Insurance Subsidies, the Affordable Care Act, and Financial Stability

Samuel Dodini
Cornell University
snd46@cornell.edu

April 19, 2021

Abstract

This paper measures the effects of subsidies in the Affordable Care Act on adverse financial outcomes using administrative tax data and financial outcomes from credit data. Using a difference-in-differences design with propensity score stratification, I find that at $100 per capita, ACA premium tax credits reduced the rate of severe mortgage delinquency by 4%, consumer bankruptcies by 13%, and the rate of severe auto delinquency by 13%. The subsidies reduced the right tail of the debt distribution, including debts in third-party collections. The benefits of the tax credits accrue to a variety of economic actors. The value of the risk protections to recipients against medical debt amounts to approximately 10-15% of the cash costs of the credits, while the subsidies provided substantial indirect transfers to external parties totaling approximately two-thirds of the program's costs.

JEL Codes: I13, D14 , H24, H51, H53

*I am grateful to Mike Lovenheim, Evan Riehl, Maria Fitzpatrick, and Corbin Miller for helpful comments and guidance. I am also grateful to Claudia Sahm, Jeff Larrimore, Ellen Merry, Barbara Robles, Mike Zabek, Erin Troland, David Buchholz and Anna Tranfaglia for their comments and help with data access. Thank you to Sean Nicholson, Kurt Wrobel, Colleen Carey, Carly Urban, and seminar participants at Cornell University for helpful discussion.

The analysis and conclusions set forth are those of the author and do not represent the views of the Federal Reserve Board, Equifax, or the Federal Reserve System.

1 Introduction

One of the core purposes of insurance is to protect against the financial risk of high-cost and relatively low-probability events. In the case of health insurance, because sickness and injury are often unpredictable and can result in large, concentrated expenditures, insured individuals and families are protected against severe financial shocks. While there is a large literature across the fields of economics, sociology, public health, and epidemiology that highlights the positive health effects of health insurance, there is comparatively less research on the effects of such insurance on financial outcomes.

The Patient Protection and Affordable Care Act (ACA) was passed in 2010 and was designed to increase health insurance coverage by incentivizing insurance enrollment through legislated guarantees against rejection for pre-existing conditions, an individual mandate to have insurance, and a series of Medicaid expansions and refundable "premium tax credits" (PTC) for low- and moderate-income households. The credits were designed to bring down the cost of private insurance to consumers with income between 100 percent of the Federal Poverty Line (FPL)—or 138 percent in Medicaid expansion states—and 400 percent FPL. The subsidies are defined in the ACA as the difference between the legislated cap on a household's spending on basic health insurance premiums at 2-9% of their income and the cost of basic health insurance available to the household in their local area. These premium tax credits represent a substantial expenditure for the federal government and a significant transfer to households totaling approximately $50 billion from 2014-2016. Despite the centrality of these premium tax credits to the ACA's stated goals of universal and affordable insurance coverage, little work has been done that directly measures the effect of these subsidies on household financial well-being. Work to date on the effects of insurance has focused on public health insurance programs, but the overall financial effects of funding private health insurance, with its various monthly premiums, copays, coinsurance, and deductible requirements, may differ substantially.

In this paper, I ask the following questions: 1) What is the effect of public money directed toward lowering the cost of private insurance on the frequency of high-cost financial outcomes such as bankruptcy, severely delinquent debt, or collections debt? 2) Where in the distribution of debt and credit health are any such effects most concentrated? 3) What is the economic incidence of the subsidies with regard to recipients and external parties such as creditors, lenders, and hospitals?

To answer these questions, I use rich information from two administrative datasets aggregated to ZIP codes. First, I use data from the IRS on actual tax credits received by residents to accurately measure the intensity with which ZIP codes were treated after 2013, which I define as premium tax credits received per person under 65 (PTC per capita). Second, I use administrative credit bureau data to measure the financial outcomes for adults under 65 living in ZIP codes that had high PTC per capita in comparison to ZIP codes that had low PTC per capita. In my analysis, I use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP), which is an anonymized 5 percent random sample of all Equifax credit files in the United States and contains data on credit card use, mortgage products, auto loans, foreclosures, bankruptcy filings, payment histories on important accounts, and Equifax 3.0 Risk Scores (credit scores). Together, these datasets provide a broad accounting of the consumer finance effects of the premium tax credits with high-quality data. The granularity of the credit data also allows me to measure the effects on the distribution of credit scores (Equifax Risk Score) as well as the intensive margin effects across the distribution of different types of debt.[1]

I estimate the causal effects of the premium tax credits by implementing two procedures in combination with a difference-in-differences design: propensity score reweighting and propensity score stratification, and I define the top quartile of PTC per capita as the "treatment" group and the bottom quartile as the "control" group.[2] The reweighting procedure is very similar to the synthetic control method (Abadie et al., 2010) in that it constructs counterfactuals for each treatment unit based on reweighting the pre-treatment outcomes of control units. My stratification procedure matches each treatment unit to control units within the same stratum of the propensity score.

Importantly, these approaches address the empirical challenge posed by the Great Recession. Specifically, I show evidence that areas that had higher PTC per capita after 2014 were financially hit harder by the effects of the Great Recession in 2009 and 2010 and experienced a more pronounced

[1]Here and in all other instances in the paper, "credit score" refers to the Equifax Risk Score.

[2]The results are robust to changes in this definition, such as splitting the "treatment" and "control" groups at the median PTC per capita (see Appendix Table A7).

recovery after 2011. This phenomenon must be addressed by any analysis of the effects of the ACA. I show with an event study model that my propensity score approaches empirically account for the pre-ACA trend differences across areas with high and low levels of PTC per capita and therefore yield unbiased estimates of the effects of the tax credits.

Next, I use my preferred estimates to calculate the economic incidence of the tax credits. For recipients, I use the expected utility framework in Finkelstein and McKnight (2008) to calculate the implied consumer welfare gains from the risk protections of insurance. In this framework, I compare the change in the risk of high-cost medical debt payments faced by consumers in a pre-ACA state of the world versus a post-ACA state of the world. In each state, I calculate the average consumer's risk premium, or their willingness to pay to mitigate risk. The change in the risk premium between the two states of the world is a measure of the change in consumer welfare from these risk protections. I then use my calculations of the subsidy effects to estimate the implied spillovers to outside parties, namely mortgage lenders, creditors, and hospitals. These exercises allow me to compare program costs with the incidence of program benefits to beneficiaries as well as other parties.

My preferred estimates suggest that \$100 per person under age 65 spent on premium tax credits each year (the difference in PTC per capita between the top and bottom quartiles) reduced the annual consumer bankruptcy filing rate by 13%, the rate of having severely delinquent debt on a mortgage by 4%, and the rate of severely delinquent auto debt by 13%. Thus, the tax credits significantly reduced the probability of having one or more of these adverse financial events.

Because insurance is designed to protect against right-tail risk, I measure the effects of the tax credits across the distribution of various types of delinquent debt. I find that debts on delinquent mortgages, credit cards, and auto loans decreased substantially only at the top of the distribution, indicating that the tax credits resulted in significant protections against right-tail, high-cost financial losses. My results also indicate that \$100 per capita in premium tax credits reduced third-party collections debt by \$640 at the top of the distribution. However, contrary to the effects of the ACA Medicaid expansion found in other work (Hu et al., 2016; Brevoort et al., 2017), the number of credit files with nonzero amounts in third-party collections did not significantly change as a result of these premium tax credits. One plausible explanation is that recipients increase their take-up of healthcare as a result of the insurance but are unaware or uninformed about when or to whom they owe even small cost-sharing payments as part of their private insurance plan, and these debts are then forwarded to collections agencies (CFPB, 2014).

As a measure of overall financial health, I find that premium tax credits led to an overall upward shift in the distribution of credit scores (Equifax Risk Score) with the largest effects concentrated around the 10th-30th percentile where the typical credit score is between 550 and 660. For every $100 per capita spent on premium tax credits, credit scores in this percentile range shifted upward approximately 4 points. The overall financial effects of the tax credits appear concentrated near the bottom of the credit score distribution.

Across various indicators of financial well-being, my results suggest that the ACA's premium tax credits significantly improved the financial stability and credit outlook of recipients and led to large reductions in the number of households experiencing catastrophic financial losses. ACA subsidies notably shifted downward the risks of medical debt at the right tail of the distribution. In an expected utility framework, risk-averse consumers newly protected from such risk experience a gain in utility. I calculate average welfare gains from protection from medical debt of approximately $500 per recipient per year for the lowest-income eligible population. Compared to average costs of $3,168-$3,528 per recipient, protection against medical debt payments alone can account for approximately 15% of program costs. This $500 welfare gain from risk protections is smaller than the $760 calculated in the Medicaid literature (Finkelstein et al., 2019a), a finding that is likely attributable to the significant cost-sharing requirements in private ACA insurance plans (Chandra et al., 2021).

The external benefits of the ACA subsidies to outside parties are large. Using empirical findings from the literature on the costs of bankruptcy to creditors, the direct costs to lenders of servicing delinquent loans, and the costs of uncompensated care to hospitals, I find average implied indirect subsidies to mortgage lenders and creditors of $6.5 billion per year from 2014 to 2016 and an indirect subsidy to hospitals of $3-$4.4 billion per year. Compared to a direct expenditure of $15.6 billion on average per year from 2014 to 2016, these external spillovers to this narrow set of parties account for approximately two-thirds of the cash costs of the tax credits.[3]

[3]Estimated costs are approximately $46,000 per bankruptcy (Li, 2007; Eraslan et al., 2017; Norberg and Velkey, 2005; Jiménez, 2009) and $2,200 in additional service costs per delinquent mortgage loan per year. Each uninsured patient costs a hospital $800 (Garthwaite et al., 2018), and I assume the estimated 5.4 million adult recipients of

I contribute to the literature on the effects of public spending for insurance on consumer welfare and financial outcomes as well as the literature on the effects of health insurance. I am the first to directly estimate the effect of premium tax credits on a wide set of financial outcomes. More broadly, I am the first to estimate the national financial effects of directly subsidizing the purchase of private health insurance rather than the effects of public insurance. I also am the first to calculate the implied incidence of the benefits to consumers as well as outside parties. These contributions are important in light of political debates about the future of the Affordable Care Act, how governments facilitate the expansion of health insurance coverage, and who benefits from the features of the ACA. This paper provides a basis for understanding the distribution of benefits of paying to expand private health insurance coverage in relation to the cash cost of the transfers. These results are particularly important to consider while the ACA marketplace subsidies are temporarily expanded through the 2021 American Rescue Plan, which extended enrollment periods, lowered the premium spending cap, and eliminated the 400% FPL income limit for tax credits.

Prior research using a variety of methods indicates that there are substantial effects of insurance coverage on utilization of medical care (Newhouse, 1993; Aron-Dine et al., 2013; Anderson et al., 2012; Card et al., 2008); self-reported health and depression (Finkelstein et al., 2012); reductions in mortality (Card et al., 2009); and consumption via reductions in out-of-pocket spending (Finkelstein and McKnight, 2008; Engelhardt and Gruber, 2011; Finkelstein et al., 2012; Baicker et al., 2013; Barcellos and Jacobson, 2015).[4] The literature also documents large effects on outside parties, such as medical care providers, who often treat the uninsured without compensation (Mahoney, 2015; Finkelstein et al., 2019a).

Work measuring the financial effects of public programs for insurance has almost exclusively focused on the Medicaid program (Hu et al., 2016; Brevoort et al., 2020; Finkelstein et al., 2012; Argys et al., 2017; Gross and Notowidigdo, 2011). This literature documents broad consensus that cost volatility, debts in collections, bankruptcies, and other types of delinquencies fall while creditworthiness increases as a result of Medicaid eligibility. The effects include a reduction in third-party collections debt of $1,140 for every new Medicaid enrollee (Hu et al., 2016); annual aggregate

PTC in my sample imposed that $800 cost onto hospitals prior to the ACA. Alternatively, assuming the 3.84 million newly insured through the tax credits estimated by Frean et al. (2017) yields an estimate of approximately $3 billion.

[4] Finkelstein et al. (2018) review these and other papers related to the effects of health insurance.

increases in creditworthiness valued at $670 million as well as a drop of 50,000 bankruptcies annually (Brevoort et al., 2017); and a decline in bankruptcy among the eligible population by as much as 8% with a 10% increase in Medicaid eligibility (Gross and Notowidigdo, 2011). *Losing* Medicaid coverage has substantial negative consequences for the financial health of recipients, and those effects are larger than the gains from being newly insured (Argys et al., 2017).

These papers use quasi-experimental methods. By contrast, the Oregon Health Insurance Experiment, a randomized experiment that allocated finite slots for Medicaid benefits, found large reductions in cost volatility and catastrophic financial outcomes among those who were treated, along with improvements in mental health and take-up of preventative health care (Finkelstein et al., 2012). Most notably for my analysis, Finkelstein et al. (2019a) use a consumption proxy to model the protections offered by Medicaid enrollment against the risk of out-of-pocket medical spending and find welfare gains of $760 per recipient per year.[5] The Oregon experiment outlines the real risk protection effects of the Medicaid program on recipients and suggests a key role for public policy to help ensure household financial stability by providing insurance broadly.

Unlike the Medicaid program, which is publicly administered health insurance, premium tax credits are a means of lowering the costs of *private* health insurance and thus may differ from Medicaid in important ways, especially considering the differences in the target populations and the existence of premiums, coinsurance, and deductibles. Recent research suggests premium tax credits in the ACA significantly increased health insurance take-up among the eligible population (Courtemanche et al., 2017; Hinde, 2017) and that these credits explain approximately a quarter of coverage gains from 2012-2015 (Frean et al., 2017). In the only paper of which I am aware to consider the financial effects of the private insurance aspect of the ACA, Gallagher et al. (2019) show that, in comparison to those just below the eligibility threshold in states that did not expand Medicaid, those who qualified for subsidies were 25 percent less likely to have difficulty making home payments and had significantly less out-of-pocket medical spending. By contrast, my analysis covers the universe of tax credit beneficiaries and allows me to measure the effects of the tax credits

[5]Notably, this is only the risk protection component of the benefit and represents one of several aspects of consumer welfare tested in that paper. This is higher than the pure insurance value of approximately $500 I find for the ACA tax credits when considering only medical debt payments using a different analytical approach best approximated by their consumption proxy. See Table 4.

on a wide variety of financial outcomes.

To date, no research has examined the effects of the ACA's subsidies on a broad set of markers of financial well-being, particularly with regard to right-tail risk. My analysis, therefore, extends the literature in an important way by directly measuring the effects of the subsidies across the entire distribution of eligibility, accounting for a broad set of outcomes from high-quality administrative data, and generating estimates based on dollars spent rather than the marginal effects of crossing the eligibility threshold. Importantly, this analysis presents the first national evidence that publicly funding private insurance promotes financial stability among lower-income households, though the existence of cost-sharing and premium requirements leads to smaller risk protections when compared to Medicaid. Finally, I also show that the benefits of increased financial stability spill over to outside parties, meaning the incidence of the program's benefits are disbursed to a variety of economic agents.

2 Policy Context

The Affordable Care Act was passed in 2010 and included reforms to the way health insurance markets operated, including bans on not offering coverage to those with pre-existing conditions, mandated coverage for certain products/services, and the elimination of price discrimination based on health history or sex. The key features of the law, however, did not take effect until January 1, 2014. The law attempted to expand health insurance coverage through two main channels: expanding Medicaid eligibility and premium tax credits to help consumers purchase private insurance. Beginning in 2014, health insurance marketplace websites, or "exchanges," were designed to provide a one-stop-shop for people who lack affordable health insurance through an employer or third party to compare available plans and to find information on their eligibility for Medicaid, premium tax credits, and cost-sharing reduction (CSR) subsidies. The ACA also created homogenized "metal" tiers of plans which differ in covered procedures, cost-sharing, and monthly premiums. These are the Platinum (the most generous and expensive), Gold, Silver, and Bronze plans (the least generous and expensive). Silver plans were a middle tier that balanced coverage and cost. Silver plan enrollees also received the greatest CSR subsidies, and the vast majority of enrollees choose this tier (DeLeire et al., 2017).[6] In states that expanded Medicaid, those under 138% FPL became eligible for Medicaid, and those above 138% until 400% FPL were eligible for subsidies. In Medicaid non-expansion states, the lower limit was 100% FPL.[7]

For the subsidy-eligible population, the ACA set limits on household spending on health insurance premiums as a percentage of their income, and those limits increase with income before phasing out at 400% FPL. Panel A of Figure 1 shows these expenditure limits for 2016 in the states that did not expand Medicaid. Under the ACA, as long as they meet income requirements, anyone who does not have insurance available through an employer or third party or whose expenditures on premiums for their current plan are above 9.5 percent of their income is eligible for subsidies.[8]

In order to calculate tax credits, these expenditure limits were benchmarked against the annual premium for what was termed the "second lowest-cost Silver plan." This is defined as the premium specific to each household's age and family structure for the Silver plan ranked second in cost within each household's "Rating Area," which is a county or 3-digit ZIP code. Premium tax credits are the difference between this annual premium and their expenditure limit. So, for a household with structure h with age(s) a in Rating Area r and income i: $PTC_{hari} = Silver2_{har} - Limit_{ih}$, where $Silver2$ is the cost for the benchmark plan for the household and $Limit$ is their maximum spending on basic premiums in the ACA given income level i.

Panel B in Figure 1 shows a concrete example of subsidy eligibility for a hypothetical family of four living in a Medicaid non-expansion state in 2016 facing two hypothetical premiums for the benchmark plan ($Silver2$). As income grows, the size of the subsidy falls because the household's contribution to their own premiums grows. Households in areas with higher costs for the benchmark plan receive more in subsidies to make up the difference.[9] Given each of these inputs, areas may

[6] Those making under 250% FPL were eligible to receive CSR subsidies, which were payments that lowered deductibles, coinsurance, copays, and out-of-pocket spending limits on Silver plans only. Unfortunately, these payments are not reported in the IRS data.

[7] Depending on the state, those under 100% FPL may have been subject to the "coverage gap," which left many low-income adults uninsured as they were not eligible for Medicaid under their state laws and not eligible for subsidies under the federal law.

[8] Nearly half of Americans in 2014 were eligible for premium tax credits based on income. 400% FPL was \$46,680 for an individual or \$62,920 for a two-person household. The average household income for the middle quintile of the distribution was \$69,000 before taxes and transfers for the average 2.6 person household. See https://www.cbo.gov/publication/53597 (Accessed June 1, 2020).

[9] Subsidies can be paid directly to insurers ("Advanced") or paid during tax season. Overpayment of subsidies relative to realized annual income must be repaid during tax filing with some limits.

receive more in premium tax credits per capita for several reasons. The most common determinant of geographic variation in subsidies is having a greater share of lower-income residents that qualify for subsidies based on income but do not qualify for Medicaid in that state. An area with more residents without employer-sponsored insurance will also have a higher rate of premium tax credits per capita. Finally, if health insurance plans are more expensive in an area due to lack of insurance competition, provider market power, or high costs of medical care, the benchmark Silver plan premiums may be more expensive to match costs, which mechanically drives up the per-recipient subsidy. These premiums can also be influenced by state policy choices about how much insurers can discriminate based on age, whether or not insurers can offer "family" based plans, and policies that further regulate insurers in the state beyond the requirements in the federal law.[10]

3 Data

I bring together two rich administrative data sources aggregated to small geographic levels to test the effects of the ACA's tax credit provisions on financial well-being: the IRS Statistics of Income (SOI) data for premium tax credits and the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) for financial outcomes. I also include data from the American Community Survey (ACS) and the Decennial Census along with data on medical providers from the Area Health Resource File (AHRF) produced by the Department of Health and Human Services' Health Resources and Services Administration.

3.1 Tax Credits from IRS Records

In order to accurately measure premium tax credit subsidies, I use IRS tax records to track actual credits received. The IRS began including premium tax credits in their published Statistics of Income products in 2014 when the tax credits took effect. The IRS produces SOI data that are aggregated to the ZIP code level. My main treatment variable is the premium tax credit amount (net of repayments or additional subsidies received during tax season) received per person under 65 in the ZIP code, including ZIP codes where total subsidies were zero. I focus on this population because those over 65 were eligible for Medicare, and tax credits could be used to subsidize the health insurance of children as well as adults. I also calculate the share of the ZIP code tax returns

[10] For additional policy details, see Appendix C.

that received premium tax credits in order to proxy the recipient population. This is important for assessing an approximation of the treatment-on-the-treated effect by dividing the intent-to-treat effects by the size of the relative recipient share.

My sample reports average aggregate annual expenditures of $15.6 billion, but there is substantial variation from year to year. Importantly, as enrollment expanded after the initial rollout, there is a large increase in total tax credits paid from 2014 to 2016: from approximately $9 billion to $17 billion to $21 billion.

3.2 Financial Outcomes from Credit Data

To accurately measure financial health and other outcomes of interest, I use individual credit file data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP). This panel follows an anonymized 5 percent random sample of all Equifax credit files in the United States and contains data on a variety of account activities as well as and Equifax 3.0 Risk Scores (credit scores). In my analysis, I limit the individual data to those age 18-64 that are part of the primary 5% sample for years 2009-2016.[11]

Because I am unable to link IRS data and the CCP, I aggregate all financial measures to the ZIP code level. Individual counts are scaled by 20 to capture population levels from the 5% random sample. For each binary outcome (below), I construct a rate by dividing the total number of credit files with each adverse event by the number of credit files. In order to match the quarterly CCP data to the annual SOI data, I use only CCP data from the 4th quarter of each year, which is reported in December, to represent the effects of the subsidies received that calendar year. This exercise also makes calculations less computationally intensive because analyses of the quarterly CCP impose prohibitively large computing costs.

I focus on the set of high-cost financial events recorded in the CCP data that health insurance is, in part, designed to mitigate. These are debts in third-party collections; having accounts in severe delinquency on a credit card, mortgage, or auto loan; and new bankruptcy filings (Chapter

[11] My study is limited by the coverage of the Consumer Credit Panel. Recent research by the Consumer Financial Protection Bureau notes that approximately 11 percent of US adults are not represented in credit bureau data. These consumers are more likely to reside in lower-income areas, have lower incomes, be a part of a racial or ethnic minority, and be at the extremes of the adult age distribution compared to the population included in credit bureau data (Brevoort et al., 2016). Given that the population eligible for PTC is slightly higher income than the Medicaid population, this is less of a concern in this study.

7 and Chapter 13). I define "severely delinquent" or "severe delinquency" as an account which is currently at least 120 days past due or contains a "major derogatory event" on the credit file related to the account such as repossession, being in collections, or being in consideration for bankruptcy. Among the population age 18-64, I use the ratio of the number of credit files experiencing each event divided by total credit files in the ZIP code as my main outcomes of interest. This measures the extensive margin of these events. I examine the distribution of intensive margin effects below.[12] I also examine credit score (Equifax Risk Score) across percentiles of the distribution of scores as an overall measure of financial health.

