The Impact of Social Insurance on Household Debt [*]

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Abstract

This paper investigates how the expansion of social insurance affects households' accumulation of debt. Insurance can reduce reliance on debt by lessening the financial impact of adverse events like illness and job loss. But it can also weaken the motive to self-insure through savings, and households' improved financial resilience can increase access to credit. Using data on 10 million borrowers and a quasi-experimental research design, we estimate the causal effect of expanded insurance on household debt, exploiting ZIP code-level heterogeneity in exposure to the staggered expansions of one of the largest US social insurance programs: Medicaid. We find that a one percentage point increase in a ZIP code's Medicaid-eligible population increases credit card borrowing by 1.17%. Decomposing this effect in a model of household borrowing, we show that increased credit supply in response to households' improved financial resilience fully accounts for this rise in borrowing and contributed 33% of the net welfare gains of expanding Medicaid.

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1 Introduction

In 2016, credit card debt became the most widely held form of household debt in the US, surpassing mortgages on primary residences (held by 43.9% versus 41.9% of households).[1] By the end of 2019, total credit card debt reached $927 billion. Despite its scale and ubiquity, *access* to credit cards varies significantly with household income.[2] The usage of credit card debt has an inverted U-shaped relationship with income: rising with income for households with below median income and decreasing for households with above median income (see Figure 1). Among households below the federal poverty line, more than two thirds do not own a credit card.[3] A key reason credit card lenders limit unsecured credit to low-income households is that they are more likely to default when faced with adverse financial shocks such as job loss or illness. In turn, the welfare costs to households of a lack of insurance against such shocks may be compounded as it limits their ability to smooth consumption using unsecured credit.

This paper investigates how changes in social insurance impact households' use of unsecured debt. Social insurance provides households a safety net against adverse financial shocks. In doing so, insurance enhances households' *financial resilience* – the ability of households to cope with adverse financial shocks. Insured households are less likely to default on their debt,[4] incentivizing lenders to provide greater access to credit. With better access to credit, insured households can use debt to better stabilize their consumption in the face of adverse events, even events that are not directly targeted by the insurance program.

The hypothesis that social insurance leads to a higher level of household debt may seem counterintuitive. When insurance reduces out-of-pocket health expenditures, households face less pressure to rely on debt to cover these expenses. Consistent with this, prior research finds that expanding Medicaid eligibility reduces medical debt, delinquency, and payday loan borrowing.[5] But the impact of expanded health insurance on credit card debt usage and access is less well understood. Households not currently facing health expenses may also change their borrowing in response to insurance as a result of improved financial resilience.

The main contribution of this paper is to estimate the equilibrium effects of expanding social insurance on household debt and welfare and quantify the channels shaping these responses. We focus on expansions of Medicaid, a program that currently provides health insurance to nearly 20% of the US population. First, using a quasi-experimental research design, we estimate that expanding Medicaid *increased* household credit card usage and reduced household default. Next, we build and estimate a structural heterogeneous-agent model with

[1] These figures come from the 2016 Survey of Consumer Finances (SCF), as reported in Bricker et al. (2017).

[2] The $927 billion figure comes from the Federal Reserve Bank of New York's Quarterly Report on Household Credit, using data from their 2019 Q4 Consumer Credit Panel.

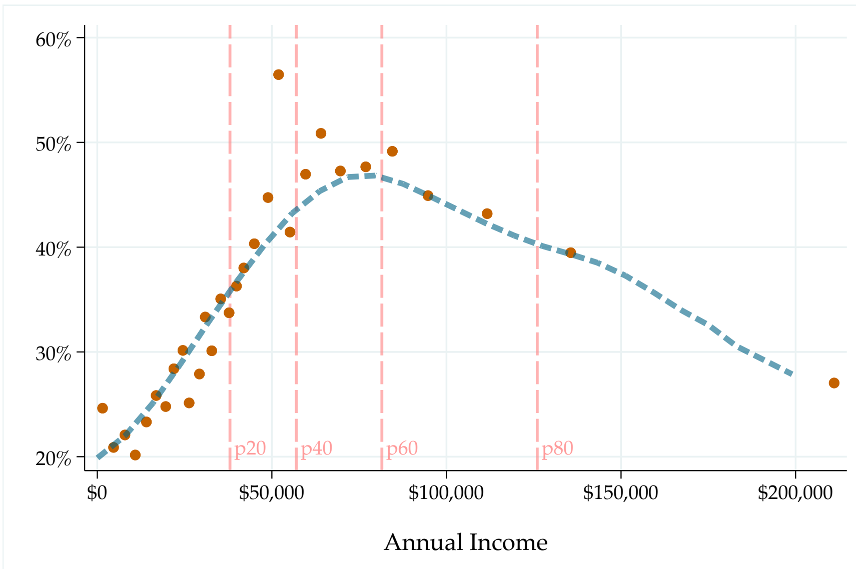
[3] Authors' calculations using survey data from the Survey of Income and Program Participation (SIPP) and the Panel Study of Income Dynamics (PSID).

[4] See, for example, Gross and Notowidigdo (2011); Gallagher, Gopalan and Grinstein-Weiss (2019b).

[5] See Allen, Swanson, Wang and Gross (2017); Hu, Kaestner, Mazumder, Miller and Wong (2018); Miller, Hu, Kaestner, Mazumder and Wong (2018).

credit card debt. The model allows us to decompose the impact of expanded health insurance coverage on debt into credit demand and credit supply channels. We find that credit supply fully accounts for the increase in credit card debt. Additionally, 33% of the welfare gains from expanding Medicaid come from an increase in credit supply. Our findings indicate that social insurance can improve households' financial resilience, and that overlooking credit market responses to social policies can overlook important welfare benefits.

Figure 1: Share of Households with Credit Card Debt (2017)



Notes: This figure plots a binscatter of the share of households with a non-zero amount of credit card debt. Data come from the 2017 PSID.

Our empirical analysis combines credit bureau data on 10 million US borrowers over 2010-2021 in a continuous difference-in-difference analysis to estimate the causal effect of increased Medicaid eligibility on a variety of credit outcomes. Our empirical strategy exploits granular variation in the *size* of eligibility changes induced by states' staggered expansions of Medicaid under the Affordable Care Act (ACA). This variation arises from two forms of heterogeneity. The first source of heterogeneity are states' pre-expansion Medicaid policies. Expanding Medicaid under the ACA required states to implement a common set of eligibility requirements. As a result, ZIP codes with even the same distribution of income saw larger increases in eligibility if their state previously had stricter requirements. The second source of variation comes from within-ZIP variation in the distribution of income among low-income households. Specifically, ZIP codes had larger increases in eligibility when more low-income households were clustered between the pre and post-expansion income eligibility thresholds.

Our difference-in-difference estimator compares credit outcomes before and after expanding across ZIP codes with higher versus lower changes in eligibility. The within-state variation in the impact of expansions makes it possible to use state-time fixed effects in our analysis, which help account for other unobserved state-level policy changes that may have coincided with expansions and also impacted credit outcomes. Identification requires that, absent expanding, credit outcomes would have evolved in parallel across ZIP codes with higher versus lower exposure. We assume that the change in eligibility is not correlated with other shocks *coinciding* with the expansion.

We find that increased Medicaid eligibility increases credit card borrowing. A one percentage point increase in eligibility leads to a 0.33 percentage point increase in the share of households with at least one credit card. The same shock increases credit card balances by 1.17 percentage points. We also document evidence consistent with credit supply playing an important role in shaping the equilibrium increase in credit card usage. Namely, we find that the ratio of credit card balances to credit limits decreases and the number of new credit cards granted per inquiry also rises. On the demand side, we find that credit card inquiries rise as well.

To investigate the role of improved financial resilience in contributing the this increase in credit card debt, we also examine default outcomes. We find that a one percentage point increase in eligibility reduces the share of households with debts 30 and 90 days past due by 0.09 and 0.10 percentage points (respectively). The same shock also reduces non-medical debt in collections by 0.43 percentage points. This reduction in default appears to translate into improved credit scores, which rise by 1.15 points in response to the same shock. Overall, we find that increased Medicaid eligibility has economically significant impacts on credit card borrowing. Expanded social insurance appears to crowd *in* rather than crowd out credit card debt.

We then construct a heterogeneous-agent model in which households have access to credit card debt. Households face idiosyncratic income shocks as well as idiosyncratic expenditure shocks. They can save using a risk-free asset or borrow via credit card debt, which they can decide not to repay. Households incur debt both by choosing credit card borrowing and as a result of experiencing expenditure shocks that they are unwilling or unable to cover on impact. The interest rate paid on credit card debt is endogenous and depends on the probability households do not pay their owed debt.

The treatment of credit card debt in our model is a hybrid of one-period and long-term debt used in the literature on consumer bankruptcy and sovereign debt. When households are in a non-delinquent state, they must roll over their debt that period. That is, credit card debt must be repaid in full to avoid delinquency. However, households have the option not to repay their debt and enter a delinquent state. In that state, they cannot take on more debt before paying their current debt in full.[6] After a stochastic amount of time, households in a delinquent state get a haircut on their debt. Since financial intermediaries who hold claims to delinquent debt are not repaid immediately, the pricing of debt has a long-term component to it.

[6]While households cannot choose to take on more debt in the delinquent state, uninsured expenditure shocks add to the households' total debt.

The delinquency option on debt allows us to capture a key aspect of the data. The relationship between having credit card debt with respect to income follows an inverse U-shape, as displayed in Figure 1. Less than 25% of households with less than $25,000 annual income have any credit card debt. This share goes up to 50% for households with an annual income of $70,000, and declines as household income goes up. If debt was always repaid in full, as in a standard Aiyagari (1994) economy, households with the lowest income level would be the ones with the most debt. The delinquency option, together with the endogenous credit supply, restricts low-income households' access to credit.

Capturing the inverse U-shape relationship between income and credit card debt is important for studying policies that target households with certain income, such as Medicaid. This is because such social insurance policies can give low-income households better access to credit. We introduce Medicaid into the model as a policy that covers a fraction of households' expenditures shocks for households below a certain income threshold.

Health insurance policies affect the aggregate level of credit card debt through three channels. First, the direct effect of more generous health insurance is increasing households' disposable income. Households can achieve the same consumption levels while borrowing less. Therefore, the direct effect of health insurance is a reduction in debt levels.

The second channel is through credit demand. Health insurance affects the demand for credit by households even if credit terms remain unchanged. The reduction in medical expenditures household face reduce their precautionary savings motive, and as a result, increases their borrowing. On the other hand, households are more likely to repay their debt in the future. This results in a higher marginal cost of borrowing, which induces them to reduce borrowing. So the effect of the credit demand channel is theoretically ambiguous.

The third channel is the credit supply channel. The reduction in delinquency rates leads to lower interest rate spreads in equilibrium. Lower interest rates induce households to take on more credit, leading to an increase in the aggregate level of credit card debt.

Consistent with our empirical findings, our model predicts that the expansion of Medicaid leads to an overall increase of 1.6% in credit card debt. The model allows us to decompose this impact into the different channels. We find that both the direct channel and the credit demand channel reduce the aggregate level of credit card debt. These two channels result in a reduction of 2.2%. The overall increase in credit card debt is solely due to the credit supply channel, which results in an aggregate credit card debt rise of 3.9%.

We use our model to study the welfare benefits associated with the expansion of Medicaid. We find that the policy is equivalent to a permanent increase in consumption of 9 basis points. 33% of the welfare gains are due to the reduction in interest rate spreads households face on their debt. This result suggests policy makers should take into account the effect social insurance has on credit supply. Disregarding the credit supply channel would substantially underestimate the welfare gains social insurance programs have.

This paper contributes to four strands of literature by bringing a new macroeconomic perspective to the effects of social insurance. First, prior empirical microeconomic research finds that expanding Medicaid eligibility reduced medical debt and borrowing for households experiencing costly health events. We build on this literature by focusing on a broader population, including people not currently experiencing an adverse shock, and by studying general equilibrium credit market consequences.

First, we build on prior empirical microeconomic research by focusing on the impact of Medicaid on credit card borrowing. This literature finds that expanding Medicaid reduces medical debt, missed debt and bill payments, reliance on expensive alternative credit sources such as payday loans, and debt in collections (Allen, Swanson, Wang and Gross, 2017; Hu, Kaestner, Mazumder, Miller and Wong, 2018; Miller, Hu, Kaestner, Mazumder and Wong, 2018; Gallagher, Gopalan and Grinstein-Weiss, 2019b; Goldsmith-Pinkham, Pinkovskiy and Wallace, 2020b). Reduced debt and delinquency improved FICO scores after expansions, leading to lower interest rates on credit card offers (Brevoort, Grodzicki and Hackmann, 2017) and increased mortgage application approval rates (Célérier and Matray, 2017). Our focus on borrowing complements the related analysis of Gallagher, Gopalan and Grinstein-Weiss (2019a) on saving. The authors find health insurance access increases saving among households not experiencing financial hardship, while reducing it among those experiencing hardship. More (or less) saving implies does not generally imply higher (or lower) gross or net borrowing.[7] Together, our findings are informative about the joint dynamics of borrowing and saving. Additionally, the model incorporates these various channels, decomposes their importance, and provides a new look at the general equilibrium impact on the amount and distribution of household debt and welfare.

