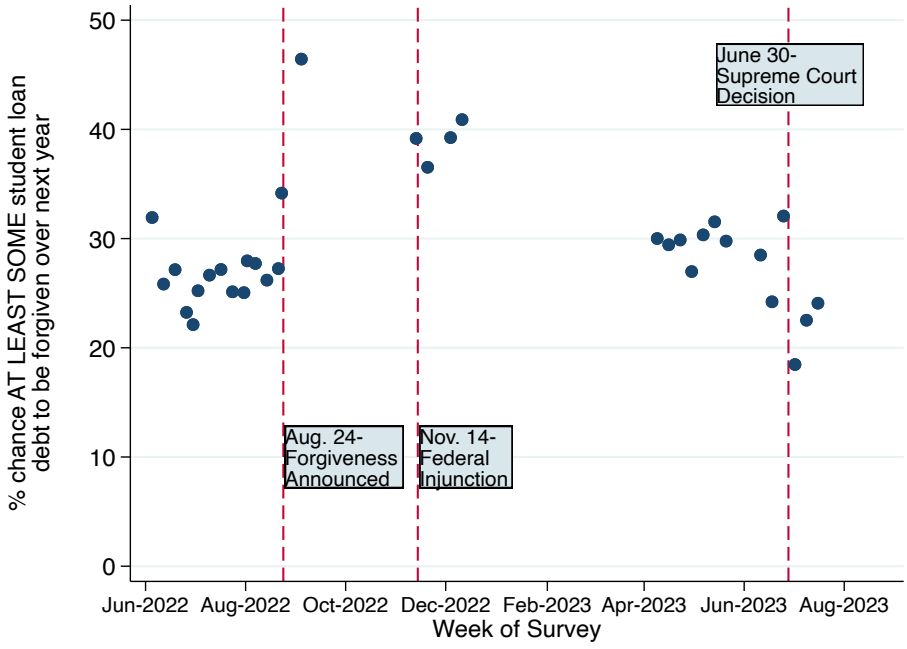
Online Appendix

A Expectations About Forgiveness from Koustas, Weber and Yannelis (2024)

In this Appendix, we examine beliefs about forgiveness using data from Koustas et al. (2024). Koustas et al. (2024) survey student loan borrowers about their beliefs about forgiveness during the period from June 2022 through July 2023. These beliefs are then linked to credit bureau data. In particular, the survey asked student loan borrowers, 'What is the percent chance AT LEAST SOME of your student loan debt will be forgiven in the next [1,2-5,10] years?" The figure below, sourced from Koustas et al. (2024), reports average beliefs about 1-year ahead forgiveness over this period. While this survey was not designed to explicitly capture beliefs about the forgiveness events we study, we can examine responses to this question for those that eventually received forgiveness to see if such individuals anticipated their forgiveness.

Figure A.1: Survey Beliefs About 1-Year Ahead Forgiveness, June 2022-July 2023



Source: Koustas et al. (2024)

The survey had 4,511 unique responses with respondents being surveyed up to four times. Since the survey responsees are linked to tradeline credit data, we can use the same algorithm

Table A.1: Tobit Regression Comparing Forgiveness Beliefs Among Ever-Forgiven Borrowers

	(1) 1-Year Ahead Forgivess Belief	(2) 2-5 Year Ahead Forgivess Belief	(3) 10-Year Ahead Forgivess Belief
Ever Forgiven	3.464	0.928	-0.833
	(2.364)	(2.643)	(3.210)
Constant	21.41***	24.47***	29.58***
	(1.337)	(1.337)	(1.725)
N	7612	7612	7612
Survey Month FE	X	X	X

Notes: Estimates from a Tobit model with lower limit at 0 and upper limit at 100. Restricted to beliefs 3 months prior to forgiveness. Standard errors clustered on respondent in parentheses.

as in the present paper to identify forgiveness. Our algorithm identifies that 333, or 7.4%, of respondents, ever receive forgiveness, which is a similar forgiveness rate among the respondents to the overall population.

To examine whether those that receive forgiveness have different beliefs than those that do not, we run the following regression for respondents for whom we have a beliefs measure prior to forgiveness:

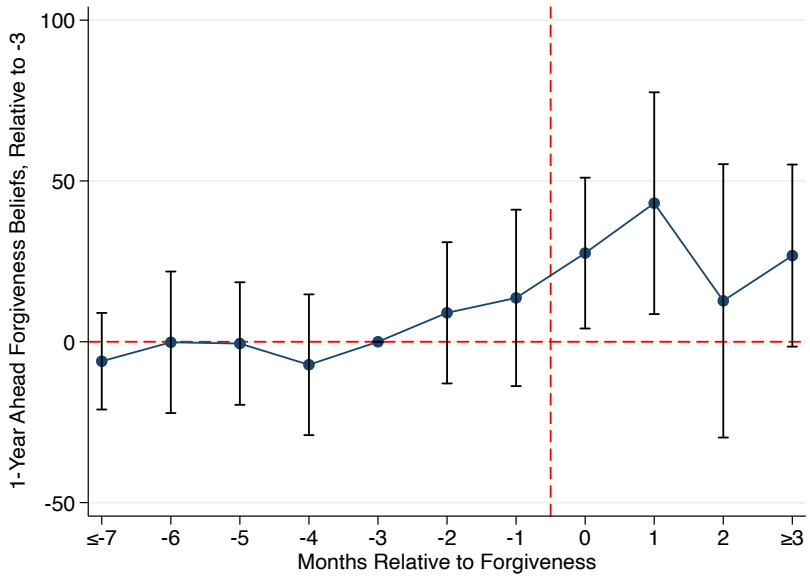
$$\pi^h_{i,t} = \alpha + \mathbb{1}\{EverForgiven_i\} + \gamma_t + \epsilon_{i,t} \tag{7}$$

where $\pi^h_{i,t}$ are h-year ahead forgiveness beleifs of individual i in survey month t, $\mathbb{1}\{EverForgiven\}$ is an indicator for eventually having at least some student loans forgiven, and γ_t is a survey month fixed effect. In practice, we estimate this specification using a Tobit regression since the outcome is bounded at 0 and 100. It is reasonable to expect that there will be some notification of forgiveness prior to forgiveness occuring in the credit bureau data. For this exercise, we examine beliefs collected at least 3 months prior to the forgiveness event, but we will also examine an event-study specification below.

Results are shown in Table A.1. We find that respondents who ever receive forgiveness have no statistically significant difference in their beliefs prior to forgiveness in either the short or long-run.

We also examine a standard event-study version of this specification around forgiveness. Interpreting the coefficients in the period post forgiveness comes with the important caveat that the survey was not designed to capture forgiveness events. The survey includes only those who self-reported positive student loan balances at the time of the first wave of the survey.

Figure A.2: Event Study of Beliefs Around Forgiveness Event



Notes: Coefficients from an event study specification estimated via Tobit model with lower limit at 0 and upper limit at 100. Bars report 95-percent confidence intervals. Standard errors clustered on respondent.

Therefore, the post periods are either identified off of follow up survey waves, respondents in the first wave who did not yet know they had their loans forgiven, or respondents who had some of their loans forgiven but not all and would therefore may be referring to their remaining student loans. Moreover it's not clear how forgiven borrowers would respond to a question about their beliefs about future forgiveness in a follow up wave. They may respond "100 percent", since forgiveness happened, or "0 percent" because they already had their loans forgiven and would not have more loans to forgive. With these caveats in mind, we present results in Figure A.2. The event study reveals a statistically insignificant increase in beliefs in -2 and -1, but no evidence of anticipation otherwise. Although we do not want to take the post-period coefficients at face value given the caveats noted above, beliefs jump up by after the forgiveness event as expected. In general, we interpret our results as having no baseline differences and no pretend between those that get forgiveness and those that do not, consistent with these forgiveness events being a "surprise" event.

A second important takeaway from the survey is that baseline beliefs about forgiveness are around 30 percent in the period prior to the Supreme Court decision in June 2023, and still around 20 percent after the decision at the date of the last survey in July 2023 (with higher beliefs at longer horizons). The permanent income hypothesis (PIH) implies that rational consumers should change their behavior based on their expectations about future forgiveness. If

households were textbook PIH consumers, this would make our MPCs a lower bound. Indeed, Koustas et al. (2024) do find that households change their repayment behavior and nondurable spending in response to large changes in expectations. On the other hand, they also present some suggestive evidence that households with the most optimistic expectations may be holding back on durable goods purchases while they wait for uncertainty to resolve, which would overstate durable MPCs. There is also a large body of empirical evidence from other contexts that households do not respond until the actual receipt of income.

B Data Construction and Validation

B.1 Data Construction

Our main data source is the Booth TransUnion Consumer Credit Panel. Because credit bureau data can often contain measurement error, fragmented records, reporting lags, and stale information (Gibbs et al., 2023) we employ various cleaning methods to ensure a clean and accurate sample. The sample is a 10% sample of all individuals in the US with a TU credit record, and each quarter a tenth of new individuals with a credit record are added to the sample. We begin with all borrowers that have an open student loan as of January 2021. There are approximately 4.9 million such borrowers in the data. We then remove any records which have been inactive for over 365 days, any borrowers that do not reside in the U.S., and borrowers who have missing records in any month between January 2021 and March 2024. Additionally we include only borrowers whose earliest recorded student loan origination is before 2020. This is done to avoid including actively enrolled students whose loans are still in deferment. These initial filters remove approximately 10% of the original sample.

Next we remove any borrowers whose birth years are either prior to 1940 or missing as these records are likely parent borrowers. Additionally, we remove any student loan borrowing cohorts prior to 1960, when modern federal student loan programs did not exist. Lastly, as mentioned in section 3, we remove borrowers who have extensive drops in reporting due to lagged servicer reporting of loan refinancing or deaths. This leaves us with a final sample of approximately 4 million active student loan borrowers. For computational purposes, we then take a random 25% sample of these borrowers which yields a data set containing just under 1 million borrowers.

The outcomes we observe for each borrower are balances, payments due, and 30 day delinquency status on student loan, mortgage, auto loan, and credit card lines. If there is no reported trade line in any of these categories for a given borrower we assume a balance and payment due of zero. Additionally, we winsorize balances and payments at the 99% level as the data

contains extreme, likely erroneous, outliers.

B.2 Data Validation

To validate our forgiveness classification we hand-collect forgiveness statistics from Department of Education (DOE) press releases. These press releases occur whenever a major forgiveness announcement has occurred and contain information on the number of borrowers affected, the amount of debt the DOE anticipates will be forgiven as a result of the announcement, and a rolling tab of all forgiveness under the Biden Administration.[34] For each major forgiveness announcement between 2021 and 2023, we collected the number of borrowers who will receive forgiveness and the amount of debt reported to be forgiven. Additionally, we collect aggregate state level forgiveness amounts. Table B.1 reports the largest of these announcements along with the number of borrowers affected and the total debt discharged.

Figure 1 plots the number of TransUnion borrowers forgiven in each month. The dashed vertical lines mark the major DOE forgiveness announcements from Table B.1. In our sample we observe large increases in the number of forgiven borrowers at the same time or just after these major announcements, confirming we have accurately identified student loan forgiveness in the TransUnion data. Figure B.1 provides further evidence by plotting the cumulative number of forgiven borrowers and the amount of debt forgiven alongside the statistics reported by the DOE. We see very similar trends and magnitudes of forgiveness between the DOE reporting and our estimates, with TransUnion numbers lagged those of the DOE.[35] As additional validation, we examine forgiveness rates by states between our estimates and the DOE reporting in Figures B.3 and B.4. We again find that our estimates closely match those of the DOE reporting, even at the state level. Importantly, our estimates closely match forgiveness per capita, which indicates that our results are not simply an artifact of large states seeing more forgiveness.

