MEDICAID AND FINANCIAL HEALTH

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ABSTRACT

This paper investigates the effects of the Medicaid expansion provision of the Affordable Care Act (ACA) on households' financial health. Our findings indicate that, in addition to reducing the incidence of unpaid medical bills, the reform provided substantial indirect financial benefits to households. Using a nationally representative panel of 5 million credit records, we find that the expansion reduced unpaid medical bills sent to collection by $3.4 billion in its first two years, prevented new delinquencies, and improved credit scores. Using data on credit offers and pricing, we document that improvements in households' financial health led to better terms for available credit valued at $520 million per year. We calculate that the financial benefits of Medicaid double when considering these indirect benefits in addition to the direct reduction in out-of-pocket expenditures.

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1 Introduction

Health insurance protects households against the financial hardships that result from adverse health shocks and helps them smooth their consumption in times of poor health. According to survey evidence from Hamel et al. (2016), over half of non-elderly adults without insurance have difficulty paying their medical bills, a rate more than double that of consumers with health insurance. These figures suggest that expanding health care coverage may significantly mitigate financial distress faced by consumers, particularly those with lower incomes who may have limited ability to bear the financial burdens that accompany adverse health shocks.

In this paper, we quantify the effect of health insurance on financial health. The existing literature highlights that consumer welfare gains from financial risk protection arise from reductions in the mean and variance of out-of-pocket medical expenses (Zeckhauser, 1970). We argue that, although low-income uninsured individuals pay only a small portion of the cost of their care, the overall benefit of insurance to them may be large. Specifically, we show that indirect effects of unpaid medical bills, through access to credit markets, may be an important factor to consider in establishing the overall value of insurance. Our empirical framework complements previous landmark studies estimating the benefits of insurance (Finkelstein and McKnight, 2008; Finkelstein, Hendren and Luttmer, 2015) by highlighting the impact of unpaid medical bills on the access to and price of credit. Our analysis also suggests that the incidence of unpaid medical bills (uncompensated care) at least partially falls on the low-income uninsured patients themselves, through this indirect *credit channel*.

We evaluate the financial benefits to consumers in the context of the Patient Protection and Affordable Care Act (ACA), which was passed into law in 2010. One of the ACA's marquee provisions sought to expand Medicaid eligibility to all individuals earning less than 138% of the federal poverty level (FPL).[1] While this expansion was intended to apply nationwide, the Supreme Court ruled that the states had to be allowed to decide for themselves whether they would adopt the expanded Medicaid eligibility rules. As a result, only about half the states had signed on when the expansion went into effect in 2014, providing us with quasi-experimental variation in the Medicaid expansion.

Our analysis combines state-level variation from the Medicaid expansion with administrative data from the Consumer Financial Protection Bureau's Consumer Credit Panel (CCP), a nationally representative panel of over 5 million de-identified credit records. An important advantage of this credit panel, when compared to other panels, e.g. Hu et al. (2016), is that it contains information on individual credit obligations (trade lines). In particular, this

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[1] Prior to passage of the ACA, Medicaid eligibility was largely determined by the states, subject to federal mandatory minimum coverage levels. Most eligible individuals were minor children or single parents.

includes whether or not the debt was reported by a medical provider and the date it was credited. As a result, we are able to separately identify unpaid medical bills that are in collection and the dates in which they were credited.

We find that the Medicaid expansion reduced the incidence of newly-accrued medical debt by 30% to 40%, with a disproportionately greater effect for larger medical debts. On average, the reform led to a large annual decline in accrued medical debt of $37 per person, or $900 per treated person, which translates into an overall reduction of $3.4 billion in the two years following the reform. When compared to overall health care utilization and out-of-pocket spending, our estimates indicate that about 50% of unpaid medical bills (uncompensated care) of the uninsured go into collection. Our findings also suggest that collection agencies are able to recover between 10% of the face value over the first two years, providing a financial incentive for health care providers to sell uncompensated medical claims to collection agencies.

The CCP also makes it possible to identify movements into an out-of-repayment delinquency for various debts. We use this to calculate the effects of the policy on delinquency and insolvency. We find that the likelihood of becoming newly delinquent on a debt obligation dropped by 2.1%. For consumers with subprime credit scores, who may be the most susceptible to financial distress, this effect was twice as large. Consequently, we measure substantial improvements in credit scores for individuals in treatment states, relative to control, following the reform. Credit score gains were also disproportionately larger for subprime borrowers, who enjoyed gains over 3 times larger than the average. We further find that the expansion led to about 50,000 fewer bankruptcies among subprime borrowers in the two years following the reform.

Next we look at how improved financial health translates into better credit outcomes. For this purpose we use novel data on direct-mail credit offers from Mintel Comperemedia (Mintel) in conjunction with aggregated lender rate sheets collected by the Fair Isaac Corporation (Fico) to assess potential effects of the policy on the availability and pricing of credit to consumers. This analysis suggests that, following the reform, individuals in adopting states received more offers of credit and at substantially better terms relative to individuals in non-adopting states. To calculate a dollar value of implied interest savings, we simulate a refinancing of debt by individuals in adopting states given improved credit terms estimated using these data. Our estimates suggest large annual interest rate savings, predominantly on credit card debt and personal loans, of about $12 per person, or $280 per treated person. This translates into $520 million in annual savings overall.

Finally, we turn to the effects on consumer welfare. To this end, we model uninsured individuals who derive utility from consumption and face a disutility from leaving medical bills unpaid. Disutility from unpaid medical bills captures costs like worsening credit options, the hassle of dealing with debt collectors, and the risk of legal action taken by creditors. Individuals choose what portion of their medical expenses to leave unpaid, trading off greater consumption with the disutility of not paying their bills. This simple framework helps formalize the notion of an indirect credit channel of insurance by decomposing uninsured's compensating variation (CV) of forgoing medical bills (e.g. insurance) into two distinct components: (1) the direct gains from reduced out of pocket spending and (2) the reduction in disutility from fewer unpaid bills. We quantify these components separately using two alternative approaches that rely on different assumptions.

In the first approach, which we call the direct approach, we simply add our calculated interest savings to the direct benefits of reduced out-of-pocket spending. Using this method, we find that the financial benefits of a mean reduction in medical bills increases by 60% when considering the indirect benefits in addition to reduced out-of-pocket spending. We view this as a conservative estimate of the financial benefits of health insurance since it ignores several other benefits, including a reduction in hassle costs of collections and legal actions.

In the second and more comprehensive revealed preference approach, we calibrate individuals' consumption utility and recover their disutility over medical debt by combining the first order condition with observed optimal repayment decisions of outstanding medical bills. In addition to obtaining closed form expressions of the CV for a mean reduction in medical bills, we implicitly quantify the risk premium and assess the value of risk protection from a reduction in the variance of medical expenditures. The revealed preference approach suggests that the financial benefits of a mean and variance reduction in medical bills more than double when considering the indirect financial benefits of insurance.

Our paper contributes to three main literatures. First, our findings add to a growing body of work studying the link between Medicaid and financial health (Finkelstein et al., 2012; Mazumder and Miller, 2016; Gross and Notowidigdo, 2011; Hu et al., 2016; Sojourner and Golberstein, 2017). In addition to providing new evidence on the effects of insurance on medical debt and financial distress at the national level, and in a policy-relevant context, we view this paper as a systematic assessment of the financial consequences of unpaid medical bills. Combining novel data on consumer debt obligations, credit worthiness, and access to and pricing of credit, we make explicit the connection between unpaid medical bills and financial consequences. We then quantify the significance of this credit channel of insurance

by contrasting interest rate savings with changes in repayments to isolate the net consumer gains in dollars.

Second, our analysis complements a number recent studies on the value of Medicaid (Finkelstein, Hendren and Luttmer, 2015) and the value of public insurance more generally (Kowalski, 2015; Cabral and Cullen, 2016). These studies investigate the overall consumer benefit of public insurance, taking financial and health related benefits into account. In the context of Medicaid, Finkelstein, Hendren and Luttmer (2015) find that beneficiaries value the program by only \$0.2 to \$0.4 per dollar of government spending, mostly stemming from reduced out-of-pocket spending. Our approach is less ambitious as we only focus on the financial benefits of Medicaid insurance. Specifically, as our data is not informative on these, we do not consider changes in health care utilization as uninsured individuals gain Medicaid insurance. Instead, we extend the analysis of financial benefits by adding the indirect benefits from a reduction in unpaid medical bills.

Third, our results shed new light on the incidence of uncompensated care. Several recent studies document the important role of uncompensated care for health care delivery (e.g., (Coughlin, 2014) and (Dranove, Garthwaite and Ody, 2016)). Notably, Garthwaite, Gross and Notowidigdo (2015) document that hospitals act as "insurers of last resort", as the uninsured pay only a small fraction of their medical bills out-of-pocket. However, very little is known about the incidence of uncompensated care. We use trade-line level variation in credits and subsequent repayment of medical debt in collection to study the incidence of uncompensated care. Specifically, we examine the likelihood with which providers seek repayment through third party collections, the rate at which new medical collections are repaid, and how these debts affect low-income uninsured patients through their subsequent interaction with broader credit markets.

The remainder of this paper is organized as follows. We start with a discussion of institutional details surrounding the Medicaid expansion and unpaid medical bills in Section 2. We describe the data in Section 3 and lay out our difference-in-difference approach in Section 4. In Sections 5 and 6 we present our main findings on medical debt and financial distress, respectively. We then examine the impact of improved financial health on credit market outcomes and quantify the dollar value of this benefit in Section 7. Turning to the effects on consumer welfare, we formalize the effects of paid and unpaid medical bills on consumer welfare in Section 8 and present our overall financial benefit estimates in Section 9. Section 10 concludes.

2 Institutional Details

2.1 The Medicaid Expansion

Signed into law in 2010, the Patient Protection and Affordable Care Act (ACA) was one of the most sweeping health care reforms in U.S. history. Among its most important and controversial provisions was its expansion of the Medicaid program to include all individuals earning less than 138% of the federal poverty level (FPL). Prior to the reform, Medicaid's principal beneficiaries were low-income children, their parents, as well as people with disabilities. Childless adults between the ages of 18 and 65 were for the most part ineligible to receive insurance in nearly all states. Under the ACA, states either had to agree to this expansion or lose their federal Medicaid funding. Twenty-six states challenged the constitutionality of this provision (and other portions of the ACA) an in its famous decision *NFIB vs. Sebelious* the Supreme Court declared the law to be unconstitutional. Instead, it required that states be allowed to maintain their existing Medicaid programs and retain the option to adopt expanded coverage.[2]

By January 1, 2014, on the eve of the expansion's intended rollout, only 24 states plus the District of Columbia had adopted the measure. Of these, 19 states expanded their Medicaid programs on January 1, 2014. The other 5 states and the District of Columbia expanded their programs prior to this date. Another 7 states would adopt expanded eligibility, but after January 1, 2014. This left 19 non-adopting states as of the date this analysis was conducted. Figure 1 illustrates the states' adoption decisions since passage of the ACA. In our analysis, we exclude consumers in the early- and late-adopting states and focus on trends in the 19 states that expanded Medicaid on January 1, 2014 (which we refer to throughout as the adopting or treatment states) and the 19 non-adopting states (control states).

Health care coverage increased substantially in adopting states. According to the *Medicaid and Children Health Insurance Program (CHIP) Enrollment Report* from January 2016, there were 6.1 million more people enrolled in Medicaid in the 19 adopting states in December 2015 than the average enrollment in these same states from July-September 2013, an increase of 31.8%. In control states, enrollment was up by 2.2 million people or 11.7%.[3] Hence, we attribute a Medicaid enrollment increase of 3.3 million, about 4.1% of the non-

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[2]*National Federation of Independent Business v. Sebelius*, 567 U.S. Also see Kaiser Family Foundation (2012) for more detail.

