Aversion to Student Debt? Evidence from Low-wage Workers*

Radhakrishnan Gopalan
Washington University in St. Louis

Barton Hamilton
Washington University in St. Louis

Jorge Sabat
Universidad Diego Portales

David Sovich
University of Kentucky

May 11, 2021

Abstract

We use payroll and consumer credit data to estimate the effect of the minimum wage on the debts of low-wage workers. In the three years following a $0.88 increase in the minimum wage, the average low-wage worker experiences a $2,712 increase in income and a $856 decrease in debt. The entire decline in debt comes from a reduction in student loan borrowing among enrolled college students. Former students and non-students, in contrast, borrow more in response to an increase in the minimum wage. Future credit constraints, changes in labor supply, buffer-stock behavior, and several other channels do not explain the reduction in student loan debt. Two consumption-savings models – one with student debt aversion and the other with a high perceived student loan interest rate – best match our empirical findings.

*This paper represents the views of the authors and not Equifax Inc. We are deeply grateful to Equifax Inc. for supporting the research and providing access to the data. We thank Sumit Agarwal, David Hirshleifer, Naser Hamdi, Jonathan Parker, Jenna Roberts, and seminar participants at Baylor University, the Labor and Finance Online Seminar, Texas A&M University, University of Houston, University of Kentucky, and Washington University in St. Louis for their helpful comments.

1 Introduction

The overall effect of the minimum wage on the welfare of low-wage workers is an important policy question. While a substantial amount of research exists on the employment aspects of this question (Card and Krueger 1995; Neumark and Wascher 2007), many non-employment aspects remain under-examined. In particular, there is limited evidence on the borrowing and debt responses to the minimum wage (Aaronson, Agarwal, and French 2012; Cooper, Luengo-Prado, and Parker 2020). This is despite the fact that such responses are useful for developing consumption-savings models and understanding low-wage workers' preferences and financial constraints (Zinman 2015).

In this paper, we use payroll and consumer credit data to estimate the borrowing and debt responses to the minimum wage. We find that, in the three years following a \$0.88 increase in the minimum wage, the average low-wage worker experiences a \$2,712 increase in income and – in sharp contrast to prior work such as Aaronson, Agarwal, and French 2012 – a \$856 decrease in debt. We find the entire decline in debt comes from a reduction in student loan borrowing among enrolled college students. Non-students and former students, in contrast, use their wage gains to finance automobile purchases. Credit constraints, changes in labor supply, income uncertainty, buffer-stock behavior, and several other channels cannot explain the reduction in student loan debt. Even more puzzling, we find that enrolled students with large amounts of credit card debt choose to borrow less student debt after they experience a wage increase. In the final section of our paper, we develop a consumption-savings model to match and explain our empirical estimates. We show that the behavior of enrolled students is consistent with either a high perceived student loan interest rate or a behavioral phenomenon known as student debt aversion (Field 2009). Specifically, we find that either a perceived student loan interest rate of in excess of 25 percent or a utility penalty of 0.159 per dollar of student debt holdings enables us to quantitatively match our estimates.

Our empirical analysis uses payroll and consumer credit data from Equifax Inc., one of the three major credit bureaus in the United States. The payroll data contains anonymized information on the wages, hours, and job tenures of employees from over 2,000 firms in the United States between the years 2010 and 2020. The consumer credit data contains anonymized information on the credit histories of all individuals in the United States (conditional on having a credit history). In contrast to most studies in the minimum wage literature, our data distinguishes between hourly and salary employees and allows us to precisely identify low-wage workers affected by the minimum wage. In addition, our data allows us to examine multiple dimensions of individual liabilities. We are unaware of any other research that uses data of this quality and breadth to study the effect of the minimum wage on the debts of low-wage workers.

To identify the effects of the minimum wage, we use a difference-in-differences framework that exploits state-level variation in the minimum wage over time. We focus on 13 states and one district that each implemented at least one large ($\geq$ \$0.25), isolated minimum wage change between the years 2014 and 2017.[1] For each treated state, we select a set of geographically adjacent control states which did not increase their minimum wage. We then restrict our final sample to border counties in the treated and control states (Dube, Lester, and Reich 2010). Our identifying assumption is that, in the absence of a minimum wage change, economic conditions in adjacent cross-border counties would have evolved similarly. In support of this assumption, we show that treated and control counties are observably similar and trend in tandem prior to an increase in the minimum wage.

We estimate our difference-in-differences models at the individual employee level. Our sample consists of incumbent hourly wage employees in treated and control counties whose pre-treatment wage is below their state's new minimum wage. We refer to these employees as *bound employees*. Bound employees are directly affected by the minimum wage and hence are of policy interest (Neumark 2018). For each treated state, our sample period is the 48 months surrounding the date of its minimum wage change (12 months before to 36 months after). Therefore, our estimates capture the medium-to-long run effects of the minimum wage on incumbent low-wage workers.

We begin our analysis by estimating the effect of the minimum wage on employment and wages. We confirm our prior finding from Gopalan et al. 2021 that an increase in the minimum wage raises the wages of incumbent bound workers without affecting their employment or average hours worked per week. Our estimates imply that, on average, bound employees experience a \$904 increase in

1. These states are Arkansas, California, Delaware, Massachusetts, Maryland, Maine, Michigan, Minnesota, Nebraska, New Jersey, New York, South Dakota, and West Virginia. The one district is Washington D.C.

annual earnings following a \$0.88 minimum wage change (\$2,712 over the 36 month post-treatment period). In support of our empirical setting, we find no evidence of differential pre-trends across bound employees in treated and control counties. We also find no evidence of wage or employment responses in the upper tail of the wage distribution.[2]

We then estimate the borrowing and debt responses to the minimum wage. In theory, bound employees should borrow in anticipation of a minimum wage increase (Japelli and Pistaferri 2010). Furthermore, the size of the borrowing response could be several times the size of the wage increase in the presence of durables or credit constraints (Aaronson, Agarwal, and French 2012). Inconsistent with these theories, we find that total debts decline by \$856, on average, in the 36 months after a minimum wage increase. We find that the decline in debt begins immediately after the minimum wage increase takes effect. Moreover, we find that the entire decline in debt comes from a reduction in student loan borrowing among enrolled college students.[3] Enrolled students have a marginal propensity to borrow (MPB) out of a minimum wage change of -0.38. Former students and non-students, in contrast, use their wage gains to finance automobile purchases and have an MPB of 0.11.[4] We find no significant changes in credit card balances following an increase in the minimum wage.[5] We also find no evidence of borrowing responses in the upper tail of the wage distribution.

From a consumption-savings standpoint, the reduction in student loan borrowing is surprising. Enrolled students have high expected future earnings but are likely constrained in their ability to smooth their consumption because of market frictions (Cadena and Keys 2013). Hence, these workers should have strong incentives to spend in response to an increase in the minimum wage. For enrolled students to save their wage gains, the benefits of borrowing less student debt must exceed the benefits of increasing and smoothing consumption. Furthermore, these perceived benefits must

2. This serves as a falsification test of our setting. Essentially, if a time-varying state-level factor drives our results, then we should expect to find significant wage and employment responses among workers earning higher wages. See Cengiz et al. 2019, Clemens and Wither 2019, and Gopalan et al. 2021.

3. In Section 5, we split our sample of bound employees into enrolled students (29 percent), former students (10 percent), and non-students (61 percent). Our classification is based on age and student loan balances.

4. Consistent with Aaronson, Agarwal, and French 2012, the increase in auto loan debt materializes around one year following a minimum wage change. This suggests that low-wage workers face credit or collateral constraints.

5. We also find no significant changes in mortgage balances (Table A.7). We choose to exclude mortgages from the main discussion because mortgages are uncommon among bound employees.

exceed the interest rate earned from reducing the use of (or paying down existing) other non-student debts (Becker and Shabani 2010). We note that the interest rate on federal student loans is lower than the interest rate on most forms of consumer credit during our sample period: the average undergraduate (graduate) student loan rate was 4.37 (6.42) percent between 2014 and 2020.

We investigate a number of potential explanations for the decline in student debt. For instance, enrolled students might borrow less student debt to improve their credit scores and hedge against future financial constraints (Rothstein and Rouse 2011). Alternatively, enrolled students might spend less on tuition after the opportunity cost of attending college increases (Brown, Fang, and Gomes 2012). We find no evidence to support either of these hypotheses. Enrolled students with both subprime and prime credit scores reduce their student loan borrowing in response to an increase in the minimum wage. In addition, we find no differential increase in employment or hours worked for enrolled students relative to former students and non-students. We also fail to find a relative decreases in college enrollment in treated counties.[6]

We explore and reject numerous other rational channels as explanations. These channels include: buffer-stock behavior (cross-sectional test = high versus low credit card utilization), future income uncertainty (cross-sectional tests = high versus low income dispersion and state graduation rates), student age, changes in state college tuition, and default costs. Even more puzzling, enrolled students with relatively high levels of credit card debt choose to accumulate less student debt instead of paying down their credit card balances. This finding rules out a variety of preference-based explanations such as habit-based consumption and precautionary savings motives.

To rationalize the borrowing response of enrolled students, we build a consumption-savings model that incorporates various frictions and a one-time minimum wage hike. In the model, an enrolled student in a minimum wage job works towards graduating college and earning a permanent income increase. The student has access to borrowing, and chooses their consumption and debt holdings every period to maximize expected lifetime utility. We calibrate the model based on standard parameter values and the average income and debt profiles of the enrolled students in

6. We also find no differential reduction in student debt among enrolled students without a home or an auto loan.

our sample. Our goal is to examine how the optimal consumption and debt holdings respond to a one-time minimum wage increase in the presence of various frictions.

We start with a frictionless model with no credit constraints or defaults (Zeldes 1989). Under these assumptions, we find that enrolled students increase their borrowing in response to an increase in the minimum wage. Introducing credit constraints, defaults, and tuition costs to the model does not generate a reduction in borrowing. This is consistent with our cross-sectional tests.

We find that two behavioral frictions allow us to generate a marginal propensity to borrow that matches our empirical estimate of -0.38. The first friction is a high perceived cost of student debt. If enrolled students perceive the student debt interest rate to be greater than 25 percent, then our model produces a negative marginal propensity to borrow. We note that the perceived interest rate that matches our estimates greatly exceeds the actuarially fair interest rate based on the model-implied likelihood of default. It is also well above the average undergraduate federal student loan interest rate during our sample period. Therefore, our model suggests that enrolled students associate several other costs with student debt beyond just the nominal interest rate.

The second behavioral friction that enables us to match our empirical estimates is a direct utility penalty of holding student debt. Following Field 2009, we refer to this penalty as student debt aversion.[7] We find that a utility penalty of 0.159 per dollar of student debt generates a marginal propensity to borrow of -0.38. From a modelling standpoint, student debt aversion generates observationally equivalent predictions as a high perceived interest rate. Hence, we cannot disentangle these two forces from one another in our empirical tests.[8]

Our paper contributes to several strands of literature. First, our paper contributes to the literature on the overall impact of the minimum wage. In particular, we provide the first large-scale estimates of the borrowing and debt responses to the minimum wage based on payroll and consumer credit data. Consistent with Aaronson, Agarwal, and French 2012, we find that non-

7. Field 2009 defines student debt aversion as a direct mental cost associated with holding student debt. In general, mental accounting and self-control problems can provide the theoretical foundations for debt aversion (Thaler 1990; Prelec and Loewenstein 1998).

8. We note, however, that the behavioral foundations of student debt aversion and a high perceived interest rate could be different. For example, debt aversion could come from the view that debt is inconsistent with one's self image as an independent and upright person (Hirshleifer 2007).

students and former students use their wage gains to finance automobile purchases. However, we find that the average debt response is negative due to a large reduction in student loan debt among enrolled students. Our heterogeneous results help reconcile the negative aggregate (i.e., MSA) debt response in Cooper, Luengo-Prado, and Parker 2020 with the positive individual auto debt response in Aaronson, Agarwal, and French 2012. Furthermore, our results highlight several potential (and often overlooked) benefits of increasing the minimum wage. For example, our auto loan results suggest that an increase in the minimum wage could help relax credit constraints for incumbent low-wage workers (á la Dettling and Hsu 2020). In addition, our student loan results suggest that an increase in the minimum wage could help reduce the aggregate growth rate of student loan balances. Indeed, our paper is one of the first to document a link between minimum wage policies and the level of student loan balances among enrolled students.

Second, our paper contributes to the literature on student debt. Recent studies have shown that student debt can impose large costs on borrowers. For example, student debt can impede home ownership (Mezza et al. 2020), reduce human capital accumulation (Chakrabarti et al. 2020) and constrain career choices (Rothstein and Rouse 2011). Consistent with individuals perceiving a high cost of student debt, we find that enrolled students borrow less student debt following an increase in the minimum wage. However, we are unable to explain the reduction in student with any of the above rational channels. Instead, we argue that the reduction in student loan debt is behavioral, and that it reflects some of the first non-experimental evidence student debt aversion along the intensive margin (Goldrick-Rab and Kelchen 2015).[9] Previous studies, such as Cadena and Keys 2013, have documented evidence consistent with student debt aversion along the extensive margin.

The remainder of the paper is organized as follows: Section 2 describes our sample of minimum wage changes, Section 3 discusses our data, Section 4 estimates the wage and employment responses, and Section 5 estimates the borrowing and debt responses. Section 6 tests explanations for the

9. Our results complement the small body of experimental and survey-based evidence on student debt aversion (Oosterbeek and Broek 2009; Meissner 2016; Caetano, Palacios, and Patrinos 2019). We note that our results are also consistent with a handful of other behavioral explanations. In particular, our results are also consistent with enrolled students viewing student debt as much costlier than the actual interest rate. This is in contrast to prior papers on price misperceptions which find that borrowers view debt as deceptively cheap (Stango and Zinman 2009).

decline in student debt. Section 7 develops our model of student debt aversion. Section 8 concludes and provides a list of caveats and implications for our results.

2 Institutional background

In this section, we describe our sample of state minimum wage changes.

2.1 State minimum wage changes

We begin by providing background on state minimum wage changes between January 2010 and December 2017 – i.e., the period which we have at least three years of post-treatment data. Following the increase in the federal minimum wage to $7.25 per hour in July 2009, few states enacted new one-time or multi-phase minimum wage changes. Of the 30 state minimum wage changes between 2010 and 2013, the vast majority were from previously enacted policies that indexed the minimum wage to inflation. However, beginning in 2014, several states enacted new one-time or multi-phase minimum wage changes. Many of these changes were for large amounts. In particular, there were 45 state minimum wage changes of at least $0.25 per hour between 2014 and 2017. There were no changes to the federal minimum wage during this period.[10]

2.2 Selection of treated and control geographies

We focus on large and isolated state minimum wage changes. Specifically, we restrict our sample to state minimum wage changes that: (1) were for at least $0.25 per hour, (2) occurred between 2014 and 2017, and (3) were not preceded by any other minimum wage change between 2010 and 2013.[11] Thirteen states and one district in the continental United States (hereafter the treated states) have minimum wage changes that satisfy the above conditions. These states are Arkansas, California, Delaware, Massachusetts, Maryland, Maine, Michigan, Minnesota, Nebraska, New Jersey, New

10. Table A.1, located in the appendix, provides a list of the 112 minimum wage changes between 2010 and 2017.

11. Imposing these conditions keeps the pre-treatment window free of any other minimum wage changes. It also ensures that our changes are not dissipated by inflation.

York, South Dakota, and West Virginia. The one district is Washington D.C. For treated states with more than one minimum wage change during the sample period, we focus on the chronologically first minimum wage change (hereafter said to occur on the treatment date).

Table 1 describes our sample of state minimum wage changes. The sample consists of one increase of \$0.25, one increase of \$0.50, six increases of \$0.75, three increases of \$1.00, two increases of \$1.25, and one increase of \$1.50. The employment-weighted average increase in the minimum wage is \$0.88 (11.6 percent). Almost all of the increases occurred during the years 2014 and 2015.

We match each treated state to a set of adjacent control states which did not increase their minimum wage. Furthermore, we follow Dube, Lester, and Reich 2010 and limit our final sample to border counties in treated and control states. Table 1 lists the 16 control states and their matched treated states. The rightmost columns list the 162 control counties and 162 treated counties.[12] Figure A.1, in the appendix, displays the geographic locations of treated and control counties.

We assign each border county to a "cross-border county pair" that is comprised of adjacent treated and control counties. Cross-border county pairs attempt to proxy for areas over which economic conditions evolve smoothly but where the level of the minimum wage varies discontinuously. While comparing employees in adjacent counties has intuitive appeal, Neumark, Salas, and Wascher 2014 question whether cross-border counties serve as valid counterfactuals. To alleviate this concern, Table A.2 compares the economic conditions in treated and control counties. We find that treated and control counties are similar across most observable dimensions. Moreover, Figure A.2 shows that adjacent treated and control counties trend in tandem prior to treatment.[13]

For each cross-border county pair, we restrict the sample period to the 48 months surrounding a minimum wage change (12 months before to 36 months after). We set the pre-treatment period of control counties to be the same as their paired cross-border treated counties.[14]

12. We exclude two border counties in Maryland that have local minimum wage ordinances.

13. We find similar results when examining treated and control units at the state level (Table A.3; Figure A.3).

14. For example, West Virginia increased its minimum wage by \$0.75 in January 2015. Kentucky is a control state that shares a border with West Virginia. Therefore, the pre-treatment period for Kentucky counties along the West Virginia border is January 2014 to December 2014. The post-treatment period of Kentucky counties along the West Virginia border is January 2015 to December 2017.

3 Data and sample selection

In this section, we describe our data and our sample of employees.

3.1 Data

Our analysis uses payroll and consumer credit data from Equifax Inc., one of the three major credit bureaus in the United States. The payroll data contains anonymized information on the monthly earnings, hours, and job tenures of employees from over 2,000 firms in the United States (roughly 20 million active employee records per month). The data distinguishes between hourly and salary employees, voluntary and involuntary turnover, and specifies exact hourly wage rates. Unlike most studies in the minimum wage literature, the payroll data allows us to precisely identify minimum wage workers.[15] The data begins in 2010 and continues until the present day.

The internet data appendix in Gopalan et al. 2021 describes the payroll data in greater detail. The data is representative of the United States labor force along several dimensions, including median personal incomes and median employee tenures. In addition, the data closely tracks aggregate monthly private sector payroll growth, hiring rates, and job separation rates. While most industries are represented in the correct proportions, the share of employment in the retail trade industry is significantly higher in the data than in the population. The average firm in the data also tends to be larger than the average firm in the United States.

We combine the payroll data with anonymized consumer credit data from Equifax Inc. The consumer credit data contains the credit histories of the entire United States population (conditional on having a credit history). At the individual level, the data contains information on credit scores, credit inquiries, and derogatory public records such as foreclosures or bankruptcies. At the credit account level, the data contains information on account types, account balances, credit limits, and any missed or late payments. The data begins in 2005 and continues until the present day. For a more detailed description of the consumer credit data, see Avery et al. 2003.

15. Most studies in the literature use proxies to identify minimum wage workers. These proxies include age (Dube, Lester, and Reich 2016), industry (Dube, Lester, and Reich 2010), location (Dettling and Hsu 2020), and the portion of self-reported household income derived from low-wage employment (Aaronson, Agarwal, and French 2012).

3.2 Sample

We conduct our analysis at the employee level. Our sample consists of incumbent *bound employees* between the ages of 18 and 64 in treated and control counties. Bound employees are hourly wage workers that have pre-treatment hourly wages below their state's new minimum wage – i.e., the level of the minimum wage after the state enacts its scheduled increase.[16] Bound employees are directly affected by the new minimum wage and hence are of policy interest (Neumark 2018). Table B.1, located in the appendix, records our employee definitions.

We restrict our sample of bound employees to those in the intersection of the payroll and the consumer credit data. We also limit employee entry to the pre-treatment period. Therefore, our sample is made up of incumbent bound employees that are employed prior to a minimum wage change and have valid credit histories. For our analysis of labor market outcomes, we drop employees from the sample after they separate from their employer. For our analysis of credit market outcomes, we continue to follow employees regardless of their labor market status.[17]

Table 2 describes our sample of 76,982 bound employees. Prior to treatment, the median bound employee is 25 years old, works 30 hours per week, and earns \$7.75 per hour. Forty percent of bound employees earn exactly the minimum wage, and 39 percent of bound employees have student debt (average student debt balance = \$7,269). The median bound employee is credit constrained with a credit score of 583, no open credit cards, and no open auto loans. However, the average bound employee has \$1,325 in credit card debt, \$2,641 in auto loan debt, and \$4,070 in open credit limits (average credit utilization = 28 percent). Nineteen percent of bound employees have a severely delinquent account on their credit report. Along most observable dimensions, bound employees in treated counties are statistically similar to bound employees in control counties.

16. We define an employee's pre-treatment hourly wage as the employee's wage in the month closest to three months prior to treatment. For employees in control counties, we define the new minimum wage as the minimum wage the county would have had if it had implemented the same increase as its cross-border treated county.

17. This is because the credit data is comprehensive while the employment data is not.

4 Wages, employment, and income

In this section, we examine the wage, employment, and income effects of the minimum wage. These tests help us interpret the borrowing and debt effects in Section 5.

4.1 Wages

To begin our analysis, we follow Aaronson, Agarwal, and French 2012 and estimate the wage response to the minimum wage. The regression model is:

$$\omega_{i,t} = \alpha + \Gamma \times \text{Treated}_s \times \text{Post}_{t,s} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t}, \tag{1}$$

where $\omega_{i,t}$ is the hourly wage of bound employee i in state s and cross-border county pair p in month t. The dummy variable Treated_s is equal to one if state s enacts a minimum wage change and zero otherwise. $\text{Post}_{t,s}$ is equal to one in all months t after the treatment date and zero otherwise. The model includes employee fixed effects (δ_i) and cross-border county pair month effects ($\delta_{p,t}$).[18] In our tightest specification, we include lagged state-level controls for house price growth and GDP per-capita growth (Clemens and Wither 2019). Standard errors are clustered at the state level.

The coefficient of interest, Γ, measures the average change in wages for bound employees in treated counties relative to adjacent control counties. Table 3 reports the coefficient estimates. We find that long-run wages are \$0.58 higher per hour, on average, following a sample average \$0.88 minimum wage change.[19] Figure 1 displays the dynamics of the coefficient estimates. We find that hourly wages increase within one month of the treatment date and do not dissipate.[20] We also find

18. The employee fixed effects control for time-invariant differences across treated and control employees. The cross-border county pair month effects control for time-varying shocks common to adjacent treated and control counties. For a time-varying omitted variable to contaminate our results, it must be correlated with the minimum wage changes and differentially affect the outcomes of bound employees in adjacent treated and control counties.

19. The short-run wage response of \$0.54 cents (-12 to +12 months) is right above the weighted average gap between the pre-treatment wages of bound employees and the new minimum wage (\$0.47). The difference is consistent with the moderate wage spillovers documented in Cengiz et al. 2019, Brochu et al. 2019, and Gopalan et al. 2021.

20. For bound employees that remain in the labor market sample, we find that wages continue to respond to later minimum wage changes (see the terminal coefficient estimate). However, because remaining employees' wages slowly begin to exceed the minimum wage (e.g., via job changes, tenure-related raises, or promotions), their wages become less responsive to minimum wage changes. See also Dube, Giuliano, and Leonard 2019.

no economically significant evidence of pre-trends. Both the timing and magnitude of the wage response support the quality of our data and the validity of our experimental design.

4.2 Employment

We next estimate the employment response to the minimum wage. Specifically, we re-estimate Equation 1 after replacing the outcome variable with either a dummy variable for employment or the average number of hours worked per week (variable definitions in Table B.2). Table 3 reports the coefficient estimates. We find no economically or statistically significant changes in long-run employment or hours in response to the minimum wage. In addition, we find no evidence of differential pre-trends across treated and control counties (Figure 2). Overall, our wage and employment responses are consistent with those in Gopalan et al. 2021: incumbent workers earn more but are not more likely to lose their jobs following an increase in the minimum wage.