[34] Visit https://www.ed.gov/news/press-releases/ to view each individual press release

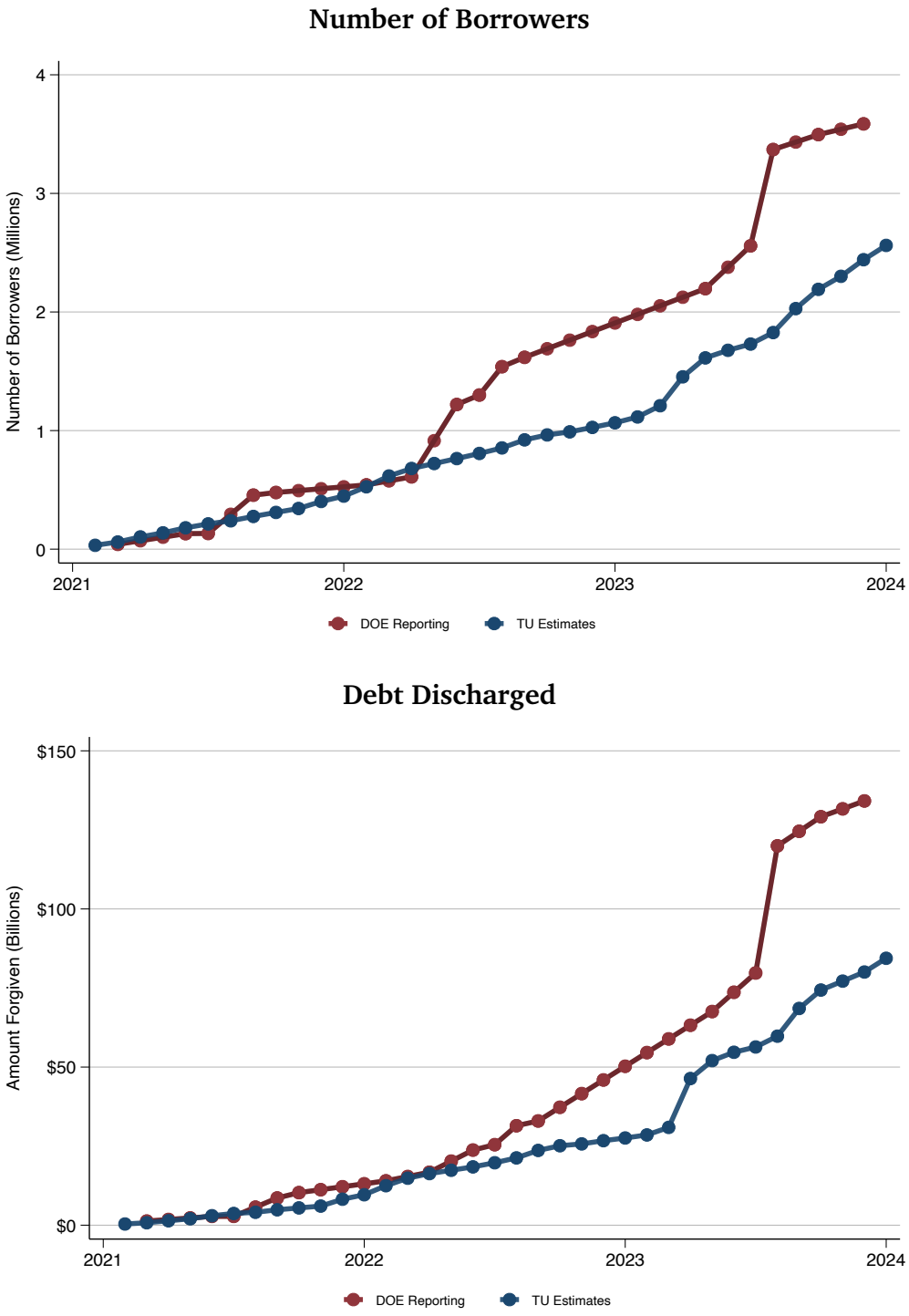
[35] It is expected that the TransUnion data would slightly underestimates both borrowers and debt amounts. This is due to the DOE reporting anticipated forgiveness for eligible borrowers, and not actual forgiveness as well as delays in borrowers applying and servicers reporting forgiveness to the DOE and TransUnion.

Table B.1: List of Major Announcements

Announcement Date	Policy Category	Total Borrowers Affected	Total Debt Discharged	Cumulative Discharged to Date
March 2021	Permanent Disability	41,000	$1.3 Billion	$1.3 Billion
July 2021	Borrower Defense	90,000	$1.5 Billion	$2.8 Billion
September 2021	Permanent Disability	323,000	$5.8 Billion	$8.6 Billion
October 2021	PSLF	22,000	$1.7 Billion	$10.3 Billion
June 2022	Borrower Defense	560,000	$5.8 Billion	$23.8 Billion
July 2022	PSLF	40,000	$7.0 Billion	$25.5 Billion
August 2022	Borrower Defense	208,000	$3.9 Billion	$31.5 Billion
September 2022	Borrower Defense	79,000	$1.5 Billion	$33 Billion
May 2023	PSLF	615,000	$42 Billion	$67.7 Billion
August 2023	IDR Adjustment	804,000	$39 Billion	$120 Billion
October 2023	PSLF	53,000	$5.2 Billion	$129 Billion
October 2023	Permanent Disability	22,000	$1.2 Billion	$129 Billion
December 2023	IDR Adjustment	46,000	$2.2 Billion	$132 Billion
December 2023	PSLF	34,400	$2.6 Billion	$132 Billion

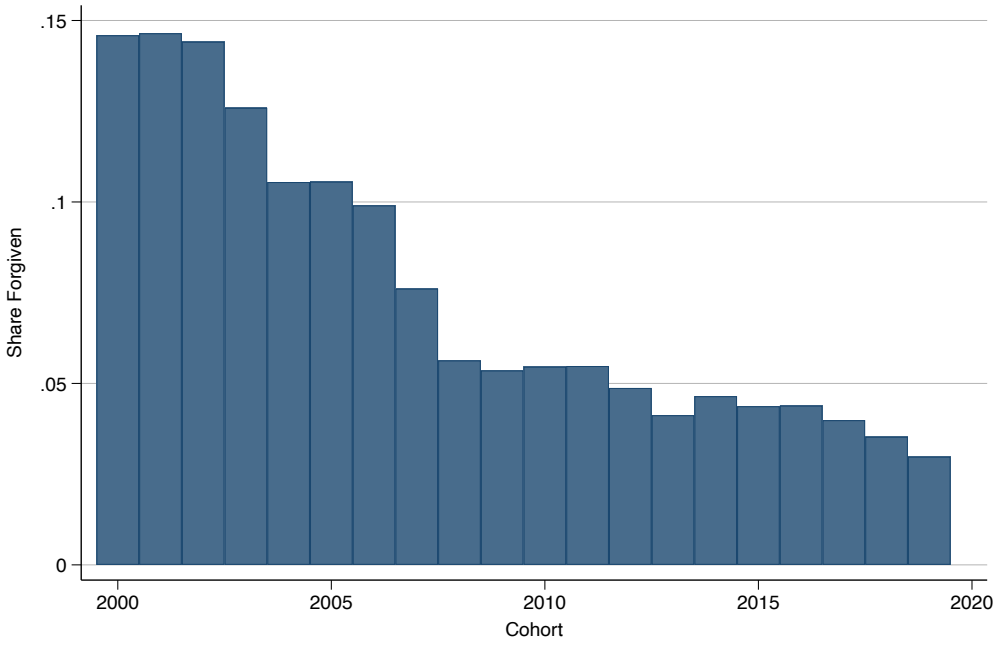
Notes: This table lists the largest student loan debt relief announcements by the Department of Education (DOE) between January 2021 and December 2023. The statistics reported represent the amount of forgiveness anticipated to be rolled out following the announcement. For additional information on each announcement visit https://www.ed.gov/news/press-releases/ Source: TransUnion and DOE

Figure B.1: Cumulative Announced Forgiveness



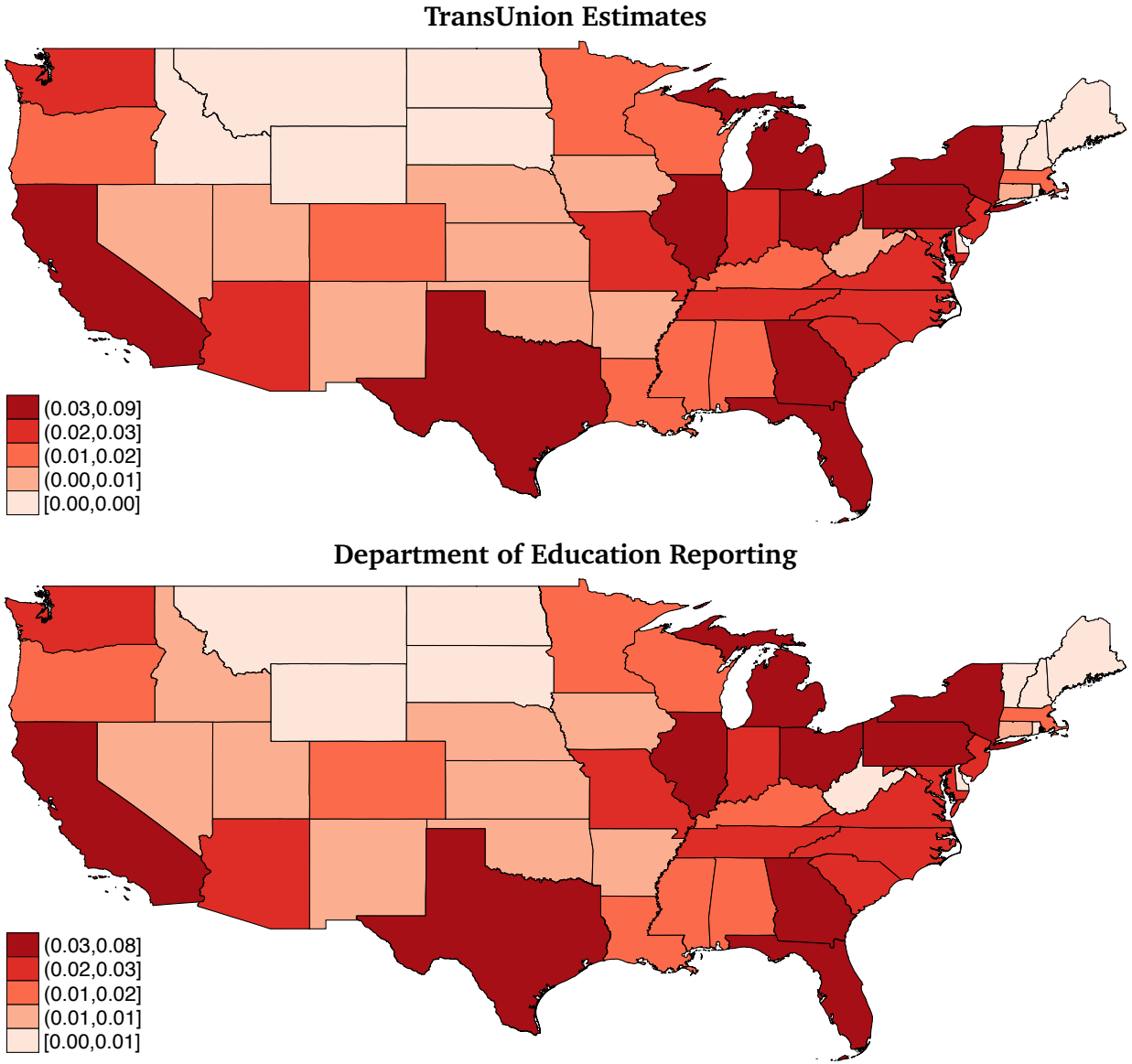
Notes: These figures compare our estimates of student loan forgiveness with the statistics reported by the Department of Education (DOE). The red lines plot the DOE reporting of the total amount of anticipated forgiveness as of each date. Gaps between DOE announcements have been linearly interpolated. The blue lines report our estimates of realized forgiveness using TransUnion data. Source: TransUnion and DOE.

Figure B.2: Forgiveness Rates by Cohort



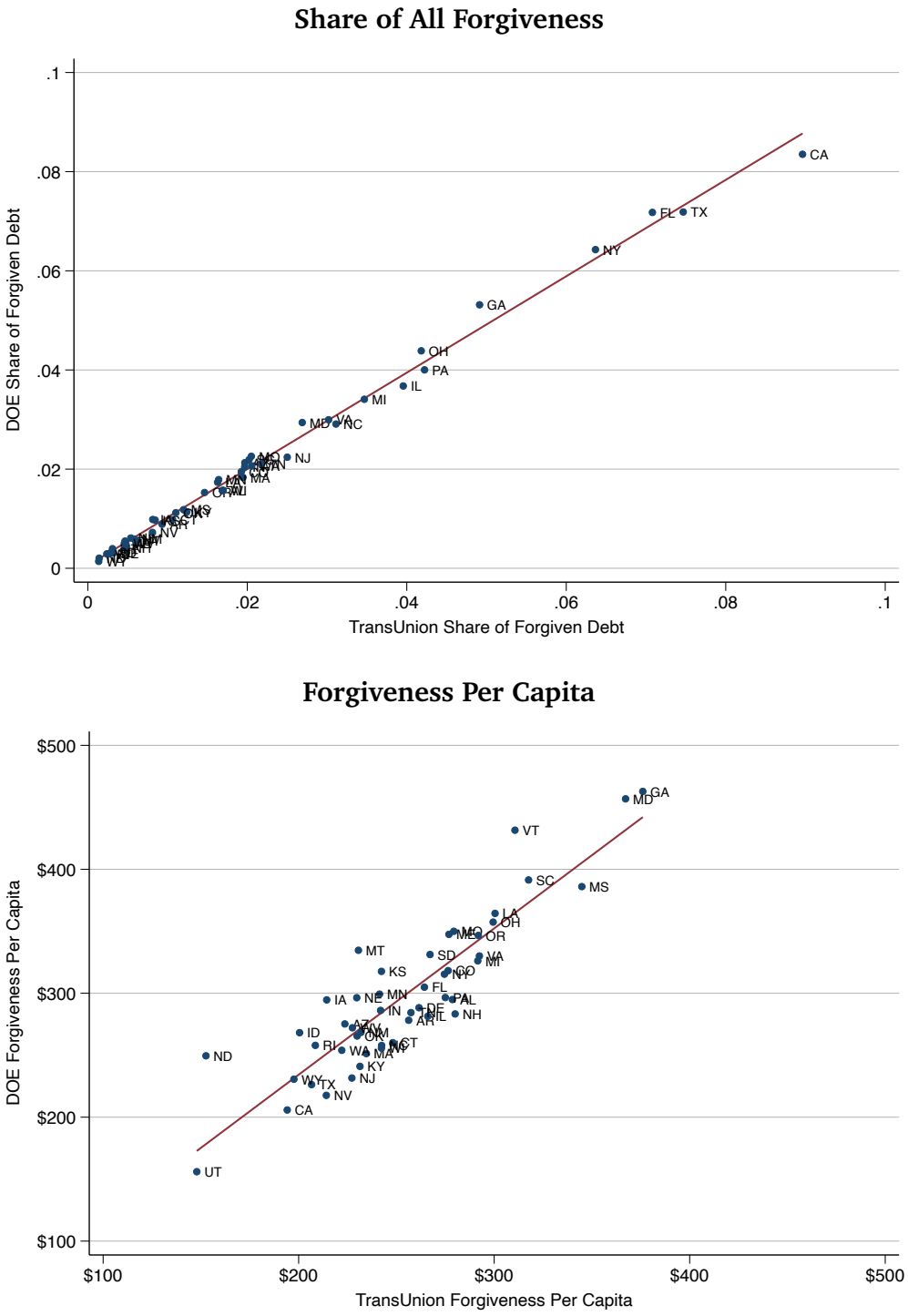
Notes: This figure plots the share of active borrowers that receive forgiveness by cohort. Cohort is defined as the earliest year we observe borrowing in the data. Source: TransUnion and DOE.