For continuous outcomes such as debt amounts in severe delinquency or third-party collections, I examine the intensive margin effects separately. I analyze where in the distribution of outcomes the effects of premium tax credits are largest. I construct percentiles (1-99) of the amounts for each type of debt conditional on a positive balance in each ZIP code-year cell as the outcomes and plot the coefficients from each separate percentile's regression similar to the way quantile treatment effects are presented in the larger economics literature.[13] Finally, I perform the same exercise for percentiles of the credit score (Equifax Risk Score) distribution within each ZIP code-year cell in order to identify which consumers are most affected by the tax credits.

In order to perform my propensity score analysis, I split my sample into the top quartile and bottom quartile of PTC per capita adjusting for Medicaid expansion as the "treatment" and "control/comparison" groups, respectively.[14]

As additional controls, I include ZIP code level statistics from the American Community Survey (ACS) and the decennial Census. Among these are the total population, racial/ethnic makeup of the ZIP code, the age distribution of the ZIP code, the unemployment rate, the share of adults with a Bachelor's degree or more, family structure, median household income, and median house price as a measure of the cost of living and housing market stability. From the Health Resource and Services

[12]If a person experiences multiple events, say, multiple severely delinquent credit cards, I count these as a single occurrence for that person. All rates are based on the total adult population age 18-64 with a credit file, which captures the equilibrium effects of the policy rather than effects on specific populations such as homeowners.

[13]I exclude zeroes because severe delinquency events are relatively rare in the adult population. The most common event in my sample is the existence of debt in third-party collections, which affects less than a third of credit files in any given year. The inclusion of zeroes simply compresses my measured effects further up the percentile distribution, making visualization more difficult.

[14]I adjust for Medicaid expansion by regressing PTC per person under age 65 on a dummy variable for Medicaid expansion and then calculating the predicted residuals.

Administration's Area Health Resource File (AHRF) dataset, I include measures of healthcare provider supply that may influence insurance or medical costs. These include the number of primary care physicians and other care workers such as physician assistants and nurse practitioners. Variables originally provided at the county level are allocated to ZIP codes based on population weights.[15] Finally, in my various robustness checks and supplemental analyses, I examine the share of the population under 400% FPL that does not have health insurance. These figures come from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) Program. These are originally produced at the county level, so I use population weights to generate the uninsured rate for ZIP codes in my sample.

In total, my primary estimation sample consists of 20,838 unique ZIP codes spanning the years 2009-2016. I provide more detailed information on variable construction and sources in Appendix B. Summary statistics are listed in Table 1. Overall, the average ZIP code had approximately 7,900 credit files for those 18-64. Just over a third of credit files have debts in third-party collections, and the mean amount of these debts was just over $3,000 from 2009-2016. About 66 files per 1,000 have severely delinquent credit card debt with average amounts of about $5,300. The typical bankruptcy and foreclosure rates from 2009-2016 were 4.35 and 7.03 per 1,000 respectively. The mean of the average credit score in a ZIP code is 679. The average ZIP code in my sample had an uninsured rate of approximately 19% among the population under 400% FPL. Notably, there is a relatively large variance in the incidence of foreclosures, bankruptcies, and severely delinquent mortgage debts: the standard deviations in these variables are often larger than their means. My Q1 and Q4 samples are not substantially different on most attributes from the full sample with the exception of a larger variance in many of the outcomes.

My sample ZIP codes cover over 139 million total tax returns of the 148 million filed in 2014 and 272.5 million of the 284 million total personal exemptions claimed nationally. Thus, my sample covers 96% of the total tax filer population and 94% of tax returns.[16] Though my sample covers

[15] This allocation ensures that, even if a medical provider is not located in an exact ZIP code, they are apportioned to a ZIP code if they are located in the same county.

[16] I mention this coverage to distinguish geographic coverage from population coverage. These tax returns are for the full filing population of any age, though the outcomes I focus on are for those ages 18-64. Approximately 10 percent of residents in the US do not file their taxes each year (Larrimore et al., 2019), so I am limited in coverage to the filing population. However, according to Cilke (2014), 38% of the non-filer population is over 65, while 60% of non-filers with wages had wages below the filing requirement for a single person. Like those without credit files, this

all but a few tax filers in the United States (excluding those living abroad), it does not cover all ZIP codes. To start, I am limited in ZIP code coverage by the IRS data. Coverage of populated ZIP codes is not complete because the IRS takes various steps to limit disclosure risk. In addition, I limit my sample to ZIP codes with at least 30 credit file observations for those age 18-64. This excludes approximately 4,800 sparsely populated ZIP codes (or 57,000 total observations) from my sample as well as some large retirement communities. Next, I keep areas that have complete ACS and Census data, and I limit my sample to a balanced panel for years 2009-2016. These limitations, though excluding a few thousand ZIP codes, exclude few residents.

4 Empirical Strategy

I use the panel nature of my constructed dataset and the 2014 rollout of the premium tax credit subsidies to identify the effects of the subsidies on these financial outcomes. A logical identification strategy in this setting would be a simple difference-in-differences model with a linear treatment variable for premium tax credits per capita. However, any analysis of the ACA in 2014—and any panel analysis covering part of the post-2008 period—must tackle the empirical challenge posed by the Great Recession. Some states and local areas were demonstrably harder hit by the financial crisis, the foreclosure crisis, unemployment, and loss of local government fiscal capacity. The labor market consequences of the recession, with its far-reaching effects on other aspects of the local economy, hit low- to moderate-income residents the hardest (Grusky et al., 2011; Smeeding et al., 2011).

In my data, areas that saw the highest peaks of foreclosures during the crisis were also those which received the most in premium tax credits. Panel A of Figure 2 shows how areas that received more in PTC per capita (quartile four) were systematically harder hit by the foreclosure crisis than areas that received less (quartile one). The recovery for those areas in the top quartile of treatment was faster in the 2011-2013 stage in part because the 2009 peak was so much higher in these areas than in quartile one. These differing pre-trends violate the parallel trends assumption and imply that a naive version of this design would likely lead to downward-biased estimates of the effects of the tax credits. The size of the reduction in adverse financial outcomes attributed to the tax credits

population is most likely to align with the Medicaid program or else be eligible for Medicare, suggesting the missing non-filer population is unlikely to strongly affect my analysis.

would be too large relative to the true effect because unobserved drivers of the pre-ACA trends also drive treatment selection.[17]

My core identification strategy addresses these differential pre-trends by pairing the difference-in-differences design with a propensity score reweighting and a stratification procedure. In this approach, I compare the top quartile of PTC per capita to the bottom quartile as the "treatment" and "control" groups respectively. I split the sample this way because the trends in foreclosures and other outcomes during the Great Recession are most pronounced for quartile four, and the PTC per capita in quartile one was only approximately \$20 per person under 65. This is a relatively small outlay compared to the \$120 per capita spent in the top quartile.

My propensity score approach uses pre-treatment variation in the outcome variables to predict the probability of "treatment" (i.e. being in quartile four). In my reweighting procedure, I apply inverse probability weights to balance the pre-trends in treatment and control units. My stratification procedure further matches treatment and control units within the same stratum of the propensity score. The rationale for this approach follows a similar logic to the synthetic control method (Abadie et al., 2010), which uses variation in pre-treatment outcomes to construct a "synthetic" counterfactual version of a single treated unit that is a weighted average of the outcomes of "donor" units. My propensity score approach similarly creates weighted counterfactuals and matched controls for each treated unit based on the distribution of predicted treatment probability.

I first estimate the propensity score using outcomes in 2009-2013 along with the total population of the ZIP code with the following logit model separately for each Y outcome:

$$Logit(Pr(Q4_z)) = \gamma_0 + \sum_{e=2009}^{2013} \gamma_{e,1} Y_{z,e} + \gamma_{e,2} Y_{z,e}^2 + \gamma_3 Population_{zt} + \nu_z \tag{1}$$

The γ_1 and γ_2 terms for each year capture linear and quadratic functions of each year's outcome. The *Population* variable simply accounts for any substantial urban/rural differences in tax credits received and differences in the severity of the effects of the Great Recession. This specification

[17] For completeness and a comparison to my preferred models, I include estimates of a naive difference-in-differences method in Appendix Table A1. To provide a sense of what unobservables may drive selection, the raw correlations between various observables such as outcome levels in 2009 during the worst of the Great Recession and PTC per capita from 2014-2016 are presented in Appendix Table A2. The pre-treatment recession peaks in foreclosures and mortgage delinquency are two of the strongest correlates of PTC. Also significant correlates are the uninsured rate, median house value (cost of living), and the share of the population age 55-64.

parsimoniously and flexibly accounts for pre-treatment level differences and trends in the outcomes without imposing a linear relationship in the relationship between treatment selection and the pre-ACA outcomes.

To avoid relying on data from ZIP codes whose propensity scores are outliers, I follow common practice in the literature and trim my estimation sample to ZIP codes with propensity scores between 0.10 and 0.90. In practice, this trims very few observations. Figure 8 shows the common support in the propensity score between the treatment (Q4) and control groups (Q1) for each outcome. The blue bars show the histogram of predicted propensity scores for ZIP codes that were in quartile one, while the gray bars show the predicted propensity score for ZIP codes in quartile four. The dark regions indicate areas of overlap. There is strong support along the entire distribution of propensity scores for most outcomes. Support for severe mortgage delinquency and foreclosures is generally the weakest among outcomes, with falling common support above approximately 0.70.

For my inverse probability weights, I standardize the weights by the sum of the propensity scores for treatment and control groups (Hirano and Imbens, 2001), which makes estimates more stable and again avoids attributing outsized influence of propensity score outliers. In my reweighting procedure, I estimate the average treatment effect on the treated (ATT) parameterization of the normalized weights.

The estimation equation for the effects of being in the "treated" group (quartile four) relative to the "control" group (quartile one) is:

$$y_{zt} = \beta_0 + \beta_1 Treatment_{zt} + X'_{zt}\beta_2 + \delta_z + \tau_t + \varepsilon_{zt} \tag{2}$$

The $Treatment$ variable takes on a value of 1 for years 2014–2016 for ZIP codes in the top quartile of PTC per capita received over that period and maintains a value of zero for all comparison units over all years and implicitly contains a $Post$ interaction. The X vector contains the various controls mentioned in Section 3, such as median household income and race/ethnic composition, family structure, education, and home values as well as my measures of medical provider supply.[18] The vector includes an indicator for living in a Medicaid expansion state in the 2014-2016 period, which

[18]Race and ethnicity come from the ACS. Neither race nor ethnicity are identifiable in tax files or credit files.

is mechanically related to tax credits. The year fixed effects (τ_t) take into account any national shocks to financial and health insurance markets such as the Great Recession or the imposition of the ACA's individual mandate and other reforms in 2014. The δ parameter takes into account time-invariant characteristics of the ZIP code.[19]

In my preferred approach, I estimate my difference-in-differences model while stratifying on the propensity score. I interact my year fixed effects with indicators for ventiles of the propensity score as the strata. I employ the same reweighting procedure, but the interacted fixed effects ensure that the coefficient of interest compares the reweighted outcomes of Q4 areas versus Q1 areas within ventiles of the propensity score, imposing common support requirements for the estimates. This approach matches treatment and control areas within the same range of predicted treatment probability, which imposes stricter trend match requirements than reweighting alone.

To compare the pre-treatment trends of a naive estimate in comparison to my preferred approaches, I estimate a regression of the form:

$$y_{zt} = \beta_0 + \sum_{t \neq 2013, t=2009}^{2016} \alpha_t \mathbb{I}(t) * Q4_{z(2014-2016)} + X'_{zt}\beta_1 + \delta_z + \tau_t + \varepsilon_{zt} \tag{3}$$

In this event study, I interact year dummy variables ($\mathbb{I}(t)$) with an indicator for being in the top quartile of total 2014-2016 PTC per capita in relation to quartile one in my split sample. A sign of a violation of parallel pre-treatment trends would be if the α coefficients for 2009-2013 trend up or down, indicating that high-receipt areas deviated from the trend in low-receipt areas just before the ACA was implemented.

Panel B of Figure 2 shows that in the naive model, quartile four ZIP codes deviated from quartile one ZIP codes in their foreclosure rates during the Great Recession and just prior to 2014 even conditional on my various controls and fixed effects. Panels C and D of Figure 2 are the results of estimating Equation 3 with inverse probability weights (Panel C) and with propensity score ventile by year fixed effects (Panel D). These panels show that the propensity score procedures

[19] In my main tables of the estimates of the treatment effects using the propensity score, I report bootstrapped standard errors with 250 draws (Bodory et al., 2020). These standard errors are nearly identical to or in some cases slightly smaller than clustered standard errors. The bootstrapped standard errors, however, are far more computationally intensive to generate, particularly for my distributional analyses, which would require nearly 25,000 replications per outcome of interest. I therefore report standard errors clustered at the ZIP code level in my estimates of the distributional effects and event-study estimates.

yield far more comparable trends and levels during the 2009-2013 pre-treatment period than the naive model, which marks a substantial improvement in model fit. Contrary to Panel B, there is a relatively flat pre-trend. The raw values and parallel trends test graphs for other outcomes are in Figures 3-7. Panels C and D across each of these figures reveal improvements in trend match, particularly for the stratification procedure. The propensity score approach greatly strengthens the case for a causal interpretation of the estimates. This improvement even extends to the "first stage" effect on the uninsured share, which fell substantially with the implementation of the tax credits (see Appendix Figure A1).

Notably, estimating my propensity score model using the share of the population under 400% FPL that is uninsured, a core input determining eligibility for tax credits, does not address these pre-treatment trend differences (see Appendix Figures A2, A3, and A4). Taken together, it is clear that the trends across high- vs low-intensity treatment areas differ based on unobserved characteristics not easily addressed by a control function or other approach to predicting treatment using observables. This provides further justification for estimating the propensity score using the pre-treatment outcomes so as to account for these unobserved factors.

In my estimates of the distributional effects of the tax credits, I report the results of the stratum match approach.[20] As a robustness test, to avoid overfitting the pre-period data, I also estimate my propensity score using outcomes from the 2009–2011 period and allow the 2012–2013 years to act as a "hold-out" period (see Appendix Figures A5, A6, and A7). These trends are similar to my preferred propensity score estimates for most outcomes with the exception of the single coefficient for 2012 for some outcomes. The net effect is only a minor change from my preferred difference-in-differences estimates (see Appendix Table A3 and A4). This robustness test ensures that matching on the entire pre-treatment period does not impose a mechanical structural break in 2014.

[20]My setting is similar to Currie and Gruber (1996) in that eligibility for a social insurance program may be correlated with a negative local shock. In Appendix C, I explain my use of a simulated instrument procedure to address any remaining concerns about local shocks and present the results of that exercise. This simulated instrument uses the rules in the ACA to construct simulated eligibility for each ZIP code and year based on a fixed sample from the 2013 CPS ASEC survey. These estimates generally support the conclusions stemming from my propensity score estimates. However, the estimates are imprecise.

5 Results

5.1 Extensive Margin Effects

I begin by presenting results for the rates of negative financial shocks or the extensive margin effects. In each of Tables 2 and 3, Column 1 shows the results of the propensity score reweighting procedure, and Column 2 incorporates the stratified match. Table 2 shows the extensive margin for the first three high-cost outcomes: severe mortgage delinquency, foreclosure, and consumer bankruptcy, while Table 3 shows the extensive margin results for third-party collections, severe credit card delinquency, and severe auto delinquency. The difference in PTC per capita between the top and bottom quartile is just over $100, so I include scaled estimates of the percent effect of the 2013 top quartile mean for every $100 per capita.

Panel A of Table 2 shows that every $100 per capita in premium tax credits received in a ZIP code reduces the rate of severe mortgage delinquency per 1,000 by approximately 8%, while Column 2, my preferred estimate, reduces the estimate to 4%. This difference in the Column 2 result relative to Column 1, like the result for foreclosures in Panel B, is likely attributable to a lack of common support in some parts of the propensity score distribution, and the stratification procedure adjusts for this by imposing common support requirements. In my preferred estimate in Column 2, the severe mortgage delinquency rate fell by approximately 4% as a result of the premium tax credits.

In Panel B, according to Column 2, there was no statistically significant change in the foreclosure rate in the most treated ZIP codes as a result of the premium tax credits. The case of foreclosures in comparison to other outcomes provides an important check on my specifications. Because the foreclosure process is so lengthy, taking anywhere from 250 to over 900 days depending on the state, the 2014-2016 window of the post-ACA period in this study is such that we would not expect premium tax credits to have a strong effect on reported foreclosures.[21] In many cases, bankruptcies and foreclosures may operate as substitutes, with bankruptcy filing being a first attempt to discharge debt while keeping one's home and restructuring their mortgage (Mitman, 2016; Li et al., 2011).

[21] For example, see https://www.attomdata.com/news/most-recent/top-10-states-with-longest-foreclosure-timeline/ (Accessed March 5, 2021). Beginning in November of 2014, the Federal Housing Finance Agency announced extensions to foreclosure timelines, allowing foreclosures in many states to take as long as 920 days without incurring fees from the agency (Goodman, 2014).

Those that do file for bankruptcy that nevertheless eventually experience a foreclosure remain in their homes an additional 28 months compared to those that do not file for bankruptcy (Carroll and Li, 2011), and an auction of their home is 70% less likely (Lindblad et al., 2015). Thus, foreclosures, while not an outcome that is expected to respond significantly to PTC over the course of only 36 months, nonetheless serve as an important marker of the strength of my empirical strategy. A parallel pre-treatment trend in foreclosures along with other outcomes of interest combined with a small or zero effect on foreclosures lends credibility to my strategy adequately controlling for unobserved confounders. The zero estimated effect in Column 2 provides greater confidence in the estimates for this approach as applied to other outcomes of interest.

In Panel C of Table 2, the propensity score estimates in Columns 1 and 2 are remarkably consistent, owing to the strong common support in the propensity scores. In quartile four, the consumer bankruptcy rate fell relative to quartile one by approximately 13% of the 2013 mean. Out-of-pocket medical costs have been shown in the prior literature to be a substantial contributor to at least a quarter of consumer bankruptcies among low-income households (Gross and Notowidigdo, 2011), so this 13% effect suggests a substantial reduction in bankruptcy as a result of expanding private insurance coverage through the premium tax credits.

In Panel A of Table 3, I show the results for the rate of having any debts in third-party collections. As the receipt of premium tax credits increases, the rate of third-party collections remains relatively unchanged. This stands in contrast to the effects of Medicaid expansion found in other studies (Hu et al., 2016; Gross and Notowidigdo, 2011). One explanation for this phenomenon is that the newly insured population may increase their use of medical care and thus incur small costs such as co-pays or deductibles that are subsequently sent to collections after a period of non-payment. The CFPB stated in a recent report: "Medical debts occur and are collected through unique circumstances and practices ... In particular, the complexity of medical billing and the third-party reimbursement processes faced by most patients and their families is a potential source of confusion or misunderstanding ... That complexity could lead some consumers to be unaware of when, to whom, or for what amount they owe a medical bill," (CFPB, 2014). In addition, according to that report, the mean amount of medical debts in collections is $579. This is far lower than even the cost-sharing requirements under Gold tier insurance plans on the ACA marketplaces, let alone the higher-deductible Silver plans chosen by most enrollees. Survey evidence reports that 70% of non-elderly adults with medical debt in the prior three years reported being insured at the time they incurred the debt (Doty et al., 2005), suggesting that purely having private health insurance coverage is not sufficient to eliminate medical debts altogether. Finally, although the incidence of having debts in third-party collections was relatively unchanged, the *amounts* of such debts appear to decline substantially at the top of the distribution, as I will show in Section 5.2.

Panel B reveals minimal effects of the tax credits on severe credit card delinquency. There is no statistically significant effect of the tax credits on this outcome after adjusting for pre-treatment trends. Credit cards are a unique form of credit in that they allow the borrower substantial flexibility in the amount of credit card debt that is paid down each month. Credit cards are also an expensive form of credit. When facing debts or out-of-pocket medical spending, an uninsured person may prioritize making at least partial payments on a high-interest credit card to avoid falling further behind on payments or incurring substantial fees, leaving other debts unpaid. Paying at least a minimum payment shields the borrower from delinquency status.

Across columns of Panel C, there is a similar relative magnitude as the effects on bankruptcy. The results here suggest that the rate of having severely delinquent auto debt fell by just over 13% in quartile four ZIP codes relative to quartile one. Auto loans are not a flexible form of credit, and if uninsured households prioritize other forms of credit such as credit cards over making car payments, they run the risk of falling into delinquency as auto loans typically do not accommodate partial payments.

It is apparent from both tables that the premium tax credits provided through the ACA substantially reduced the frequency of serious financial loss. Provision of private insurance through these channels lowered the rate of severe mortgage delinquency, consumer bankruptcy, and delinquency on auto loans. The case of auto loans is interesting in that vehicle access is an important part of many household's ability to commute to a job. Severe delinquency on a car payment runs the risk of repossession or default, which could negatively affect a household's future economic security.

These results are robust to "holding out" the 2012-2013 portion of the pre-treatment period in the definition of the propensity score. Appendix Tables A3 and A4 compare the results from my "hold-out" specification of the propensity score to my preferred estimates, and the magnitudes and directions of the estimates are all substantively similar, meaning that my results are not an artifact of overfitting the propensity score on the pre-period outcomes. This is useful because it demonstrates that using the entire 2009-2013 period to estimate the propensity score does not run the risk of statistically forcing a structural break across outcomes when the ACA was implemented.

5.2 Intensive Margin Effects Across the Distribution

The incidence of severely adverse financial events may not capture heterogeneity in the monetary effects of adverse health shocks once they occur. For example, the balance of severely delinquent debt can vary between borrowers, as can the value of the debts sent to third-party collections. To capture heterogeneity across the distribution of each outcome, I present results of 99 separate regressions corresponding with percentiles 1-99 of the within-ZIP code distribution of each outcome. In this exercise, I examine the balances of severely delinquent mortgage debts, credit card debts, and auto debts; the balances of accounts sent to third-party collections; and credit score (Equifax Risk Score). Each of these represents the intensive margin rather than the extensive margin effects measured earlier, while the credit score analysis captures overall shifts in financial health. For credit scores, the estimates convey the effect of the tax credits on the nth percentile of the within-ZIP credit score distribution.

I present the results of these regressions for negative financial outcomes in Figure 9. In each of the panels, the blue line represents the point estimate for each percentile as the outcome, and the red shaded regions denote the 95% confidence interval. The green vertical bars mark the average value across ZIP codes at the 10th, 25th, 50th, 75th, and 99th percentiles in the top quartile of PTC per capita in 2013. These vertical bars provide some context on the size of the effects relative to their baseline values.[22] Each of these are the result of the propensity score stratification procedure with standard errors clustered at the ZIP code level.

Panel A shows that from about the 20th percentile upward, premium tax credits meaningfully lowered the balance of severely delinquent mortgage debt. At the 99th percentile, \$100 spent per capita on premium tax credits lowered the balance of severely delinquent mortgage debt by approximately \$32,000. Below the 10th percentile in the distribution, there is a small upward

[22] Full tables of the percentile-specific point estimates and standard errors for each outcome are in Appendix Tables A5 and A6.

shift in severe mortgage debts, suggestive of small, newly delinquent debts. A small proportion of the adult population may have struggled to make mortgage payments as a result of new payment requirements for premiums or deductibles.[23]

The results for third-party collections (Panel B) are quite noisy below the very top of the distribution. At the 99th percentile, each $100 in premium tax credits per capita led to a reduction of $640 in debts in third-party collections, or a reduction of approximately 5%. If the PTC population is concentrated in this right tail of the the distribution, this effect would be notably smaller than the effects of Medicaid expansion found by Hu et al. (2016), who find that new enrollees into Medicaid experienced reductions in third-party collections of about $1,100, as well as Brevoort et al. (2020), who find that newly insured Medicaid recipients reduced their medical debts by an average of $1,231 per person per year. These coefficients on the shift in third-party collections debt are particularly important for my calculation of the consumer welfare effects of these subsidies, which I describe in Section 6.1.