4.3 Income

In response to an $0.88 increase in the minimum wage, bound employees experience a $0.58 increase in wages per hour. At the same time, employment and hours remain unchanged. Given that bound employees work an average of 30 hours per week, our estimates imply that the average worker experiences a $904 increase in annual income following a minimum wage change (7.4 percent from a base of $12,200 per year; $2,712 over the 36 month post-treatment period).[21] We estimate that the elasticity of bound employee earnings to the minimum wage is 0.638 (= 7.4 / 11.6 percent).

4.4 Robustness

We perform several robustness tests. A brief description of each test is provided below.

21. Formal estimates, presented in Table 3, are consistent with this back-of-the-envelope calculation.

4.4.1 Falsification

To rule out competing explanations for our findings, we estimate employment and wage responses across the rest of the wage distribution (Cengiz et al. 2019). Essentially, if a time-varying state-level confounder drives our results, then we should expect to find significant wage and employment responses in other parts of the wage distribution (e.g., the upper tail). However, if our results reflect the causal effect of the minimum wage, then we should only expect to find significant wage and employment responses in the lower part of the wage distribution (e.g., near the minimum wage).

To test this hypothesis, we estimate the following stacked version of Equation 1:

$$y_{i,b,t} = \alpha + \sum_{b'=-1}^{b'=14} \Gamma_{b'} \times \text{Treated}_s \times \text{Post}_{t,s} \times \text{Bin}_{b'} + \delta_i + \delta_{p,b,t} + \gamma_b' X_{s,t-12} + \varepsilon_{i,b,t}, \tag{2}$$

where the outcome variable, $y_{i,b,t}$, is either the hourly wages or employment of employee i in wage bin b in month t.[22] The dummy variable $\text{Bin}_{b'}$ is equal to one if employee i resides in wage bin $b = b'$ and zero otherwise. For each bin b, the model includes a separate set of fixed effects and different control variable coefficients. The coefficients of interest, the $\Gamma_{b'}$'s, measure the average relative change in the outcome variable for employees in each wage bin.

Figures A.4 and A.5 display the coefficient estimates. As expected, we find that hourly wages rise and employment remains unchanged for bound employees.[23] More importantly, all of the action is concentrated around the new minimum wage; we find no significant evidence of wage or employment responses in the mid-to-upper tails of the wage distribution. These localized effects suggest that our estimates capture the causal effect of the minimum wage and not a confounder.

22. We define the wage bins as follows. Bin $b = -1$ corresponds to exactly the "old" minimum wage. Bin $b = 0$ corresponds to the interval between the old minimum wage and the new minimum wage – i.e., the interval $(\text{MW}_s, \text{MW}_s + \Delta_s)$, where Δ_s is the size of the minimum wage increase (or hypothetical increase for control states) in state s. Finally, bin $b \geq 1$ corresponds to the wage interval that is between b and $b + 1$ increments of size Δ_s above the old minimum wage: $[\text{MW}_s + b \cdot \Delta_s, \text{MW}_s + (b + 1) \cdot \Delta_s)$. Intuitively, bins $b = -1$ and $b = 0$ correspond to bound employees while bins $b \geq 1$ correspond to non-bound employees. We cap the wage bins at $b = 14$; the corresponding wage interval is $[\text{MW}_s + 14 \cdot \Delta_s, \infty)$.

23. Consistent with Brochu et al. 2019 and Gopalan et al. 2021, we find evidence of moderate wage spillovers extending up to three wages bins – or, around \$2.50 – above the new minimum wage.

4.4.2 Standard errors and fixed effects

In unreported results, we re-estimate our models using different clustering schemes (e.g., clustering on counties and companies, double clustering on state and month, etc.) and fixed effects (e.g., company month effects, tenure month effects, etc.). We find that our main results do not change.

4.4.3 Spillovers

Neumark 2018 notes that cross-border studies may be biased against finding disemployment effects because of spillovers from worker mobility. Gopalan et al. 2021 test this claim in a similar empirical setting as ours. They find no evidence of biases arising from worker mobility.

4.4.4 Heterogeneity

In Figure A.6, we re-estimate our models across the size of the minimum wage change relative to the median state wage. We find a slight reduction in employment in states that enacted the highest minimum wage changes. For states with more moderate minimum wage changes, we find no change in employment and an increase in average hours worked per week.

5 Debt and borrowing

In this section, we examine the debt and borrowing effects of the minimum wage.

5.1 Debt

We start by estimating the debt response to the minimum wage. The regression model is:

$$y_{i,t} = \alpha + \Gamma \times \text{Treated}_s \times \text{Post}_{t,s} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t}, \tag{3}$$

where the outcome variable is the total debt of bound employee i in month t. Similar to Equation 1, the coefficient of interest, Γ, measures the average change in debt for bound employees in treated counties relative to adjacent control counties. Standard errors are clustered at the state level.

Table 4 reports the coefficient estimates. If bound employees behave according to the standard consumption-savings framework, then the Γ coefficient should be greater than or equal to zero. However, we find the opposite is true in the data. Long-run debts are \$856 lower, on average, in the 36 months after a minimum wage change.[24] The \$856 reduction in debt bounds the average marginal propensity to consume (MPC) out of a minimum wage change above at 0.684. This upper bound is much lower than what is predicted by consumption-savings models with credit constraints and a permanent wage increase (Japelli and Pistaferri 2010). We estimate that the marginal propensity to borrow (MPB) out of a minimum wage change is -0.316 .

5.2 What drives the decline in debt?

To better understand the reduction in debt, we begin by re-estimating Equation 3 across categories of consumer credit. We focus on the three major categories of consumer credit used by bound employees: credit cards, auto loans, and student loans. Table 4 reports the coefficient estimates. We find that the entire decline in debt comes from a reduction in student loan balances ($\Gamma = -\$944$; $t = -3.26$). Auto loan balances increase ($\Gamma = \$117$; $t = 1.74$) and credit card balances do not change ($\Gamma = \$18$; $t = 1.11$) following an increase in the minimum wage. The negative relation between student debt and the minimum wage is a novel finding of our paper. In contrast, a handful of other studies have found that low-wage workers use wage gains to finance automobile purchases (e.g., Aaronson, Agarwal, and French 2012; Cookson, Gilje, and Heimer 2020).

5.3 Less borrowing or greater repayment?

We next examine whether the reduction in student debt comes from less borrowing or greater repayment.[25] To do this, we split our sample into three groups: enrolled students (29 percent),

24. Table A.4 reports coefficient estimates from Equation 3 with changes in debt as the outcome variable (i.e., the impulse response coefficients). The estimated 36 month cumulative decline in debt from this model is $\$1,235$. This estimate falls within the 95% confidence interval of our baseline estimate.

25. In the even-numbered columns of Table 4, we report coefficient estimates from Equation 3 when the outcome variable is the number of open credit accounts. Consistent with a reduction in borrowing, we find that the number

former students (10 percent), and non-students (61 percent). Enrolled students are bound employees with positive pre-treatment student loan balances and: (a) are between the ages of 18 and 22 or (b) have an increasing pre-treatment amount of non-delinquent student debt. Non-students are bound employees with zero pre-treatment student loan balances, and former students are the remaining bound employees with positive pre-treatment student loan balances. Conceptually, enrolled students are teenagers or adults working their way through college, whereas former students are college drop-outs or graduates that experienced poor labor market outcomes. Non-students are career low-wage employees.[26] Given that non-students do not have student debt, we restrict our sample to enrolled students and former students going forward. Table B.1 records our definitions.

Enrolled students and former students differ in terms of their observable characteristics (Table A.5) and their expected future incomes. Furthermore, while enrolled students are likely to be in their student loan borrowing cycle, former students are likely to be in their repayment cycle. This implies that a reduction in student loan debt among enrolled students should correspond to less borrowing, whereas a reduction in student loan debt among former students should correspond to greater repayment. To capture this, we estimate the following model:

$$\begin{aligned} y_{i,t} = \alpha &+ \beta \times \mathbf{E}_i \times \text{Treated}_s \times \text{Post}_{t,s} + \Gamma \times \text{Treated}_s \times \text{Post}_{t,s} \\ &+ \delta_i + \delta_{p,t} + \delta_{\mathbf{E},t} + \gamma' X_{s,t-12} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where the outcome variable is the student loan debt of enrolled student i in month t. The dummy variable $\mathbf{E}_i$ is equal to one if bound employee i is an enrolled student and zero otherwise. The model includes the same set of fixed effects $(\delta_i, \delta_{p,t})$ and control variables $(X_{s,t-12})$ as in Equation 3. In addition, the model includes separate cross-border county pair month effects for enrolled and

of student loan accounts declines (in relative terms) following an increase in the minimum wage. The coefficient of -0.14 represents a 10 percent decline relative to the pre-treatment mean of 1.45.

26. Our definitions are subject to two sources of misclassification error. First, the sample of non-students might include misclassified enrolled students that are not currently accruing student debt because of parental support or scholarships. This source of misclassification error does not necessarily pose a problem for us, however, if misclassified students continue not to accrue student debt. In Figure 5, we test to see if non-students accrue student debt after the minimum wage increase. We do not find any differential increase in student debt. Therefore, enrolled students that are misclassified as non-students do not contribute to explaining our results. Second, our sample of enrolled students might include some former students. We discuss this issue in greater detail in Footnote 38.

former students ($\delta_{\mathbf{E},t}$). Standard errors are clustered at the state level.

In the model, the Γ coefficient measures the average relative change in student loan debt among former students. If the reduction in student loan debt comes in-part from greater repayment, then this coefficient should be negative. The β coefficient measures the average differential change in student loan debt among enrolled students. If the reduction in student loan debt also comes from incrementally less borrowing, then this coefficient should be negative as well. Finally, the coefficient sum, $\Gamma + \beta$ captures the average relative change in student loan debt for enrolled students.

Table 5 reports the coefficient estimates. For former students, we find no significant change in student loan balances after an increase in the minimum wage ($\Gamma = \$117$; $t = 0.92$). Instead of repaying their student loans, former students increase their auto loan balances ($\Gamma = \$282$; $t = 2.50$) and hold more total debt ($\Gamma = \$307$; $t = 2.21$). We estimate that former students have an implied MPC (MPB) out of a minimum wage change of 1.11 (0.11). This MPC is consistent with consumption-savings models with permanent wage increases and credit constraints.

Figure 3 displays the dynamics of the coefficient estimates for former students. Consistent with Aaronson, Agarwal, and French 2012, we find that the increase in auto loan balances materializes around one year after the increase in the minimum wage. This pattern suggests that former students could be using their wage gains to accumulate down payments and resolve credit constraints (Dettling and Hsu 2020). There are no changes in credit card balances among former students.

We find that the entire decline in student loan debt comes from less borrowing among enrolled students. As shown in Table 5, both the triple-differences coefficient estimate ($\beta = -\$1,142$; $t = -2.68$) and the coefficient sum ($\Gamma + \beta = -\$1,025$) are negative and significant. We estimate that enrolled students have an implied MPC out of a minimum wage change of 0.62. Equivalently, their marginal propensity to borrow out of a minimum wage change is -0.38.

Figure 4 plots the dynamics of the coefficient estimates for enrolled students. We find that student loan balances gradually decline starting one quarter after a minimum wage change. This pattern persists throughout the entire post-treatment period. Similar to former students, enrolled students experience a delayed increase in auto loan balances after an increase in the minimum wage.

In addition, we find no economically or statistically significant evidence of differential pre-trends.

Throughout the remainder of the paper, we focus on explaining the reduction in student loan borrowing among enrolled students. Briefly, we note that the borrowing and debt responses of non-students mirrors those of former students (which, in turn, mirror those in Aaronson, Agarwal, and French 2012). Figure 5 displays the coefficient estimates from Equation 3 estimated on our sample of non-students. We find that average auto loan and credit card balances increase following an increase in the minimum wage. Akin to enrolled and former students, the increase in auto loan balances occurs over one year after the increase in the minimum wage. We find no changes in student loan balances among non-students, and we find no evidence of differential pre-trends.

5.4 Robustness

We perform several robustness tests. A brief description of each test is provided below.

5.4.1 Falsification

If our empirical setting captures the causal effect of the minimum wage, then we should only find significant debt responses in the vicinity of the new minimum wage. To test this hypothesis, we re-estimate Equation 2 after replacing the outcome variable with either total debt, credit card debt, auto loan debt, or student loan debt (all scaled by pre-treatment income). Figure A.7 displays the coefficient estimates. Consistent with our baseline results, we find that the reduction in debt is concentrated in the wage bins around the new minimum wage. More importantly, we find no economically significant changes in debt in the mid-to-upper parts of the wage distribution. The null results across the rest of the wage distribution suggest that our estimates capture the causal effect of the minimum wage and not a time-varying state-level confounder.[27]

27. In particular, the null results across the rest of the wage distribution indicate that concomitant state-level student debt relief policies or general low-income policies do not drive our main results. The null results also indicate that differences in the composition of lenders (e.g., private versus federal student loans) and their collections policies across state borders is not the driving factor.

5.4.2 Standard errors and fixed effects

In unreported results, we re-estimate our models using different clustering schemes (e.g., clustering on counties and companies, double clustering on state and month, etc.) and fixed effects (e.g., company month effects, tenure month effects, etc.). We find that our main results do not change.

5.4.3 Transformations of the outcome variables

In Table A.7, we report coefficient estimates from models that apply log and inverse hyperbolic sine transformations to the outcome variables.[28] We find that our main results do not change. Enrolled students reduce student debt while former and non-students increase their auto loan balances.

5.4.4 Heterogeneity

In Figure A.8, we re-estimate our models across the size of the minimum wage change relative to the median state wage. The reduction in student loan debt occurs in states with both high and low minimum wage changes. The smaller absolute effect in states with the largest minimum wage changes could be due to the negative employment effects in these states (Figure A.6).

6 Why do enrolled students borrow less?

In this section, we examine the reasons behind the decline in student loan debt. The tests in this section restrict the sample to enrolled students.

6.1 The financial constraints channel

From a consumption-savings standpoint, the reduction in student loan borrowing is surprising. Enrolled students have high expected earnings but cannot perfectly smooth their consumption because of market frictions. Hence, these workers should have strong incentives to spend and borrow in response to an increase in the minimum wage. For enrolled students to save their wage gains,

28. The log transformation is $\log(1+y)$. The inverse hyperbolic sine transformation is $\log\left(y^2+\sqrt{y^2+1}\right)$

the benefits of borrowing less student debt must exceed the benefits of increasing and smoothing consumption. Furthermore, the benefits of reducing student debt must exceed the interest rate earned from borrowing less (or paying down existing) non-student debts. We note that the interest rate on federal student loans is lower than the interest rate on most other forms of consumer credit during our sample period: the average undergraduate (graduate) student loan rate was 4.37 (6.42) percent between 2014 and 2020 (Table A.8).[29]

We examine several potential explanations for the decline in student debt. First, enrolled students might borrow less student debt to improve their credit scores and hedge against future financial constraints (Rothstein and Rouse 2011).[30] To test this explanation, we split our sample of enrolled students into credit constrained students (pre-treatment credit score ≤ 620; 52 percent of the sample) and unconstrained students (pre-treatment credit score > 620; 48 percent of the sample). We then estimate the following triple-differences model:

$$\begin{aligned} y_{i,t} = \alpha &+ \beta \times \mathbf{C}_i \times \text{Treated}_s \times \text{Post}_{t,s} + \Gamma \times \text{Treated}_s \times \text{Post}_{t,s} \\ &+ \delta_i + \delta_{p,t} + \delta_{\mathbf{C},t} + \gamma' X_{s,t-12} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where the outcome variable, $y_{i,t}$, is the student loan balances or open student loan accounts of enrolled student i in month t. The dummy variable $\mathbf{C}_i$ is equal to one if enrolled student i is credit constrained and zero otherwise. Standard errors are clustered at the state level.

Columns (1) and (4) of Table 6 report the coefficient estimates. For unconstrained students, we continue to find a significant reduction in student loan borrowing after an increase in the minimum wage ($\Gamma = -\$851$; $t = -2.04$). We find little-to-no evidence of heterogeneity across the degree of credit constraints. The triple-differences coefficient is negative ($\beta = -\$312$) but statisti-

29. A significant fraction of federal student loans are also subsidized during the enrollment period (Cadena and Keys 2013). Zinman 2015 finds that student loans determine the "true" risk-free rate for just four percent of households.

30. Student debt imposes a significant consumption commitment after graduation (Chetty and Szeidl 2007). For constrained individuals, the presence of this commitment can induce drastic reductions in other forms of consumption (e.g., food) and increase the likelihood of default in response to negative income shocks. Hence, enrolled students that anticipate being credit constrained might choose to avoid student debt. Recent surveys also find that individuals view student debt as an impediment to home ownership (Shahdad 2014). Consistent with these surveys, Mezza et al. 2020 find that student debt depresses home ownership rates due to its effect on credit scores and debt-to-income ratios.

cally insignificant ($t = -1.00$). Overall, the results suggest that credit scores and future financial constraints do not explain the entire decline in student debt.[31]

6.2 The uncertainty channel

Given that student debt is more difficult to discharge in bankruptcy than other forms of consumer credit, the presence of future income uncertainty might encourage enrolled students to borrow less following a minimum wage change (Carroll 2001a). In particular, enrolled students might reduce their borrowing to hedge against states in which they do not graduate but are saddled with debt (Brown, Fang, and Gomes 2012). Note, however, that the availability of income-based repayment plans for student debt reduces the consumption risk from income fluctuations (see subsection 6.4.5). Essentially, the lender is willing to share in the income uncertainty and convert the debt claim to an equity claim in the bad states of the world. Notwithstanding this, to test an income uncertainty explanation, we split our sample of enrolled students based on above-median and below-median state college graduation rates (four-year state median = 58 percent). We then re-estimate Equation 5 after replacing $\mathbf{C}_i$ with a dummy variable for below-median graduation rates. If uncertainty over future income explains our results, then the reduction in student debt should be concentrated in states with below-median graduation rates.

Columns (3) and (6) of Table 6 report the coefficient estimates. For enrolled students in states with above-median graduation rates, we continue to find a significant reduction in student loan borrowing ($\Gamma = -\$867$; $t = -2.19$). We also find no difference in the effect for states with below-median graduation rates. The triple-differences coefficient is positive ($\beta = \$192$) and statistically insignificant ($t = 0.24$). Table A.10, in the appendix, finds similar results after re-estimating the model across different measures of income uncertainty and average state incomes. Overall, the results suggest that future labor market uncertainty does not explain the decline in student debt.

31. We also examine heterogeneity based on whether an enrolled students has an auto loan or a home loan prior to treatment. We find no differential effects across either dimension (Table A.9).

6.3 The buffer-stock channel

Enrolled students might use student debt to hedge against uncertain future expenses (Cadena and Keys 2013).[32] In response to an increase in the minimum wage, the demand for such buffer-stock borrowing should decrease. To test whether buffer-stock behavior explains the reduction in student loan debt, we split our sample of enrolled students into those with below-median credit card utilization and above-median credit utilization.[33] We then re-estimate Equation 5 after replacing $\mathbf{C}_i$ with a dummy variable for below-median card utilization. If buffer-stock behavior explains our results, then the reduction in student loan borrowing should be concentrated among enrolled students with above-median credit card utilization (i.e., those students with fewer options to smooth consumption other than through student debt).

Columns (3) and (4) of Table 6 report the coefficient estimates. We find that enrolled students with below-median credit card utilization borrow \$925 less in student debt, on average, after an increase in the minimum wage. However, we find no significant differences between the response of these students and those with above-median credit card utilization ($\beta = \$ - 221$; $t = -0.59$). The lack of heterogeneity suggests that the buffer-stock behavior does not explain the decline in student debt.

6.4 Other rational channels

We examine several other rational channels. None can explain the reduction in student debt among enrolled students. A brief description each channel is provided below.

32. Enrolled students face uncertain costs during school (e.g., hospital bills) and often have insufficient resources to cover such expenses. Given the subsidized nature of federal student debt and the presence of credit constraints, borrowing in anticipation of such negative shocks could be optimal even in the presence of fixed origination costs.

33. The unconditional median card limit for enrolled students is \$0 and hence the median credit card utilization is 100 percent. Therefore, we use the conditional median credit card utilization of 46 percent to split the sample. Our results are robust to using both the unconditional and conditional median. Our results are also robust to splitting the sample based on credit card limits instead of utilization (conditional median = \$1,300). See Table A.9.

6.4.1 Labor supply

An increase in the minimum wage increases the opportunity cost of attending college. As a result, enrolled students might choose to work more, spend less time in school, and thereby borrow less student debt (Brown, Fang, and Gomes 2012). To test this hypothesis, we re-estimate our employment model on the sub-sample of enrolled students. We find no significant changes in employment ($\Gamma = 0.001$; $t = 1.25$) or hours ($\Gamma = -0.011$; $t = -0.08$) following a minimum wage change. In addition, we find no significant changes in college enrollment (Figure A.11) in the counties of the enrolled students. Combined, these results suggest that changes in labor supply do not explain the decline in student debt.

6.4.2 Tuition costs

An increase in the minimum wage could coincide with a decrease in in-state college tuition. As a result, enrolled students might borrow less student debt because of a simple price effect. To test whether a decline in tuition explains our results, we re-estimate Equation 3 after controlling for lagged tuition at the colleges located in our counties. We find that controlling for tuition does not affect our results.[34] We also find that the average tuition rates in treated and control counties trend in tandem before-and-after a minimum wage change (Figure A.10). Combined, these results suggest that a decline in college tuition does not explain the decline in student debt.

6.4.3 The savings rate

Enrolled students might borrow less student debt because doing so provides a slightly above-market risk-free return equal to the student loan interest rate (Becker and Shabani 2010). To test this explanation, we re-estimate Equation 5 across enrolled students with above (conditional) median and below (conditional) median credit card balances (conditional median = $\$2,940$).[35] Because

34. For the full (enrolled student) sample, the coefficient estimate changes from $-\$1,021$ ($-\$970$) without tuition controls to $-\$1,002$ ($-\$1,131$) with tuition controls. The coefficient estimate is different than the $-\$944$ estimate in Table 4 because this test restricts our sample to counties with tuition data. We include fees with tuition.

35. The conditional median amount of credit card debt is large relative to average incomes (= 25 percent). Hence, these are likely interest accruing balances and not just transactions which are paid-off in full at the end of the month.

credit cards have much higher interest rates than student debt, enrolled students should prioritize paying down their credit card balances over borrowing less student debt (Agarwal, Liu, and Souleles 2007). However, in Table A.11, we find that enrolled students with below-median and above-median credit card debt both borrow less student debt after a minimum wage change ($\Gamma = -\$949$; $t = -2.33$; $\beta = -\$244$; $t = -0.56$). Moreover, enrolled students with above-median credit card debt do not reduce their credit card balances more than those with below-median credit card debt ($\Gamma = -\$22$; $t = 0.91$; $\beta = -\$17$; $t = -0.27$). The choice of borrowing less student debt over paying down credit card debt also rules-out explanations that center around the permanence of the wage increase.

6.4.4 Student age

Student debt can impede major life events such as marriage (Gicheva 2009), child birth (Shao 2015), and enrolling in a graduate degree program (Chakrabarti et al. 2020). If these major life events are still on the horizon, then enrolled students might find it optimal to borrow less student debt following an increase in the minimum wage. To test this channel, we re-estimate Equation 5 across younger (below 22 years) and older (above 22 years) students.[36] Inconsistent with an age or life-cycle related channel, we find that the reduction in student debt is present in both younger students ($\Gamma = -\$931$; $t = -2.14$) and older students ($\beta = \$114$; $t = 0.19$).

6.4.5 Income-based repayment plans, wage garnishment laws, and expected family contributions

Under income-based repayment (IBR) plans, student loan borrowers must allocate 10 to 15 percent of their discretionary incomes towards repaying their debts. For borrowers in the repayment cycle, an increase in income would mechanically generate a decrease in debt. However, because enrolled students are still in the borrowing cycle, IBRs cannot explain the reduction in student debt. Wage

36. We assume that younger students have more major life events on the horizon than older students and hence should have stronger incentives to borrow less student debt. For context, the median age of an enrolled student is 21 years and the age distribution is significantly right-skewed (Figure A.9).

garnishment also cannot explain our results because of the borrowing cycle.[37] Expected family contribution (EFC) rules also cannot explain our results because these rules only pertain to federal subsidized student loans and not unsubsidized loans or PLUS loans.