Second, we add to a large macroeconomic literature on heterogeneous agent models with uninsurable risk (Bewley, 1986; Aiyagari, 1994; Huggett, 1993). This literature highlights how precautionary savings play a key role in shaping the macroeconomy. Our work studies how insurance provision can reduce the precautionary savings motive and traces the macroeconomic implications. We take a partial equilibrium approach, i.e., the risk-free rate in the economy is taken as given. So our approach is similar to the work of Imrohoroğlu (1989), Zeldes (1989), and Deaton (1991). Hubbard, Skinner and Zeldes (1995) who also study how social insurance affects precautionary savings motive. We build on this work by taking into account the impact social insurance has on the endogenous debt pricing schedule.

Third, our model builds on the macroeconomic literature on consumer bankruptcy and default (e.g., Chatterjee, Corbae, Nakajima and Ríos-Rull, 2007; Livshits, MacGee and Tertilt, 2007; Mitman, 2016). This literature focuses on the drivers of default, in particular the role of bankruptcy policy. We study a policy that does not directly target bankruptcy or default: public health insurance. This policy can reduce default and increase both credit access and

[7] In contrast to standard models of consumption and saving, household borrowing presents a "credit card puzzle" in that households tend to hold both high-interest credit card debt and low-interest savings simultaneously Gross and Souleles (2002). This behavior is consistent with a motive to maintain a liquidity buffer in the presence of incomplete markets (Telyukova, 2013; Druedahl and Jørgensen, 2018).

borrowing.

Finally, our work is related to a recent literature that investigates the relationship between household debt and the macroeconomy. This literature finds that increases in household debt can portend macroeconomic downturns and financial crises (Jordà, Schularick and Taylor, 2015, 2016; Mian, Sufi and Verner, 2017; Gomes, Grotteria and Wachter, 2019; Mian, Sufi and Verner, 2020). By focusing on *how* institutional features such as social insurance affect borrowing across households, this paper sheds new light on the relationship between household debt and the macroeconomy. In particular, a high *level* of household debt can indicate that households are well-insured and financially resilient.

This paper is organized as follows. Section 2 presents background on the Medicaid expansions and the empirical analysis of the impact of expansions on credit card debt. Next, Section 3 presents the model. Section 4 analyzes policy counterfactuals on debt (its distribution and aggregate level) as well as welfare. We decomposes the effect of expanding health insurance on borrowing into its direct impact on debt for households experiencing adverse shocks and its general equilibrium impacts through credit demand and supply. Section 5 concludes.

2 The Effect of Social Insurance on Household Debt: Evidence from Medicaid Expansions

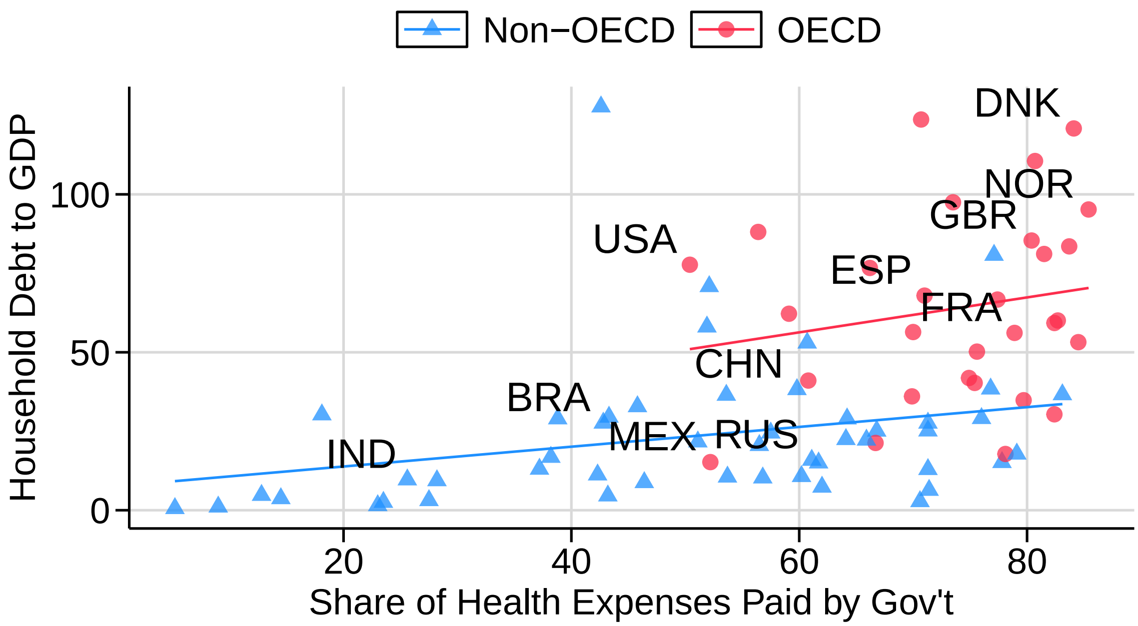
At the macro-level, cross-country comparisons indicate the generosity of social insurance is *positively* related to household debt. Figure 2 plots the ratio of household debt to GDP versus the share of total health expenses paid by the government, a proxy for social insurance provision, across countries. Countries with more generous insurance have significantly higher levels of household debt. On the top right corner are the Scandinavian countries, which have both a high provision of social insurance and high levels of household debt. Through the lens of our hypothesis, one reason Scandinavian households take on higher levels of debt is because they are more financially resilient—they are better insured against adverse events.

This section estimates the effect of expanded social insurance on household debt. We study one of the largest changes to the US social safety net in recent decades: the expansion of Medicaid under the Affordable Care Act (ACA). Our empirical strategy exploits both the staggered nature of the Medicaid expansions across states and within-state granular heterogeneity in the impact of the expansions. Examining a variety of credit outcomes, we find a positive relationship between credit card debt and Medicaid eligibility, as well as supporting evidence consistent with credit supply playing an important role in shaping the equilibrium response.

2.1 Institutional Background: Medicaid

Medicaid is a joint state and federal program that offers low-income households free or low-cost health insurance. In 2019, 64.7 million individuals received health insurance through

Figure 2: Household Debt and Social Insurance Across Countries



Notes: Data come from the IMF Global Debt and WHO Global Health Observatory data repository.

Medicaid, nearly 20% of the US population. Medicaid spending totaled $597.4 billion in 2018, comprising 16% of aggregate health expenditures. To qualify for Medicaid, a household must have income below a specified threshold.[8]

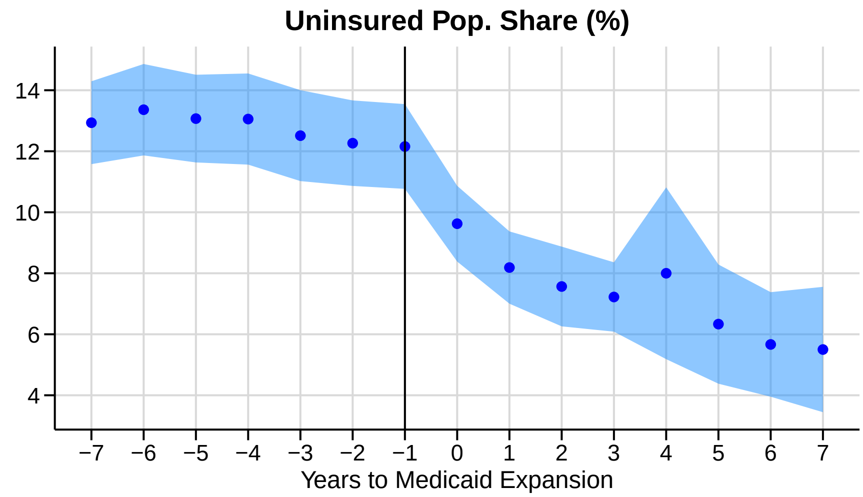
The ACA expanded Medicaid in participating states by requiring states to set the income eligibility threshold to at least 138% of the federal poverty level (FPL) for *all* adults. Participating states receive federal funds to support the costs of the Medicaid expansion. Prior to the ACA, only a handful states offered Medicaid to adults aged 64 or under without dependents. The eligible population expanded significantly in adopting states; on average the uninsured population fell by over 50% in expansion states within five years of adoption (see Figure 3).

Participating in the expansion is optional, and the timing of adoption varied significantly across time (see Figure 4). 2014 was the most common year of adoption, but some states opted to expand as early as 2010. As of 2019, 34 states have expanded Medicaid eligibility under the ACA, with Idaho, Nebraska, and Utah set to expand in 2020. The staggered adoption of Medicaid expansions creates quasi-experimental variation in access to health insurance. The staggered nature makes it possible to compare states within the same time period that differ in whether or not they expanded Medicaid eligibility.

The ACA was primarily financed by cuts to government spending on healthcare (mainly

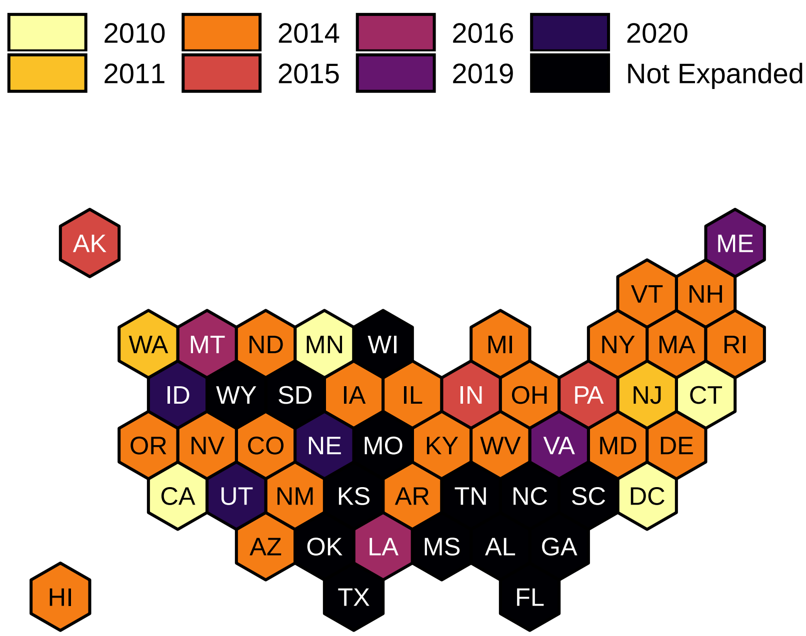
[8]Several states also use an asset-based means test in addition to the income threshold to determine eligibility. For a state to expand Medicaid under the ACA, they were required to remove any asset-based means tests.

Figure 3: Uninsured Rate Pre vs. Post Expansion



Notes: This graph plots the average uninsured population for states that eventually expanded Medicaid. Each point is an average across states for a given number of years relative to the expansion. The shaded area is a 95% confidence interval.

Figure 4: Medicaid Expansion Dates



Notes: Dates come from the Kaufman Family Foundation.

related to Medicare), taxes on insurers, and taxes on individuals. Congressional Budget Office (CBO) estimates projected the ACA to *reduce* budget deficits overall during 2013—2022 by

$109 billion dollars (Congrssional Budget Office, 2012). The ACA's projected costs to the Federal Government of expanding Medicaid, the Children's Health Insurance Program (CHIP), Health Insurance Exchanges, and other non-coverage provisions totaled $1,455 billion (approximately 0.6% of 2020's GDP per year). Healthcare-related government spending cuts were projected to save $741 billion over this same time period, accounting for 50.9% of the total cost. The primary source of these cuts were reductions in payment rates for hospital services rendered to Medicare and Medicare Advantage patients and reductions in Disproportionate Share Hospital (DSH) payments. DSH payments help compensate hospitals for the cost of uncompensated care (i.e., missing or partial payments owed by patients).

2.2 Data

This section describes the two main datasets used in our reduced-form analysis. The first is credit bureau data. The second dataset records Medicaid eligibility at the ZIP-level. Throughout, we deflate nominal variables to real 2020 dollars.

Experian Data: To study credit outcomes, we use credit bureau data from Experian for a random sample of ten million US residents. Our Experian sample is an annual panel spanning 2010 to 2021 and contains over 90 million borrower-level observations. A subset of outcomes are measured at a quarterly frequency over 2010–2020. Our sample is geographically representative in the sense that individuals are sampled from ZIP codes in proportion to the their ZIP code's population share. In our empirical analysis, we aggregate the borrower-level data to the ZIP code-level (dropping ZIP codes with fewer than 150 borrowers reporting data). After this restriction, we have 13,019 unique ZIP codes over twelve years.

Experian Summary Statistics: Table 1 presents summary statistics for our main credit outcomes of interest in the ZIP-level sample. We consider both extensive and intensive measures of credit card usage. On average, 84% of borrowers in a ZIP have at least one credit card and 22% obtained a new credit card in the past year. Average borrower-level credit card balances are $4,239.

We also consider measures that may better reflect either credit supply or demand. Our credit card supply measures are (1) utilization rates (the ratio of balances to credit limits); (2) credit limits; and (3) the ratio of new credit cards to credit card inquiries over the past year. Average utilization is 32% and average limits are $17,591. Limits exhibit substantial variance across ZIP codes; its standard deviation is $8,564. The ratio of new credit cards to inquiries reflects the success rate of borrower requests for credit cards. The average ratio is 0.52, indicating that typically two 2 inquiries are necessary to obtain one credit card. Our demand measure is the number of credit card inquiries per year, which average 0.44 per borrower.