Figure B.3: Map of Forgiveness by State



Notes: These figures plot the share of total student loan forgiveness by state. The top panel uses the estimates from our TransUnion sample. The bottom panel uses the statistics reported by the Department of Education (DOE) in December of 2023. The state level DOE reporting is restricted to PSLF and IDR payment adjustment forgiveness only. Source: TransUnion and DOE.

Figure B.4: Binscatter of Forgiveness by State



Notes: These figures plot a binscatter of the share of total student loan forgiveness and forgiveness per capita by state as reported by the Department of Education (y-axis) and our TransUnion estimates (x-axis). A line of best fit is plotted in red and state labels are included in black. Loan forgiveness at the state level is limited only to forgiveness resulting from IDR payment count adjustments and PSLF. Source: TransUnion, DOE, and U.S. Census.

C Additional Tables and Figures

Table C.1: Alternative Forgiveness Targeting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			All Earners			Excl. Public Service	Public Service
Panel A: Control = Non-Forgiven Student Loan Borrowers (10% Sample)							
	933.94***	490.81***	411.11***	399.05***	365.46***	21.87	765.31***
	(26.78)	(26.71)	(26.25)	(26.61)	(25.58)	(33.86)	(40.86)
Observations	306,316	305,375	305,112	305,112	305,142	180,874	120,268
Panel B: Control = General Population (1% Sample)							
	947.14***	619.51***	509.16***	493.30***	458.30***	144.38***	811.32***
	(21.98)	(21.52)	(21.11)	(21.19)	(20.44)	(26.00)	(34.40)
Observations	477,139	475,727	475,358	475,358	468,644	306,717	163,927
Borrower Cohort (Panel A)		X	X	X	X	X	X
Age FE (Panel B), and Gender							
Education Level FE			X	X	X	X	X
Zip Code FE				X	X	X	X
Industry FE					X	X	

Notes: This table presents estimates of β using the following OLS equation:

$$Earnings_i = \beta Forgiveness_i + \gamma X_i + \epsilon_i$$

where $Earnings_i$ are the monthly earnings for individual i in December 2019 and $Forgiveness_i$ is an indicator for if individual i received student loan forgiveness as of time t. X_i are the fixed effects labeled in the bottom of the table. Standard errors are robust and are presented in parentheses below each estimate. Panel A restricts to borrowers that had open student loans in January of 2021. Panel B adds a 1% sample of all borrowers with earnings data that do not have open student loans in January 2021. We use sample weights to appropriately account for the 1% sample of non-student borrowers. The sample is limited to borrowers with available demographics and earnings information. Source: Employment records.

*$p < .1$, ** $p < .05$, *** $p < .01$

Table C.2: Extensive and Intensive Margins

	Extensive Margins		Intensive Margins		
	(1)	(2)	(3)	(4)	(3)
	Num. of Lines	Any Open Line	Balances	Payments Due	Delinquency
Panel A: Student Loans					
Dynamic DID	-2.046***	-0.883***	-31778.402***	-63.134***	-0.024***
	(0.168)	(0.025)	(3988.683)	(12.047)	(0.004)
Two-Way FE	-2.236***	-0.858***	-32219.048***	-71.614***	-0.029***
	(0.110)	(0.024)	(3253.473)	(7.563)	(0.006)
Panel B: Mortgages					
Dynamic DID	0.008***	0.007***	-216.917	-0.095	-0.000
	(0.001)	(0.001)	(255.283)	(1.483)	(0.000)
Two-Way FE	0.007***	0.007***	23.804	1.521	-0.000
	(0.001)	(0.001)	(252.112)	(1.421)	(0.000)
Panel C: Auto Loans					
Dynamic DID	0.009***	0.007***	-637.807***	-11.736***	-0.000
	(0.002)	(0.002)	(43.787)	(0.972)	(0.001)
Two-Way FE	0.010***	0.008***	-560.164***	-10.439***	-0.001
	(0.001)	(0.001)	(51.332)	(0.987)	(0.000)
Panel D: Credit Cards					
Dynamic DID	0.042***	0.005***	98.254***	1.995*	0.001
	(0.008)	(0.001)	(37.138)	(1.149)	(0.002)
Two-Way FE	0.060***	0.007***	66.954**	1.813*	0.000
	(0.006)	(0.001)	(27.860)	(1.102)	(0.001)
Calendar Month FE	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Observations	38,699,271	38,699,271	38,699,271	38,699,271	38,699,271
Number of Individuals	992,289	992,289	992,289	992,289	992,289

Notes: This table presents estimates of the average treatment effect on the treated. The rows labeled "Dynamic DID" use De Chaisemartin and d'Haultfoeuille (2024) and rows labeled "Two-Way FE" use two way fixed-effects. Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. In the dynamic DID rows group-specific average treatment effects on the treated are averaged with weights based on group size. Grouping is done at the forgiveness month level which is econometrically identical to the individual level. Standard errors are clustered by forgiveness cohort and are presented in parentheses below each estimate. Unique observations is the number of unique borrower-month observations in the data. The intensive margin trade lines included in columns 3-5 are limited to only trade lines that were opened prior to forgiveness. Source: TransUnion $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table C.3: Effects on Credit Score and Relocations

	Outcomes	
	(1) Credit Score	(2) Relocate Indicator
Dynamic DID	-1.062	-0.001
	(0.818)	(0.001)
Two-Way FE	0.093	-0.001**
	(0.323)	(0.000)
Calendar Month FE	✓	✓
Individual FE	✓	✓
Observations	38,699,271	38,699,271
Number of Individuals	992,289	992,289

Notes: This table presents estimates of the average treatment effect on the treated using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Group-specific average treatment effects on the treated are averaged with weights based on group size. "Fixed effects" refers to how we define groups (either by forgiveness cohort or by individual) and the set of potential comparison borrowers (all not-yet-treated or not-yet-treated borrowers who started borrowing in the same year). Standard errors are clustered by forgiveness cohort and are presented in parentheses below each estimate. Unique observations is the number of unique borrower-month observations in the data. Source: TransUnion $^{*}p < .1$, ** $p < .05$, *** $p < .01$

Table C.4: Longer Run Effects on Credit Outcomes

	Outcomes		
	(1) Balances	(2) Payments Due	(3) Delinquency
Panel A: Mortgages			
Dynamic DID	2845.056***	23.321***	-0.000
	(659.477)	(3.725)	(0.000)
Two-Way FE	2832.404***	23.178***	-0.000*
	(493.514)	(2.725)	(0.000)
Panel B: Auto Loans			
Dynamic DID	218.211***	4.704***	-0.001
	(56.382)	(1.592)	(0.001)
Two-Way FE	279.606***	5.765***	-0.001
	(37.302)	(0.903)	(0.000)
Panel C: Credit Cards			
Dynamic DID	251.042***	6.135***	0.004
	(49.846)	(1.518)	(0.003)
Two-Way FE	211.120***	5.850***	0.003**
	(47.949)	(1.489)	(0.001)
Calendar Month FE	✓	✓	✓
Individual FE	✓	✓	✓
Observations	38,699,271	38,699,271	38,699,271
Number of Individuals	992,289	992,289	992,289

Notes: This table presents estimates of the average treatment effect on the treated. The rows labeled "Dynamic DID" use De Chaisemartin and d'Haultfoeuille (2024) and rows labeled "Two-Way FE" use two way fixed-effects. Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. In the dynamic DID rows group-specific average treatment effects on the treated are averaged with weights based on group size. Grouping is done at the forgiveness month level which is econometrically identical to the individual level. Standard errors are clustered by forgiveness cohort and are presented in parentheses below each estimate. Effects are estimated over a 12-month horizon post-forgiveness. Source: TransUnion
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table C.5: IV Balance Regressions

	Age	Credit Score	Share Black	Share Asian
Servicer Leniency	9.859*	11.903	0.003	0.001
	(5.372)	(14.408)	(0.004)	(0.002)
Observations	723983	723978	723983	723983
	Share Female	Household Income	Democrat	Share College Degree
Servicer Leniency	-0.000	-532.423	-0.123	-0.003
	(0.000)	(616.108)	(0.502)	(0.003)
Observations	723983	723983	723983	723983

Notes: This table presents estimates of β the following OLS equation:

$$Y_i = Leniency_i + \epsilon_{it}$$

where Y_i is the outcome labeled above each column and $Leniency_i$ is the share of borrowers that received forgiveness under individual i's servicer. Race, household income, education, and political affiliation are the state level averages of individual i found in the 2021 ACS. Age, credit score, and state residence are reported by TransUnion. Each row represents a separate regression. Only the borrowers found in Table 6 who are observed over the full six months before and after forgiveness are included. Source: TransUnion $^{*}p < .1$, ** $p < .05$, *** $p < .01$

Table C.6: Effects by Months of High Policy Specific Forgiveness

	Most Common Policy in Selected Months (> 90%)			
	Disability	**Borrower Defense**	**PSLF**	**IDR**
	(1)	(2)	(3)	(4)
Panel A: Student Loans				
Balances	-12144.399***	-27553.796***	-41065.647***	-37550.854***
	(1319.354)	(4311.206)	(9602.688)	(3997.530)
Payment Due	-82.608***	-57.430***	-45.309***	-96.912***
	(9.892)	(9.854)	(12.403)	(6.002)
Delinquency	-0.019***	-0.024**	-0.017***	-0.018***
	(0.005)	(0.010)	(0.007)	(0.006)
Panel B: Mortgages				
Balances	4570.422**	4087.896**	2321.452*	847.236***
	(1797.095)	(1687.724)	(1239.113)	(111.263)
Payment Due	22.827**	31.292***	19.217***	6.613***
	(10.951)	(8.932)	(5.904)	(0.449)
Delinquency	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Panel C: Auto Loans				
Balances	212.542	182.537	269.713**	315.764***
	(353.376)	(197.966)	(106.774)	(84.654)
Payment Due	3.183	3.634	5.554***	7.482***
	(5.401)	(3.551)	(1.947)	(1.064)
Delinquency	-0.001	-0.002*	0.000	0.004***
	(0.004)	(0.001)	(0.001)	(0.001)
Panel D: Credit Cards				
Balances	228.024**	178.915**	276.423***	182.965***
	(103.659)	(83.911)	(70.267)	(25.218)
Payment Due	3.988	4.065**	6.682***	5.660***
	(2.599)	(2.047)	(2.172)	(0.372)
Delinquency	0.000	0.005	0.001	0.008***
	(0.005)	(0.004)	(0.002)	(0.002)
Calendar Month FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Observations	36,501,855	36,614,253	37,060,023	36,736,050
Num. Forgiven Individuals	2,194	5,076	16,506	8,199

Notes: This table presents estimates of the average treatment effect on the treated using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Group-specific average treatment effects on the treated are averaged with weights based on group size. Grouping is done at the forgiveness month level which is econometrically identical to the individual level. Standard errors are clustered by borrower cohort and are presented in parentheses below each estimate. Effects are estimated over a 6-month horizon post-forgiveness. Disability months are March 2021 and September 2021. Borrower defense months are July 2021, June 2022, August 2022, and September 2022. PSLF months are October 2021, July 2022, and May 2023. IDR is August 2023. Source: TransUnion $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table C.7: No Payment Group Outcomes