6.4.6 The cost of default

In general, federal student debt is more difficult to discharge in bankruptcy than other forms of consumer credit. However, federal student debt also has an attractive IBR option that is especially valuable to the low-wage workers in our sample. Given their income, the average bound employee would have a $0 payment towards student debt under an IBR. Hence, we do not expect the inability to discharge student debt in bankruptcy to materially contribute to our results.[38]

Nevertheless, to provide some empirical evidence on whether default costs help explain the reduction in student debt, we re-estimate Equation 3 across sub-samples of former students based on their ex-ante default status.[39] If default costs are excessively high, then we should expect former students that are in default to use an increase in income to become current on their debts. Table A.12, however, shows this is not the case. Former students in default do not repay student debt more aggressively or exit default more often following an increase in the minimum wage.[40] Combined, these results suggest that the costs of default do not explain the reduction in student debt.

37. The magnitude of the effect (i.e., one-third of the increase in income is used to reduce debt) is also too large to be explained by IBRs or wage garnishment laws. IBRs require payments of 10 to 15 percent of discretionary income (i.e., income above 150 percent of the federal poverty line) and wage garnishment laws require payments of 15 percent of disposable income (i.e., income above $217.50 per week). Under both of these programs, the average minimum wage workers would owe $0 each month. In addition, no more than 15 percent of the increase in income would be captured by either program. Federal student debt wage garnishment laws supersede state and local laws.

38. Furthermore, this also guards us against the presence of former students in our enrolled students sample. If there are any, given the presence of IBR, we do not expect them to materially contribute to our findings.

39. Because federal student debt bankruptcy laws supersede state and local laws and enrolled students are still in the borrowing cycle, it is difficult to cross-sectionally test whether the cost of default can explain the reduction in student debt. At best, we can examine the actions of former students in default and not in default. Aside from the lack of limited liability, the default costs of student debt are similar to the default costs of other forms of consumer credit (e.g., derogatory marks on the credit report). Low-wage workers would effectively owe $0 under default.

40. As expected, former student that are current on their debts default less following a minimum wage change.

6.4.7 Habits

In the presence of habits, the initial marginal propensity to consume out of a minimum wage change will be less than one (Carroll 2001b). This initial, but gradually fading, savings response could generate a reduction in student debt among enrolled students. However, habits cannot explain the increase in total debt among former students and non-students.[41] Furthermore, habits cannot explain the choice to borrow less student debt instead of paying down credit card debt.

6.4.8 Precautionary motives

Meer and West 2016 and Gopalan et al. 2021 find that companies reduce hiring in response to an increase in the minimum wage. Given that a slow-down in hiring makes future earnings more volatile, enrolled students might save a portion of the minimum wage change due to precautionary reasons (Carroll 1997). Similar to habits, however, precautionary motives cannot explain the increase in total debt among former students and non-students. If anything, former students and non-students should save the *most* following a minimum wage change because they will experience the largest increase in earnings volatility. Precautionary motives also cannot explain the enrolled students' choice to borrow less student debt instead of paying down credit card debt.

7 Student debt aversion

In this section, we develop a consumption-savings model to highlight some potential frictions that may help us quantitatively match our empirical estimates. Specifically, we explore the effects of two behavioral frictions on the marginal propensity to borrow out of a minimum wage change: (1) a high perceived student loan interest rate and (2) student debt aversion. Our goal is to estimate the level of each friction that allows us to quantitatively match our empirical estimates.

41. For former students and non-students, the implied marginal propensity to consume is above one. This is inconsistent with habit-based models but consistent with credit constraints models (e.g., Aaronson, Agarwal, and French 2012). To explain the reduction in student debt, the habit must be specific to enrolled students.

7.1 The baseline model

We start by considering a standard consumption-savings model with initial indebtedness and labor income risk. Formally, let c_t denote the consumption of the enrolled student in period t (measured in years). In each period, the enrolled student chooses current and future consumption to maximize expected lifetime utility:

$$\mathbf{E}_t \sum_{i=0}^{T-t} \beta^i \cdot u\left(c_{t+i}\right), \tag{6}$$

where β is the subjective discount factor, T is the planning horizon, $\mathbf{E}_t$ is the expectation operator conditional on information at time t, and $u\left(\cdot\right)$ is the one-period CRRA utility function with coefficient of relative risk aversion γ:

$$u\left(c_t\right) = \frac{c_t^{1-\gamma} - 1}{1-\gamma}. \tag{7}$$

We assume that, in period $t = 0$, the enrolled student works in a minimum wage job. This job provides a risky income stream of y_t per period. We also assume the enrolled student starts off with an initial debt load of b_0, and that the interest rate on this debt is r per period.[42] Given an amount of debt d_t borrowed or repaid at period t, the intertemporal budget constraint is:

$$c_t = y_t + d_t, \tag{8}$$

and the stock of debt evolves as:

$$b_t = \left(b_{t-1} + d_t\right) \cdot \left(1 + r\right). \tag{9}$$

where we assume that b_t is bounded below at zero.[43] Following Zeldes 1989, we assume that the

42. The debt in our model represents student debt. Introducing another form of unsecured debt and limiting student loan borrowing to an enrollment period does not affect our results.

43. Given our baseline parameter values, the $b_t \geq 0$ constraint never binds along the equilibrium path. Hence, our results are not sensitive to removing this assumption.

enrolled student cannot default on their debt. Therefore, the following terminal condition:

$$c_T = y_T - b_{T-1} \geq 0. \tag{10}$$

must also hold with probability one.[44]

Finally, the income process is:

$$y_t = y_t^* + \ddot{y}_t. \tag{11}$$

where y_t^* denotes the life-cycle portion of income and $\ddot{y}_t$ denotes the graduation portion of income. The life-cycle portion of income is comprised of a deterministic and a stochastic component:

$$y_t^* = \bar{y}_t \cdot \delta\left(\omega_t\right). \tag{12}$$

The deterministic component of income is:

$$\bar{y}_t = \begin{cases} y_0 \cdot \prod_{i=1}^{t}\left(1 + \mathbf{g}_t\right) & \text{if } t \leq T' \\ y_0 \cdot \prod_{i=1}^{T'}\left(1 + \mathbf{g}_t\right) & \text{otherwise} \end{cases} \tag{13}$$

where $\mathbf{g}_t$ is the income growth rate in period t, and T' is the end of the income growth period $(0 < T' < T)$. The stochastic component of income, δ, depends on a state variable ω_t that follows a Rouwenhorst AR(1) process with autocorrelation parameter ρ across K states of the world.[45] Thus,

44. The "no default" constraint is satisfied whenever the stock of debt is bounded above at the present value of future labor income along the worst possible income path.

45. This generates a Markov chain characterized by the transition probability $p_{\omega,\omega'}$ of transitioning from state ω this period to state ω' next period.

the life-cycle portion of income is:

$$\bar{y}_t \cdot \delta(\omega_t) = \begin{cases} \bar{y}_t \cdot \delta_1 & \text{if } \omega_t = 1 \\ \bar{y}_t \cdot \delta_2 & \text{if } \omega_t = 2 \\ ... & ... \\ \bar{y}_t \cdot \delta_K & \text{if } \omega_t = K \end{cases}. \tag{14}$$

where $\delta_1 < \delta_2 < ... < \delta_K$.

The graduation portion of income depends on an absorbing state variable π_t. This state variable represents graduation from college. We assume that graduation can occur with probability q during any of the first τ periods of the model. If the enrolled student graduates ($\pi_t = 1$), then their permanent income increases by $\Upsilon > 0$. If the student does not graduate during the first τ periods ($\pi_t = 0$), then she "drops out" of college and does not experience an increase in income. Hence, the graduation portion of income is equal to:

$$\ddot{y}_t = \begin{cases} 0 & \text{if } \pi_t = 0 \\ \Upsilon & \text{if } \pi_t = 1. \end{cases} \tag{15}$$

7.2 Incorporating minimum wage hikes

To examine the impact of the minimum wage on debt and borrowing, we simulate the model with and without a minimum wage hike. We model the minimum wage hike as an unexpected Δ percent increase in the life-cycle portion of income for individuals that have not graduated (yet). The income process in the model with the minimum wage hike is:

$$y_t' = y_t^* \cdot (1 + m_t) + \ddot{y}_t, \tag{16}$$

where m_t captures the minimum wage hike:

$$m_t = \begin{cases} \Delta & \text{if } \pi_t = 0 \\ 0 & \text{if } \pi_t = 1. \end{cases} \tag{17}$$

7.3 Calibration

We calibrate the model to the parameter values listed in Table 7. For non-standard parameter values, we list their sources in the right-most column.

7.4 Baseline results

Table 8 reports our estimate of the three-year marginal propensity to borrow out of a minimum wage change. We find that the MPB is 0.39 in our baseline model. Both the magnitude and the sign of the MPB is inconsistent with our empirical estimate of -0.38 from Section 5.

Figure A.12 presents the simulated average debt holdings and consumption across the life-cycle. Consistent with the traditional permanent income hypothesis, we find that the enrolled student borrows while young and pays down debt while old. The shape of the average debt holdings is inconsistent with the immediate reduction in student debt among enrolled students.

7.5 Credit constraints, tuition costs, and defaults

Next, we introduce credit constraints, tuition costs, and defaults to the model. Following Alonso 2018, we model credit constraints as the minimum of the natural borrowing limit $\bar{b}_t$ and an exogenous fraction χ of current income. The natural borrowing limit is equal to the present value of future labor income along the worst possible income path. For example, the worst possible path at $t = 0$ is the one in which $\omega_t = 1$ and $\pi_t = 0$ for all t. We model tuition as a per-period cost of κ during each of the first N periods. Finally, we model default as a minimum limit on consumption $\bar{a}$ during the last period (i.e., $b_T = \min(b_T, y_T - \bar{a})$ is repaid). In the model with default, we adjust the interest rate on debt so that lenders break even. Our goal is to examine whether introducing these frictions can generate a negative marginal propensity to borrow. Table 8 reports our estimates of the MPB.[46] There are three key takeaways.

First, although introducing credit constraints greatly reduces the MPB, the enrolled student still spends their entire increase in income from the minimum wage.[47] Therefore, credit constraints cannot explain the observed reduction in student debt in response to the minimum wage. Second, introducing tuition costs increases the MPB. This is because the enrolled student must now borrow more to finance their investment in education. Third, introducing defaults reduces the MPB, but not by enough to match our empirical estimate.[48] Overall, the inability of credit constraints, tuition costs, and defaults to generate a negative MPB is consistent with our tests in Section 6.

7.6 The perceived cost of student debt

We now introduce behavioral frictions to the model. To start, we allow the enrolled student to perceive an unrealistically high interest rate on student debt. As shown in Table 8, we find that an interest rate in excess of 25 percent can generate a negative MPB out of a minimum wage change. Even with this high an interest rate, the negative MPB is greater than our empirical estimate of -0.38. Note that this interest rate is well above our model-implied likelihood of default and the average undergraduate student loan interest rate during our sample period.

The intuition behind our model with a high perceived interest rate is similar to our model with defaults. All else equal, a higher interest rate increases the opportunity cost of consumption and depresses the present value of expected future income. Both of these forces encourage the enrolled student to save more and borrow less in response to an increase in the minimum wage.[49]

46. Figures A.13, A.14, and A.15 plot the simulated average consumption and debt holdings.

47. The intuition is as follows. Given her high expected future income, the enrolled student wants to borrow to smooth consumption. However, her high initial debt load causes the credit constraint to bind at the onset of the model. The increase in the minimum wage is not large enough to relax the credit constraint. Hence, the best the enrolled student can do is spend her entire increase in income from the minimum wage change.

48. The intuition is as follows. Letting the enrolled student default forces the lender to charge a higher break-even interest rate. The higher interest rate, in turn, discourages the enrolled student from borrowing out of the minimum wage change. The higher interest rate also reduces the desire to consume through its effect on the present value of expected future income and the terminal budget constraint.

49. Figure A.16 plots the average consumption and debt holdings over the life-cycle.

7.7 Student debt aversion

We also consider a model with student debt aversion. We model student debt aversion as a direct utility penalty associated with holding student debt (á la Field 2009). The one-period CRRA utility function with student debt aversion is:

$$u(c_t) = \frac{c_t^{1-\gamma} - 1}{1-\gamma} - \theta \cdot b_t. \tag{18}$$

where θ is the student debt aversion parameter. All else equal, a higher θ parameter will incentivize the enrolled student to save more and borrow less. Our goal is to calculate the level of θ that allows us to generate a marginal propensity to borrow of -0.38.

Table 8 reports our calibrated student debt aversion parameter. We find that a student debt aversion parameter of $\theta = 0.159$ generates a MPB out of a minimum wage change of -0.38. Figure A.17 plots the average consumption and debt holdings over the life-cycle. Consistent with our prior estimates, the enrolled student gradually reduces their debt holdings after a minimum wage change.

7.7.1 A note on former students

One interesting result in our paper is that former students do not reduce their student debt following an increase in the minimum wage. Although this behavior seems to contradict the predictions from our model with student debt aversion, it could still be consistent given the structure of most student loan repayment plans (e.g., income-based repayment plans). Essentially, the average former student would have a monthly payment of zero under these repayment plans. Hence, the market value of their student debt would be zero. This, in turn, would mitigate the effects of student debt aversion and result in them not wanting to pay back their student debt.

8 Conclusion

In this paper, we use precise payroll and consumer credit data to examine the effects of the minimum wage on the debts of low-wage workers. We find the effects are nuanced. In the three years following a \$0.88 increase in the minimum wage, the average low-wage worker experiences a \$2,712 increase in income and a \$856 decrease in debt. We find the entire decline in debt comes from a reduction in student loan borrowing among enrolled college students. Non-students and former students, in contrast, borrow more in response to an increase in the minimum wage. Credit constraints, changes in labor supply, buffer-stock behavior, and several other channels cannot explain the reduction in student loan borrowing. Even more puzzling, enrolled students choose to accumulate less student debt instead of reducing their higher interest credit card balances. We find that a consumption-savings model with student debt aversion best matches our empirical findings.

Our results should be interpreted with several caveats in mind. First, we estimate the effect of the minimum wage on the debts of incumbent low-wage workers. This effect could be different than the aggregate effect of the minimum wage if firms reduce hiring (e.g., Gopalan et al. 2021). Second, we focus on enrolled students inframarginal to the college attendance decision. An increase in the minimum wage could also affect the initial decision to attend college as well as the decision to finance education with debt.[50] Third, although our sample contains historically large minimum wage changes, these changes are still much smaller than those recently proposed in the Raise the Wage Act. Finally, our estimates alone cannot be used to understand the total welfare effects of the minimum wage. For a comprehensive analysis of welfare, please see MaCurdy 2015.

Our paper has a number of important implications for both policy makers and researchers. Ours is one of the first papers to highlight a strong link between minimum wage policies and student loan balances. Our results imply that the recent growth in student loan balances may be partially due to the higher rate of inflation in college tuition relative to minimum wages.[51] Therefore, an important consequence of increasing the federal minimum wage to \$15 per hour could be a reduction

50. We note, however, that we find no changes in county-level college enrollment (Section 6).
51. See Sherman 2020 and McGill and Rust 2021.

in the aggregate rate of growth of student loan balances. We are also among the first to provide large sample evidence consistent with student debt aversion among low-wage workers. This is an important characteristic of low-wage workers that student loan policy makers and researchers modelling the preferences of low-wage workers should take into account. Exploring a potential rational basis for student debt aversion could be a fruitful area for future research.

Finally, we note that our payroll and consumer credit data provide us with several advantages over other studies in the minimum wage literature. First, the data allows us to precisely identify minimum wage workers and examine multiple dimensions of their liabilities. This is important because the borrowing and debt responses to the minimum wage vary across different groups of workers (e.g., enrolled students versus former students) and categories of consumer credit. For example, our heterogeneous results across categories of consumer debt help reconcile the positive auto debt response in Aaronson, Agarwal, and French 2012 with the negative aggregate debt response in Cooper, Luengo-Prado, and Parker 2020. Second, the data allows us to pin-point the source of our effects in the wage distribution and over a long post-period of time. As noted in Agarwal and Qian 2014 and Cengiz et al. 2019, this can be informative about model validity and the constraints faced by low-wage workers. Overall, our findings should be useful for developing consumption-savings models and understanding low-wage workers' preferences and financial constraints (Zinman 2015).

References

Aaronson, Daniel, Sumit Agarwal, and Eric French. 2012. "The spending and debt responses to minimum wage hikes." *American Economic Review* 102 (7): 3111–3139.

Agarwal, Sumit, Chunlin Liu, and Nicholas S. Souleles. 2007. "The reaction of consumer spending and debt to tax rebates - Evidence from consumer credit data." *Journal of Political Economy* 115 (6): 986–1019.

Agarwal, Sumit, and Wenlan Qian. 2014. "Consumption and debt responses to unanticipated income shocks: Evidence from a natural experiment in Singapore." *American Economic Review* 104 (12): 4205–4230.

Alonso, Cristian. 2018. "Hard vs. soft financial constraints: Implications for the effects of a credit crunch." *Journal of Macroeconomics* 58:198–223.

Avery, Robert B., Raphael W. Bostic, Paul S. Calem, and Glenn B. Canner. 2003. "An overview of consumer data and credit reporting." *Federal Reserve Bulletin* February:47–73.

Becker, Thomas A., and Reza Shabani. 2010. "Outstanding debt and the household portfolio." *The Review of Financial Studies* 23 (7): 2900–2934.

Brochu, Pierre, David A. Green, Thomas Lemieux, and James Townsend. 2019. "The minimum wage, turnover, and the shape of the wage distribution." Working paper.

Brown, Jeffrey R., Chichun Fang, and Francisco Gomes. 2012. "Risk and returns to education." NBER Working Paper no. 18300.

Cadena, Brian C., and Benjamin J. Keys. 2013. "Can self-control explain avoiding free money: Evidence from interest-free student loans." *Review of Economics and Statistics* 95 (4): 1117–1129.

Caetano, Gregorio, Miguel Palacios, and Harry A. Patrinos. 2019. “Measuring aversion to debt: an experiment among student loan candidates.” *Journal of Family and Economic Issues* 40 (1): 117–131.

Card, David, and Alan B. Krueger. 1995. *Myth and measurement: The new economics of the minimum wage.* Princeton: Princeton University Press.

Carroll, Christopher D. 2001a. “A theory of the consumption function, with and without liquidity constraints.” *The Journal of Economic Perspectives* 15 (3): 23–45.

———. 1997. “Buffer-stock savings and the life-cycle / permanent income hypothesis.” *The Quarterly Journal of Economics* 112 (1): 1–55.

———. 2001b. “’Risky habits’ and the marginal propensity to consume out of permanent income.” *International Economic Journal* 14 (4): 1–44.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. “The effect of minimum wages on low-wage jobs.” *The Quarterly Journal of Economics* 134 (3): 1405–1454.

Chakrabarti, Rajashri, Slava Fos, Andres Liberman, and Constantin Yannelis. 2020. “Debt and human capital: Evidence from student loans.” Working paper.

Chetty, Raj, and Adam Szeidl. 2007. “Consumption comittments and risk preferences.” *The Quarterly Journal of Economics* 122 (2): 831–877.

Clemens, Jeffrey, and Michael Wither. 2019. “The minimum wage and the Great Recession: Evidence of effects on the employment and income trajectories of low-skilled workers.” *Journal of Public Economics* 170:53–67.

Cookson, J. Anthony, Erik P. Gilje, and Rawley Z. Heimer. 2020. “Shale shocked: The long-run effect of wealth on household debt.” Working paper.

Cooper, Daniel, Maria J. Luengo-Prado, and Jonathan A. Parker. 2020. “The local aggregate effects of minimum wage increases.” *Journal of Money, Credit, and Banking* 52 (1): 5–35.

Dettling, Lisa J., and Joanne W. Hsu. 2020. "Minimum wage and consumer credit: Impacts on access to credit and traditional and high-cost borrowing." *The Review of Financial Studies* Forthcoming.

Dube, Arindrajit, Laura Giuliano, and Jonathan Leonard. 2019. "Fairness and frictions: The impact of unequal raises on quit behavior." *American Economic Review* 109 (2): 620–663.

Dube, Arindrajit, T. William Lester, and Michael Reich. 2010. "Minimum wage effects across state borders: Estimates using contiguous counties." *The Review of Economics and Statistics* 92 (4): 945–964.

———. 2016. "Minimum wage shocks, employment flows and labor market frictions." *Journal of Labor Economics* 34 (3): 663–704.

Field, Erica. 2009. "Educational debt burden and career choice: Evidence from a financial aid experiment at NYU Law School." *American Economic Journal: Applied Economics* 1 (1): 1–21.

Gicheva, Dora. 2009. "Student loans or marriage? A look at the highly educated." *Economics of Education Review* 53 (1): 207–216.

Goldrick-Rab, Sara, and Robert Kelchen. 2015. "Making sense of loan aversion: Evidence from Wisconsin." *Student Loans and the Dynamics of Debt:* 317–377.

Gopalan, Radhakrishnan, Barton Hamilton, Ankit Kalda, and David Sovich. 2021. "State minimum wages, employment, and wage spillovers: Evidence from administrative payroll date." *Journal of Labor Economics* Forthcoming.

Hirshleifer, David A. 2007. "Psychological bias as a driver of financial regulation." *European Financial Management* 14 (5): 856–874.

Japelli, Tullio, and Luigi Pistaferri. 2010. "The consumption response to income changes." *Annual Review of Economics* 2:479–506.

MaCurdy, Thomas. 2015. “How effective is the minimum wage at supporting the poor?” *Journal of Political Economy* 123 (2): 497–545.

McGill, Brian, and Max Rust. 2021. “How much does the federal minimum wage buy you? Now vs. Then.” *The Wall Street Journal.* Accessed May 10, 2021. `https://www.wsj.com/articles/how-much-does-the-federal-minimum-wage-buy-you-now-vs-then-11614866413`.

Meer, Jonathan, and Jeremy West. 2016. “Effects of the minimum wage on employment dynamics.” *The Journal of Human Resources* 51 (2): 500–522.

Meissner, Thomas. 2016. “Intertemporal consumption and debt aversion: an experimental study.” *Experimental Economics* 19 (2): 281–298.

Mezza, Alvaro, Daniel Ringo, Shane Sherlund, and Kamila Sommer. 2020. “Student loans and homeownership.” *Journal of Labor Economics* 38 (1): 215–260.

Neumark, David. 2018. “The econometrics and economics of the employment effects of the minimum wages: Getting from known unknowns to known knowns.” Working paper.

Neumark, David, Ian J.M. Salas, and William Wascher. 2014. “Revisiting the minimum wage-employment debate: Throwing out the babay with the bathwater?” *Industrial and Labor Relations Review* 67 (3): 608–648.

Neumark, David, and William L. Wascher. 2007. “Minimum wages and employment.” *Foundations and Trends in Microeconomics* 3 (1): 1–182.

Oosterbeek, Hessel, and Anja van den Broek. 2009. “An empirical analysis of borrowing behaviour of higher education students in the Netherlands.” *Economics of Education Review* 28 (2): 170–177.

Prelec, Drazen, and George Loewenstein. 1998. “The red and the black: Mental accounting of savings and debt.” *Marketing science* 17 (1): 4–28.

Rothstein, Jesse, and Cecilia E. Rouse. 2011. “Constrained after college: Student loans and early-career occupational choices.” *Journal of Public Economics* 95 (1): 149–163.

Shahdad, Sarah. 2014. “What younger renters want and the financial constraints they see.” *Fannie Mae.* Accessed February 8, 2021. https://www.fanniemae.com/portal/research-insights/perspectives/050514-shahdad.html.

Shao, Ling. 2015. “Debt, marriage, and children: The impact of student loans on marriage and fertility.” Working paper.

Sherman, Erik. 2020. “College tuition is rising at twice the rate of inflation – while students learn at home.” *Forbes.* Accessed May 10, 2021. https://www.forbes.com/sites/zengernews/2020/08/31/college-tuition-is-rising-at-twice-the-inflation-rate-while-students-learn-at-home/?sh=307e03842f98.

Stango, Victor, and Jonathan Zinman. 2009. “Exponential growth bias and household finance.” *Journal of Finance* 64 (6): 2807–2849.

