to be negative. Lastly, the coefficient β_6 indicates whether the relatively stronger default sensitivity of IBR eligible student borrowers to home price changes is mitigated after 2009. If the introduction of the IBR plan provides student borrowers with insurance against income shocks, then β_6 should be positive.

Table 11 presents the results. As column (1) shows, home prices continue to be negatively associated with student loan defaults also during the extended sample period. Furthermore, IBR eligible student borrowers—those with high ratios of student debt to income—are more likely to default on their student loans. In column (2), we estimate the triple difference specification described in equation (3). As is shown, the coefficient on IBR Eligible, β_2, is positive, and the coefficient on IBR Eligible $\times$ Post, β_4, is negative.

Both coefficients are significant at the ten percent level or higher. Together, these results imply that student borrowers with high ratios of student debt to income are more likely to default on their student loans, and that this effect is mitigated after the introduction of the IBR plan in 2009. Further, the coefficient on Home Price × IBR Eligible, β_5, is negative, while the coefficient on Home Price × IBR Eligible × Post, β_6, is positive. Both coefficients are significant at the ten percent level. Accordingly, while student borrowers with high ratios of student debt to income are more sensitive to home price changes, this effect is attenuated after 2009, suggesting that the IBR pogram is, at least partially, sucessful at insuring student borrowers against income shocks. Overall, the results in Table 11 show that the IBR program has led to a significant reduction in student loan defaults as well as their sensitivity to home price fluctuations.

The coefficients β_4 and β_6 indicate how student loan defaults and their sensitivity to home price fluctuations change after the introduction of the IBR plan in 2009. Both coefficients have the predicted sign, but they are only marginally significant. A potential concern is that student borrowers with high ratios of student debt to income may be unobservably different from student borrowers with low ratios. We address this concern in column (3) by dropping student borrowers with low ratios from our sample, thereby reducing the sample size by more than half. Effectively, we are thus comparing student borrowers who all exhibit a high degree of illiquidity, some of which are eligible for the IBR plan, while others are not.[20] As can be seen, all results are qualitatively similar to those in column (2). Notably, the two main coefficients of interest, β_4 and β_6, are now significant at the five percent level. In column (4), we account for unobserved heterogeneity among IBR eligible and ineligible student borrrowers by including individual borrower fixed effects. While some of the coefficients are now insignificant due to lack of within borrower variation, the two main coefficients of interest, β_4 and β_6, are highly significant, at the one and five percent level, respectively.

The main identifying assumption underlying our difference-in-differences analysis is

[20] Under the means test, student borrowers are eligible for the IBR plan if $0.15 \times (E_{it} - \overline{E_{it}}) < P_{it}$. The sample restriction imposed in column (3) requires that $0.075 \times (E_{it} - \overline{E_{it}}) < P_{it}$, thus eliminating all student borrowers with low ratios of student debt to discretionary income.

that IBR eligible and ineligible student borrowers exhibit parallel trends prior to the introduction of the IBR program in 2009. In columns (3) and (4), we have addressed potential unobserved heterogeneity among IBR eligible and ineligible student borrowers by narrowing down the sample to borrowers with a relatively high degree of illiquidity and including individual borrower fixed effects, respectively. Figure 6 provides further evidence. The white bars show student loan default rates of IBR ineligible borrowers. The gray bars show student loan default rates of IBR eligible borrowers. Eligiblity is based on the means test, $0.15 \times (E_{it} - \overline{E_{it}}) < P_{it}$, which implies that it can be computed in any given year, including years prior to the introduction of the IBR plan. Indeed, the purpose of Figure 6 is to compare the default rates of student borrowers with high and low ratios of student debt to income *prior* to the plan's introduction. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, student loan default rates in year $t + 1$ reflect eligibility (or take-up) status in year t. Beginning in 2009—showing up as 2010 in the figure due to the one-year time lag—we furthermore distinguish between IBR eligible student borrrowers who took up the IBR repayment option (in black) and IBR eligible student borrowers who did not take up the IBR repayment option (in gray). Thus, prior to the introduction of the IBR plan, the gray bars pertain to IBR eligible student borrowers in general, while after the introduction of the IBR plan, they pertain to IBR eligible student borrowers who did not take up the IBR repayment option.

Figure 6 provides three main results. First, and most important, IBR eligible and ineligible student borrowers are on similar trends prior to 2009. Second, IBR eligible student borrowers who did *not* take up the IBR repayment option (gray) continue on this trend after 2009. Consequently, our results are not explained by IBR eligible student borrowers suddenly experiencing a positive shock in 2009, which happens to coincide with the introduction of the IBR program. Third, default rates of IBR eligible student borrowers who took up the IBR repayment option (black) are very low, suggesting that the IBR program has been successful at reducing student loan defaults for those student borrowers who enrolled in the program.

To provide further evidence that IBR eligible and ineligible student borrowers are on similar trends prior to the introduction of the IBR program, we estimate a variant of the specification in column (2) in which Home Price $\times$ IBR Eligible $\times$ Post is replaced with Home Price $\times$ IBR Eligible $\times$ t, where $t = 2007, ..., 2011$. The yearly coefficients $\beta_{6,t}$ indicate the extent to which the (higher) default sensitivity of IBR eligible student borrowers to home price changes is mitigated in a given year relative to the baseline year of 2006. The coefficients are plotted in Panel A of Figure 7 along with a 95 percent confidence interval. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, the coefficient associated with a given year t is plotted in the following year, $t + 1$.

There are three main results. First, IBR eligible and ineligible student borrowers are on similar trends before the introduction of the IBR program: the coefficients associated with 2007 and 2008 are statistically indistinguishable from the 2006 baseline coefficient. Second, when the IBR plan is introduced, there is a significant jump in the coefficient. Third, the coefficients continue to rise after 2009, suggesting that the impact of the IBR plan has gradually increased over time. To understand this pattern, Panel B of Figure 7 shows the take-up rate of the IBR plan, as a percentage of all student borrowers in repayment. As can be seen, the take-up rate is slow initially, but then gradually increases over time, consistent with the gradual pattern shown in Panel A of Figure 7.