[3]See https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/monthly-reports/index.html, last accessed on June 26, 2017. Enrollment figure for the control states exclude Maine, for which data are unavailable. The increase in enrollment is concentrated among adults. We find only small changes in CHIP enrollment over this period.
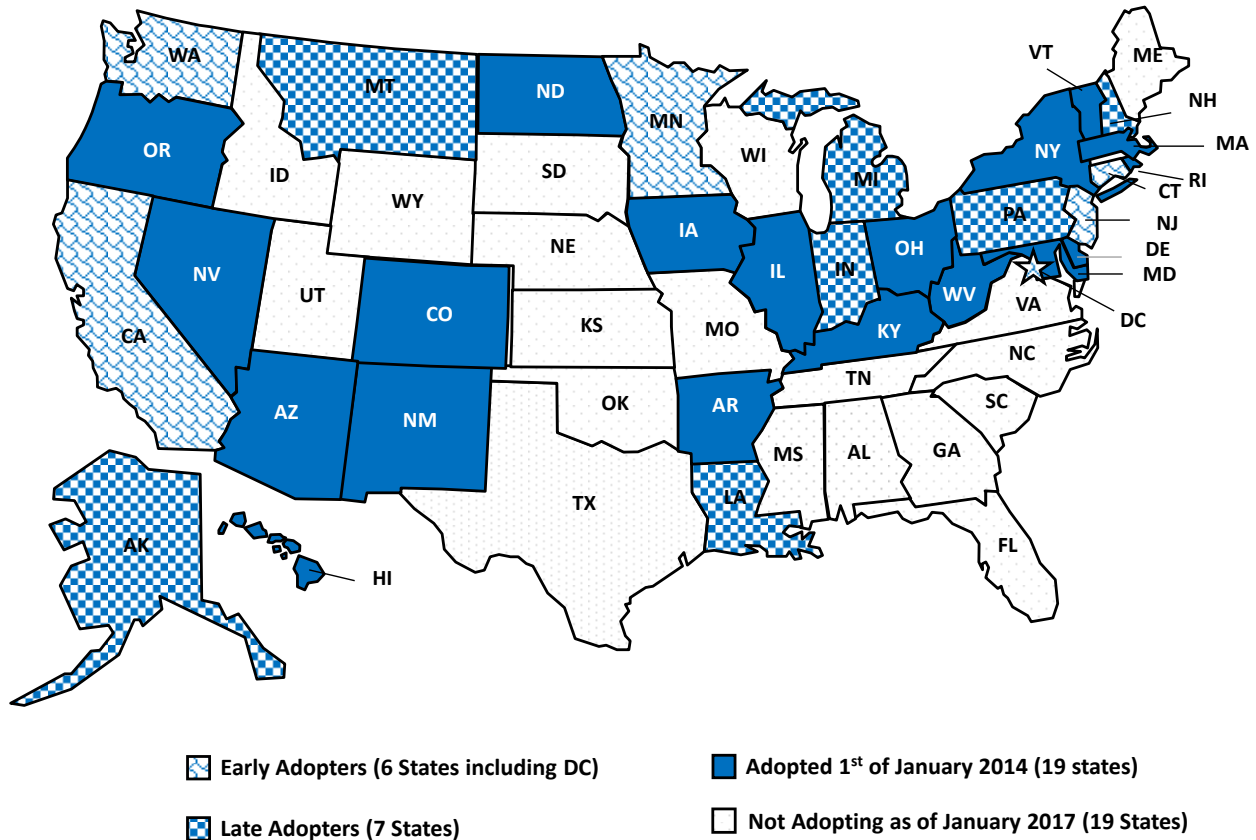
Figure 1: Medicaid Adoption Across States

Source: *Kaiser Family Foundation, see http://kff.org/health-reform/slide/current-status-of-the-medicaid-expansion-decision/ for further details.*

elderly population, to the Medicaid expansion, which is roughly consistent with estimates from the literature.[4]

2.2   Unpaid Medical Bills in Uninsured's Balance Sheet

Recent survey evidence from the Kaiser Family Foundation (KFF) (Hamel et al., 2016) notes that about a quarter of non-elderly adults in the U.S. have difficulties paying their medical bills, with that figure rising to more than half among the uninsured. Not surprisingly, previous studies have found that the uninsured pay only up to 20% of medical bills out-

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[4] Most closely related to our context, Courtemanche et al. (2016) find a coverage increase of 5.9 percentage points among the non-elderly adults in Medicaid expansion states by the end of 2014. In contrast, coverage increased by only 3 percentage points in non-expansion states suggesting an additional 2.9 percentage point increase due to the Medicaid expansion. Frean, Gruber and Sommers (2016) find that the ACA Medicaid expansion increased insurance coverage by 9 percentage points among individuals who were newly eligible for Medicaid with no evidence that the expansion crowded out private insurance.

of-pocket (Finkelstein, 2007), or \$480 out of about \$2,400 in overall annual health care spending according to recent estimates based on data from the Medical Expenditure Panel Survey (MEPS). The remaining cost is left as uncompensated care (Coughlin, 2014).

Uncompensated care comprises both charity care and uninsured care or bad debt. According to the American Hospital Association (AHA), charity care comprises services for which the hospital never received but also never expected payment, possibly because of the patient's inability to pay. Bad debt consists of services for which the hospital anticipated but did not receive payment. While charity care is not charged to consumers, 'bad debt' is billed to consumers through third party collection agencies. Collection accounts placed on individuals' records severely impact their credit worthiness, reducing the quality of credit options available to them.

In practice, the distinction between charity care and bad debt is blurry and hospitals often struggle to draw the distinction. Not surprisingly, there is little empirical evidence on the relative magnitudes of charity care and bad debt. Instead, studies have focused on quantifying the prevalence of uncompensated care in general and how it is affected by the Medicaid expansion. For example, (Bachrach, Boozang and Lipson, 2015) find that the Medicaid expansion led to a net reduction in uncompensated care in hospitals of about \$2.6 billion per year in expansion states. This translates into a reduction in total uncompensated care of about \$4.3 billion considering that hospitals provide about 60% of uncompensated care to the uninsured, see (Coughlin, 2014). An important advantage of our data is that we can document changes in medical debt in collection directly, allowing us to provide new evidence on the relative importance of bad debt when compared to charity care. We discuss these estimates in detail below.

3 Data

3.1 Consumer Credit Panel

The main data used in this study come from the Consumer Financial Protection Bureau's Consumer Credit Panel (CCP), a nationally representative 1-in-48 random sample of de-identified credit records drawn quarterly from a nationwide credit reporting company (NCRC). The CCP contains de-identified account-level information about sampled consumers' individual debt obligations (trade lines), including each account's opening date, current balance, and past payment history. Although de-identified, credit records in the CCP are linked over time, allowing us to study the evolution of debts for consumers in our sample.

Information in the CCP on individual trade lines makes it possible to determine the source of a debt obligation and the debt-origination date on which reported debts originated. Specifically, we can identify medical debts as those that were either directly reported by a medical provider or were reported by third-party debt collectors as unpaid medical bills.[5] We focus on the flow of new medical debts incurred each quarter because this measure better reflects the effects of Medicaid expansion than the stock of outstanding medical debt. This definition of medical debt is somewhat narrow by necessity. For example, credit card balances that are acquired by paying for medical services could be considered a type of medical debt. However, while credit records contain information about outstanding credit card balances, the information is insufficient to determine the portion of those balances derived from medical services versus other types of expenditures. Consequently, we exclude debts from paid medical bills in our definition of medical debt.[6]

Like medical debt, we base our measures of financial distress on flows, which better depict the timing of delinquency and bankruptcy decisions and allow us to more cleanly identify changes in the distribution of distress following reform. For each credit account, the CCP includes up to 84 months of payment history. Using this information, we can determine whether each account transitioned into a higher state of delinquency during each quarter. Such transitions could include accounts that were current in the previous quarter but are now (at least) 30 days past due. This also includes accounts that had been 30 days past due but became 90 days past due during this quarter.[7]

We restrict our analysis to a balanced sample of adults aged 18-64 in the 19 adopting (treatment) states and the 19 non-adopting (control) states (Figure 1).[8] We aggregate the data to the year-quarter level and focus on outcomes in the 10 quarters before and 8 quarters following the expansion.[9] This covers the period 2011Q3 to 2015Q4.[10] Oftentimes there are significant lags between when debts are acquired and when they are reported to the NCRCs,

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[5]The data, however, do not include any information that reveals the name of the medical provider or the type of medical service provided.

[6]In Appendix B.2 we evaluate the effects of Medicaid expansion on the credit card debt position of households and find significant effects.

[7]We consider any account that starts a quarter as 90 days past due or worse to be in default and do not include further transitions, such as charge-offs or repossessions, which often reflect lender-initiated actions, as instances of financial distress.

[8]Attrition in administrative credit record data is exceedingly rare. We balance the sample to exclude (1) accounts that were flagged as fraudulent and (2) accounts created during the sample period, or account for individuals just entering the formal credit sector.

[9]Our analysis is limited to the 10-quarters before the expansion of Medicaid because the variable necessary to determine which third-party collection accounts were medical is not available in the data for quarters prior to September 2011.

[10]Quarterly intervals allow us to smooth out monthly variation in the accrual of medical debt and in measures of financial distress (like bankruptcy) that can be rare and highly volatile.

though the delay does not affect the reported trade line's opening date. To account for this lag, we use a one quarter forward archive to identify new medical debts in our analysis. For example, we measure new medical debts acquired in quarter q using the CCP archive for quarter $q+1$. Our analysis suggests that this lag provides the most complete coverage of the amount of medical debt reported. Finally, our baseline sample covers approximately 2.13 million credit records and 38 million quarterly observations.

Table 1 provides summary information on the measures of medical debt and financial distress used in the analysis. Column 1 in the table shows overall means in the data. Columns 2 and 3 summarize the data separately for the pre- and post-reform quarters, respectively, and for adopting (treatment) and non-adopting (control) states. As shown in the table, about

Table 1: CCP Summary Statistics

	All		Pre-Expansion	Post-Expansion
	(1)		(2)	(3)
New Medical Collections				
Receiving (p.p.)	4.94	*Not Adopting*	6.14	6.08
		Adopting	3.63	3.19
Average Number	1.67	*Not Adopting*	1.68	1.71
		Adopting	1.62	1.60
Average Value ($)	1,186	*Not Adopting*	1,227	1,325
		Adopting	1,032	944
Delinquency Rate (p.p.)				
Any New Delinquency	6.58	*Not Adopting*	6.81	6.70
		Adopting	6.46	6.21
Consumer Risk				
Credit Score (Fico)	675	*Not Adopting*	664	672
		Adopting	681	689
Observations	38,270,034	*Not Adopting*	11,897,972	9,554,005
		Adopting	9,363,158	7,454,899

Notes: *This table shows summary statistics of medical debt and financial distress from the CFPB's Consumer Credit Panel (CCP). The data are quarterly for 19 adopting and 19 non-adopting states (see Figure 1 for list of states) from 2011Q3 to 2015Q4. Medical debts and Delinquencies are counted as flows in that quarter.*

5% of consumers acquired a new medical debt each quarter during the analysis period, and the propensity was somewhat lower in adopting states than in non-adopting states. This difference can at least partially be attributed to differences in the fraction of uninsured individuals across treatment and control states. In the post reform period, new collections remained largely stable in non-adopting states, while the prevalence was falling by about 12% in adopting states. Moreover, an average consumer with new medical debt accrues 1.7 new obligations with an average value of about $1,200. The number and value of new

medical debts, among those who acquire them, is also greater in non-adopting states and decreases following the implementation of the reform for adopting states.

About 6.6% of individuals in our sample become newly delinquent (e.g. new 30-day or new 90-day delinquency) on an existing debt. This rate is slightly higher in non-adopting states and declines more following reform in adopting states. On average, their credit score, measured by their Fico score as of the end of each quarter, is 675. This score is considered as Prime for purposes of credit.[11] Note that, although credit scores went up on average following the reform, they increased slightly more in adopting states.

Medicaid is a means-tested program. As a result, a large portion of American households remained unaffected by the expansion. Average effects, although large, may mask substantial heterogeneity in the impact of the policy across wealthier and more modest communities. Because the CCP provides geographic information on accounts at the Census tract level, we can explore this heterogeneity by merging demographic data on Census Tract poverty rates from the American Community Survey (ACS). For this match we use the 2009-2013 ACS 5-year averages. Using pre-reform eligibility criteria by state for childless adults as of January 1, 2013, and the policy's new eligibility benchmark of 138% of the federal poverty line (FPL), we calculate the proportion of non-elderly adults in each Census tract that would be newly eligible for Medicaid following the expansion. We calculate this fraction in treatment states (which expanded Medicaid) as well as control states, which we refer to as the fraction of newly eligible non-elderly adults.

3.2   Loan Offers and Pricing (Mintel and MyFico)

To study the effect of improved financial health on consumer's credit option, we use data on loan offers and pricing from Mintel Comperemedia (Mintel) and MyFico. We focus on the four most common sources of debt for the Medicaid population: (1) credit cards (2) personal loans (3) auto loans (4) mortgages.