	Outcomes		
	(1) Balances	(2) Payments Due	(3) Delinquency
Panel A: Student Loans			
Dynamic DID	-31785.419***	3.331	0.003
	(1782.878)	(4.574)	(0.007)
Two-Way FE	-32815.239***	-5.394**	-0.015***
	(787.646)	(2.310)	(0.003)
Panel B: Mortgages			
Dynamic DID	2952.566***	20.520***	-0.000
	(689.489)	(4.087)	(0.000)
Two-Way FE	3312.197***	21.891***	-0.001
	(418.283)	(2.541)	(0.000)
Panel C: Auto Loans			
Dynamic DID	216.932***	5.225***	-0.001
	(79.368)	(1.608)	(0.001)
Two-Way FE	276.827***	6.163***	-0.002***
	(48.720)	(0.718)	(0.001)
Panel D: Credit Cards			
Dynamic DID	232.613***	5.393***	0.004
	(39.156)	(1.267)	(0.003)
Two-Way FE	181.769***	4.346***	0.002*
	(32.258)	(0.849)	(0.001)
Calendar Month FE	✓	✓	✓
Individual FE	✓	✓	✓
Observations	29,285,022	29,285,022	29,285,022
Number of Individuals	750,898	750,898	750,898

Notes: This table presents estimates of the average treatment effect on the treated. The rows labeled "Dynamic DID" use De Chaisemartin and d'Haultfoeuille (2024) and rows labeled "Two-Way FE" use two way fixed-effects. Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. In the dynamic DID rows group-specific average treatment effects on the treated are averaged with weights based on group size. Grouping is done at the forgiveness month level which is econometrically identical to the individual level. Standard errors are clustered by forgiveness cohort and are presented in parentheses below each estimate. Effects are estimated over a 6-month horizon post-forgiveness. The no payment group consists of forgiven borrowers who receive forgiveness at least 6-months before the federal student loan payment pause resumed and had no payments due in the month prior to forgiveness as well as non-forgiven borrowers who had no payments due in the month before the federal student loan payment pause resumed. Source: TransUnion $^{*}p < .1$, ** $p < .05$, *** $p < .01$

Table C.8: Dynamic DID Alternative Clustering

	Outcomes		
	(1)	(2)	(3)
Cluster Level	Balances	Payments Due	Delinquency
Panel A: Mortgages			
	2318.755***	17.468***	-0.000
Forgiveness Cohort	(511.819)	(2.770)	(0.000)
Borrowing Cohort	(229.452)	(1.839)	(0.000)
Panel B: Auto Loans			
	232.043***	4.804***	0.000
Forgiveness Cohort	(41.583)	(0.945)	(0.001)
Borrowing Cohort	(27.926)	(0.723)	(0.000)
Panel C: Credit Cards			
	222.049***	5.337***	0.004***
Forgiveness Cohort	(39.766)	(1.181)	(0.002)
Borrowing Cohort	(12.508)	(0.395)	(0.001)
Calendar Month FE	✓	✓	✓
Individual FE	✓	✓	✓
Observations	38,699,271	38,699,271	38,699,271
Number of Individuals	992,289	992,289	992,289

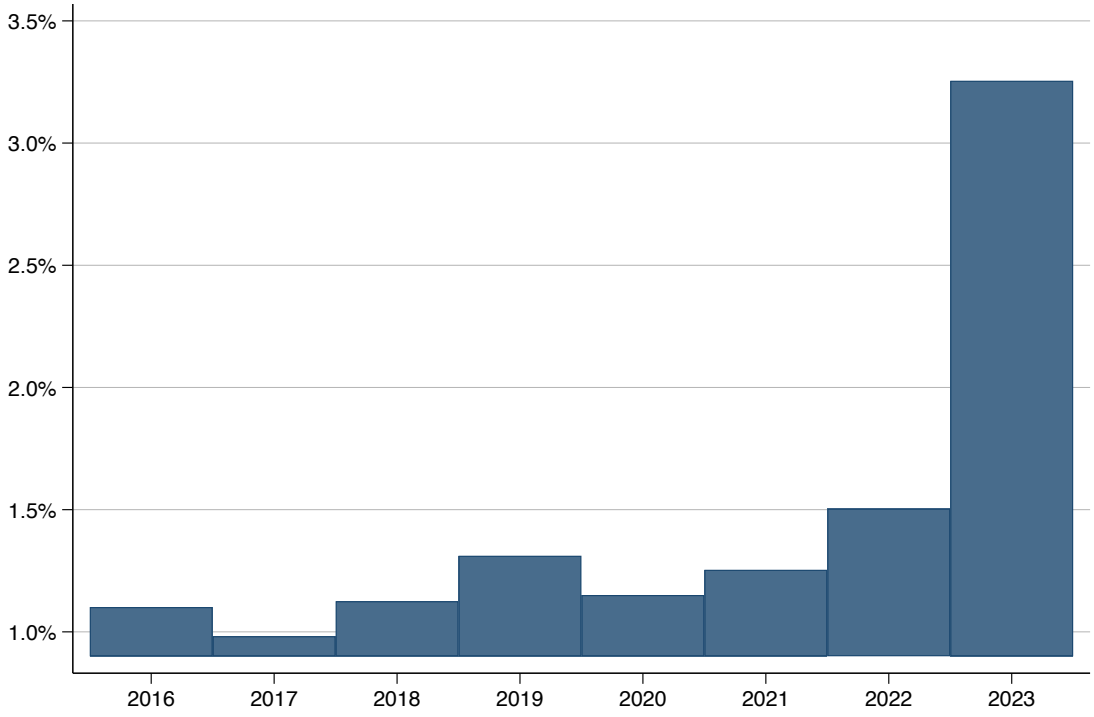
Notes: Notes: This table presents estimates of the average treatment effect on the treated using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Group-specific average treatment effects on the treated are averaged with weights based on group size. Grouping is done at the forgiveness month level which is econometrically identical to the individual level. The first column clusters standard errors by forgiveness cohort and the second column clusters them by borrowing cohort. Standard errors are presented in parentheses below each estimate. Source: TransUnion $^{*}p < .1$, ** $p < .05$, *** $p < .01$

Table C.9: Longer Run Effects on Earnings and Employment

	Earnings	Log Earnings	Any Employment	New Employment	New Industry	Public Service	Hours Worked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Forgiveness	-68.57***	-0.036***	-0.010***	0.0006**	0.0007***	-0.008**	-1.545***
	(14.11)	(0.007)	(0.003)	(0.0003)	(0.0002)	(0.0002)	(0.426)
Calendar Month FE	✓	✓	✓	✓	✓	✓	✓
Forgiveness Cohort FE	✓	✓	✓	✓	✓	✓	✓
Observations	22,245,614	22,245,614	57,226,857	57,226,857	57,226,857	57,226,857	12,666,655
Period -1 Average	5809.94	8.30	0.61	0.007	0.004	0.233	138.72

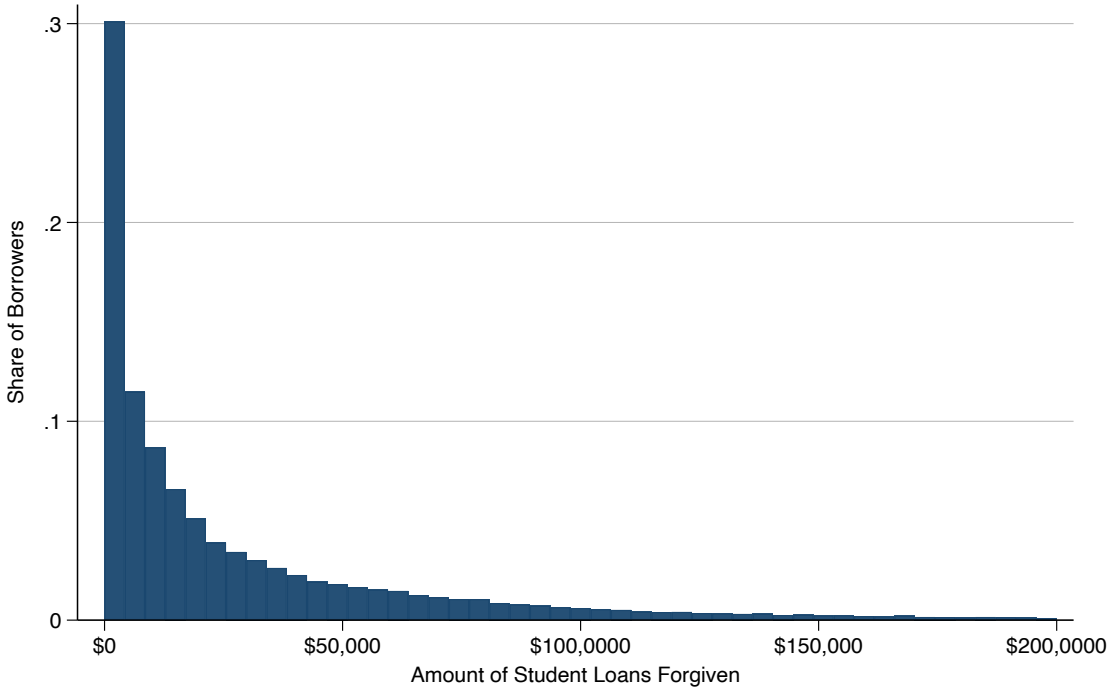
Notes: This table presents estimates of the average treatment effect on the treated using De Chaisemartin and d'Haultfoeuille (2024) with a 12 month post-treatment horizon. Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Group-specific average treatment effects on the treated are averaged with weights based on group size. "Fixed effects" refers to how we define groups (by forgiveness cohort) and the set of potential comparison borrowers (all not-yet-treated or not-yet-treated borrowers who started borrowing in the same year). Standard errors are clustered by forgiveness cohort and are presented in parentheses below each estimate. Outcomes are labeled above each column. Public service employment is defined as being employed in an industry that falls under the NAICS sectors of public administration, health care, and social assistance, or educational services. Source: Employment records.
$^{*}p < .1$, ** $p < .05$, *** $p < .01$

Figure C.1: Forgiveness Rates by Year



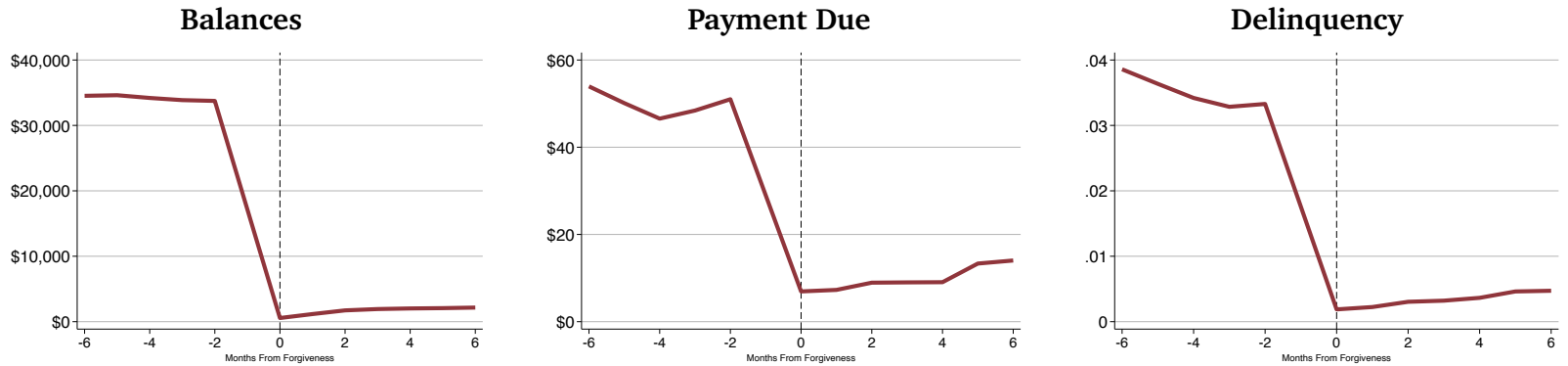
Notes: This figure plots the percentage of active student loan borrowers who received student loan forgiveness in each year from 2016 to 2023. Student loan forgiveness is identified using the methodology outlined in Section 3.2. Source: TransUnion.