For default, we examine both measures of delinquency and whether borrowers have debt in collections. On average, 10% and 7% of borrowers have some debt that is 30 and 90 or

Table 1: Summary Statistics for ZIP-Level Credit Outcomes

	Mean	SD	25th %	50th %	75th %	N
1[Has CC] (%)	84.29	8.82	79.02	85.8	91.08	106621
1[New CC] (%)	21.84	4.76	18.61	21.98	25.06	106621
CC Bal.	4239.24	1739.1	2998.79	3921.51	5146.71	352561
CC Rev. Bal.	3627.83	1442.68	2609	3381.93	4385.51	352561
1[Revolver] (%)	60.01	11.55	52.01	60.2	68.61	352561
CC Util. (%)	31.89	12.25	22.4	30.74	40.14	106621
CC Lim.	17591.68	8564.41	11377.12	15612.22	22094.91	106621
New CC to Inq.	0.52	0.12	0.43	0.52	0.6	106621
CC Inq. (#)	0.44	0.14	0.34	0.43	0.53	106621
30+ Delinq. (%)	10.33	4.02	7.44	10.03	12.77	106621
90+ Delinq. (%)	7.32	3.26	4.97	7	9.24	106621
1[Any Col.]	23.73	11.84	14.62	22.04	31.03	106621
Col. Bal.	664.84	433.46	353.54	568.17	873.63	106621
Vantage Score	681.37	36.7	656.89	682.18	707.5	106621

Notes: This table reports ZIP-level summary statistics for the main credit outcomes of interest from the Experian data. All variables are reported annually (June of each year) except for credit card balances (total and revolving) and percent of people that have revolving balances ("revolvers"). The latter are reported quarterly. We calculate revolving (i.e., unpaid) balances by subtracting credit card payments from total credit card balances. Nominal variables are CPI-adjusted to be in terms of 2020 dollars. Throughout, "CC" denotes "credit card". The "Has CC" variable indicates the fraction of borrowers with at least one credit card while the "New CC" variable captures people that obtained at least one new credit card in the past year. Balances, limits, and utilization are calculated across all credit cards. Utilization and limit calculations include households with zero credit cards. The "inquiries" variables reflect total activity in the past year. The delinquency variables reflect if borrowers had any debt 30+ or 90+ days past due (excluding collections). The collections variables indicate the fraction of households with some debt in collections (non-medical and medical debt are tabulated separately). Our credit score measure is the Vantage Score.

more days past due (respectively). These measures of delinquency exclude debt in collections, which is even more common. On average 23% of borrowers have at least some debt in collections.

Medicaid Eligibility and Enrollment Data: We combine several data sources to estimate Medicaid eligibility at the ZIP-level. Adult household members are eligible for Medicaid if their income falls below a threshold, where the income threshold depends on household size and the number of dependents. Directly calculating eligibility requires individual-level data containing ZIP codes, income, and household composition. Because such data is difficult to access, we instead estimate the eligible population share. Our estimation approach first estimates the income distribution for each ZIP-year using data from the IRS Statistics of Income (SOI). Next, relying on the law of iterated expectations and Bayes' rule, we use the joint distribution of income and household size from the YEAR American Community Survey (ACS) to estimate the share of households with income below their corresponding Medicaid threshold. For details on our procedure see Appendix B. We use IRS SOI data from 2009–2019 in our calculations. We obtain annual ZIP-level data on Medicaid enrollment from the ACS.

Eligibility Summary Statistics: Table 2 reports summary statistics for our eligibility and enrollment data.

Table 2: Summary Statistics for ZIP-Level Eligibility and Income Data

	Mean	SD	25th %	50th %	75th %	N
Elig. (%)	17.51	12.06	6.41	12.46	27.82	106,621
ΔElig.	11.56	11.78	0.00	8.00	22.18	7,845
Avg. HH Inc.	78.82	61.30	50.74	62.45	84.51	106,621

Notes: This table reports ZIP-level summary statistics for the eligibility measures and income. Eligibility is calculated as described in the text, with additional details provided in Appendix B. The first row reports average eligibility across all ZIP codes and years. The second row reports the average change in eligibility in the first year of expansion (this excludes ZIP codes in states that did not expand). Average household income is the average adjusted gross income (AGI) reported in the ZIP code. Nominal variables are CPI-adjusted to be in terms of 2020 dollars.

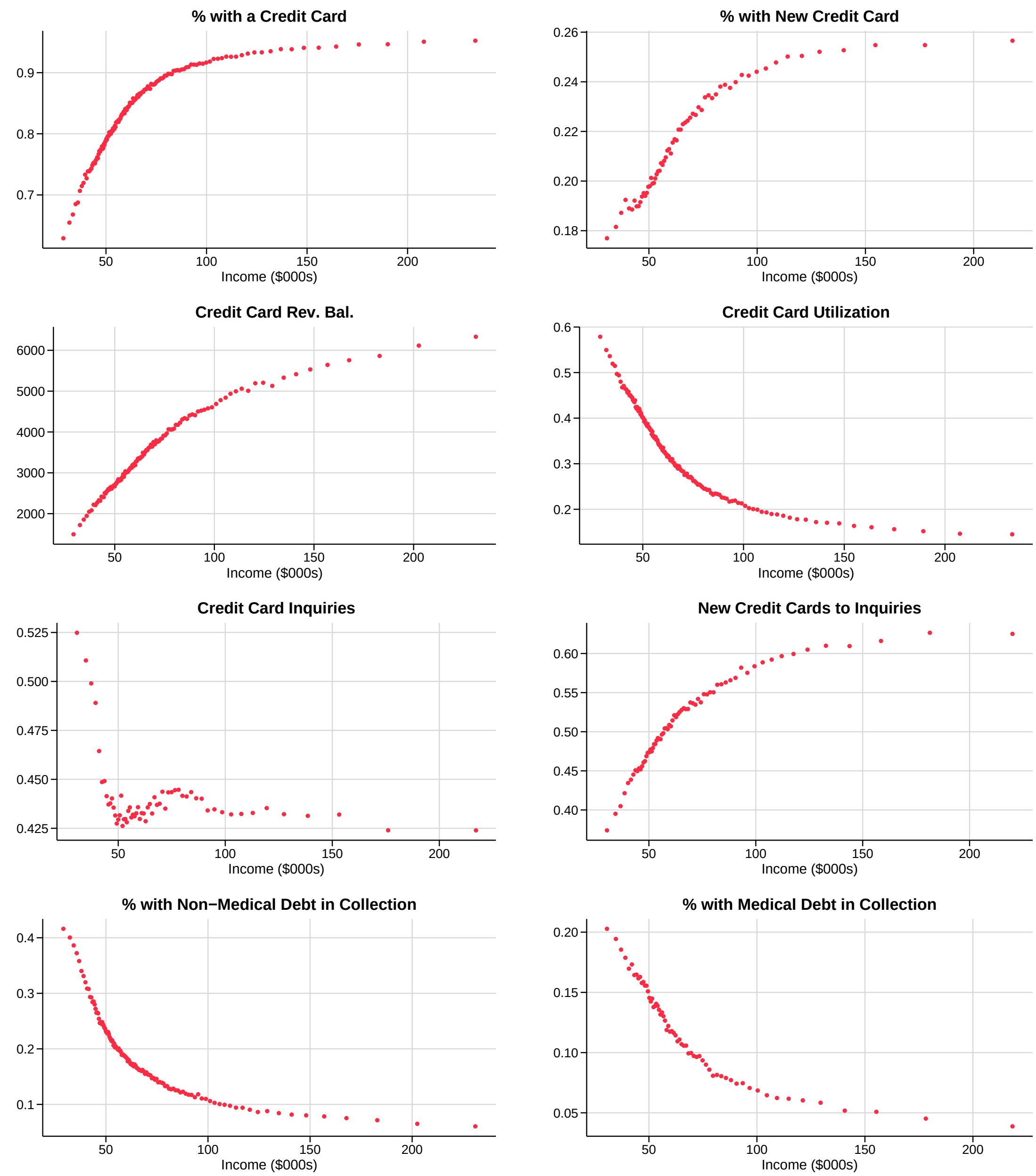
2.3 Empirical Strategy: Continuous Difference-in-Difference

Our analysis quantifies the impact of changes in Medicaid eligibility on credit outcomes. Identifying the causal effect of eligibility is challenging for two reasons. The first is that eligibility depends on income, which is likely correlated with omitted variables. The second is that state-level expansions, especially the more recent ones, coincided with other political changes such as a the election of a Democratic governor. Such events may have accompanied other policy changes that also impact credit outcomes.

To overcome these identification challenges, we exploit quasi-experimental variation in the *size* of Medicaid expansions in a difference-in-difference (DID) analysis. We rely on two main sources of variation. First, we exploit cross-state variation arising from states' *pre-existing* Medicaid eligibility rules. Expanding under the ACA required states to raise the income eligibility limit to a common threshold of 138% of the federal poverty level for all adults aged 64 or less. States with previously stricter eligibility rules, such as lower income thresholds or rules precluding adults without dependents from eligibility, tended to experience larger changes in eligibility when expanding. Second, we exploit within-state variation due to differences in the *distribution* of income among low-income households. Specifically, ZIP codes where more households had income lie between the pre and post-expansion income eligibility thresholds experienced a larger increase in eligibility.

Formally, our empirical strategy is a continuous difference-in-difference (DID) analysis. The DID compares ZIP codes with larger versus smaller changes in eligibility induced by expanding Medicaid under the ACA. We estimate

Figure 5: ZIP-Level Credit Access and Income Facts



Notes: This figures plots average income against credit outcomes, with all variables measured as the average within a ZIP code for a given year.

$$Y_{zcst} = \alpha_1 \text{Post}_{st} + \alpha_2 \Delta\text{Elig}_{zs} + \beta \left(\text{Post}_{st} \times \Delta\text{Elig}_{zs}\right) + \phi_{ct} + \gamma X_{zcst} + \varepsilon_{zcst}. \tag{1}$$

Above, Y_{zcst} is an average credit outcome in ZIP code z (located in county c of state s) in year t. Post_{st} equals one if state s has expanded Medicaid as of year t. We capture the intensity of treatment with a continuous variable, ΔElig_{zs}, which corresponds to the change in the Medicaid-eligible share of the population in ZIP z over the first year of state s's expansion (relative to the year before its expansion). All specifications include county-year fixed effects to account for the effects of other observed time-varying county and state-level shocks. We include time-varying controls (X_{zcst}) such as logged ZIP-level income per household. The coefficient of interest is β on the interaction term, which reflects the causal effect of an expansion that induced a one percentage point increase in eligibility.

When does OLS estimation of the above equation identify the causal effect β? The key identifying assumption is that household credit outcomes would have evolved in parallel—across locations with high versus low changes in eligibility—if Medicaid had not expanded. Phrased differently, we assume that the size of changes in eligibility is uncorrelated with other factors *changing* at the time of the expansion. This assumption would fail if other policies were implemented along with the expansions that also targeted the newly-eligible population. The ZIP-level variation also makes it possible to include state-year fixed effects (we opt for the more granular county-year fixed effects). These fixed effects help account for the impact of other state or county-level policy changes on credit outcomes.

2.4 Empirical Results: The Effects of Medicaid Eligibility on Household Debt

We start by examining the response of credit card debt. Table 3 reports results from estimating the DID for these outcomes. We first document positive effects of increased eligibility on the extensive margin of credit card access. A one percentage point increase in a ZIP code's Medicaid-eligible population leads to a 0.33 percentage point increase in the fraction of borrowers that has a credit card. The fraction of households that received a new credit card in the last year grows by 0.21 percentage points in response to the same shock. Per newly-eligible household, these correspond to a 33 and 21 percentage point increase (respectively).

In terms of credit card balances, average ZIP-level balances increase one percentage point in response to a one percentage point increase in eligibility. This corresponds to approximately a $42.39 increase in average balances. Per newly-eligible household, this corresponds to a $4,239 increase in balances, which is approximately 59% of recent average household-level credit card balances.[9] This effect is large and is consistent with much of the total effect coming from households going from little-to-no credit card usage to newly having access to

[9] The 59% figure comes from dividing $4,239 by $7,210, where the $7,210 is average household-level credit card balances as of 2019. We calculate this figure using the aggregate credit card balance data from the Federal Reserve Bank of New York's Consumer Credit panel and household population count data from the American Community Survey.

a credit card, and beginning to catch up to more typical levels of credit card balances.

Table 3: DID Results for Credit Card Debt

	1[Has CC] (1)	1[New CC] (2)	log(CC Bal.) (3)	log(CC Rev. Bal.) (4)
$\Delta\text{Elig}_{zs} \times \text{Post}_{st}$	0.327***	0.205***	0.999***	0.742***
	(0.05)	(0.04)	(0.24)	(0.21)
ΔElig_{zs}	-0.493***	-0.242***	-1.337***	-1.108***
	(0.08)	(0.04)	(0.28)	(0.25)
$\log(\text{AGI}_{zcst})$	0.110***	0.022***	0.629***	0.560***
	(0.01)	(0.00)	(0.02)	(0.02)
Obs	106,616	106,616	352,537	352,533
R2	0.781	0.707	0.855	0.819
Mean	84%	22%	$4,239	$3,628

Notes: This table reports results from estimating the DID in Equation (1). Each specification uses county-year fixed effects and controls for logged ZIP-level average adjusted gross income (AGI). Standard errors are clustered by state. Nominal variables are CPI-adjusted to be in terms of 2020 dollars. The dependent variable is labeled above the column number and its mean is reported in the bottom row. Statistical significance: 10%*, 5%**, and 1%***.