We measure changes in credit card and personal loan rates using data on direct mail offers from Mintel Comperemedia (Mintel) from January 2012 to December 2016. The Mintel data are generated via a nationally representative survey of approximately 2,000 households, or 4,000 individuals. Each month participating households are asked to provide Mintel with all mail solicitations they received during the month, which include offers of new credit

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[11]Prime consumers are often defined as having a credit score higher than 620. If the consumer has a credit record that the credit scoring model deemed unscorable, we treat the consumer as subprime. For a detailed discussion of what makes credit records unscorable and the characteristics of 11% of adults with such records, see Brevoort, Grimm and Kambara (2016).

from any lender in the marketplace.[12] Direct mail remains one of the most popular and effective channels by which lenders advertise both credit cards and personal loans to potential customers. Furthermore, we observe the county of residence of each resident. As a result, these data are uniquely suited for exploring changes in credit terms offered to consumers following the Medicaid expansion.

In our analysis we focus on new acquisitions of credit card and personal loan offers that have been pre-screened.[13] Pre-screened offers are made to potential customers whose credit quality has been previously checked and as a result are targeted toward specific risk types.[14]

Table 2 shows summary information on credit card and personal loan offers and pricing by the fraction of newly eligible non-elderly adults. For each respective loan product, and by quartile of indigent adults, the table shows the proportion receiving offers and the average rate on those offers. Slightly less than half of surveyed individuals receive credit card offers,

Table 2: Mintel Credit Card and Personal Loan Offers

	All	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)
Credit Card Offers					
Percent Receiving	49.82	49.71	50.27	48.55	51.04
Average Rate	16.53	16.34	16.54	16.90	17.82
Personal Loans					
Percent Receiving	12.46	11.68	12.44	13.77	20.51
Average Rate	8.24	7.86	8.24	9.08	9.80
Observations	105,973	46,349	43,678	13,499	2,447

Notes: The table shows summary information on credit card and personal loan offers from Mintel comperemedia by the fraction of newly-eligible non-elderly adults. The proportion of individuals receiving is the *un-weighted* proportion of individuals in the sample receiving at least one offer. The average rate is conditional on receiving and is *weighted* by a *mail-volume* variable calculated by Mintel.

and this proportion remains stable across poorer and richer communities. On average, recipients are offered a 16.5% interest rate on purchases, with rates increasing in the share of poor adults. Personal loans, often advertised as 'credit consolidation' loans, are part of a much newer and smaller market that frequently targets subprime consumers. As shown in the table, the incidence of personal loan offer rates is about 12.5%, or one quarter that of

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[12]These include nearly all marketing solicitations and are not restricted to direct credit offers.

[13]Pre-screened offers are identified via a flag for the presence of a pre-screen opt out disclosure. Opt-out disclosures are required by law for pre-screened mail out offers.

[14]Often mail out offers are made without screening consumers. These often occur with the roll out of new products in an effort to learn their profitability.

credit cards. Moreover, this proportion is increasing with the rate of poor adults. Individuals living in the poorest communities are more than 60% more likely to be offered these products. The average rate on a personal loan offer is lower than for a credit card, at just more than 8%. This is in part because, unlike credit cards, personal loans are installment loan products which do not provide an open ended line of credit. However, like credit card offers, rates on offered personal loan products are higher in lower income communities.

Mortgages and auto loans are less commonly offered through direct mail. However, in pricing mortgage and auto loans, lenders often set rates uniformly within credit score ranges. These *rate sheets*, which are often statewide or nationally determined, make translating credit score ranges into lower interest rates less complicated. We use publicly available rate sheet information on published by Fair Isaac Corporation, the creator of the widely-used FICO score, in their *MyFico* web tool. This information, which is aggregated from lender rate sheets, provides credit score ranges that are widely used for lenders for both products and the prevailing market interest rates for each of those ranges.

Table 3 shows the *MyFico* aggregated rate sheets for 5-year auto loans and 30-year fixed rate mortgages as of March 19, 2017. In the analysis we estimate potential interest rate

Table 3: Rate Sheets for Auto Loans and Mortgages

Auto Loan Pricing Tiers						
Credit Score Bin	500-589	590-619	620-659	660-689	690-720	>720
Auto Loan APR	15.117	13.970	9.653	6.948	4.863	3.514
Mortgages Pricing Tiers						
Credit Score Bin	620-639	640-659	660-679	680-699	700-759	>760
Mortgage APR	5.484	4.938	4.508	4.294	4.117	3.895

Notes: This table shows rate sheets for Mortgages and Auto Loans from the Fair Isaac Corporation's (FICO) *MyFico* web page (http://www.myfico.com/credit-education/calculators/loan-savings-calculator).

effects of the policy by assigning each consumer the interest rate they would have qualified for in that quarter based on their credit score (see Table 1). Consumers with credit scores below the bottom price tiers are excluded from calculations, as they are not eligible for a loan. This imputation implies that any changes in average rates arise directly from the changes in credit scores.

4 Difference-in-Difference Design

We now turn to our main empirical strategy, which exploits the quasi-experimental variation provided by states' option to expand Medicaid. We apply a difference-in-differences (DD) approach to identify the effects of the reform on medical debt accruals, the rate of flows into delinquency, and lenders' pricing and offers of credit to consumers. Specifically, we provide graphical and regression based evidence on two different levels of aggregation. First, we graphically compare outcomes in expansion states relative to non-expansion states before versus after the reform. Under the standard parallel trend assumption, we interpret differential changes in expansion states in the post-reform years as the intent-to-treat (ITT) effect of the Medicaid expansion.

These effects may be relatively small given that only about 4.1% of the non-elderly adults in the expansion states gained Medicaid coverage because of the expansion. To corroborate the graphical evidence, we exploit more granular variation in Medicaid eligibility at the census-tract level in our primary regression specification:

$$y_{ct}^k = \alpha_c^k + \eta_t^k + \delta^k \cdot (ER_c \cdot Post_t) + \beta^k \cdot (ER_c * \cdot Post_t \cdot Exp_{s(c)}) + \epsilon_{ct}^k. \tag{1}$$

Here, y_{ct}^k denotes the respective average outcome k in census tract c in year-quarter t. The specification includes census tract fixed effects α_c^k and quarter-year fixed effects η_t^k. $Post_k$ is an indicator for the post expansion period, and ER_c denotes the fraction of newly-eligible non-elderly adults in the census tract. Finally, $Exp_{s(c)}$ is an indicator variable that turns on if the census tract is located in an expansion state.

Our primary parameter of interest is β^k which now captures differential effects of the Medicaid expansion across census tracts. Specifically, we expect larger effects in those census tracts that have a larger fraction of Medicaid eligible non-elderly adults if the state expands its coverage criteria. Again, we interpret the β^k coefficients as intent-to-treat effects since Medicaid eligibility does not imply Medicaid take-up (treatment). Therefore, we construct the average treatment effect on the treated (ATT) by dividing the reform effect in an average census tract, $\beta^k * \overline{ER_c}$, by 0.041.

In the following sections, we turn to the results, considering two main effects. The first, the *Direct Effect* on medical debt, measures the effects of the reform on medical debt obligations. The second, the *Indirect Effect* on distress, measures the effects on of the reform financial distress, as measured by the flow of delinquencies and subsequent improvements in consumers' credit risk and offered rates. In each we use the following basic specification

to measure these effects and finally to calculate potential interest rate savings to consumers resulting from the reform.

5   Direct Effects of Medicaid on Medical Debt

In this Section, we present graphical and regression-based evidence on the direct effects of the Medicaid expansion on medical debt.

5.1   Average Effects

We begin by presenting graphical evidence in Figure 2, which plots raw data trends in newly-accrued medical collections for treatment and control states, respectively. Plotted trends are normalized by the pre-expansion mean for each respective group. In the Figure, the left panel shows trends in the overall propensity to receive a collection, the middle panel shows the total number of collections credited to the record in a given quarter, and the right panel shows the total value of new collections reported. As illustrated in the figure, two-years
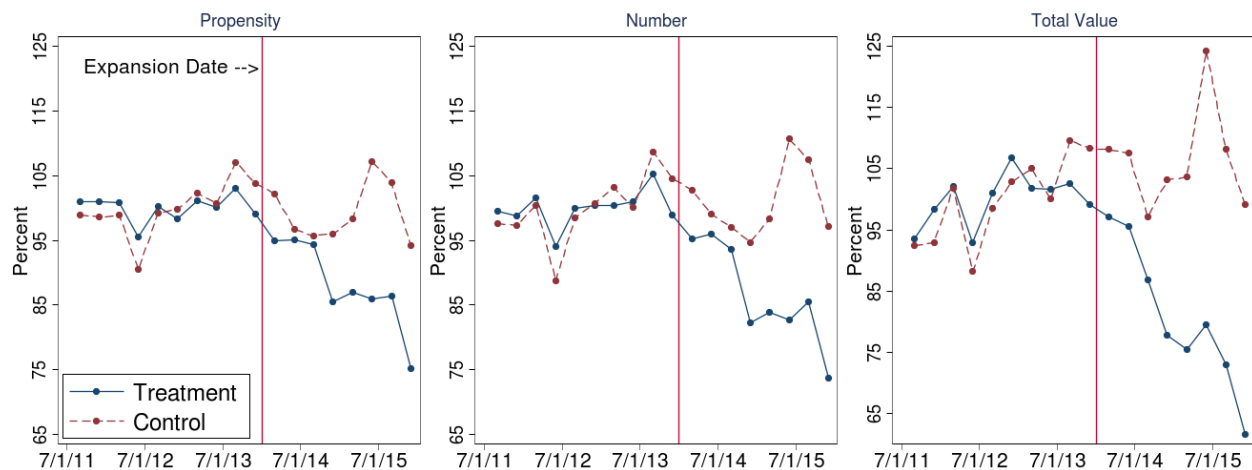

Figure 2: Trends in Newly Accrued Medical Debt

Notes: *The figure shows trends in the incidence, frequency, and value of newly-accrued medical collections. Data are from the CFPB's Consumer Credit Panel described in section 3. Trends are quarterly means of newly-accrued collections for treament and control states, respectively, and are normalized by the pre reform mean for each group. Vertical lines highlight the implementation date of the expansion - January 1st, 2014.*

after the reform, the propensity to accrue new medical debt fell by 20% in treatment states relative to control states. These effects are of similar relative magnitudes when looking at the instances and total value of collections received, the middle and right most panels,

respectively. Within 24 months following the reform, the average number of collections and the average total value of newly accrued medical debt were approximately 20% and 30% lower, respectively, in treatment states relative to control states.

We corroborate these findings in two robustness checks. First, the findings are not driven by systematic changes in collection activities in expansion states. We find no evidence for changes in non-medical collections. Second, the findings are not driven by differential openings of private market insurance exchanges in treatment states. Repeating the analysis among states which use the federal platform leaves the findings largely unchanged. For details on these robustness checks see the Appendix Section B.1.

Turning next to the regression-based evidence, Figure 3 shows the census tract specific treatment effects by the fraction of newly-eligible adults: $\hat{\beta} * ER_c$. The left figure presents the quarterly percentage reduction in new medical debt along with the 95% confidence interval.[15] The vertical lines denote the 25th, the 50th, and the 75th percentile of census tracts when ordered by the fraction of newly eligible adults. For instance, about 20% of the adults in the median census tract are newly-eligible for Medicaid and see a 20% reduction in the amount of new medical debt. As expected, the decline in newly-accrued debt is greater in tracts with a larger proportion of eligible individuals. In tracts with 12% of newly eligible adults (25th percentile), accrued medical debt per person-quarter decreased by approximately 10%, while that reduction was closer to 35% for tracts with 30% of newly-eligible adults (75th percentile).

In the right panel, we simply scale the estimates by the the average pre-reform amount of new medical debt in collection in the given census tract, to measure the quarterly reduction in dollars. At the 25th percentile of tract eligibility, medical collections per person decreased by about $5 per quarter. The reduction for those living in tracts at the 75th percentile of eligibility was on average 5 times larger, or $25 dollars per person-quarter.