The same pattern holds for severely delinquent credit card and auto debts as presented in Panel C and Panel D. At the 99th percentile, quartile 4 of PTC per capita experienced a drop of $1,035 in severely delinquent credit card debt (4%) and $1,560 in severely delinquent auto debt (9%). Delinquent auto debts are unique because those debts fell across the entire distribution and not just at the top. Overall, the intensive margin effects across outcomes reveal that the composition of debts fell substantially at the top of the debt distribution. Any effects of the PTC on mean debt amounts appear to be driven by strong reductions above the 90th percentile for most outcomes.

As a composite measure of overall financial health, Figure 10 shows the change in the within-ZIP code distribution of credit scores (Equifax Risk Score) that results from the premium tax credits. This captures where in the distribution of credit health the effects of the subsidies load. The figure reveals that the effects are concentrated below the median credit score. The size of the effect is most pronounced between the 10th and 30th percentiles where scores are 550-660, with null effects or small negative effects above the 60th percentile (with scores of 720-760). At the 30th percentile of the credit score distribution, scores in the top quartile of treatment shifted upward by approximately

[23]The average health insurance premium after tax credits for marketplace enrollees was $105 in 2015, which is a non-trivial new expenditure for households that did not previously have health insurance and never experienced a health shock. See the HHS report (Accessed March 5, 2021).

4 points.[24] Given the share of the tax-filing population that received tax credits (approximately 5%), this 4 point increase implies substantial credit score gains for recipients whose credit scores are likely to be below median.

Overall, the effects across the distribution suggest that the premium tax credits in the ACA strongly affected the risk of right-tail loss both on the extensive margin and on the intensive margin. Even though private health insurance plans require premiums and cost sharing, these do not have deleterious effects on the financial health of the vast majority of recipients. We see uniformly positive gains for credit scores below the 60th percentile. The only notable deleterious effect in this analysis is the small proportion of mortgage borrowers whose delinquent balances grew modestly. There is also strong evidence of substantial overall gains in financial well-being at the bottom of the credit score distribution.

These effects could theoretically be driven by an "insurance" effect or a "liquidity" effect due to the simple cash value of the transfer. I argue the vast majority of these effects are driven by insurance effects because, 1) the effects appear in the right-tail of the distribution, consistent with protections against large losses, and 2) if the effects were driven by liquidity, we should see effects driven by inframarginal changes in insurance coverage and some substitution from employer-sponsored plans with premiums over 10% of household income toward non-group insurance plans, which includes exchange enrollment. In the US as a whole, employer-sponsored insurance coverage *increased* from 55% of the population below age 65 in 2013 to 56% in 2016, while the non-group share increased from 6% to 8% over the same period. Medicaid increased from 18% to 22% while the uninsured rate fell from 17% to 10%.[25] The primary effects of the subsidies appear to be on the extensive margin of coverage, as the "first stage" effect on the uninsured rate reaches 1.5 percentage points by 2016 (see Appendix Figure A1), which is over three quarters of the overall change in non-group coverage. Furthermore, both sampling error and measurement error arising from allocating uninsured rates from the county to the ZIP code may attenuate the measured effects. Enrollment for lower-income

[24]This 4 point increase is marginally larger than the increase attributed to Medicaid expansion in the ACA (Brevoort et al., 2020). The 4 point increase from premium tax credits is interesting in light of the 2.78 point decline that occurred in Tennessee in 2005 when individuals were suddenly *disenrolled* from Medicaid (Argys et al., 2017). The relatively large effect of the premium tax credits may be due to the fact that the PTC population is more likely to participate in formal credit markets than the Medicaid population.

[25]See the analysis from Kaiser Family Foundation, (Accessed March 5, 2021)

adults drops precipitously as subsidy generosity falls, though enrollment is still incomplete even with generous subsidies (Finkelstein et al., 2019b).

6 Discussion

I now turn to an analysis of the economic incidence of the tax credits. I first measure the welfare effects on recipients from protection against medical debt. I then analyze the spillover effects that accrue to other economic actors: creditors, mortgage lenders, and hospitals.

6.1 Value of Risk Reduction

Following Finkelstein and McKnight (2008), I contextualize my empirical results in an expected utility framework to simulate the value of risk reduction for recipients. As shown previously, ACA subsidies shifted downward the right tail of the distribution of third-party collections debts and the probability of bankruptcy, severe mortgage delinquency, and auto delinquency, which are costly to consumers.[26] In an expected utility framework, consumers experiencing this protection from risk will experience a gain in utility. This gain in utility is calculated by examining the change in their risk premium between two states of the world. The risk premium is the difference between the expected outcome for a choice that includes risk and what a consumer would be willing to accept if there were no risk.

I consider a simple framework in which utility is a function of consumption income net of costs associated with medical debts. I calculate the change in consumer welfare as the difference in the risk premium before and after the premium tax credits subsidized insurance ($\pi_b - \pi_a$). The risk premium depends on consumption income (y), the probability distribution of various medical costs and catastrophic negative outcomes ($f(o)$), and the shape of the utility function $u()$.

There are two π parameters, one for before the receipt of PTC and one after—in other words, when facing the different distributions of probabilities and costs in two states of the world. Analogous to Finkelstein and McKnight (2008), who examine the shift in cost distributions between 1963 and 1970 (before and after the implementation of Medicare), I consider two periods: before, b (2013), and after receiving subsidies, a (2014-2016). Here, o represents the distribution of annual

[26] Also note that there are implicit costs associated with collections, mortgage delinquency, and bankruptcies, such as the increased cost of credit, and psychic and social costs which are not captured in this analysis. The analysis also excludes the costs of vehicle repossession and eviction because they are not captured in the credit bureau data.

payments on medical debts.

$$u(y-\pi_b)=\int_0^{\bar{o}_b} u(y-o_b)f(o_b)do_b|Year=2013 \tag{4}$$

$$u(y-\pi_a)=\int_0^{\bar{o}_a} u(y-o_a)f(o_a)do_a|\overline{PTC} \tag{5}$$

My dataset is limited because I cannot directly observe out-of-pocket medical spending—either those paid without being sent to collections or those actually paid after being sent to collections. I can, however, infer spending on medical debts based on third-party collections information and the recent literature. Two recent papers from researchers at the CFPB, whose consumer credit dataset does contain medical debts separate from other types of collections debt, inform my assumptions. First, CFPB (2014) finds that approximately half (52%) of all third-party collections debts in the United States are owed to medical providers. Second, Brevoort et al. (2020) show that the one-year repayment rates of medical debts in collections are 38% of the face value of the debt and that this proportion is relatively constant across quantiles of medical debt. With these in mind, I assume that out-of-pocket spending annually for debts in third-party collections is just over 19% of the total value of the debt in collections (52% * 38% * third-party collections debt) and that this proportion is uniform across the distribution.[27] After these assumptions, this out-of-pocket medical debt spending distribution is designed to be analogous to the measures in Finkelstein and McKnight (2008) and Finkelstein et al. (2019a), though my measure is admittedly less precise.

In two states of the world, 2013 and post-PTC world, I consider the shift in outcomes in treatment quartile four attributable to the subsidies in my propensity score stratification design and subtract these effects from the observed 2013 distribution of expected costs. For example, I subtract the coefficient for the 99th percentile of debts in collections (scaled by 0.52*0.38 for medical debts) in quartile four from the 2013 mean of the 99th percentile of such debts in quartile four to get the "post PTC" measure of payment risk.

The change in the risk premium that occurs with this shift in risk is my measure of consumer welfare gains. In this consumption framework, by assumption, a one dollar increase in out-of-pocket

[27] While this 52% assumption leads to an admittedly coarse estimate of annualized out-of-pocket medical debt payments, there is no work of which I am aware which breaks down specific shares of third-party collections debt due to medical debts across the debt distribution.

medical spending leads to a one dollar decrease in consumption. This assumption is similarly invoked in Finkelstein et al. (2019a) and Finkelstein and McKnight (2008). There are two main choices for the researcher in this exercise: assumed risk aversion parameters and assumed income. I consider constant relative risk aversion (CRRA) utility functions with a risk aversion parameter, θ, of 2, 3, and 4 as is common in the literature with the functional form:

$$u(c) = \frac{1}{1-\theta} c^{1-\theta} \text{ if } \theta > 1 \tag{6}$$

I ground my consumption assumptions on Finkelstein et al. (2019a), who find non-medical consumption of \$9,214 per capita for the uninsured compliers in the Oregon Health Insurance Experiment. Because the population eligible for tax credits had slightly higher incomes, I increase this level incrementally from \$11,000 to \$14,000 and assume that 2% of their previous non-medical consumption is newly directed to health insurance premiums. Inasmuch as monthly premiums place a burden on household budgets which could translate into negative financial outcomes, this incorporates the net effect of new payment obligations and risk protections into my base consumption measures. These dimensions of income and risk aversion parameters provide a broad view of possible gains in consumer welfare due to the risk protections from medical debt payments via subsidized insurance. After calculating the ITT measures of the welfare gains, in order to approximate a treatment-on-the-treated parameter, I divide the overall change in utility by the share of the adult tax-filing population that received PTC in the top quartile of PTC per capita.

I present a table of these estimates of the consumer welfare gains for these four income levels and three CRRA risk aversion parameters in Table 4. Panel A shows that the consumer welfare gains are \$487 for assumed consumption income of \$11,000 at a CRRA risk aversion parameter of 3. This is smaller than the results presented by Finkelstein et al. (2019a), who estimate welfare gains based on a consumption proxy and find a pure insurance component for medical spending through the Medicaid program of \$760 with the same risk parameter. Because there is evidence that low-income individuals and those experiencing acute stress have higher levels of risk aversion (Haushofer and Fehr, 2014; Cahlíková and Cingl, 2017), a value for θ of 4 may be more appropriate considering the low income of PTC recipients.

This exercise suggests that the risk protections from Medicaid may be larger than the risk protections from the premium tax credits, a difference likely due to differences in cost-sharing and premium payments across the two programs as well as the fact that Medicaid subsidies are very large. It also may be attributable to differences in health outcomes that come from cost sharing, as copay and deductible requirements have been shown in recent work to decrease take-up of essential care and prescription drugs, decrease health quality, and increase mortality risk (Chandra et al., 2021).

These estimates represent a lower bound on the risk protections of the PTC program. Putting a dollar value on avoiding severe delinquency on a mortgage, auto loan, or credit card is beyond the scope of this paper, so I am limited in what welfare effects I can adequately measure. Because I cannot directly measure out-of-pocket medical spending, there may be other effects of the subsidies on consumption through this channel. In addition, though the costs of eviction and the upheaval it generates are large, I cannot observe those in my dataset because evictions are not listed on credit reports. Losing a vehicle to debt obligations or repossession may lessen financial stability if stable employment is threatened by having inconsistent transportation. My analysis cannot measure the indirect protections from preventing auto delinquency. Finally, these estimates cannot directly measure the health effects of insurance coverage. Inasmuch as better health translates into more stable financial outcomes, I only capture an indirect, second-order effect of insurance on health. Health and physical well-being likely have independent welfare value to recipients outside of their effects on financial well-being.

As with any analysis of public policy, we want to know the relative costs and benefits. Because the exact size of the recipient population of tax credits is not clear in the tax data, I infer costs from two sources: HHS reports and my calculation of dollars per recipient from the SOI data. I infer the recipient population by multiplying the number of recipient returns by the average non-dependent personal exemptions per return (1.33). According to HHS reports, the average adult recipient of advanced premium tax credits received \$264 per month in 2014, \$268 per month in 2015, and \$294 per month in 2016 in premium tax credits, or \$3,168 to \$3,528 annually.[28] Dividing total tax credits in high-treatment areas by my estimated number of non-dependent recipients yields a nearly

[28] See, for example, the report from HHS, (Accessed June 10, 2020).

identical estimated cost of $3,314 per recipient from 2014–2016. This bolsters the case for using this measure of the number of recipients to scale my intent-to-treat estimates.

Panel B of Table 4 presents the range of estimates for the average annual cost per recipient of the program from HHS reports, the individual insurance value or welfare gain from my various Panel A cells, and the share of costs realized in risk protections from medical debt payments. The fourth line in Panel B suggests that risk protections from out-of-pocket medical debt payments alone sum to as much as 15% of the annual cost of the subsidies. On a total average annual cost from 2014-2016 of $15.6 billion in my sample, annual aggregate welfare gains sum to approximately $2.3 billion. Again, these figures notably do not include any health effects (physical or mental), effects on renters' ability to avoid eviction, protections against vehicle repossession, or effects operating through increases in credit-worthiness.

6.2 External Spillovers

Using back of the envelope calculations, I find that the external spillovers of ACA subsidies are substantial. My estimates of the effects of the subsidies are based on the difference in PTC per capita between quartile one (approximately $20) and quartile four (approximately $120). Using these estimates, I assume linearity in the marginal effects per dollar spent.[29] The average PTC per person under age 65 from 2014-2016 across all ZIP codes was $58.69, so in order to estimate spillovers on a national level, I scale my estimates of the effect of $100 per capita to $58.69 per capita. With this scaled effect in mind, I predict the total number of bankruptcies and delinquent accounts prevented by the premium tax credits nationwide. In all, the premium tax credits annually prevented approximately 136,000 bankruptcies, 112,000 severe mortgage delinquencies, and 582,000 severe auto delinquencies from being reported on consumers' credit files from 2014–2016. I present the predicted indirect transfers to outside parties in Panel C of Table 4.

Bankruptcy is an important outcome to analyze because bankruptcy is considered a form of implicit insurance (Brevoort et al., 2020; Mahoney, 2015). With a conservatively estimated cost of bankruptcy to creditors of $46,425 per bankruptcy using insights from various papers,[30] I calculate

[29]This assumption is supported by the fact that scaled effects per $100 per capita are nearly identical when splitting my "treatment" and "control" groups at the median PTC per capita rather than the top and bottom quartiles. These estimates are in Appendix Table A7.

[30]Work using a national sample of bankruptcy filings suggests that the median unsecured debt in Chapter 7 asset

that the ACA premium tax credits provide an indirect subsidy to creditors of approximately $6.3 billion annually.

Severe mortgage delinquency imposes significant service costs on lenders and GSEs. According to the Mortgage Bankers Association, in 2013, loans that were nonperforming cost lenders $2,357 to service versus $156 for performing mortgage loans, a difference of $2,201 (Goodman, 2014). At an estimated 112,000 severe mortgage delinquencies prevented by the ACA premium tax credits, this implies an indirect subsidy to mortgage lenders and GSEs of approximately $246 million. Many of these severe mortgage delinquencies would likely end in foreclosure. However, the process of foreclosure is a very long one. Beginning in November of 2014, the Federal Housing Finance Agency announced extensions to foreclosure timelines for before which loan servicers would have to pay compensatory fees to GSEs, allowing foreclosures across states to take anywhere from 300 to 920 days without incurring fees (Goodman, 2014). If the premium tax credits reduced significantly delinquent payments, we might not expect to see a significant effect on foreclosures until as late as 2018 in many states. Foreclosure prevention would significantly increase the indirect subsidies to mortgage lenders as well as neighboring home owners and local governments.

Finally, an increase in the insured population that comes with expanding insurance coverage directly benefits hospitals and medical practitioners. According to Garthwaite et al. (2018), each uninsured patient costs a hospital or practitioner $800. Taking the estimated number of recipients from the my sample area tax data (an average of 5.4 million each year) as a one-to-one change from uninsured to insured, this implies a total transfer to hospitals of approximately $4.4 billion. Alternatively, the estimates in Frean et al. (2017) suggest approximately 3.84 million people gained coverage from having no coverage due to the tax credits, for a transfer of $3.07 billion.[31]

cases was $61,916 (Jiménez, 2009) at the beginning of 2007 near the end of the housing boom and just before the housing bust. Notably, 93% of cases were "no asset" cases, meaning recovery of debts to unsecured creditors was even less likely. The recovery rate on unsecured debts may be as little as 8 cents on the dollar (Jiménez, 2009). For Chapter 13 bankruptcy cases, recovery rates on secured and unsecured debt may be approximately 20-30 percent of the face value of the debts (Li, 2007; Eraslan et al., 2017; Norberg and Velkey, 2005). Given that Chapter 13 requires repayments to creditors of unsecured debts be equal to that of Chapter 7 filings, I assume this recovery rate holds across filing types. I assume a 25% recovery rate on average debts of $61,900 per filing, for a total loss of $46,425 per filing.

[31] This aligns with the change of approximately two percentage point increase in the share of non-elderly adults insured in the non-group market after 2013, which is approximately 3.9 million people.

7 Conclusion

In this paper, I have measured the causal effects of premium tax credits as a funding mechanism for private health insurance on high-cost financial outcomes using a propensity score stratification and reweighting design.

Among the non-elderly adult population, premium tax credits from 2014-2016 significantly reduced the rates of severe delinquency on a mortgage, bankruptcy, and severe delinquency on auto loans. While these tax credits did not substantially alter the share of non-elderly adults with debts in third-party collections, they did decrease the amounts of these debts at the top of the distribution. Likewise, debt amounts that are severely delinquent fall significantly at the top of the debt distribution across mortgage accounts, credit cards, and auto debts. The overall credit effects load heavily on those with low credit scores, and there is substantial improvement in credit scores for those below 660 as a result of the premium tax credits.

I also find that the economic incidence of the tax credits fall upon a range of economic actors. I find that consumer welfare as measured by the change in the risk premium from reduced medical debts increased significantly. When comparing to the Medicaid program, due to the differences in premium and cost-sharing rules and the size of the transfers, welfare gains from ACA tax credits through pure insurance from medical debts are smaller than the protections from out-of-pocket sending through the Medicaid program. Using conservative assumptions, 10-15% of the monetary costs of the credits are realized in welfare gains to recipients through this single channel. These welfare gains are substantial despite being very narrow in scope (medical debts paid annually) and excluding several other channels through which subsidies may provide welfare gains to recipients.

I also find that there are substantial implied spillovers of these tax credits to outside parties such as mortgage lenders, creditors whose debtors discharge obligations through bankruptcy, and hospitals. In all, these indirect transfers to these four groups totaled approximately $10 billion per year on average from 2014 to 2016, which is approximately two-thirds of the total cash value of the transfer. The benefits of these premium tax credits do not accrue to recipients alone but land on a wide variety of actors in the economy that interact with consumers experiencing greater financial stability.

I am limited in my analysis in my ability to directly connect subsidy receipt with individual credit outcomes. Thus, my main estimates are an "intent-to-treat" effect. In addition, I do not detail the economic incidence of the taxes levied to fund this program, nor of the cross-subsidization of health insurance costs that came with the other ACA provisions. My analysis focuses intentionally on answering the first-order question of the immediate financial benefits. Future work in this area may attempt to detail the full cost-benefit calculation of these subsidies in a general framework and full social welfare context.

This paper sheds light on the balance of direct cash costs and risk protection benefits from providing subsidies for private health insurance. It gives a broad accounting of the effects of this type of policy regime on consumer financial outcomes and provides clarity on who benefits most from this policy approach. The benefits do not just accrue to recipients, but to a broad set of agents in the economy.

Current debates around methods of expanding health insurance coverage most often focus on expanding current public programs like Medicaid or Medicare, while policies focusing on expanding access to private health insurance tend to lag behind in terms of popularity or political airtime. As the first paper to analyze the effects of this type of national policy change, this analysis can contextualize that debate for policymakers and interested parties by showing that there is a viable role for public funding to support the purchase of private health insurance, with meaningful positive effects on recipients' financial health. The pure financial insurance value to recipients from protections against medical debt payments accounts for a sizable portion of program costs, even when excluding possible benefits via health, creditworthiness, and protections against eviction or vehicle repossession. That the policy indirectly benefits other agents in the economy may provide some sense of who might be tapped to bear some of the funding responsibility in order to internalize the costs associated with the indirect benefits they accrue. These debates will likely grow as the premium tax credit expansions from the 2021 American Rescue Plan approach expiration and Congress takes up the question of whether or not to extend them beyond 2022.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of* *the American Statistical Association*, 105(490): 493–505.

Anderson, Michael, Carlos Dobkin, and Tal Gross. 2012. “The Effect of Health Insurance Coverage on the Use of Medical Services.” *American Economic Journal: Economic Policy*, 4(1): 1–27.

Argys, Laura M, Andrew Friedson, M Melinda Pitts, and Daniel Tello-Trillo. 2017. “Losing Public Health Insurance: TennCare Disenrollment and Personal Financial Distress.” *FRB Atlanta Working Paper.*

Aron-Dine, Aviva, Liran Einav, and Amy Finkelstein. 2013. “The RAND Health Insurance Experiment, Three Decades Later.” *Journal of Economic Perspectives*, 27(1): 197–222.

Baicker, Katherine, Sarah L Taubman, Heidi L Allen, Mira Bernstein, Jonathan H Gruber, Joseph P Newhouse, Eric C Schneider, Bill J Wright, Alan M Zaslavsky, and Amy N Finkelstein. 2013. “The Oregon Experiment: Effects of Medicaid on Clinical Outcomes.” *New England Journal of Medicine*, 368(18): 1713–1722.

Barcellos, Silvia Helena, and Mireille Jacobson. 2015. “The Effects of Medicare on Medical Expenditure Risk and Financial Strain.” *American Economic Journal: Economic Policy*, 7(4): 41–70.

Bodory, Hugo, Lorenzo Camponovo, Martin Huber, and Michael Lechner. 2020. “The Finite Sample Performance of Inference Methods for Propensity Score Matching and Weighting Estimators.” *Journal of Business & Economic Statistics*, 38(1): 183–200.

Brevoort, Kenneth, Daniel Grodzicki, and Martin B Hackmann. 2017. “Medicaid and Financial Health.”Technical report, National Bureau of Economic Research.

Brevoort, Kenneth, Daniel Grodzicki, and Martin B Hackmann. 2020. “The Credit Consequences of Unpaid Medical Bills.” *Journal of Public Economics*, 187, p. 104203.

Brevoort, Kenneth P, Philipp Grimm, and Michelle Kambara. 2016. “Credit Invisibles and the Unscored.” *Cityscape*, 18(2): 9–34.

Cahlíková, Jana, and Lubomir Cingl. 2017. “Risk Preferences Under Acute Stress.” *Experimental Economics*, 20(1): 209–236.

Card, David, Carlos Dobkin, and Nicole Maestas. 2008. “The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare.” *American Economic Review*, 98(5): 2242–58.

Card, David, Carlos Dobkin, and Nicole Maestas. 2009. “Does Medicare Save Lives?” *The Quarterly Journal of Economics*, 124(2): 597–636.

Carroll, Sarah W, and Wenli Li. 2011. “The Homeownership Experience of Households in Bankruptcy.” *Cityscape* 113–134.