5 Conclusion

Student loan default rates have been soaring since the onset of the Great Recession. A leading explanation is that the rise in student loan defaults is largely driven by compositional shifts toward "non-traditional" student borrowers attending community colleges and, especially, for-profit institutions. Our paper informs this debate by focusing on adverse labor market shocks. As prior research has shown, the collapse in home prices during the Great Recession triggered a sharp drop in consumer demand by households, leading to massive employment losses. Our estimates suggest that the collapse in home prices accounts for approximately 24 to 32 percent of the rise in student loan defaults, operating primarily through an aggregate labor market channel.

In the wake of the Great Recession, the federal government rolled out the Income Based Repayment (IBR) program to reduce student loan defaults and insure student borrowers against income shocks by making their loan repayments contingent on discretionary income. To assess the efficacy of the IBR program, we compare the default responses of IBR eligible versus ineligible student borrowers to home price changes before and after the program's introduction. We find that the IBR plan was successful at reducing both student loan defaults and their sensitivity to home price fluctuations, and that this result is driven by IBR eligible student borrowers who actually enrolled in the IBR program.

6 References

Amromin, Gene, Janice Eberly, and John Mondragon, 2016, The Housing Crisis and the Rise in Student Loans, mimeo, Northwestern University.

Autor, David, Lawrence Katz, and Melissa Kearney, 2008, Trends in U.S. Wage Inequality: Revising the Revisionists, Review of Economics and Statistics 90, 300–323.

Avery, Christopher, and Sarah Turner, 2012, Student Loans: Do College Students Borrow Too Much—or Not Enough? Journal of Economic Perspectives 26, 165–192.

Baker, Scott, 2016, Debt and the Consumption Response to Household Income Shocks, forthcoming, Journal of Political Economy.

Barr, Andrew, and Sarah Turner, 2013, Expanding Enrollments and Contracting State Budgets: The Effect of the Great Recession on Higher Education, Annals of the American Academy of Political and Social Science 650, 168-193.

Barr, Andrew, and Sarah Turner, 2015, Out of Work and into School: Labor Market Policies and College Enrollment during the Great Recession, Journal of Public Economics 124, 63–73.

Bhutta, Neil, and Benjamin Keys, 2016, Interest Rates and Equity Extraction During the Housing Boom, American Economic Review 106, 1742–1774.

Bound, John, Michael Lovenheim, and Sarah Turner, 2010, Why Have College Completion Rates Declined? An Analysis of Changing Student Preparation and Collegiate Resources, American Economic Journal: Applied Economics 2, 129–157.

Brown, Meta, Sarah Stein, and Basit Zafar, 2015, The Impact of Housing Markets on Consumer Debt: Credit Report Evidence from 1999 to 2012, Journal of Money, Credit and Banking 47, 175–213.

Cellini, Stephanie, and Claudia Goldin, 2014, Does Federal Student Aid Raise Tuition? New Evidence on For-Profit Colleges, American Economic Journal: Economic Policy 6, 174–206.

Chapman, Bruce, 2014, Income Contingent Loans: Background, in: Bruce Chapman, Timothy Higgins, and Joseph Stiglitz (eds.), Income Contingent Loans: Theory, Practice and Prospects. Basingstoke, UK: Palgrave Macmillan.

Charles, Kerwin, Erik Hurst, and Matthew Notowidigdo, 2016, Housing Booms and Busts, Labor Market Opportunities, and College Attendance, mimeo, University of Chicago.

Council of Economic Advisers (CEA), 2016, Investing in Higher Education: Benefits, Challenges, and the State of Student Debt. Damascus, MD: Penny Hill Press.

Davis, Steven, R. Jason Faberman, and John Haltiwanger, 2012, Labor Market Flows in the Cross Section and Over Time, Journal of Monetary Economics 59, 1–18.

Deming, David, Claudia Goldin, and Lawrence Katz, 2012, The For-Profit Post Secondary School Sector, Journal of Economic Perspectives 26, 139–164.

Earnest Operations LLC, 2016, Student Loans Are Changing the Job Hunt for Recent Grads.

Giroud, Xavier, and Holger Mueller, 2017, Firm Leverage, Consumer Demand, and Employment Losses during the Great Recession, Quarterly Journal of Economics 132, 271–316.

Goldin, Claudia, and Lawrence Katz, 2008, The Race between Education and Technology. Cambridge, MA: Harvard Universiy Press.

Ji, Yan, 2016, Job Search under Debt: Aggregate Implications of Student Loans, mimeo, MIT.

Kaplan, Greg, Kurt Mitman, and Giovanni Violante, 2016, Non-Durable Consumption and Housing Net Worth in the Great Recession: Evidence from Easily Accessible Data, NBER Working Paper No. 22232.

Katz, Lawrence, and Kevin Murphy, 1992, Changes in Relative Wages, 1963—1987: Supply and Demand Factors, Quarterly Journal of Economics 107, 35–78.

Keys, Benjamin, Tomasz Piskorski, Amit Seru, and Vincent Yao, 2014, Mortgage Rates, Household Balance Sheets, and the Real Economy, NBER Working Paper No. 20561.

Looney, Adam, and Constantine Yannelis, 2015, A Crisis in Student Loans? How Changes in the Characteristics of Borrowers and in the Institutions They Attended Contributed to Rising Loan Defaults, Brookings Papers on Economic Activity, Fall, 1–68.

Lovenheim, Michael, 2011, The Effect of Liquid Housing Wealth on College Enrollment, Journal of Labor Economics 29, 741–771.