5.2   Distributional Effects

We next divide the analysis by the dollar amount of underlying medical collection, to assess whether the Medicaid expansion differentially affected larger collections. To this end, we build on our regression model, equation (1), and separately investigate the effects of the Medicaid expansion for large ($\geq \$1,000$) and small ($< \$1,000$) collections. The top panel of Figure 4 shows larger reductions for large collections when compared to small collections. The panel shows regressions results using equation 1 where the dependent variable is

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[15]Standard errors are clustered at the census tract level and we use the STATA package "predictnl" to construct the confidence intervals.
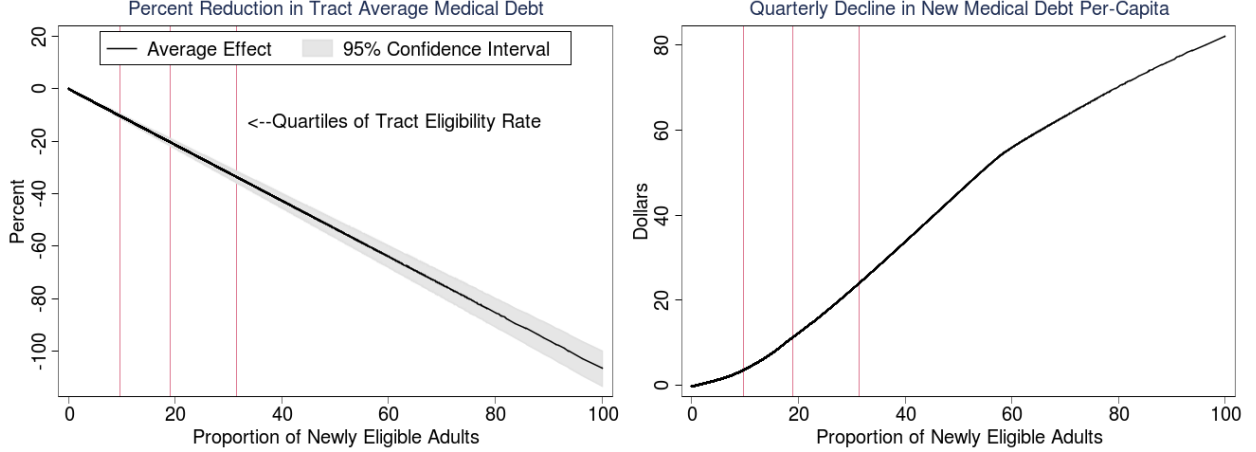
Figure 3: Medicaid Expansion and Declines in Medical Debt

Notes: *The figure shows percent changes in and level changes in newly-accrued medical debt by Census tract eligibility rate. The left panel of the figure shows estimates from equation 1 with related point-wise 95% confidence intervals. The effect for a given eligibility rate is defined as $\hat{\beta} \times ER_c$. Regressions are weighted using the number of adults in the Tract. All standard errors are clustered at the Census tract level. The right panel of the figure plots the corresponding level effects, $\hat{\beta} \times ER_c \times MD_c^{pre}$, where MD_c^{pre} abbreviates the average pre-reform amount of new medical debt in collection. The panel shows a smoothed trend using weighted local linear regression. In each panel, the vertical lines represent Census tract eligibility rate quartiles. From left to right, these denote the 25th, 50th, 75th percentiles of Tract level eligibility rates, respectively. Data are from the CFPB's CCP and quarterly from July 2012 to July 2015 for 19 adopting (treatment) and 19 non-adopting (control) states.*

$\mathbb{1}$[New Medical Debt $\in j$], $j = \{$small, large$\}$. While the propensity to accrue large unpaid medical collections is less than a third of that for small medical collections, the decline in accrual due to the reform is substantially greater. For example, in a community with a 12% eligibility rate, the 25th percentile, the propensity to receive large medical collections declines by approximately 0.4 percentage points, or 52%. In that same community, the expected decline in the incidence of small unpaid medical collections is closer to 0.2 percentage points, or 7%. Often small-value medical collections result from clerical errors in doctors' bills or disputes about insurance coverage, whereby insured individuals may incur collections without any knowledge of a missed payment (Brevoort and Kambara, 2015). In contrast, large value medical collections are significantly more likely to arise from emergency room visits or hospital admissions of uninsured individuals. Consequently, a relatively greater impact on large value medical debts supports the idea that newly insured individuals are no longer incurring large medical bills after treatment.

The bottom panel of Figure 4 presents further evidence on changes in the distribution of newly-accrued medical debt. In the bottom left panel, we present regression outcomes for
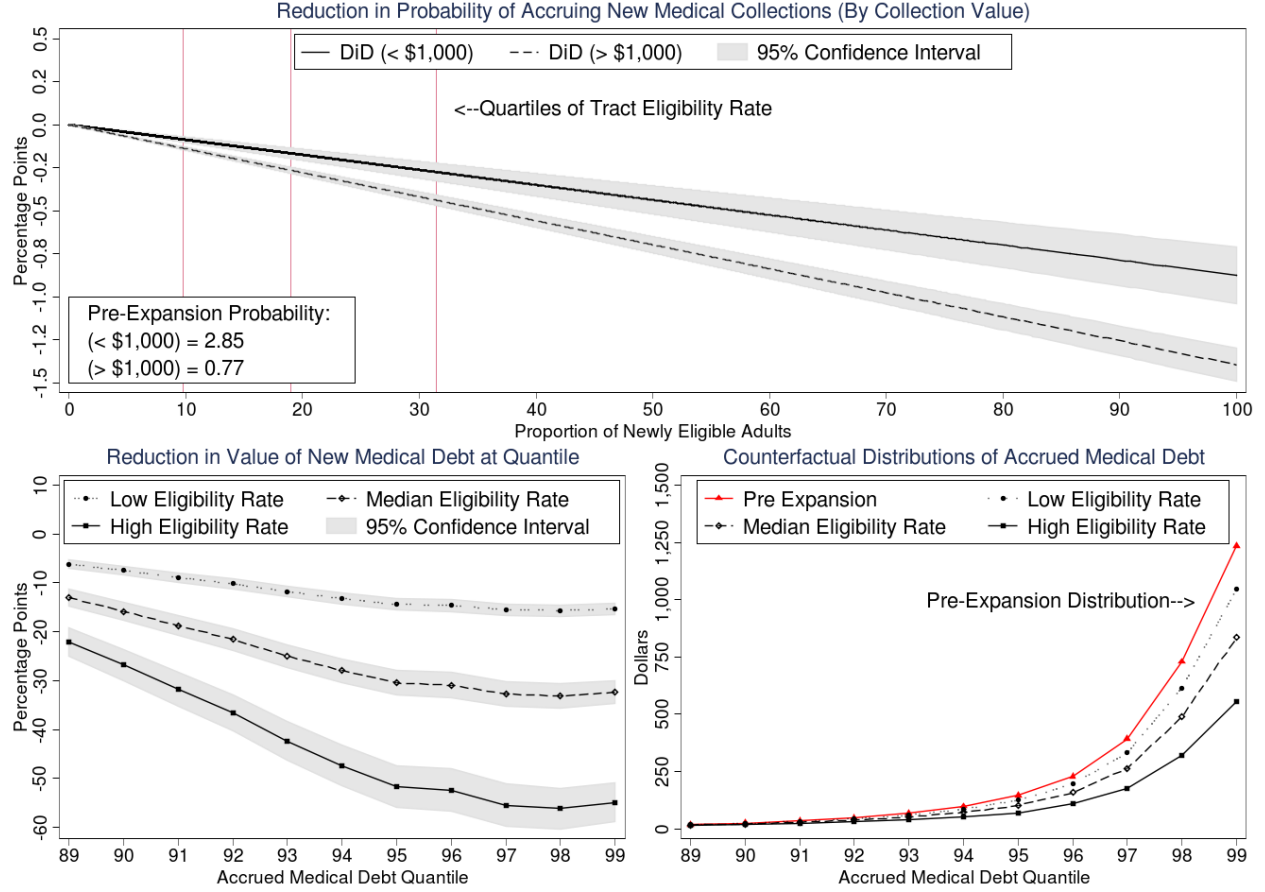
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Figure 4: Distributional Effects of Expansion on Medical Debt

Notes: *The figure shows distributional effects of the reform on the accrual of medical debt. Data are from CFPB's CCP. The top panel show treatment effects and 95% confidence intervals for large ($\geq \$1,000$) vs. small ($< \$1,000$) collections using Equation 1. The bottom left panel plots treatment effects and confidence intervals at each quantile of medical debt in tract c and quarter t. Regressions are weighted using the proportion of adults in a Census tract. In all regressions, standard errors are clustered at the Census tract level. From left to right, these denote the 25th, 50th, 75th percentiles of Tract level eligibility rates, respectively. Data are from the CFPB's CCP and quarterly from July 2012 to July 2015 for 19 adopting (treatment) and 19 non-adopting (control) states.*

each of the highest percentiles in the medical debt distribution. The point estimates for each percentile summarize the results of a separate regression, where the dependent variable is simply the corresponding percentile in the distribution of newly-accrued medical debt at the census tract quarter level. Instead of presenting the full linear extrapolation by eligibility, we only present the effects for (1) low eligibility tracts (25th percentile of eligibility), (2) median eligibility tracts (50th percentile of eligibility), and (3) high eligibility tracts (75th percentile of eligibility). The bottom right panel then plots the corresponding level effects, where we simply scaled the percentage reduction with the pre-reform levels.

Our findings suggest that the effect of the expansion increases for higher quantiles and again more so in high eligibility tracts. Among high eligibility tracts, for example, the policy induced reduction in new medical debt rises from approximately 20% at the 89th percentile to nearly 60% at the 99th percentile.[16] The dollar reductions (bottom right) further confirm the assertion. Among high eligibility tracts, an average 20% reduction at the 89th percentile, on a base of about $20 in average debt at the quantile, translates to a modest savings of only $4. However, the savings become quite substantial past the 95th percentile. For the highest quantile, a nearly 60% reduction in the accrual of new medical debt translates into roughly $700 of savings or about 60% the average size of a newly accrued medical bill in collections (Table 1).

5.3   Medical Debt and Consumer Payments

In this section, we use our parameter estimates to calculate the amount of new medical debt that is not accrued annually due to the reform. We then combine these with estimated repayment patterns of medical collections to calculate how much of this decline in accrual translated directly into reductions in out-of-pocket payments for treated tracts. As shown in Table 5, the policy led to an average annual reduction in new medical debt of about ($\sim$ $37.71) per person. Scaled by the population of non-elderly adults in treatment states, this amounts to a $1.7 billion annual reduction overall. More than half this decline ($\sim$ $860m$) came from individuals living in the poorest communities, where per-capita reductions were nearly about 4 times the average. Overall, our results show that the program was progressive, investing heavily in low income neighborhoods and less so in wealthy communities.

Although the accrual of medical debt fell sharply, the majority of unpaid medical bills sent to collections are not repaid. As a result, fewer accrued medical debts do not necessarily translate directly into a reduction in consumer payments. The middle panel in Table 5 shows repayment and removal rates of medical collections up to two years after a medical collection appears on an individual's credit report for those living in treatment states prior to the expansions. One difficulty with ascertaining repayment rates is that a sizable proportion of collections are removed from records within one or two years of their appearance. Collections often are removed from a credit record in cases where individuals were wrongly billed and a complaint was placed with the provider, although removal could occur for any number of other reasons. Since the data provide no information regarding the repayment status of removed collections we form bounds on repayment rates. The lower bound of repayment

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[16]Although fewer than 5% of consumer receive a medical collection in each quarter on average, this may mask some variation across census tracts. This is why we can identify effects at the 89th quantile.

Table 4: Reduction and Repayment of Medical Debt

	All	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)
Annual Decrease in Accrued Medical Collections					
Average Per Person ($)	37.71	4.57	20.80	58.21	145.96
Total ($Billions)	1.69	0.08	0.26	0.49	0.86
Proportion of New Medical Collections Repaid (p.p)					
After One Year					
Repaid	7.85	9.49	8.83	8.78	6.00
Repaid or Removed	36.83	33.94	35.44	37.48	38.11
After Two Years					
Repaid	9.05	10.53	10.19	10.26	6.94
Repaid or Removed	51.68	48.08	49.78	52.67	53.22
Annual Decrease in Per Person Expected Medical Debt Payment ($)					
After One Year					
Lower Bound	2.96	0.43	1.84	5.11	8.76
Upper Bound	13.89	1.55	7.37	21.82	55.62
After Two Years					
Lower Bound	3.41	0.48	2.12	5.97	10.13
Upper Bound	19.49	2.20	10.36	30.66	77.68
Population 18-64 in Expansion States (Millions)	44.86	18.22	12.32	8.38	5.93

Notes:*This table presents estimates of annual per-capita average reduction in medical debt, repayment rates, and total accrued savings using estimates from equation 1 in Figure 3. Repayment rates are within eligibility rate quartile. Percent repaid is the proportion of new medical collections in quarter t that were repaid one and two years later, respectively. Percent removed is the proportion of new medical collections in quarter t that were removed one and two year later, respectively. The lower and upper bound correspond to repaid and repaid or removed medical collections, respectively. The CCP Population is calculated by multiplying the number of records in 2013Q4 by 48, the sampling rate of the data (Section 3)*

assumes none of the removed collections were repaid, and the upper bound of repayment assumes all of the removed collections were repaid.

