Which Debts Get Paid Last?*

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Abstract

This paper exploits the scheduled expiration dates of property tax breaks to study how homeowners' credit consumption and debt payment behavior respond to anticipated expense shocks. When tax breaks end, credit card balance, home equity credit line balance, new debt inquiries, and mortgage balance do not change, implying that credit consumption is smooth. However, homeowners become persistently delinquent on their student loan payments, which suggests that the marginal utility of consumption and from staying current on other debt (e.g., mortgage, auto, and credit card) is larger than the disutility from becoming delinquent on student loan payments. When budget constraints bind, student loans lie at the bottom of the debt repayment preference ranking. The results also show that expense shocks matter for student loan repayment, even for homeowners.

Keywords: Property tax abatement, debt repayment

JEL Classification: E2, G4, G5, R2

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1 Introduction

An important question in the household finance literature is – how do people repay debt? Optimal debt repayment minimizes the cost of debt. For example, across different credit card accounts, borrowers should pay off the highest-interest account first, proceed to the next high-interest account, and so on. Existing research shows that, within debt types (e.g., credit card debt), borrowers do not follow an optimal repayment rule because they suffer from behavioral biases such as inattention and mental accounting (Ponce et al., 2017).

This paper brings new perspectives to the literature by using a natural experiment to study how borrowers prioritize payments across different types of consumer debt accounts (e.g., student loans, credit card debt, auto loans, and mortgages). Philadelphia's property tax abatement program gives newly constructed or heavily renovated properties 10 years of property tax discount where the owner does not pay tax on the improvement portion of the assessment. When the abatement expires, the owner pays tax on the property's total assessed value. Using a homeowner-level panel data set, where we observe the homeowner's property tax expense and credit panel, in a stacked event study regression approach, we exploit the abatement expiration date as a plausibly exogenous anticipated expense shock to study how treated homeowners' credit consumption and debt repayment behavior changes in response to the shock compared to that of yet-to-be-treated homeowners.

We have two main findings. First, treated homeowners' credit consumption does not change. Specifically, we find null effects on credit card balance, auto loan balance, home equity line of credit (HELOC) balance, new credit inquiries, and mortgage balance, suggesting that credit consumption is smooth when homeowners face anticipated expense shocks. Second, treated homeowners' student loan balances increased because treated homeowners are more likely to become persistently delinquent on their student loan payments. We provide suggestive evidence that liquidity constraint is an important driver of the delinquency result.

Taken together, the two results yield several important insights about people's consumption and saving decisions. First, we confirm findings from previous works that consumers tend to smooth consumption when faced with anticipated expense shocks (Coulibaly and Li, 2006; Scholnick, 2013; Baugh et al., 2021) and add to this line of work by showing that the smoothing is made possible by *not* repaying student loans. It also follows that the marginal utility of consumption is larger than the marginal disutility of becoming delinquent on student debt, which implies that adjustments to student payments serve as one of the frontline shock-absorbing mechanisms. Second, our findings reveal that there is a

preference ranking to debt repayment where student loans are the least important. In contrast to many existing works in the debt repayment literature, this ranking is potentially optimal with respect to cost minimization. Relative to other uncollateralized debt (e.g., credit card debt), student loans tend to have lower interest rates, and, relative to collateralized debt (e.g., auto loan and mortgages), student loans plausibly have lower total cost of default because there is no potential loss of durable assets that carry large income-generating and consumption values (e.g., cars and homes).

This paper is also the first to provide empirical evidence supporting expense shocks as a contributor to student debt delinquency, which have the highest rates of transition to serious delinquency of any consumer debt (Federal Reserve Bank of New York, 2025). The primary explanations for these high student debt default rates have been low lifetime income, due to dropout or attending low-return colleges, and income shocks, due to job loss during recessions. While student loan repayment policies offer flexibility to insure against income shocks, they do not offer similar insurance against expense shocks, such as higher tax bills. Therefore, our results further stress the role of expense shocks in consumer debt repayment, as highlighted by Fulford and Low (2024).

Lastly, the delinquency result provides a potential explanation for the recent observation that more individuals carry high balances of student debt into old age (Li and Goodman, 2015; Butrica and Mudrazija, 2020; Chen et al., 2023), which is worrying because student debt is supposed to be paid off when income peaks in middle age. Through the lens of this paper, the high student debt balances are scars from negative net income, gross income minus expenses, shocks because individuals smooth consumption by not paying down student debt, either by becoming delinquent or switching to a less burdensome payment plan.

2 Literature Review and Contribution

It is well-known that borrowers' debt repayment behavior is suboptimal when compared to the rational benchmark, which predicts that consumers should prioritize paying off the costliest debt first. An example is debt that carries the highest interest rate. Using observational data from the United Kingdom, Gathergood et al. (2019) find that borrowers use a balance-matching heuristic to pay credit card debt. Using observational data from Mexico, Ponce et al. (2017) find that, due to limited attention (Amornsiripanitch et al., 2025) and mental accounting (Thaler, 1999), borrowers do not pay credit card debt optimally. Suboptimal debt repayment behavior also appears in experimental settings (Gärtner et al., 2023; Guttman-Kenney, 2025) and other types of debt, account overdrafts (Gathergood and Olafsson,

2024), mortgages (Liebersohn et al., 2024), student loans (Katz, 2023), and payday loans (Carter et al., 2022).

Unlike previous works that focus on a single type of debt, we contribute to the literature by using Philadelphia's property tax abatement expiration dates as a natural experiment to learn about homeowners' ranking of debt repayment across different types of debt (e.g., student loan, credit card debt, auto loan, and mortgage). We find that homeowners, when faced with an anticipated expense shock that makes budget constraints bind, choose to repay student loans last. This finding reveals that there is a ranking of debt repayment where student loans lie at the bottom, which implies that these homeowners view student loans as the least costly to default on. This revealed preference ranking of debt repayment is potentially optimal with respect to cost minimization as student loans tend to carry lower interest rates than other uncollateralized debt (e.g., credit card debt) and carry lower total default cost than collateralized debt (e.g., auto loans and mortgages).

This paper contributes to the literature on student debt repayment by considering expense shocks as an understudied mechanism of delinquency. The primary explanation for why people default on student debt revolves around borrower earnings. Rising student debt default rates can be attributed to the increasing composition of borrowers at for-profit and two-year colleges, who are more likely to be unemployed and earn less (Deming et al., 2012; Looney and Yannelis, 2015). This composition channel is exacerbated by changes to policies that increase availability of credit to such low-return colleges (Looney and Yannelis, 2022). Furthermore, reduced opportunities in the labor market during the Great Recession led to an increase in student debt default (Mueller and Yannelis, 2019; Pinto and Steinbaum, 2023).

Our research finds that expense shocks, such as higher property taxes, are also a determinant of student debt delinquency. Beyond identifying additional mechanisms of student debt delinquency, our findings also have implications regarding who defaults on consumer debt. Earnings shocks as a determinant of delinquency focuses on students who do not complete college or attend low-return institutions (e.g. for-profit or community colleges). In contrast, expense shocks can impact a larger set of borrowers, as expense shocks are twice as prevalent as income shocks (Fulford and Low, 2024). Although property tax changes are small relative to the lost income associated with unemployment, our results show that even small expense shocks have meaningful impacts on student debt repayment.