Thaler, Richard H. 1990. “Saving, fungibility, and mental accounts.” *Journal of Economic Perspectives* 4 (1): 193–205.

Zeldes, Stephen P. 1989. “Optimal consumption with stochastic income deviations from certainty equivalence.” *The Quarterly Journal of Economics* 104 (2): 275–298.

Zinman, Jonathan. 2015. “Household debt: Facts, puzzles, theories, and policies.” *Annual Review of Economics* 7:251–276.

Table 1: Descriptive statistics: state minimum wage changes

Treated state (1)	MW Δ date (2)	BOP MW (3)	MW Δ amount (4)	Control states (5)	Treated counties (6)	Control counties (7)
AR	201501	7.25	0.25	(OK, TX, LA, MS, TN)	19	25
CA	201407	8.00	1.00	(NV)	10	8
DC	201407	8.25	1.25	(VA)	1	1
DE	201406	7.25	0.50	(PA)	1	1
MA	201501	8.00	1.00	(NH)	4	3
MD	201501	7.25	0.75	(PA, VA)	12	15
ME	201702	7.50	1.50	(NH)	2	3
MI	201409	7.40	0.75	(WI, IN)	9	10
MN	201408	7.25	0.75	(ND, IA, WI)	25	25
NE	201501	7.25	0.75	(WY, KS, IA)	25	21
NJ	201401	7.25	1.00	(PA)	7	5
NY	201401	7.25	0.75	(PA)	10	9
SD	201501	7.25	1.25	(WY, ND, IA)	16	14
WV	201501	7.25	0.75	(PA, KY, VA)	21	22

NOTE.—This table describes the sample of state minimum wage changes. There are 14 treated states and 16 control states. The definition of treated and control states is provided in section 2. The columns are defined as follows: MW Δ date is the year-month in which a treated state changes its minimum wage, BOP MW is the state's minimum wage at the beginning of the sample period, MW Δ amount is the size of the minimum wage change, Control states is the set of control states for each treated state, Treated counties is the number of counties in the treated state that border a county in a control state, and Control counties is the number of counties in the control states that border at least one county in a treated state. There are 324 border counties in the analysis, 162 of which are from the treated states.

Table 2: Descriptive statistics: bound employees

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	Treated (6)	Control (7)	Diff (8)	t(Diff) (9)
Hourly wage	7.82	0.53	7.30	7.75	8.25	7.88	7.78	0.10	0.34
Hours per week	29.18	10.46	20.00	30.00	40.00	28.60	29.74	-1.14	-0.58
Tenure (months)	16.87	31.71	1.00	6.00	18.00	15.72	17.82	-2.10	-0.45
Age (years)	30.70	12.56	21.00	25.00	39.00	30.14	31.16	-1.02	-0.70
Enrolled student? (1/0)	0.29	0.45	0.00	0.00	1.00	0.27	0.30	-0.03	-0.40
Former student? (1/0)	0.10	0.30	0.00	0.00	0.00	0.10	0.10	0.01	0.70
Credit score	582	126	516	583	671	579	585	-6	-0.78
Has active trade? (1/0)	0.75	0.43	0.00	1.00	1.00	0.74	0.76	-0.02	-1.41
Has credit card? (1/0)	0.48	0.50	0.00	0.00	1.00	0.49	0.48	0.01	0.33
Has auto loan? (1/0)	0.20	0.40	0.00	0.00	0.00	0.19	0.21	-0.01	-0.49
Has student loan? (1/0)	0.39	0.49	0.00	0.00	1.00	0.38	0.40	-0.02	-0.30
Total balances	11499	19750	0	3644	15388	10900	11995	-1094	-0.87
Card balances	1325	4305	0	0	661	1333	1318	15	0.09
Auto balances	2641	6941	0	0	0	2455	2796	-341	-0.60
Student balances	7269	16980	0	0	7900	6892	7581	-689	-0.38
Card credit limits	4070	11693	0	0	2000	3854	4250	-396	-0.51
Card credit utilization	0.28	2.91	0.00	0.00	0.36	0.30	0.26	0.04	1.04
Is 90+ delinquent? (1/0)	0.17	0.38	0.00	0.00	0.00	0.16	0.18	-0.02	-1.58
Card 90+ delinquent? (1/0)	0.09	0.28	0.00	0.00	0.00	0.09	0.09	0.00	0.80
Auto 90+ delinquent? (1/0)	0.03	0.16	0.00	0.00	0.00	0.02	0.03	-0.01	-1.69
Student 90+ deqlinquent? (1/0)	0.06	0.24	0.00	0.00	0.00	0.06	0.07	-0.01	-0.79

NOTE.—This table contains descriptive statistics for the 76,982 bound employees. The descriptive statistics are as-of the month closest to three months prior to treatment. The right-most columns are defined as follows: Treated is the mean value in treated counties, Control is the mean value in control counties, Diff is the difference in means between treated and control counties, and t(Diff) is the t-statistic for the difference in means.

Table 3: Wages, employment, and incomes

	Hourly wage		Employment		Hours		Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	0.651***	0.576***	0.000	0.000	0.267	0.221	1058***	912***
	(7.80)	(25.73)	(-0.59)	(-0.31)	(1.28)	(1.30)	(3.99)	(7.60)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y	Y	Y
Control variables		Y		Y		Y		Y
N	2,021,644	2,014,193	2,021,644	2,014,193	884,581	881,318	884,581	881,318
R^2	0.76	0.76	0.13	0.13	0.84	0.84	0.82	0.82

NOTE.—This table reports coefficient estimates from Equation 1. The dependent variable in Columns (1) and (2) is the hourly wage. The dependent variable in Columns (3) and (4) is a dummy variable for employment. The dependent variable in Columns (5) and (6) is the average number of hours worked per week. The dependent variable in Columns (7) and (8) is annual income. The sample is restricted to bound hourly wage employees that remain employed. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 4: Debt balances and open accounts

	Total		Card		Auto		Student	
	Balances	Accounts	Balances	Accounts	Balances	Accounts	Balances	Accounts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	-856***	-0.09*	18	0.05**	117*	0.01*	-944***	-0.14***
	(-2.76)	(-1.71)	(1.11)	(2.31)	(1.74)	(1.67)	(-3.26)	(-3.96)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
N	3,732,264	3,732,264	3,732,264	3,732,264	3,732,264	3,732,264	3,732,264	3,732,264
R^2	0.85	0.87	0.79	0.85	0.65	0.70	0.90	0.89

NOTE.—This table contains coefficient estimates from Equation 3. The dependent variable in Columns (1) and (2) is total debt balances and open accounts. The dependent variable in Columns (3) and (4) is credit card balances and open accounts. The dependent variable in Columns (5) and (6) is auto loan balances and open accounts. The dependent variable in Columns (7) and (8) is student debt balances and open accounts. The sample is restricted to bound hourly wage employees. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 5: Enrolled students versus former students

	Total		Card		Auto		Student	
	Balances	Accounts	Balances	Accounts	Balances	Accounts	Balances	Accounts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	307**	0.12***	-2	0.03	282**	0.04***	117	0.05**
	(2.21)	(4.30)	(-0.04)	(1.11)	(2.50)	(7.13)	(0.92)	(1.98)
Treated × Post × Enrolled student	-1,185**	-0.28***	29	-0.00	-82	-0.03***	-1,142***	-0.25***
	(-2.34)	(-3.81)	(0.44)	(-0.03)	(-1.08)	(-4.66)	(-2.68)	(-4.63)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
N	1,446,763	1,446,763	1,446,763	1,446,763	1,446,763	1,446,763	1,446,763	1,446,763
R^2	0.87	0.85	0.79	0.83	0.64	0.69	0.88	0.85

NOTE.—This table contains coefficient estimates from Equation 4. The dependent variable in Columns (1) and (2) is total debt balances and open accounts. The dependent variable in Columns (3) and (4) is credit card balances and open accounts. The dependent variable in Columns (5) and (6) is auto loan balances and open accounts. The dependent variable in Columns (7) and (8) is student debt balances and open accounts. The sample is restricted to enrolled students and former students. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 6: Why do enrolled students borrow less student debt?

	Balances			Accounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post	-851**	-925**	-867**	-0.19***	-0.22***	-0.18***
	(-2.04)	(-2.16)	(-2.19)	(-3.66)	(-5.66)	(-4.56)
Treated * Post * Credit constrained	-312			-0.03		
	(-1.00)			(-0.48)		
Treated * Post * High credit utilization		-221			0.08	
		(-0.59)			(1.15)	
Treated * Post * Low graduation rate			192			0.05
			(0.24)			(0.46)
Employee FE	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y
N	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176
R^2	0.88	0.88	0.88	0.85	0.85	0.85

NOTE.—This table contains coefficient estimates from Equation 5. The dependent variable in Columns (1) through (3) is student loan balances. The dependent variable in Columns (4) through (6) is open student loan accounts. The sample is restricted to enrolled students. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 7: Model parameters

Parameter	Symbol	Value	Source
Coefficient of relative risk aversion	γ	2	Aaronson, Agarwal, and French 2012
Subjective discount factor	β	0.93	Aaronson, Agarwal, and French 2012.
Number of time periods	T	40	
Autocorrelation of income	ρ	0.995	Aaronson, Agarwal, and French 2012.
Income risk	σ	23.45%	Aaronson, Agarwal, and French 2012.
Deterministic income growth	$\mathbf{g}$	1.08%	Aaronson, Agarwal, and French 2012.
States of the world	K	5	
Income growth periods	T'	20	Aaronson, Agarwal, and French 2012
Initial debt	b_0	$19, 200	Average bound employee debt in Table 2.
Interest rate	r	4%	Average undergraduate federal student loan interest rate during sample period.
Initial income	y_0	$10,243	Average bound employee income in Table 2.
Income jump at graduation	Υ	$10,000	Average income jump upon graduation from the National Longitudinal Survey of Youth 1997
Per-period graduation probability	q	0.08	Average per-period attrition probability of enrolled students in sample.
Potential graduation periods	τ	6	
Minimum wage increase	Δ	7.81%	Average minimum wage hike during sample period.
Protected assets	$\bar{a}$	$2,575	Average wildcard exemption in California, South Dakota, Massachusetts, Michigan, Nebraska, and West Virginia
Credit constraint	χ	34%	Alonso 2018.

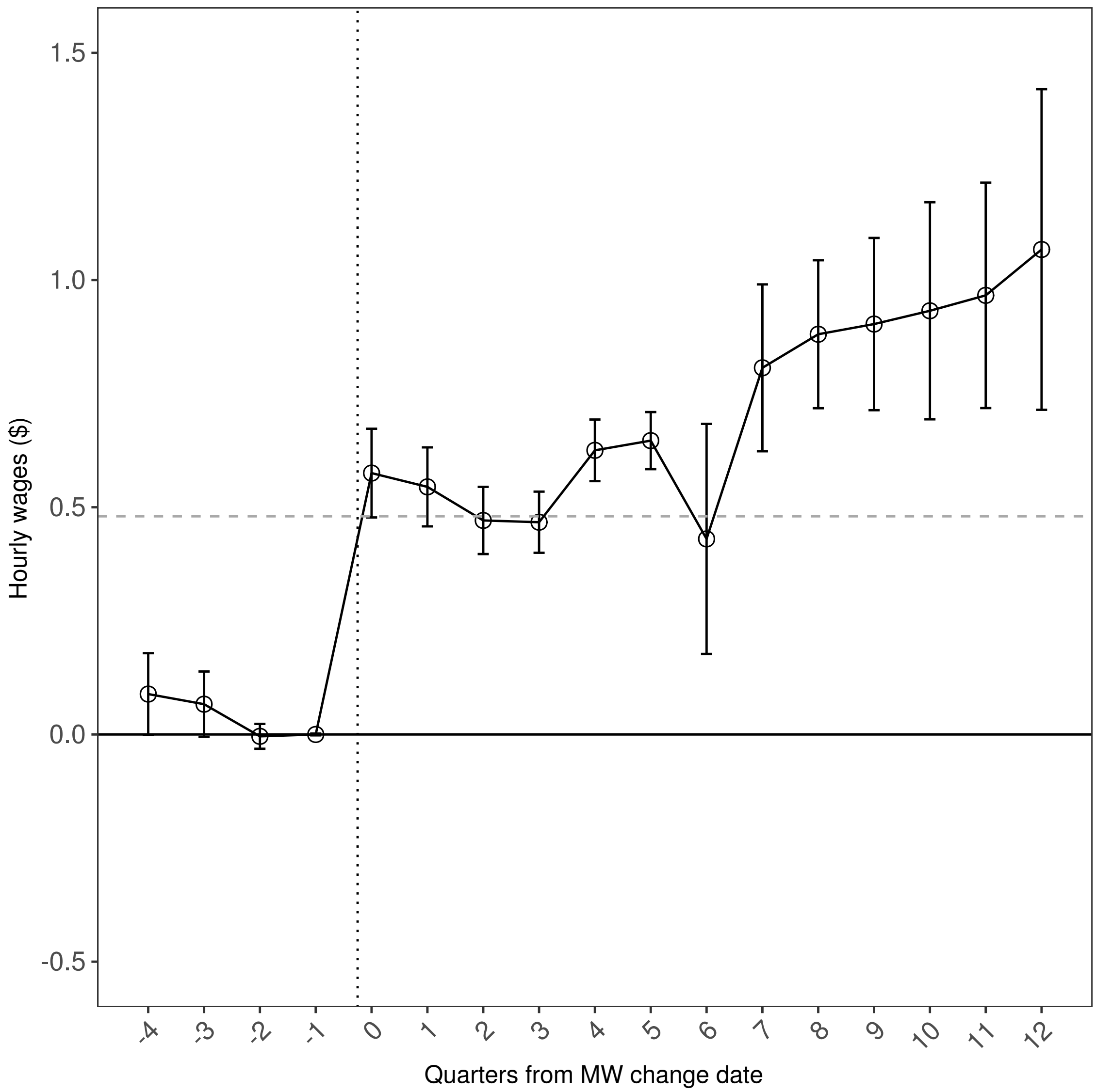
NOTE.— This table contains the model parameters.

Table 8: Marginal Propensity to borrow out of a minimum wage change

Model	MPB	Fitted values
Baseline (no frictions)	0.39	
Credit constraints	0.00	
Tuition costs	0.59	
Defaultable debt	0.30	$r^* = 4.6\%$
Perceived interest rate	-0.15	$r^* = 25.0\%$
Student debt aversion	-0.38	$\theta = 0.159$

NOTE.— This table contains estimates of the marginal propensity to borrow out of a minimum wage change. The columns are defined as follows: *Model* is the estimated model, *MPB* is the estiamte of the marginal propensity to borrow, and *Fitted values* are other calibrated parameters from the model.

Figure 1: Wage response

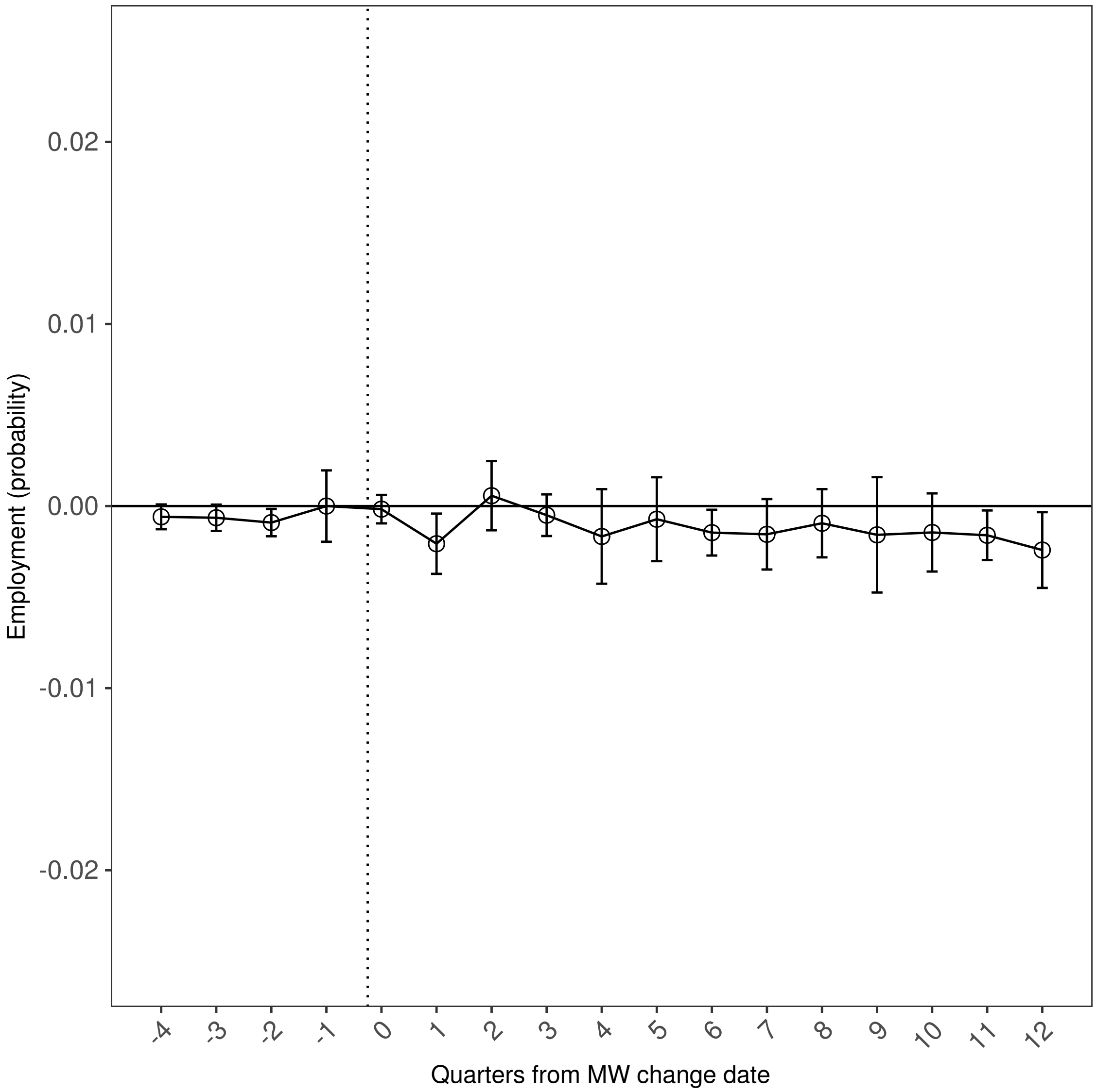


NOTE.—This figure plots coefficient estimates from a dynamic version of equation 1:

$$\omega_{i,t} = \alpha + \sum_{\tau=-4}^{12} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when quarter t is τ quarters away from a minimum wage increase in state s. The outcome variable is the hourly wage. The x-axis corresponds to the number of quarters from a minimum wage increase. The circles correspond to the coefficient estimates. The vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. In the estimation, quarter $\tau = -1$ is excluded as the reference level.

Figure 2: Employment response

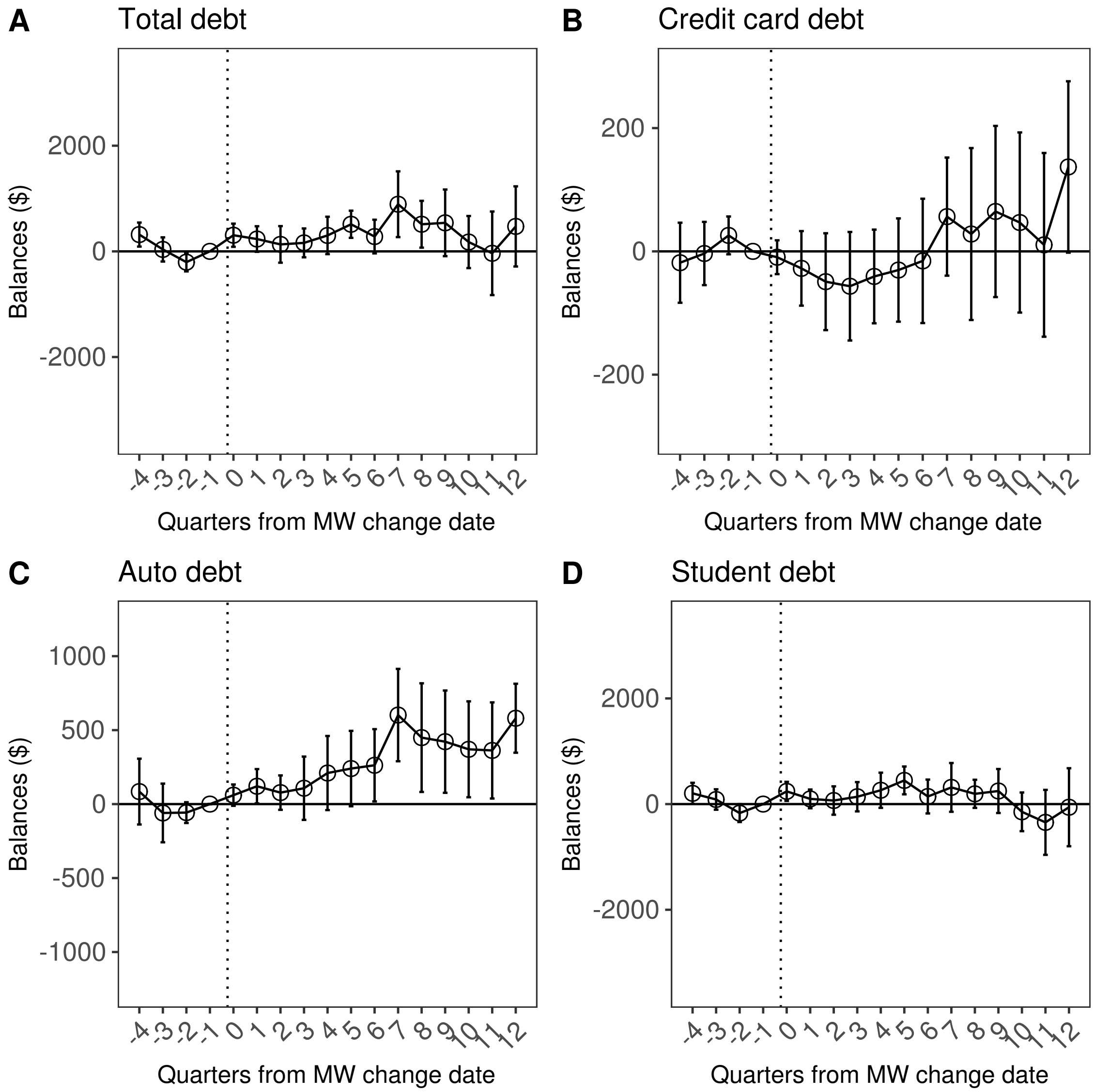


NOTE.—This figure plots coefficient estimates from a dynamic version of Equation 1:

$$y_{i,t} = \alpha + \sum_{\tau=-4}^{12} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when quarter t is τ quarters away from a minimum wage increase in state s. The outcome variable is a dummy variable for employment. The x-axis corresponds to the number of quarters from a minimum wage increase. The circles correspond to the coefficient estimates. The vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. In the estimation, quarter $\tau = -1$ is excluded as the reference level.