We advise some caution in interpretation when scaling the coefficients by the change in the eligible population. One reason is that we estimate the response of credit card usage for up to twelve years before and after expanding. For each household made newly eligible at the time of expansion, more households likely end up eligible in the following years due to adverse events such as job loss. An elasticity with respect to the *total* directly affected population should take these households into account. Additionally, credit demand and supply may also change for borrowers that never become eligible during the period of study. For example, households at risk of adverse events leading them to potentially rely on Medicaid may modify their borrowing knowing that they are more likely to be eligible (even if these adverse events aren't actually realized). And credit supply may respond positively to non-eligible households if underwriting models suggest they present a lower risk of default after the expansion. In our structural analysis, our model allows these effects to be present.

To shed further light on the role of supply and demand, we examine proxies for these two forces in Table 4. For our supply proxies, we consider ratio of credit card balances to credit limits (utilization), credit limits themselves, and the ratio of new credit cards to credit card inquiries (over the past year). Overall we find evidence consistent with a positive credit supply response to expansion. A one percentage point increase in a ZIP code's eligibility leads to a 0.55 percentage point decrease in utilization, indicating a relaxation of credit constraints. Given the positive effects documented for balances, this suggests that this decline in utilization is due to an increase in credit card limits. Examining limits directly, we estimate a the same 1% eligibility increase leads to a 1.26 percentage point increase in credit card limits (a

Table 4: DID Results for Credit Card Supply and Demand Proxies

	Supply			Demand
	CC Util. (%)	log(CC Lim.)	New CC to Inq.	CC Inq. (#)
	(1)	(2)	(3)	(4)
$\Delta \text{Elig}_{zs} \times \text{Post}_{st}$	-0.550***	1.258***	0.292***	0.209***
	(0.07)	(0.21)	(0.05)	(0.05)
ΔElig_{zs}	0.739***	-1.703***	-0.423***	-0.143**
	(0.09)	(0.28)	(0.07)	(0.07)
$\log(\text{AGI}_{zcst})$	-0.161***	0.789***	0.095***	-0.070***
	(0.01)	(0.03)	(0.01)	(0.01)
Obs	106,616	106,616	106,616	106,616
R2	0.824	0.860	0.717	0.866
Mean	32%	$17,592	0.52	0.44

Notes: This table reports results from estimating the DID in Equation (1). Each specification uses county-year fixed effects and controls for logged ZIP-level average adjusted gross income (AGI). Standard errors are clustered by state. Nominal variables are CPI-adjusted to be in terms of 2020 dollars. The dependent variable is labeled above the column number and its mean is reported in the bottom row. Statistical significance: 10%*, 5%**, and 1%***.

$222 increase). Lastly, we find that after expanding Medicaid, credit card inquiries are more likely to result in a new credit card. A one percentage point increase in eligibility leads to a 0.30 percentage point increase in the ratio of new credit cards to inquiries.

Our proxy for credit card demand is the number of credit card inquiries per borrower in the past year. We estimate that a one percentage point increase in a ZIP code's eligible population increases inquires by 0.0021 per borrower (approximately 1 new inquiry per 500 individuals). This suggests demand may also be contributing to the equilibrium rise in credit card balances. However, we note that inquiries are an equilibrium outcome that may be influenced by marketing practices of credit card lenders and households' perceptions of lending standards, making them an imperfect proxy for demand. We ultimately rely on our model (in upcoming sections) to definitively separate supply and demand.

Finally, we turn to measures of default and find evidence indicating that increased eligibility improved households' financial resilience in Table 5. We find that increased eligibility reduces delinquency. A one percentage point increase in eligibility reduces the likelihood of being 30 and 90 days delinquent by 0.09 and 0.10 percentage points (respectively). Examining more severe measures of default, we also find a reduction in debt in collections. The same 1% increase in eligibility reduces the likelihood of having debt in collections by 0.40 percentage points. The average amount of debt in collections decreases 0.84 percentage points ($ 5.59) in response to a 1% increase in eligibility.

The improved financial resilience of borrowers appears to translate into higher credit scores. We estimate that a one percentage point increase in eligibility leads to a 1.15 point increase in borrowers' average Vantage Score. This is approximately a 0.17 percentage point

Table 5: DID Results for Default and Credit Scores

	1[Delinquency]		Debt in Collections		Credit Score
	30+ Days	90+ Days	1[Any Col.]	log(Col. Bal.)	Vantage Score
	(1)	(2)	(3)	(4)	(5)
$\Delta \text{Elig}_{zs} \times \text{Post}_{st}$	-0.093***	-0.098***	-0.404***	-0.837***	1.15***
	(0.03)	(0.03)	(0.07)	(0.27)	(0.15)
ΔElig_{zs}	0.143***	0.145***	0.579***	2.032***	1.85***
	(0.04)	(0.04)	(0.09)	(0.38)	(0.22)
log(Avg. Inc.)	-0.055***	-0.044***	-0.160***	-0.775***	58.42***
	(0.00)	(0.00)	(0.01)	(0.06)	(2.87)
Obs	106,616	106,616	106,616	106,616	106,616
R2	0.718	0.706	0.817	0.780	0.836
Mean	10%	7.3%	23%	$665	681.37

Notes: This table reports results from estimating the DID in Equation (1). Note that the delinquency measure here is not restricted to delinquency on credit cards. It will also reflect delinquency on mortgages, student loans, etc. Each specification uses county-year fixed effects and controls for logged ZIP-level average adjusted gross income (AGI). Standard errors are clustered by state. Nominal variables are CPI-adjusted to be in terms of 2020 dollars. The dependent variable is labeled above the column number and its mean is reported in the bottom row. Statistical significance: 10%*, 5%**, and 1%***.

increase relative to the average Vantage Score of 681.

To sum up, we find that expanding Medicaid eligibility increased both the prevalence of credit cards and total credit card balances. We find evidence suggesting both supply and demand contributed to the increase in equilibrium credit card usage. Lastly, we document that default decreased and credit scores improved, which could drive an increase in credit supply in response to expanded Medicaid eligibility.

Comparison to Prior Evidence on Financial Outcomes. By testing whether the credit demand and supply channels can dominate in equilibrium, we build on prior work analyzing partial equilibrium effects of expanded health insurance access. The key mechanism underlying these channels is that insurance enhances financial resilience, incentivizing both borrowing and lending. Prior work documents that insurance access significantly reduces default and medical expenses, suggesting that insurance can significantly enhance financial resilience.[10] In support of the credit supply channel, Brevoort et al. (2017) estimates that the reduction in delinquencies induced by the Medicaid expansions led to improvements in credit

[10] For example, expanded access to Medicaid and Medicare reduce delinquency and collections (for medical and non-medical debt), unpaid bills, out-of-pocket medical expenses, and bankruptcy filings (Gross and Notowidigdo, 2011; Finkelstein et al., 2012; Barcellos and Jacobson, 2015; Hu et al., 2018; Gallagher et al., 2019b; Goldsmith-Pinkham et al., 2020a).

card terms worth $520 million per year.

Analyses of savings behavior suggest that Medicaid eligibility on average can reduce savings, but increase them for households experiencing financial hardship. Gallagher et al. (2019a) estimates that newly eligible households on average either reduced or left savings out of tax refunds unchanged. But this masks heterogeneity among those whose precautionary savings motive decrease and those experiencing adverse financial events (e.g., households reporting skipping meals for financial reasons), as the latter group on average increased savings. This suggests the average response to insurance access may differ from the direct effect.

Our analysis builds on this work by focusing on borrowing rather than saving. Many households simultaneously hold both high-interest credit card debt and low-interest savings (Gross and Souleles, 2002), which presents a "credit card puzzle" for standard models of consumption and saving. This may be driven by a liquidity motive to avoid states of the world in which the household has no liquid savings and no access to additional credit card borrowing.[11] It is not obvious if gross borrowing would always rise when households reduce gross savings, as households might reduce borrowing if they were doing so in order to maintain a target level of gross savings. This makes our analysis of borrowing complementary to Gallagher et al. (2019a), and together informative about the joint dynamics of borrowing and saving.

3 Model

In this section, we develop an incomplete-markets heterogeneous-agents model with health expenditure shocks, credit delinquency, and health insurance. Households face idiosyncratic income shocks as well as idiosyncratic health expenditure shocks. They can save and borrow using a one-period non-state-contingent asset, and can choose not to repay their debt obligations. After reneging on their debt obligations, their debt enters a delinquent state, and the household is excluded from financial markets and suffers a utility loss. In every period, delinquent debt can stochastically get a haircut, i.e., be reduced by some percent. Households can exit the delinquency state by repaying their debt.

Credit to households is supplied by credit card companies. These companies have access to funds at the risk-free interest rate, which households take as given. The assumption that the risk-free rate is constant, rather than the aggregate net supply of debt, allows us to study how different policies affect the aggregate stock of household debt in the economy. We assume that credit card companies are risk neutral and behave competitively so that the spread they charge on a household's loan is such that their expected profits equal zero.

We use the model to study the effects of different insurance policies on the aggregate stock of debt, wealth inequality, and welfare.

[11] For liquidity-based explanations of the credit card puzzle, see Telyukova (2013), Druedahl and Jørgensen (2018), and Fulford (2015).

3.1 Household problem

There is a continuum of measure one of households in the economy, denoted by $i \in (0,1)$. Household's i income at time t is denoted by y_{it} and evolves according to a compound Poisson process:

$$\ln y_{it} = \begin{cases} \rho \ln y_{it-1} + \epsilon^{y}_{it} & \text{w.p.} \quad \lambda_y, \\ \rho \ln y_{it-1} & \text{w.p.} \quad 1-\lambda_y. \end{cases} \tag{2}$$

where λ_y is the probability that an income shock arrives in a period. If such shock does not arrive, the household's income does not change. Given an income shock, the household income follows an AR(1) process, where ρ is the degree of persistence and ϵ^{y}_{it} is an idiosyncratic income shock with mean zero and variance $\sigma^2_{\epsilon,y}$.

In addition to income risk, households are subject to stochastic medical expenditure shocks, denoted by m_{it}. The stochastic expenditure shocks follow a log-normal distribution with mean μ_e and variance σ^2_e.

Households medical bills are partially covered by their health insurance. We allow insurance to vary exogenously with the household income. Health insurance covers a share of the medical bill due. We denote the share of medical bills the households have to pay out-of-pocket as $o(y_{it})$. Note that the out-of-pocket share depends only on the current household income, as we assume insurance varies only with household income.

Each household has access to non-state-contingent one-period debt, denoted by b_{it}. A negative value of b_{it} represents household savings. In the beginning of each period, the household can choose to repay or renege on its debt obligations. The household's decision to repay debt depends on their total debt, their level of income, and the size of their current medical bill. Households face an interest rate schedule for the amount of borrowing they choose, which we denote by $r(b', y)$.[12] The price of debt is denoted by $q(b', y) = \frac{1}{1+r(b',y)}$. We denote the total amount of repayments owed by the household by $\tilde{b}_{it} = b_{it} + o(y_{it})m_{it}$. Note that $\tilde{b}$ is the relevant state variable from the perspective of the household.

At the beginning of each period, a household learns its current income and medical expenditure shock, and then chooses whether to repay its debt or to renege and declare delinquency. It's present discounted value is denoted by $V(\tilde{b}, y)$, where $\{\tilde{b}, y\}$ are its individual state variables. This value function is given by the max between the present discounted value of repaying debt obligations, denoted by $V^r(\tilde{b}, y)$, and the value of reneging and declaring delinquency, denoted by $V^d(\tilde{b}, y)$:

$$V(\tilde{b}, y) = \max\left\{V^r(\tilde{b}, y), V^d(\tilde{b}, y)\right\}. \tag{3}$$

Conditional on the decision to repay its debt obligations, the recursive problem of the

[12] The size of medical bill does not appear in the interest rate schedule as it is independent across periods.

household with total debt obligations $\tilde{b}$ and income y is given by

$$
\begin{aligned}
V^r(\tilde{b}, y) = & \max_{c, b'} u(c) + \beta \mathbb{E} V \left(b' + o(y')m', y'\right), \\
\text{s.t.} \qquad & c + \tilde{b} \leq y + q(b', y)b',
\end{aligned} \tag{4}
$$

where $u(\cdot)$ is the utility of the household from consumption, which is assumed to be strictly increasing, concave, and continuously differentiable. The household's discount factor is β.

When a household reneges on its debt obligations, the debt moves into a delinquency state. A household with debt in a delinquency state cannot save or borrow, and suffers a utility cost ξ. At the end of the period, the household receives a stochastic haircut on its debt obligations. The haircut, denoted by δ, is assumed to follow a compound Poisson process. With probability, λ_δ, the household receives a positive haircut. Conditional on a haircut, the share of debt forgiven follows a Beta distribution with shape parameters α_1 and α_2. The value of the household in the delinquent state is given by

$$
V^d(\tilde{b}, y) = u(y) - \xi + \beta \mathbb{E} V \left((1-\delta)\tilde{b} + o'(y')m', y'\right). \tag{5}
$$

The timeline in every period is as follows. First, the household learns its current income and medical bill. Then, it decides whether to repay its outstanding debt obligations or not. If it decides to repay its debt obligations, it chooses the level of consumption and borrowing. If it decides to renege on its debt obligations, it consumes its income, suffers a utility loss, and at the end of the period has a chance of drawing a stochastic haircut rate.