This paper also contributes to the literature on consumption smoothing (Ando and Modigliani, 1963; Friedman, 1957) by confirming that households smooth consumption when faced with anticipated expense shocks (Scholnick, 2013) and providing evidence that the smoothing is done by adjusting their

savings behavior. Coulibaly and Li (2006) exploit the mortgage maturity date as an exogenous but anticipated positive income shock to study whether and how homeowners smooth consumption. They find that homeowners who pay off their mortgage debt indeed smooth consumption by increasing financial savings and savings into durable goods. Since consumption and savings behavior can be asymmetric with respect to the sign of the shock (Baugh et al., 2021), our work studies homeowners' response to an anticipated expense shock and find that homeowners smooth credit consumption by dissaving through not making student loan payments.

There are two related papers that warrant some discussion. This paper builds on Coste (2024), which shows that Philadelphia's property tax abatements are fully capitalized into house prices. Together with the existing work, our results help provide a fuller picture of how the property tax abatement policy affected Philadelphians' financial well-being. Wong (2024) studies the impact that changes in property tax burden have on homeowners' credit outcomes. Using a high-frequency event study approach, he finds that increases in property tax bill increase the likelihood that homeowners become financially distressed. His results can be interpreted as studying the impact of unexpected changes in property tax burden because year-to-year changes in a homeowner's property tax bill are caused by the combination of changes in the home's assessed value and changes in the local property tax rate. Other than assessed value appeals, both components are outside of the homeowner's control and plausibly unexpected. Our paper complements this work by studying the impact of a scheduled increase in property tax from abatement expiration, which is not a trivial exercise because, as we have learned from the consumption smoothing literature, consumers react differently to expected and unexpected expense shocks.

3 Institutional Details

Philadelphia enacted its tax abatement program in 2000 to improve the city's attractiveness to prospective developers and residents after "decades of disinvestment, population loss, stagnant home ownership rates and increased poverty" (Rhynhart, 2018). The program excluded the value of newly constructed or majorly renovated residential, commercial, and industrial properties from property tax assessments for the first decade of the property's life, such that property owners were required only to pay taxes on the value of the underlying land until the abatement expires. Any existing abatement on a property would be automatically transferred to the new owner in the event of a sale (Coste, 2024). The program was phased out for new applicants in January 2022 (Kelsen et al., 2021).

As of 2017, 60 percent of properties receiving abatements through the program were new builds

with the remaining 40 percent granted to improvements or conversions of existing buildings (Rhynhart, 2018). Additionally, the vast majority (96 percent) of abatements were granted for residential use, with 49 percent granted to single-family homes, 38 percent to condominiums, and 10 percent to apartment buildings (Rhynhart, 2018).

4 Data

4.1 Data Sources

The first data set that we use is the Credit Risk Insight Servicing McDash (CRISM) database, which contains Equifax credit bureau data on individual consumers' credit histories matched to mortgage-level servicing data from McDash. The CRISM database contains consumer information (e.g., year of birth, zip code, etc.), credit information (e.g., total balances, number of trade lines, Risk Score, credit inquiries within the past 12 months, etc.), and mortgage information (e.g., mortgage date, mortgage amount, mortgage balance, etc.) for individuals going back to 2005. The CRISM data set is a consumer-month panel data set.

We also use two of CoreLogic's Real Estate databases, Owner Transfer-Mortgage Basic and Historical Property Basic, both of which contain property-level public records data for residential and commercial properties within the United States. We rely on the CoreLogic Owner Transfer-Mortgage Basic dataset for mortgage information (e.g., mortgage type, mortgage amount, etc.). We use the Corelogic Historical Property Basic dataset for property tax information (e.g., assessed value, annual tax amount, etc.) and building information (e.g., year built). The year built variable allows us to determine the property's participation in the Philadelphia property tax abatement program as well as the year of tax abatement expiration.

4.2 Sample Construction

We first link properties from the CoreLogic Owner Transfer-Mortgage Basic dataset to those in CoreLogic Historical Property Basic using unique property identifiers (CLIP). Then we link the property information in the merged CoreLogic dataset to individuals in the CRISM dataset using mortgage date, mortgage amount, and zip code. We collapse CRISM's monthly credit panel information to annual averages to match the annual property tax data from CoreLogic. We then restrict the sample to consumer-year

panels with purchase fixed-rate mortgages for owner-occupied homes built between 2000 and 2021 in Philadelphia County, Pennsylvania.

We identify the treatment year (i.e., year of tax abatement expiration) for every panel in our sample as being ten years after the mortgaged home was built. Homeowners who experience the tax abatement expiration in year t belong to the treatment group and homeowners who will experience the expiration in later years, but not in the event window (the not-yet-treated), belong to the control group. Our six-year event window extends from two years before the tax expiration year, $t-3$, to three years after the tax expiration year, $t+2$. Therefore, control panels for cohort t must experience their tax expiration in years $t+3$ or later. For a panel to be included in the treated sample of a given cohort year, it must have at least one observation year of data before the tax abatement expiration (pre-treatment period) and at least one observation year of data after the tax abatement expiration (post-treatment period). Since the 10-year tax abatement policy began for buildings constructed after the year 2000, our first cohort of "treated" individuals experienced their tax abatement expiration in 2011 and our final cohort experienced theirs in 2017.[1] We stack these cohorts of treated and control panels such that year t in cohort t corresponds to year zero in the event-study timeline. Finally, for our analysis on student loan outcomes, we restrict our sample to only homeowners that have a positive student loan balance in the pre-treatment period.[2]

Table 1 presents summary statistics of key variables used in the regressions discussed below for the full sample (Panel A) and the student loan sample (Panel B). The table also shows mean differences between the treatment and control groups at time $t-1$. Treatment groups tend to have lower debt balances of all types, likely because they are older and have longer tenures in their properties. Treated groups have lower credit scores and lower imputed income (PIM) suggesting higher credit risk. However, among the sample with student debt (Panel B), treated and control groups seem to face similar levels of liquidity constraints as the differences in their debt-to-income ratios and scheduled student debt payments are economically and statistically small. Our regression analysis accounts for notable differences in age, credit score, and income by including these variables as controls and any differences in time-invariant characteristics by including household fixed effects.

[1] We intentionally cut the sample such that we exclude the COVID-19 pandemic from our analysis so that our ATT estimates are not contaminated by economic forces related to the pandemic and the policy responses.

[2] Appendix Table A1 presents the number of control and treatment group observations in each event cohort.