Figure 3: Debt response of former students

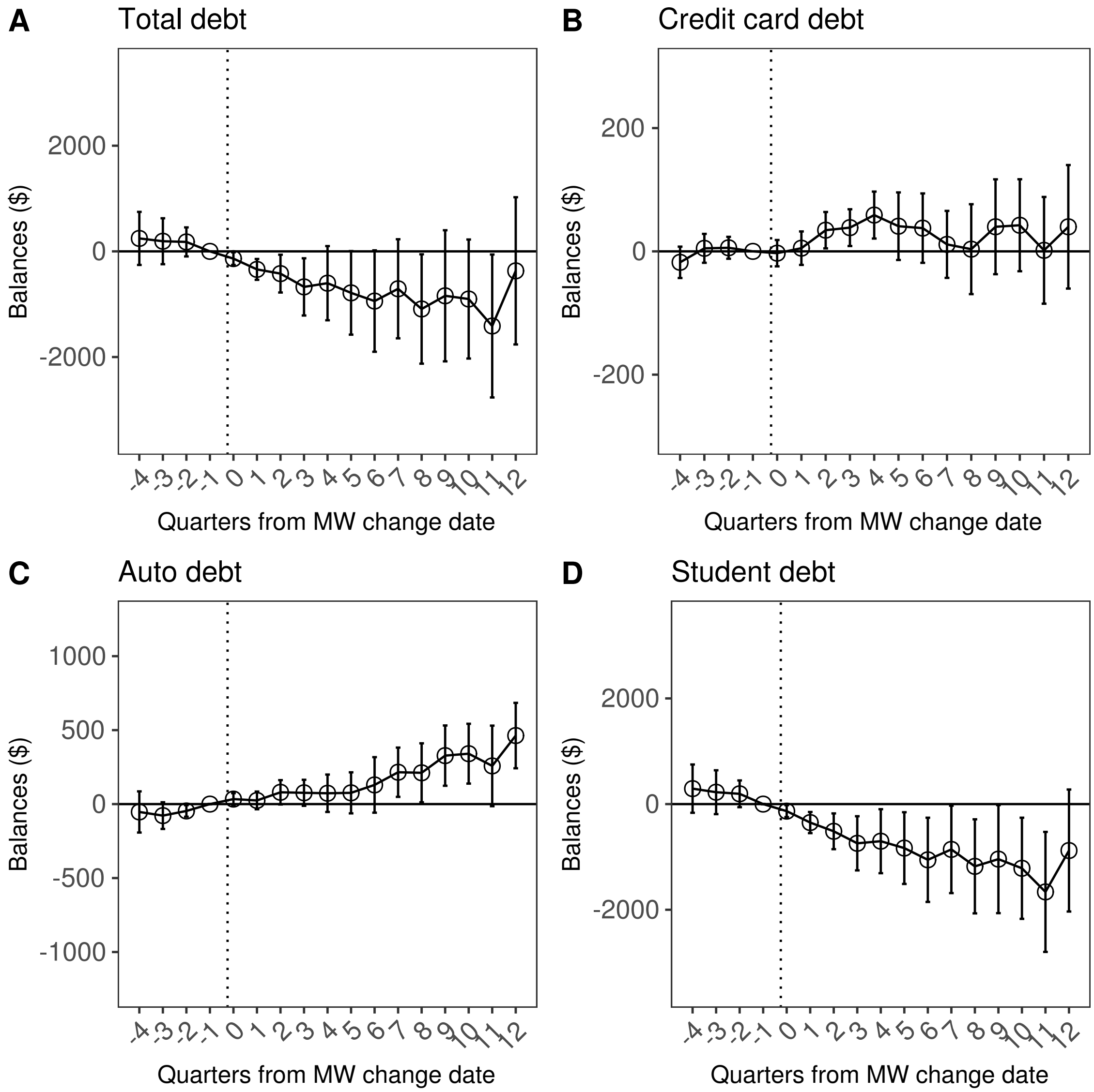


NOTE.—This figure plots coefficient estimates from a dynamic version of Equation 3:

$$y_{i,t} = \alpha + \sum_{\tau=-4}^{12} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when quarter t is τ quarters away from a minimum wage increase in state s. The sample is restricted to former students. The outcome variable is either total debt, credit card debt, auto loan debt, or student loan debt. The x-axis corresponds to the number of quarters from a minimum wage increase. The circles correspond to the coefficient estimates. The vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. In the estimation, quarter $\tau = -1$ is excluded as the reference level.

Figure 4: Debt response of enrolled students

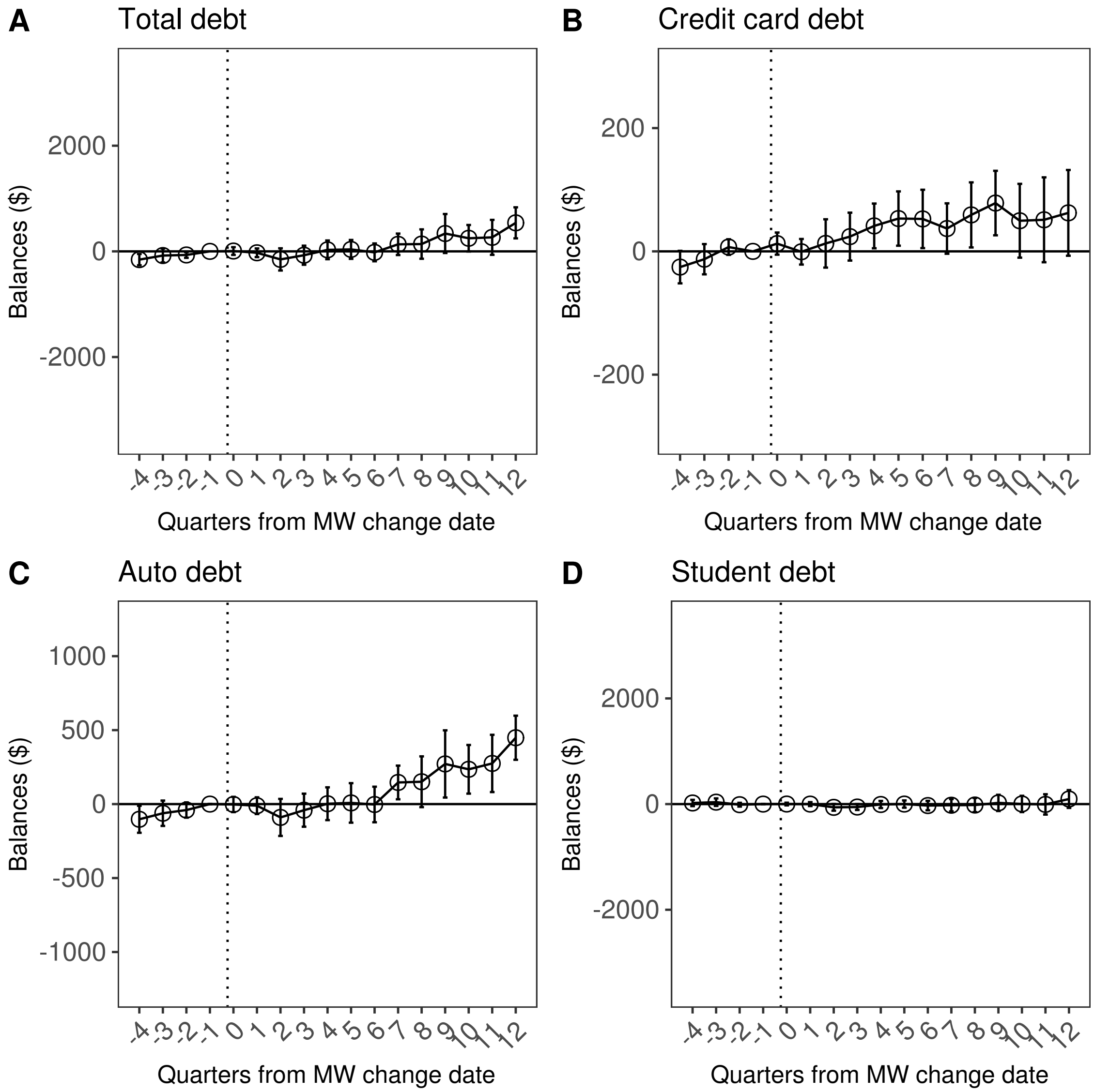


NOTE.—This figure plots coefficient estimates from a dynamic version of Equation 3:

$$y_{i,t} = \alpha + \sum_{\tau=-4}^{12} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when quarter t is τ quarters away from a minimum wage increase in state s. The sample is restricted to enrolled students. The outcome variable is either total debt, credit card debt, auto loan debt, or student loan debt. The x-axis corresponds to the number of quarters from a minimum wage increase. The circles correspond to the coefficient estimates. The vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. In the estimation, quarter $\tau = -1$ is excluded as the reference level.

Figure 5: Debt response of non-students



NOTE.—This figure plots coefficient estimates from a dynamic version of Equation 3:

$$y_{i,t} = \alpha + \sum_{\tau=-4}^{12} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when quarter t is τ quarters away from a minimum wage increase in state s. The sample is restricted to non-students. The outcome variable is either total debt, credit card debt, auto loan debt, or student loan debt. The x-axis corresponds to the number of quarters from a minimum wage increase. The circles correspond to the coefficient estimates. The vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. In the estimation, quarter $\tau = -1$ is excluded as the reference level.

Appendix

Table A.1: List of state minimum wage changes

State	BOP MW	2010	2011	2012	2013	2014	2015	2016	2017	EOP MW
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
AK	7.75	0.5	0	0	0	0	1	1	0.05	9.8
AL	7.25	0	0	0	0	0	0	0	0	7.25
AR	7.25	0	0	0	0	0	0.25	0.5	0.5	8.5
AZ	7.25	0	0.1	0.3	0.15	0.1	0.15	0	1.95	10
CA	8	0	0	0	0	1	0	1	0.5	10.5
CO	7.25	-0.03	0.11	0.28	0.14	0.22	0.23	0.08	0.99	9.3
CT	8.25	0.25	0	0	0	0.45	0.45	0.45	0	9.6
DC	8.25	0	0	0	0	1.25	1	1	0	11.5
DE	7.25	0	0	0	0	0.5	0.5	0	0	8.25
FL	7.25	0	0.06	0.36	0.12	0.14	0.12	0	0.05	8.1
GA	7.25	0	0	0	0	0	0	0	0	7.25
HI	7.25	0	0	0	0	0	0.5	0.75	0.75	9.25
IA	7.25	0	0	0	0	0	0	0	0	7.25
ID	7.25	0	0	0	0	0	0	0	0	7.25
IL	8	0.25	0	0	0	0	0	0	0	8.25
IN	7.25	0	0	0	0	0	0	0	0	7.25
KS	7.25	0	0	0	0	0	0	0	0	7.25
KY	7.25	0	0	0	0	0	0	0	0	7.25
LA	7.25	0	0	0	0	0	0	0	0	7.25
MA	8	0	0	0	0	0	1	1	1	11
MD	7.25	0	0	0	0	0	1	0.5	0.5	9.25
ME	7.5	0	0	0	0	0	0	0	1.5	9
MI	7.4	0	0	0	0	0.75	0	0.35	0.4	8.9
MN	7.25	0	0	0	0	0.75	1	0.5	0	9.5
MO	7.25	0	0	0	0.1	0.15	0.15	0	0.05	7.7
MS	7.25	0	0	0	0	0	0	0	0	7.25
MT	7.25	0	0.1	0.3	0.15	0.1	0.15	0	0.1	8.15
NC	7.25	0	0	0	0	0	0	0	0	7.25
ND	7.25	0	0	0	0	0	0	0	0	7.25
NE	7.25	0	0	0	0	0	0.75	1	0	9
NH	7.25	0	0	0	0	0	0	0	0	7.25
NJ	7.25	0	0	0	0	1	0.13	0	0.06	8.44
NM	7.5	0	0	0	0	0	0	0	0	7.5
NV	7.55	0	0.7	0	0	0	0	0	0	8.25
NY	7.25	0	0	0	0	0.75	0.75	0.25	0.7	9.7
OH	7.3	0	0.1	0.3	0.15	0.1	0.15	0	0.05	8.15
OK	7.25	0	0	0	0	0	0	0	0	7.25
OR	8.4	0	0.1	0.3	0.15	0.15	0.15	0.5	0.5	10.25
PA	7.25	0	0	0	0	0	0	0	0	7.25
RI	7.4	0	0	0	0.35	0.25	1	0.6	0	9.6
SC	7.25	0	0	0	0	0	0	0	0	7.25
SD	7.25	0	0	0	0	0	1.25	0.05	0.1	8.65
TN	7.25	0	0	0	0	0	0	0	0	7.25
TX	7.25	0	0	0	0	0	0	0	0	7.25
UT	7.25	0	0	0	0	0	0	0	0	7.25
VA	7.25	0	0	0	0	0	0	0	0	7.25
VT	8.06	0	0.09	0.31	0.14	0.13	0.42	0.45	0.4	10
WA	8.55	0	0.12	0.37	0.15	0.13	0.15	0	1.53	11
WI	7.25	0	0	0	0	0	0	0	0	7.25
WV	7.25	0	0	0	0	0	0.75	0.75	0	8.75
WY	7.25	0	0	0	0	0	0	0	0	7.25

Table A.2: County descriptive statistics

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	Treated (6)	Control (7)	Diff (8)	t(Diff) (9)
Population	106045	239747	10293	30570	85466	107732	104358	3374	0.13
Unemployment rate	6.06	2.54	4.10	5.60	7.50	6.02	6.09	-0.07	-0.24
Employment	38736	95777	2396	7812	26715	39213	38258	955	0.09
# Establishments	2801	6569	272	688	1972	2946	2655	291	0.40
Total hires	8050	18694	614	1737	5895	8228	7875	353	0.16
Total separations	7885	17563	726	1958	6040	8182	7594	588	0.29
Average weekly wage	750	199	640	719	810	760	739	21	0.94
% Nontradable	0.32	0.15	0.23	0.31	0.38	0.31	0.33	-0.02	-1.06
% Tradable	0.04	0.08	0.00	0.01	0.05	0.04	0.05	-0.01	-1.00
% Construction	0.12	0.08	0.08	0.11	0.16	0.12	0.13	-0.01	-1.15
% Other	0.50	0.17	0.44	0.51	0.59	0.51	0.49	0.02	1.32
Fraction of employment <= 35 years old	0.33	0.03	0.30	0.32	0.34	0.33	0.33	0.00	-0.01
Fraction of employment White or Latino	0.88	0.13	0.86	0.94	0.97	0.89	0.87	0.02	1.37
Public 4-year tuition	8886	2961	6863	7946	10992	8515	9247	-732	-1.00
Public 2-year tuition	4448	1693	3314	4410	5358	4258	4765	-506	-1.39
Private 4-year tuition	26725	9071	21572	27424	32785	26162	27254	-1093	-0.49
Private 2-year tuition	12718	6532	6635	12442	16386	11420	14757	-3337	-1.06

NOTE.—This table contains descriptive statistics for the 324 border counties. The descriptive statistics are as-of the end of 2013. The right-most columns are defined as follows: Treated is the mean value of treated counties, Control is the mean value of control counties, Diff is the difference in means between treated and control counties, and t(Diff) is the *t*-statistic for the difference in means.

Table A.3: State descriptive statistics

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	Treated (6)	Control (7)	Diff (8)	t(Diff) (9)
Population	6631	8284	1856	4124	6675	7525	5848	1677	0.55
Population growth	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.00	-0.41
Unemployment rate	6.14	1.53	4.95	6.20	7.10	6.39	5.93	0.47	0.83
Average weekly earnings	826	149	720	792	882	868	788	80	1.50
GDP PC	52.07	22.07	43.13	48.16	53.82	57.73	47.12	10.61	1.33
GDP PC growth	0.00	0.02	-0.01	0.00	0.01	0.00	0.00	0.00	-0.44
HPI growth	0.05	0.05	0.03	0.04	0.06	0.05	0.05	0.00	0.26
Beginning minimum wage	7.38	0.31	7.25	7.25	7.25	7.46	7.31	0.14	1.31
Public 4-year tuition	8379	2393	6810	7880	10198	8794	8016	778	0.89
Public 2-year tuition	3985	1424	3147	3605	4507	4074	3912	162	0.30
Private 4-year tuition	26017	7262	20739	26672	31615	27659	24581	3079	1.17
Private 2-year tuition	12902	6209	9484	12121	15881	12318	13616	-1297	-0.46

NOTE.—This table contains descriptive statistics for the 30 states. The descriptive statistics are as-of the end of 2013. The right-most columns are defined as follows: Treated is the mean value of treated states, Control is the mean value of control states, Diff is the difference in means between treated and control states, and t(Diff) is the *t*-statistic for the difference in means.

Table A.4: First-difference transformation of the outcome variable

Horizon	Total balances (1)	Card balances (2)	Auto balances (3)	Student balances (4)
$T = 6$ (i.e., $\sum_{\tau=0}^{6} \Gamma_\tau$)	-452**	-34*	-85	-344**
	(-2.21)	(-1.90)	(-0.94)	(-2.33)
$T = 12$ (i.e., $\sum_{\tau=0}^{12} \Gamma_\tau$)	-723*	-47*	-112	-601**
	(-1.72)	(-1.65)	(-0.08)	(-2.14)
$T = 18$ (i.e., $\sum_{\tau=0}^{18} \Gamma_\tau$)	-1068*	-85*	-153	-854**
	(-1.65)	(-1.85)	(-0.53)	(-2.04)
$T = 24$ (i.e., $\sum_{\tau=0}^{24} \Gamma_\tau$)	-1213	-110*	-121	-1010*
	(-1.42)	(-1.81)	(-0.30)	(-1.88)
$T = 30$ (i.e., $\sum_{\tau=0}^{30} \Gamma_\tau$)	-1343	-147**	-114	-1137*
	(-1.30)	(-2.02)	(-0.21)	(-1.73)
$T = 36$ (i.e., $\sum_{\tau=0}^{36} \Gamma_\tau$)	-1235	-159*	-79	-1186
	(-1.13)	(-1.71)	(-0.24)	(-1.62)

NOTE.—This figure plots coefficient estimates from the impulse response version of Equation 3:

$$\Delta y_{i,t} = \alpha + \sum_{\tau=-12}^{36} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{s,t,\tau} + \delta_i + \delta_{p,t} + \gamma' X_{s,t-12} + \varepsilon_{i,t},$$

where $D_{s,t,\tau}$ is equal to one when month t is τ months away from a minimum wage increase in state s. The outcome variable is either the month-over-month change in total debt (Column (1)), credit card debt (Column (2)), auto loan debt (Column (3)), or student loan debt (Column (4)). The sample is restricted to bound hourly wage employees. The rows under the Horizon header correspond to cumulative impulse responses. t statistics, presented below the cumulative coefficient estimates, are calculated by clustering the standard errors at the state level and then applying the Delta method. In the estimation, month $\tau = -1$ is excluded as the reference level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.5: Enrolled and former student descriptive statistics

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	Enrolled (6)	Former (7)	Diff (8)	t(Diff) (9)
Hourly wage	7.73	0.48	7.25	7.60	8.00	7.71	7.79	-0.08	-2.39
Hours per week	28.31	10.58	20.00	28.00	40.00	27.68	29.95	-2.27	-6.24
Tenure (months)	12.79	20.70	1.00	5.00	16.00	11.73	15.82	-4.10	-3.43
Age (years)	25.97	9.14	20.00	22.00	28.00	23.53	32.90	-9.36	-29.70
Credit score	598	92	535	592	664	607	571	36	10.43
Has active trade? (1/0)	1.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00
Has credit card? (1/0)	0.45	0.50	0.00	0.00	1.00	0.43	0.51	-0.08	-4.30
Has auto loan? (1/0)	0.18	0.38	0.00	0.00	0.00	0.15	0.27	-0.13	-11.87
Has student loan? (1/0)	1.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00
Total balances	22246	25607	6426	14250	28546	21329	24853	-3524	-4.55
Card balances	977	3358	0	0	494	693	1786	-1093	-8.24
Auto balances	2210	6065	0	0	0	1780	3431	-1651	-11.85
Student balances	18740	22985	5500	11246	23518	18555	19267	-712	-1.13
Card credit limits	2352	7952	0	0	1186	1553	4627	-3074	-8.99
Card credit utilization	0.29	4.38	0.00	0.00	0.38	0.28	0.34	-0.07	-1.52
Is 90+ delinquent? (1/0)	0.23	0.42	0.00	0.00	0.00	0.11	0.58	-0.46	-38.64
Card 90+ delinquent? (1/0)	0.08	0.28	0.00	0.00	0.00	0.06	0.14	-0.08	-9.88
Auto 90+ delinquent? (1/0)	0.02	0.15	0.00	0.00	0.00	0.01	0.05	-0.03	-7.05
Student 90+ deqlinquent? (1/0)	0.16	0.37	0.00	0.00	0.00	0.03	0.51	-0.48	-35.37

NOTE.—This table contains descriptive statistics for the 22,094 enrolled students and 7,760 former students (29,860 total). The descriptive statistics are as-of the month closest to three months prior to treatment. The right-most columns are defined as follows: Enrolled is the mean value for enrolled students, Former is the mean value in former students, Diff is the difference in means between enrolled and former students, and t(Diff) is the *t*-statistic for the difference in means.

Table A.6: Non-student descriptive statistics

	Mean	SD	P25	P50	P75
	(1)	(2)	(3)	(4)	(5)
Hourly wage	7.88	0.54	7.35	7.85	8.25
Hours per week	29.68	10.37	20.00	31.00	40.00
Tenure (months)	19.46	36.81	1.00	6.00	20.00
Age (years)	33.70	13.47	22.00	30.00	45.00
Credit score	573	142	508	573	679
Has active trade? (1/0)	0.59	0.49	0.00	1.00	1.00
Has credit card? (1/0)	0.50	0.50	0.00	1.00	1.00
Has auto loan? (1/0)	0.22	0.41	0.00	0.00	0.00
Has student loan? (1/0)	0.00	0.06	0.00	0.00	0.00
Total balances	4689	10108	0	99	4293
Card balances	1545	4797	0	0	799
Auto balances	2915	7429	0	0	0
Student balances	0	0	0	0	0
Card credit limits	5159	13425	0	0	2850
Card credit utilization	0.27	1.28	0.00	0.00	0.36
Is 90+ delinquent? (1/0)	0.13	0.34	0.00	0.00	0.00
Card 90+ delinquent? (1/0)	0.09	0.29	0.00	0.00	0.00
Auto 90+ delinquent? (1/0)	0.03	0.17	0.00	0.00	0.00
Student 90+ deqlinquent? (1/0)	0.00	0.06	0.00	0.00	0.00

NOTE.—This table contains descriptive statistics for the 47,122 non-students. The descriptive statistics are as-of the month closes to three months prior to treatment.

Table A.7: Log and inverse hyperbolic sine transformations of debt balances

	Enrolled students		Former students		Non-students	
	Log	IHS	Log	IHS	Log	IHS
	(1)	(2)	(3)	(4)	(5)	(6)
Total balances	-0.174***	-0.185***	0.047*	0.048*	0.195***	0.210***
Card balances	0.007	0.005	0.062	0.067	0.162***	0.176***
Auto balances	0.104*	0.111*	0.295***	0.318***	0.115*	0.124*
Student balances	-0.206***	-0.220***	-0.004	-0.006	0.002	0.002
Mortgage balances	-0.007	-0.007	-0.049	-0.051	-0.035*	-0.037*

NOTE.—This table contains coefficient estimates from Equation 3 estimated across the sub-sample of enrolled students (Columns (1) and (2)), former students (Columns (3) and (4)), and non-students (Columns (5) and (6)). The dependent variable is either total debt, credit card debt, auto loan debt, student loan debt, or mortgage debt. A log transformation is applied to the dependent variable in the odd-numbered columns and an inverse hyperbolic sine transformation is applied in the even-numbered columns. t statistics, not presented, are calculated by clustering at the state level

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.8: Federal student loan interest rates

	Undergraduate		Graduate	
	Subsidized	Unsubsidized	Unsubsidized	PLUS
School year	(1)	(2)	(3)	(4)
2019-2020	4.53	4.53	6.08	7.08
2018-2019	5.05	5.05	6.60	7.60
2017-2018	4.45	4.45	6.00	7.00
2016-2017	3.76	3.76	5.31	6.31
2015-2016	4.29	4.29	5.84	6.84
2014-2015	4.66	4.66	6.21	7.21
2013-2014	3.86	3.86	5.41	6.41

NOTE.— This table contains annual federal student loan interest rates between 2014 and 2020 from `https://studentaid.gov/understand-aid/types/loans/interest-rates`. School years refer to July 1 to June 30. Subsidized loans do not accrue interest during the period of enrollment. Federal student loans also have a fixed loan fee that is deducted from the total loan amount (i.e., the borrower receives less than the total amount borrowed). For the 2019-2020 school year, the loan fee for direct subsidized and unsubsidized loans (PLUS loans) was 1.059 (4.236) percent. Increasing a loan amount by 1.059 (4.236) percent is equivalent to increasing the interest rate from 4.37 (6.42) percent to 4.46 (7.35) percent for a $25,000 ten year loan.