Lovenheim, Michael, and C. Lockwood Reynolds, 2013, The Effect of Housing Wealth on College Choice: Evidence from the Housing Boom, Journal of Human Resources 48, 1–35.

Mian, Atif, and Amir Sufi, 2011, House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis, American Economic Review 101, 2132–2156.

Mian, Atif, and Amir Sufi, 2014, What Explains the 2007—2009 Drop in Employment? Econometrica 82, 2197–2223.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household Balance Sheets, Consumption, and the Economic Slump, Quarterly Journal of Economics 128, 1–40.

Poterba, James, 1984, Tax Subsidies to Owner-Occupied Housing: An Asset Market Approach, Quarterly Journal of Economics 99, 729–752.

Rosen, Harvey, 1979, Housing Decisions and the U.S. Income Tax: An Econometric Analysis, Journal of Public Economics 11, 1–23.

Society for Human Resource Management (SHRM), 2010, Background Checking: The Implications of Credit Background Checks on the Decision to Hire or Not to Hire.

Stroebel, Johannes, and Joseph Vavra, 2016, House Prices, Local Demand, and Retail Prices, mimeo, New York University.

Turner, Sarah, 2006, For-Profit Colleges in the Context of the Market for Higher Education, in: David Breneman, Brian Pusser, and Sarah Turner (eds.), Earnings from Learning: The Rise of For-Profit Universities. Albany, NY: State University of New York Press.

Figure 1
Time Series Evidence

This figure shows the relationship between home prices and student loan defaults based on aggregated U.S. time series data. The solid line depicts the Zillow Home Value Index, which is normalized to one in 1996. The dashed line depicts the two-year cohort default rate, defined by the last year in which the cohort has been in repayment for two years. A student loan goes into default if it is more than 270 days past due. When a loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Accordingly, there is approximately a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS. Cohort default rates are based on a four percent random sample of the NSLDS.

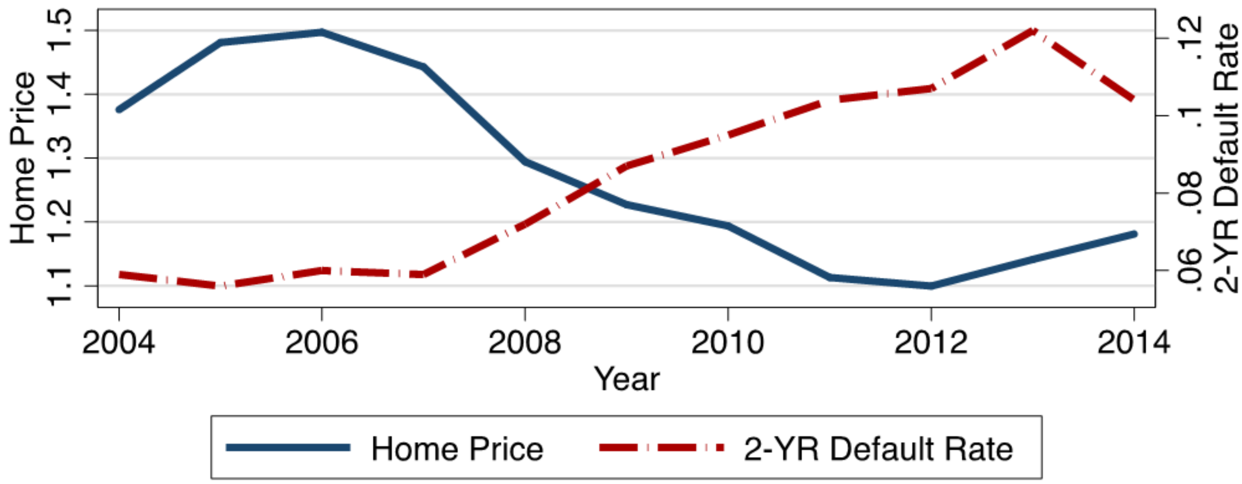
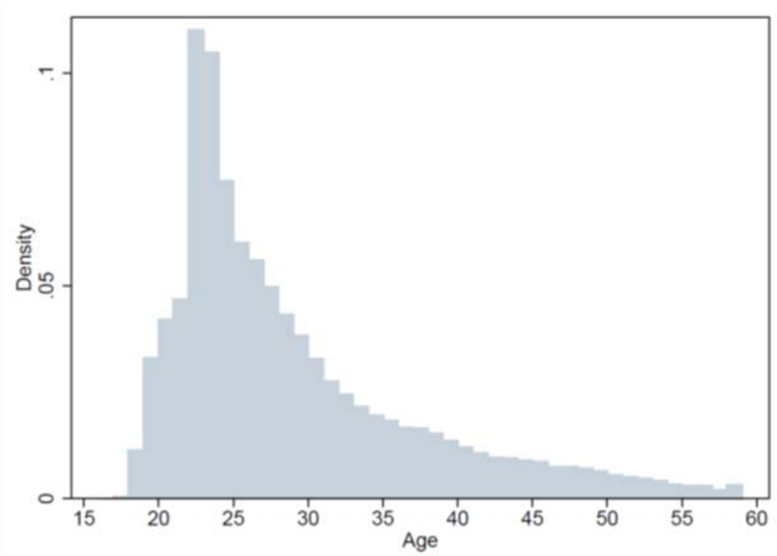


Figure 2
Age Distribution of Student Borrowers

Panel A shows the age distribution of student borrowers when they enter into repayment. Student borrowers typically enter into repayment within six months after leaving their degree granting institution. Panel B shows the age distribution of all student borrowers in repayment. The sample constitutes a four percent random sample of the NSLDS.