5 Methodology

Since the property tax abatement expiration shocks occur in a staggered nature, we use the stacked event study regression approach (Cengiz et al., 2019; Baker et al., 2022; Bradt and Aldy, 2025) to estimate the average treatment effect on the treated (ATT) of the property tax abatement expiration shock. Specifically, we estimate variants of the following ordinary least squares (OLS) regression equation:

$$y_{it} = \alpha + \beta(Treated_i \times Post_t) + \gamma' \mathbf{x}_{it} + \delta_{ci} + \zeta_{ct} + \epsilon_{it}. \tag{1}$$

Homeowners are indexed by i, years are indexed by t, and cohorts are indexed by c. The regression sample is constructed such that each event is a property tax abatement expiration that occurs in year t. The event window covers years $t-3$ through $t+2$. $Treated$ equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. $Post$ equals one for years t to $t+2$. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort.

$\mathbf{x}_{it}$ is a vector of homeowner by year control variables, which include log Risk Score, log estimated income (PIM), age, and age squared.[3] Risk Score is an Equifax-generated measure that indicates the likelihood of a consumer becoming seriously delinquent (90+ days past due). The scores range from 280 (highest risk) to 850 (lowest risk). The annual average Risk Score value is used. PIM is the estimated annual personal income in thousands of dollars. The estimate is Equifax-generated and is based on credit file attributes and behavior. The annual average PIM value is used. We include cohort by homeowner fixed effects δ_{ci} to account for the fact that a single homeowner may appear in multiple cohorts. For example, a homeowner may appear in the control group in one cohort and in the treatment group in another cohort. Likewise, we include cohort by year fixed effects ζ_{ct} to account for the fact that a single calendar year appears in multiple cohorts.[4]

In this setup, if the parallel trend assumption holds, then β gives the ATT of the abatement shock on y. To verify that the parallel trend assumption holds for each of our main result, we estimate variants of the following stacked event study OLS regression equation:

[3] Age is highly correlated with credit access Amornsiripanitch (2023) and financial sophistication (Amornsiripanitch et al., 2026).

[4] The year fixed effects also absorb Philadelphia's time-varying property tax rate. Importantly, each property in Philadelphia County pays the same property tax rate. See `https://www.phila.gov/media/20250422110017/Philadelphia-Historic-Tax-Rate-April-2025.pdf`. Therefore, there is no need to include finer geographical fixed effects to absorb finer variation in property tax rates across smaller "tax jurisdictions" (Amornsiripanitch, 2020).

$$y_{it} = \alpha + \sum_{t=-3}^{2} \beta_t (Treated_i \times D_t) + \gamma' \mathbf{x}_{it} + \delta_{ci} + \zeta_{ct} + \epsilon_{it}. \quad (2)$$

D_t is the indicator variable for year t within the event window. We plot the set of β_t coefficients to check for pre-treatment trends.

6 Results

6.1 Abatement Expiration Shock

We begin our empirical analysis by first checking the size of the property tax abatement shock and that it is plausibly exogenous. Columns 1 and 2 of Table 2 present the ATT estimates of the abatement expiration shock. We use the full sample (Panel A of Table 1) to produce these results. We find that the treated property's net taxable amount increased by \$46,695, which is more than a 100% increase relative to the treatment group's pre-treatment sample mean (\$46,646), and the annual property tax amount increased by \$252, which is greater than a 16% increase relative to the treatment group's pre-treatment sample mean (\$1,576).[5]

To verify that the shock is plausibly exogenous, i.e., free of pre-treatment trends that would invalidate the main identifying assumption, we estimate variants of equation 2 and plot the time trend estimates in figures 1 and 2. Both figures show no visible pre-treatment trend as the pre-treatment point estimates are all very close to zero. The figures also show that the economic magnitudes of these abatement expiration shocks are much larger than what the single difference-in-differences (DiD) point estimate suggests. For example, Figure 2 shows that the average increase in property tax amount reaches approximately \$500 by year $t+1$, which is twice as large as the point estimate presented in column 2 of Table 2. Therefore, the nature of the shock that we study is dynamic in nature; that is, its magnitude grows over time.

[5] The property tax amount does not increase by the same percentage amount as the net taxable value plausibly because of Philadelphia's homestead exemption program. Exemption take up cannot be cleanly observed in the CoreLogic data and so we cannot accurately verify this claim. However, the difference in magnitude appears to be roughly correct. See `https://www.phila.gov/services/payments-assistance-taxes/taxes/property-and-real-estate-taxes/get-real-estate-tax-relief/get-the-homestead-exemption/`.

6.2 Credit Consumption

The remaining columns (3 through 8) of Table 2 present the ATT that the abatement expiration has on credit consumption. Our measures of credit consumption are: credit card balance, auto loan balance, HELOC balance, other debt balance, mortgage balance, and number of credit inquiries over the past 12 months.[6] Since the CRISM data set is a consumer-month panel data set, we compute these variables as annual averages. The regression results can be summarized as statistically null result with little economic significance. The estimated ATTs are approximately equal to or less than 1% of the respective treated group's pre-treatment sample means.[7]

A weakness of the CRISM data set is that, when debt balances change, we cannot be sure that the change is caused by changes in repayment activity or by consumption activity. Specifically, suppose that we observe that credit card debt balance increased from time t to time $t+1$. We cannot conclude that the increase is caused by the consumer increasing consumption of credit card debt or by the consumer's failure to pay the full balance amount and, therefore, interest and fees accrued. Therefore, the null result that we document in Table 2 may not be good evidence for consumption smoothing; that is, credit card debt balance may have stayed flat because consumption fell, repayment fell, but interest and fees rose. Thankfully, using the same regression specification, we also find null results for financial distressed, as measured by overall short-term and long-term delinquencies (see Appendix Table A3). Therefore, we are reassured that the null results that we document in Table 2 can be interpreted as evidence for credit consumption smoothing.

6.3 Student Loans

In this section, we turn our attention to student loans. We separate out the student loan analysis from the credit consumption analysis because, unlike the other types of debt that we considered in the previous section, student loan is used to make investment in long-term human capital and does not reflect consumption via credit usage. In people's life cycle, they take out student debt early on so that they can gain long-term human capital and then pay off this debt over time. This debt balance dynamic is very distinct from other "consumption debt" (e.g., credit card debt and auto loan).

[6] Mortgage balance includes cash-out refinance, which can be considered as a measure of consumption. We use dollar amount outcome variables instead of the natural log of dollar amounts because balances can be equal to zero and we do not want to introduce the econometrics problem of using log(1+Y) as the outcome variable (Chen and Roth, 2024). Other debt is defined as anything else that shows up in the credit panel that does not fit into the remaining categories.

[7] The number of observations change across the columns due to variation in data availability of the outcome variables. The results are qualitatively similar when we use log(Y) as the outcome variable for the balance regressions and when we use a Poisson regression for the creit inquiry regression.

For this analysis, we focus on homeowners who carry a positive student loan balance in the pre-treatment period (Panel B of Table 1) because we are interested in how the abatement expiration shock affects homeowners' ability to repay student debt. Table 3 presents the regression results. Column 1 presents results from a specification where we use student loan balance in USD as the outcome variable. We find that the shock led to a weakly statistically significant increase in student loan balance with an ATT estimate of \$2,256, which is approximately equal to a 6% increase relative to the treated group's pre-treatment sample mean (\$37,775). Figure 3 presents the event study regression plot, which shows a strong upward pre-shock trend. Therefore, we do not interpret the student loan balance DiD result as being strictly caused by the abatement expiration. We discuss this point in more detail below.