Figure C.2: Distribution of Forgiveness Amounts



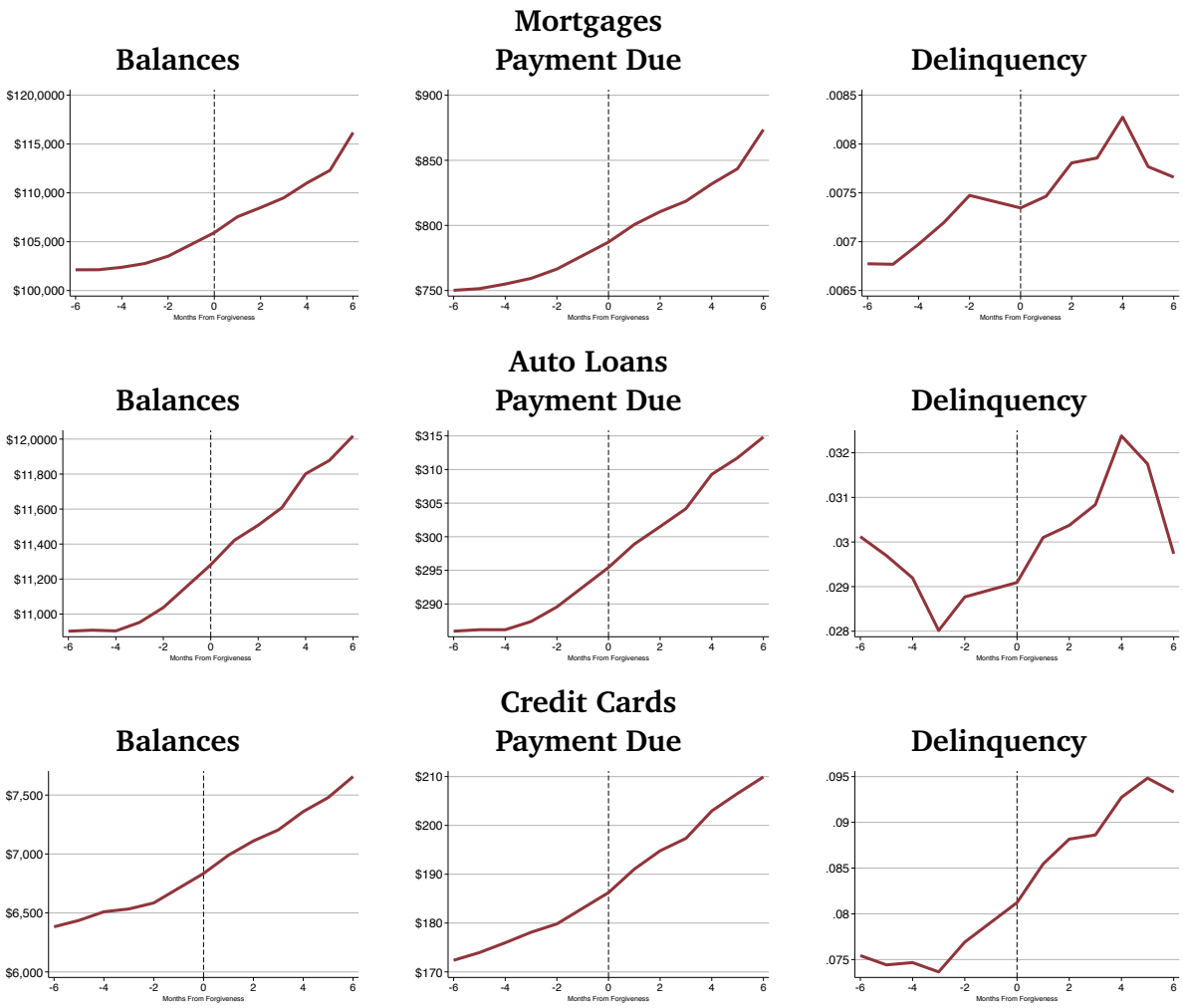
Notes: This figure plots the distribution of dollar amount of student loan forgiveness amount borrowers who receive forgiveness. Student loan forgiveness is identified using the methodology outlined in Section 3.2. Source: TransUnion.

Figure C.3: Student Loan Raw Means



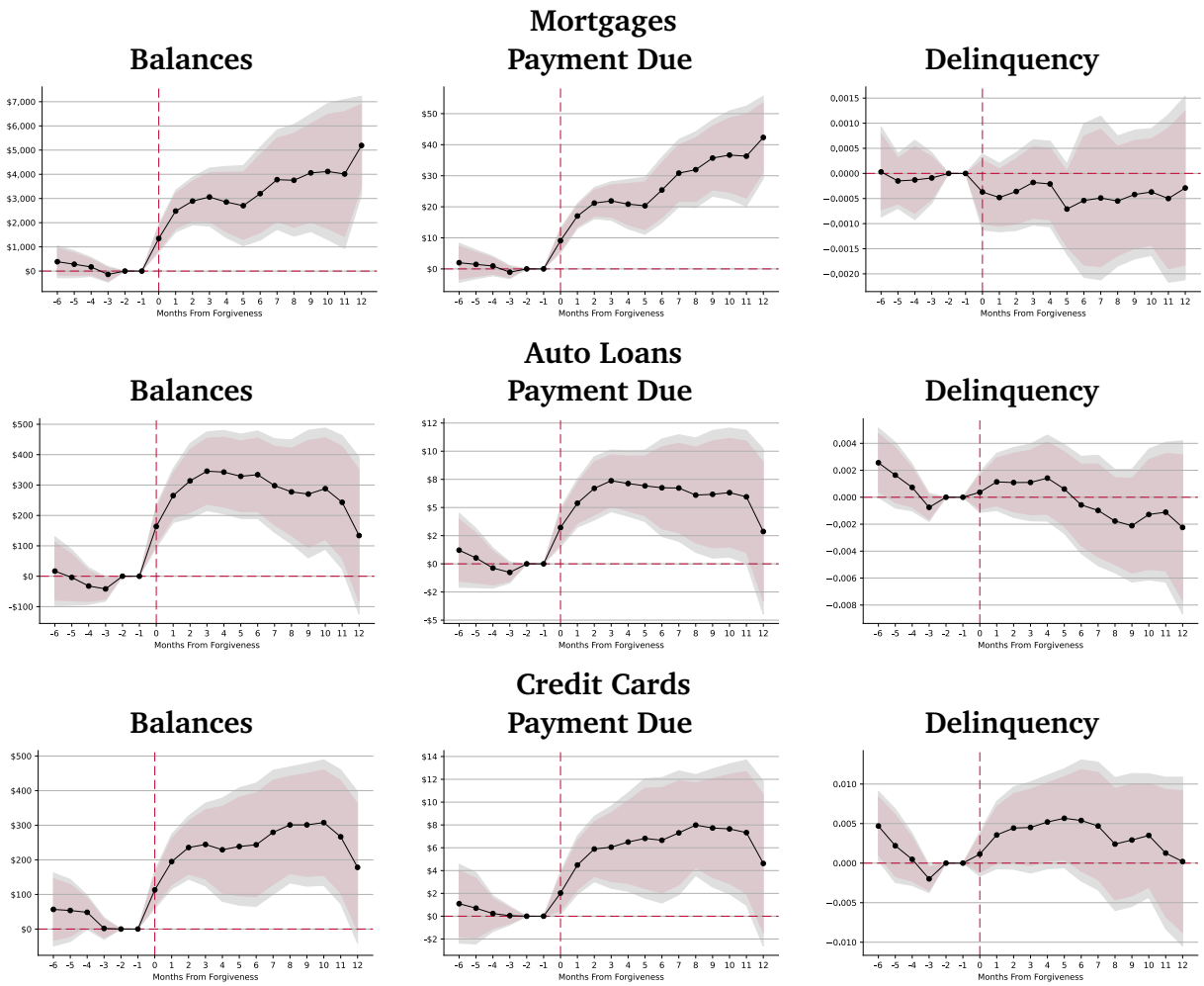
Notes: These figures plot average balances, payments, and delinquency status among those who received student loan forgiveness in the six months leading up to and after forgiveness. The dashed vertical line indicated the month in which forgiveness was received. Source: TransUnion

Figure C.4: Credit Outcomes Raw Means



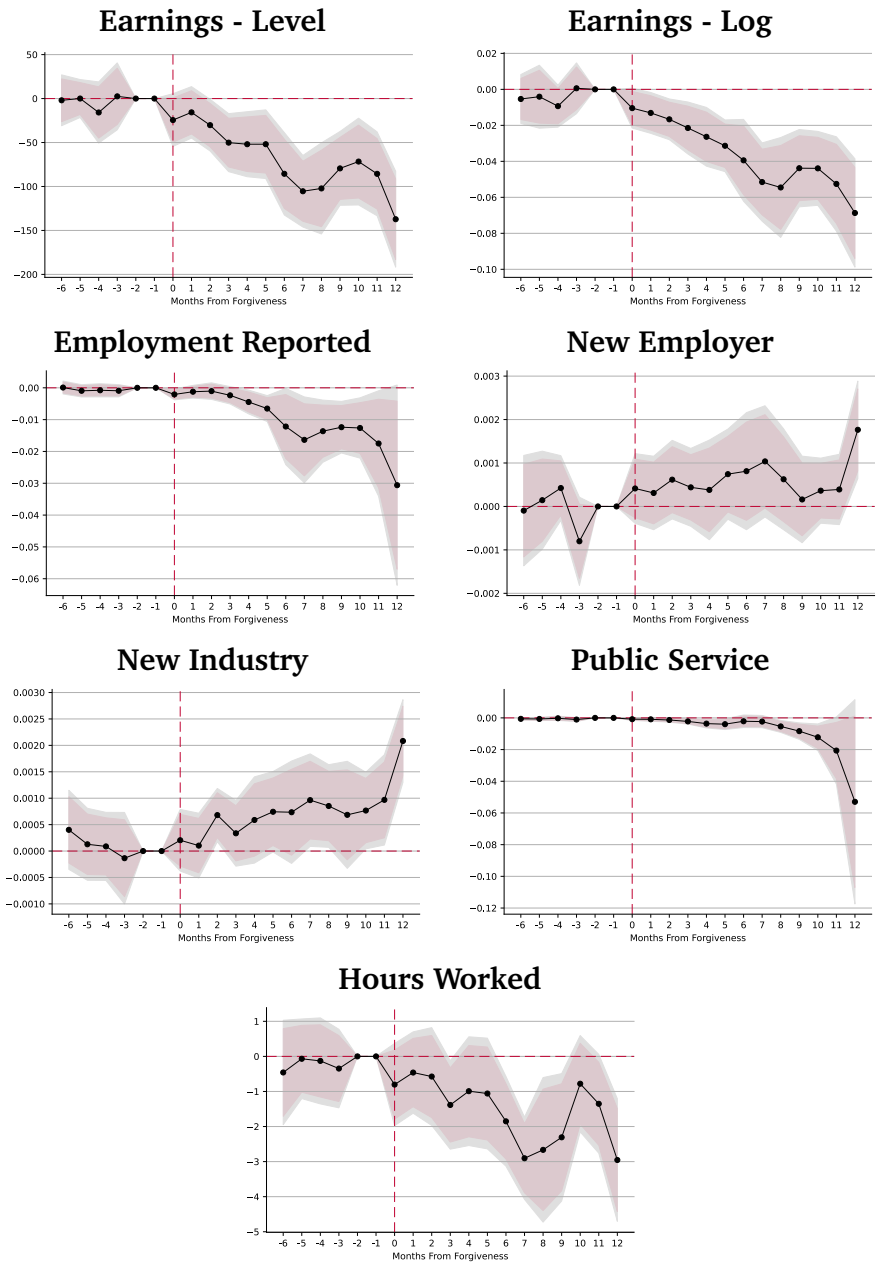
Notes: These figures plot average balances, payments, and delinquency status among those who received student loan forgiveness in the six months leading up to and after forgiveness. The dashed vertical line indicated the month in which forgiveness was received. Source: TransUnion

Figure C.5: Longer Run Effects on Credit Outcomes



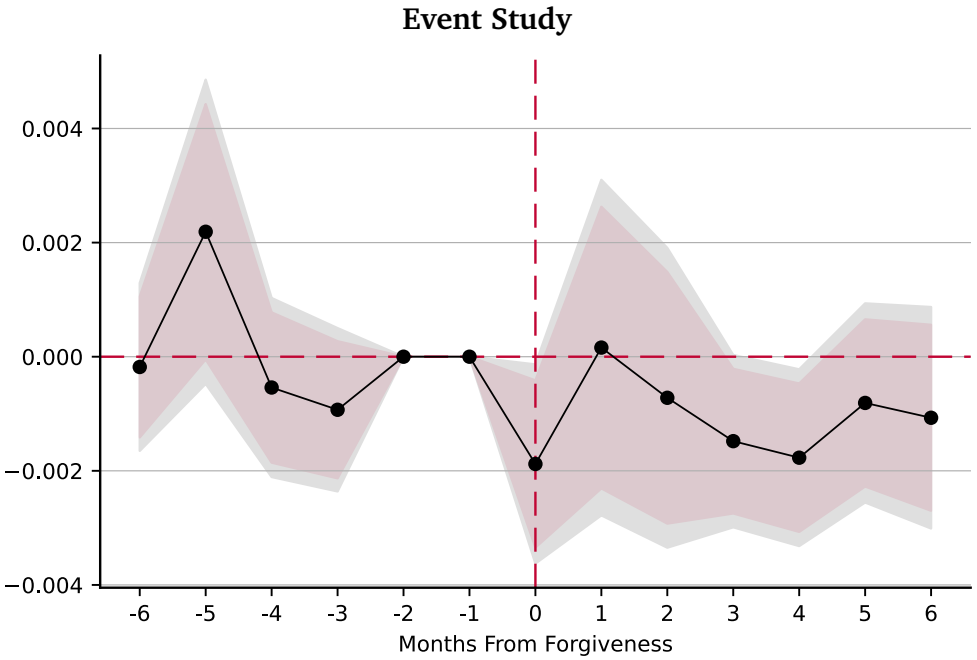
Notes: This figure plots estimates, 95% confidence intervals (grey) and 90% confidence intervals (red) of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. Source: TransUnion