Panel A: Age of student borrowers when entering into repayment



Panel B: Age of student borrowers in repayment

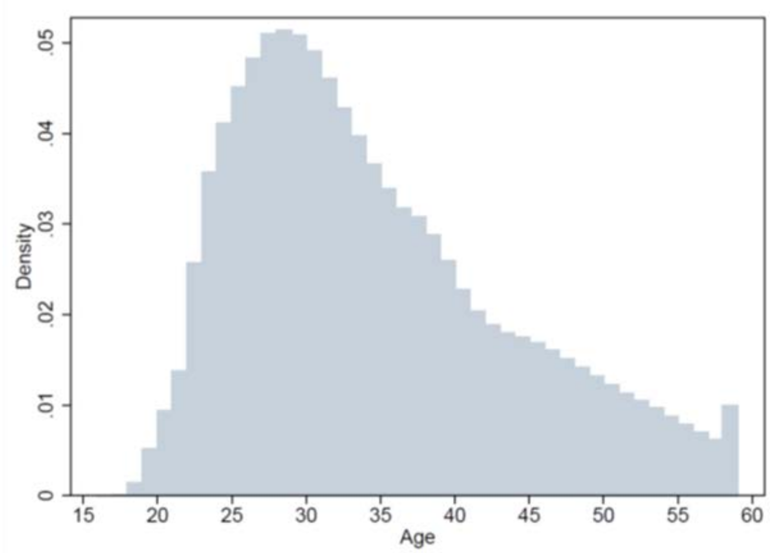
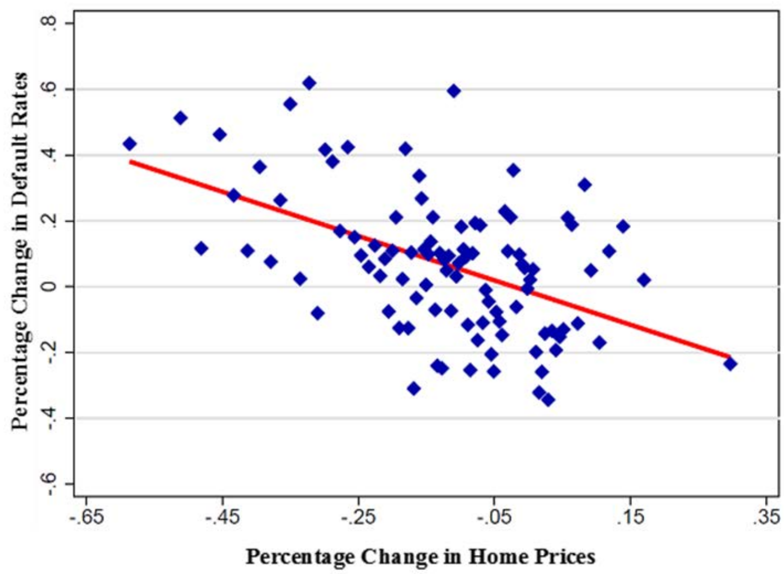


Figure 3
Cross Sectional Evidence

Panel A shows the relationship between the percentage change in student loan defaults at the Zip code level, Δ Log Default$_{07\text{-}10}$, and the percentage change in home prices at the Zip code level, Δ Log Home Price$_{06\text{-}09}$. Zip codes are weighted by total student loan balances. For each percentile of Δ Log Home Price$_{06\text{-}09}$, the plot shows the mean values of Δ Log Home Price$_{06\text{-}09}$ and Δ Log Default$_{07\text{-}10}$, respectively. Panel B shows the relationship between the percentage change in individual labor earnings at the Zip code level, Δ Log Earnings$_{06\text{-}09}$, and the percentage change in home prices at the Zip code level, Δ Log Home Price$_{06\text{-}09}$. Home price data are from Zillow. Default and earnings data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

Panel A: Changes in home prices and changes in student loan default rates



Panel B: Changes in home prices and changes in labor earnings

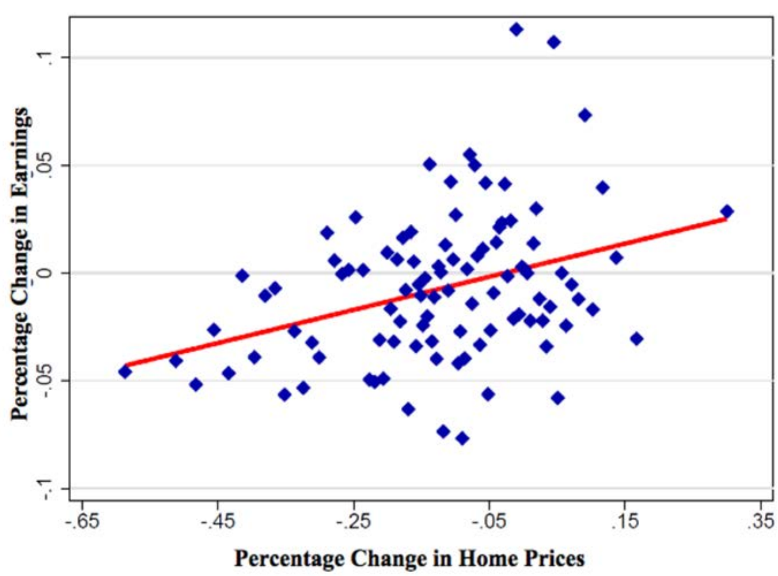


Figure 4
Labor Earnings and Student Loan Defaults

This figure shows the relationship between individual labor earnings, grouped into earnings deciles, and student loan defaults in the following year. A student loan goes into default if it is more than 270 days past due. When a loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Accordingly, there is approximately a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS. Earnings are Medicare wages plus self-employment earnings. Default and earnings data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