CFPB. 2014. “Consumer Credit Reports: A Study of Medical and Non-Medical Collections.” *Consumer Financial Protection Bureau.*

Chandra, Amitabh, Evan Flack, and Ziad Obermeyer. 2021. “The Health Costs of Cost-Sharing.”Technical report, National Bureau of Economic Research.

Cilke, James. 2014. “The Case of the Missing Strangers: What We Know and Don’t Know About Non-Filers.” In *107th Annual Conference of the National Tax Association, Santa Fe, New Mexico*. JSTOR.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. 2017. “Early Empacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States.” *Journal of Policy Analysis and Management*, 36(1): 178–210.

Currie, Janet, and Jonathan Gruber. 1996. “Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women.” *Journal of Political Economy*, 104(6): 1263–1296.

DeLeire, Thomas, Andre Chappel, Kenneth Finegold, and Emily Gee. 2017. “Do Individuals Respond to Cost-Sharing Subsidies in Their Selections of Marketplace Health Insurance Plans?” *Journal of Health Economics*, 56 71–86.

Doty, Michelle M, Jennifer N Edwards, and Alyssa L Holmgren. 2005. “Seeing Red: Americans Driven Into Debt by Medical Bills.” *The Commonwealth Fund*, 4.

Engelhardt, Gary V, and Jonathan Gruber. 2011. “Medicare Part D and the Financial Protection of the Elderly.” *American Economic Journal: Economic Policy*, 3(4): 77–102.

Eraslan, Hülya, Gizem Koşar, Wenli Li, and Pierre-Daniel Sarte. 2017. "An Anatomy of US Personal Bankruptcy Under Chapter 13." *International Economic Review*, 58(3): 671–702.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer. 2019a. "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment." *Journal of Political Economy*, 127(6): 2836–2874.

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard. 2019b. "Subsidizing Health Insurance for Low-Income Adults: Evidence from Massachusetts." *American Economic Review*, 109(4): 1530–67.

Finkelstein, Amy, Neale Mahoney, and Matthew J Notowidigdo. 2018. "What Does (Formal) Health Insurance Do, and for Whom?" *Annual Review of Economics*, 10 261–286.

Finkelstein, Amy, and Robin McKnight. 2008. "What Did Medicare Do? The Initial Impact of Medicare on Mortality and Out of Pocket Medical Spending." *Journal of Public Economics*, 92(7): 1644–1668.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year." *The Quarterly journal of economics*, 127(3): 1057–1106.

Frean, Molly, Jonathan Gruber, and Benjamin D Sommers. 2017. "Premium Subsidies, the Mandate, and Medicaid Expansion: Coverage Effects of the Affordable Care Act." *Journal of Health Economics*, 53 72–86.

Gallagher, Emily A, Radhakrishnan Gopalan, and Michal Grinstein-Weiss. 2019. "The Effect of Health Insurance on Home Payment Delinquency: Evidence from ACA Marketplace subsidies." *Journal of Public Economics*, 172 67–83.

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo. 2018. "Hospitals as Insurers of Last Resort." *American Economic Journal: Applied Economics*, 10(1): 1–39.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8): 2586–2624.

Goodman, Laurie. 2014. "Servicing is an Underappreciated Constraint on Credit Access." *Urban Institute Housing Finance Policy Center Brief*, URL: https://www.urban.org/sites/default/files/publication/33451/2000049-Servicing-Is-an-Underappreciated-Constraint-on-Credit-Access.pdf.

Gross, Tal, and Matthew J Notowidigdo. 2011. "Health Insurance and the Consumer Bankruptcy Decision: Evidence from Expansions of Medicaid." *Journal of Public Economics*, 95(7-8): 767–778.

Grusky, David B, Bruce Western, and Christopher Wimer. 2011. *The Great Recession.*: Russell Sage Foundation.

Haushofer, Johannes, and Ernst Fehr. 2014. "On the Psychology of Poverty." *Science*, 344(6186): 862–867.

Hinde, Jesse M. 2017. "Incentive (Less)? the Effectiveness of Tax Credits and Cost-Sharing Subsidies in the Affordable Care Act." *American Journal of Health Economics*, 3(3): 346–369.

Hirano, Keisuke, and Guido W Imbens. 2001. "Estimation of Causal Effects Using Propensity Score Weighting: An Application to Data on Right Heart Catheterization." *Health Services and Outcomes Research Methodology*, 2(3): 259–278.

Hu, Luojia, Robert Kaestner, Bhashkar Mazumder, Sarah Miller, and Ashley Wong. 2016. "The Effect of the Patient Protection and Affordable Care Act Medicaid Expansions on Financial Well-being."Technical report, NBER Working Paper 22170.

Jiménez, Dalié. 2009. "The Distribution of Assets in Consumer Chapter 7 Bankruptcy Cases." *American Bankruptcy Law Journal*, 83, p. 795.

Larrimore, Jeff, Jacob Mortenson, and David Splinter. 2019. "Household Incomes in Tax Data: Using Addresses to Move from Tax Unit to Household Income Distributions." *Journal of Human Resources* 0718–9647R1.

Larrimore, Jeff, and David Splinter. 2019. "How Much Does Health Insurance Cost? Comparison of Premiums in Administrative and Survey Data." *Economics Letters*, 174 132–135.

Li, Wenli. 2007. "What Do We Know About Chapter 13 Personal Bankruptcy Filings?" *Business Review*(Q4): .

Li, Wenli, Michelle J White, and Ning Zhu. 2011. "Did Bankruptcy Reform Cause Mortgage Defaults to Rise?" *American Economic Journal: Economic Policy*, 3(4): 123–47.

Lindblad, Mark R, Roberto G Quercia, Melissa B Jacoby, Ling Wang, and Huifang Zhao. 2015. "Bankruptcy During Foreclosure: Home Preservation Through Chapters 7 and 13." *Housing Policy Debate*, 25(1): 41–66.

Mahoney, Neale. 2015. "Bankruptcy as Implicit Health Insurance." *American Economic Review*, 105(2): 710–46.

Mitman, Kurt. 2016. "Macroeconomic Effects of Bankruptcy and Foreclosure Policies." *American Economic Review*, 106(8): 2219–55.

Newhouse, Exp. Group, Joseph P. 1993. *Free for All?: Lessons from the RAND Health Insurance Experiment.*: Harvard University Press.

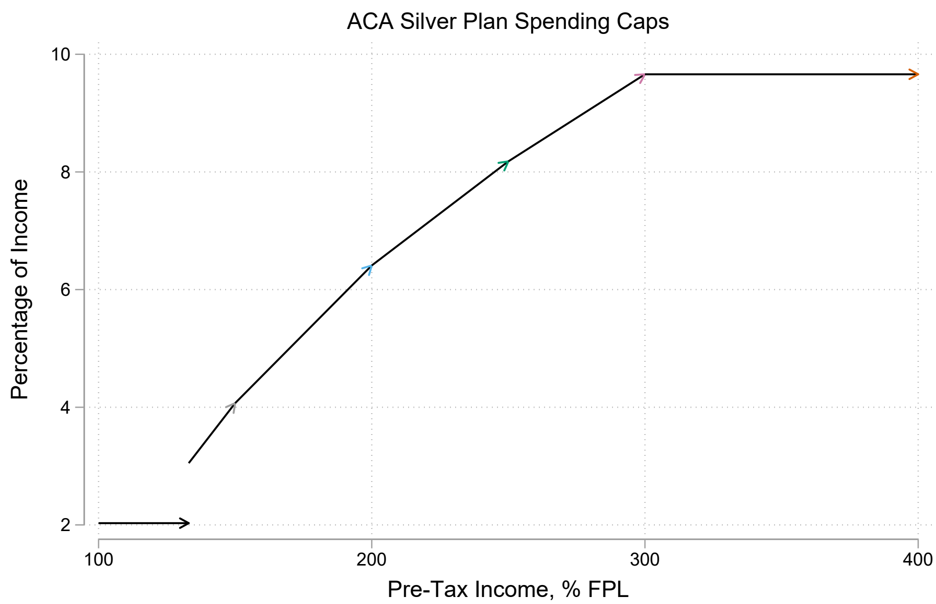
Norberg, Scott F, and Andrew J Velkey. 2005. "Debtor Discharge and Creditor Repayment in Chapter 13." *Creighton Law Review*, 39, p. 473.

Smeeding, Timothy, Jeffrey P Thompson, Asaf Levanon, Burak Ho, and Beste Esra. 2011. "Poverty and Income Inequality in the Early Stages of the Great Recession."

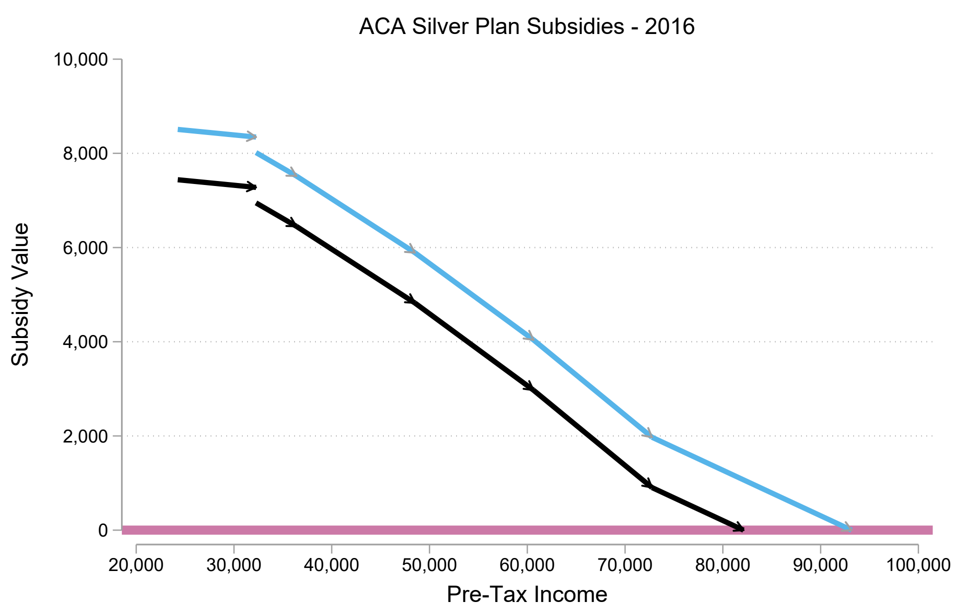
Figures

Figure 1: ACA Legislated Spending Caps and Example Subsidy Payments for a Family of 4 in a Medicaid Non-Expansion State Facing Benchmark Premiums of $7,932 (Black) or $9,000 (Blue)

Panel A

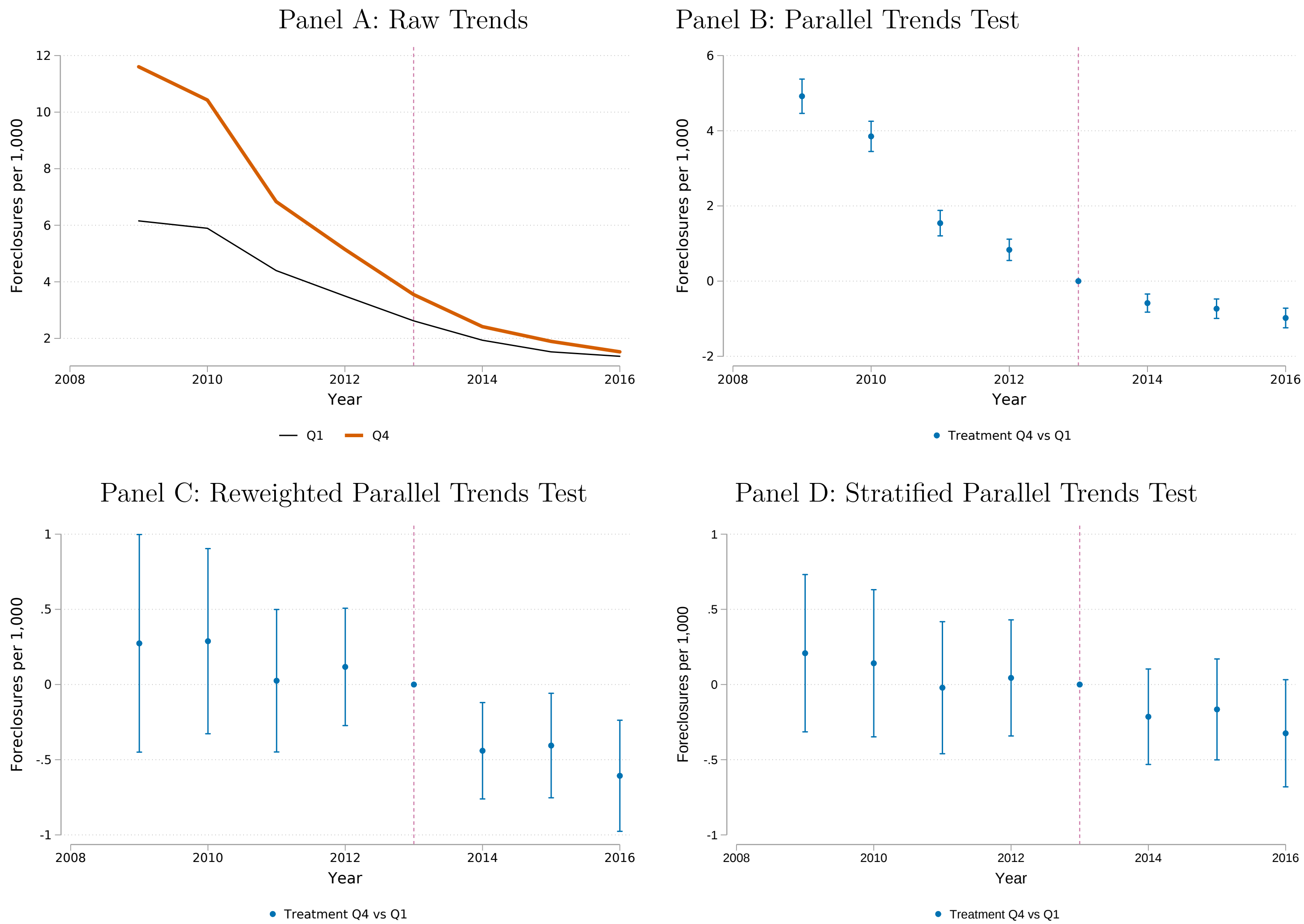


Panel B



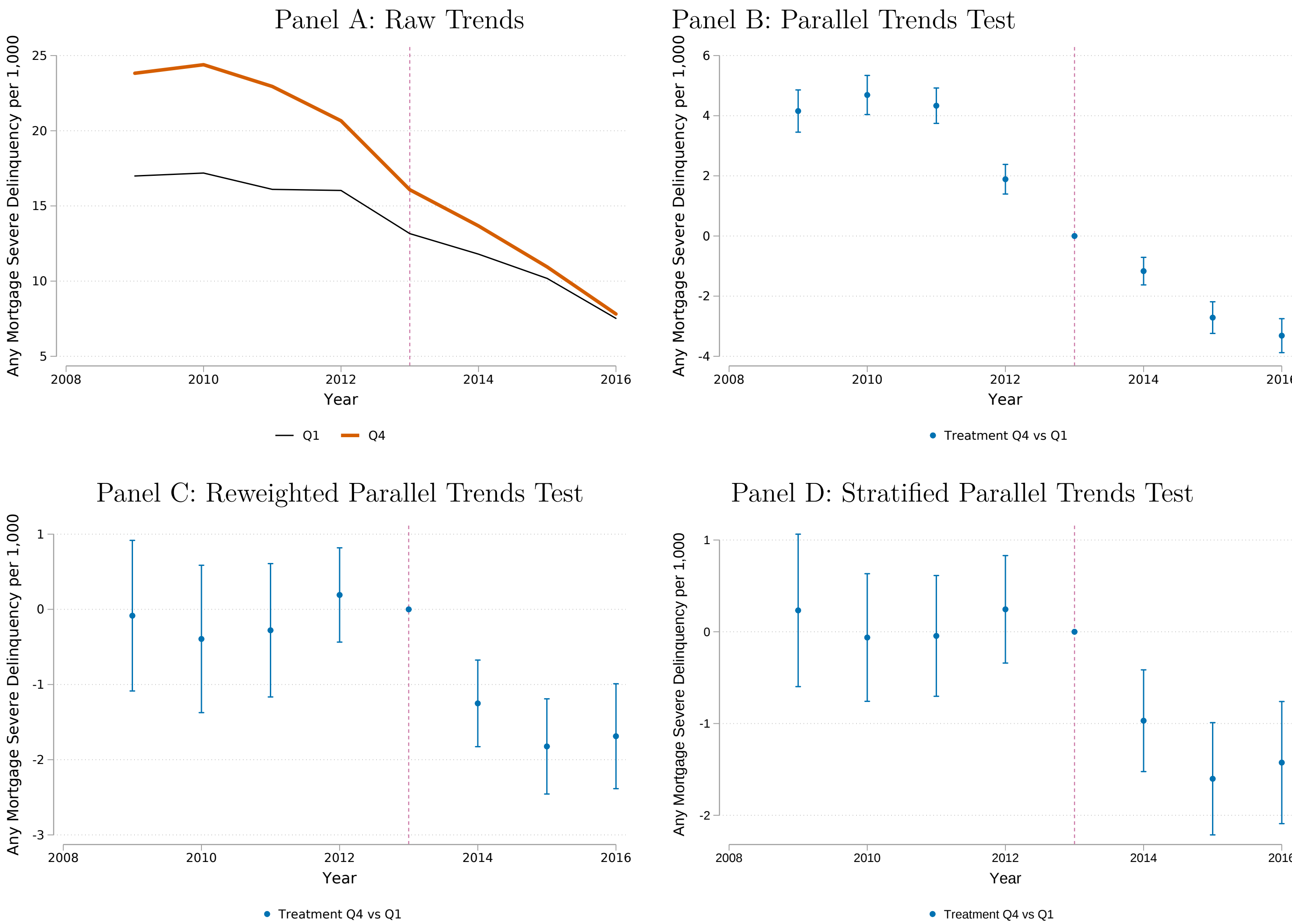
Source: Author's example calculations of legislated income limits and subsidies in the Affordable Care Act.
Note: Pre-tax income here is Modified Adjusted Gross Income (MAGI). Spending limits and the premium for the "second lowest-cost Silver plan" are from 2016. Arrows mark kinks or discontinuities in the subsidy schedule. The jump at 138% FPL is due to a large level shift in spending limits in Medicaid non-expansion states.

Figure 2: Foreclosure Rate Trends and Parallel Trends Test



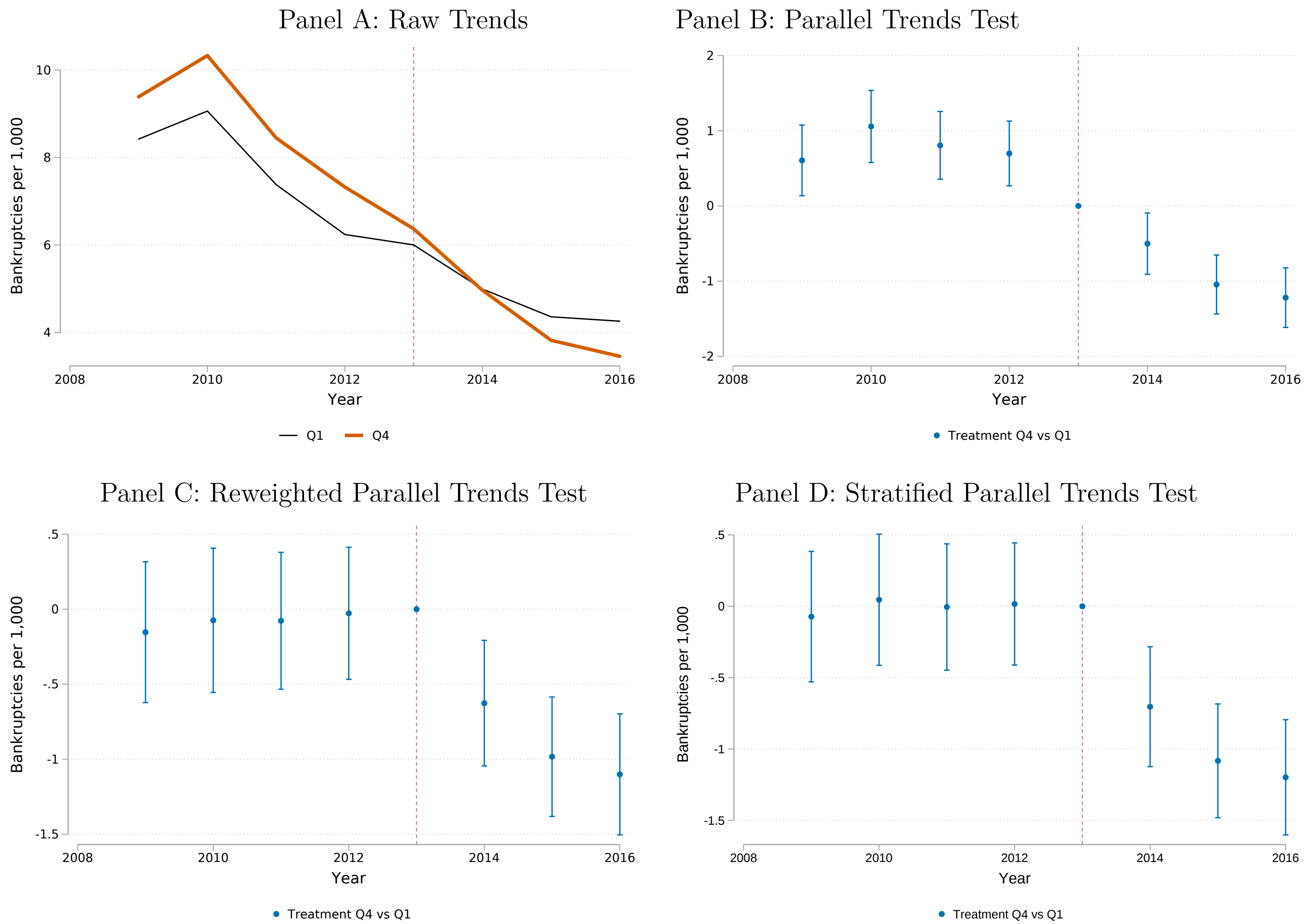
Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