Student loan balance can increase for three reasons. First, the consumer switches to a lower payment plan such as an income-driven repayment plan (IDR), which would cause his or her student loan balance to increase because more interest will accrue.[8] Second, the consumer decides to go back to school and take on more debt. Last, the consumer becomes delinquent in his or her student loan payment.

Columns 2 through 4 of Table 3 present results from regression specifications that test these three channels. In column 2, we use scheduled monthly payment as the outcome variable. We find a null result, which suggests that treated consumers did not renegotiate for a more manageable repayment plan. In column 3, we use the number of student loan trade lines as the outcome variable. We also find a null result, which means that the treated consumer decided to take on more student debt. In column 4, we use an indicator variable that equals one if any of the consumer's student loan payment became delinquent during the year and zero otherwise. Here, we find that, for treated homeowners, the probability of being delinquent on student loan payments increased by 3.6%, which is equivalent to a 24% increase relative to the treated group's pre-treatment sample mean (15%).

Figure 4 presents the event study regression plot, which shows that the parallel trend assumption holds and, hence, the plot implies that the result admits a causal interpretation. A notable pattern that Figure 4 reveals is that the delinquency effect is persistent, i.e., it lasts for at least three years (t to $t+2$). Linking this result back to the student loan balance result tells us that part of the increase in student loan balance that we observe after the abatement expiration is caused by a subset of borrowers who become delinquent on their student loan payment.[9]

[8] See `https://studentaid.gov/manage-loans/repayment/plans/income-driven`.

[9] The CRISM data set does not allow us to observe the number of days that a particular student loan account has been delinquent and, therefore, we cannot sharply determine whether this delinquency effect is causing borrowers to go into default, which is typically defined as being delinquent for more than 270 days. See `https://studentaid.gov/manage-loans/default`.

It is important to note that these ATTs are likely to be lower bound estimates of the true ATT because treated homeowners always have the option to sell their houses and avoid the property tax expense shock. Intuitively, selection into selling should be positively correlated with the probability that their budget constraints bind as a result of the shock.[10]

Column 5 Table 3 presents regression results that provide suggestive evidence that the delinquency effect is caused by binding liquidity constraints. In this specification, we interact the $Treated_i \times Post_t$ term with a proxy for liquidity constraint: an indicator variable for high DTI ratio at origination, which equals one if the DTI ratio at origination is greater than or equal to 45%. The triple interaction term is positive and statistically significant at the 10% level. It is notable that the coefficient is also economically large, i.e., it is five times larger than the coefficient on the $Treated_i \times Post_t$ term. This result is suggestive that liquidity constraint is an important contributor to the student loan delinquency result. Appendix Tables A2 and A4 present credit consumption and non-student debt delinquency regression results for the student loan sample and find null effects, which suggest that households in the student loan sample prefer to pay their student debt *last*, when they are liquidity constrained.

7 Discussion and Conclusion

Taken together, the results show that there is a debt repayment ranking; that is, when faced with an expense shock that makes budget constraints bind, consumers prefer to be delinquent on student debt before other types of debt. This revealed preference for debt repayment order seems rational because, when forced, a rational agent would prefer to default on debt that has the lowest total cost of default. In terms of interest rate, student debt is less costly to become delinquent on than credit card debt because it carries a much lower interest rate. Compared to collateralized debt, student debt is also a sensible choice; becoming delinquent on auto loans and mortgages translate to losing one's means of transportation or one's place of residence and an important investment vehicle (Benetton et al., 2022), which is likely to be costlier than the total cost of defaulting on student debt.[11]

The existence of this potentially rational debt repayment ranking has three important implications.

[10] Appendix Figure A1 presents an event study regression result plot where an arm's length sale indicator variable is regressed on the interaction terms between the treated indicator variable and event year indicator variables. The sample is composed of approximately 136,000 property-year observations for single-family homes that were constructed in Philadelphia County after 2000 and have a tax abatement ending in or before 2019. The plot shows an upward trend in sale probability leading up to and after the expiration year. However, the difference-in-differences point estimate is small and statistically indistinguishable from zero.

[11] The shadow cost of defaulting on auto loans may include loss of income due to the inability to travel to the workplace (Van Doornik et al., 2024) and frictions in adjusting one's durable asset stock (Aaronson et al., 2012).

First, previous work has found that consumers do not pay off credit card debt rationally (Gathergood et al., 2019). Our findings show that consumers' debt repayment behavior may be rational across different types of debt (e.g., credit card, student loan, auto loan, and mortgage), but not within the same type of debt (e.g., different credit card accounts). Second, the ranking implies that models of default probabilities that are used for risk management should not model each debt-type account separately or independently. Concretely, the results presented above show that, all else equal, a consumer is less likely to become delinquent on her credit card debt payments when he or she carries student debt because she can make adjustments on student-debt-related margins first. Third, the large impacts of expense shocks on student debt delinquency are not addressed by existing repayment programs. Current income-driven repayment plans, which allow flexibility by providing insurance for low-income periods, have been shown to reduce default (Mueller and Yannelis, 2019). However, as these plans are based on taxable income relative to federal poverty definitions, relatively small changes to expenses would not be insured, even though these shocks have meaningful impacts on repayment.

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Figure 1: Event Study Plot – Net Taxable Amount (USD)

This figure plots the coefficients and their respective 95% confidence intervals from a stacked event study OLS regression where net taxable amount in USD is regressed onto the *Treated* indicator variable is interacted with cohort year indicator variables. An event is defined as tax abatement expiration that occur in year t, shown as $t = 0$ here. The event window covers years $t - 3$ and $t + 2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. The control homeowners are those that will experience an abatement expiration in years $t + 3$ or later. All homeowners that appear in an event are considered to belong to a cohort. Control variables include Risk Score, estimated income, and age. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. Data sources: CoreLogic and CRISM.