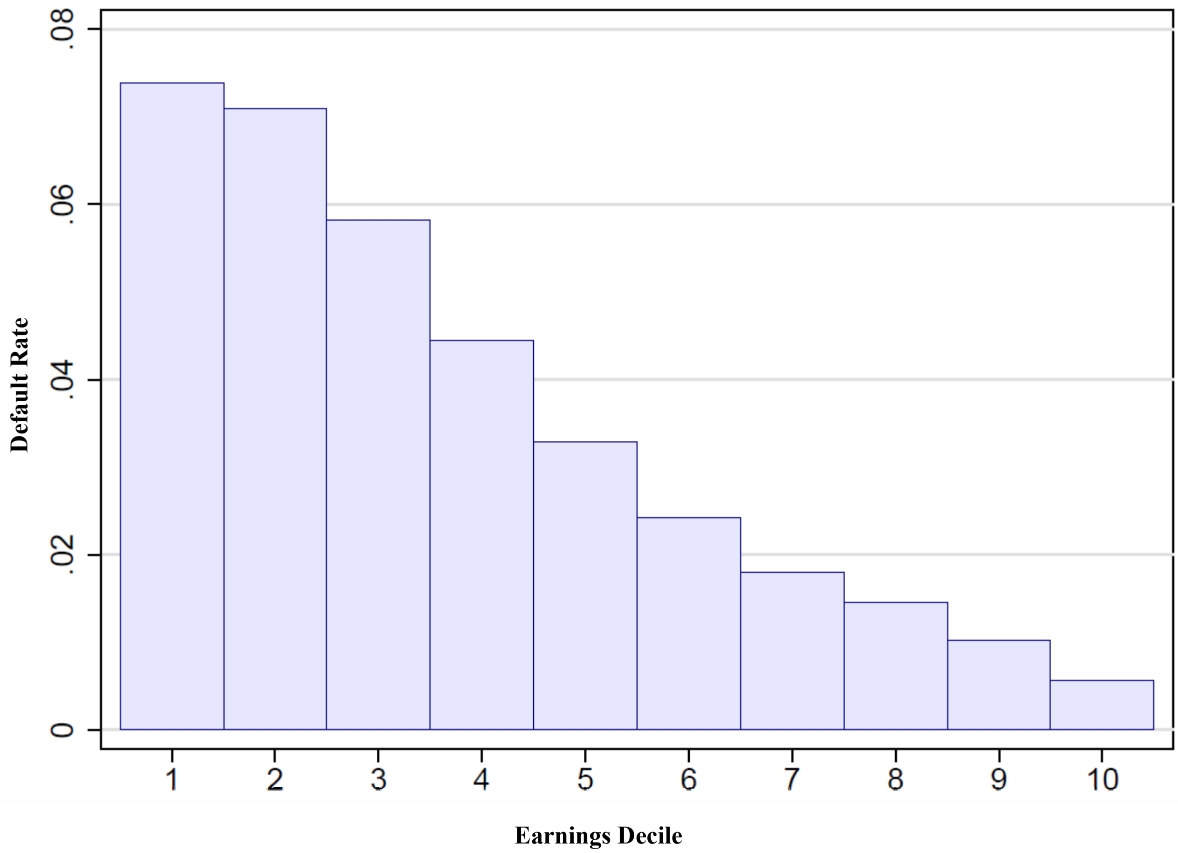


Figure 5
Employment Loss Event Study

This figure plots the coefficients β_j from equation (2) showing the differential student loan default rates of individuals who face an employment loss in year T relative to those who do not, both before and after the event. Employment loss is a drop in earnings of 50 percent or more relative to the previous year's earnings. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, the coefficient associated with a given year t is plotted in the following year, t+1. The specification includes earnings and school type controls as well as year, Zip code, and cohort year fixed effects. Standard errors are clustered at the Zip code level. The dashed lines represent a 95 percent confidence interval. Default and earnings data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

Figure 6
IBR Eligibility, Take-Up, and Student Loan Defaults

This figure shows student loan default rates of IBR eligible and ineligible student borrowers. The white bars show student loan default rates of IBR ineligible student borrowers. The gray bars show student loan default rates of IBR eligible student borrowers (before the introduction of the IBR plan) and IBR eligible student borrowers who did not take up the IBR repayment option (after the introduction of the IBR plan), respectively. The black bars show student loan default rates of IBR eligible student borrowers who took up the IBR repayment option. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, student loan default rates in year t+1 reflect eligibility (or take-up) status in year t. The IBR plan was introduced in 2009, meaning its impact on student loan defaults shows up for the first time in 2010. IBR eligibility in a given year is based on the means test and described in Section 4. Default and earnings data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