Table A.9: Credit constraints and buffer-stock channel

	Balances			Accounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	-1,027***	-969**	-1,058***	-0.20***	-0.19***	-0.23***
	(-2.64)	(-2.33)	(-2.16)	(-2.83)	(-4.16)	(-5.66)
Treated × Post × Has home loan?	377			0.03		
	(0.54)			(0.23)		
Treated × Post × Has auto loan?		-266			-0.07	
		(-0.61)			(-0.87)	
Treated × Post × High credit limits			160			0.12**
			(0.51)			(2.03)
Employee FE	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y
N	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176
R^2	0.88	0.88	0.88	0.85	0.85	0.85

NOTE.—This table contains coefficient estimates from equation 5. The dependent variable in Columns (1) through (3) is student loan balances. The dependent variable in Columns (4) through (6) is open student loan accounts. The sample is restricted to enrolled students. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.10: Income uncertainty channel

	Balances			Accounts		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post	-9,48*	-1,121*	-1,310***	-0.17**	-0.15*	-0.26***
	(-1.99)	(-1.66)	(-2.95)	(-2.31)	(-1.73)	(-4.93)
Treated * Post *	-435			-0.09		
High wage GINI?	(-0.51)			(-0.75)		
Treated * Post *		79			-0.07	
Low income interdecile range?		(0.10)			(-0.75)	
Treated * Post *			315			0.13
Low median income?			(0.37)			(1.17)
Employee FE	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y
N	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176	1,070,176
R^2	0.88	0.88	0.88	0.85	0.85	0.85

NOTE.—This table contains coefficient estimates from equation 5. The dependent variable in Columns (1) through (3) is student loan balances. The dependent variable in Columns (4) through (6) is open student loan accounts. The sample is restricted to enrolled students. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.11: Savings rate and preferences channel

	Student balances (1)	Card balances (2)	Student balances (3)	Card balances (4)
Treated × Post	-949**	22	-864**	41
	(-2.33)	(0.91)	(-2.21)	(0.70)
Treated × Post × High credit card debt	-245	-17	-240	-78
	(-056)	(-0.27)	(-0.60)	(-1.21)
Employee FE	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Credit card debt above zero?			Y	Y
N	1,070,176	1,070,176	1,070,176	1,070,176
R^2	0.88	0.75	0.89	0.75

NOTE.—This table contains coefficient estimates from equation 5. The dependent variable in Columns (1) and (3) is student loan balances. The dependent variable in Columns (2) through (4) is credit card balances. The sample is restricted to enrolled students. The sample in Columns (3) and (4) is restricted to enrolled students with pre-treatment credit card balances above zero. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.12: Cost of default channel

	Student balances		Student debt in default?		Student balances in default		% Student balances in default	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated × Post	50	-43	-0.01	0.00	-528**	-251	-0.01	0.00
	(0.25)	(-0.28)	(-0.91)	(-0.34)	(-2.09)	(-0.55)	(-0.88)	(0.07)
Treated × Post ×	158		0.02		633		0.03	
Ex-ante default	(0.58)		(0.89)		(1.40)		(1.14)	
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Border-pair month FE	Y	Y	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y	Y	Y
Exclude ex-ante not in default?		Y		Y		Y		Y
N	376,587	192,983	376,587	192,983	376,587	192,983	376,587	192,983
R^2	0.90	0.89	0.66	0.44	0.72	0.72	0.64	0.47

NOTE.—This table contains coefficient estimates from equation 3 across ex-ante default status. The dependent variable in Columns (1) and (2) is student debt balances. The dependent variable in Columns (3) and (4) is a dummy variable equal to one if the employee has student debt in default and zero otherwise. The dependent variable in Columns (5) and (6) is the amount of student debt balances in default. The dependent variable in Columns (7) and (8) is the percent of student debt balances in default. The sample is restricted to former students. t statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

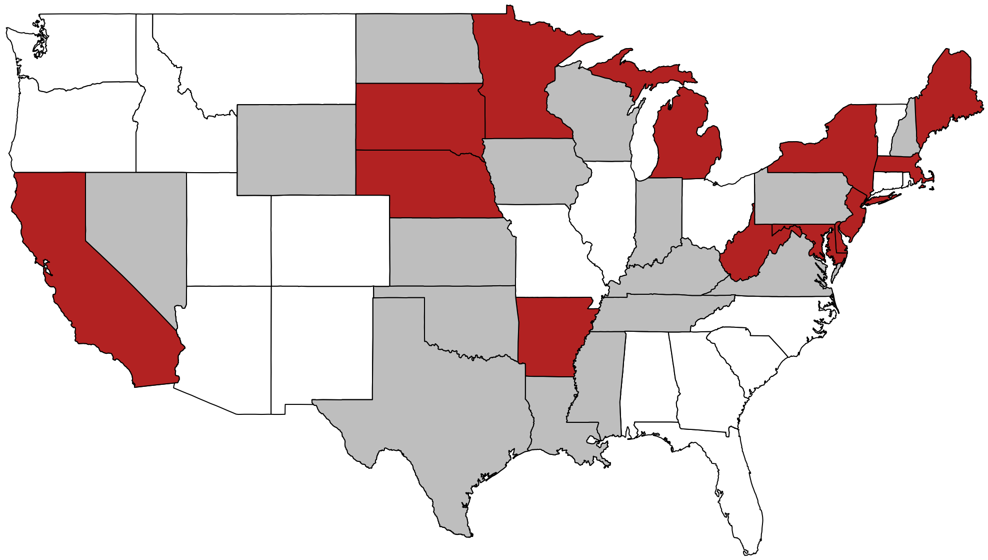
* Significant at the 10% level.

** Significant at the 5% level.

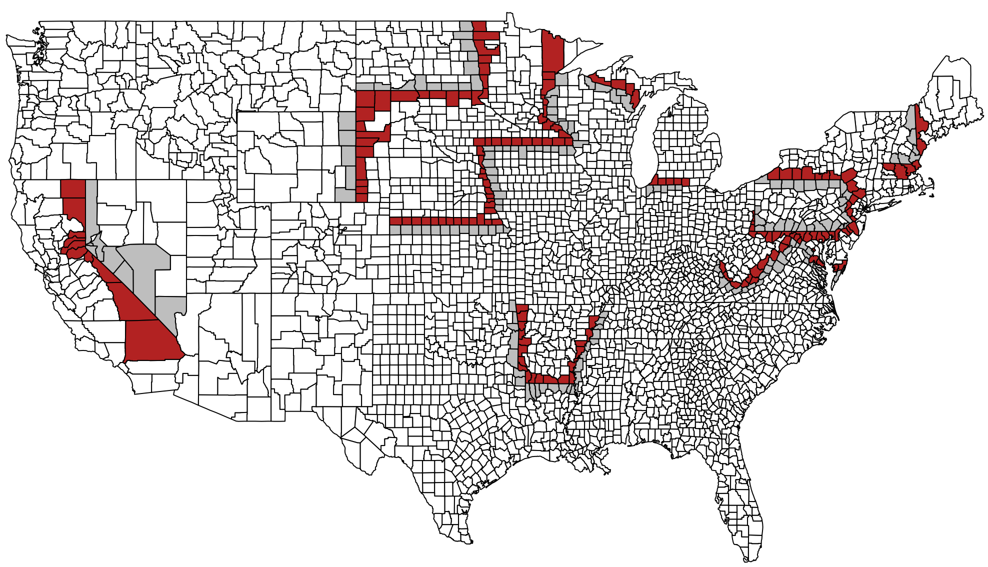
*** Significant at the 1% level.

Figure A.1: Map of treated and control geographies

Panel A: Map of treated and control states

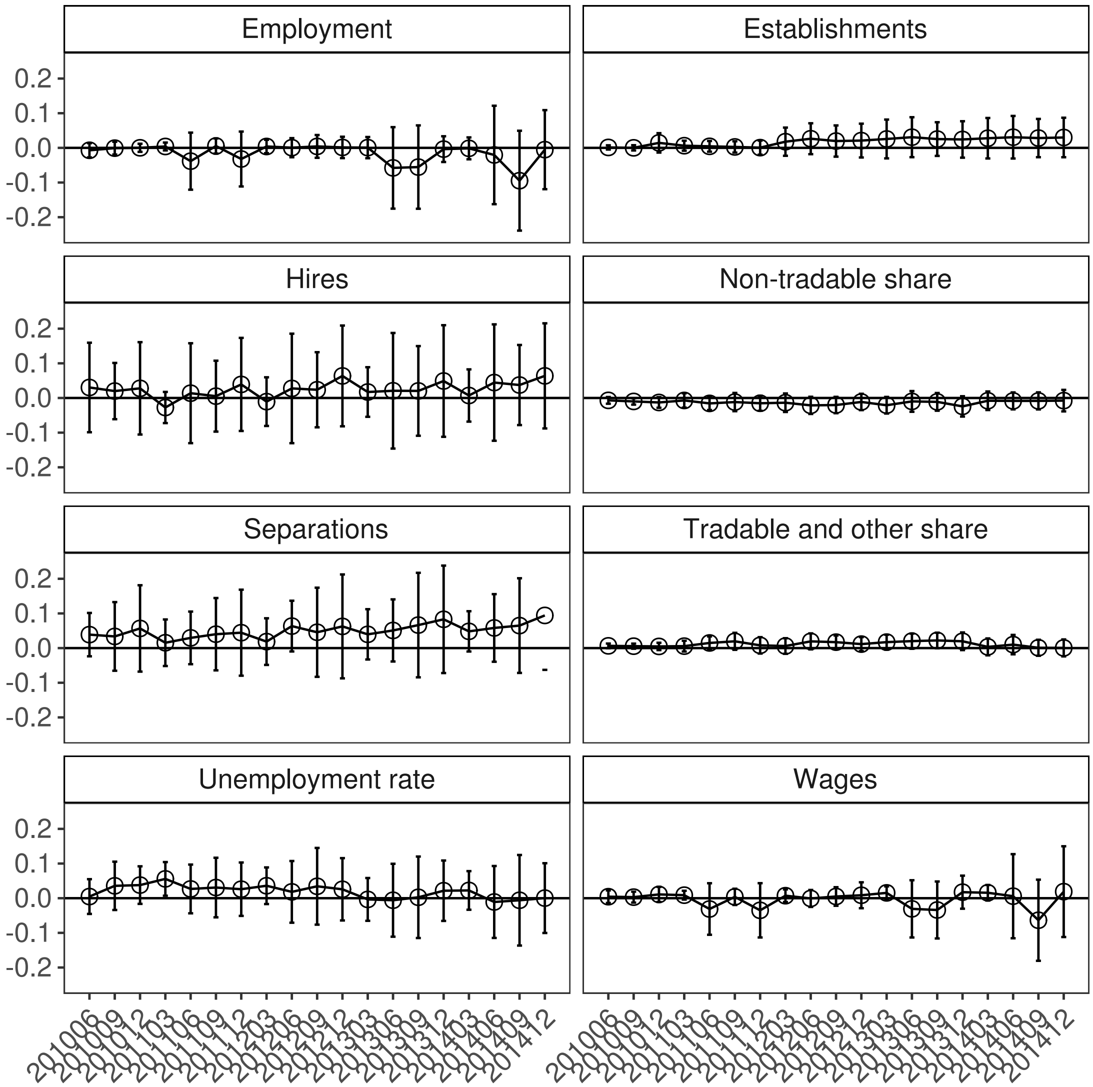


Panel B: Map of treated and control border counties



NOTE.—This figure plots the treated and control geographies. Panel A contains the treated and control states. The states with the dark red shading are treated states. The states with the gray shading are the control states. The states with the white shading are excluded from the analysis. Panel B contains the treated and control counties. The counties with the dark red shading are the treated border counties. The counties with the gray shading are the control border counties.

Figure A.2: County macroeconomic trends

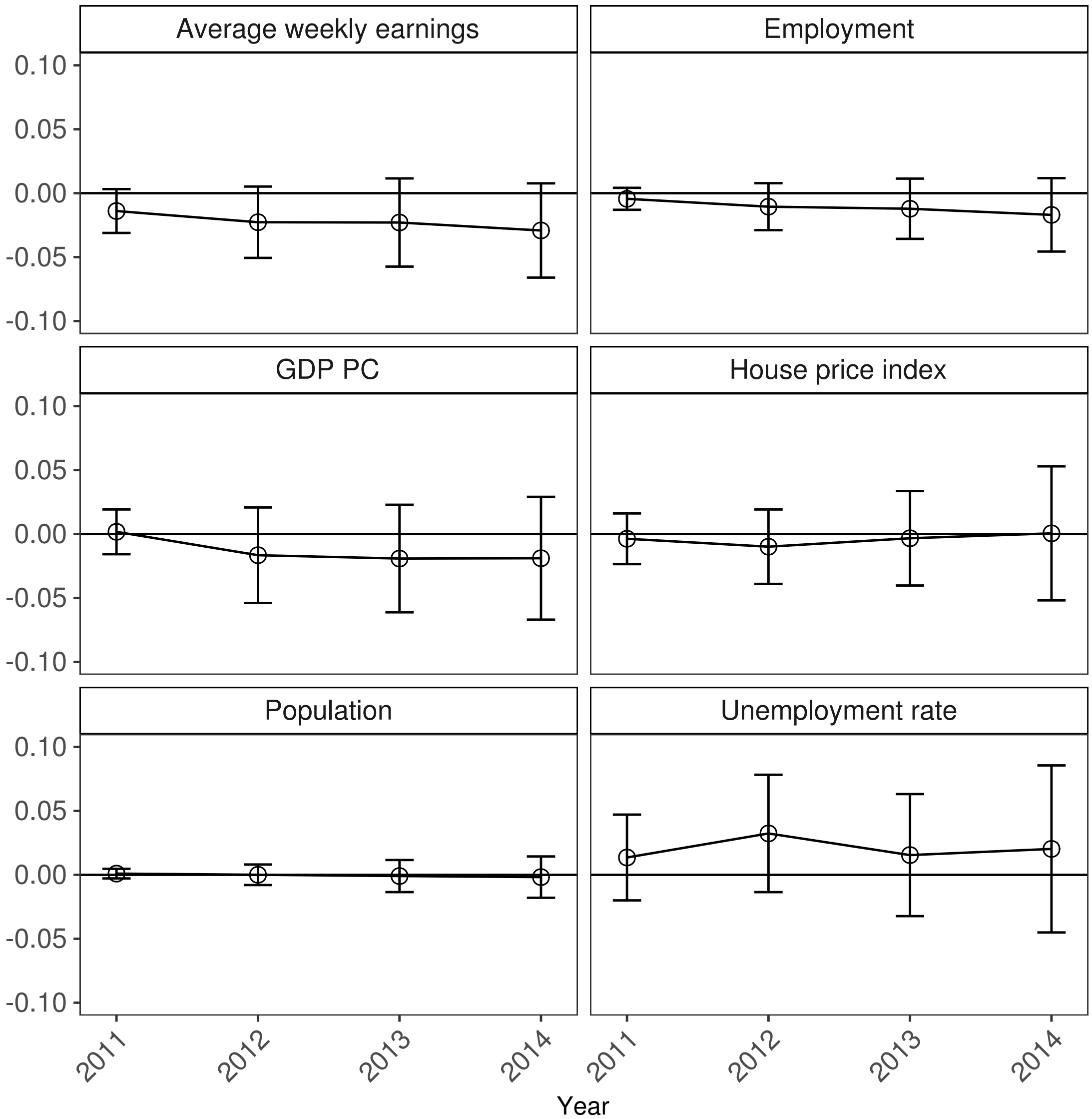


NOTE.—This figure plots coefficient estimates from panel regressions of the form:

$$y_{c,t} = \alpha + \sum_{\tau=2010.02}^{2013.04} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{t,\tau} + \delta_c + \delta_{p,t} + \varepsilon_{c,t},$$

where Treated_s is equal to one if state s is treated, $\text{D}_{t,\tau}$ is equal to one when quarter t is equal to τ, δ_c are county fixed effects, and $\delta_{p,t}$ are cross-border county pair quarter fixed effects. The panels correspond to logged county macroeconomic variables. The circles correspond to coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. The first quarter of 2010 is excluded as the reference level.

Figure A.3: State macroeconomic trends

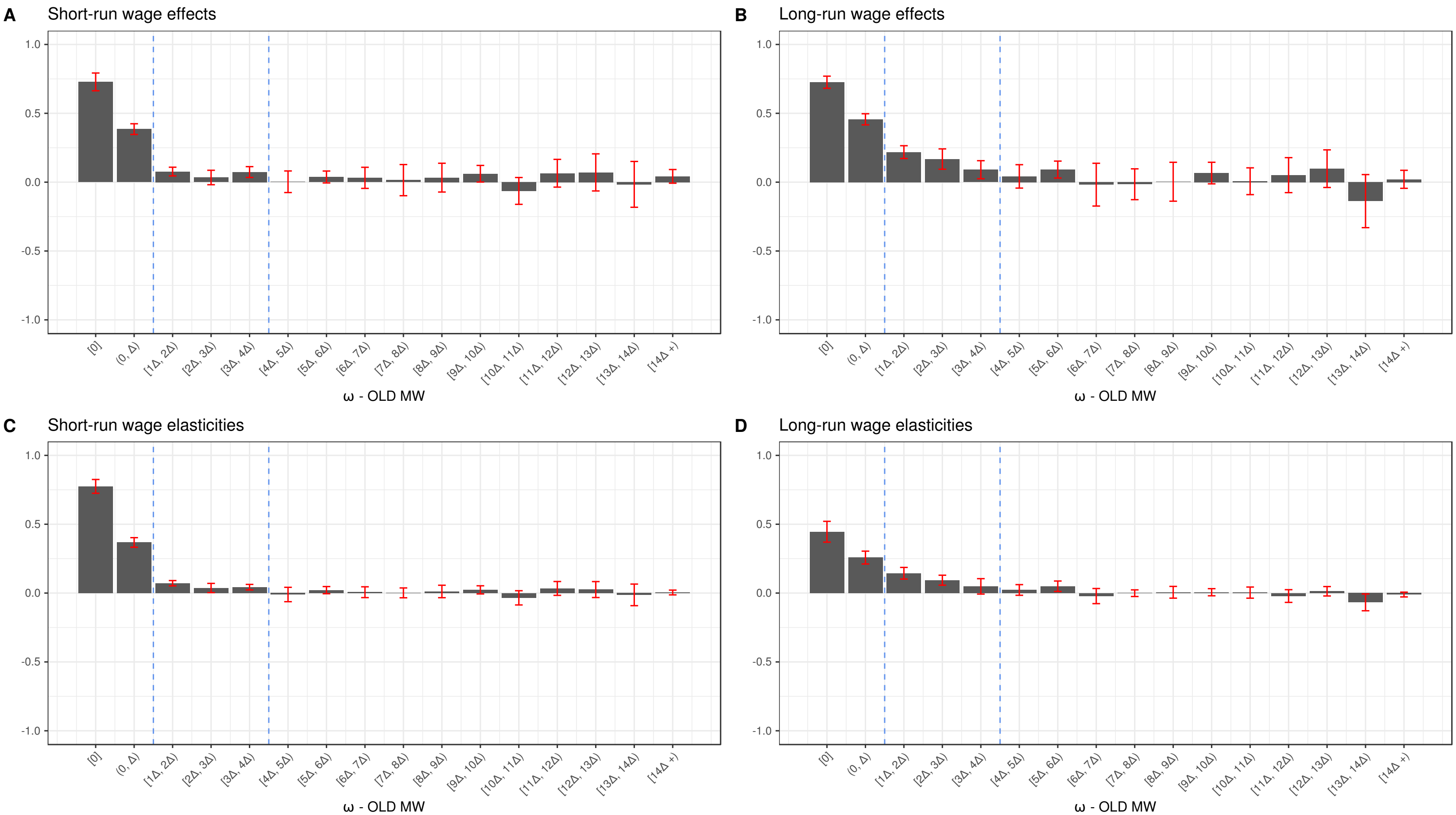


NOTE.—This figure plots coefficient estimates from panel regressions of the form:

$$y_{s,t} = \alpha + \sum_{\tau=2011}^{2013} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{t,\tau} + \delta_s + \delta_{tr(s),t} + \varepsilon_{s,t},$$

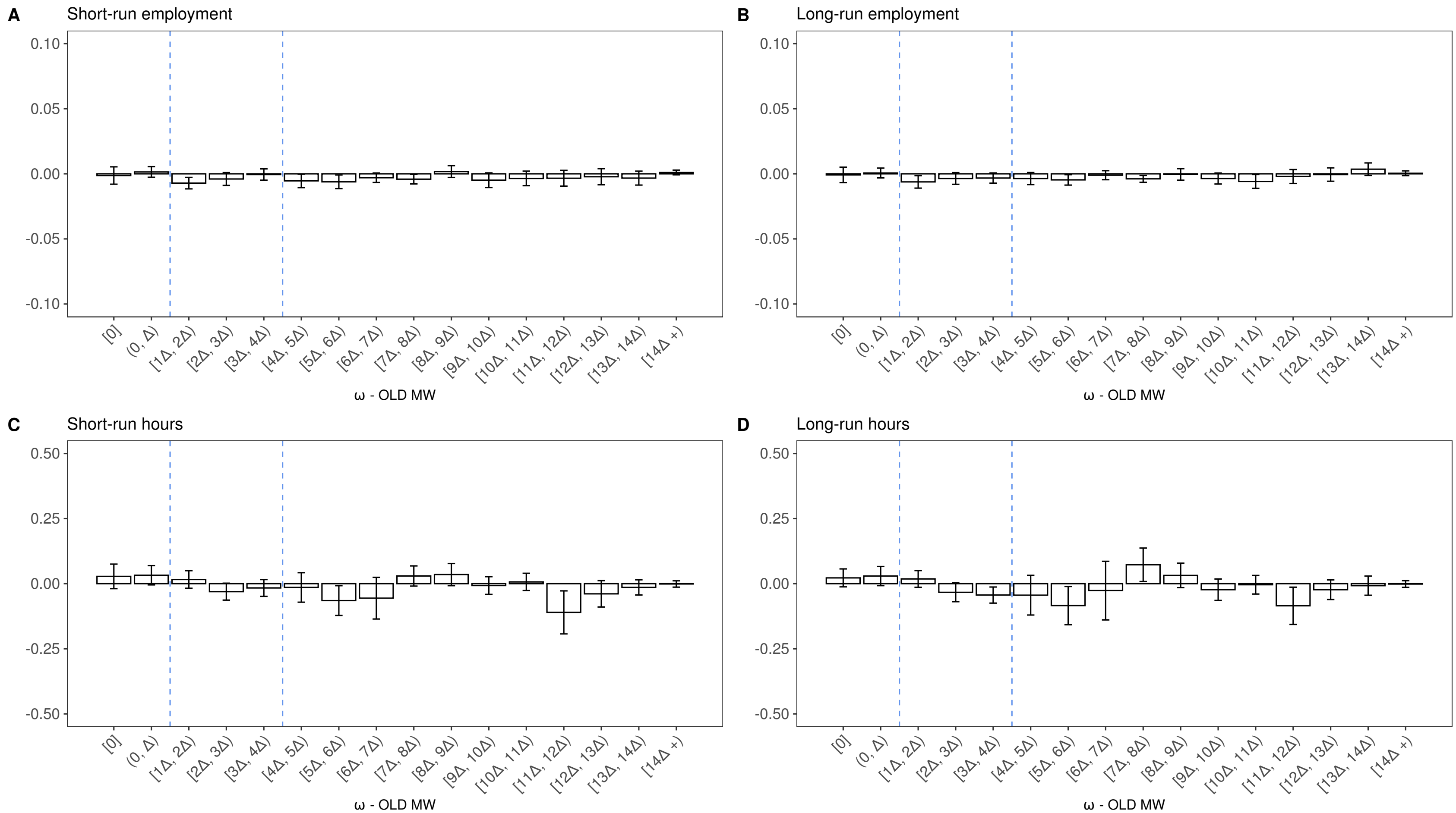
where Treated_s is equal to one if state s is treated, $\text{D}_{t,\tau}$ is equal to one when year t is equal to τ, δ_s are state fixed effects, and $\delta_{tr(s),t}$ are matched treated state year fixed effects. The panels correspond to logged state macroeconomic variables. The circles correspond to coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. The year 2010 is excluded as the reference level.