Figure C.6: Longer Run Effects on Earnings and Employment



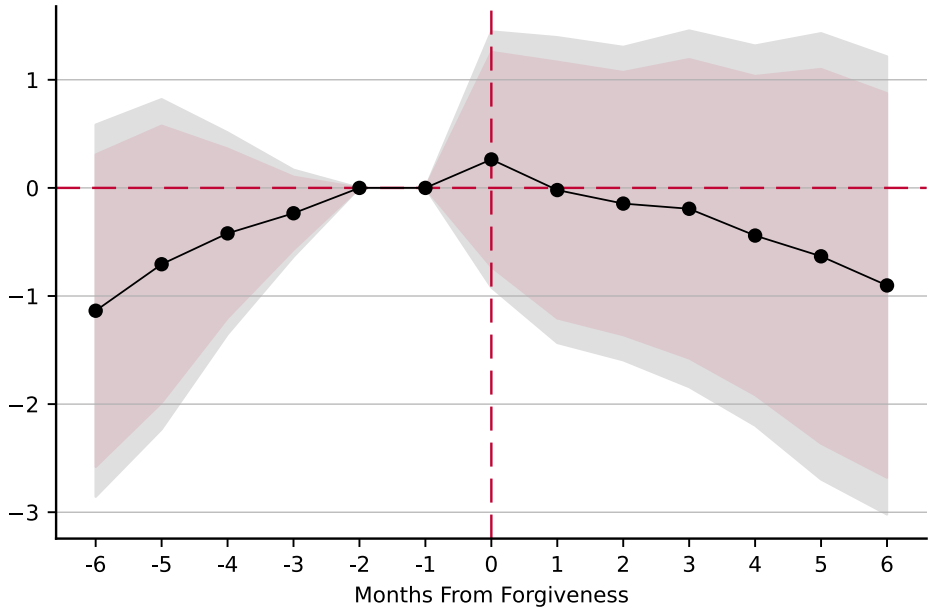
Notes: This figure plots estimates, 95% confidence intervals (grey) and 90% confidence intervals (red) of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. Source: Employment data

Figure C.7: Relocation Event Study



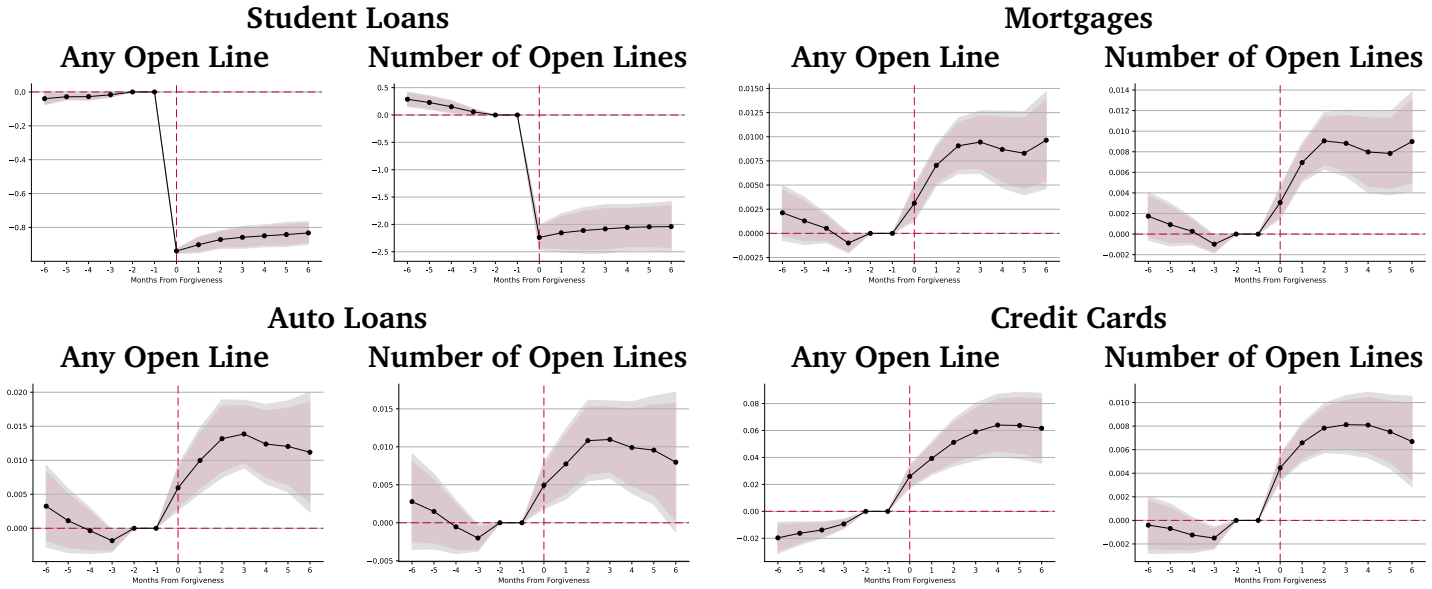
Notes: This figure plots estimates and 95% confidence intervals of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. Source: TransUnion

Figure C.8: Credit Score Event Study



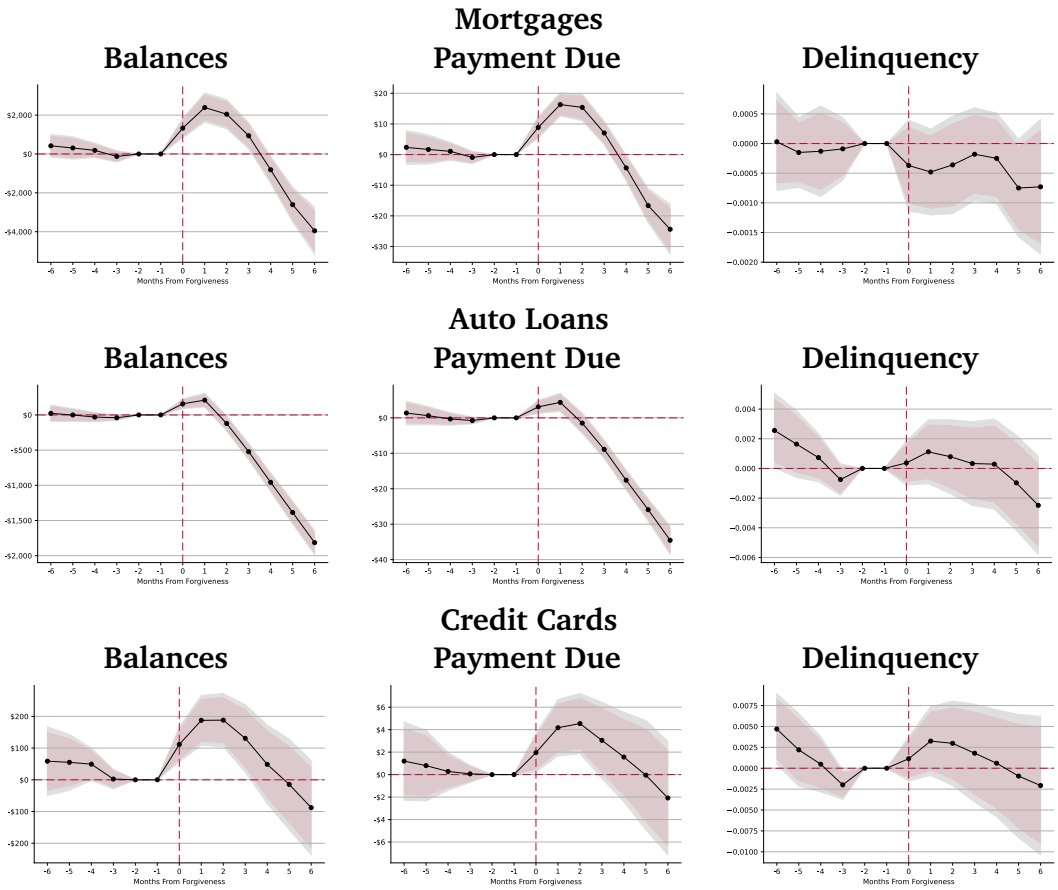
Notes: This figure plots estimates and 95% confidence intervals of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. Source: TransUnion

Figure C.9: Extensive Margin Event Studies



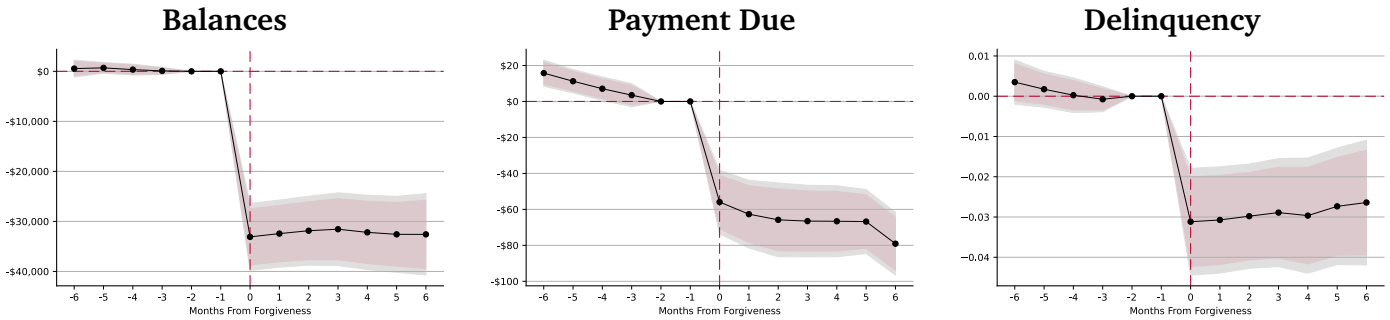
Notes: Notes: These figures plot estimates and 95% confidence intervals of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. Source: TransUnion

Figure C.10: Intensive Margin Event Studies



Notes: These figures plot estimates and 95% confidence intervals of the average treatment effect on the treated in each of the six months leading up to and after forgiveness using De Chaisemartin and d'Haultfoeuille (2024). Comparison borrowers are those who have yet to have forgiveness or never will have forgiveness in sample. Forgiveness cohort-specific average treatment effects on the treated are averaged with weights based on cohort size. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the treatment event to occur in time 0 or -1. The trade lines of forgiven borrowers are limited to only trade lines that were opened prior to forgiveness. Source: TransUnion

Figure C.11: Effects on Student Loans (Two Way Fixed Effects)

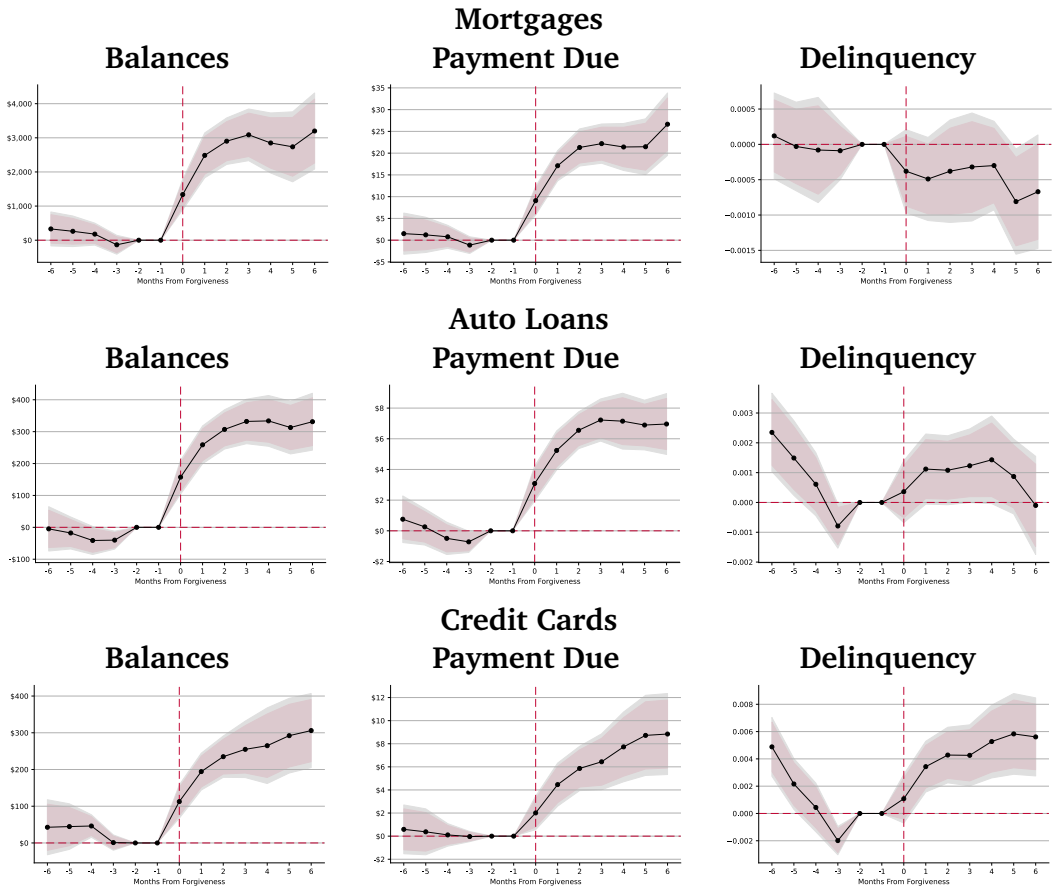


Notes: These figures plot the coefficients β_T and 95% confidence intervals using the following dynamic difference-in-difference event study specification:

$$Y_{it} = \alpha_g + \alpha_t + \sum_{T=-6}^{T=6} \beta_T \times Forgiveness_i \times 1[TSE_{it} = T] + \epsilon_{it}$$

where Y_{it} is the outcome for individual i at month t and $Forgiveness_i$ is an indicator for if individual i ever receives forgiveness. TSE_{it} is 'time since event' which is the number of months individual i is from receiving forgiveness as of month t. α_t and α_g are calendar time and forgiveness cohort fixed effects. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the event to occur in 0 or -1. Source: TransUnion