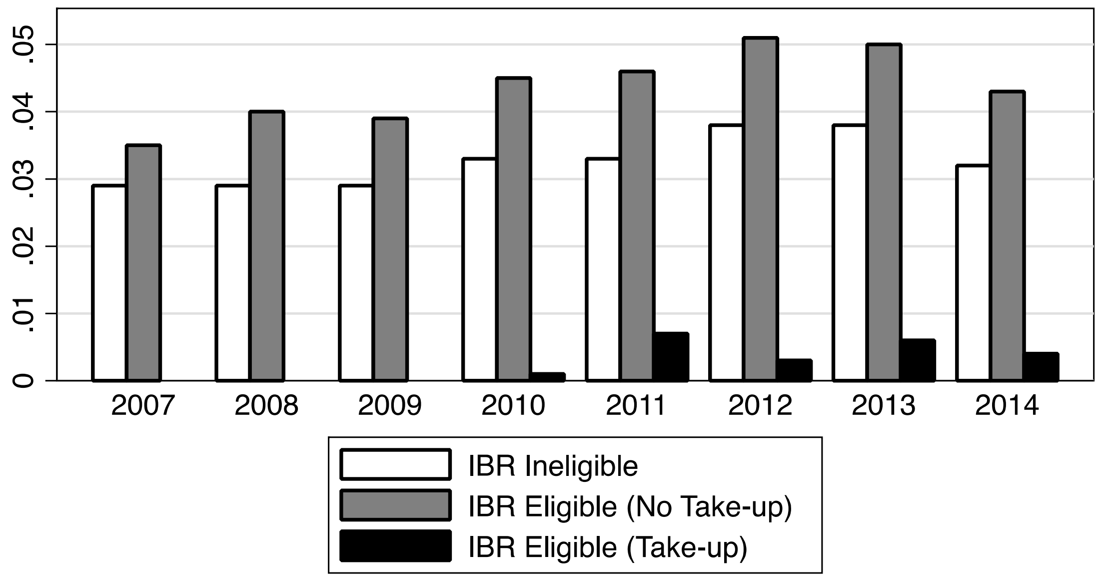
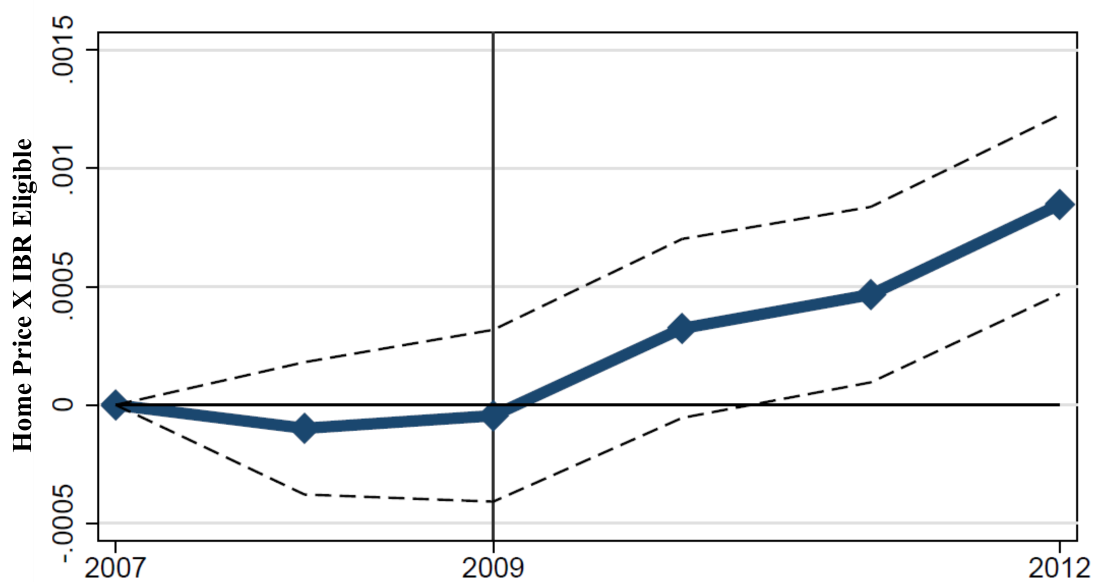


Figure 7
IBR Insurance Value and Take-Up Rate

Panel A plots the yearly coefficients $\beta_{6,t}$ from a variant of equation (3) in which Home Price × IBR Eligible × Post is replaced with Home Price × IBR Eligible × t, where t = 2007, ... ,2011. The yearly coefficients indicate the extent to which the default sensitivity of IBR eligible student borrowers to home price changes is mitigated in a given year relative to the baseline year of 2006. Given that there is a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS, the coefficient associated with a given year t is plotted in the following year, t+1. The IBR program was introduced in 2009, meaning its impact on student loan defaults shows up for the first time in 2010. IBR eligibility in a given year is based on the means test and described in Section 4. The specification includes year and Zip code fixed effects. Standard errors are clustered at the Zip code level. The dashed lines represent a 95 percent confidence interval. Panel B plots the take-up rate of the IBR program, as a percentage of all student borrowers in repayment. Home price data are from Zillow. Default and earnings data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

Panel A: IBR insurance value



Panel B: IBR take-up rate

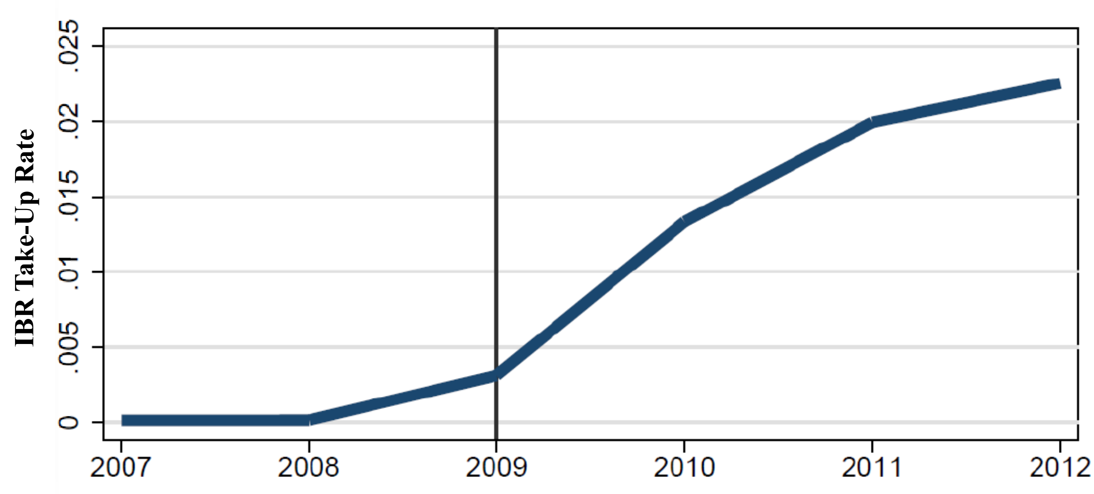


Table 1
Summary Statistics

This table shows basic summary statistics. Means and standard deviations are based on 1,071,048 annual observations at the individual borrower level. Observations are weighted by individual loan balances. Labor Earnings are Medicare wages plus self-employment earnings. Total Income additionally includes non-labor income. Employment loss is a drop in labor earnings of 50 percent or more relative to the previous year's earnings. Repayment Cohort is the year in which a student borrower enters into repayment. Default is an indicator of whether a student borrower defaults on her student loans for the first time. A student loan goes into default if it is more than 270 days past due. When a loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Accordingly, there is approximately a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS. Home prices are measured at the Zip code level. All variables are measured over the 2006 to 2009 period, except default, which is measured over the 2007 to 2010 period. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data.