We denote the delinquency policy function of a household with total debt obligations $\tilde{b}$ by

$$
d(\tilde{b}, y) = \mathbb{1}\left[V^r(\tilde{b}, y) < V^d(\tilde{b}, y)\right], \tag{6}
$$

where $\mathbb{1}$ is the indicator function. The function $d(\tilde{b}, y)$ equals 1 when the household defaults. When indifferent, we assume the household repays its debt obligations.

3.2 Credit supply

Credit to households is supplied by risk-neutral credit card companies. Perfect competition among these companies ensures an expected zero-profits condition holds in equilibrium. We assume credit card companies have unlimited access to funds at the risk-free interest rate, which we denote by r^f.

Debt in the economy is a hybrid of short-term and long-term debt. Debt is of short-maturity in nature, as households need to repay their debt obligations in the following period. However, when debt becomes delinquent, credit card companies do not receive payments within that period. Instead, they need to wait until the household decides to repay its debt. Either because it received a haircut, or because its income level changes so that it decides to repay.

The zero-profits condition that pins down the price of debt, $q(b', y)$, is

$$q(b', y)(1 + r_f) = \left[1 - \mathbb{E}\left(d(b' + o(y')m', y')\right)\right] \\ + \mathbb{E}\left[d(b' + o(y')m', y')(1 - \delta')q\left((1 - \delta')(b' + o(y')m'), y'\right)\right]. \quad (7)$$

That is, the credit companies equate the cost of their loan (LHS) with its return (RHS). The return from the loan is the sum of two parts. If the debt does not go delinquent, the credit company receives its full face value. If the debt goes delinquent, which happens with probability $\mathbb{E}\left(d(b' + o(y')m', y')\right)$, then the creditor is left with a claim on a delinquent debt. The worth of such claim, following a possible haircut, is given by $(1 - \delta')q\left((1 - \delta')(b' + o(y')m'), y'\right)$. The fixed point function $q(\cdot)$ that solves equation (7) is the debt pricing schedule.

Proposition 1. *Given a default policy function, $d(\tilde{b}, y)$, there exists a unique pricing schedule $q(b', y)$ which satisfies equation (7).*

3.3 Stationary Equilibrium

We denote the joint distribution of households across total debt obligations and income levels at the beginning of the period, after the expenditure shock realization, by $\Lambda\left(\tilde{b}, y\right)$. Four components characterize the law of motion for this joint distribution: (i) the borrowing decision of households – $b'(\tilde{b}, y)$, (ii) the debt pricing schedule – $q(b', y)$, (iii) the household's default decision – $d(\tilde{b}, y)$, and (iv) the exogenous processes of income, expenditure shocks, and haircuts. The law of motion for the joint distribution is defined as follows. For all Borel sets $\mathcal{B} \times \mathcal{Y} \subset \mathbb{R} \times \mathbb{R}^+$,

$$\Lambda'\left(\mathcal{B} \times \mathcal{Y}\right) = \int_{m'} \int_{y' \in \mathcal{Y}} \int_{\mathscr{B}\left(\tilde{b}, y, m'\right)} d\Lambda(\tilde{b}, y) dF(y'|y) dG(m') \quad (8) \\ + \int_{\delta} \int_{m'} \int_{y' \in \mathcal{Y}} \int_{y, ((1-\delta)\tilde{b} + o(y')m') \in \mathcal{B}} \mathbb{1}\left[d\left(\tilde{b}, y\right)\right] d\Lambda(\tilde{b}, y) dF(y'|y) dG(m') dH(\delta),$$

and

$$\mathscr{B}\left(\tilde{b}, y, m'\right) = \left\{(\tilde{b}, y) \quad \text{s.t.} \quad d\left(\tilde{b}, y\right) = 0 \quad \text{and} \quad b'\left(\tilde{b}, y\right) + o(y')m' \in \mathcal{B}\right\},$$

where $F(\cdot)$, $G(\cdot)$, and $H(\cdot)$, are the CDF of the different exogenous variables. In the stationary equilibrium, the distribution $\Lambda(\tilde{b}, y)$ is constant over time. The definition of the stationary Markov-perfect equilibrium is as follows.

Definition 1 (Equilibrium)**.** *A stationary Markov-perfect equilibrium is given by a default policy function $d(\tilde{b}, y)$, a borrowing policy function $b'(\tilde{b}, y)$, a debt pricing schedule $q(b', y)$, and a joint distribution of households across total debt and income levels, $\Lambda(\tilde{b}, y)$ such that*

1. *The default and borrowing policy functions solve the household's problem given the debt pricing schedule.*

2. *The debt pricing schedule satisfies the zero-profits condition, (7).*

3. *The joint distribution of households across debt and income levels is stationary.*

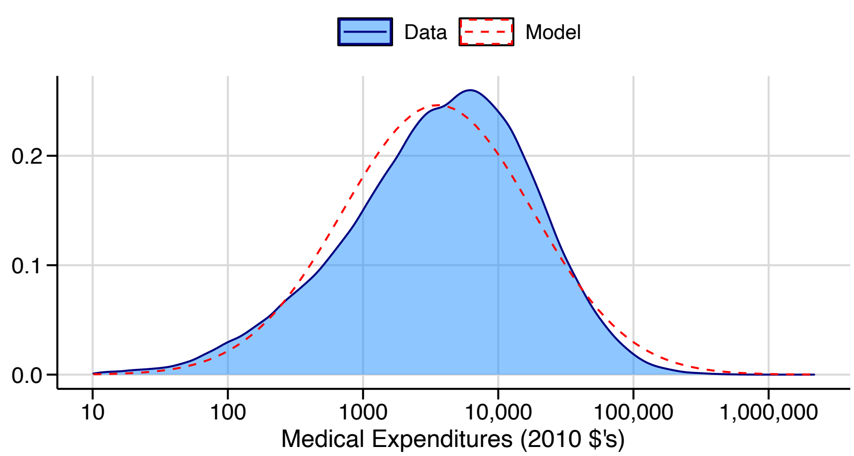
3.4 Calibration

We calibrate the risk-free interest rate in the economy to 2%. There are five sets of structural parameters in the model, in addition to the risk-free rate. First, there are three preference parameters - the discount factor β, the CRRA γ, and the disutility of delinquency ξ. Second, there are three haircut process parameters - the axrrival rate of haircuts λ_δ, and the two shape parameters of haircuts α_1 and α_2. Third, there are three parameters governing the income process - the arrival rate of income shocks λ_y, the persistence of income ρ, and the variance of income shocks $\sigma^2_{\epsilon,y}$. Fourth, there are two parameters governing the health expenditure process - its log mean μ_e and variance σ^2_e. Finally, we need to calibrate the out-of-pocket share function $o(y)$.

We proceed as follows. We use the Medical Expenditure Panel Survey (MEPS) to calibrate the parameters governing health expenditure shocks and the out-of-pocket function. We then calibrate the income process, preference, and haircut parameters to match several features of credit card debt in the data.

Health expenditure and insurance parameters. We calibrate the mean log expenditure and its variance to match the distribution of annual medical expenditure of families in the MEPS data, which covers the 2000-2017 period. This results in a mean expenditure of 8% of median income and a variance of 2.62. We present the calibrated distribution relative to the data one in Figure 6. The calibrated parameters imply that a medical expenditure one s.d. above the average equals 40% of median income. Recall that the expenditure shocks, both in the data and in the model, are not the amounts that households have to pay out-of-pocket.

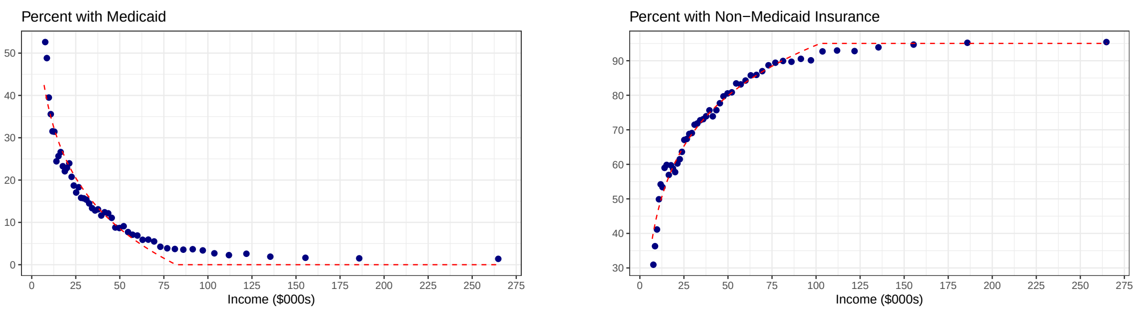
Figure 6: Distribution of annual medical expenditure



Notes: Data source - Medical Expenditure Panel Survey (MEPS).

The MEPS dataset contains also information on households' income, insurance type, and out-of-pocket expenditures. To construct the out-of-pocket share as a function of income we proceed in two steps. First, we split insurance types into three categories: (i) Medicaid, (ii) uninsured, and (iii) other insurance. We approximate the share of households insured in each category by income level using a log-linear function. These shares and the log-linear approximation is presented in Figure 7. Second, we compute the average out-of-pockets share in each insurance type. The average out-of-pocket share in Medicaid is 6.8%, 27.5% under other insurance types, and 63% for the uninsured. We combine the two steps to have obtain the out-of-pocket share along the income distribution. The advantage of this two-step approach relative to directly estimating the out-of-pocket share along the income distribution is that we can conduct counterfactuals in which we change the share of households under each insurance type.

Figure 7: Health insurance type along the income distribution



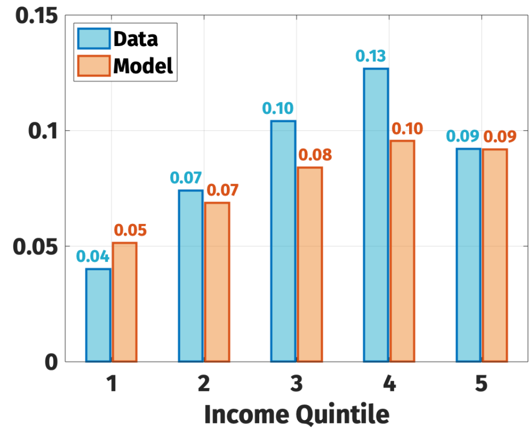
Notes: Data source - Medical Expenditure Panel Survey (MEPS). The figures present binscatter plots of the data in blue, and the model fit in dashed red lines.

Income, preference, and haircut parameters. (*Preliminary*) There are nine remaining structural parameters: the income process parameters $(\lambda_y, \rho_y, \sigma^2_{\epsilon,y})$, preference parameters (β, γ, ξ) and the haircut parameters $(\lambda_\delta, \alpha_1, \alpha_2)$. Our initial calibration targets the distribution of credit card debt across households of different income levels. This results in the following parameterization. An income shock arrives on average every 2.3 years ($\lambda_y = 0.42$). The income shock persistence is 0.88 (ρ_y) and the volatility of the innovation is 7.3% ($\sigma^2_{\epsilon,y}$). The calibrated discount rate is 0.92 (β), which induces households to borrow. The disutility of delinquency is 0.34 (ξ), and the coefficient of relative risk aversion is 3 (γ). Finally, the annual probability of a haircut is 0.92 (λ_d), and the shape parameters of the Beta distribution of haircuts are 1.7 and 9 (α_1, α_2).

3.5 Equilibrium properties

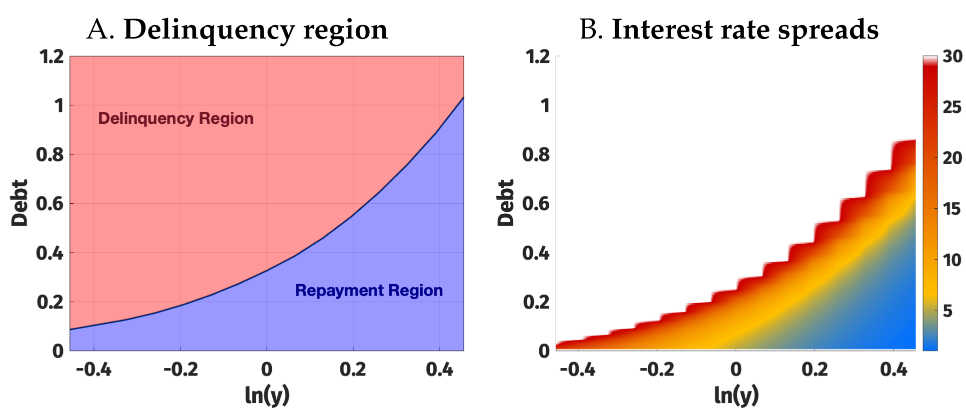
We solve the model globally, and compute the stationary distribution across income and debt levels. Panel A of Figure 9 presents the regions of the state space where households choose to repay or renege on their debt obligations. In general, lower income implies a lower debt threshold, above which households do not repay their debt. Because the utility function is concave, low-income households are more tempted not to repay their debt and increase their contemporaneous consumption. As a result, low-income households cannot maintain a high level of debt.

Figure 8: Credit card debt along the income distribution



Notes: Data source - Panel Study of Income Dynamics (PSID)

Figure 9: Equilibrium properties



Notes: This figure presents the regions where households choose to repay their debt or go delinquent.

The probability of delinquency affects the interest rate spreads households face. Panel B of Figure 9 presents the interest rates spreads households face in equilibrium. The horizontal axis is the current income level of the households and the vertical axis represent the debt obligations promised to be repaid in the following period. Because high-income households are less likely to renege on their debt obligations, they face lower interest rate spreads. In a similar fashion, low-income households face very high interest rate spreads.