Figure C.12: Effects on Credit Outcomes (Two Way Fixed Effects)

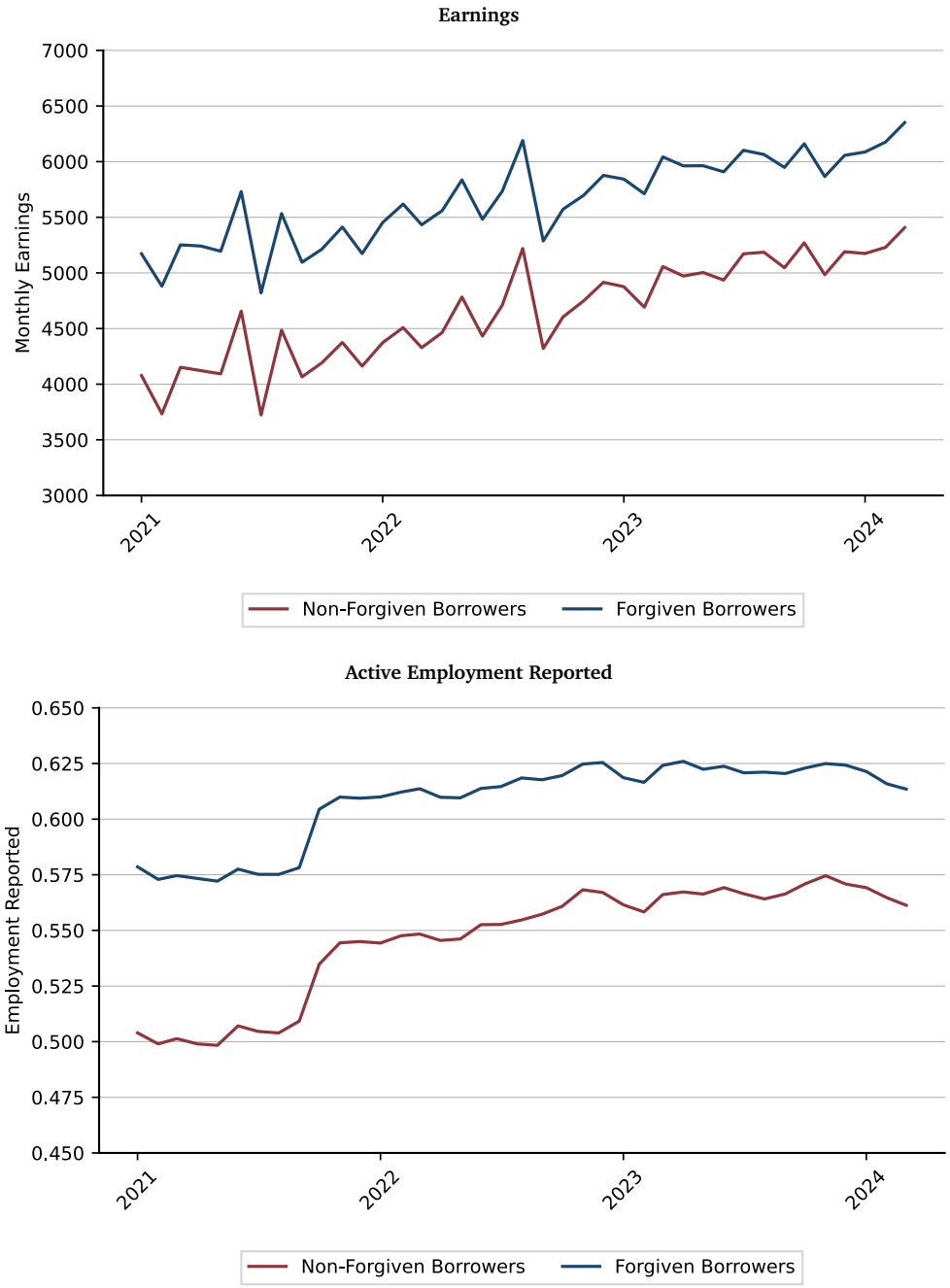


Notes: These figures plot the coefficients β_T and 95% confidence intervals using the following dynamic difference-in-difference event study specification:

$$Y_{it} = \alpha_g + \alpha_t + \sum_{T=-6}^{T=6} \beta_T \times Forgiveness_i \times 1[TSE_{it} = T] + \epsilon_{it}$$

where Y_{it} is the outcome for individual i at month t and $Forgiveness_i$ is an indicator for if individual i ever receives forgiveness. TSE_{it} is 'time since event' which is the number of months individual i is from receiving forgiveness as of month t. α_t and α_g are calendar time and forgiveness cohort fixed effects. Standard errors are clustered by forgiveness cohort. We normalize period $T = -2$ to be 0 and omit period $T = -1$ as credit bureau reporting lags can cause the event to occur in 0 or -1. Source: TransUnion

Figure C.13: Means of Earnings and Employment through Time



D Employment and Earnings Data Appendix

D.1 Overview

In this appendix, we provide more background and validation on the employment and earnings data obtained from a large credit bureau used in our paper ("employment records"). These data are collected for the purpose of employment and income verification, such as when applying for a new credit line. The employment records provide national coverage of employment history and monthly earnings from approximately 150 million unique individuals and 3 million employers.[36] On average, 2.5 job records are observed per individual.

This data appendix both complements and updates earlier data validation provided in the data Appendix to Gopalan et al. (2021), which used a smaller subset of these data for the period 2010-2015. Our paper draws from a 10% random sample, with active linked records available from 2017 to present.

D.2 Coverage

D.2.1 Comparison the BLS establishment survey

We begin by examining raw counts of jobs, and comparing these counts to the BLS establishment survey. Since we have a 10% sample, we inflate by 10 to approximate total coverage.

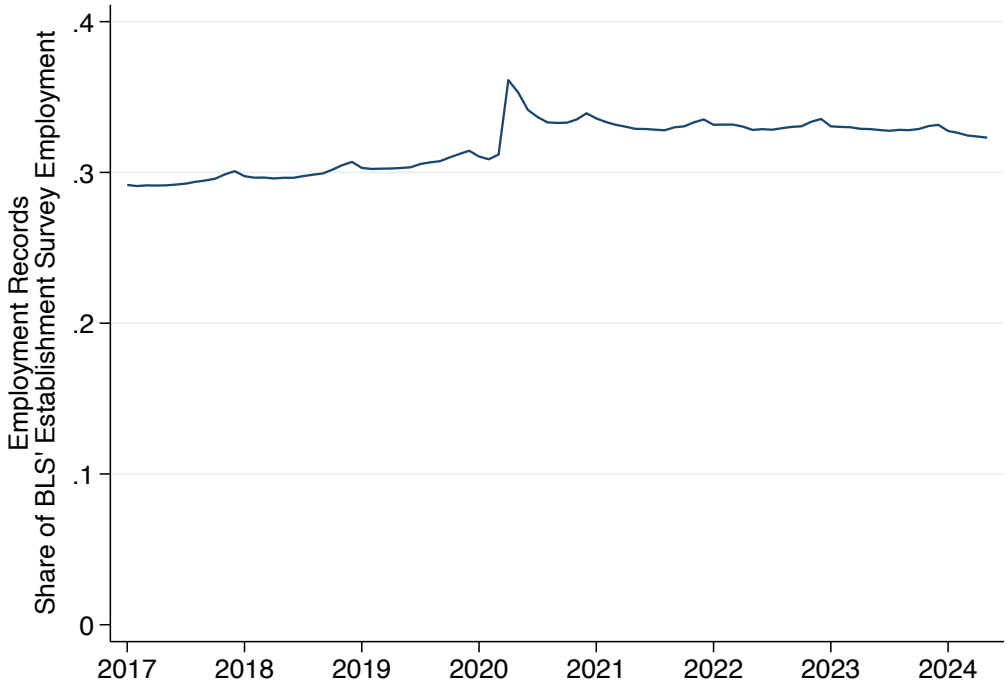
Figure C.1 compares counts of jobs in our employment records, based on start and end dates, with the BLS establishment survey, since 2017. In recent years, the employment records contain around 1/3 of total employment of the establishment survey in each month. It appears that the employment share increased somewhat around COVID, which may be due to the bias towards larger firms that were more likely to survive and/or how temporary layoffs were recorded in the data.

D.2.2 Industry Distribution

Table C.1 compares the distribution of 2 digit NAICS in the employment records to the CPS, for both 2019 and 2023. We find the distribution to be broadly similar to the overall NAICS distribution, with a few exceptions. Retail tends to be overrepresented in the employment records, whereas services are somewhat underrepresented, namely "Professional, Scientific and Technical services"and "Other Services." "Arts, Entertainment and Recreation" and "Public administration" is also underrepresented.

[36] As of May 2024. The data we have access to have 3-digit NAICS industry codes, but not firm-level identifiers.

Figure C.1: Employment, Share of Total Employment



Note: Employment inferred from starting and termination dates of jobs, as a share of total nonfarm employment from the BLS establishment survey. U.S. Bureau of Labor Statistics, All Employees, Total Nonfarm [PAYEMS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PAYEMS.

Table C.1: Industry Comparison Between CPS and Employment Records, 10 Percent Sample

NAICS	Description	CPS 2019	10 perc 2019	CPS 2023	10 perc 2023
11	Agriculture, Forestry, Fishing and Hunting	0.000	0.001	0.000	0.000
21	Mining, and Oil and Gas Extraction	0.000	0.002	0.000	0.002
22	Utilities	0.000	0.011	0.000	0.010
23	Construction	0.000	0.007	0.000	0.006
31	Manufacturing	0.023	0.029	0.021	0.023
32	Manufacturing	0.023	0.040	0.023	0.031
33	Manufacturing	0.055	0.059	0.050	0.045
42	Wholesale Trade	0.023	0.005	0.021	0.005
44	Retail Trade	0.078	0.120	0.070	0.077
45	Retail Trade	0.034	0.110	0.040	0.110
48	Transportation and Warehousing	0.032	0.028	0.030	0.024
49	Transportation and Warehousing	0.019	0.024	0.024	0.026
51	Information	0.021	0.017	0.023	0.014
52	Finance and Insurance	0.054	0.060	0.053	0.048
53	Real Estate and Rental and Leasing	0.017	0.006	0.015	0.005
54	Professional, Scientific, and Technical Services	0.088	0.032	0.096	0.029
55	Management of Companies and Enterprises	0.000	0.001	0.000	0.001
56	Administrative and Support Services	0.121	0.074	0.124	0.133
61	Educational Services	0.089	0.110	0.087	0.096
62	Health Care and Social Assistance	0.144	0.135	0.143	0.120
71	Arts, Entertainment, and Recreation	0.021	0.006	0.022	0.004
72	Accommodation and Food Services	0.075	0.081	0.069	0.051
81	Other Services (except Public Administration)	0.042	0.004	0.042	0.005
92	Public Administration	0.044	0.010	0.048	0.010
99	Non-classifiable	0.000	0.024	0.000	0.023
	Obs Total	21552	15226	17958	14634

Note: This table shows share of individuals (CPS) or jobs (employment records, 10 percent) by NAICS 2 digit code. The CPS is restricted to employed individuals and employment records are restricted to actively employed jobs. The CPS uses samples from December of 2019 and 2023. Employment record 10 percent sample uses data of 2019 November and 2023 December to stay consistent with the demographics summary statistics.

While we are not provided any firm characteristics beyond the NAICS industry, our understanding is that the employment records firm size distribution skews towards larger and more established firms.

D.3 Earnings

We next turn to earnings. We begin by comparing annual earnings for 2017-2022 with the CPS' Annual Social and Economic Supplement (ASEC). Comparisons are shown in Figure C.2, where we report the interquartile range, mean and median.

We first examine jobs held over the full year in panel (a). CPS and the employment earnings coverage look quite comparable. Mean gross earnings in the employment records are somewhat higher, about 9 percent on average, as there is a thicker upper tail in gross earnings in the employment records compared to CPS. The ratio of the 25th and 50th percentiles are on

average within 5 percent.

We next look at all workers in panel (b). Comparing the means, the employment records contain around 71% of average annual earnings, likely due to its incomplete coverage of annual employment.