Figure 3: Severe Mortgage Delinquency Rate Trends and Parallel Trends Test



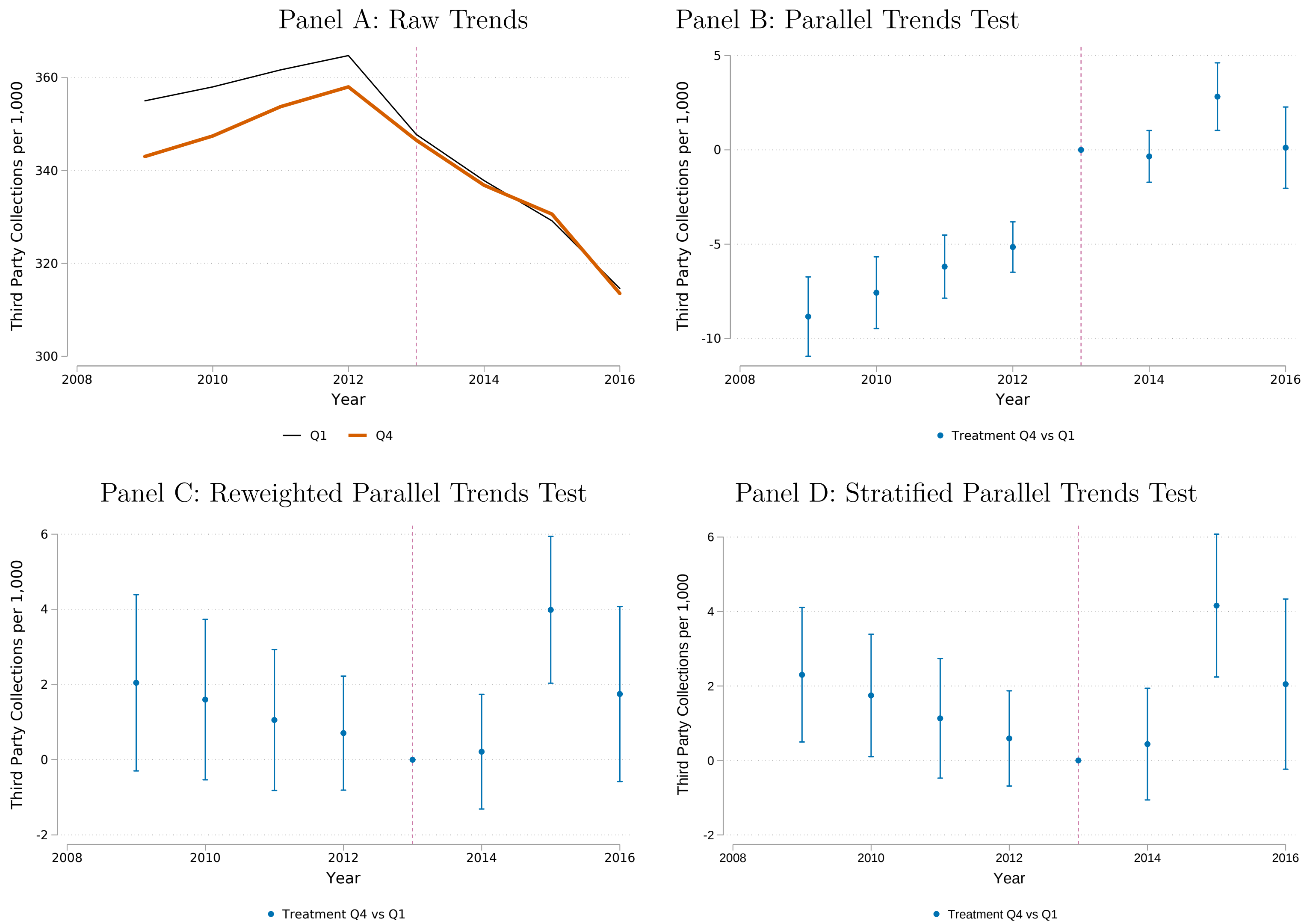
Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

Figure 4: Bankruptcy Rate Trends and Parallel Trends Test



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

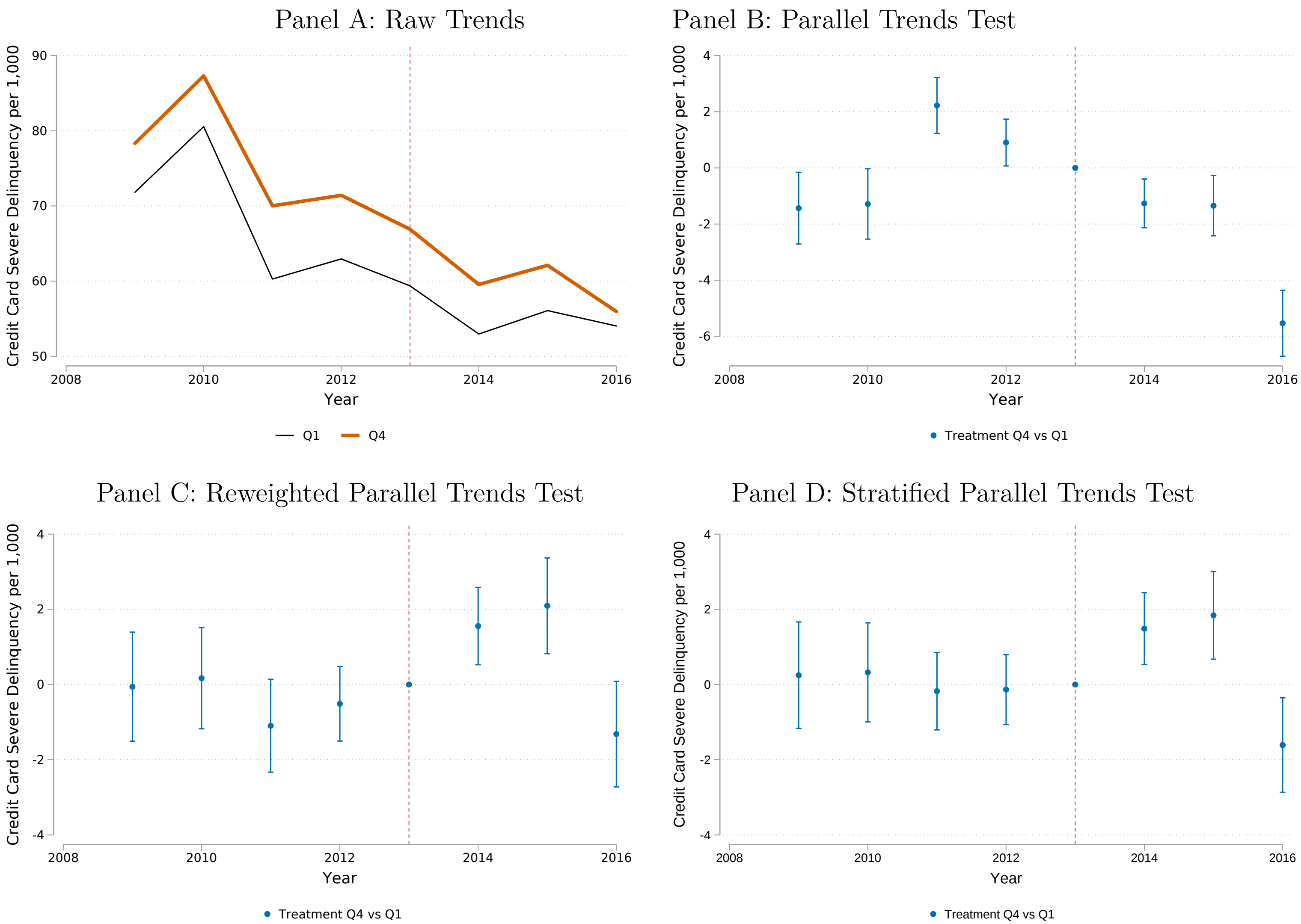
Figure 5: Third-Party Collections Rate Trends and Parallel Trends Test



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.

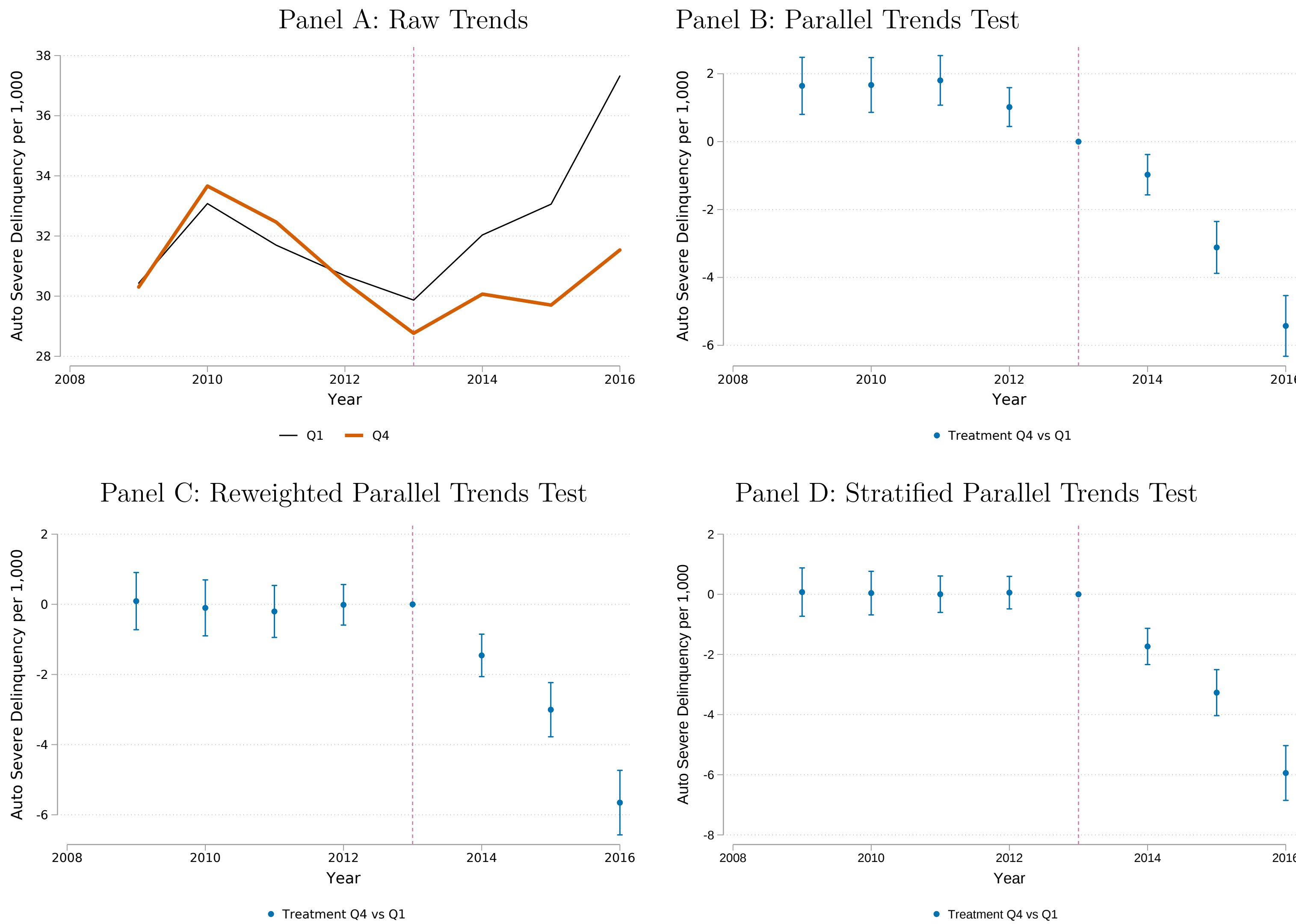
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

Figure 6: Severe Credit Card Delinquency Rate Trends and Parallel Trends Test



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

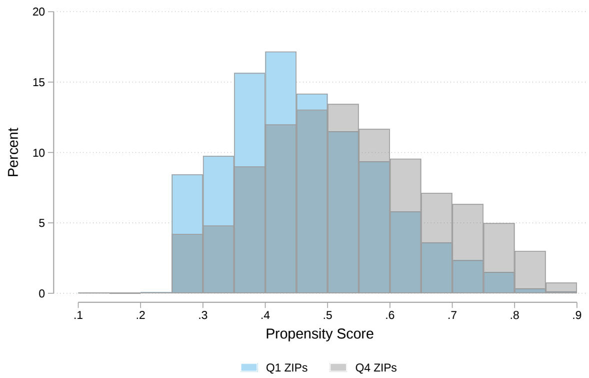
Figure 7: Severe Auto Delinquency Rate Trends and Parallel Trends Test



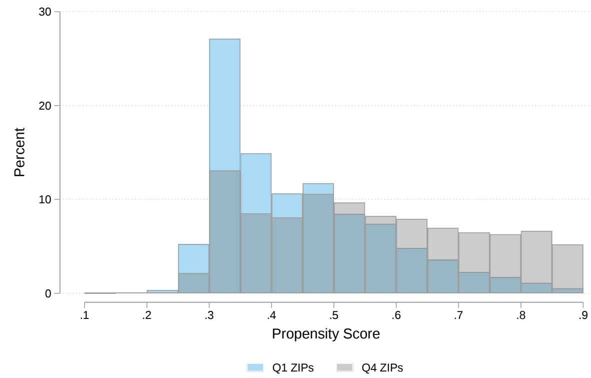
Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

Figure 8: Common Support

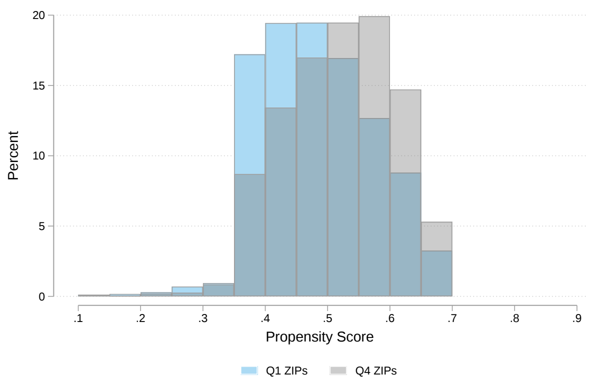
Panel A: Severe Mortgage Delinquency



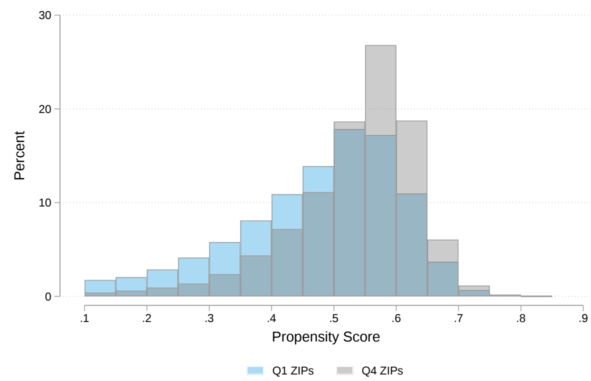
Panel B: Foreclosures



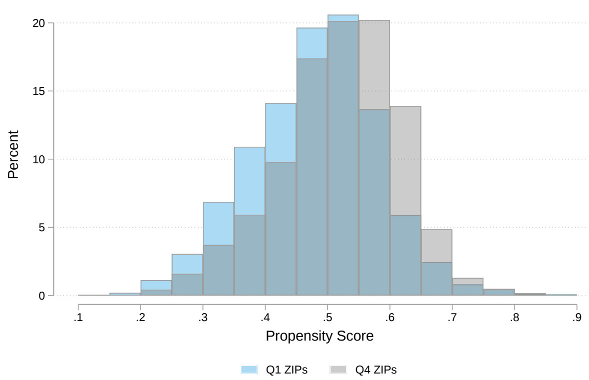
Panel C: Bankruptcy



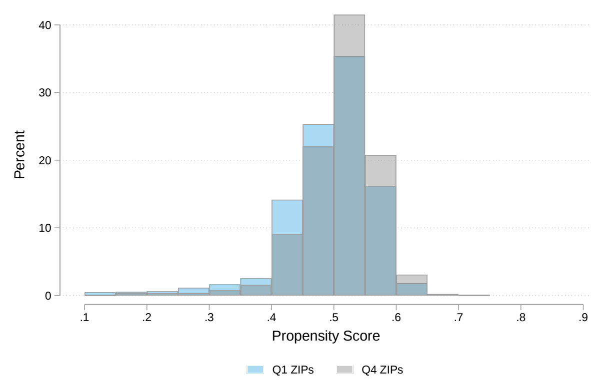
Panel D: Third Party Collections



Panel E: Severe Credit Card Delinquency

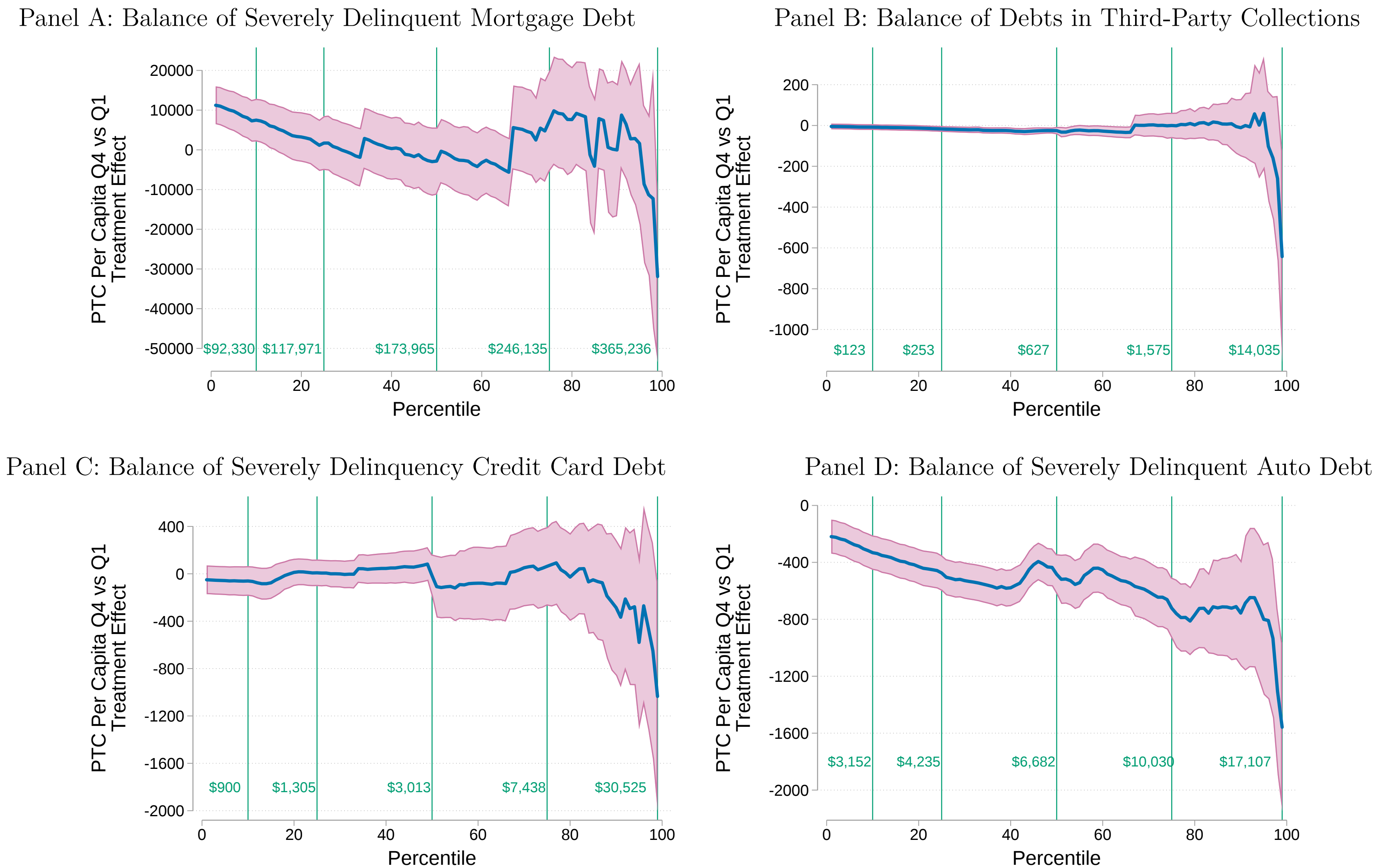


Panel F: Severe Auto Delinquency



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. Propensity scores are based on estimates of Equation 1

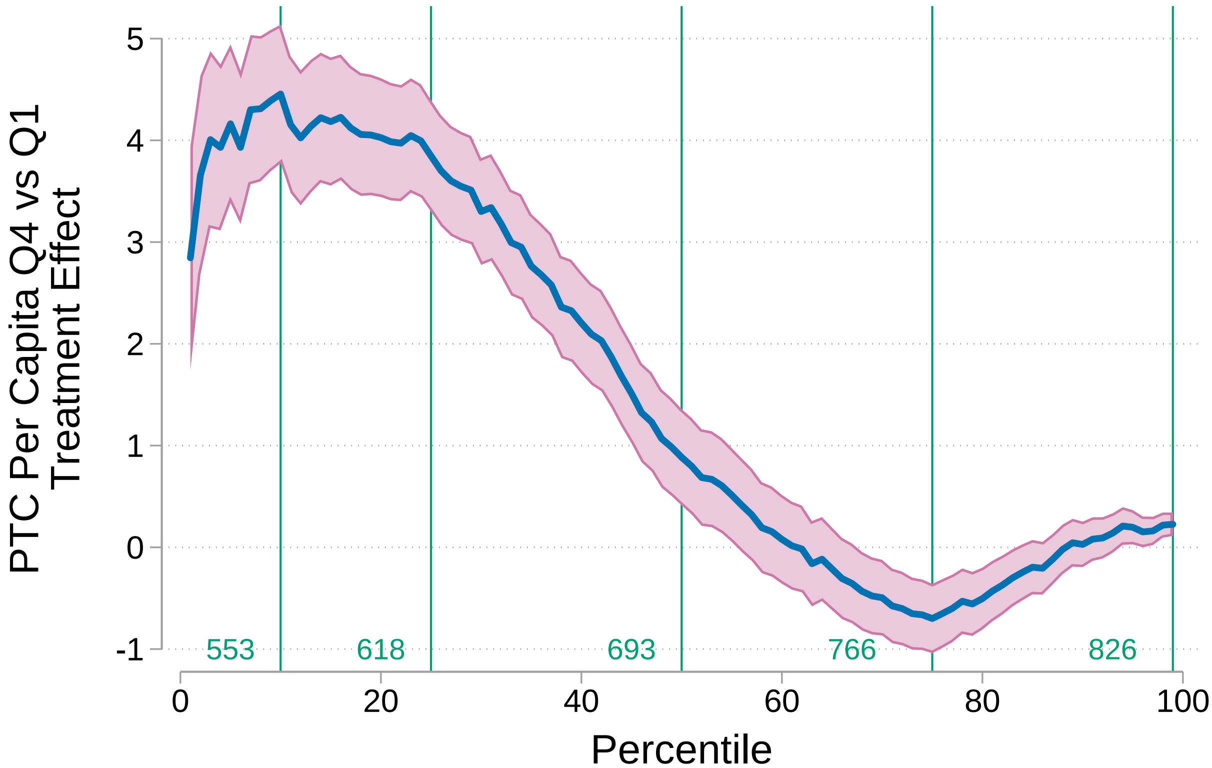
Figure 9: Distributional Effects on Negative Financial Outcomes



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.

Note: Coefficients are for separate regressions for the nth percentile of the within-ZIP code distribution of each outcome conditional on having a positive balance. Estimates correspond to the propensity score stratification procedure detailed in Section 4. The vertical bars correspond to the mean values of 10th, 25th, 50th, 75th, and 99th percentiles of the distribution across ZIP codes in the top quartile of PTC per capita in 2013.

Figure 10: Distributional Effects: Credit Score (Equifax Risk Score)



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Coefficients are for separate regressions for the nth percentile of the within-ZIP code distribution of Equifax Risk Scores. Estimates correspond to the propensity score stratification procedure detailed in Section 4. The vertical bars correspond to the mean values of 10th, 25th, 50th, 75th, and 99th percentiles of the distribution across ZIP codes in the top quartile of PTC per capita in 2013.