The interest rate schedule faced by low-income households effectively limit their access to credit. Policies that reduce the delinquency probability of these households expand their credit access by lowering these interest rate spreads. We now turn to study the effects of one such policy - the expansion of Medicaid.

4 The Effect of Social Health Insurance on Household Debt and Welfare

In this section we study how different health insurance policies shape the distribution of debt across households in the economy, and study their welfare implications. We start by studying the channels through which health insurance policy can affect households' accumulation of debt. We then study the effect of Medicaid expansion in our model. The policy broadens Medicaid health insurance and increases the share of insured households by 1.56%. This is the increase we identified Medicaid expansion had in our state-level empirical analysis.

4.1 Theoretical analysis

We model health insurance as a change in the out-of-pocket share of medical expenditure households of different income levels face, $o(y)$. A more generous health insurance policy corresponds to a reduction in the out-of-pocket share different households pay for medical shocks.

Health insurance policy affects households' accumulation of debt in several ways. The direct effect of more generous health insurance is increasing households' disposable income. Households can achieve the same consumption levels while borrowing less. Therefore, the direct effect of health insurance is a reduction in debt levels. To study the indirect channels, consider the household's optimality condition with respect to debt accumulation, which is given by

$$u'(c)\frac{\partial\left(q(b',y)b'\right)}{\partial b} = \beta\mathbb{E}\mathbb{1}_{V^r \geq V^d} u'\left(c(b'+o(y')m',y')\right) + \beta\mathbb{E}\mathbb{1}_{V^r < V^d} V_1^d\left(b'+o(y')m',y'\right) \quad (9)$$

The household equated the benefits from borrowing (LHS) to the costs of borrowing (RHS). By increasing debt obligations, b', the household increases its current funds by $\frac{\partial(q(b',y)b')}{\partial b}$. Note that the household internalizes how its borrowing decision affects the interest rate it pays on debt. There are two potential costs of borrowing. If the household repays its debt in the following period ($V^r \geq V^d$), the marginal cost of debt obligations is simply the marginal utility of consumption. Alternatively, if the household goes delinquent ($V^d > V^r$), the household's cost of debt obligations are $\frac{\partial V}{\partial \tilde{b}}$.

The first indirect channel through which social insurance affects household debt is a reduction in the *precautionary savings motive*. A reduction in $o(y')$ reduces the volatility of out-of-pocket medical expenditure, o(y')m'. This results in a lower volatility of future consumption. If the utility function features prudence ($u'''(\cdot) > 0$), as it does in our calibration, then such reduction in volatility results in a smaller cost of borrowing. The reduction in the marginal cost of borrowing induces households to take on more debt. That is, through the precautionary savings channel, social insurance raises household debt levels.

The second indirect channel is the *debt aversion* channel. Borrowing is more costly in the states where households repay their debt obligations. Debt is less costly in the delinquency state as households expect to pay it only in the future, and potentially after a haircut. More generous insurance policy raises the probability of repayment, $\mathbb{E}\mathbb{1}_{V^r \geq V^d}$, as medical expenditures that would have pushed households into delinquency are now partially insured. The increase in the repayment probability increases the cost of borrowing, as households are more averse to debt when they are more likely to repay it. Therefore, through the debt aversion channel, social insurance reduces household debt levels.

Both the precautionary savings motive and the debt aversion channels do not depend on lenders changing their behavior. That is, they do not depend on the supply side of loans. We refer to the combined effect of these two channels as the *credit demand* channel.

The final indirect channel is the *credit supply* channel. The reduction in delinquency probability induces lenders to lower interest rate spreads, $q(b', y)$. This raises the benefits from debt obligations b'. For each unit of consumption promised to be repaid in the following period, households receive more units of consumption in the current period. This induces households to increase their debt obligations. So, through the credit supply channel, social insurance increases household debt levels.

Overall, the effect of social insurance on the aggregate level of household debt is ambiguous. The direct channel as well as the debt aversion channel lead to a reduction in debt levels, while the precautionary savings motive and the credit supply channels lead to an increase in debt levels. We now turn to study the expansion of Medicaid in our model, and quantitatively asses the strength of the different channels.

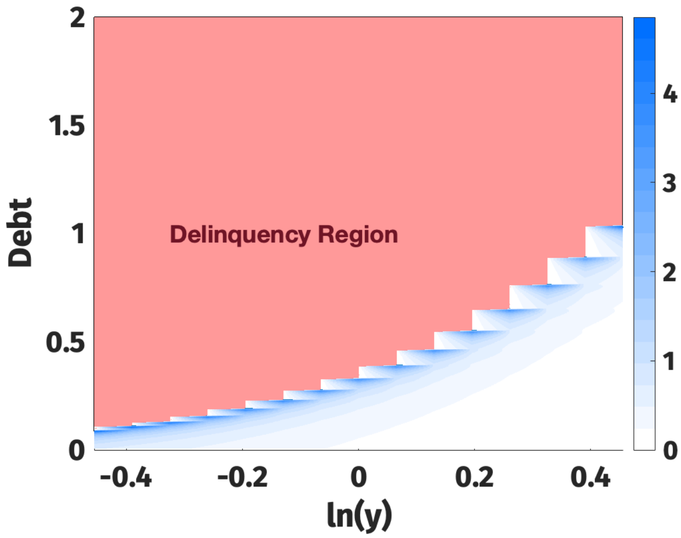
4.2 Medicaid expansion

Our benchmark specification assumes that the share of households covered by Medicaid insurance is log-linear in income. Low-income households are more likely to be covered by Medicaid. In this section we consider a policy that mimics the expansion of Medicaid as part of the Affordable Care Act in the data. We change the intercept of the Medicaid coverage function, so that an additional 1.56% of households are covered by Medicaid. This magnitude corresponds to our empirical estimate for the effect of Medicaid expansion on the share of insured households. We solve the model and compute the stationary distribution. We assume out-of-pocket share of the Medicaid policy remains unchanged at a rate of 6.8%.

The expansion of Medicaid reduces the delinquency probability of households, as health expenditure shocks that would push households into the delinquency region are not partially covered by their health insurance. This results in lower interest rate spread in equilibrium. The reduction in equilibrium spreads as a result of the policy is plotted in Figure 10. Households who are close to the delinquency region are now facing interest rate spreads up to 5 percentage points lower relative to the interest rate spreads before the expansion of Medicaid.

The reduction in interest rate spreads affects households who tend to be close to the default frontier. So, it primarily affects the behavior of low- and medium-income households.

Figure 10: Reduction in interest rate spreads due to policy



Notes: This figure presents the reduction in equilibrium interest rate spreads in percentage points.

Table 6: Decomposing the effect of Medicaid expansion

Not budget neutral

	Total impact	Direct impact	Credit demand	Credit supply
Credit card debt	**+1.32%**	**-1.14%**	**-1.43%**	**+3.9%**
Total welfare	**+0.18%**	**+0.15%**	**+0.0001%**	**+0.03%**

Budget neutral

	Total impact	Direct impact	Credit demand	Credit supply
Credit card debt	**+1.63%**	**-1.00%**	**-1.25%**	**+3.88%**
Total welfare	**+0.09%**	**+0.06%**	**+0.0001%**	**+0.03%**

High income households, who often do not hold any debt, are less affected by the expansion of Medicaid.

The expansion of Medicaid in our model leads to a long-run increase of 1.33% in credit card debt. Consistent with our empirical findings, the overall impact on credit card debt is positive. While the expansion of Medicaid reduces the amount of medical debt, its total impact on household debt is also positive. The policy increases household debt by 0.86%.

Our model allows us to decompose the effect Medicaid expansion has on credit card debt to the three theoretical channels we laid out in the previous subsection: the direct channel, the credit demand channel, and the credit supply channel. The decomposition results are summarized in the top panel of Table 6.

To get the direct impact of Medicaid expansion, we keep the debt pricing schedule as well as policy functions of households as they are prior to the expansion. The only change we consider here is the change to the out-of-pocket share of medical expenditure, $o(y)$. The direct impact of the policy on debt is a decline of 1.14% in the aggregate level of credit card debt.

The credit demand channel is computed by keeping the debt pricing schedule at its levels prior to the expansion of Medicaid but allowing households to re-optimize given the original pricing schedule. The credit demand channel reduces the aggregate level credit by an additional 1.43%. This implies that the debt aversion channel is much stronger than the precautionary savings channel.

Finally, the credit supply channel is computed by updating also the debt pricing schedule so that financial intermediaries make zero profits. The reduction in interest rates, which can be seen in Figure 10, leads to a large increase in credit card debt. The credit supply channel raises the aggregate level of credit card debt by 3.9%, dominating over the cumulative effect of the direct and the credit demand channels.

Our model also allows us to study the welfare impact of the policy. If the policy is not budget-neutral, all households will benefit from it. The model is useful in studying how important are the different channels in driving welfare, as well as comparing the welfare benefits across different households. Following Chatterjee et al. (2007), we calculate welfare by computing what is the percentage drop in consumption in all periods following the expansion of Medicaid which would make households indifferent between implementing and not implementing the policy. On average, the policy leads to a welfare benefit of 29 basis points in consumption equivalent terms. That is, the average household in the economy is willing to incur a 0.29% drop in consumption in all periods so that Medicaid expansion remains in place. In terms of wealth, on average, households are willing to pay a one-time payment of 94% of the median income in order to implement an expansion of Medicaid starting from the following period.

Our model allows us to decompose the effects of the Medicaid expansion to the three channels. The results are presented in the second row of Table 6. The reduction in out-of-pocked medical expenditure accounts for the majority of welfare benefits. This is expected - we assumed households do not pay any cost to implement the policy. The direct channel accounts for 83% of the welfare gains.

The credit demand channel has only negligible welfare effect. This is simply the envelope theorem. Households were optimizing their borrowing decision prior to the policy. So adjusting their borrowing decision following the policy can only lead to second-order welfare gains.

Unlike the credit demand channel, the credit supply channel leads to sizable welfare benefits, 0.03% out of a total of 0.18%. That is, 17% out of the total welfare gains of the expansion of Medicaid can be attributed to the reduction in interest rate spreads households pay. This result suggests policy makers should take into account the impact of social insurance policies on the supply of credit. Disregarding the effect of social insurance on the supply of credit understates its welfare benefits.

Finally, we consider an alternative in which the policy is financed through a uniform tax levied on all households. Medicaid expansion reduces uncompensated medical care. We choose the uniform tax rate so that the tax revenues are equal to the cost of enacting the policy net of the reduction in uncompensated medical care.[13] The resulting uniform tax is 0.08%. We find that 66% of the expansion of Medicaid is financed through a reduction in uncompensated medical care. The bottom panel of Table 6 presents the effect of the budget-neutral Medicaid expansion on debt and welfare.

The aggregate impact on credit card debt is larger under the budget-neutral policy. As households disposable income is lower due to the tax, their debt level goes up. The direct welfare benefits from the program falls from 0.15% to 0.06%. Note, however, that the welfare benefits attributed to the credit supply channel remains approximately the same. The credit supply channel amplifies the direct welfare benefits of Medicaid expansion by 50%.

5 Conclusion

This paper investigates how social insurance affects household debt. We exploit the staggered expansions of Medicaid as a source of quasi-experimental variation in households' access to health insurance. Using an instrumental variables strategy, we estimate that a one percentage point increase in health insurance coverage leads to a 1.4% increase per capita credit card debt. Our estimates imply that expanding Medicaid (to non-elderly adults with no dependents) on average increased credit card debt by 2.2% ($20.4 billion dollars in terms of aggregate debt).

Our paper builds on prior empirical work by focusing on general equilibrium channels and both macroeconomic and distributional outcomes. We develop a heterogeneous-agent model where households face permanent and transitory differences in their income, health expenditure shocks, and incomplete markets. Households incur debt both by choosing how much to borrow on a credit card and as a result of health expenditure shocks. Using the model, we explore the impact of expanding health insurance.

While insurance can help households avoid taking on debt when experiencing adverse events like job loss and illness, it can also increase borrowing by enhancing households' financial resilience. Insurance softens the financial impact of adverse events, making it easier to avoid default and/or states of the world in which consumption is extremely low. In doing so, insurance can dampen households' precautionary savings motive and raise lenders' expected returns, increasing both credit demand and supply. Our empirical evidence suggests that these credit demand and supply channels dominate the direct impact on borrowing in equilibrium. Our model is also able to match this finding. Our findings suggest that institutions like social insurance can have an important impact on the quantity and distribution of household debt as well as welfare.

[13] Uncompensated medical care is defined as the sum of unpaid out-of-pocket medical bills net of the market value of medical debt due to unpaid medical bills.