On average, 8% of newly accrued debt is repaid within one year of appearing on an individual's credit report, and 9% within two years. About half of newly-accrued debt is removed entirely from the credit record within two years, the majority of that within one year. Although the repayment rate is lower in high eligibility, often low-income, communities, the proportion of debt repaid or removed is higher. For example, in the lowest-eligibility communities, the bottom quartile, about 11% of debt is repaid and 48% is repaid or removed. In high-eligibility communities, the top quartile, that proportion changes to 7 and 53%, respectively.

The bottom panel of Table 4 combines effects on collections and repayments to calculate upper and lower bounds on reductions in medical debt repayments. As aforementioned, the lower bound assumes that bills removed were not repaid by consumers while the upper bound assumes that all collections removed were repaid. Given this, we calculate that annual repayments per person declined by between $3.40 and $19.49. Despite lower repayment rates,

the largest reductions came from the poorest communities, for which the decline was up to 20 times greater than for the richest communities.

Table 5 also allows us to benchmark our results to previous work on Medicaid provision. Note from the top row of column 1 in the table that the Medicaid expansion led to a $37.71 annual per person reduction in medical debt accrual. Dividing this point estimate by an estimated coverage gain of 4.1 percentage points from Medicaid expansion we calculate a debt reduction of $-\frac{\$37.71}{0.041} = -\$920$ per newly-insured person per year. As a point of comparison, estimates from the landmark Oregon Health Insurance Experiment imply a treatment effect of Medicaid insurance on medical debt of -$390 (standard error 177) per treated person per year (Finkelstein et al., 2012). When accounting for differences in the measurement of medical collections resulting from attrition (e.g. $\sim 50\%$ of collections disappear after two years) we find a debt reduction per treated person per year of approximately $460. Although the Oregon experiment focused on a small and geographically concentrated sample of consumers, we find its estimated savings to be remarkably close to our national averages. We interpret this congruence in two ways. First, we see it as further evidence in favor of the validity of our approach in identifying the exogenous effects of the reform. Second, we see it as verifying a natural generalization of the experimental result to the context of a large national reform.

Our estimates also provide evidence on the relative significance of uninsured care or bad debt in uncompensated care, an estimate that is not readily available from the literature, to the best of our knowledge. As outlined in Section 2.2, we assume that the uninsured pay about 20% of overall health care utilization, worth $2,400 per year, out-of-pocket. This suggests that uncompensated care equals about $1,920 per uninsured person and year.[17] We find a reduction in medical debt in collation of about $920 per treated person, which is about 38% of overall health care utilization or about 48% of uncompensated care. Hence, we conclude that about half of uncompensated care is sent to collection.

6   Indirect Effect of Medicaid on Financial Health

Newly reported medical collections often indicate a broader financial hardship, raising the likelihood of future delinquencies in non-medical debt repayment and even bankruptcy. As a result, unpaid medical bills sent to third party collections and reported to credit bureaus

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[17]This is roughly consistent with the evidence from Garthwaite, Gross and Notowidigdo (2015), who find that each additional uninsured person costs a local hospital about $900 annually in uncompensated care, given that hospitals only provide about 60% of the overall uncompensated care to the uninsured, see (Coughlin, 2014).

can directly impact consumers' credit scores, potentially making credit both less available and more expensive. Using an event study framework, we provide evidence of these effects by documenting a steep rise in delinquency and a sharp decline in credit scores following a newly credited medical collection (See Appendix A for details). Motivated by this evidence, we turn to the indirect effects of the Medicaid expansion on consumer delinquency and credit scores.

6.1 Repayment Delinquencies

Consumers in financial distress are more likely to miss payments on their outstanding loans. This is why credit delinquency rates are commonly-used indicators of financial distress and prospective borrower risk. Using the payment history for each account in the CCP, we determine the extent to which the expansions affected consumer transitions into a delinquency on outstanding loans. Our measure includes mild delinquency, a transition from current to 30 days or more past due, moderate delinquency, a transition from 30 to 60 days past due, or serious delinquency, a transition from 60 into 90 or more days past due. We consider any of these transitions on any loan a new delinquency. Isolating flows into missed repayments, rather than looking at contemporaneous payment status of all outstanding accounts, allows us to focus on episodes of worsening distress. We use the resulting worsening delinquency rate to explore whether the Medicaid expansion reduced the likelihood of financial distress.

We start with the graphical evidence in the left two panels of Figure 5, which plot raw (normalized) data trends in worsening delinquency for treatment and control states. The left panel shows trends for the whole CCP population while the middle panel shows trends for individuals with baseline credit scores below 620, the ex-ante *subprime* group .[18] While the trends for both groups are similar during the pre-expansion period, delinquency rates trend notably lower after the expansion in states that expanded Medicaid (e.g. treatment states). As is shown in the figure, this is especially true for our ex-ante subprime group, for whom the proportional decline is nearly twice as large. Subprime borrowers are more likely to be positively affected by the Medicaid expansion for several reasons. First, their low scores suggest past financial distress(past payment history is generally the most important factor used to generate scores) or have characteristics, such as a high utilization rate on their revolving accounts, that indicate that they are more likely to become delinquent in the future. Second, lower income consumers, who are more likely to be eligible for Medicaid, are

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[18]Industry standards consider individuals with credit scores below 620 as subprime. We separate prime and subprime consumers by their score as of the first of quarter in the sample, their baseline.
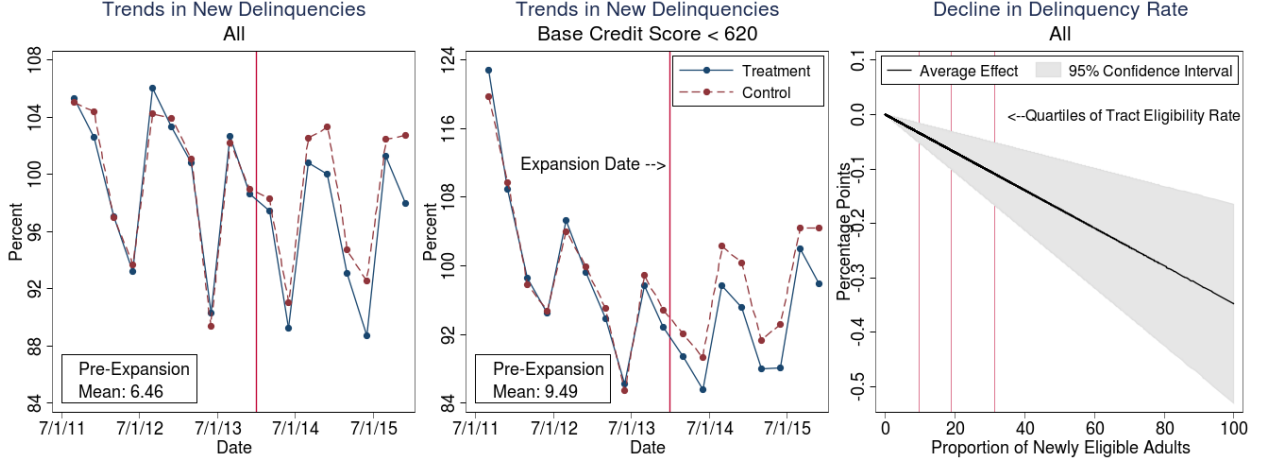
Figure 5: Medicaid Expansion and Growing Delinquency

Notes: *The figure shows quarterly flows into new delinquency for consumers in treament and control states. Trends are normalized by the pre-reform mean for each group. Delinquency is defined as consumers having one or more credit accounts that became 30, 60, 90, or more days past due during the quarter. The left panel shows normalized trends for all consumers in the data (see notes in Figure 2) and the middle panel shows normalized trends among individuals with a credit score less than 620 as of the first quarter of the sample period (the subprime group). The right panel shows percentage point declines in new delinquencies from Equation 1, with respective point-wise 95% confidence intervals. All standard errors are clustered at the Census tract level.*

more likely to have subprime credit scores. Third, the declines in the incidence of medical debt observed in section 5 were concentrated in this group.

We present the regression-based evidence for all borrowers in the right panel, based on equation (1), which plots the estimated percentage point reduction in worsening delinquency by the fraction of newly eligible adults in the the census tract. Consistent with the graphical evidence, we find that the Medicaid expansion reduced delinquency rates and more so in census tracts with a larger fraction of newly-eligible adults. At the 50th percentile, new delinquencies decreased by approximately 0.08 percentage points, or about $0.08/0.041 = 1.95$ percentage points per treated person. This translates into a 30% reduction relative to the pre-expansion mean, suggesting that the the reform's effect on financial distress was substantial.

6.2 Credit Scores

On-time repayment of existing debt is among the most important determinants of future credit worthiness, which is often summarized by a consumer credit score. In turn, credit scores are used pervasively by lenders for credit underwriting and pricing. The fall in medical

debt accrual and new delinquencies resulting from the Medicaid expansion likely benefit consumers in the form of higher credit scores.

The top left and top middle panel of Figure 6 present normalized credit scores in treatment and control states for all and subprime consumers, respectively. As shown in the figure,
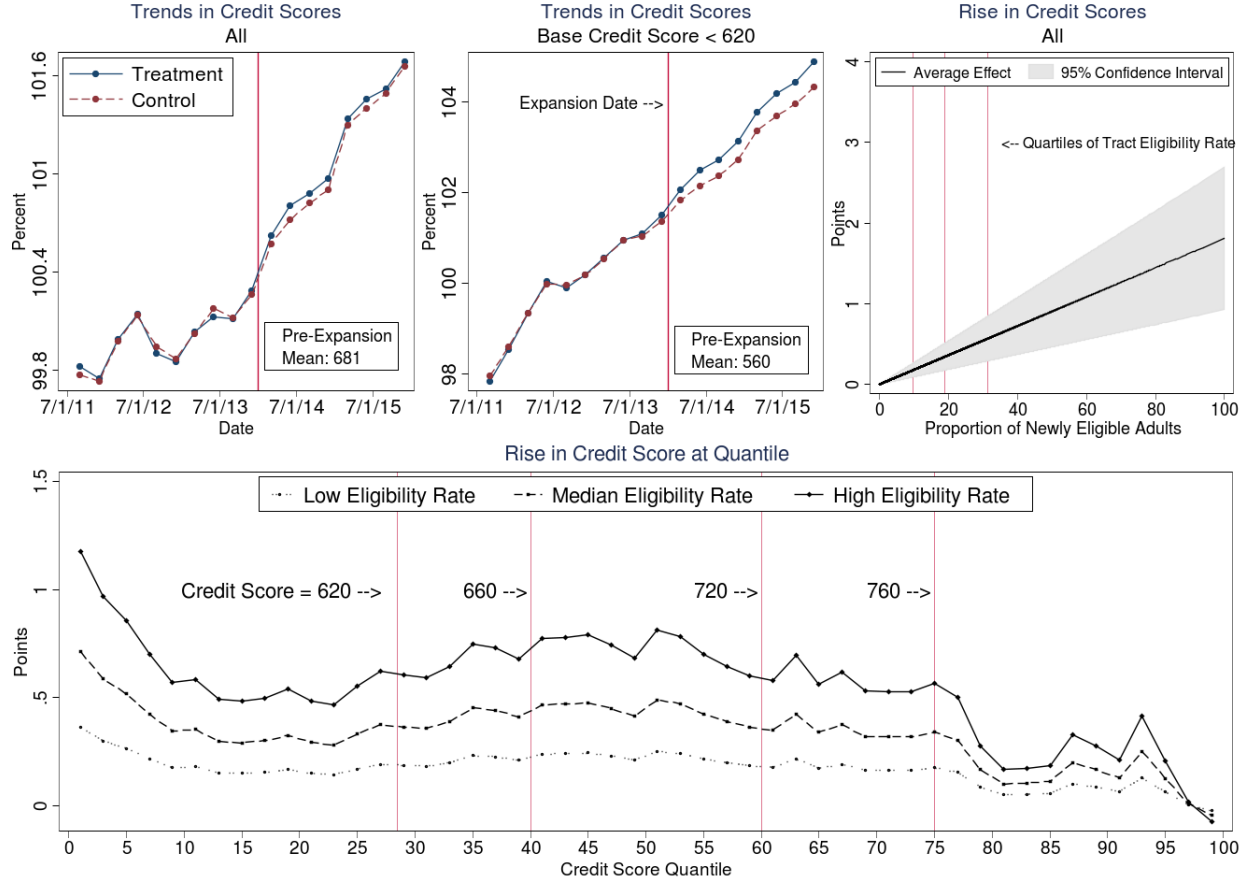

Figure 6: Medicaid Expansion and Credit Scores

Notes: *The top left and top middle panels of the figure show normalized trends in the credit scores of consumers in treament and control states, respectively (see notes in Figure 2). The top left panel shows trends for all the entire CCP sample with a credit score. The top middle panel shows normalized trends among individuals with a credit score less than 620 as of the first quarter of the sample period (the subprime group). The top right panel shows percentage point declines in end of quarter credit scores (the dependent variable) from Equation 1, with respective point-wise 95% confidence intervals. The bottom panel shows regression from Equation 1 with the credit score quantile q_{ct} as the dependent variable (See notes in Figure 4 for details). All standard errors are clustered at the Census tract level.*

the overall effect on credit scores is noticeable yet small. Nevertheless, the effect of the expansion on the ex-ante sub-prime group (base credit score < 620) is more than 4 times larger. This can occur for several reasons. First, a given 'level' decrease in risk will mechanically imply larger point gains for individuals who have low scores to begin with, a mechanical

effect. Second, and more substantively, individuals who are ex-ante more financially vulnerable are also those most likely to gain most from receiving insurance, as shown above (Figure 5). Third, as credit worthiness is often associated with income, subprime individuals likely reside in Census tracts with high eligibility. As a result, they are more likely to be treated.