Figure A.4: Wage response across wage distribution



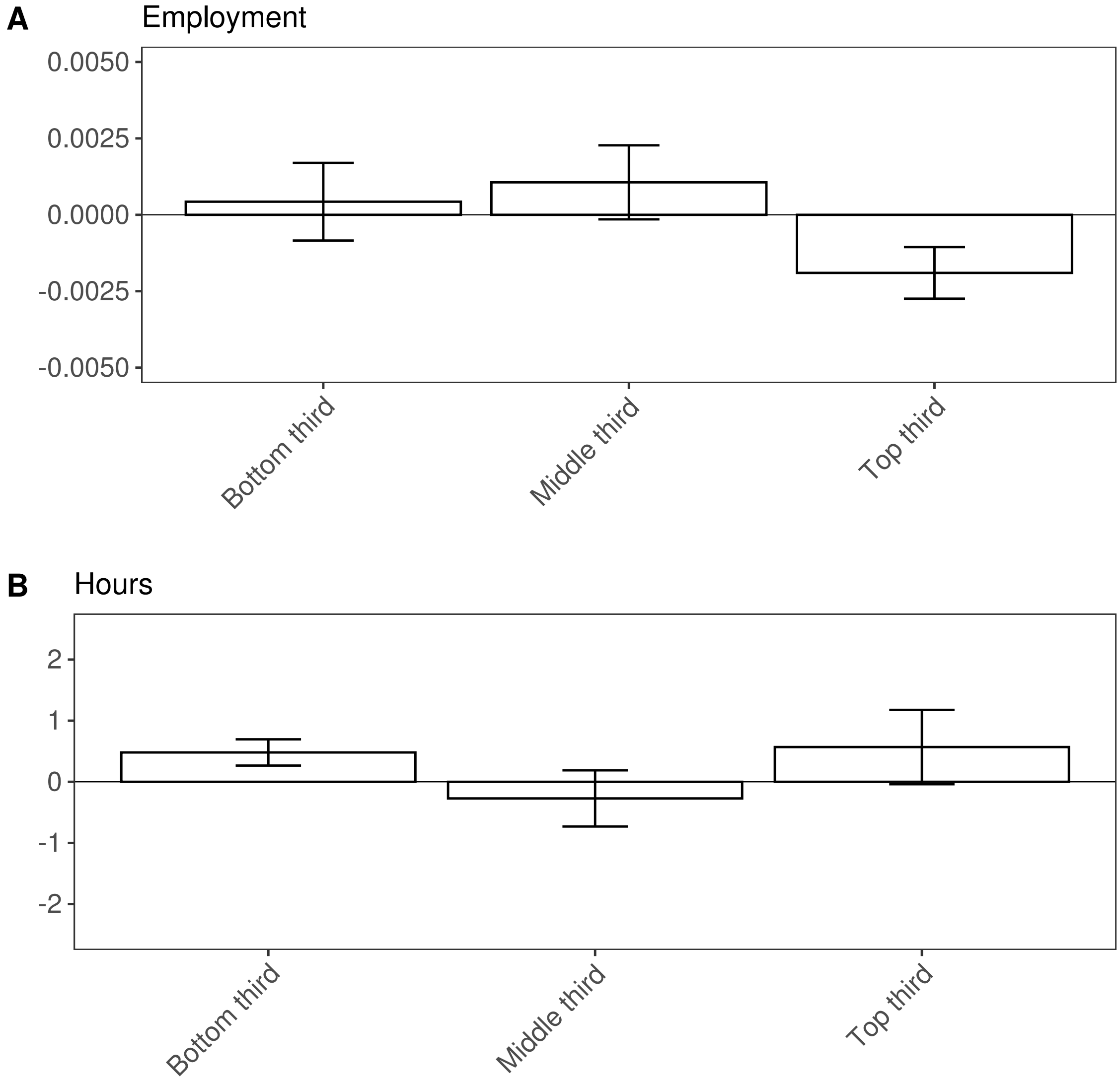
NOTE.—This figure plots coefficient estimates from Equation 2. The dependent variable is hourly wages or the log of hourly wages. The height of the columns correspond to coefficient estimates. The vertical bars correspond to 95 percent confidence intervals with standard errors clustered at the state level. The x-axis corresponds to wage bins ($b = -1$ to $b = 19$). The left-most dashed vertical line corresponds to the new minimum wage. The right-most dashed vertical line corresponds to the end of the wage spillover region as defined in Gopalan et al. 2021. Long-run refers to models estimated over the full sample period (-12 months to +36 months). Short-run refers to models estimated over the 12 months period surrounding a minimum wage change (-12 months to +12 months).

Figure A.5: Employment response across wage distribution



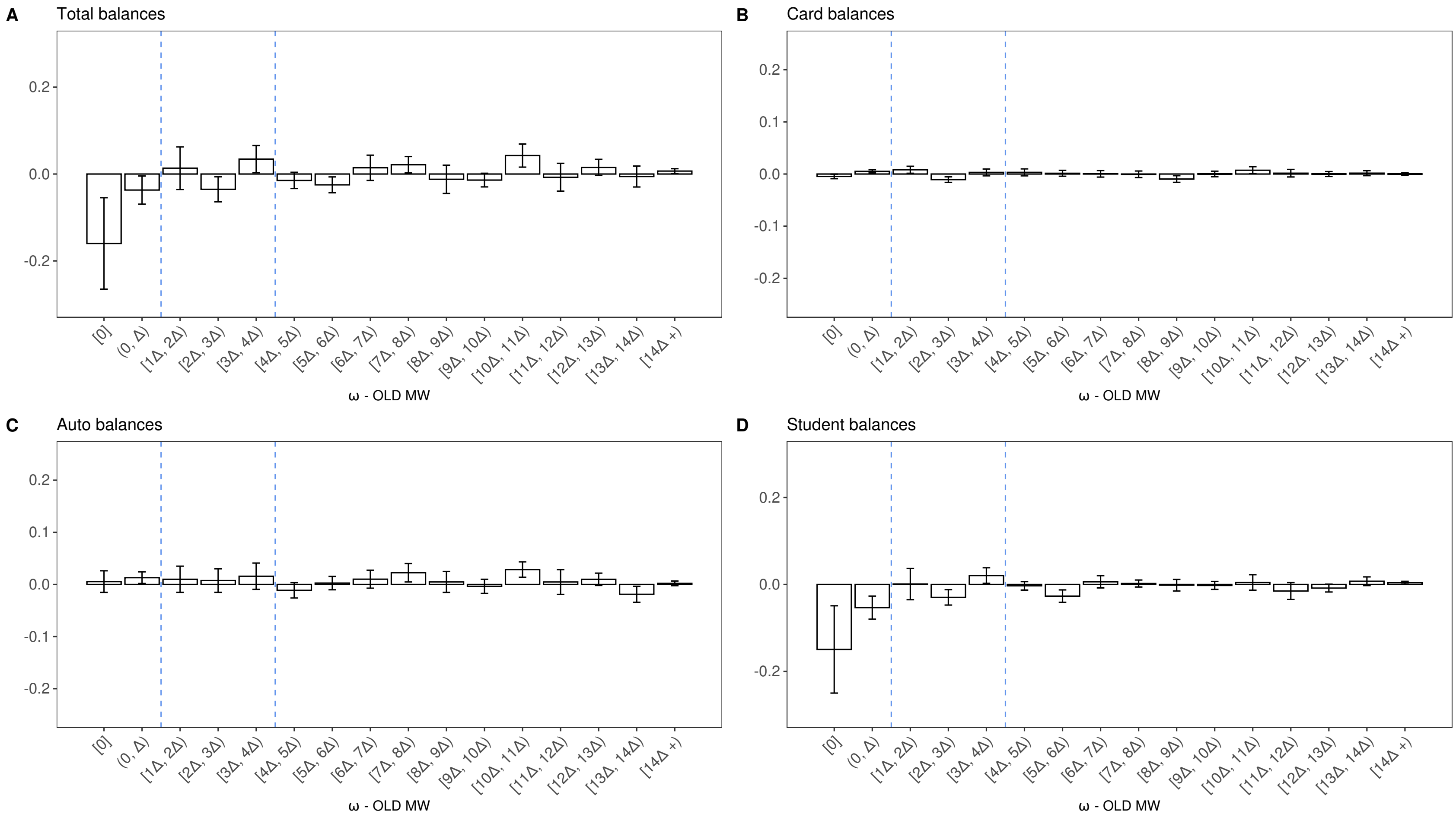
NOTE.—This figure plots coefficient estimates from Equation 2. The dependent variable is either employment or average hours worked per week. The height of the columns correspond to coefficient estimates. The vertical bars correspond to 95 percent confidence intervals with standard errors clustered at the state level. The x-axis corresponds to wage bins ($b = -1$ to $b = 19$). The left-most dashed vertical line corresponds to the new minimum wage. The right-most dashed vertical line corresponds to the end of the wage spillover region as defined in Gopalan et al. 2021. Long-run refers to models estimated over the full sample period (-12 months to +36 months). Short-run refers to models estimated over the 12 months period surrounding a minimum wage change (-12 months to +12 months).

Figure A.6: Employment response across size of minimum wage change



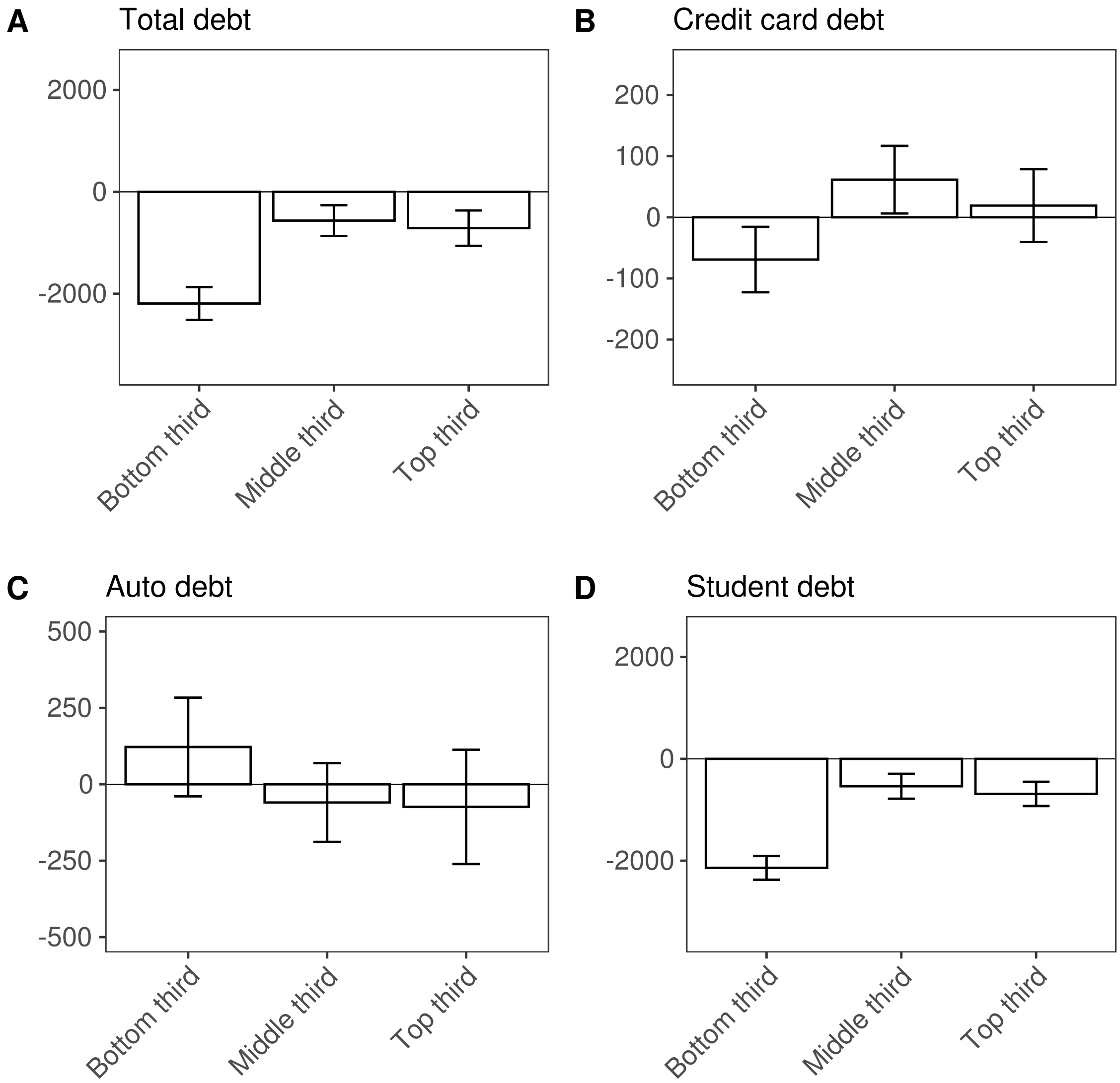
NOTE.—This figure plots coefficient estimates from Equation 1 across the size of the minimum wage change (relative to the median state wage). The dependent variable is either employment or average hours worked per week. The height of the columns correspond to coefficient estimates. The vertical bars correspond to 95 percent confidence intervals with standard errors clustered at the state level. The x-axis corresponds to state-wise terciles of the size of the minimum wage change (relative to the median state wage).

Figure A.7: Debt response across wage distribution



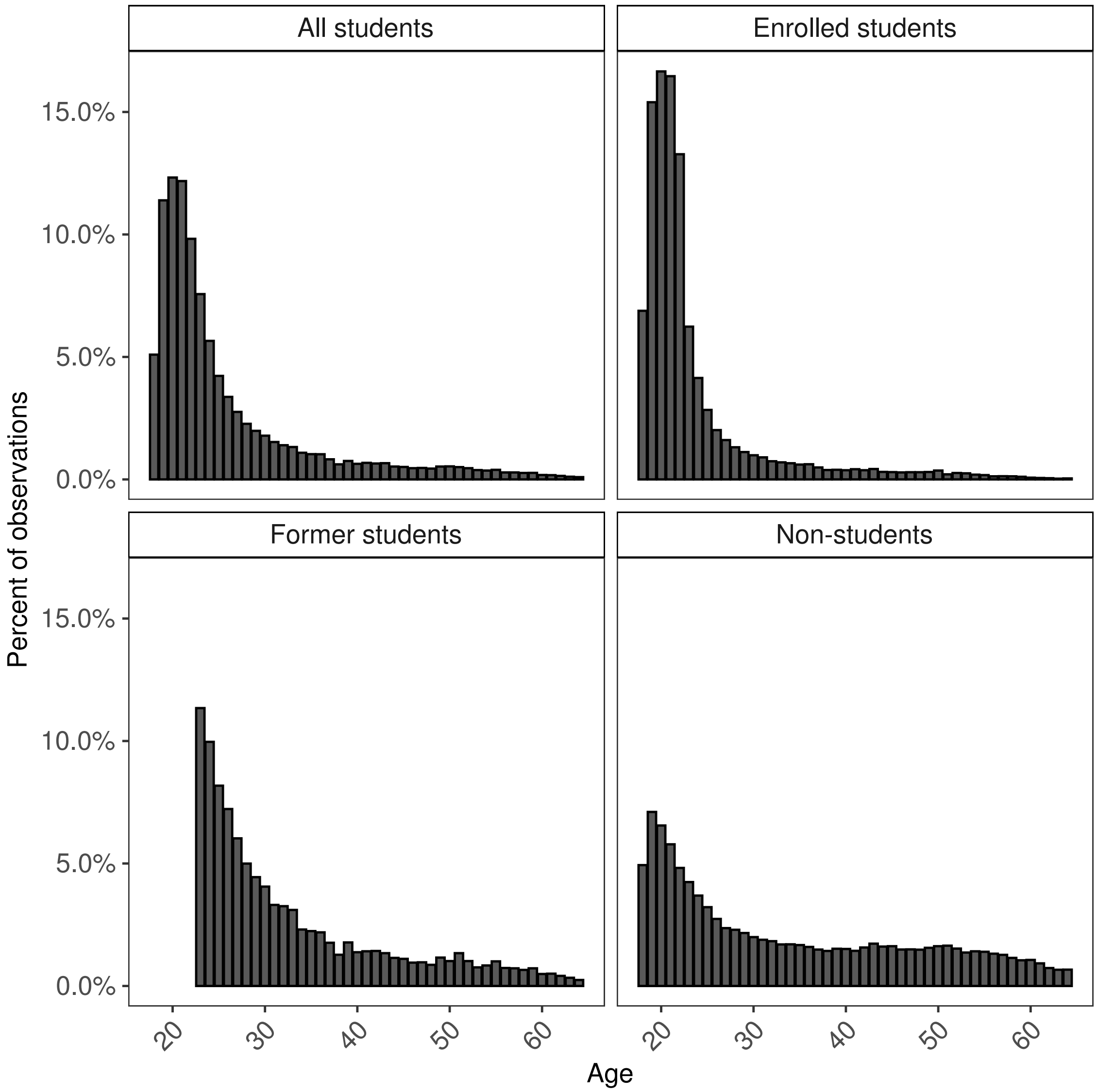
NOTE.—This figure plots coefficient estimates from Equation **??**. The dependent variable is either total debt, credit card debt, auto loan debt, or student loan debt. The height of the columns correspond to coefficient estimates. The vertical bars correspond to 95 percent confidence intervals with standard errors clustered at the state level. The x-axis corresponds to wage bins ($b = -1$ to $b = 19$). The left-most dashed vertical line corresponds to the new minimum wage. The right-most dashed vertical line corresponds to the end of the wage spillover region as defined in Gopalan et al. 2021.

Figure A.8: Debt response across size of minimum wage change



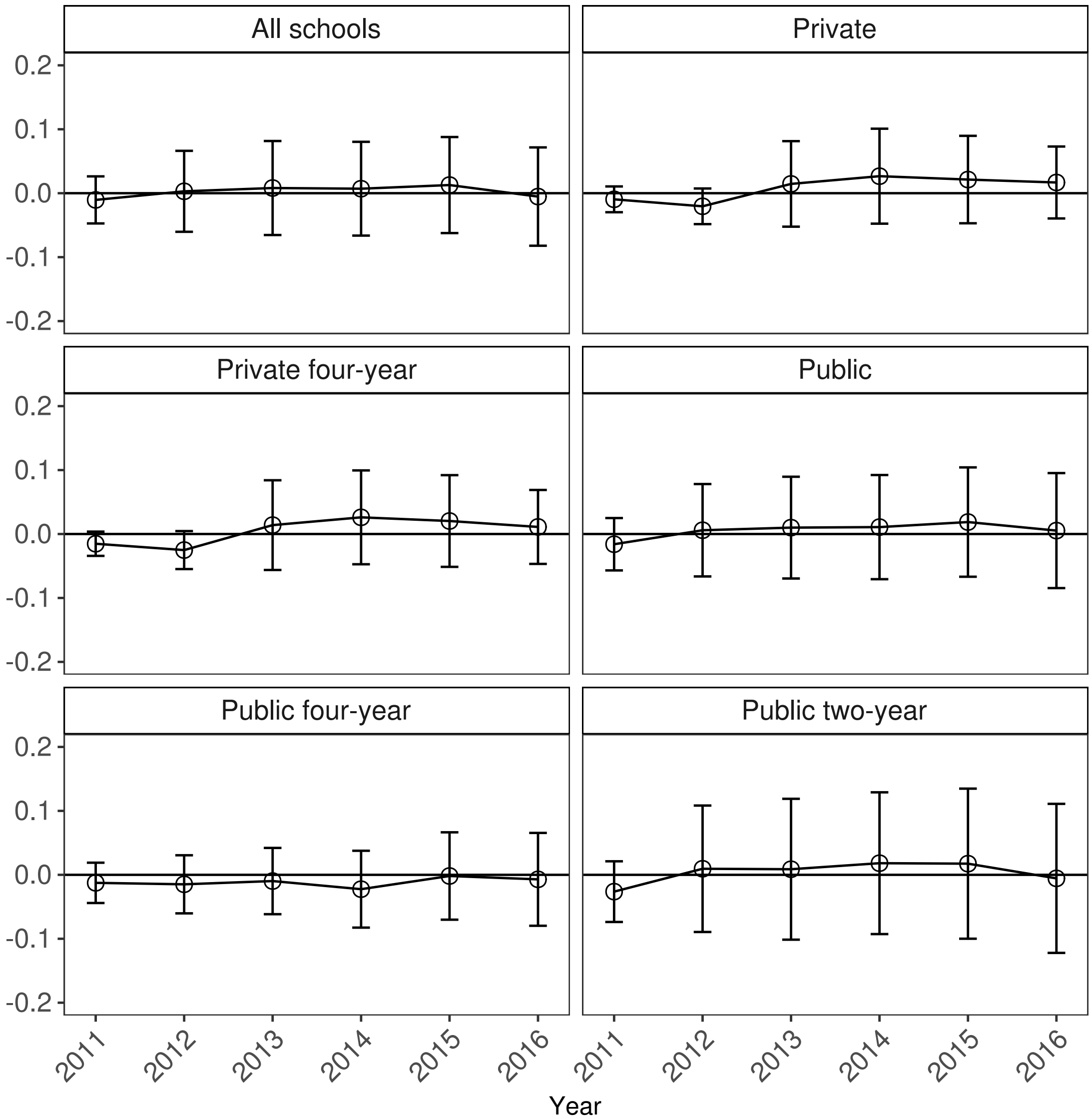
NOTE.—This figure plots coefficient estimates from Equation 3 across the size of the minimum wage change (relative to the median state wage). The dependent variable is either total debt, credit card debt, auto loan debt, or student loan debt. The height of the columns correspond to coefficient estimates. The vertical bars correspond to 95 percent confidence intervals with standard errors clustered at the state level. The x-axis corresponds to state-wise terciles of the size of the minimum wage change (relative to the median state wage).

Figure A.9: Age distribution



NOTE.—This figure plots the histogram of employee ages. The top-left panel corresponds to all students (enrolled and former). The top-right panel corresponds to enrolled students. The bottom-left panel corresponds to former students. The bottom-right panel corresponds to non-students.

Figure A.10: County tuition trends

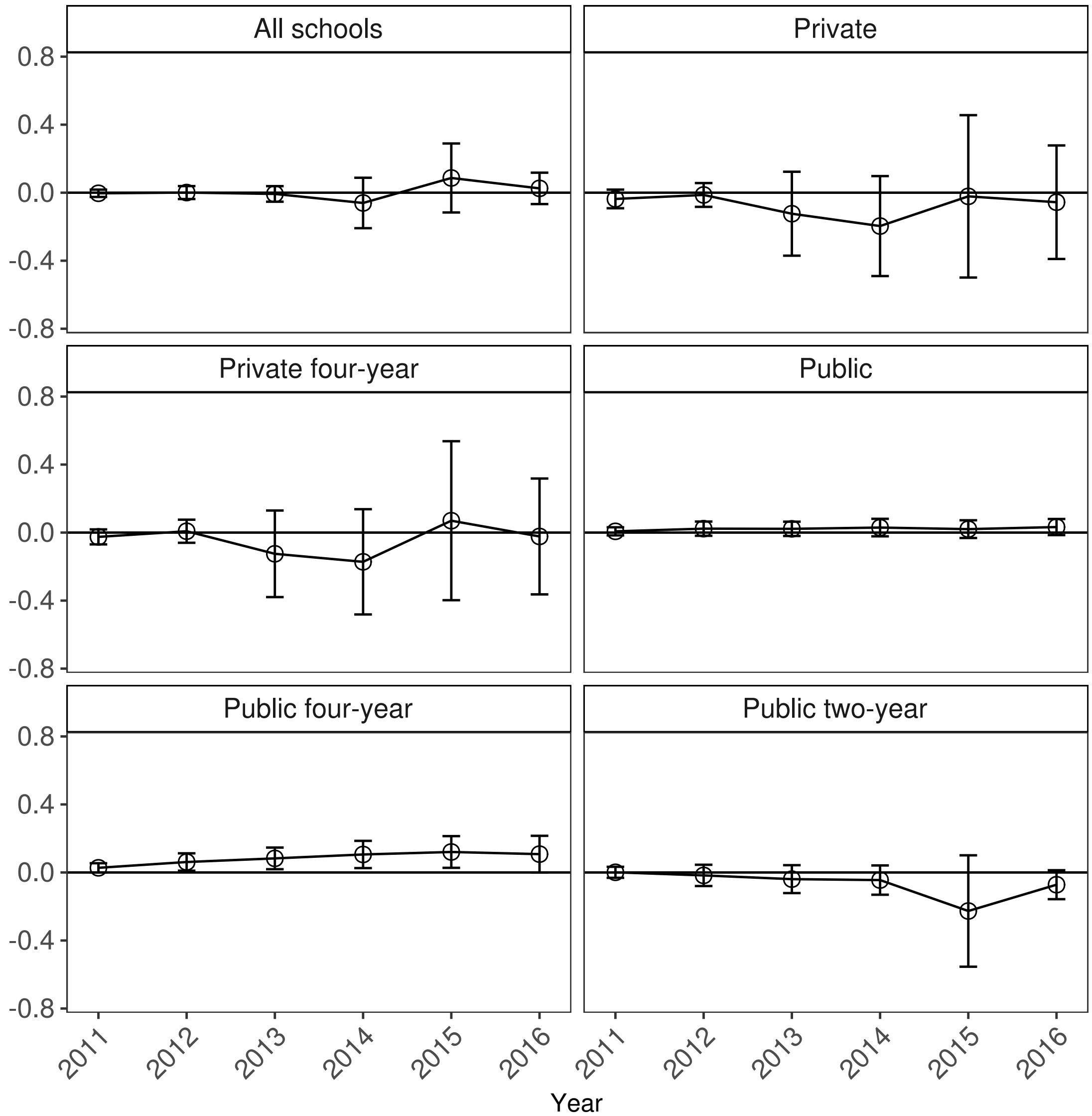


NOTE.—This figure plots coefficient estimates from panel regressions of the form:

$$y_{c,t} = \alpha + \sum_{\tau=2010.02}^{2013.04} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{t,\tau} + \delta_c + \delta_{p,t} + \varepsilon_{c,t},$$

where Treated_s is equal to one if state s is treated, $\text{D}_{t,\tau}$ is equal to one when year t is equal to τ, δ_c are county fixed effects, and $\delta_{p,t}$ are cross-border county pair year fixed effects. The panels correspond to the logged county tuition rates of various types of colleges and universities. The circles correspond to coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. The first quarter of 2010 is excluded as the reference level.