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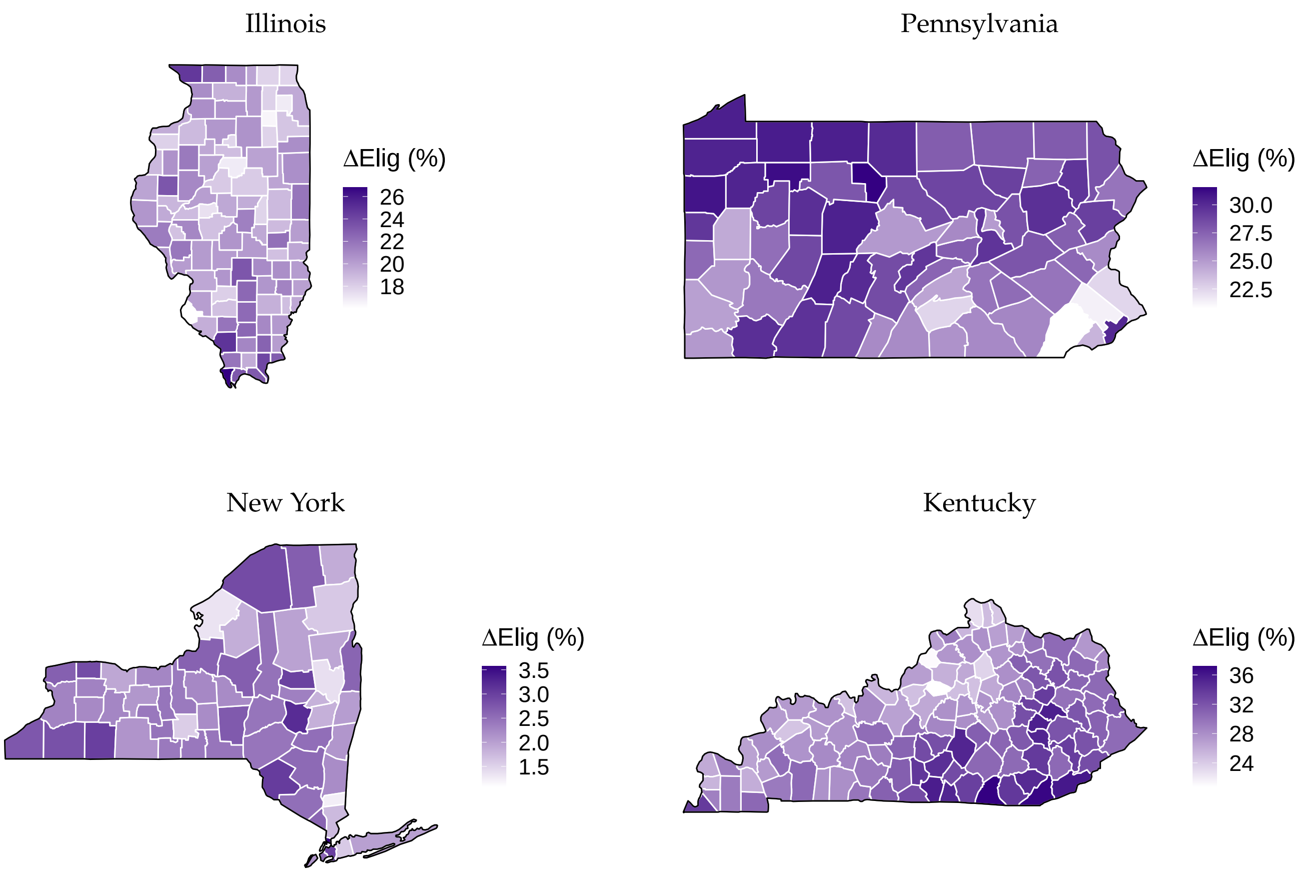
Appendix

A Additional Figures

Figure A.1: County-Level Variation in Impact of Expansions on Eligibility



Notes: These maps display the change in the share of households eligible for Medicaid. The change is measured from the year prior to the state's expansion of Medicaid to the year of the expansion.

B Eligibility Estimation

This appendix describes how we generate a measure of Medicaid eligibility at the zip $\times$ year level.

Data: We use the following data sets from 2009 to 2016:

1. IRS SOI: ZIP-level individual income tax statistics
2. KFF: Medicaid eligibility limits
3. ACS: joint distribution of income and household-size

4. KFF: Medicaid expansion date data

B.1 Estimand

We want estimates of the fraction of adults eligible for Medicaid in year t and zip z. Let E denote the event a household is eligible for Medicaid. Denote the probability that a household is eligible in (t, z) by $P_{tz}(E)$. $P_{tz}(E) = P(E|t, z)$. The probability that a household of size n is eligible depends on the probability that their income is below the relevant cutoff c^n_{tz}. We can write out the probability above into the sum of probabilities for these different cases using the law of iterated expectations:

$$P_{tz}(E) = P_{tz}(y \leq c) = \sum_{n=1}^{N} P_{tz}(y \leq c^n_{tz}|c = c^n_{tz})P(c = c^n_{tz})$$

where y is income and c^n_{tz} is the eligibility cutoff for a household of size n in $\{z, t\}$. We can rewrite each term using Bayes' rule to get:

$$P_{tz}(y \leq c^n_{tz}|c = c^n_{tz})P(c = c^n_{tz}) = P_{tz}(c = c^n_{tz}|y \leq c^n_{tz})P(y \leq c^n_{tz}).$$

The first term is the probability that a household is of a given size:

$$P_{tz}(c = c^n_{tz}|y \leq c^n_{tz}) = P_{tz}(\tilde{N} = n|y \leq c^n_{tz}) = g_{tz}(n|y \leq c^n_{tz})$$

where g_{tz} is the probability mass function of a household size conditional on income being below the relevant threshold. The second term $P(y \leq c^n_{tz})$ is the probability that the household's income is below the threshold. Let $F_{tz}(\cdot)$ denote the cumulative distribution function of income in $\{t, z\}$. Then

$$P(y \leq c^n_{tz}) = F_{tz}(c^n_{tz}).$$

Household Size Notation: Households of size two may be comprised of either a head and a dependent or a head an a non-dependent (e.g., a parent and child versus a childless couple). The eligibility thresholds can differ across these situations. To capture both, we use 2 to indicate a household with a head an a dependent and 2^* to indicate a two-person household with no dependents. Let n denote household size, and we write $n \in n\{1, 2, 2^*, 3, 4, ..., N\}$, where N is the largest observed household size.

Note on Cutoffs: Income cutoffs vary over time due to changes in the threshold and federal poverty line. They also differ across states, specifically Alaska and Hawaii generally have higher thresholds in each year.

B.2 Estimation

We estimate $P_{tz}(E)$ using the following steps:

1. We procure the number of tax returns and annual gross income by income bins for each zip code and year using IRS SOI.

2. Then, we interpolate the CDF $\hat{F}_{tz}(\cdot)$ of income between the known bins. With that, we estimate $\hat{F}_{tz}(c^n_{tz})$ where c^n_{tz} is obtained from medicaid eligibility limits. Note that this equals the second term of the probability, $P(y \leq c^n_{tz})$. We generate this for $n \in N$ household sizes where N is defined above.

3. We keep one observation per zip and year.

4. We use the ACS data to calculate $P(\tilde{N} = n | y \leq c^n_{tz})$ for each n We do this using income and household size information available by zip code and year. Note that this equals the first term of the probability, $g_{tz}(n | y \leq c^n_{tz})$.

5. We can calculate the probability that a household of size n is eligible for medicaid by multiplying the first and second terms for each n.

6. Then, $P_{tz}(E)$ is equal to the sum of the probabilities calculated in the step above.

C Results from Alternative Empirical Analyses

C.1 State-Level Analysis of Credit Card Borrowing

C.1.1 Empirical Strategy: Instrumental Variables

The goal of our analysis is to estimate the causal effect of health insurance coverage on credit card borrowing. Specifically, we estimate the following model:

$$\ln(\text{CC}_{s,t}) = \text{Insured}_{s,t}\beta + X_{s,t}\gamma + \theta_s + \tau_t + \varepsilon_{s,t} \tag{10}$$

where $\text{CC}_{s,t}$ is credit card debt per capita, $\text{Insured}_{s,t}$ is the share of the population with health insurance, and $X_{s,t}$ is a vector of controls. The indexes s and t denote state and time, respectively. Our coefficient of interest is β. Directly estimating (10) directly with OLS would likely yield biased estimates understating the true value of β. We anticipate a negative bias because credit card borrowing is countercyclical – people use it to smooth out shocks in downturns – while insurance coverage is procyclical – likely due to the widespread reliance on employer-provided insurance.[14]

Identification. To identify the causal effect of insurance coverage, we use an instrumental variables strategy. For each observation we construct an indicator for whether or not state s has expanded Medicaid as of time t (denoted $1[\text{Expanded}]_{s,t}$). We instrument for the insured

[14] In our sample, health insurance coverage is positively correlated with GDP (both measured at the state-level), with a correlation coefficient of 0.10. Credit card debt is negatively correlated with GDP, with a correlation coefficient of -0.05. The correlations strengthen and retain the same sign after partialing out state and time fixed effects.

share of the population with this indicator in a two-stage least squares (TSLS) estimation. Formally, our first stage is

$$\text{Insured}_{s,t} = 1[\text{Expanded}]_{s,t}\pi + X_{s,t}\widetilde{\gamma} + \widetilde{\theta}_s + \widetilde{\tau}_t + \eta_{s,t}. \tag{11}$$

This approach exploits the staggered timing of the Medicaid expansions to obtain plausibly exogenous variation in insurance coverage. The staggered timing means that we can use time fixed effects to absorb macroeconomic trends, such as the recession and recovery, that also affect borrowing and insurance coverage. Additionally, by using state fixed effects we can net out the effect of any persistent cross-state differences related to borrowing and insurance coverage. The key identifying assumption, the exclusion restriction, is that expanding Medicaid only affects credit card debt through health insurance coverage. In practice, this assumption requires that the timing of expansions is unrelated to other events affecting credit card debt.

Data. We build an annual state-level panel dataset, where credit card debt per capita and insurance coverage rates are our primary variables of interest. The panel includes all 50 states and DC. The sample spans 2003 to 2017, making for 765 observations in total. The American Community Survey (ACS) is the underlying data source for our state-level measures of the insured population share. To measure credit card debt per capita, we use the Federal Reserve Bank of New York's state-level aggregates of their Consumer Credit Panel (CCP). The CCP's credit aggregates are calculated from a 5% random sample of individual-level credit bureau data. We obtain state-level control variables from the ACS and National Income and Product Accounts (NIPA). Our control variables are the unemployment rate, log population, log house prices, annual house price growth, and annual GDP growth (measured at the state-level).

C.1.2 Results: The Effect of Health Insurance Coverage on Debt

We find that increased health insurance coverage leads to more credit card debt per capita. Table C.1 presents estimation results for the second and first stage, as well as OLS estimates. Our preferred specification (column 4) implies that a one percentage point increase in the insured share of the population leads to 1.41 percentage point increase in credit card debt per capita.

Our preferred specification is column 4, which includes a variety of controls as well as state and time fixed effects. Including state fixed effects helps absorb persistent differences across states that are related to both insurance coverage and credit card borrowing. The time fixed effects account for time-varying factors like the recession and recovery that also impacted credit card debt and insurance coverage.

An especially useful control is state-level GDP growth because it helps address a measurement limitation in the CCP data. The CCP's measure of credit card debt reflects credit card balances, which includes both revolving and non-revolving balances. Revolving balances reflect actual borrowing – i.e. unpaid balances on which the borrower pays interest. Total balances might conflate spending and borrowing. Controlling for state-level GDP helps account for state-level changes in aggregate spending, which means our estimates more likely reflect a response driven by borrowing rather than spending.

Table C.1: Effect of Insurance Coverage on Credit Card Borrowing

	TSLS				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2nd Stage: outcome = $\ln(CC)_{s,t}$				outcome = $\ln(CC)_{s,t}$			
$\text{Insured}_{s,t}$	-2.60***	-1.79***	2.69***	1.41***	-2.00***	-1.05***	-0.76***	0.06
	(0.29)	(0.31)	(0.78)	(0.35)	(0.15)	(0.16)	(0.14)	(0.09)
	1st Stage: outcome = $\text{insured\%}_{s,t}$							
$1[\text{Expanded}]_{s,t}$	5.05***	3.37***	2.61***	1.56***				
	(0.31)	(0.20)	(0.38)	(0.19)				
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE			✓	✓			✓	✓
State FE		✓		✓		✓		✓
Stage 1 F	262.05	287.67	46.97	65.8				
Observations	765	765	765	765	765	765	765	765

Notes: Time-varying, state-level controls include the unemployment rate, log(population), log(house prices), annual house price growth, and GDP growth. All nominal variables and their growth rates are computed in real 2010 dollars. Coefficients are scaled so that 2nd stage estimate describes approximately the percent change in credit card debt associated with a 1% change in the insurance rate. The 1st stage coefficient reflects the percentage point increase in insurance coverage associated with adopting the Medicaid expansion. Statistical significance: 0.10^{+}, 0.05*, 0.01*, 0.001***.

In the first stage of the preferred specification, we estimate that expanding Medicaid increased the insured share of the population by 1.56 percentage points on average. Combined, the first and second stage estimates imply that expanding Medicaid increased credit card borrowing by 2.2 percentage points. The first stage F-statistic is 65.8 in the preferred specification, which is well above the threshold of 10, indicating that bias due to weak instruments is unlikely. Additionally, the analogous OLS estimate is 0.06, which is much smaller than our TSLS estimate of 1.41. This suggests that if there is bias due to weak instruments, if any our estimate would understate the effect of insurance on borrowing. The 1.56% increase in coverage is smaller than the 6.4% average change post-expansion visible in Figure 3. The estimated growth in coverage induced by expanding medicaid diminishes as we add state and time fixed effects (columns 1-4 in Table C.1). This is because states that opted to expand Medicaid on average had a smaller uninsured population. Additionally, insurance was generally growing over this time period in response to other incentives such as the ACA tax penalty for lacking health insurance.