Turning again to the regression based evidence for all borrowers, the top right panel shows percentage point declines in end of quarter credit scores, by the fraction of newly eligible adults. At the 25th percentile of eligibility (low eligibility) the effect is somewhat small at roughly 0.2 points increase. At the 75th percentile of eligibility (high eligibility), this effect is much larger, about 0.5 points. To put these estimates into perspective, we again divide the estimate for the 50th percentile by the fraction of newly-insured Medicaid beneficiaries. This suggests a $0.35/0.041 = 8.8$ point increase in the credit score per treated person. We will return to the interest rate implications in the next section.

Finally, the bottom panel of Figure 6 shows the distributional effects similar to those in Figure 4. As shown in the figure, the impact of the policy is greatest at the bottom of the credit score distribution, with an average effect of more than 1 point per person in high eligibility tracts. While this effect declines for higher quantiles, it remains somewhat strong in the middle portion of the distribution. Importantly, it has a very small effect at the very top of the credit score distribution, where likely few individuals are treated and those who are treated are financially less fragile.

7   Pricing and Availability of Credit

To facilitate the interpretation of the indirect effects on financial health and to assess their economic significance, we now turn to the effects on access and price of credit. Specifically we study the four most common types of debt obligations held by consumers: (1) Credit Cards (2) Personal Loans (Unsecured installment credit) (3) Auto loans (4) Mortgages. We estimate the effects of the reform on credit cards and personal loans using offer data from Mintel and the effects on auto loans and mortgages using rate sheet data from MyFico (See Section 3 for details). Specifically, we impute automobile and mortgage interest rates based on observed credit scores and the credit score interest rate crosswalk provided by the rate sheets. Finally, we calculate how changes in credit terms might translate into lower monthly payments (savings) by simulating a debt refinance under these new credit terms.

7.1 Changes in Availability and Terms of Credit

We begin with an analysis of the reform's effects on offered credit card interest rates. The left panel of Figure 7 shows (normalized) trends in the credit card rates in treatment and control states. Consistent with our findings on delinquency rates and credit scores, we see a relative decline in the interest rate in treatment states following the expansion. The right panel shows the regression based evidence, building on equation (1). We leverage the county of residence information on survey participants in the Mintel data, and aggregate the individual data to the county-year-quarter level. Therefore, we present the credit interest rate changes by the fraction of newly eligible non-elderly adults in the respective county. Again we see a significant decline in the offered credit card rate of about 0.5 percentage points at the the 50th percentile of eligibility. This effect is significant and increasing in county eligibility rates, reaching more than 1 percentage point in counties with a high fraction of eligible adults.
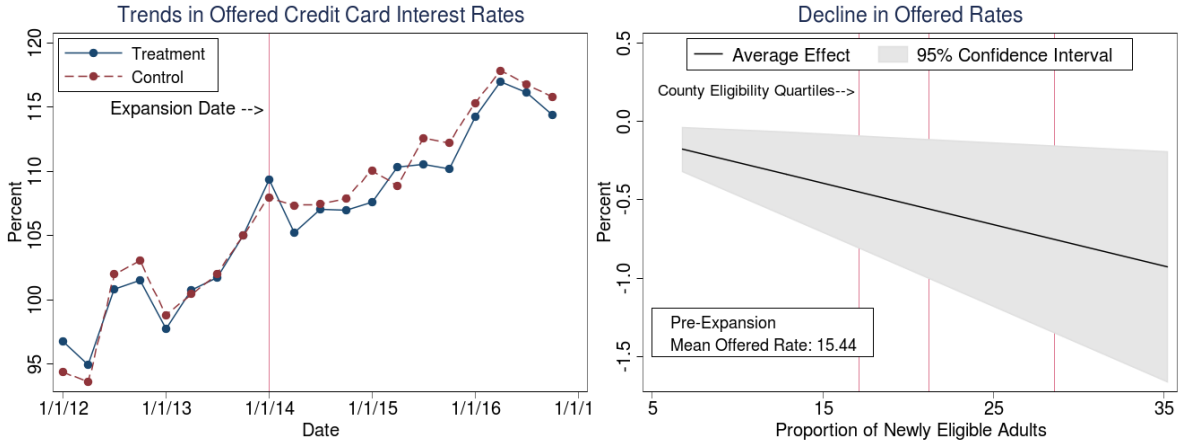

Figure 7: Medicaid Expansion and the Pricing of Credit Cards

Notes: The left panel of the figure shows normalized trends in offered credit card rates for adopting (treatment) and non-adopting (control) states. (See notes in Figure 2 for details.) The right panel shows regression results and related 95% confidence intervals for a regression using Equation 1 where the dependent variable is the mean rate of offers sent to a respondent. Regressions and trends are weighted using Mintel's mail-volume weight. (See section 3 for details). Standard errors are clustered at the county level.

Figure 8 presents analogous effects for interest rates on personal loans. Unlike credit cards, personal loans form part of a smaller and nascent market which largely focuses on highly indebted subprime customers (Section 3). As a result, the incidence of personal loan offers in the data is much lower than for credit cards (Table 2). This smaller sample size on offers leads to noisier trends. Nevertheless, as shown in the left panel of Figure 8, offered rates on personal loans seem to decline for recipients in expanding states relative to non-
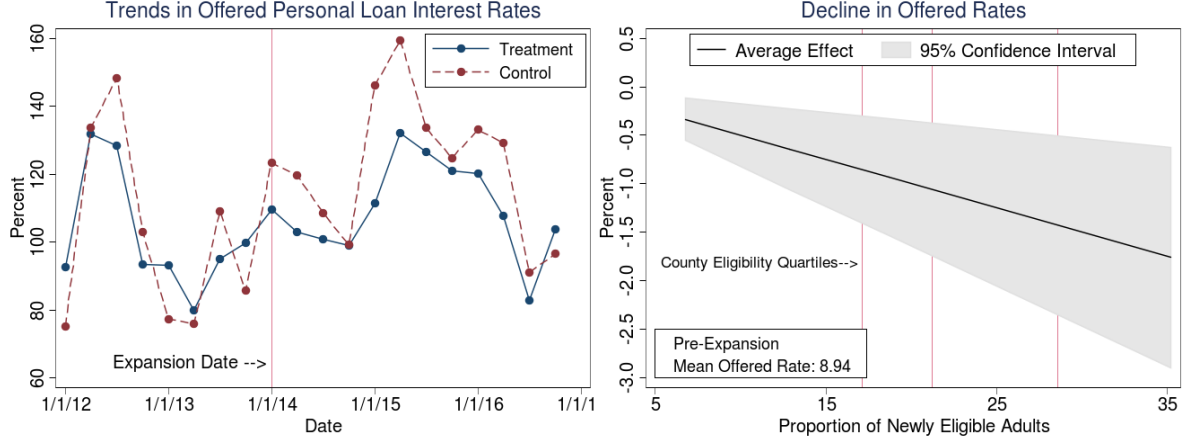
Figure 8: Medicaid Expansion and the Pricing of Personal Loans

Notes: *The figure shows trends (left panel) and treatment effects (right panel) for offered rates on personal loans using the Mintel data. See notes in Figure 7 for details.*

expanding states following the reform. In the right panel of the figure, we confirm that this effect is nonetheless statistically significant and larger in counties with more newly eligible adults. Moreover, the absolute decrease in rates is larger for personal loans relative to credit cards. This result is consistent with the fact that this market focuses on indebted sub-prime borrowers. For this segment of consumers, a modest improvement in credit worthiness can considerably increase outside borrowing options, prompting substantial responses from lenders making personal loan offers.

With respect to access to credit, we find evidence for a positive effect of the Medicaid expansion on credit card offer rates not only when comparing treatment and control states, but also when leveraging the more granular variation in eligibility at the county level. The evidence for personal loans is mixed. Overall, this points to increased access to credit following the expansion, providing an additional indirect financial benefit of health insurance. In what follows, we abstract away from this potential benefit suggesting that our primary estimates may provide a conservative estimate of the indirect benefits. For details on the access to credit, see the Appendix Section B.3.

Returning to changes in interest rates, Figure 9 shows the regression based evidence for imputed auto (left panel) and mortgage (right panel) rates based on equation 1.[19] Auto loans and mortgages are for the most part priced using lender rate sheets. Consequently, the effects documented in the figure reflect almost mechanically from the policy's impact on individual's credit scores (Figure 6). As shown in the figure, the expected reduction in these loan types,

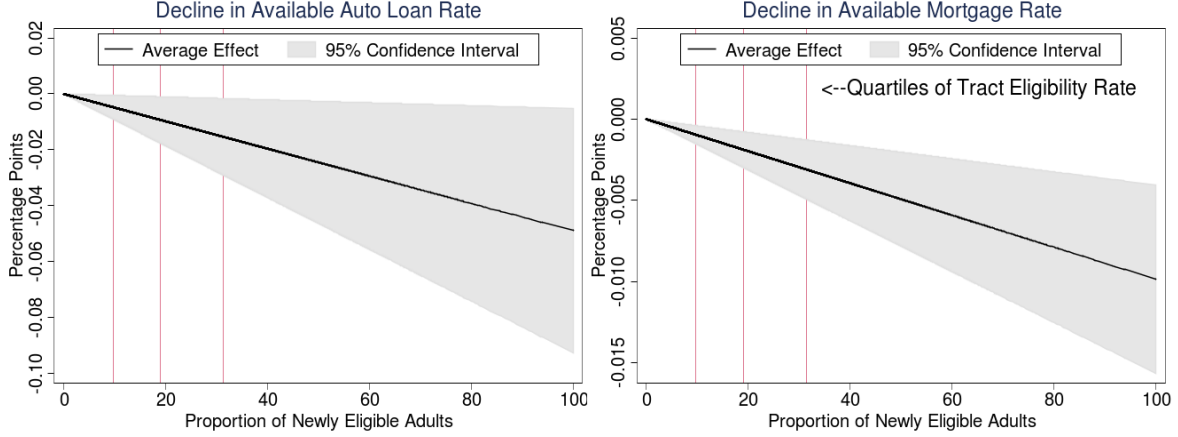---

[19]See Section 3 and Appendix C.

Figure 9: Medicaid Expansion and Available Rates for Auto Loans and Mortgages

Notes: The figure shows regression results from Equation 1 with dependent variables (1) imputed auto loan rate (left panel) and (2) imputed mortgage rates (right panel). Auto loan and mortgage rates are imputed using MyFico rate sheets (Table 3). For imputation details see Section 3.

although modest, is statistically significant and increasing in tract eligibility. Also, while mechanical, we believe these effects provide further meaningful information regarding the improved terms of credit potentially available to consumers, which we use in the simulation below.