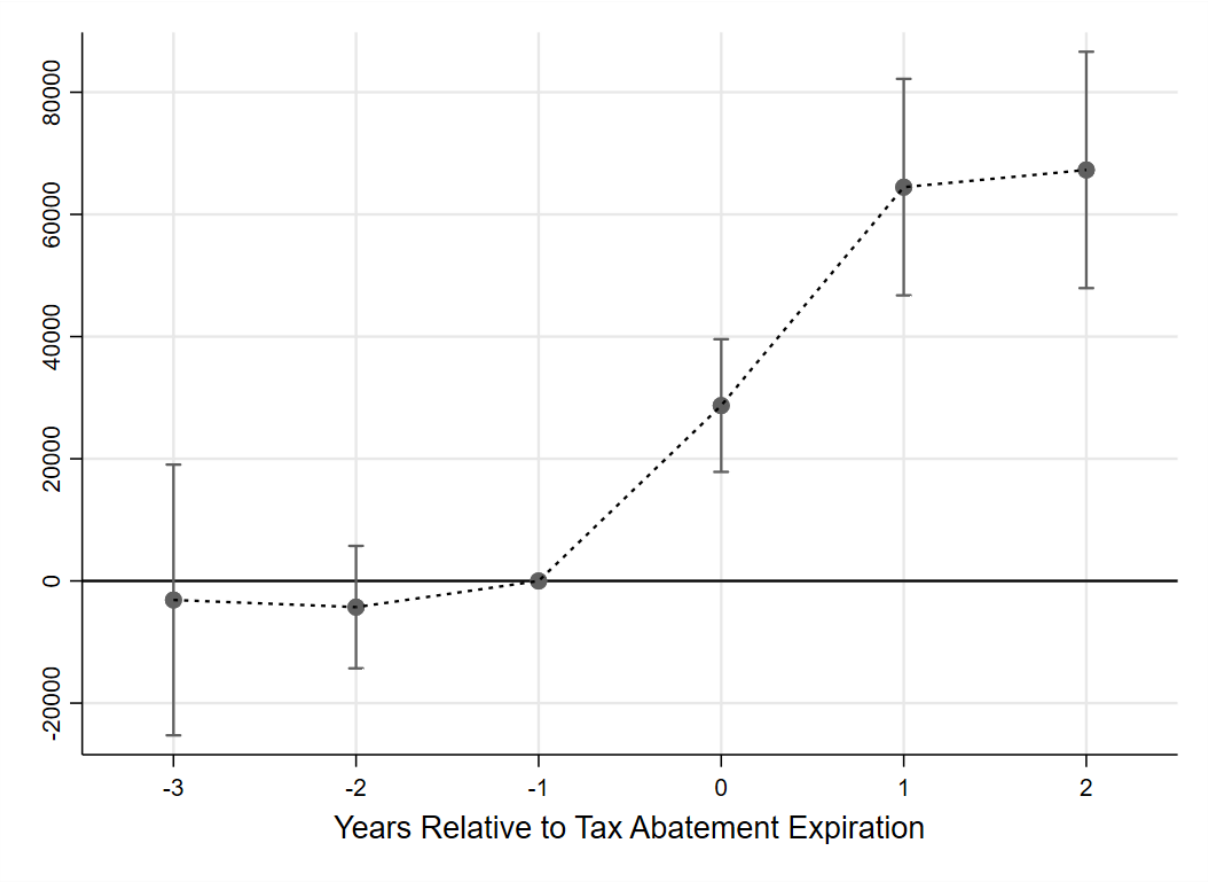


Figure 2: Event Study Plot – Property Tax Amount (USD)

This figure plots the coefficients and their respective 95% confidence intervals from a stacked event study OLS regression where annual property tax amount in USD is regressed onto the *Treated* indicator variable is interacted with cohort year indicator variables. An event is defined as tax abatement expiration that occur in year t, shown as $t = 0$ here. The event window covers years $t - 3$ and $t + 2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. The control homeowners are those that will experience an abatement expiration in years $t + 3$ or later. All homeowners that appear in an event are considered to belong to a cohort. Control variables include Risk Score, estimated income, and age. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. Data sources: CoreLogic and CRISM.

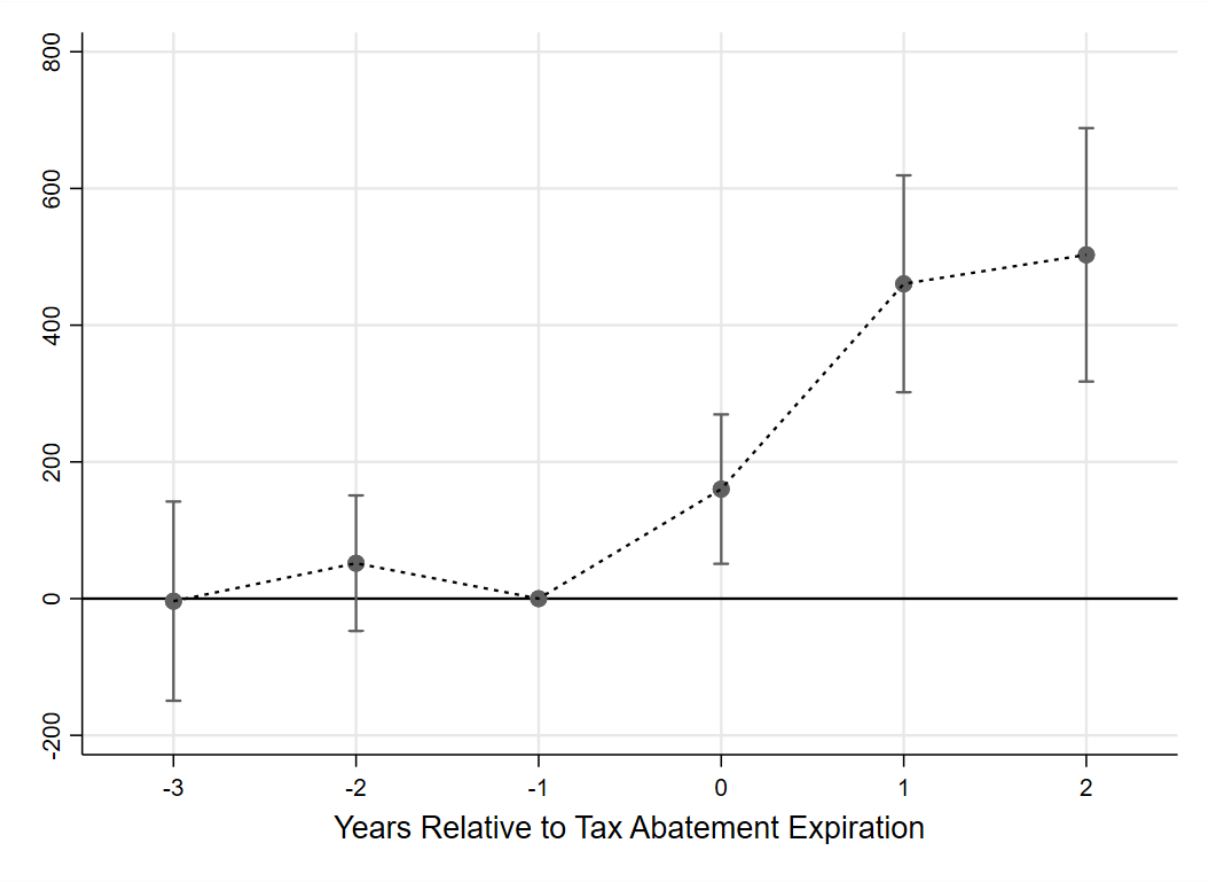


Figure 3: Event Study Plot – Student Loan Balance (USD)

This figure plots the coefficients and their respective 95% confidence intervals from a stacked event study OLS regression where student loan balance in USD is regressed onto the *Treated* indicator variable is interacted with cohort year indicator variables. Student loan balance is the average student loan balance in year t computed over all 12 months. An event is defined as tax abatement expiration that occur in year t, shown as $t = 0$ here. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort. The sample includes all homeowners that have a positive student loan balance in the pre-period. Control variables include Risk Score, estimated income, and age. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. Data sources: CoreLogic and CRISM.