In Table C.2, we examine characteristics of the pay cycle and pay frequency. 62.7 percent of the employment workforce are paid hourly, and 31.1 percent are salaried (6.2 percent have missing information). It is most common to be paid biweekly, as around half of workers are paid biweekly. Around one-quarter are paid weekly.

Table C.2: Characteristics of Pay Cycle and Frequency, 2023

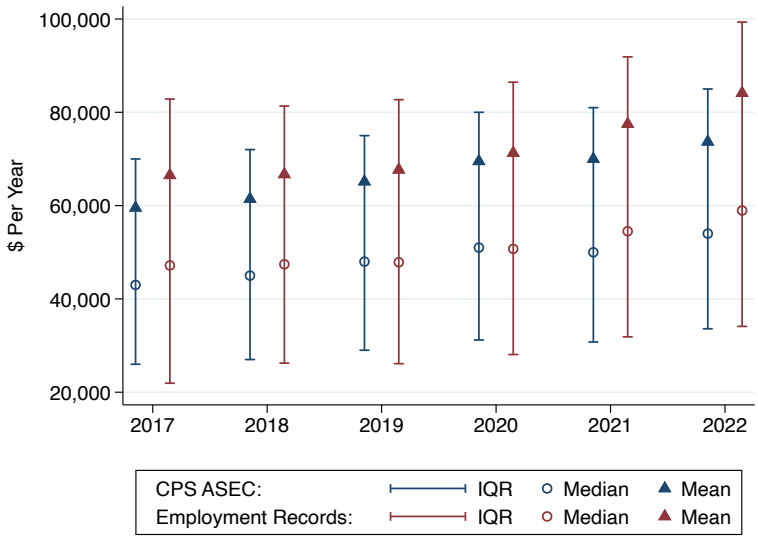
	%
Hourly	62.7
Salaried	31.1
Missing	6.2
Paycheck frequency	
Weekly	24.5
Biweekly	46.7
Semi Monthly	6.7
Monthly	4.5
Other	1.1
Missing	16.4
N job×months	51,555,341
N individuals	5,315,731

Note: 1 percent sample of all workers active in 2023.

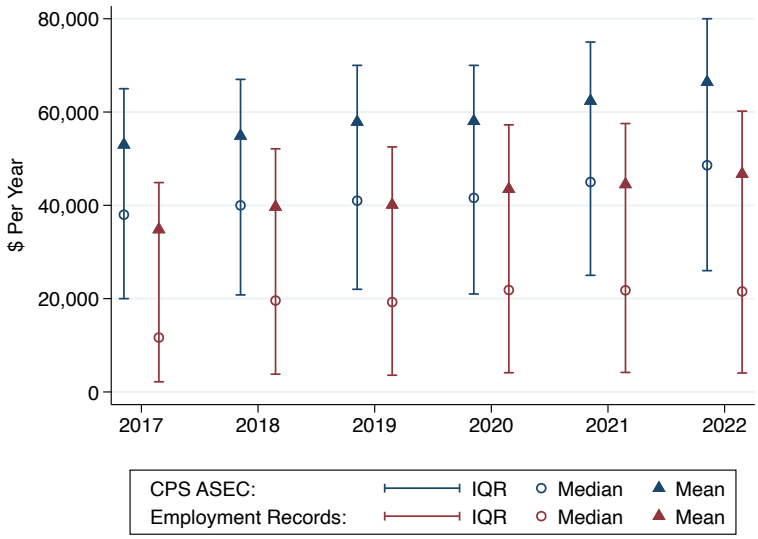
In Table C.3, we examine the distribution of tenure (all workers), and components of pay for full-year workers. Average gross compensation in 2023, conditional on working the full-year, was $90,387. On average, 79.5 percent came from base pay, 5.3 percent from overtime, 8 percent from bonuses, 1.7 percent from commissions, and 6.0 percent was classified as "other." In Figure C.3, we examine the bonus share of all workers and overtime share of hourly workers, by percentile of the base wage distribution, following Grigsby et al. (2021), who use data from ADP. Compared to Grigsby et al. (2021), the bonus share follows a similar pattern across the wage distribution. The overtime share among hourly workers is higher in the employment records, which may in part reflect a different part of the business cycle.

Figure C.2: Annual Earnings Comparison Between CPS and Employment Records

(a) Full-Year Workers



(b) All Workers



Note: "CPS ASEC" is annual earnings from the Annual Social and Economic Supplement to the Current Population Survey, collected in year + 1. Panel (a) is restricted to jobs that lasted for 12 months. In the CPS ASEC, we restrict to individuals who reported working 52 weeks and examine earnings from the longest-held job. In Panel (b), we examine total earnings over all jobs, for both CPS and the employment records.

Table C.3: Distribution of Tenure and Gross Compensation, 2023

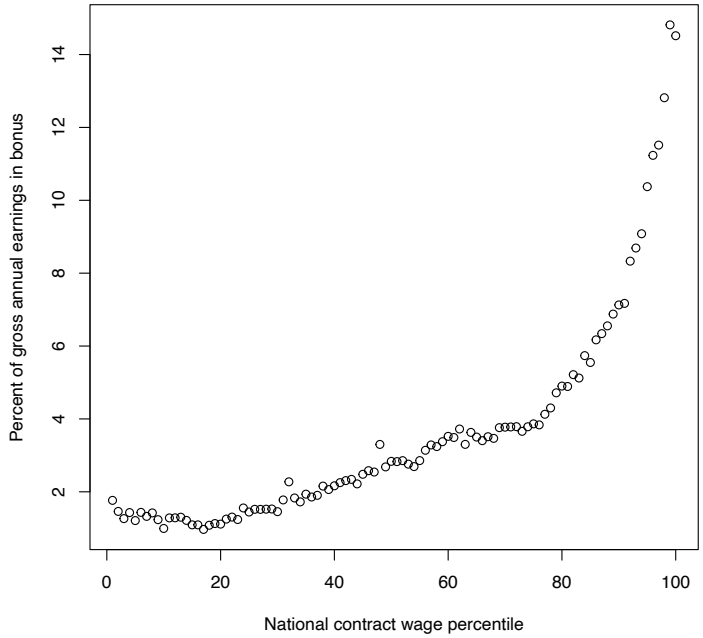
	Mean	Mean, <p99	SD, <p99	p5	p25	p50	p75	p95	p99
Job tenure (years)	5.00	4.65	6.86	0.00	0.33	1.58	6.17	22.67	34.75
Total compensation	90,387	76,965	64,823	8,584	35,530	59,774	100,714	221,025	448,053
Base pay	71,807	63,695	48,946	6,783	30,997	50,315	86,235	173,372	288,837
Overtime	4,804	2,338	5,460	0	0	28	1,792	15,771	40,226
Bonus	7,156	4,077	10,745	0	0	41	2,681	26,400	98,686
Commissions	1,581	308	2,624	0	0	0	0	0	38,310
Other income	5,420	3,304	7,751	0	0	186	3,326	18,985	74,486

Note: 1 percent sample of employment records in 2023. Tenure is for all workers. Components of total compensation restricted to full-year workers.

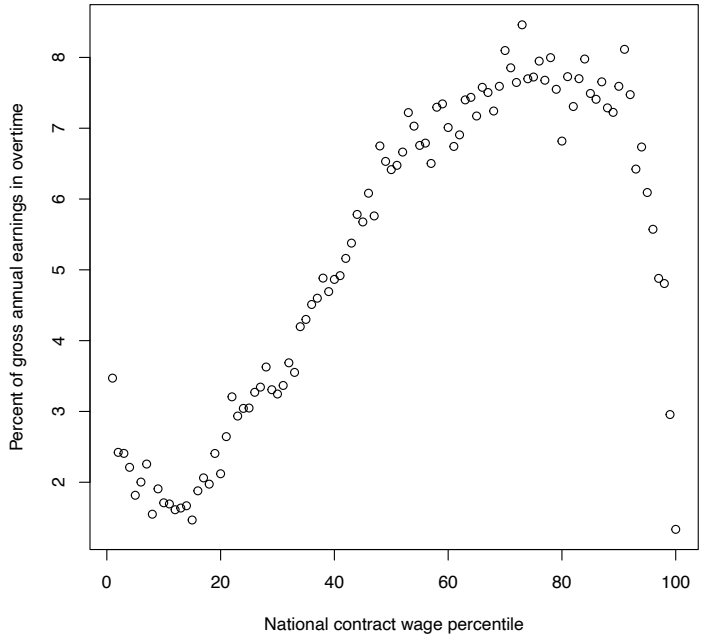
Finally, we examine earnings dynamics in our sample period, constructing figures comparable to Grigsby et al. (2021), who use data from ADP. In Figure C.4, we examine annual changes in earnings, following Grigsby et al. (2021) Figure 2, and find a very similar distribution for base wage changes. Following Grigsby et al. (2021) Figure 6, our Figure C.5 examines the time-series of changes over our period, which includes the COVID recession. Compared to previous months, January and February 2021 were associated with a reduction in wage changes, namely from a reduction in positive wage changes rather than an increase in negative changes (unlike the Great Recession studied in Grigsby et al. (2021)).

Figure C.3: Bonus and Overtime Share by Employee Base Wage Percentile: Full-Year Job-Stayers

(a) Bonus share all workers



(b) Overtime share hourly workers



Note: 1 percent sample of workers.

Figure C.4: Twelve-Month Nominal Base Wage Change Distribution, Job-Stayers

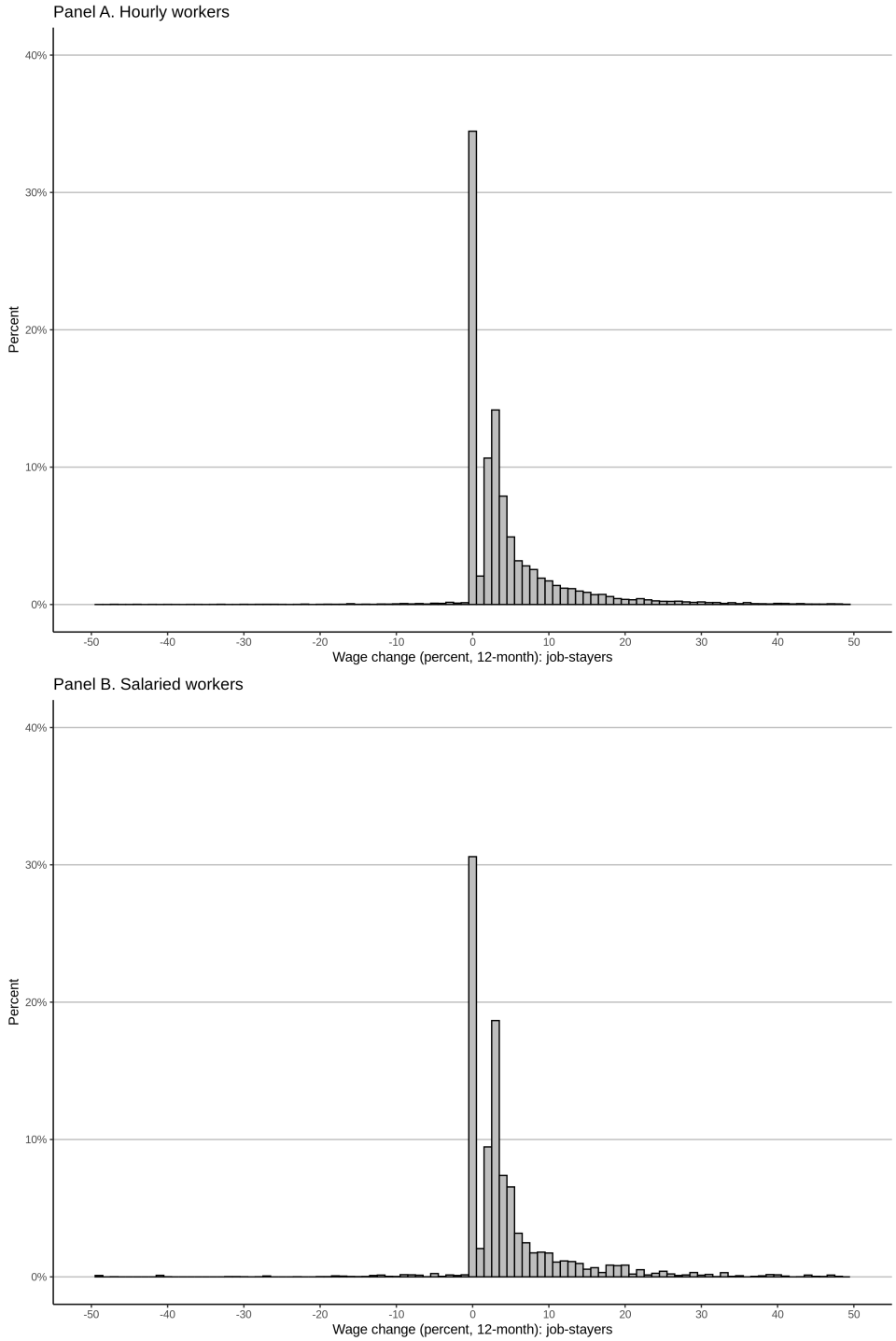


Figure C.5: Time Series of Nominal Base Wage Adjustments: Job-Stayers