7.2   Dollar Value of Improved Financial Health

We use our results on the pricing of credit to calculate the potential dollar value of improved financial health by simulating a refinancing of debt held by consumers in treatment states under the expectation of new credit terms. We restrict our population to individuals living in treatment states and consider a refinancing of their debt just prior to the expansion, e.g. December 2013. We further assume that the credit cards and personal mortgages are amortized over 36 months, that auto loans are refinanced as 5-year loans, and that mortgages are refinanced at 30-year, fixed-rate loans. This is consistent with the interest rates published by FICO. Moreover, for credit cards and personal loans, which, unlike mortgages and auto loans, are not backed by valuable assets, we net out any effects due to increased repayments. We express savings in annual terms. The details of our simulation are set out in the Appendix C.

Table 5 shows the results from our simulation exercise. The table shows per-person and aggregate annual savings, which we interpret as the intent-to-treat effects. As in Table 4, simulation results are shown separately by eligibility quartile (Columns 2-5) as well as overall

(Column 1). As shown in the table, the overall savings to consumers are substantial. We

Table 5: Simulated Interest Rate Savings

	All	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	(1)	(2)	(3)	(4)	(5)
Credit Cards					
Average Per Person ($)	8.19	4.30	8.76	12.12	13.43
Total ($Millions)	367.34	78.41	107.92	101.57	79.43
Personal Loans					
Average Per Person ($)	2.81	1.01	2.55	4.77	6.15
Total ($Millions)	126.05	18.35	31.36	39.97	36.36
Auto Loans					
Average Per Person ($)	0.22	0.08	0.21	0.37	0.47
Total ($Millions)	10.01	1.52	2.62	3.09	2.78
Mortgages					
Average Per Person ($)	0.40	0.26	0.46	0.55	0.48
Total ($Millions)	17.89	4.78	5.69	4.59	2.83
All					
Average Per Person ($)	11.63	5.66	11.98	17.81	20.52
Total ($Millions)	521.29	103.07	147.59	149.23	121.40
Population 18-64 in Expansion States (Millions)	44.86	18.22	12.32	8.38	5.93

Notes:*The table shows results from simulations of consumer savings using Intent-to-Treat estimates in Figures 7-9. The table shows per person effects and total effects calculated using the CCP Population. See Appendix C for further details.*

find interest savings worth $11.63 per person and year, which is about 30% of the per-person reduction in medical debt (Table 4). To put this estimate into perspective, we again divide by the fraction of non-elderly adults that gained Medicaid insurance because of the reform and find annual interest savings of about $11.63/0.041=$284 per treated person. Savings on unsecured loans, and in particular credit cards dominate the total effect. Simulated savings for credit cards and personal loans add up to about $11, or ∼95% of the total. This is consistent with other studies showing that the most at risk individuals carry a disproportionate amount of unsecured debt, which can be discharged at bankruptcy (Domowitz and Sartain, 1999; White, 2006). Lenders react accordingly by increasing prices more on these types of loans relative to loans backed by an asset. The dollar value of improved financial health then might largely flow through reduced prices on this type of credit.

Also shown in Table 5, per-capita and aggregate savings varied by rate of newly eligible adults in a tract. As might be expected, savings in tracts at the top quartile of eligibility (Column 5) were nearly four times larger than those in tracts at the bottom quartile of eligibility (Column 2). Nevertheless, a smaller population in tracts with a high proportion of new Medicaid-eligible adults implies that aggregate savings were greatest in the third quartile

of eligible tracts (Column 4). Interestingly, although still important, the share of savings from lower credit card rates is lower in tracts with a high rate of eligible adults. Whereas in the bottom quartile (Column 2) the share of savings due to refinancing credit card debt is approximately 75%, the share at the top quartile (Column 5) is closer to 65%. The difference is explained by added savings from personal loan refinancing among individuals in these tracts. As higher Medicaid eligibility occurs in more financially modest communities, this change in the mix of savings is further consistent with personal loans being used primarily by individuals in greater financial distress.

An important detail to note is that the CCP provides end-of-quarter snapshots of loan balances for respective individuals. Although this is not a concern for installment loans, whose balances reflect true debt, it is possible that a portion of credit card balances may not constitute credit card borrowing. This is because a portion of reported credit card balances may still be held within the 'grace' period, and as a result not incur any finance charges.[20] However, we note that aggregate credit card borrowing rates measured in the CCP accord quite well with more direct measures of credit card borrowing taken from the CFPB's Credit Card Database (CCDB) (Bureau, 2015).[21] Moreover, individuals' credit card utilization rate (e.g. the ratio of balances to credit limit) is surprisingly stable over time, helping to quell potential concerns of large fluctuations over time in borrowing (Fulford and Schuh, 2017).

8   Medical Bills and Consumer Welfare

In this section, we illustrate how paid and unpaid medical bills affect consumer welfare. Within a simple framework, we show how restricting attention to changes in out-of-pocket spending (paid bills) can vastly understate the full financial benefit of insurance against paid and unpaid medical bills. The outlined model leverages the observation that the share of the total medical bill that is paid out-of-pocket provides information on the disutility of higher debt levels. Finally, we turn to a quantitative analysis of the effects on consumer welfare in the next section.

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[20]Note that individuals who pay off their balance at the end of the billing cycle, e.g. while still in their grace period, are commonly called *transactors*. Individuals who carry, or revolve, balances across billing cycles are called *revolvers*. The latter type often accrue finance, or interest, charges on those carried balances. Once a balance has been carried across a billing cycle, there is no longer a grace period on any balances until the account is repaid in full.

[21]The CFPB's CCDB is a large de-identified panel of credit card accounts that provides direct evidence of revolving behavior.

8.1 Paid vs. Unpaid Medical Bills

We consider a static environment in which consumers derive positive utility from consumption, $g(c)$, and face a utility loss from medical debt in collection, $-h(D)$. Utility losses from unpaid bills capture costs such as future reductions in consumption due to worse credit options, through pricing and availability, disutility from dealing with debt collectors, as well as legal costs related to unpaid bills and bankruptcy. Consider then consumer preferences of the form

$$U = g(c) - h(D) \tag{2}$$

with $g'(\cdot) > 0, g''(\cdot) < 0$ and $h'(\cdot) > 0, h''(\cdot) \geq 0$. Consumers' marginal utility of consumption is decreasing while their marginal disutility of medical debt is weakly increasing. Consumers earn income Y and are exposed to random medical bills $\epsilon_{MB} \sim G$, where G denotes the underlying distribution function. We assume that a fixed fraction of medical bills, $0 \leq \alpha_{charity} \leq 1$, goes as charity care, and is not held financially against the patient. The remainder, $1 - \alpha_{charity}$, is either paid out-of-pocket or goes into collection and becomes medical debt. To simplify the theoretical analysis, we assume $\alpha_{charity} = 0$ and revisit the role of charity care in the numerical analysis in Section 9.

We assume that consumers have existing medical debt $\bar{D}$ and decide on the optimal amount of new medical bills $0 \leq b \leq \epsilon_{MB}$ that goes unpaid, trading off utility from consumption and disutility from medical debt. Conditional on a realized medical bill, ϵ_{MB}, consumers maximize:

$$\max_{0 \leq b \leq \epsilon_{MB}} g(Y - (\epsilon_{MB} - b)) - h(\bar{D} + b) \tag{3}$$

where in optimality

$$g'(Y - (\epsilon_{MB} - b^*)) - h'(\bar{D} + b^*) = 0 . \tag{4}$$

Introducing a trade-off between consumption utility and disutility from medical debt changes the consumer welfare implications from reductions in the mean and the variance in medical bills. We discuss these implications in detail below.

8.2 Mean Reduction and Consumer Welfare

We start with an analysis of the effect of mean reductions in medical bills on consumer welfare. To this end, we ignore uncertainty in medical bills and evaluate the financial harm of a fixed medical bill (ϵ_{MB}). The key implications of the model are discussed graphically in Figure 10. The Figure depicts consumption on the horizontal axis and marginal (dis) utility on the vertical axis. For simplicity, we assume linear marginal utility functions. The
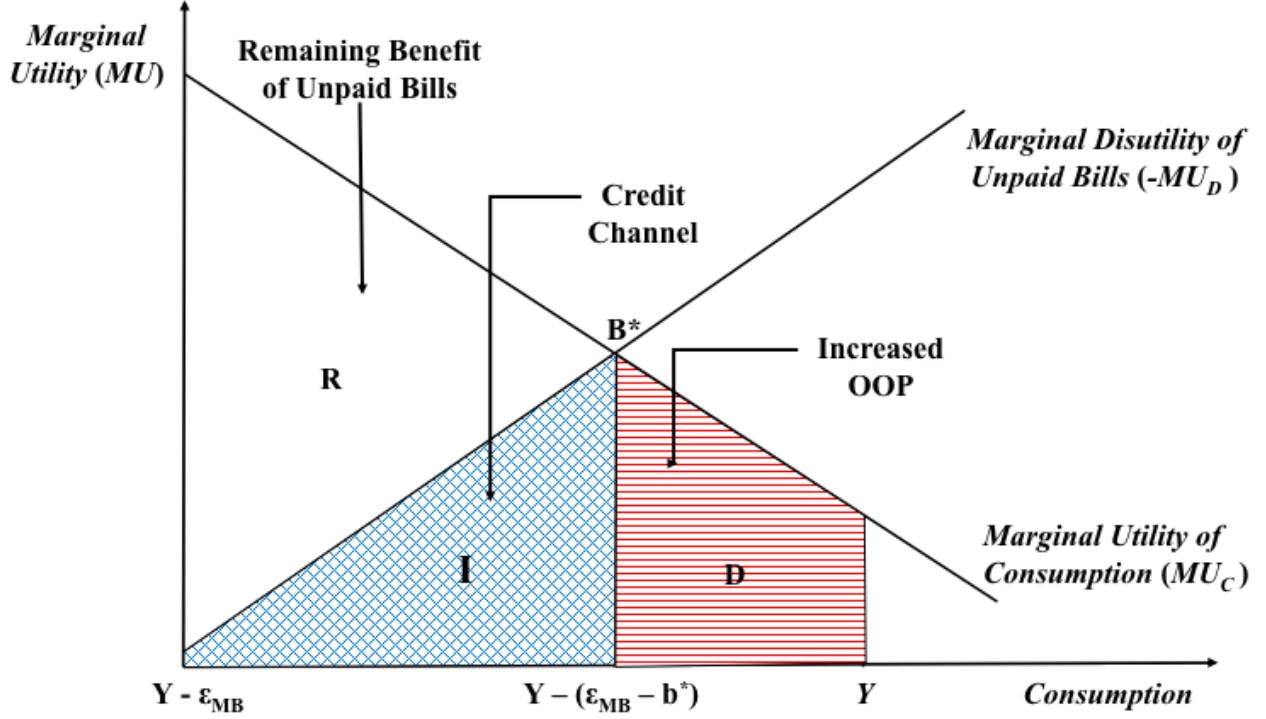
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Figure 10: Welfare Benefits of Mean Reduction: Example

downward sloping line is the marginal utility of consumption (MU_C), and the upward sloping line is the marginal disutility of medical debt $(-MU_D)$.

Absent any medical expenses, an individual consumes her income Y. When facing a medical bill of size ϵ_{MB}, she decides on the amount that she is willing to pay out-of-pocket, $\epsilon_{MB} - b^*$. In an optimum, the marginal utility of an additional dollar of consumption must equal the marginal disutility of an additional dollar in medical debt. This is depicted in point B^*. We can then define the welfare loss resulting from a medical bill as the sum two effects: (1) the direct effect on out-out of pocket spending and (2) the indirect effect, or the *credit channel*.

In the figure, the red area D bounded by the marginal utility of consumption, the individual's baseline income Y, and her final consumption, $Y - (\epsilon_{MB} - b^*)$, captures the direct effect, or the utility loss from reduced consumption due to increased out-of-pocket payments. The indirect, or *credit channel* effect is then the blue area, bounded by the marginal disutility of medical debt, final consumption, $Y - (\epsilon_{MB} - b^*)$, and final consumption minus the borrowed amount $Y - \epsilon_{MB}$. As described above, this *credit channel* highlights the potentially adverse consequences of unpaid bills on access to and the price of credit as well as other costs associated with not paying bills. The sum of the two areas captures the overall utility loss from the

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medical bill shock ϵ_{MB}. Finally, the white area (R) captures any remaining net benefit from unpaid medical bills. To see this, note that were the individual to pay the entire amount out-of-pocket, the utility loss would be the entire area underneath the marginal utility of consumption between: $(= R + I + D)$.