	Mean	SD
Loan Balance	23,757	31,520
Labor Earnings	44,930	54,254
Family Income	42,675	54,394
Total Income	62,369	98,345
Employment Loss	0.08	0.27
Repayment Cohort	2002	6
Default	0.04	0.19
Home Owner	0.39	0.49
Home Prices	244,882	171,694

Table 2
Cross Sectional Evidence

In columns (1) and (2), the dependent variable is the change in the student loan default rate at the Zip code level from 2007 to 2010, Δ Default$_{07\text{-}10}$. In column (3), the dependent variable is the percentage change in the student loan default rate at the Zip code level from 2007 to 2010, Δ Log Default$_{07\text{-}10}$. A student loan goes into default if it is more than 270 days past due. When a loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Accordingly, there is approximately a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS. Δ Log Home Price$_{06\text{-}09}$ is the percentage change in home prices at the Zip code level from 2006 to 2009. Changes in home prices are measured from December to December, except in column (2), where they are measured from July 2006 to March 2009. Zip codes are weighted by total loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Default$_{07\text{-}10}$		Δ Log Default$_{07\text{-}10}$
	Main (1)	Peak to Trough (2)	(3)
Δ Log Home Price$_{06\text{-}09}$	-0.0090***	-0.0110***	-0.4179***
	(0.00420)	(0.00510)	(0.11669)
Observations	12,749	12,749	12,749

Table 3
Main Results

The dependent variable is an indicator of whether an individual student borrower defaults in year t+1, $Default_{t+1}$. A student loan goes into default if it is more than 270 days past due. When a loan goes into default, the loan servicer has up to 90 days to report the default to the NSLDS. Accordingly, there is approximately a one-year time lag between when a payment is missed and when a default is recorded in the NSLDS. Home $Price_t$ is the home price (in logs) in year *t* at the Zip code level. Columns (1) to (3) include Zip code fixed effects, column (4) includes Zip code and cohort year fixed effects, column (5) includes Zip code × cohort year fixed effects, and column (6) includes individual borrower fixed effects. All columns include year fixed effects. Column (3) additionally includes loan balance, borrowing duration, family income, school type, and Pell grant aid as controls. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level, except in column (2), where they are clustered at the county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$					
	Main	County Cluster	Controls	Cohort Year FE	Zip Code x Cohort Year FE	Individual FE
	(1)	(2)	(3)	(4)	(5)	(6)
Home $Price_t$	-0.0113***	-0.0113***	-0.0114***	-0.0105***	-0.0114***	-0.0107***
	(0.00280)	(0.00287)	(0.00280)	(0.00281)	(0.00309)	(0.00352)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Unit Fixed Effects	Zip Code	Zip Code	Zip Code	Zip Code, Cohort Year	Zip Code x Cohort Year	Individual
Observations	1,071,049	1,071,049	1,071,049	1,071,049	1,071,049	1,071,049

Table 4
Main Results by Individual Loan Balances

This table presents variants of the specification in column (1) of Table 3 in which the sample is divided into subsamples based on percentiles of individual loan balances. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$				
	Full (1)	≤ 25th Pctl (2)	25th-75th Pctl (3)	75th-90th Pctl (4)	≥ 90th Pctl (5)
$Home\ Price_t$	-0.0113***	-0.00426	-0.00516*	-0.0112**	-0.0168***
	(0.00280)	(0.00531)	(0.00273)	(0.00473)	(0.00570)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,071,049	252,340	520,524	170,928	127,257

Table 5
Main Results by Individual Labor Earnings

This table presents variants of the specification in column (1) of Table 3 in which the sample is divided into subsamples based on individual labor earnings. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$				
	Full	≤ $20,000	$20-$40,000	$40-$60,000	≥ $60,000
	(1)	(2)	(3)	(4)	(5)
Home $Price_t$	-0.0113***	-0.0176**	-0.0129**	-0.0113**	-0.00498
	(0.00280)	(0.00687)	(0.00536)	(0.00538)	(0.00396)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,071,049	353,771	341,299	197,294	178,685

Table 6
Home Prices and Employment Losses

This table presents variants of the specifications in Table 5 in which the dependent variable is Employment $Loss_t$. Employment loss is a drop in individual labor earnings of 50 percent or more relative to the previous year's earnings. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Employment $Loss_t$				
	Full (1)	≤ $20,000 (2)	$20-$40,000 (3)	$40-$60,000 (4)	≥ $60,000 (5)
Home $Price_t$	-0.00690**	-0.0135**	-0.0108**	0.00682	-0.000485
	(0.00289)	(0.00662)	(0.00466)	(0.00423)	(0.00397)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,071,049	353,771	341,299	197,294	178,685

Table 7
Employment Losses and Student Loan Defaults

This table presents variants of the specifications in Table 5 in which the main independent variable is Employment $Loss_t$. Employment loss is a drop in individual labor earnings of 50 percent or more relative to the previous year's earnings. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$				
	Full	≤ $20,000	$20-$40,000	$40-$60,000	≥ $60,000
	(1)	(2)	(3)	(4)	(5)
Employment $Loss_t$	0.0123***	0.00884***	0.00559***	0.00357	0.00337
	(0.00124)	(0.00178)	(0.00202)	(0.00341)	(0.00465)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,094,737	361,747	348,840	201,540	182,610