Tables

Table 1: Summary Statistics of Key Analysis Variables

	Full Sample		Q1 and Q4 Sample	
Treatment and Control Variables	Mean	SD	Mean	SD
PTC Per Capita	58.69	59.38	70.38	76.84
Medicaid Expansion (2014-2016)	0.56	0.50	0.51	0.50
Average Total PTC per Year in Sample (2014-2016)	15.6 billion		8.67 billion	
2009-2016 Outcomes				
Total Credit Files	7851.46	8276.80	6813.77	8069.45
Third Party Collections per 1,000	349.67	152.41	346.09	156.29
Credit Card Severe Delinquency per 1,000	65.76	31.76	65.45	33.82
Auto Severe Delinquency per 1,000	32.25	24.99	31.80	26.64
Any Mortgage Severe Delinquency per 1,000	15.78	15.02	15.43	16.17
Foreclosures per 1,000	4.35	7.24	4.46	7.89
Bankruptcies per 1,000	7.03	8.56	6.57	8.99
Mean Credit Score	679.44	36.39	680.25	37.20
Mean Third Party Collections Debt	1367.03	1250.56	1384.14	1482.34
Mean Severe Derogatory CC Debt	5334.79	5668.34	5476.65	6775.76
Mean Severe Derogatory Auto Debt	7859.45	4251.03	7954.06	4386.43
Mean Severe Derogatory Mortgage Debt	166289.30	155624.40	174519.40	166066.90
Share Population Under 400% FPL Uninsured	18.91	6.87	19.32	7.18
AHRF Supplier Variables				
# Primary Care Physicians	472.22	1023.88	451.26	1005.55
# OBGYN Specialists	81.60	183.56	77.31	179.02
# Physician Assistants	169.91	328.92	158.64	314.40
# Nurse Practitioners	259.04	480.33	248.74	473.12
# Clinical Nurse Specialists	11.34	25.43	10.52	24.17
Number of ZIP Codes	20,838		10,419	

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64, IRS SOI data, AHRF data, and ACS data at the ZIP code level.
Note: Analysis sample is described in Section 3. Debt amounts are conditional on having any positive debt amount.

Table 2: Results for Housing and Bankruptcy Outcomes

	Panel A	
	(1)	(2)
VARIABLES	Severe Mortgage Delinquency Rate per 1,000	
Q4 vs Q1 Treatment Effect	-1.369***	-0.720***
	(0.238)	(0.222)
Observations	83,336	83,336
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	16.17	16.17
Effect per $100 per capita	-1.33	-0.70
Pct Effect per $100 per capita	-8.23%	-4.33%
	Panel B	
	(1)	(2)
VARIABLES	Foreclosure Rate per 1,000	
Q4 vs Q1 Treatment Effect	-0.415***	0.0208
	(0.134)	(0.106)
Observations	83,022	83,022
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	3.62	3.62
Effect per $100 per capita	-0.40	0.02
Pct Effect per $100 per capita	-11.14%	0.56%
	Panel C	
	(1)	(2)
VARIABLES	Bankruptcy Rate per 1,000	
Q4 vs Q1 Treatment Effect	-0.893***	-0.878***
	(0.093)	(0.106)
Observations	83,176	83,176
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	6.37	6.37
Effect per $100 per capita	-0.87	-0.85
Pct Effect per $100 per capita	-13.63%	-13.40%

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table 3: Results for Third-Party Collections and Other Debts

	Panel A	
	(1)	(2)
VARIABLES	Third Party Collections Rate per 1,000	
Q4 vs Q1 Treatment Effect	1.544**	0.689
	(0.734)	(0.735)
Observations	82,235	82,235
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	337.9	337.9
Effect per $100 per capita	1.50	0.67
Pct Effect per $100 per capita	0.44%	0.20%

	Panel B	
	(1)	(2)
VARIABLES	Severe Credit Card Delinquency Rate per 1,000	
Q4 vs Q1 Treatment Effect	0.797	0.652
	(0.409)	(0.403)
Observations	83,312	83,312
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	66.97	66.97
Effect per $100 per capita	0.77	0.63
Pct Effect per $100 per capita	1.16%	0.95%

	Panel C	
	(1)	(2)
VARIABLES	Severe Auto Delinquency Rate per 1,000	
Q4 vs Q1 Treatment Effect	-3.916***	-3.748***
	(0.324)	(0.325)
Observations	82,968	82,968
Propensity Score Reweighting	X	X
Propensity Score Stratification		X
Dep. Mean in Q4 in 2013	27.91	27.91
Effect per $100 per capita	-3.81	-3.64
Pct Effect per $100 per capita	-13.64%	-13.05%

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table 4: Incidence of Consumer Welfare Gains and External Spillovers
Panel A: Welfare Gains from Risk Protection from Medical Debt

	CRRA Parameter		
Income Assumption	2	3	4
$11,000	363	487	496
$12,000	353	464	471
$13,000	345	446	437
$14,000	338	433	413

Panel B: Program Costs vs Estimated Benefits

Annual Cost Per Recipient (HHS)	[3,168; 3,528]
Estimated Cost Per Recipient in Q4 (SOI Data)	3,314
Individual Insurance Value (Range)	[338; 496]
Pct of Costs Realized in Medical Debt Protections	[10.1%;15.0%]

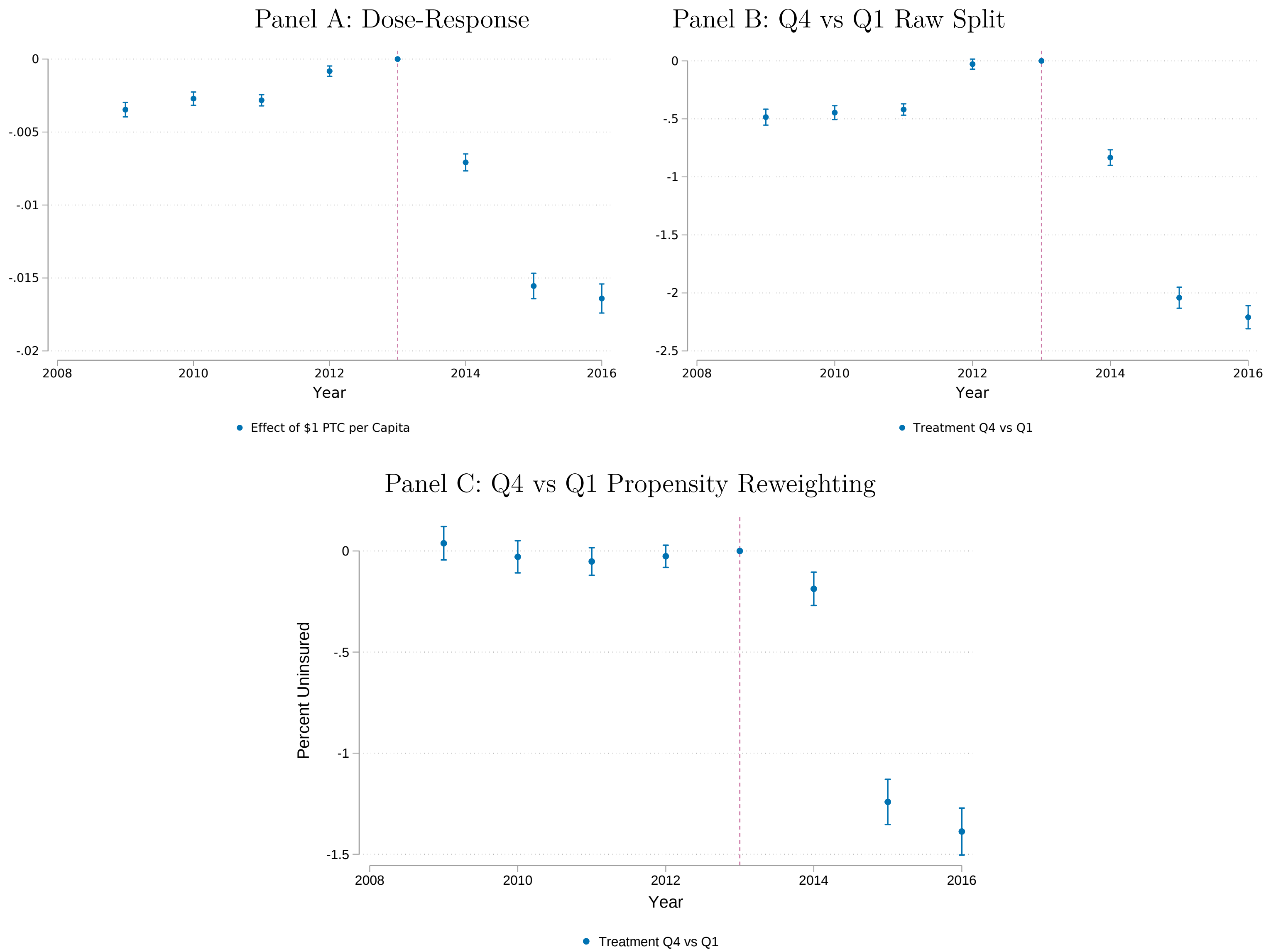
Panel C: Estimated External Spillovers

Annual Subsidy to Creditors via Reduced Bankruptcy	6.3 billion
Annual Subsidy to Mortgage Lenders via Service Costs	246 million
Annual Subsidy to Hospitals	[3.07 billion; 4.4 billion]
Average Annual PTC Cost (2014-2016)	15.6 billion

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.
Notes: Estimates are from the change in risk premium from 2013 baseline distributions from the causal estimates from the propensity score stratification and reweighting procedure in the text. Insurance value calculations are based on expected utility framework in Equations 4 and 5. The number of PTC recipients is estimated by multiplying the average number of tax returns that received tax credits by the average non-dependent exemptions claimed on returns (1.33).

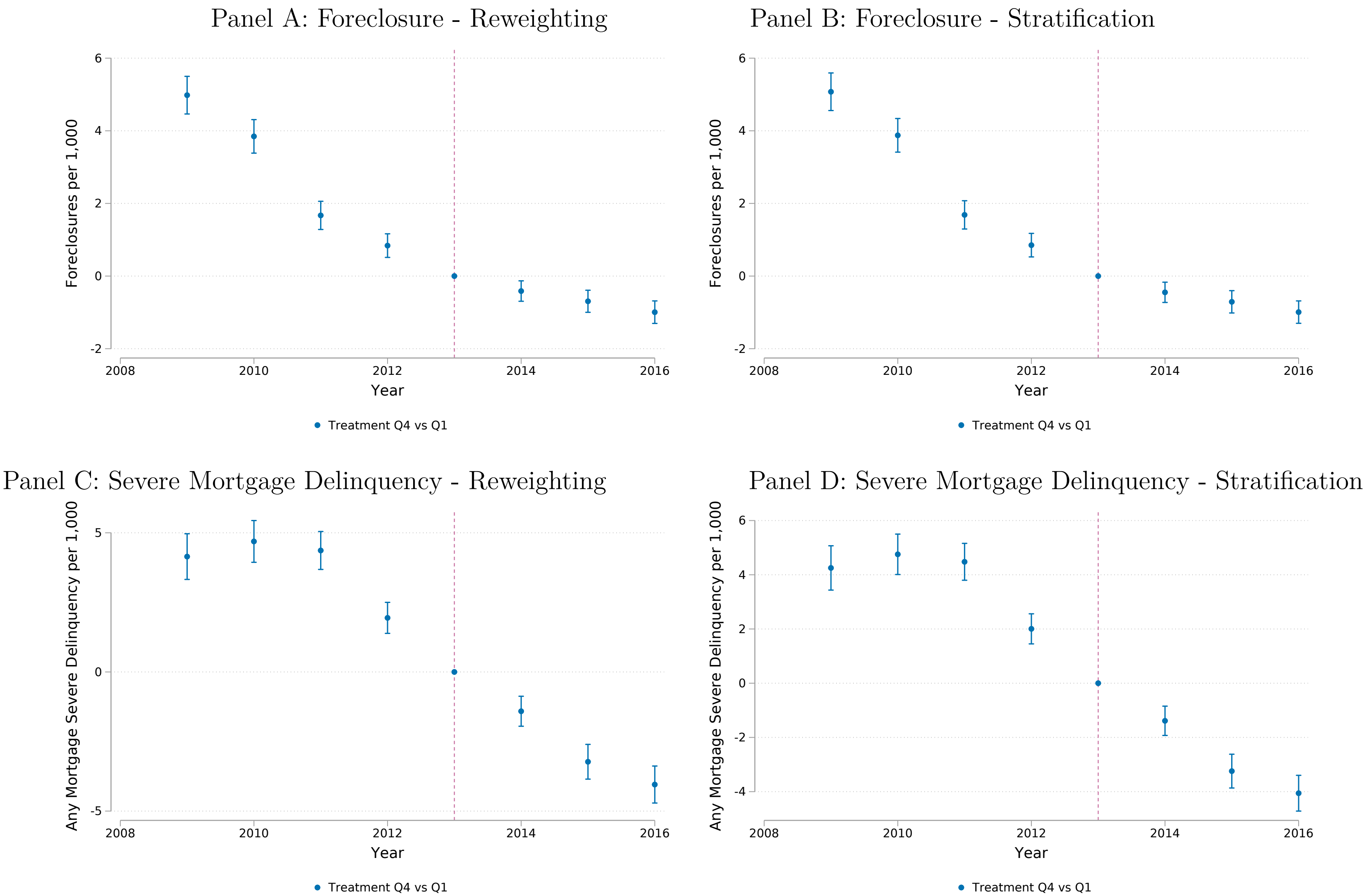
A Figures and Tables Appendix (Not For Publication)

Figure A1: Effect of PTC on the Uninsurance Rate for those Under 400% FPL



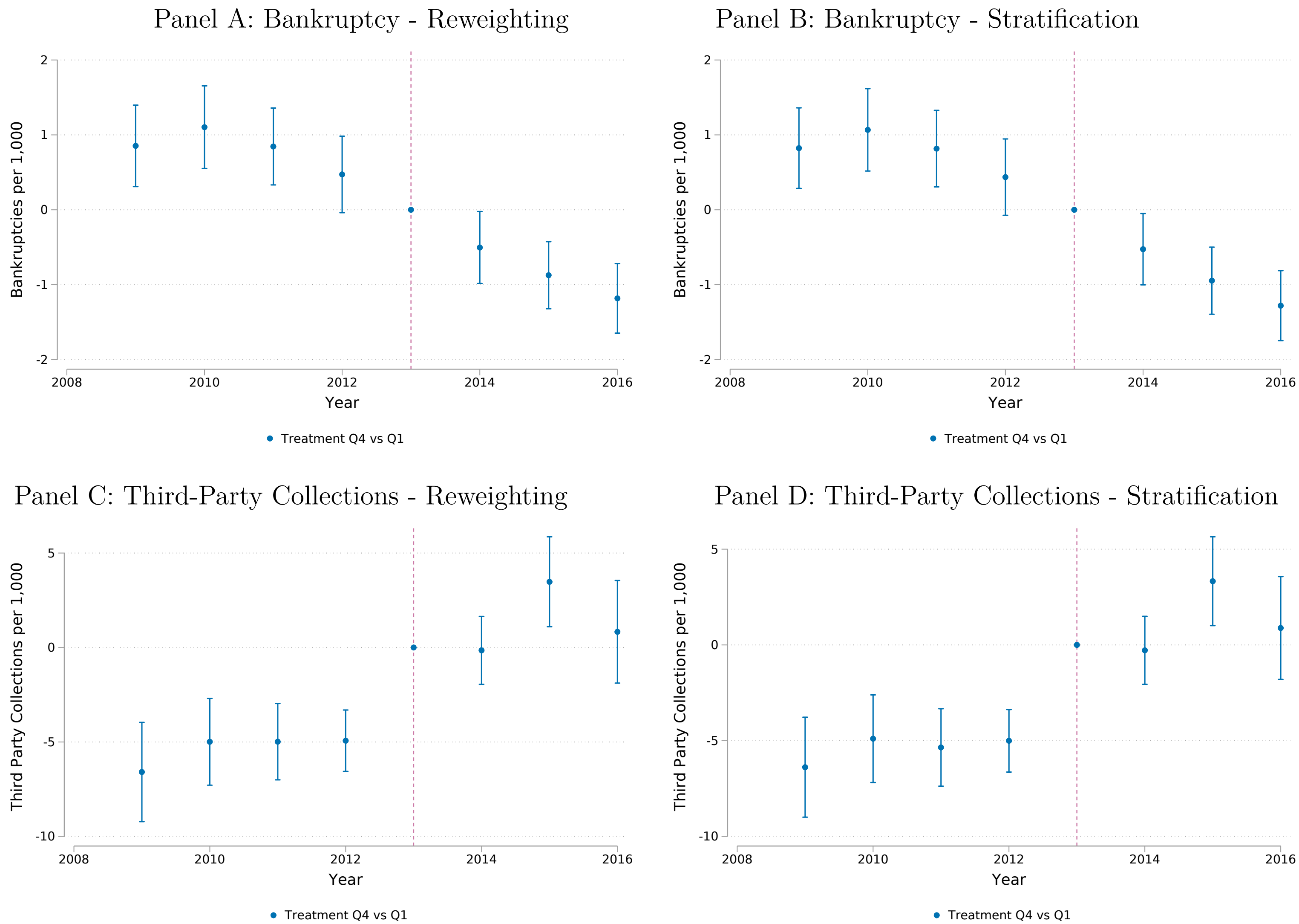
Source: Author's calculations based on Small Area Health Insurance Estimates (SAHIE) data for those under 400% FPL and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The coefficients come from Equation 3. The reweighted outcomes are based on Equation 1. Standard errors are clustered at the ZIP code level.

Figure A2: Parallel Trends for Housing Outcomes: Uninsured Rate Under 400% FPL in the Propensity Score



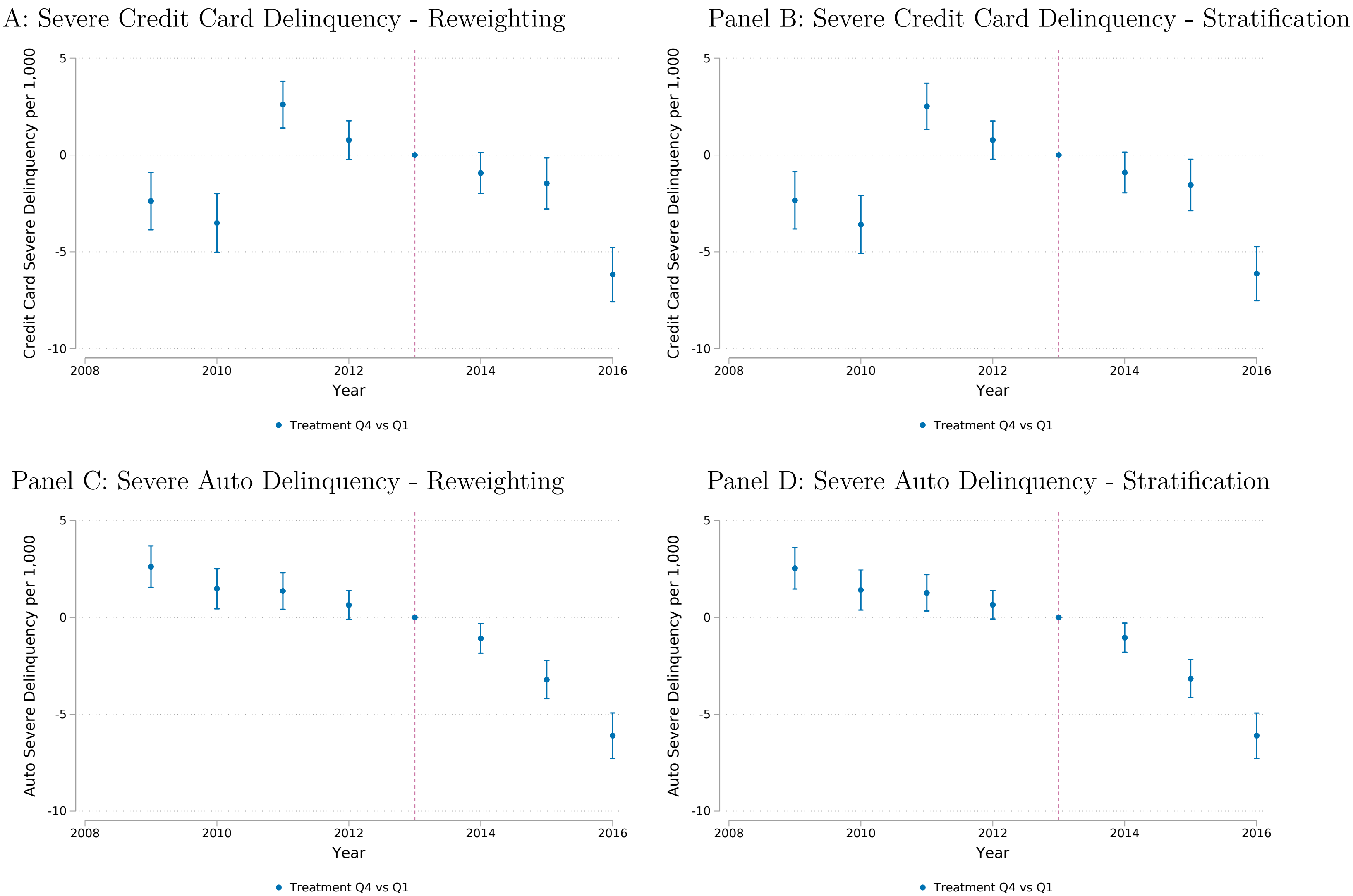
Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using the share of the population under 400% FPL without insurance before 2014 for the propensity score. Standard errors are clustered at the ZIP code level.

Figure A3: Parallel Trends for Bankruptcy and Third-Party Collections: Uninsured Rate Under 400% FPL in the Propensity Score



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using the share of the population under 400% FPL without insurance before 2014 for the propensity score. Standard errors are clustered at the ZIP code level.