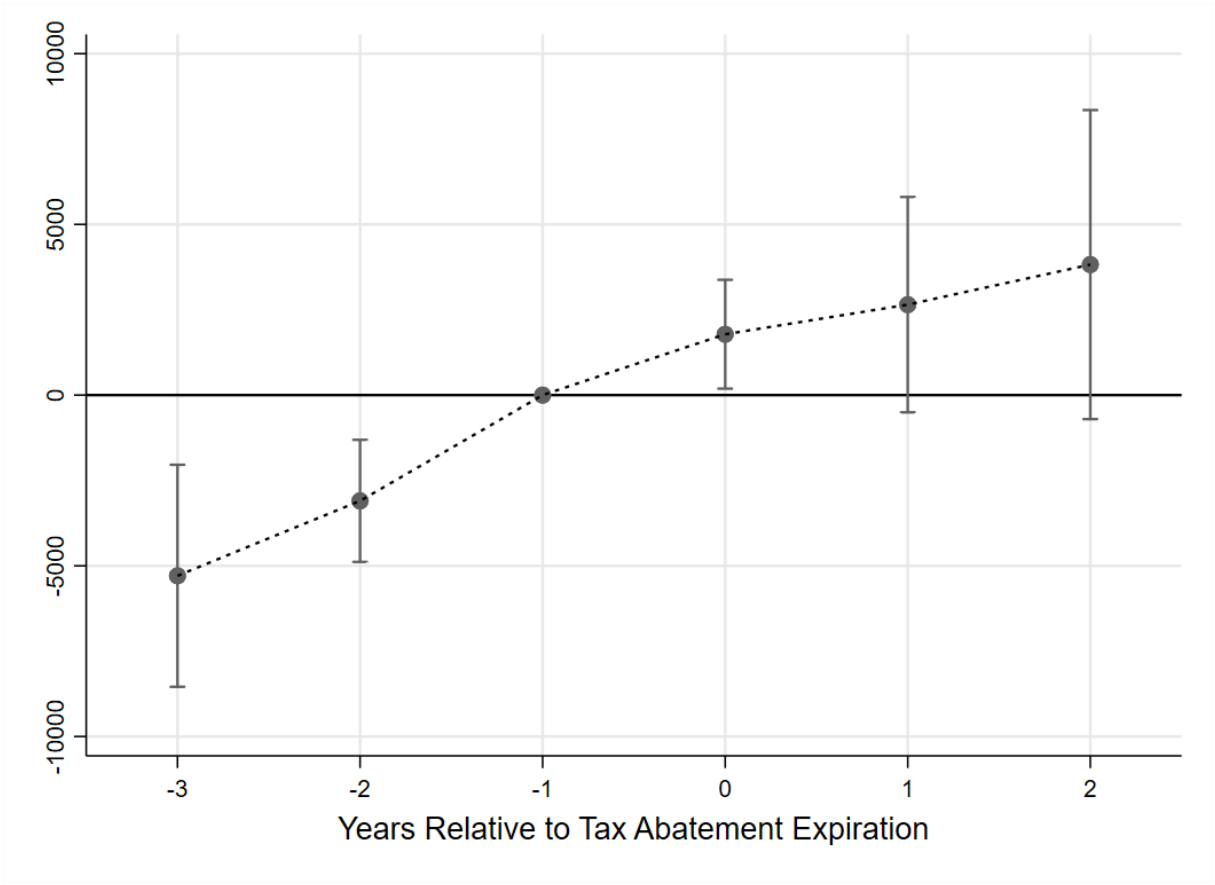


Figure 4: Event Study Plot – Student Loan Payment Delinquency

This figure plots the coefficients and their respective 95% confidence intervals from a stacked event study OLS regression where the student loan repayment delinquency indicator variable is regressed onto the *Treated* indicator variable is interacted with cohort year indicator variables. Student loan repayment delinquency equals one if at least one student loan account is delinquent in that year and zero otherwise. An event is defined as tax abatement expiration that occur in year t, shown as $t = 0$ here. The event window covers years $t - 3$ and $t + 2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. The control homeowners are those that will experience an abatement expiration in years $t + 3$ or later. All homeowners that appear in an event are considered to belong to a cohort. The sample includes all homeowners that have a positive student loan balance in the pre-period. Control variables include Risk Score, estimated income, and age. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. Data sources: CoreLogic and CRISM.