Table 8
Direct Liquidity Channel

This table presents variants of the specifications in Table 3 in which $Owner_t$ and $Home\ Price_t \times Owner_t$ are included as regressors. Owner is an indicator of whether an individual took the mortgage interest deduction in a given year. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level, except in column (2), where they are clustered at the county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$					
	Main	County Cluster	Controls	Cohort Year FE	Zip Code x Cohort Year FE	Individual FE
	(1)	(2)	(3)	(4)	(5)	(6)
$Home\ Price_t$	-0.0112***	-0.0112***	-0.0113***	-0.0105***	-0.0109***	-0.0107***
	(0.00285)	(0.00297)	(0.00285)	(0.00286)	(0.00318)	(0.00354)
$Home\ Price_t \times Owner_t$	0.000972	0.000972	0.00101	0.000832	-0.000479	0.0000859
	(0.000882)	(0.000896)	(0.000885)	(0.000881)	(0.00120)	(0.000140)
$Owner_t$	-0.0439***	-0.0439***	-0.0431***	-0.0390***	-0.0225	-
	(0.0108)	(0.0110)	(0.0109)	(0.0108)	(0.0148)	-
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Unit Fixed Effects	Zip Code	Zip Code	Zip Code	Zip Code, Cohort Year	Zip Code x Cohort Year	Individual
Observations	1,062,914	1,062,914	1,062,914	1,062,914	1,062,914	1,062,914

Table 9
Home Ownership, Labor Earnings, and Total Income

This table presents variants of the specification in column (1) of Table 8 in which $Earnings_t$ and $Home\ Price_t \times Earnings_t$ (column (1)) or $Income_t$ and $Home\ Price_t \times Income_t$ (column (2)) are included as regressors. (Labor) Earnings are Medicare wages plus self-employment earnings. (Total) Income additionally includes non-labor income. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	$Default_{t+1}$	
	Labor Earnings	Total Income
	(1)	(2)
$Home\ Price_t$	-0.0109***	-0.0111***
	(0.00285)	(0.00285)
$Home\ Price_t \times Owner_t$	-0.00104	-0.0000870
	(0.000902)	(0.000915)
$Owner_t$	-0.0279***	-0.0345***
	(0.0108)	(0.0109)
$Home\ Price_t \times Earnings_t$	0.000211***	
	(0.0000181)	
$Earnings_t$	-0.00325***	
	(0.000219)	
$Home\ Price_t \times Income_t$		0.0000889***
		(0.0000171)
$Income_t$		-0.00142***
		(0.000202)
Year Fixed Effects	Yes	Yes
Zip Code Fixed Effects	Yes	Yes
Observations	1,062,914	1,062,914

Table 10
Home Ownership Results by Repayment Cohort

This table presents variants of the specification in column (1) of Table 8 in which the sample is divided into subsamples based on repayment cohorts. Repayment Cohort is the year in which a student borrower enters into repayment. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Default_{t+1}		
	< 2000 (4)	2000-2005 (5)	> 2005 (6)
Home Price_t	-0.0142**	-0.00898**	-0.0107**
	(0.00606)	(0.00397)	(0.00449)
$\text{Home Price}_t \times \text{Owner}_t$	-0.00167	0.000619	0.000887
	(0.00208)	(0.00118)	(0.00149)
Owner_t	0.00370	-0.0350**	-0.0513***
	(0.0257)	(0.0144)	(0.0182)
Year Fixed Effects	Yes	Yes	Yes
Zip Code Fixed Effects	Yes	Yes	Yes
Observations	283,557	470,889	423,021

Table 11
Income Based Repayment Pogram

This table presents variants of the specification in column (1) of Table 3 in which the sample is extended to include student loan defaults up until 2012, and in which IBR Eligible_t, Home Price_t × Post, IBR Eligible_t × Post, Home Price_t × IBR Eligible_t, and Home Price_t × IBR Eligible_t × Post are included as regressors. IBR Eligible_t is a dummy indicating whether an individual student borrower passes the means test in a given year. The means test is described in Section 4. Post is a dummy that equals one beginning in 2009. In column (3), the sample is restricted to student borrowers with relatively high ratios of student debt to income. Columns (1) to (3) include Zip code fixed effects. Column (4) includes individual borrower fixed effects. All columns include year fixed effects. Observations are weighted by individual loan balances. Home price data are from Zillow. All other data are from a four percent random sample of the NSLDS matched to de-identified IRS tax data. Standard errors (in parentheses) are clustered at the Zip code level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Default_{t+1}			
	Full (1)	Full (2)	Restricted (3)	Full (4)
Home Price_t	-0.00419**	-0.00338	-0.00439	-0.00441*
	(0.00209)	(0.00209)	(0.00326)	(0.00231)
IBR Eligible_t	0.0256***	0.0425**	0.0510**	0.0274
	(0.000531)	(0.0183)	(0.0235)	(0.0229)
Home Price_t × Post		-0.000366	-0.00168	-0.000967
		(0.000816)	(0.00138)	(0.000928)
IBR Eligible_t × Post		-0.0404*	-0.0594**	-0.0707***
		(0.0215)	(0.0269)	(0.0258)
Home Price_t × IBR Eligible_t		-0.00259*	-0.00345*	-0.00157
		(0.00146)	(0.00188)	(0.00184)
Home Price_t × IBR Eligible_t × Post		0.00314*	0.00467**	0.00513**
		(0.00173)	(0.00217)	(0.00209)
Year Fixed Effects	Yes	Yes	Yes	Yes
Unit Fixed Effects	Zip Code	Zip Code	Zip Code	Individual
Observations	1,556,296	1,556,296	658,504	1,556,296