Figure A4: Parallel Trends for Credit Card and Auto Delinquency: Uninsured Rate Under 400% FPL in the Propensity Score

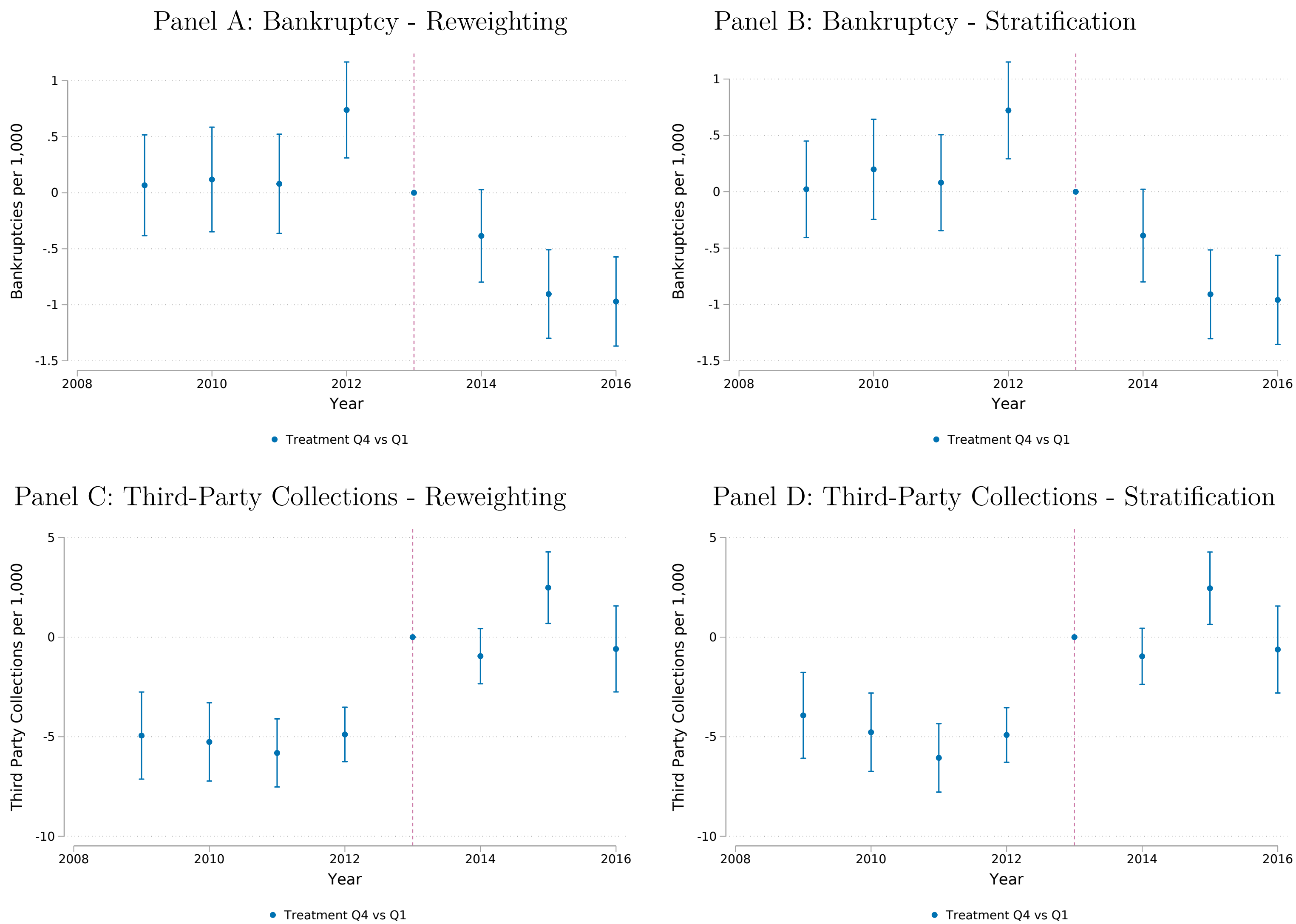


Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using the share of the population under 400% FPL without insurance before 2014 for the propensity score. Standard errors are clustered at the ZIP code level.

Figure A5: Parallel Trends for Housing Outcomes: 2009-2011 Outcomes in the Propensity Score

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using outcomes from 2009 to 2011 for the propensity score rather than 2009 to 2013. Standard errors are clustered at the ZIP code level.

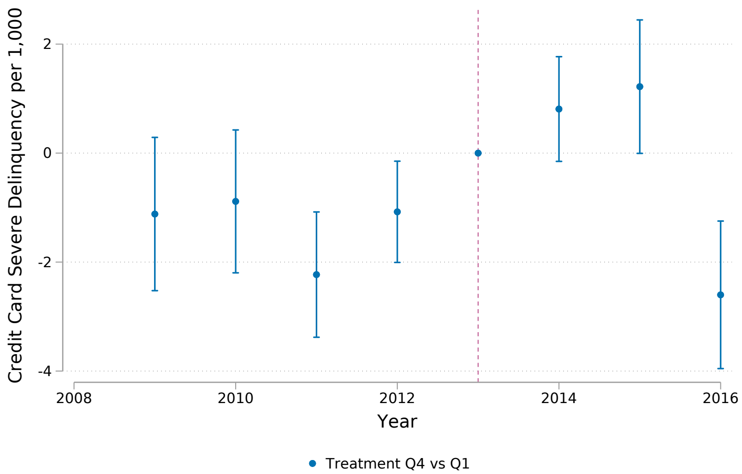
Figure A6: Parallel Trends for Bankruptcy and Third-Party Collections: 2009-2011 Outcomes in the Propensity Score



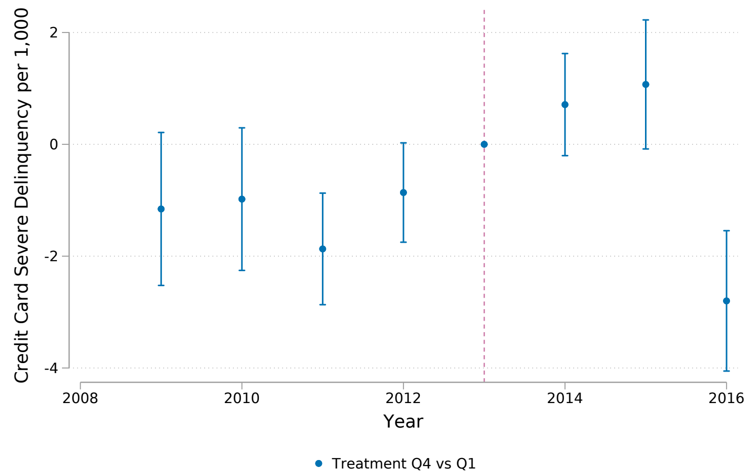
Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.
Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using outcomes from 2009 to 2011 for the propensity score rather than 2009 to 2013. Standard errors are clustered at the ZIP code level.

Figure A7: Parallel Trends for Credit Card and Auto Delinquency: 2009-2011 Outcomes in the Propensity Score

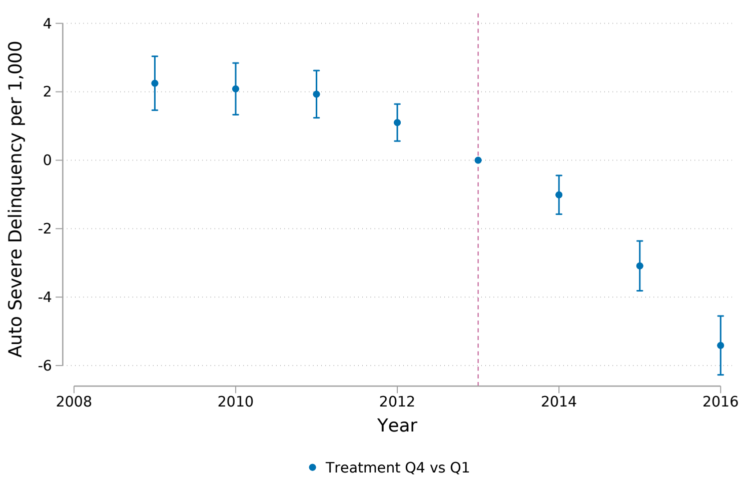
Panel A: Severe Credit Card Delinquency - Reweighting



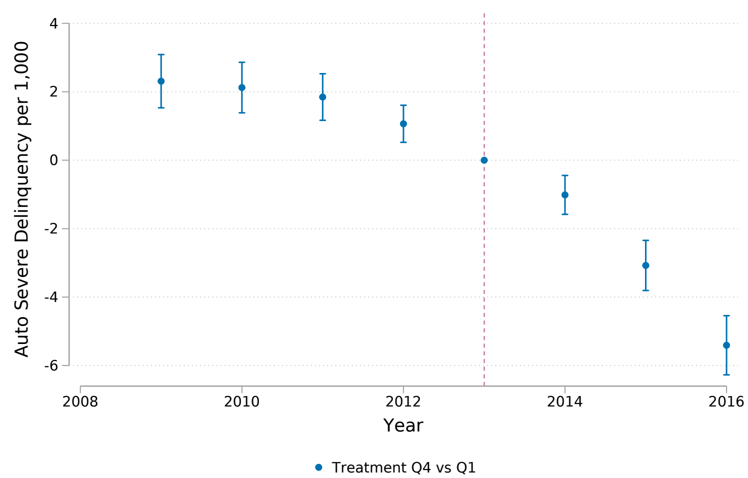
Panel B: Severe Credit Card Delinquency - Stratification



Panel C: Severe Auto Delinquency - Reweighting



Panel D: Severe Auto Delinquency - Stratification



Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS Statistics of Income data at the ZIP code level.

Note: Q1 and Q4 are quartiles of total PTC per capita from 2014-2016 adjusted for Medicaid expansion status. The parallel trends test coefficients come from Equation 3. The reweighted outcomes are based on Equation 1 using outcomes from 2009 to 2011 for the propensity score rather than 2009 to 2013. Standard errors are clustered at the ZIP code level.

Table A1: Naive Difference-in-Differences Estimates

	Panel A		
VARIABLES	(1) Mortgage Delinquency/1,000	(2) Foreclosures/1,000	(3) Bankruptcies/1,000
PTC Per Capita	-0.0300***	-0.0169***	-0.00569***
	(0.00171)	(0.000827)	(0.000740)
Observations	162,242	162,242	162,242
Dep. Mean in Q4 in 2013	16.08	3.55	6.37
Effect per $100 per capita	-3.00	-1.69	-0.57
Pct Effect per $100 per capita	-18.66%	-47.61%	-8.93%

	Panel B		
VARIABLES	(1) Third-Party Collections/1,000	(2) Credit Card Delinquency/1,000	(3) Auto Delinquency/1,000
PTC Per Capita	0.0183***	-0.0217***	-0.0247***
	(0.00541)	(0.00298)	(0.00202)
Observations	162,242	162,242	162,242
Dep. Mean in Q4 in 2013	346.4	66.98	28.76
Effect per $100 per capita	1.83	-2.17	-2.47
Pct Effect per $100 per capita	0.53%	-3.24%	-8.59%

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table A2: Select Correlates of Treatment Intensity

Variables	Average PTC Per Capita	PTC Per Capita Q4	CC Delinq 2009	Auto Delinq 2009	Third-Party 2009	Bank. 2009	Forecl. 2009	Mort. Delinq 2009	Tot Pop	Share <400% FPL Uninsured	Median HH Income	Median House Value	% Unemployed in CLF	% 55 to 64
Average PTC Per Capita	1													
PTC Per Capita Q4	0.7385	1												
CC Delinquency 2009	0.072	0.0584	1											
Auto Delinquency 2009	-0.0452	-0.0328	0.434	1										
Third-Party Collections 2009	-0.0818	-0.07	0.5159	0.6321	1									
Bankruptcy 2009	0.0004	-0.0092	0.1789	0.2252	0.1237	1								
Foreclosure 2009	0.2131	0.1971	0.3303	0.1688	0.0331	0.1661	1							
Mortgage Delinquency 2009	0.1508	0.1364	0.3889	0.2615	0.1208	0.3038	0.7048	1						
Total Population (10,000)	-0.0141	-0.032	0.2028	0.0762	0.0231	0.01	0.2502	0.2418	1					
Share <400% FPL Uninsured	0.1957	0.1804	0.2664	0.2888	0.36	-0.0295	0.25	0.1953	0.2419	1				
Median HH Income	-0.0592	-0.039	-0.3576	-0.4034	-0.6817	-0.1208	0.0588	0.0156	0.1077	-0.0948	1			
Median House Value	0.1188	0.1242	-0.2128	-0.3421	-0.5384	-0.1466	0.0901	-0.0008	0.2196	0.0449	0.7196	1		
% Unemployed Persons in CLF	0.0543	0.0568	0.3944	0.3874	0.543	0.1005	0.1132	0.1695	0.0918	0.1498	-0.4413	-0.218	1	
% 55 to 64	0.2743	0.2074	-0.1464	-0.1464	-0.1781	-0.0111	-0.0992	-0.0997	-0.3711	-0.1533	0.0587	0.0219	-0.0947	1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table A3: Housing and Bankruptcy Outcomes: 2009-2011 Outcomes in the Propensity Score

	Panel A		
	(1)	(2)	(3)
VARIABLES	Severe Mortgage Delinquency Rate per 1,000		
Q4 vs Q1 Treatment Effect	-0.720***	-1.376***	-0.783***
	(0.222)	(0.319)	(0.218)
Observations	83,336	83,352	83,352
“Hold-out” 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	16.17	16.17	16.17
Effect per $100 per capita	-0.70	-1.34	-0.76
Pct Effect per $100 per capita	-4.33%	-8.27%	-4.71%
	Panel B		
	(1)	(2)	(3)
VARIABLES	Foreclosure Rate per 1,000		
Q4 vs Q1 Treatment Effect	0.0208	-0.495***	-0.0795
	(0.106)	(0.177)	(0.105)
Observations	83,022	83,268	83,268
“Hold-out” 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	3.62	3.62	3.62
Effect per $100 per capita	0.02	-0.48	-0.08
Pct Effect per $100 per capita	0.56%	-13.29%	-2.13%
	Panel C		
	(1)	(2)	(3)
VARIABLES	Bankruptcy Rate per 1,000		
Q4 vs Q1 Treatment Effect	-0.878***	-0.953***	-0.956***
	(0.106)	(0.117)	(0.106)
Observations	83,176	83,200	83,200
“Hold-out” 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	6.37	6.37	6.37
Effect per $100 per capita	-0.85	-0.93	-0.93
Pct Effect per $100 per capita	-13.40%	-14.54%	-14.59%

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author’s calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table A4: Third-Party Collections and Other Debts: 2009-2011 Outcomes in the Propensity Score

	Panel A		
	(1)	(2)	(3)
VARIABLES	Third Party Collections Rate per 1,000		
Q4 vs Q1 Treatment Effect	0.689	4.421***	4.168***
	(0.735)	(0.877)	(0.884)
Observations	82,235	82,243	82,243
"Hold-out" 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	337.9	337.9	337.9
Effect per $100 per capita	0.67	4.30	4.05
Pct Effect per $100 per capita	0.20%	1.27%	1.20%
	Panel B		
	(1)	(2)	(3)
VARIABLES	Severe Credit Card Delinquency Rate per 1,000		
Q4 vs Q1 Treatment Effect	0.652	0.885*	0.647
	(0.403)	(0.504)	(0.440)
Observations	83,312	83,320	83,320
"Hold-out" 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	66.97	66.97	66.97
Effect per $100 per capita	0.63	0.86	0.63
Pct Effect per $100 per capita	0.95%	1.28%	0.94%
	Panel C		
	(1)	(2)	(3)
VARIABLES	Severe Auto Delinquency Rate per 1,000		
Q4 vs Q1 Treatment Effect	-3.748***	-4.578***	-4.568***
	(0.325)	(0.325)	(0.322)
Observations	82,968	83,116	83,116
"Hold-out" 2012-2013		X	X
Propensity Score Reweighting	X	X	X
Propensity Score Stratification	X		X
Dep. Mean in Q4 in 2013	27.91	27.91	27.91
Effect per $100 per capita	-3.64	-4.45	-4.44
Pct Effect per $100 per capita	-13.05%	-15.95%	-15.91%

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

Table A5: Distributional Effects Regressions
Severely Delinquent Debts and Third-Party Collections

Percentile	Mortgage Debt Coef	Mortgage Debt SE	Collections Coef	Collections SE	Credit Card Coef	Credit Card SE	Auto Coef	Auto SE
1	11228	2431	-5	7	-50	62	-219	61
2	11006	2460	-5	7	-52	62	-224	61
3	10529	2467	-5	7	-54	62	-236	61
4	10048	2513	-6	7	-56	62	-243	61
5	9745	2561	-6	7	-57	62	-260	61
6	9131	2578	-7	7	-60	63	-276	61
7	8450	2618	-7	7	-59	63	-286	62
8	8081	2659	-8	7	-61	64	-305	62
9	7300	2686	-8	7	-62	64	-317	62
10	7484	2742	-8	7	-60	64	-332	62
11	7263	2785	-8	7	-65	65	-338	62
12	6840	2834	-9	7	-76	67	-351	62
13	6042	2873	-9	7	-84	69	-358	62
14	5769	2935	-10	7	-83	69	-366	62
15	5176	3007	-10	7	-76	69	-380	63
16	4778	3055	-11	8	-53	70	-392	63
17	4155	3093	-11	7	-35	67	-396	63
18	3576	3118	-11	8	-14	62	-409	63
19	3360	3163	-12	8	-1	62	-416	63
20	3232	3182	-13	7	12	59	-430	63
21	2996	3190	-13	7	17	58	-441	64
22	2703	3221	-14	7	16	57	-446	64
23	1912	3257	-15	7	12	58	-451	65
24	1148	3302	-16	7	8	57	-457	64
25	1706	3465	-17	7	9	57	-475	64
26	1715	3531	-18	7	7	58	-505	65
27	858	3563	-18	8	6	56	-512	65
28	481	3610	-19	8	0	59	-521	64
29	-73	3616	-20	8	1	59	-519	65
30	-461	3654	-20	8	-1	59	-528	65
31	-911	3697	-21	8	-5	60	-534	65
32	-1521	3747	-21	8	-3	60	-539	65
33	-1877	3764	-21	8	-3	62	-545	65
34	2868	3943	-24	8	44	62	-553	66
35	2471	3973	-24	8	43	63	-561	66
36	1878	3991	-25	8	38	63	-569	66
37	1402	3979	-24	8	41	64	-581	66
38	1063	4008	-24	8	43	65	-570	66
39	567	4044	-25	8	45	66	-582	66
40	318	4000	-26	8	45	66	-579	66
41	462	4025	-28	8	49	67	-562	67
42	196	4038	-29	8	49	68	-546	67
43	-1129	4101	-30	9	55	69	-502	68
44	-1303	4140	-28	9	60	69	-450	68
45	-1712	4172	-27	9	58	71	-416	68
46	-1217	4279	-26	9	57	72	-394	68
47	-2168	4307	-25	8	64	72	-410	68
48	-2693	4344	-25	8	72	73	-432	68
49	-2966	4385	-25	8	82	73	-435	68
50	-2835	4317	-25	9	-16	92	-484	72
51	-344	4155	-33	13	-108	133	-519	88
52	-772	4149	-32	12	-116	133	-517	88

Table A5: Distributional Effects Regressions
Severely Delinquent Debts and Third-Party Collections

Percentile	Mortgage Debt Coef	Mortgage Debt SE	Collections Coef	Collections SE	Credit Card Coef	Credit Card SE	Auto Coef	Auto SE
53	-1408	4181	-27	12	-110	134	-529	89
54	-2193	4200	-23	12	-106	136	-555	88
55	-2612	4260	-22	13	-120	143	-542	89
56	-2669	4423	-24	13	-91	148	-492	89
57	-2855	4440	-26	13	-93	149	-469	89
58	-3689	4411	-25	13	-83	153	-441	89
59	-4205	4418	-26	14	-80	158	-440	88
60	-3218	4362	-28	14	-79	157	-453	87
61	-2608	4335	-29	14	-79	156	-482	88
62	-3262	4369	-30	14	-84	157	-495	88
63	-3622	4389	-32	14	-88	158	-512	89
64	-4388	4371	-33	15	-78	160	-528	89
65	-5049	4398	-34	15	-79	160	-534	89
66	-5638	4431	-33	15	-82	164	-547	89
67	5608	5415	2	26	12	161	-569	108
68	5369	5429	1	26	19	164	-578	107
69	5161	5490	1	29	34	164	-588	108
70	4648	5499	3	29	51	166	-606	108
71	4295	5517	3	29	59	168	-626	108
72	2474	5579	0	29	65	168	-645	108
73	5464	6513	1	30	34	168	-645	108
74	4758	6554	-1	33	48	171	-661	108
75	7259	6490	0	32	63	169	-721	109
76	9830	6981	-1	33	78	181	-760	122
77	9192	7047	5	36	93	181	-788	122
78	9015	7107	4	37	35	183	-787	123
79	7657	7179	10	39	10	185	-812	123
80	7622	6778	3	35	-28	189	-769	128
81	9187	6669	12	39	8	195	-723	143
82	8760	6867	14	40	42	196	-722	144
83	8335	6997	5	40	44	198	-757	144
84	-1233	8784	17	46	-68	224	-712	169
85	-4126	8881	14	47	-51	229	-720	171
86	7868	6486	7	52	-65	251	-713	176
87	7421	6470	7	53	-75	251	-714	177
88	624	8365	9	65	-186	270	-722	187
89	172	8799	-5	68	-235	296	-711	189
90	-25	8513	-11	72	-285	293	-756	190
91	8759	7093	0	81	-366	301	-686	242
92	6474	7119	-7	86	-212	312	-647	250
93	2770	7222	57	125	-293	330	-648	250
94	2861	8556	2	134	-278	338	-719	262
95	1601	10451	59	142	-579	375	-801	270
96	-8621	10121	-102	138	-270	432	-808	282
97	-11302	10372	-159	154	-457	439	-934	285
98	-12279	16703	-260	206	-651	466	-1307	296
99	-31906	11004	-643	264	-1035	494	-1558	301

Note: Estimates correspond with those in Figure 9. Standard errors are clustered at the ZIP code level.

Table A6: Distributional Effects Regressions
Credit Score (Equifax Risk Score)

Percentile	Credit Score Coef.	Credit Score SE
1	2.8448	0.5596
2	3.6582	0.4988
3	4.0074	0.4432
4	3.9305	0.4162
5	4.1632	0.3974
6	3.9308	0.3845
7	4.3015	0.3737
8	4.3104	0.3642
9	4.3893	0.3546
10	4.4558	0.3474
11	4.1534	0.3425
12	4.0242	0.3385
13	4.1365	0.3335
14	4.2230	0.3255
15	4.1840	0.3212
16	4.2264	0.3152
17	4.1214	0.3118
18	4.0575	0.3080
19	4.0531	0.3023
20	4.0272	0.2979
21	3.9865	0.2946
22	3.9722	0.2910
23	4.0472	0.2868
24	3.9949	0.2836
25	3.8469	0.2793
26	3.7016	0.2786
27	3.6014	0.2762
28	3.5479	0.2734
29	3.5110	0.2713
30	3.3006	0.2678
31	3.3396	0.2679
32	3.1782	0.2656
33	2.9945	0.2648
34	2.9510	0.2641
35	2.7639	0.2615
36	2.6782	0.2576
37	2.5797	0.2567
38	2.3610	0.2558
39	2.3258	0.2555
40	2.2049	0.2546
41	2.0950	0.2539
42	2.0308	0.2538
43	1.8670	0.2531
44	1.6807	0.2520
45	1.5120	0.2499
46	1.3236	0.2480
47	1.2321	0.2484
48	1.0687	0.2466
49	0.9846	0.2448
50	0.8849	0.2413
51	0.7974	0.2417
52	0.6855	0.2422
53	0.6691	0.2406

Table A6: Distributional Effects Regressions
Credit Score (Equifax Risk Score)

Percentile	Credit Score Coef.	Credit Score SE
54	0.6069	0.2382
55	0.5135	0.2351
56	0.4135	0.2344
57	0.3194	0.2317
58	0.1929	0.2284
59	0.1545	0.2259
60	0.0787	0.2227
61	0.0157	0.2206
62	-0.0163	0.2176
63	-0.1612	0.2140
64	-0.1162	0.2107
65	-0.2119	0.2072
66	-0.3065	0.2036
67	-0.3551	0.2000
68	-0.4324	0.1972
69	-0.4779	0.1932
70	-0.4949	0.1897
71	-0.5758	0.1871
72	-0.6015	0.1845
73	-0.6518	0.1805
74	-0.6633	0.1769
75	-0.6999	0.1737
76	-0.6512	0.1724
77	-0.6007	0.1694
78	-0.5299	0.1645
79	-0.5566	0.1603
80	-0.5041	0.1551
81	-0.4300	0.1520
82	-0.3709	0.1482
83	-0.3008	0.1437
84	-0.2451	0.1402
85	-0.1951	0.1364
86	-0.2061	0.1321
87	-0.1180	0.1271
88	-0.0207	0.1245
89	0.0451	0.1199
90	0.0283	0.1141
91	0.0805	0.1093
92	0.0924	0.1037
93	0.1403	0.0992
94	0.2094	0.0945
95	0.1968	0.0857
96	0.1518	0.0773
97	0.1609	0.0710
98	0.2184	0.0632
99	0.2264	0.0586

Note: Estimates correspond with those in Figure 10. Standard errors are clustered at the ZIP code level.