Figure A.11: County enrollment trends



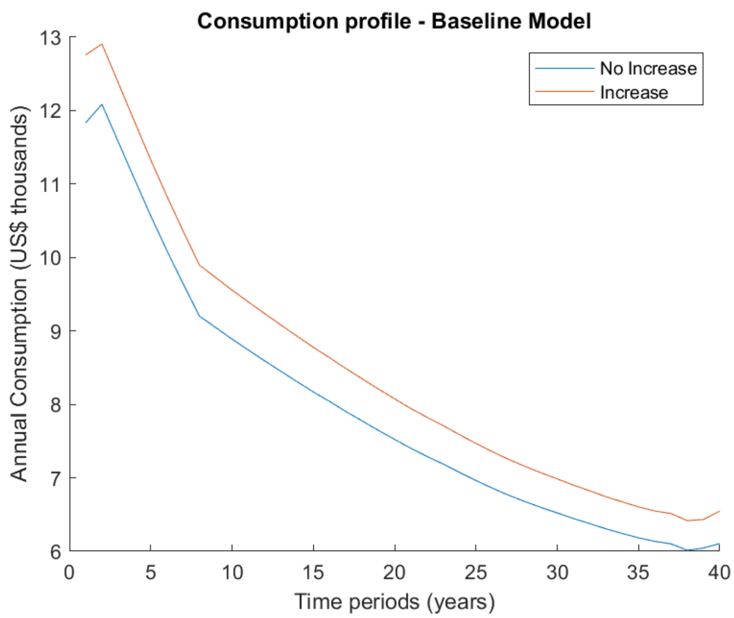
NOTE.—This figure plots coefficient estimates from panel regressions of the form:

$$y_{c,t} = \alpha + \sum_{\tau=2010.02}^{2013.04} \Gamma_\tau \times \text{Treated}_s \times \text{D}_{t,\tau} + \delta_c + \delta_{p,t} + \varepsilon_{c,t},$$

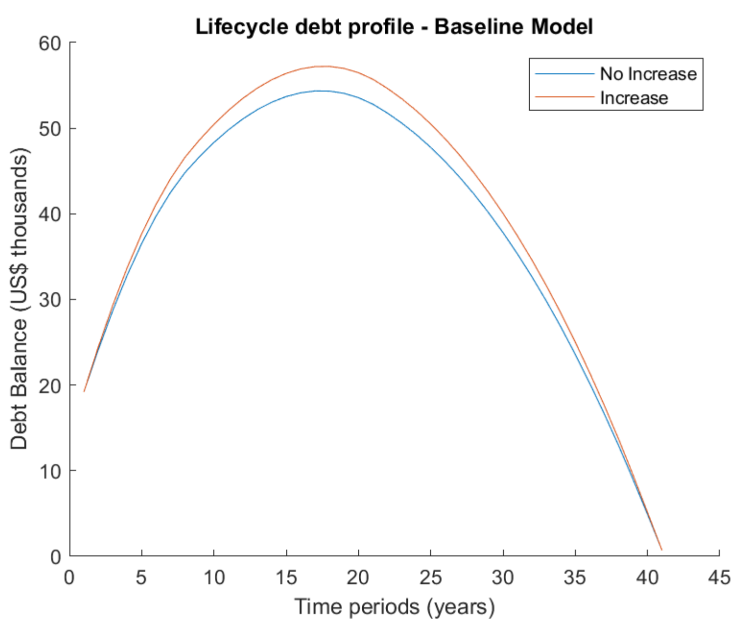
where Treated_s is equal to one if state s is treated, $\text{D}_{t,\tau}$ is equal to one when year t is equal to τ, δ_c are county fixed effects, and $\delta_{p,t}$ are cross-border county pair year fixed effects. The panels correspond to the logged county enrollment amounts of various types of colleges and universities. The circles correspond to coefficient estimates, and the vertical bars correspond to 95 percent confidence intervals. Standard errors are clustered at the state level. The first quarter of 2010 is excluded as the reference level.

Figure A.12: Baseline model solution

Panel A: Debt profile



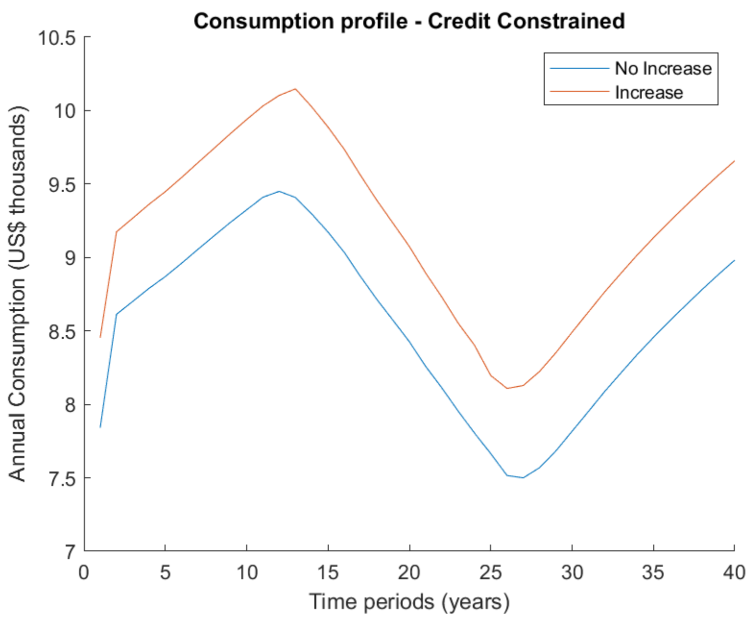
Panel B: Consumption profile



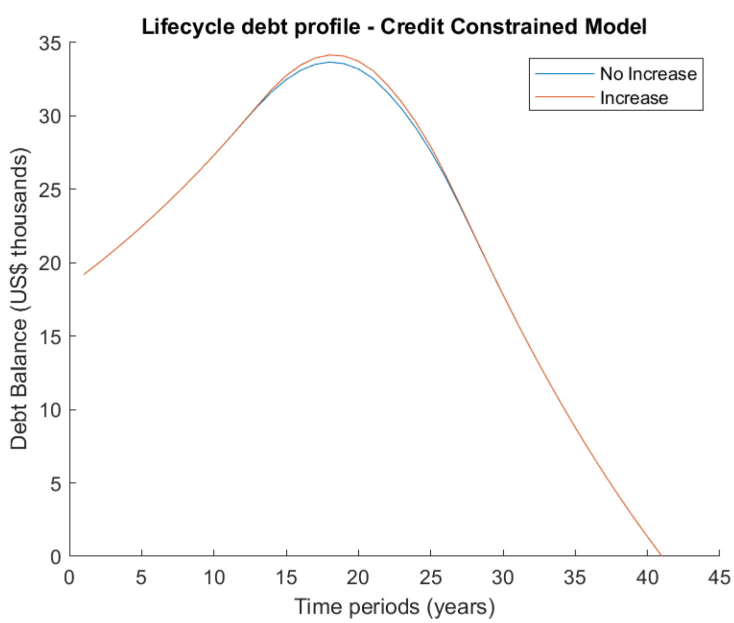
NOTE.—This figure plots the average debt and consumption profiles from the baseline model.

Figure A.13: Model with credit constraints

Panel A: Debt profile



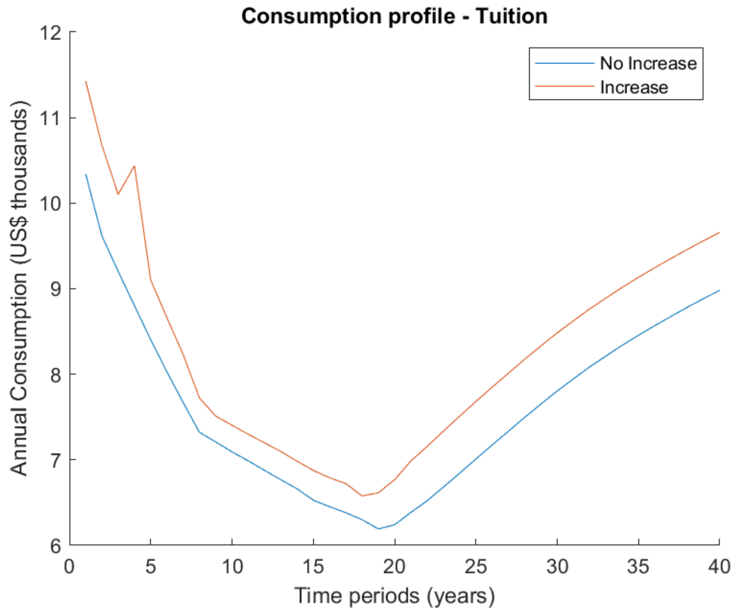
Panel B: Consumption profile



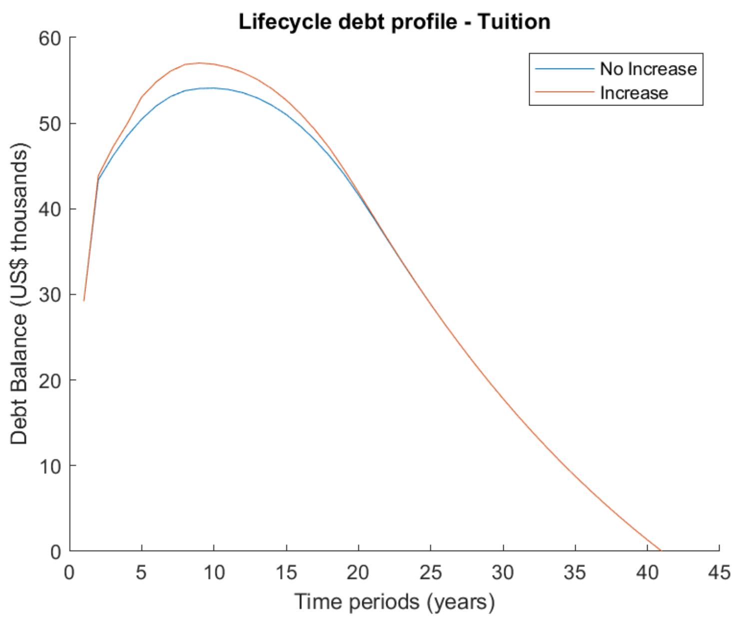
NOTE.—This figure plots the average debt and consumption profiles from the model with credit constraints.

Figure A.14: Model with tuition costs

Panel A: Debt profile



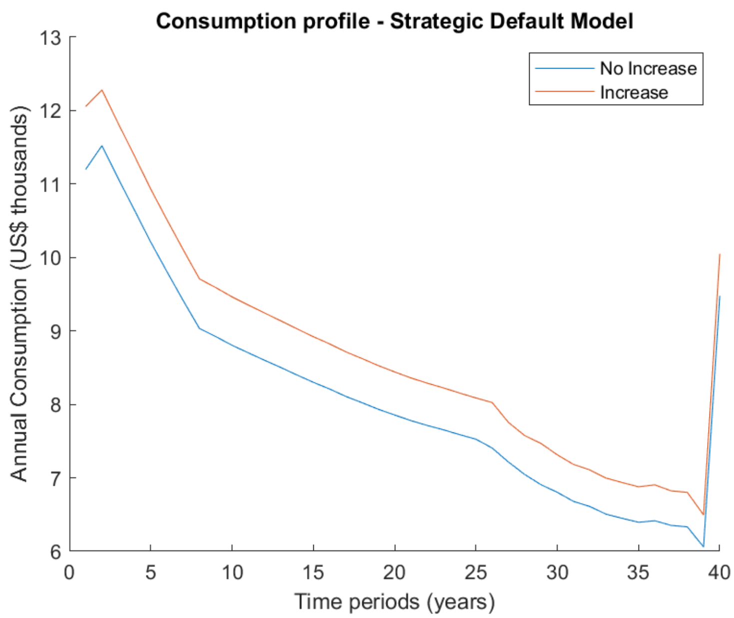
Panel B: Consumption profile



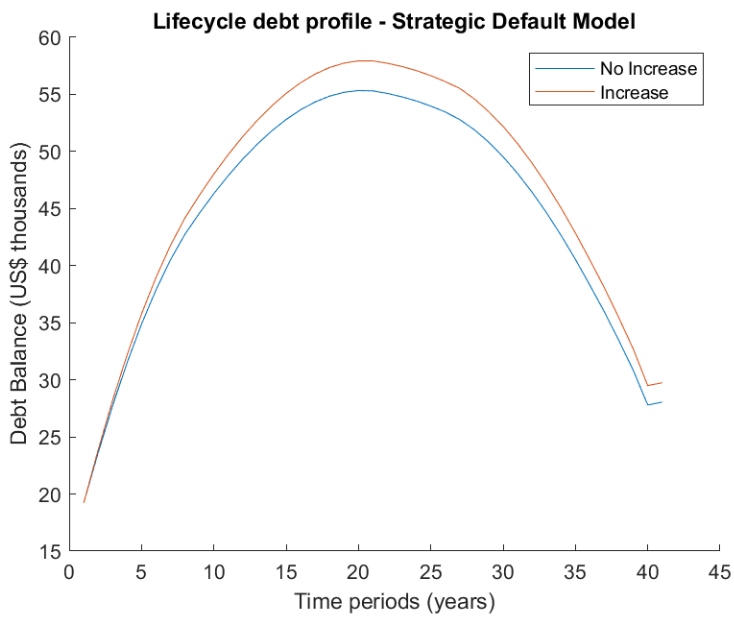
NOTE.—This figure plots the average debt and consumption profiles from the model with tuition costs.

Figure A.15: Model with default

Panel A: Debt profile



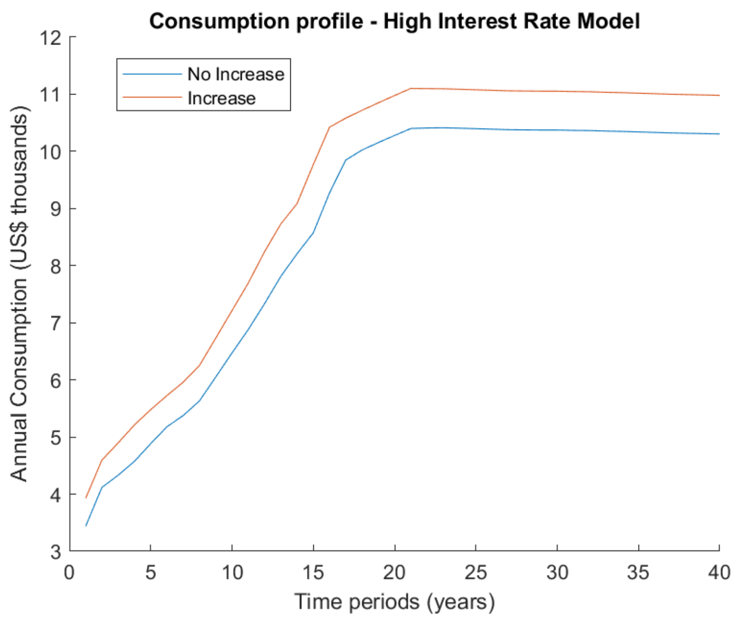
Panel B: Consumption profile



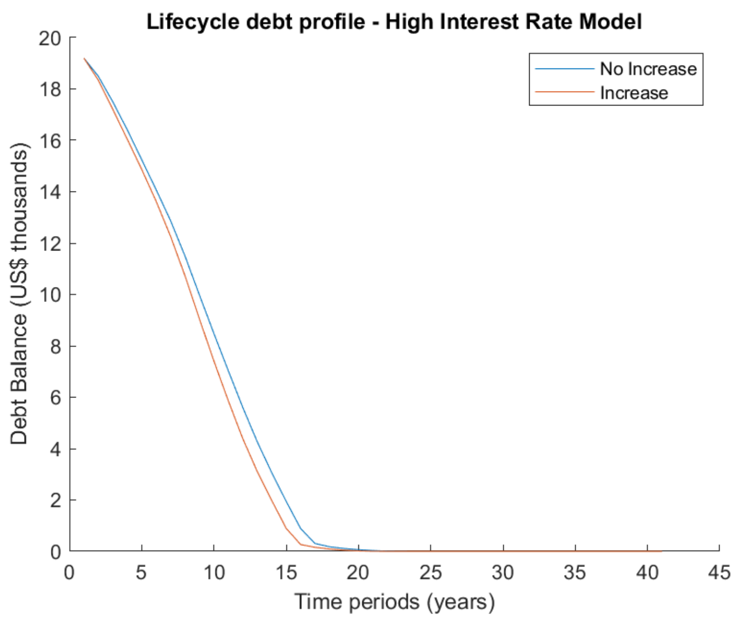
NOTE.—This figure plots the average debt and consumption profiles from the model with strategic default.

Figure A.16: Model with high perceived interest rate

Panel A: Debt profile



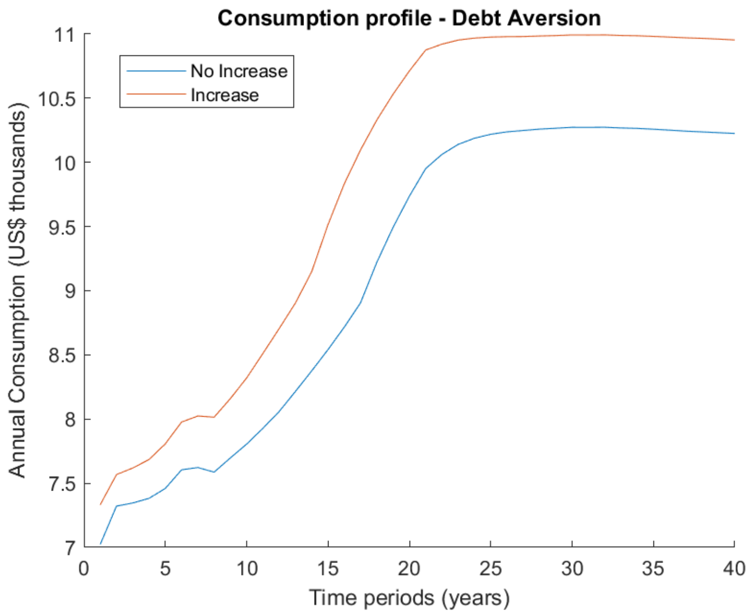
Panel B: Consumption profile



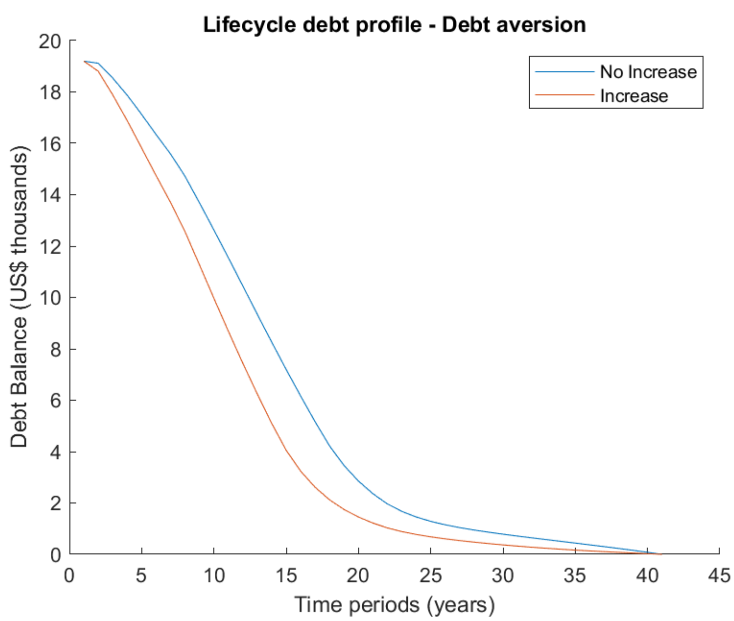
NOTE.—This figure plots the average debt and consumption profiles from the model with a high perceived interest rate.

Figure A.17: Model with student debt aversion

Panel A: Debt profile



Panel B: Consumption profile



NOTE.—This figure plots the average debt and consumption profiles from the model with student debt aversion.

Table B.1: Definition of employee subgroups

Group name	**Description**	**Wage limits**	**Additional filters**
Bound employees	Employees earning below the new minimum wage.	$\omega_i <$ NEW MW_s	Ages 18 to 64. Valid credit history prior to treatment.
Enrolled students	Bound employees with student debt and actively enrolled in college.	$\omega_i <$ NEW MW_s	Bound employee. Positive student debt balances prior to treatment. Between the ages of 18 and 22 or has non-delinquent and increasing student debt balances or trades prior to treatment.
Former students	Bound employees with student debt but not actively enrolled in college.	$\omega_i <$ NEW MW_s	Bound employee. Positive student debt balances prior to treatment. Not considered an enrolled student.
Non-students	Bound employees without student debt.	$\omega_i <$ NEW MW_s	Bound employee. Zero student debt balances prior to treatment.

NOTE.—This table describes the employee subgroups. The terms are defined as follows. ω_i is individual i's hourly wage in the pre-treatment period and NEW MW_s is the new minimum wage after state s enacts a minimum wage increase.

Table B.2: Variable definitions

Variable	Description
Hourly wage ($\omega_{i,t}$)	The hourly wage of employee i in month t
Employment	An indicator variable equal to one if employee i remains employed in month t.
Hours	The estimated average hours worked per week by employee i in month t. If estimated hours are not reported, then this variable is left as null and the observation is excluded from the sample.
Balances	The dollar amount of credit card, auto loan, student loan, and personal loan balances for employee i in month t.
Card balances	The dollar amount of credit card balances for employee i in month t.
Auto balances	The dollar amount of auto loan balances for employee i in month t.
Student balances	The dollar amount of student loan balances for employee i in month t.
Accounts	The amount of open credit card, auto loan, student loan, and personal loan accounts for employee i in month t.
Card accounts	The amount of open credit card accounts for employee i in month t.
Auto accounts	The amount of open auto loan accounts for employee i in month t.
Student accounts	The amount of open student loan accounts for employee i in month t.

NOTE.—For the labor market outcomes, employees are removed from the sample the month after they separate from their job. For the credit market outcomes, employees remain in the sample regardless of their employment status.