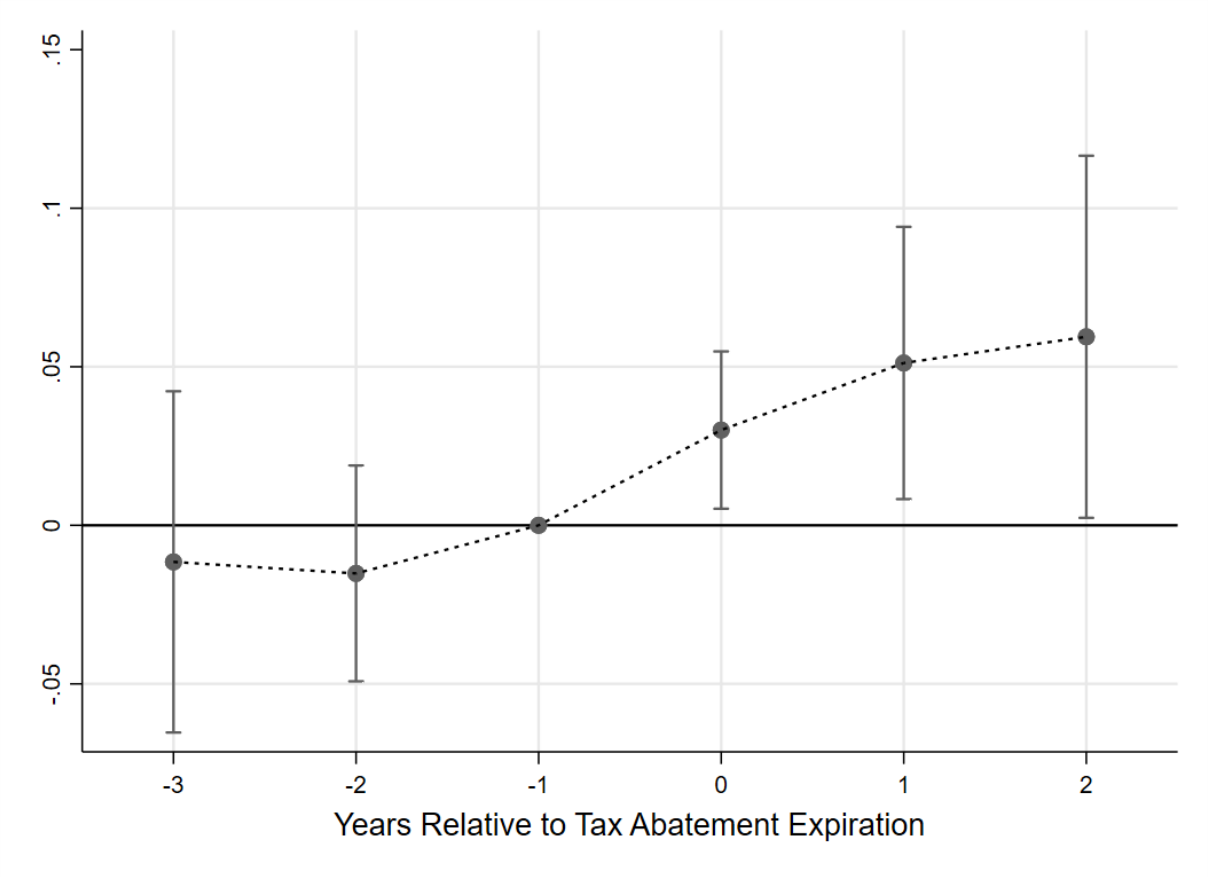


Table 1: Sample Summary Statistics

This table presents summary statistics of key variables for the year before property tax abatement ends (event time $t-1$). Panel A presents summary statistics for the full sample. Panel B presents summary statistics for the student loan sample. Dollar amounts are not adjusted for inflation. The middle column presents statistical significance, if any, for the difference in sample means. We show only key variables of interest that appear in the subsequent regression tables. *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

Panel A	Control			Treatment	
	Mean	SD		Mean	SD
Net taxable amount (USD)	57,608.36	90,646.85	***	46,646.19	69,387.13
Tax amount (USD)	1,675.65	2,062.70	*	1,576.71	1,900.37
Credit card balance (USD)	6,158.41	10,039.95	**	5,458.81	7,617.33
Auto loan balance (USD)	6,630.27	10,879.41		6,187.59	9,892.33
HELOC balance (USD)	7,895.24	49,901.68	***	4,227.80	23,724.63
Other debt balance (USD)	1,200.00	9,110.00		1,311.00	4,718.00
Mortgage balance (USD)	317,157.12	179,411.54	***	225,356.95	187,478.17
New credit inquiry count	17.18	30.81	***	20.58	33.51
Age (years)	40.23	11.94	***	44.47	13.35
Riskscore	749.93	81.58	***	705.44	113.21
PIM	62.71	21.61	***	50.80	22.47

Panel B	Control			Treatment	
	Mean	SD		Mean	SD
Student loan balance (USD)	42,360.95	54,997.08	*	37,775.84	48,738.03
Student loan scheduled payment (USD)	718.40	3,147.05		617.10	1,518.37
Number of student loan accounts	3.11	3.21	***	4.22	4.45
Student loan delinquency	0.08	0.27	***	0.15	0.35
Age (years)	35.29	8.22	***	39.51	12.03
Riskscore	731.61	81.82	***	672.99	115.46
PIM	60.98	18.84	***	46.96	20.00
DTI ratio (%)	36.61	13.73	*	38.37	12.70

Table 2: Credit Consumption Regression Results

This table presents OLS stacked event study regression results where measures of credit consumption are regressed onto the property tax abatement expiration shock indicator variable. An event is defined as tax abatement expiration that occur in year t. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. Post equals one for years t to $t+2$. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort. Net taxable amount, tax amount, credit card balance, auto loan balance, HELOC, other debt, and mortgage balances are presented in nominal USD. Credit inquiry is the number of mortgage credit inquiries that appears in the homeowner's credit panel in the last 12 months. All credit panel outcome variables are computed as or from average monthly values within a year. The sample includes all homeowners that have at least one viable observation in the pre-treatment period and one in the post-treatment period. Control variables include Risk Score, estimated income, age, and age squared. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

	Net taxable amount	Tax amount	Credit card balance	Auto loan balance	HELOC balance	Other balance	Mortgage balance	Credit inquiry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	46,695***	252.2***	57.58	37.90	23.33	138.6	2,762	0.729
	(6.453)	(4.205)	(0.308)	(0.143)	(0.0527)	(0.943)	(1.134)	(0.600)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Cohort × Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.549	0.647	0.801	0.654	0.800	0.658	0.911	0.347
N	9,921	22,394	22,452	22,452	22,452	22,452	21,527	22,452

Table 3: Student Loan Regression Results

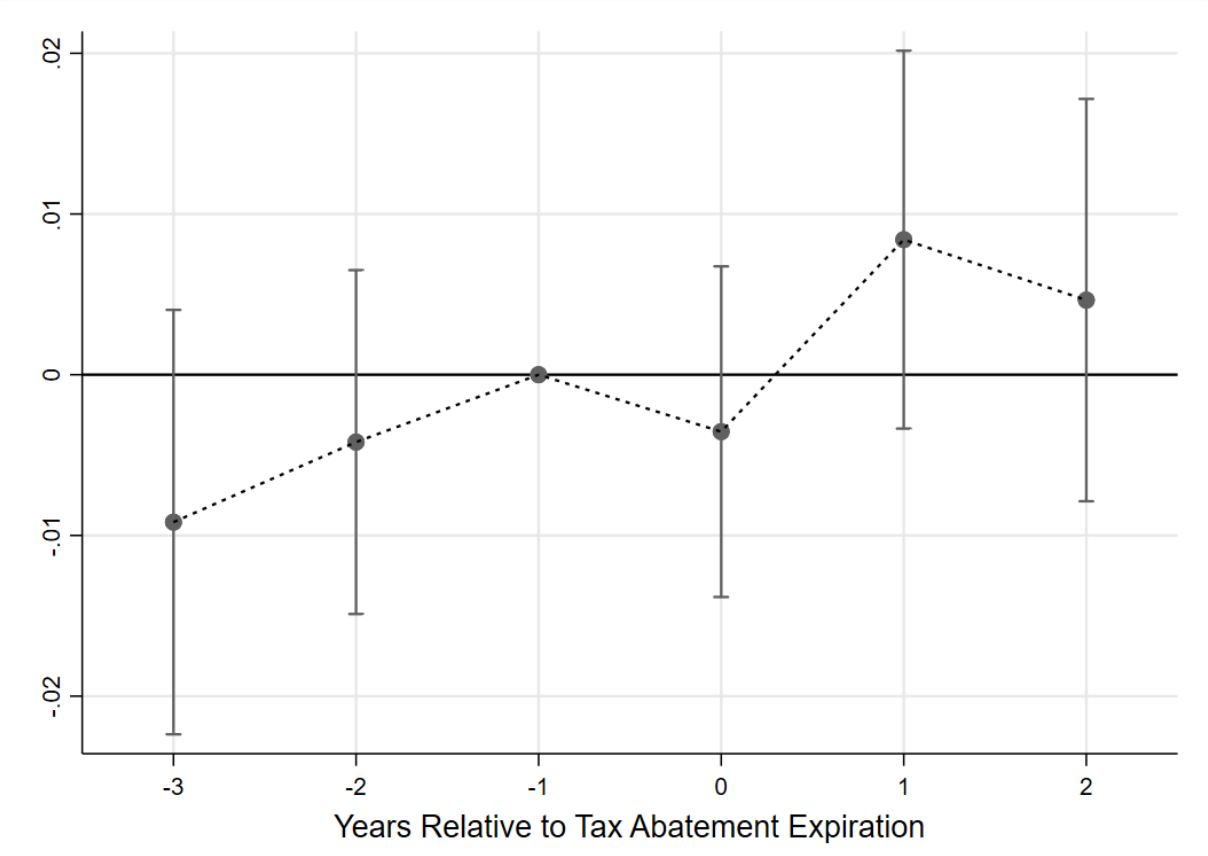
This table presents OLS stacked event study regression results where student debt repayment activity variables are regressed onto the property tax abatement expiration shock indicator variable. An event is defined as tax abatement expiration that occur in year t. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. Post equals one for years t to $t+2$. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort. Student loan balance and scheduled monthly payment are presented in nominal USD. Student loan trade line is the number of student loan accounts that appears in the homeowner's credit panel. Student loan repayment delinquency equals one if at least one student loan account is delinquent in that year and zero otherwise. All credit panel outcome variables are computed as or from average monthly values within a year. High DTI equals one if DTI at origination is above 45% and zero otherwise. The sample includes all homeowners that have a positive student loan balance in the pre-period and at least one viable observation in the pre-treatment period and one in the post-treatment period. Control variables include Risk Score, estimated income, age, and age squared. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