Table A7: Propensity Score Stratification Estimates Splitting Treatment and Control at Median

	Panel A		
	(1)	(2)	(3)
VARIABLES	Mortgage Delinquency/1,000	Foreclosures/1,000	Bankruptcies/1,000
Above Median Treatment	-0.739***	-0.104*	-0.584***
	(0.123)	(0.0589)	(0.0673)
Observations	166,696	166,696	166,632
Dep. Mean in Q4 in 2013	16.08	3.55	6.37
Effect per $100 per capita	-1.20	-0.17	-0.95
Pct Effect per $100 per capita	-7.46%	-4.75%	-14.88%

	Panel B		
	(1)	(2)	(3)
VARIABLES	Third-Party Collections/1,000	Credit Card Delinquency/1,000	Auto Delinquency/1,000
Above Median Treatment	1.162**	0.0730	-2.090***
	(0.548)	(0.276)	(0.209)
Observations	166,600	166,680	166,536
Dep. Mean in Q4 in 2013	346.4	66.98	28.76
Effect per $100 per capita	1.89	0.12	-3.39
Pct Effect per $100 per capita	0.54%	0.18%	-11.79%

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.

B Data Appendix

This section contains key details about the construction of the main sample as well as detailed notes on the generation of each key variable.

All variables are constructed for the 2009-2016 time period.

The base sample of SOI ZIP code data includes a total of 145 million tax returns filed in 2014 out of a total of 148 million that year and 284 million personal exemptions compared to a total US population of 318 million that year. Coverage of populated ZIP codes is not complete because the IRS takes various steps to limit disclosure risk. These include masking the actual ZIP code identity of any ZIP codes with fewer than 100 returns and those that are nonresidential or single buildings; excluding those living abroad; excluding items with fewer than 20 returns filled for that item; excluding returns with negative adjusted gross income; rounding the number of returns to the nearest 10; and excluding returns filed without a ZIP code or whose ZIP did not match their state code.

The IRS Statistics of Income figures are available for roughly 25,545 ZIP codes with complete AHRF and Census data. This total is out of 40,000 or so total ZIP codes in the United States. By comparison, there are approximately 32,000 ZIP Code Tabulation Areas designated by the Census Bureau as containing any residents. I restrict my sample further to areas with at least 30 credit file records in the CCP for individuals age 18-64 in order to avoid complications of small samples. This eliminates another 4,800 ZIP codes (57,600 total observations) from my sample, most of which are sparsely populated or do not have large under 65 populations because they represent large retirement communities.

In total, my primary estimation sample consists of 20,838 unique ZIP codes spanning the years 2009-2016. My sample ZIP codes cover 139 million total tax returns of the 148 million filed in 2014 and 272.5 million of the 284 million total personal exemptions claimed nationally. Thus, my sample covers 96% of the total tax filer population and 94% of tax returns.

Though my sample covers nearly the whole tax filing population in the United States, it does not cover all ZIP codes.

Data on the ACA exchanges

While data on all health plans offered on the Federal insurance exchange (Healthcare.gov) are available for all years in 2014-2016, there are several states who are missing 2014 data on the health plans available on their state-based exchanges. These states are Colorado, Connecticut, District of Columbia, Hawaii, Kentucky, Maryland, Massachusetts, Minnesota, Nevada, New York, Oregon, Rhode Island, Vermont, and Washington.

In terms of state-specific policies that drive exogenous variation in simulated eligibility, New York and Vermont both set their age curves to be completely flat, i.e. that there was no differential pricing by age for individuals on the exchange. Notably, New York and Vermont both of these states set these policies before the implementation of the ACA in 2014 and continued to use those policies. District of Columbia, Massachusetts, Minnesota, Utah, and New Jersey each set their own age curves for different groups, including children. In DC, Minnesota, and Utah, the 3:1 ratio for age 64 to age 21 was maintained, but differences within the 22-63 range were meaningful.

Two states enacted their own family tiers on their exchanges. In New York, a single parent with one or more children under 21 could be charged at maximum of 1.7 times the "base" adult individual rate. For a two-parent household, the maximum ratio an insurer could charge was 2.85 times the base individual rate. In Vermont, these ratios were 1.93 and 2.81 for a single parent and two-parent household with one or more children.

Table B1 lists each variable used in the analysis, its source, and a description of details relevant to its construction.

Table B1: Variable Sources and Description

Variable	Source	Description
PTC Per Capita	IRS	This is the total amount in premium tax credits received by filers in the ZIP code divided by the population below age 64 according to the American Community Survey or Decennial Census.
Total Credit Files	CCP	The total number of credit files for residents of the ZIP code. This is the total number of scored files in the full CCP multiplied by 20 to scale up the 5% random sampling. For separate credit score ranges (Equifax Risk Score), this is the total number of credit files with scores in the particular range.
Third-Party Collections per 1,000	CCP	The total number of credit files with a positive debt amount in third-party collections divided by total number of credit files multiplied by 1,000.
Credit Card Severe Delinquency per 1,000	CCP	The total number of credit files with a positive debt amount designated as being 120 days past due, with a “severe derogatory” event such as repossession, in collections, or as part of a bankruptcy divided by total number of credit files multiplied by 1,000.
Auto Severe Delinquency per 1,000	CCP	The same construction as credit card severe delinquency, but for auto loans from a bank as well as other auto financing reported to credit bureaus.
Any Mortgage Severe Delinquency per 1,000	CCP	The same construction as credit card severe delinquency, but for debts on any mortgage including first mortgages, HELOANs, HELOCs, or junior liens.
Foreclosures per 1,000	CCP	The number of credit files with a foreclosure in the last 12 months divided by total credit files in the ZIP code. At scale, this number is lower than that reported in private sector estimates of foreclosure because it does not capture foreclosure for the population 65+. These appear to be relatively conservative estimates in comparison to other data sources which capture the number of properties rather than the number of credit files.
Bankruptcies per 1,000	CCP	The number of individual credit files which a change in bankruptcy status from year to year. This isolated “new” bankruptcies as opposed to having a bankruptcy on the credit file.
Mean Credit Score (Equifax Risk Score)	CCP	The mean of all Equifax 3.0 risk scores in the ZIP code.
Mean Amount in Third-Party Collections	CCP	Mean amount in third-party collections in a ZIP code conditional on having a positive balance.
Mean Amount of Credit Card Debt	CCP	Mean amount of credit card debt on credit files in a ZIP code conditional on having a positive balance.
Mean Amount of Severe Derogatory CC Debt	CCP	Mean amount of credit card debt that is 120 days past due or worse on credit files in a ZIP code conditional on having a positive balance.

Mean Amount of Severe Derogatory Auto Debt	CCP	Mean amount of auto debt that is 120 days past due or worse on credit files in a ZIP code conditional on having a positive balance.
Mean Amount of Severe Derogatory Mortgage Debt	CCP	Mean amount of mortgage debt that is 120 days past due or worse on credit files in a ZIP code conditional on having a positive balance.
Percentiles of continuous outcomes (Equifax Risk Score/credit score, delinquent balances)	CCP	For various outcomes (Equifax Risk Score/credit score, debt in third-party collections, severely delinquent debts), this is the nth percentile (1-99) taken within the ZIP code. Each of these are used as an outcome in a separate regression.
Median HH Income	ACS	Median household income in the ZIP code (2016 dollars using the PCE deflator); for all variables from the ACS, I rely on the midpoint of 5-year estimates. For example, year 2009 data come from 2007-2011 5-year estimates for the ZIP code.
Median House Value	ACS	Median house value in the ZIP code (2016 dollars using the PCE deflator)
% Unemployed Persons in CLF	ACS	Percent of the civilian labor force that is unemployed in the ZIP code
% Bachelor degree or higher	ACS	Percent of adults over 25 with a Bachelor's degree or higher
% White alone	ACS	Percent of the total population that identifies as "white"
% Black alone	ACS	Percent of the total population that identifies as "black"
% Asian alone	ACS	Percent of the total population that identifies as "Asian"
% Hispanic or Latino of any race	ACS	Percent of the total population that identifies as "Hispanic" or "Latino"
% Single Mothers	ACS	Percent of households headed by a single mother with children under age 18
% 20 to 24	ACS	Percent of the population age 20-24
% 25 to 34	ACS	Percent of the population age 25-34
% 35 to 44	ACS	Percent of the population age 35-44
% 45 to 54	ACS	Percent of the population age 45-54
% 55 to 64	ACS	Percent of the population age 55-64
% Uninsured	SAHIE	Share of the population under 400% FPL without health insurance
# Primary Care Physicians	AHRF	The number of primary care physicians active in the ZIP code. All incomplete AHRF data are linearly interpolated between years. Any AHRF variables based on county-level data are apportioned to ZIP codes via population weights.
# OBGYN Specialists	AHRF	The number of OBGYN specialists active in the ZIP code.
# Physician Assistants	AHRF	The number of Physician Assistants active in the ZIP code.
# Nurse Practitioners	AHRF	The number of Nurse Practitioners active in the ZIP code.
# Clinical Nurse Specialists	AHRF	The number of Clinical Nurse Specialists active in the ZIP code.

Second Lowest-Cost Silver Plan Premium	CMS RWJF	This is the second lowest cost Silver plan for a 30 year old individual in each ZIP code. This is calculated based upon either the posted age-specific premium for every plan, or the standardized "age curve" required by states. If Rating Areas are the county level, each plan premium is apportioned to ZIP codes based on population weights.
Statewide Average Silver Plan Premium	CMS RWJF	The average Silver plan premium for an individual age 30 across all Rating Areas. This approximates the statewide expected cost of insuring the newly enrolling marketplace population. States with systematically higher premiums may have a different proportion of sick people entering the exchanges or else have other regulations that determine exchange premiums.
Number of Insurers on the Exchange	CMS RWJF	This is the number of "issuers" listed as offering a Silver plan in each Rating Area in the QHP or SBE.

C Additional Policy Context and Simulated Instrument

C.1 Additional Policy Context

The Affordable Care Act's premium tax credits are based in part on Silver plan premiums at the local level and are a function of two main choices by the state as well as three main choices by insurers. First, each state decided whether or not to expand Medicaid. Second, each state decided if they wanted to create their own "age curve" and "family tier ratios," apart from federal guidelines. This allowed states to differentially set limits on premiums charged to families (as opposed to individuals) as well as limits on how different premiums could be for younger enrollees in relation to older enrollees. For example, in Minnesota, insurers may differentially charge premiums to 64 year-olds and 21 year-olds at a 3:1 ratio, while in Massachusetts, that ratio is 2:1. As another example, in Vermont, a family of any size with at least one child can be charged at most 2.85 times the base individual rate.

Each insurer had three main questions to answer each year. First, given what they expect the enrolling population to look like and any state-specific regulations, what base premium would they charge at the state level for a basic individual Silver plan? Second, in which Rating Areas should they offer their Silver plans? Third, how should they adjust their statewide base premium across different parts of the state? The results of the first choice reflect the insurers' best guess of what their costs would be to cover the enrolling population as well as state-specific regulations that drive costs up or down. The results of the second choice created different levels of competition across areas within states. The third choice, called a "geographic factor," was constrained by ACA rules to only reflect the differences in costs for delivering medical services and not the morbidity risk of the local population. These costs are most often a function of existing contracts between medical providers and certain insurers, differences in the way medical practitioners order and bill services, as well as competition among providers.[32]

The interaction of these choices is straightforward. Medicaid expansion choices by states influence insurer choices about statewide base premiums for individual Silver plans (e.g. an individual age 30). Entry choices and competition in different Rating Areas and "geographic factors" influence the premiums insurers charge for that basic age 30 individual Silver plan in each county. Finally, how that basic individual Silver plan in each Rating Area translates into a specific premium for each household given their age and family structure depends on the "age curve" and "family tier ratio" policies of the state. In terms of the $Silver2_{har}$ in Section 2, the choices insurers make set the terms for the r portion of the benchmark Silver plan, while *states* determine the remaining h and a components of that plan cost. An individual could, therefore, face two different benchmark Silver plan premiums across state lines even if the base premium for a 30-year old individual is the same because two states differ in their age curves. A family of four could face two different benchmark premiums across state lines because one state limits the premiums for an entire family regardless of size and the other allows insurers to charge per-child premiums. Differences in these premiums then drive differences in the tax credits a household receives.

My simulated instrument controls for these three insurer choices and relies on cross-state variation in these two state regulations to estimate the effects of the subsidies.

[32]Based on personal conversations with an active actuary tasked with calculating exchange premiums.

C.2 Simulated Instrument: CPS and Health Insurance Plans

I construct the simulated instrument in the spirit of Currie and Gruber (1996). For my fixed, national sample, I use the 2013 Current Population Survey Annual Social and Economic Supplement (CPS ASEC), which contains detailed information on health insurance coverage and premium payments, the availability of employer-sponsored insurance plans, family structure, age, and income—in short, the characteristics upon which all the legislated determinants of tax credit eligibility on the consumer side depend.[33]

The legislated determinants of subsidy eligibility also depend on the "Second lowest-cost Silver plan" available on a consumer's ACA exchange website and each state's Medicaid expansion status. For information on these plans, I use the public use Qualified Health Plan (QHP) Landscape files produced by the Center for Medicare and Medicaid Services (CMS). These data files contain the universe of health insurance plans available on the federal health exchange website in each insurance Rating Area, which is usually a county or 3-digit ZIP code. For state-based exchanges, similar measures are available from the CMS Center for Consumer Information and Insurance Oversight (CCIIO) in the form of the State-based Exchange Public Use Files (SBE PUF). When these are not available, as in some states in 2014-2015, I include public-use data from the Robert Wood Johnson Foundation HIX Compare datasets. If an ACA Rating Area is listed at the county level, I allocate these values to ZIP codes using the share of the population in each ZIP code as a weight.[34] I also pull each state's age curve and family tier rules from the CMS database.[35]

My simulated instrument, which is constructed from these datasets, uses *statutory* eligibility as an instrument for *actual* subsidy receipt. To construct the instrument, I first take the 2013 CPS ASEC supplement as a fixed sample. Using data on household health insurance coverage, income, and family structure, I run each household in the CPS through the exchange rules applicable to them in every ZIP code for which I have premium data. Based on Medicaid expansion in each ZIP code's state in each year and the benchmark premium in each ZIP code-year-age-family structure cell, I calculate the per capita eligibility for premium tax credits in every ZIP code-year cell for that fixed sample. The instrument then reveals what the per capita eligibility for tax credits would be in every ZIP code if that ZIP code had the distribution of income, family structure, and health insurance coverage of the nationally representative 2013 ASEC.

I estimate a two-stage least squares model in which ZIP code simulated per capita PTC eligibility from the CPS acts as an instrument for actual PTC receipt per capita:

$$TaxCredits_{zt} = \alpha_0 + \alpha_1 SimulatedPTC_{zt} + X'_{zt}\alpha_2 + E'_{zt}\alpha_3 + \delta_z + \tau_t + \eta_{zt} \tag{7}$$

$$y_{zt} = \beta_0 + \beta_1 \widehat{TaxCredits}_{zt} + X'_{zt}\beta_2 + E'_{zt}\beta_3 + \delta_z + \tau_t + \varepsilon_{zt} \tag{8}$$

This approach uses simulated PTC per capita in the first stage to predict actual take-up of premium tax credits per capita in each ZIP code. The E vector is a set of important controls relevant to the simulated instrument, which I explain below. The identifying assumptions of the simulated instrument design are, first, that the drivers of statutory PTC only affect financial outcomes through their effects on PTC take-up (the exclusion restriction); and second, that simulated PTC strongly predicts actual take-up of PTC (the relevance criterion).

Variation in simulated PTC per capita comes from two features: the Medicaid expansion status for each state, and the premium charged for the "second lowest-cost Silver plan" in the ZIP code for each specific age band and family structure. Importantly, how a baseline individual premium in each ZIP code translates into age-specific premiums or family structure-specific premiums is a function of state policy. Isolating this exogenous variation in eligibility from possibly endogenous insurer choices is the goal of the E vector of controls.

Simulated instruments like mine are special applications of a Bartik/shift-share instrument. In the canonical wage and employment setting common to many labor models, Bartik instruments implicitly rely on industry shares as instruments for exposure to a treatment, which may be problematic if industry shares predict outcomes through

[33] The underestimation of health insurance premiums in the CPS in comparison to administrative records in Larrimore and Splinter (2019) will not bias my simulated instrument estimates because it will be applied broadly to all ZIP codes in my sample.

[34] Because I am missing some states' exchange information for 2014, the sample size of each regression using this simulated instrument is slightly smaller. In this list are Colorado, Connecticut, District of Columbia, Hawaii, Kentucky, Maryland, Massachusetts, Minnesota, Nevada, New York, Oregon, Rhode Island, Vermont, and Washington. To make sure that sample composition is not driving any major differences in my estimates, I show OLS results with the full sample as well as the IV sample.

[35] See https://www.cms.gov/CCIIO/Programs-and-Initiatives/Health-Insurance-Market-Reforms/state-rating. (Accessed June 1, 2020).

unobserved or alternative channels outside the treatment being measured (Goldsmith-Pinkham et al., 2020). In simulated instruments, the "industry shares" portion is an assumed exogenous policy variation across space. In my setting, these are the premiums for the "second lowest-cost Silver plan" that determine statutory eligibility, which may be responsive to endogenous insurer choices that predict financial outcomes outside of their effects on simulated eligibility. In a Bartik setting, if the determinants of industry shares that could affect wages or employment outside of their driving the local intensity of a national shock were known, the researcher could control for those endogenous determinants with fixed controls (Goldsmith-Pinkham et al., 2020). With simulated instruments, endogenous determinants of policy variation can be known and controlled in the model.

Because the premium set for baseline individual Silver plans may be heavily affected by the choices of insurers and therefore may be correlated with the financial outcomes of local residents, it is important to control in the model for these choices. The E vector consists of proxies for the choices discussed previously. To proxy for the state base (single age) individual premium set by insurers that reflects state-specific rules that drive costs, insurer expectations about enrollment, and within-state competition, I include a control for the average Silver premium in each state for an individual age 30. To control for entry choices in Rating Areas in each state, I include the number of insurers offering Silver plans in each ZIP code.[36] Finally, to control for the effects of each insurer's geographic factors as well as other unobserved local determinants of insurance costs on the benchmark Silver plan for individuals, I include the premium for benchmark Silver plan for an individual age 30. These controls remove variation from simulated PTC that is attributable to insurer pricing and entry choices. Local deviations from this single age premium over age and family structure are set by the state. Therefore, conditional on these controls, the remaining variation driving simulated PTC comes from state policies. These policies affect eligibility for premium tax credits independently of other considerations and thus are likely to satisfy the exclusion restriction.[37] A violation of this restriction requires that these state policies affect financial outcomes directly through a channel outside their effects on PTC eligibility. Because the policies only apply to the individual exchange market, this is unlikely.

The second assumption of the simulated instrument, which is testable, is that simulated eligibility is a relevant predictor of actual take-up. I test this by testing the features of the first stage regression (Equation 7). There are two reasons this test is necessary. First, fewer than ten states set their own age curves and family tier ratios, so variation across these states must be sufficient to drive meaningful variation in take-up across states. Second, the control variables in my regression are quite restrictive. Nevertheless, there is a strong first-stage correlation between statutory eligibility and actual PTC take-up even conditional on these restrictive controls (32 cents in take-up for every dollar of simulated PTC). The high Kleibergen-Paap rk Wald statistic value of 475 suggests that the simulated instrument satisfies the relevance criterion (see Appendix Table C1). Table C2 shows the results of the two-stage least squares estimates using this exercise.

The results are typically similar to my propensity score estimates, particularly with regard to bankruptcies, foreclosures, and third-party collections, though the relatively wide standard errors make it difficult to draw any strong conclusions from the estimates.

[36] I include this as a linear term because dummy variables for the number of insurers result in linear effects.

[37] For more information on state-specific policies regarding age and family premium pricing, see Appendix B.

Table C1: First Stage Results from Two-Stage Least Squares Estimate

VARIABLES	(1) Actual PTC Per Capita
Simulated PTC Per Capita	0.317***
	(0.0144)
Medicaid Expansion	-21.69***
	(0.846)
Benchmark Silver Plan Premium (30 Yr Old Adult)	-0.205***
	(0.0145)
Number of Issuers on Local Exchange	-2.13***
	(0.100)
Statewide Mean Silver Plan Premium (30 Yr Old Adult)	-0.031***
	(0.0064)
Constant	73.57***
	(8.63)
Observations	162,242
R-squared	0.696
K-P Wald F statistic	487.3

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations of QHP landscape files for the second lowest-cost Silver plan, the 2013 CPS ASEC supplement, ACS/Census, and the Area Health Resource File.
Note: Results are from the first stage regression of actual PTC per person on simulated PTC per person. Standard errors are clustered at the ZIP code level. The Kleibergen-Paap rk Wald statistic tests for weak identification when errors are not homoskedastic i.i.d. The value indicates strong first-stage performance.

Table C2: Two-Stage Least Squares Estimates

Panel A			
	(1)	(2)	(3)
VARIABLES	Mortgage Delinquency/1,000	Foreclosures/1,000	Bankruptcies/1,000
PTC Per Capita	0.0228**	-0.00247	-0.0103**
	(0.0105)	(0.00470)	(0.00518)
Observations	162,242	162,242	162,242
Dep. Mean in Q4 in 2013	16.08	3.55	6.37
Effect per $100 per capita	2.28	-0.25	-1.03
Pct Effect per $100 per capita	14.18%	-6.96%	-16.17%

Panel B			
	(1)	(2)	(3)
VARIABLES	Third-Party Collections/1,000	Credit Card Delinquency/1,000	Auto Delinquency/1,000
PTC Per Capita	0.0784**	-0.0450**	0.00846
	(0.0378)	(0.0202)	(0.0136)
Observations	162,242	162,242	162,242
Dep. Mean in Q4 in 2013	346.4	66.98	28.76
Effect per $100 per capita	7.84	-4.50	0.85
Pct Effect per $100 per capita	2.26%	-6.72%	2.94%

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on Federal Reserve Bank of New York/Equifax Consumer Credit Panel data for those age 18-64 and IRS SOI data.