The point estimate implies expanding Medicaid had an economically significant effect on credit card debt. By means of a back-of-the-envelope calculation (assuming a uniform treatment effect across debt levels), the estimated 2.2 percentage point increase corresponds to a \$20.4 billion increase in credit card debt.[15] The estimate implies that the overall 6.4% rise in insurance coverage following the expansions increased credit card debt 9.02%, corresponding to a \$83.65 billion increase in credit card debt.

Our finding of a positive effect on credit card borrowing suggests that the credit demand and supply channels dominate the "direct" effect of increased health insurance. Insurance incentivizes borrowing through a credit demand channel by reducing households' precautionary savings motives. Additionally, insurance can increase credit supply by reducing households' default risk, which in turn increases creditors' expected returns and incentivizes lending. Together, these two forces result in a positive relationship between borrowing and insurance coverage. In contrast, the "direct" effect on households using insurance likely implies a negative relationship between borrowing and insurance coverage. When insurance reduces the share of medical expenses borne by households, these directly affected households may now incur less medical and credit card debt than they otherwise would have.

C.2 County-Level Analysis of Medicaid Eligibility and Household Debt

C.2.1 Empirical Strategy: Treatment-Intensity Difference-in-Difference

There are several important limitations to empirical strategies using only the state-level variation in the timing of Medicaid expansions, motivating a new empirical strategy that we introduce here. Inference can be more challenging as the aggregate nature of a state-level shocks leads to less variation across households. Additionally, pre-existing differences in states' economies and Medicaid programs resulted in Medicaid expansions under the ACA having significantly different impacts on Medicaid eligibility. Rich within-state heterogeneity in treatment underlies the binary state-level adoption indicator. This granular variation in treatment intensity can improve statistical precision and support heterogeneity analyses estimating treatment effects in sub-populations. In terms of identification, bias can arise in state-level analyses when the timing of states opting into Medicaid in non-random or correlated with other economic events. Many of the later Medicaid expansions occurred after the election of a Democratic governor or by ballot measure, which can coincide with other major state-level changes in policies.

Approach. These limitations motivate our novel use of a treatment-intensity difference-in-difference approach to estimate the causal effect of Medicaid Eligibility on household debt. This approach exploits rich heterogeneity in the impact of Medicaid expansions on eligibility. The granular nature of this data also makes it possible to include state-year fixed effects, which help net out the effect of other state-level trends that affect household borrowing.

This difference-in-difference strategy exploits heterogeneity across counties and expan-

[15] This is calculated relative to the aggregate amount of credit card debt in 2019 of \$927 billion.

sions in the impact of adopting the Medicaid expansion. Geographic variation in the change in the eligible share of the population was driven by differences in states' pre-ACA Medicaid income limits and differences in the distribution of income within locations. Expanding under the ACA required states to raise the income eligibility limit to 138% of the federal poverty level for all adults aged 64 or less. This primarily impacted adults without dependents, who generally faced stricter income limits prior to the expansion. All else equal, counties in states with a lower pre-ACA limit (for adults with no dependents) experienced a larger rise in the eligible population. The impact of expansions also differed within and across states due to variation in distribution of income among low-income households. Counties with more households whose income fell between the pre and post ACA eligibility limits, all else equal, experienced a larger rise in eligibility.

Our approach compares borrowing in counties with larger versus smaller changes in eligibility before and after expanding Medicaid. We estimate

$$\mathrm{DTI}_{c,t} = 1[\mathrm{Adopted}_{s,t}]\alpha_1 + \Delta\mathrm{Elig}_c\alpha_2 + \Delta\mathrm{Elig}_c \times 1[\mathrm{Adopted}_{s,t}]\beta + \kappa_c + \tau_t + \xi_{s,t} + \varepsilon_{s,t} \quad (12)$$

where $\mathrm{DTI}_{c,t}$ is the ratio of household debt-to-income (DTI) in county c in year t. The variable $1[\mathrm{Adopted}_{s,t}]$ indicates whether state s has adopted the Medicaid expansion as of year t. Our measure of treatment intensity is $\Delta\mathrm{Elig}_c$, which denotes the change in the percentage of the population eligible for Medicaid, induced by the Medicaid expansion, in county c. We estimate this specification using OLS.

The coefficient of interest is β, which captures the effect on borrowing of a $\Delta\mathrm{Elig}_c$% increase in the Medicaid-eligible population. This specification exploits variation in both the timing and impact of the Medicaid expansions. The county fixed effect nets out persistent differences in borrowing across counties that experienced high versus low changes in eligibility. The time fixed effect accounts for impact of macroeconomic trends on borrowing. A key strength of this specification is that we can also include state-year fixed effects, which absorbs the effect of other time-varying state-level factors influencing household borrowing.

Identification. Our approach to identification makes use of both variation in the timing and intensity of the change in Medicaid eligibility induced by the adoption of expansions. Variation in the eligible population share comes from two sources. First, state-level differences in pre-expansion Medicaid income eligibility thresholds resulted in greater *rises* in eligibility where pre-expansion threshold were *lower*. Adopting the expansion brought states up to a common threshold of 138% of the federal poverty level. Second, variation in the distribution of income among low-income households also shapes the treatment intensity of Medicaid expansions. Counties with a larger mass of low-income households concentrated just under the 138% threshold, all else equal, experienced larger increases in eligibility.

Additionally, by estimating the *change* in the relationship between eligibility and borrowing before versus after a state's expansion, we exploit variation in the timing of treatment. The difference-in-difference aspect of the regression means that we can account for persistent differences in places that would tend to have a larger versus smaller treatment effects induced by expanding Medicaid. Because we have within-state variation in treatment intensity, we can compare households in the same state policy environment but with different exposure to one specific policy change: Medicaid eligibility.

The key identifying assumption for this empirical strategy is that household borrowing would have evolved in parallel – across locations with high versus low changes in eligibility – if Medicaid had not expanded. Intuitively the identifying assumption boils down to treatment intensity being uncorrelated with other factors *changing* at the time of the expansion. The identifying assumption would be violated if another event coinciding with expansions systematically affected counties with high versus low changes in eligibility differently.

Data. Our measure of household DTI is calculated as the county-level sum of credit card, residential mortgage, and auto debt divided by the sum of income. We obtain this data from the Board of Governors of the Federal Reserve System.[16] To calculate our treatment intensity measure we use data on income and Medicaid eligibility rules. We obtain Medicaid income eligibility limits from the Kaiser Family Foundation (KFF).[17] To calculate eligibility, we use data on the distribution of income within ZIP codes from the US Internal Revenue Service's Statistics on Income (IRS SOI).[18]

Summary Statistics. Table C.2 presents county-level summary statistics. In the average county, 18.4% of households are eligible for Medicaid while 22.9% of the population is enrolled. The enrollment figure is higher because the denominator is population, and households enrolled in Medicaid are more likely to have children (making their households larger than the average). The average increase in the eligible share of the population, from the year before to the year of the expansion, is 10.4 percentage points.

The impact on eligibility varied significantly; its standard deviation was 11.5 percentage points. Compared to the average increase of 10.4%, the median rise was 2.6%. Appendix Figure A.1 displays county-level maps of changes in the eligible population for several states. Household debt averages 174.8% of income, and also varies significantly across counties (with a standard deviation of 87.3%).

[16]Source: https://www.federalreserve.gov/releases/z1/dataviz/household_debt/county/map. The county-level debt measures are calculated from individual-level data available in the Federal Reserve Bank of New York's Consumer Credit Panel.

[17]Data on income limits is available for parents from 2002-2020 at: https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-parents. Data on income limits for adults that are non-elderly, non-disabled, and with no dependents is available for 2011-2020 at: https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-other-non-disabled-adults.

[18]The ZIP-level income data are available at: https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.

Table C.2: County-Level Summary Statistics

Variable	Mean	SD	25^{th}	50^{th}	75^{th}	*N*
Pop. Enrolled in Medicaid (%)	18.4	6.6	13.9	17.9	21.9	9,741
Pop. Eligible for Medicaid (%)	22.9	11.0	10.2	26.9	31.7	12,991
ΔElig_c (%)	10.4	11.5	0.0	2.6	21.5	12,886
DTI (%)	174.8	87.3	116.6	162.0	211.8	12,978
Average AGI ($000s)	65.7	24.2	49.9	60.1	72.4	12,991

Notes: The first two variables are the share of the county population enrolled in and eligible for Medicaid (respectively). The next variable, ΔElig_c is the change in the share of county population eligible for Medicaid from the year prior to the year after expansion. DTI is the ratio of household debt (mortgage, auto, and credit card) to income. Average AGI is the county-level average of households' adjusted gross income (AGI). Nominal variables are CPI-adjusted to be in terms of 2010 dollars. All statistics are calculated using population weights, where population is measured using the number of tax returns filed in the county.

C.2.2 Results: The Effect of Medicaid Eligibility on Household Debt

We find that expanding Medicaid eligibility increases household debt. Table C.3 reports results from estimating the treatment-intensity DID specified in equation (12). Our preferred specification (column 3) includes state-year and county fixed effects. The point estimate of column 3 implies that a one percentage point increase in the share of the population eligible for Medicaid leads to a 0.85 percentage point rise in households' DTI. Dividing this point estimate by the average DTI of 174.83% implies that a one percentage point rise in the eligible population share leads to a 0.49% increase in household debt. The positive effect of Medicaid eligibility on household debt is consistent with either increased credit supply or a reduced precautionary savings motive (and increased credit demand) resulting from households' improved financial resilience.

Take-Up. To what extent does a rise in Medicaid eligibility lead to a rise in enrollment? Take-up can be less than 100% simply due to low-income households already having insurance, for example, by receiving it through an employer and or as a young adult through a parent's insurance. Additionally, stigma, inattention, misperceived ineligibility, and complexity in the sign-up process can also deter participation.[19]

We employ our treatment-intensity DID strategy to estimate the average take-up rate of the Medicaid expansions under the ACA. We obtain county-level data on Medicaid enrollment from the American Community Survey (ACS). An estimate of a positive effect, especially one similar to prior estimates of take-up, helps validate our empirical strategy. Table C.4 reports our estimates. Column 3's estimate implies a take-up rate of 19%: for every 100 newly-eligible people, 19 enrolled in Medicaid. This estimate is similar in magnitude to estimates from expansions to pregnant women in the 1980s (Currie and Gruber, 1996) and low-

[19] See for example Aizer (2003); Currie (2004); Baicker, Congdon and Mullainathan (2012); Desmond, Laux, Levin, Huang and Williams (2016); Wright, Garcia-Alexander, Weller and Baicker (2017).

Table C.3: Effect of Medicaid Eligibility on Household DTI

	(1)	(2)	(3)
$\text{Adopted}_{s,t} \times \Delta\text{Elig}_c$	0.27	0.53	0.85*
	(0.18)	(0.54)	(0.43)
$\text{Adopted}_{s,t}$	5.40+		
	(3.03)		
ΔElig_c	-11.80***	-11.92***	
	(2.35)	(2.42)	
$\ln(\text{income}_{c,t})$	-12.84*	-12.72*	-11.69*
	(5.13)	(5.20)	(5.69)
State × Year FE		✓	✓
County FE			✓
Observations	12,873	12,873	12,873
R^2	0.18	0.19	0.97

Notes: The outcome variable is county-level household debt-to-income (DTI) in percentage points. The change in eligibility (ΔElig_c) is scaled in percentage points, so its point estimate correspond to the percentage point change in DTI for a given percentage point change in eligibility. Our county-level measure of income is the (demeaned) log of the average adjusted gross income (AGI) reported in the IRS SOI data. We weight observations by the number of households (measured as the number of tax returns filed in the county each year). All specifications include state and year fixed effects. Standard errors are clustered by county. Statistical significance: 0.10+, 0.05*, 0.01*, 0.001***.

income parents (Busch and Duchovny, 2005) of 34% and 15%, respectively. Multiplying the average change in eligibility (10.4%) by the point estimate implies that the average expansion increased the share of the population enrolled in Medicaid by 1.97 percentage points (an 8.61% rise in enrollees).

Table C.4: Effect of Medicaid Eligibility on Medicaid Enrollment (Take-Up)

	(1)	(2)	(3)
$\text{Adopted}_{s,t} \times \Delta\text{Elig}_c$	0.02**	0.20***	0.19***
	(0.01)	(0.05)	(0.02)
$\text{Adopted}_{s,t}$	-0.76***		
	(0.22)		
ΔElig_c	1.05***	0.93***	
	(0.17)	(0.18)	
$\ln(\text{income}_{c,t})$	-2.60***	-2.62***	-1.24***
	(0.53)	(0.54)	(0.29)
State × Year FE		✓	✓
County FE			✓
Observations	9,667	9,667	9,667
R^2	0.65	0.66	0.99

Notes: The outcome variable is county-level Medicaid enrollment, measured as the fraction of population enrolled in Medicaid (in percentage points). The change in eligibility (ΔElig_c) is scaled in percentage points, so its point estimate correspond to the percentage point change in the Medicaid enrollment for a given percentage point change in eligibility. Our county-level measure of income is the (demeaned) log of the average adjusted gross income (AGI) reported in the IRS SOI data. We weight observations by the number of households (measured as the number of tax returns filed in the county each year). All specifications include state and year fixed effects. Standard errors are clustered by county. Statistical significance: 0.10^{+}, 0.05*, 0.01*, 0.001***.