	Student loan balance	Scheduled payment	Student loan trade line	Student loan delinquency	
	(1)	(2)	(3)	(4)	(5)
Treated × Post	2,256*	75.46	0.157	0.0361**	0.0165
	(1.764)	(1.604)	(1.159)	(2.370)	(0.730)
Post × High DTI					-0.00636
					(-0.298)
Treated × Post × High DTI					0.0829*
					(1.822)
Control variables	Y	Y	Y	Y	Y
Cohort × Household FE	Y	Y	Y	Y	Y
Cohort × Year FE	Y	Y	Y	Y	Y
Adjusted R-squared	0.927	0.586	0.850	0.508	0.471
N	7,619	6,795	7,619	7,619	4,522

A Appendix Figures

Figure A1: Event Study Plot – Home Sale Probability

This figure plots the coefficients and their respective 95% confidence intervals from a stacked event study OLS regression where the home sale indicator variable is regressed onto the *Treated* indicator variable is interacted with cohort year indicator variables. Home sale equals one if the home was sold in an arm's length transaction in that year and zero otherwise. An event is defined as tax abatement expiration that occur in year t, shown as $t = 0$ here. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homes, which are those that experienced an abatement expiration in year t and zero otherwise. The control homes are those that will experience an abatement expiration in years $t + 3$ or later. All homes that appear in an event are considered to belong to a cohort. The sample includes all single family homes constructed in Philadelphia County after the year 2000 that appear in the CoreLogic data set. Cohort by home and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. Data sources: CoreLogic and CRISM.



B Appendix Tables

Table A1: Cohort Observation Counts

This table presents the number of observations in the control and treatment groups in each event cohort for the full sample and the student loan sample.

	Full Sample		Student Loan Sample	
Cohort	Control	Treatment	Control	Treatment
2011	710	224	222	82
2012	652	251	212	90
2013	381	228	133	81
2014	287	248	104	82
2015	274	247	107	76
2016	304	325	104	106
2017	374	285	130	82

Table A2: Credit Consumption Regression Results – Student Loan Sample

This table presents OLS stacked event study regression results where measures of credit consumption are regressed onto the property tax abatement expiration shock indicator variable. Everything is exactly the same as the analysis presented in Table 2 except for the sample, which is the "student loan sample." *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

	Net taxable amount	Tax amount	Credit card balance	Auto loan balance	HELOC balance	Other balance	Mortgage balance	Credit inquiry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	44,252***	265.2***	260.3	-528.4	-156.9	-30.42	-898.7	1.529
	(4.390)	(3.468)	(0.764)	(-1.245)	(-0.281)	(-0.117)	(-0.272)	(0.797)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Cohort × Household FE	Y	Y	Y	Y	Y	Y	Y	Y
Cohort × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.552	0.644	0.817	0.624	0.725	0.534	0.906	0.330
N	3,367	7,596	7,619	7,619	7,619	7,619	7,318	7,619

Table A3: Financial Distress Regression Results

This table presents OLS stacked event study regression results where measures of financial distress are regressed onto the property tax abatement expiration shock indicator variable. An event is defined as tax abatement expiration that occur in year t. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. Post equals one for years t to $t+2$. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort. The outcome variables are all indicator variables. Delinquency indicator equals one if, at any time during the year, the consumer has at least one delinquent account of the specified type. The sample includes all homeowners that have at least one viable observation in the pre-treatment period and one in the post-treatment period. Control variables include Risk Score, estimated income, age, and age squared. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

	Delinquency indicator				
	Auto	Credit card	Other	HELOC	Mortgage
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.002	0.011	-0.005	-0.002	0.010
	(-0.234)	(1.208)	(-0.869)	(-0.497)	(1.198)
Control variables	Y	Y	Y	Y	Y
Cohort × Household FE	Y	Y	Y	Y	Y
Cohort × Year FE	Y	Y	Y	Y	Y
Adjusted R-squared	0.476	0.542	0.498	0.511	0.618
N	22,452	22,452	22,452	22,452	22,452

Table A4: Financial Distress Regression Results – Student Loan Sample

This table presents OLS stacked event study regression results where measures of financial distress are regressed onto the property tax abatement expiration shock indicator variable. An event is defined as tax abatement expiration that occur in year t. The event window covers years $t-3$ and $t+2$. Treated equals one for treated homeowners, which are those that experienced an abatement expiration in year t and zero otherwise. Post equals one for years t to $t+2$. The control homeowners are those that will experience an abatement expiration in years $t+3$ or later. All homeowners that appear in an event are considered to belong to a cohort. The outcome variables are all indicator variables. Delinquency indicator equals one if, at any time during the year, the consumer has at least one delinquent account of the specified type. The sample is the student loan sample. Control variables include Risk Score, estimated income, age, and age squared. Cohort by homeowner and cohort by year fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the zip code level. t-statistics are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: CoreLogic and CRISM.

	Delinquent indicator				
	Auto	Credit card	Other	HELOC	Mortgage
	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.0185	0.0143	-0.0161	-0.0002	0.0030
	(-1.611)	(0.830)	(-1.384)	(-0.0303)	(0.212)
Control variables	Y	Y	Y	Y	Y
Cohort × Household FE	Y	Y	Y	Y	Y
Cohort × Year FE	Y	Y	Y	Y	Y
Adjusted R-squared	0.449	0.567	0.525	0.534	0.634
N	7,619	7,619	7,619	7,619	7,619