8.2.1   Transfer Gain from Insurance: Compensating Variation

To gauge the transfer gain from insurance, in dollars, we analyze the compensating variation (CV). In this context, the CV describes the amount of income a person is willing to forgo if the medical bill of the amount ϵ_{MB} is removed:

$$CV = e(p_0, u_0) - e(p_1, u_0) = e(\epsilon_{MB}, u_0) - e(0, u_0) .$$

Here, $e(\cdot)$ denotes the underlying expenditure function. Naturally, we have $CV = \epsilon_{MB}$ if the person pays the entire bill out-of-pocket. Conversely, if only a portion of the medical bill is paid out-of-pocket, then we have $\Delta OOP \leq CV \leq \epsilon_{MB}$, where ΔOOP denotes the counterfactual savings in out-of-pocket payments. Building on the graphical intuition from Figure 10, $Y - CV$ corresponds to the point on the horizontal axis, where the area underneath the marginal utility of consumption curve bounded by $Y - CV$ from the left and Y from the right equals the sum of the blue and the red area (D+I).

It is evident from this graphical characterization that the CV depends on the shape of the marginal utility curves and, of course, the underlying medical bill amount. To quantify the CV, we adopt two alternative approaches that rely on different assumptions. The first approach builds on the financial benefit estimates discussed above. We refer to this approach as the *direct approach*. Specifically, we add the implied annual interest savings to the reductions in out-of-pocket payments to find:

$$CV = \Delta OOP + \Delta Interest .$$

We view this approach as a conservative lower bound for the CV as it ignores the benefits from increased access to credit as well as reduced hassle costs from dealing with debt collectors.

8.2.2   Revealed Preference Approach

Our second approach builds directly on the outlined utility model and provides a more comprehensive evaluation of the financial benefits from paid and unpaid medical bills. In this approach, we calibrate the utility over consumption and reveal the disutility over med-

ical debt from realized out-of-pocket payments. We refer to this approach as the *revealed preference approach.*

To infer preferences over medical debt, we need to impose two additional simplifying assumptions. First, and building on the graphical analysis, we use a linear approximation to the marginal utility function around b^*. This implies that we only need to characterize the first and the second derivative of the disutility of medical debt. Second, and supported by our data, we assume that the fraction of unpaid bills, τ is "locally" constant: $\frac{b^*}{\epsilon_{MB}} = \bar{\tau}$.[22]. Using the first order condition and the implicit function theorem, we can then express the disutility of medical debt, and importantly the CV, in terms of the utility over consumption and the fraction of unpaid bills, see the appendix for details. In what follows we focus on the CV under increasing marginal disutilities in medical debt, $h''(\cdot) > 0$, which provides a lower bound for the case, $h''(\cdot) = 0$, see the Online Appendix for details.

An advantage of this approach is that we can also consider the comparative statics of the CV with respect to the underlying bill amount, the repayment rate, and the curvature in utility as stated in the following proposition, see the Online Appendix for proofs:

Proposition 1 *If $g'(\cdot) > 0, g''(\cdot) < 0$ and $h(\cdot) > 0, h''(\cdot) > 0$ and $b^* = \bar{\tau}\epsilon_{MB}$, then the linear approximation to the marginal utility function around b^* can be characterized as follows*

1. *The CV is given by:*

$$CV = -\phi(\cdot) + (1 - \bar{\tau})\epsilon_{MB} + \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon_{MB}^2},$$

   where $\phi(\cdot) = -\frac{g'(\cdot)}{g''(\cdot)}$ and $\cdot = Y - (1 - \bar{\tau})\epsilon_{MB}$ if $\epsilon_{MB} \leq \frac{\phi(\cdot)}{1 - \bar{\tau}}$.

2. *The CV is increasing in $\phi(\cdot)$*

3. *The CV is decreasing in $\bar{\tau}$ if $\frac{g'''(\cdot)g'(\cdot)}{g''(\cdot)^2} \leq 2$ and $\epsilon_{MB} < min\{\frac{\phi(\cdot)}{\bar{\tau} + \frac{1}{8}}, 4\phi(\cdot)\}$*

4. *CV over ϵ_{MB} is decreasing in the medical bill amount if $\frac{g'''(\cdot)g'(\cdot)}{g''(\cdot)^2} \leq 1 + \frac{\phi(\cdot)}{1 - \bar{\tau}}$.*

The proposition shows that the CV can be expressed in terms of three objects: the inverse curvature of individuals' consumption utility, $\phi(\cdot)$ the share of unpaid medical bills, $\bar{\tau}$, and the size of the medical bill, ϵ_{MB}.[23] More specifically, the CV is decreasing in the curvature

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[22]In contrast, $h''(\cdot) = 0$ implies quasilinear preferences. In this case, individuals repay medical bills up to given amount and borrow the rest in the form of medical debt. In the data, we observe that consumers choose to repay a positive (relatively constant) portion of their medical bills, which is inconsistent with quasilinear preferences.

[23]The condition $\epsilon_{MB} \leq \frac{\phi(\cdot)}{1 - \bar{\tau}}$ requires that the extrapolated marginal utility of consumption at $c = Y$ is weakly greater than zero.

of consumption utility. Holding the repayment rate fixed, the implicit function theorem reconciles less curvature in consumption with less curvature in the disutility of medical debt. Graphically speaking, a decrease in curvature flattens out both marginal utility curves in Figure 10. This reduces the value of borrowing and hence raises the CV. For example, as $g''(\cdot)$ converges to zero, both marginal utility curves become horizontal and the CV converges to ϵ_{MB}.

Furthermore, the CV decreases in the share of unpaid medical bills $\bar{\tau}$, provided minimal curvature and sufficiently small medical bills as outlined in the proposition. An extreme case is $\bar{\tau} = 0$, in which case medical bills are fully repaid, the CV equals ϵ_{MB}. Intuitively, there are two reasons for this finding. First, a decrease in $\bar{\tau}$ raises out-of-pocket spending and hence the CV. Second, a decrease in $\bar{\tau}$ signals that additional medical debt is costly from the point of view of the patient (otherwise a higher fraction of medical bills would go unpaid). This also raises the CV. Finally, the ratio of CV over the medical bill, ϵ_{MB}, decreases in ϵ_{MB}, provided minimal curvature as outlined in the proposition. This suggests that the credit channel is relatively more important for smaller medical bills.

Overall, the analysis suggests that considering the reduction of unpaid medical bills can increase the CV from $(1-\bar{\tau})\epsilon_{MB}$ to ϵ_{MB}, a factor of $\frac{1}{1-\bar{\tau}}$. This can be quite large given that uninsured patients pay only about $1 - \bar{\tau} = 20\%$ of health care services out-of-pocket. We revisit the CV in a numerical example in Section 9.

8.3 Variance Reduction and Consumer Welfare

Next we turn to the effects of the reduction in the variance of medical bills on consumer welfare, which corresponds to the value of risk protection. To this end, we reintroduce uncertainty in medical bills and quantify the risk premium RP, which isolates the the financial benefits from a variance reduction in medical bills. The risk premium is implicitly defined by the following equation:

$$EU = g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB} - RP) - h(\bar{D} + \bar{\tau} \cdot \bar{\epsilon}_{MB}) \ ,$$

where EU denotes expected utility, $\bar{\epsilon}_{MB}$ denotes the average medical bill, and $\bar{\tau} \cdot \bar{\epsilon}_{MB}$ is the average increase in medical debt.

To quantify the risk premium, we consider a second order Taylor approximation to consumer utility, evaluated at average medical bills $\bar{\epsilon}_{MB}$ holding the repayment ratio $(1 - \bar{\tau})$ fixed. We again calibrate utility over consumption, and leverage the first order condition and the implicit function theorem to express $h'(\cdot)$ and $h''(\cdot)$ in terms of $g'(\cdot)$, $g''(\cdot)$, and $\bar{\tau}$.

Finally, we can implicitly express RP as follows, see the Online Appendix for details:

$$g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) - g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB} - RP) \tag{5}$$
$$= -\frac{1}{2} \cdot (1 - \bar{\tau}) \cdot g''(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) \cdot var(\epsilon_{MB}) .$$

We then benchmark the derived risk premium to its counterpart in a more simplistic model, which ignores the role of unpaid medical bills: $h(\cdot) = 0$. We refer to the risk premium from this out-of-pocket benchmark model as RP^{oop}. Based on a second order Taylor approximation, first order condition, and implicit function theorem, we derive an analogues implicit condition for the risk premium RP^{oop}:

$$g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) - g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB} - RP^{oop}) \tag{6}$$
$$= -\frac{1}{2} \cdot (1 - \bar{\tau})^2 \cdot g''(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) \cdot var(\epsilon_{MB}) .$$

Comparing equations (5) and (6), we find that:

$$RP^{oop} < RP < \frac{1}{1 - \bar{\tau}} \cdot RP^{oop} ,$$

suggesting that considering unpaid medical bills can increase the risk premium by factor of $\frac{1}{1-\bar{\tau}}$. We quantify the risk premium in a numerical example in Section 9.

9 Overall Effects of Medicaid on Financial Health

In this last section, we quantify the consumer welfare gains from reductions in paid and unpaid medical bills. We start with the revealed preference approach before discussing the findings from the direct approach.

9.1 Revealed Preference Approach

We begin with a numerical analysis of the mean reduction of unpaid medical bills. To this end, we consider CRRA utilities with parameters of relative risk aversion ranging between 2 and 4. Following (Finkelstein, Hendren and Luttmer, 2015) we normalize income to 3, 800. We assume that patients pay 20% of the original medical bill out-of-pocket. Motivated, by the direct evidence on reductions in medical debt, we also assume that 40% of medical bills

go as charity care, such that individuals are only held responsible $1 - \alpha_{charity} = 0.6$ of medical bills.[24]

In Figure 11, we plot the ratio of the implied compensating variation (CV) over the corresponding medical bill ($\frac{CV}{Medical\ Bill}$) (vertical axis) against the underlying medical bill (horizontal axis). As implied by the model, this ratio decreases from a maximum of 60% for small bills to $1 - \bar{\tau} = 0.2$ for large bills. Moreover, $\frac{CV}{Medical\ Bill}$ is convex in the underlying medical bill amount suggesting that evaluating the ratio at the average medical bill amount wound understate the expected $\frac{CV}{Medical\ Bill}$ when considering the full distribution in medical bills. Evaluated at $\theta = 3$, this ratio exceeds 50% (30%) for medical bills worth less than
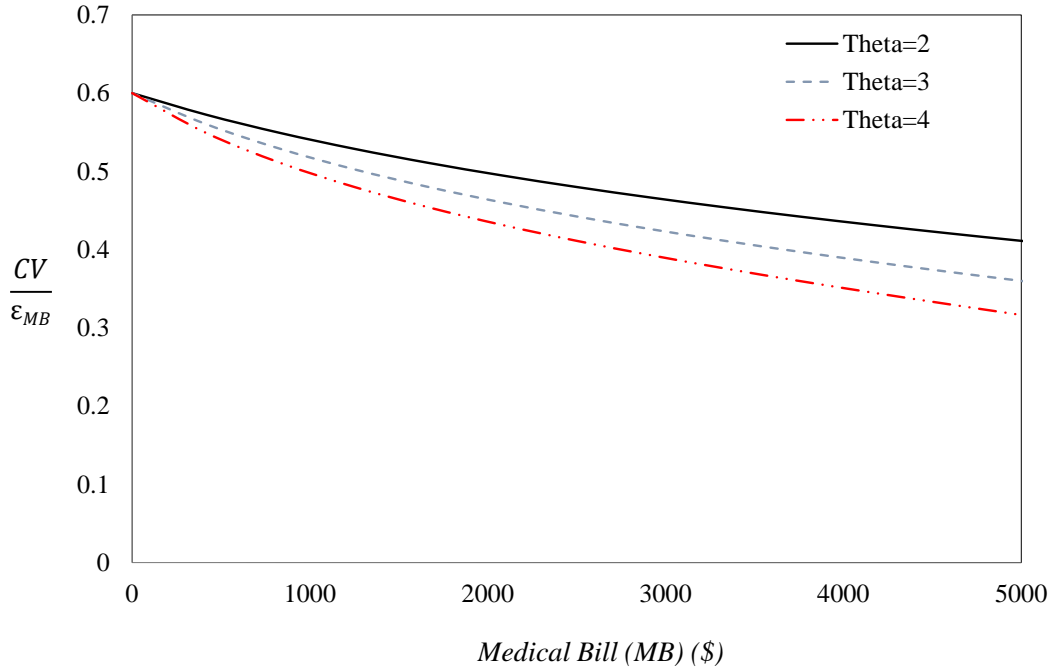

Figure 11: Compensating Variation/Medical Bill by Medical Bill

$1,000 ($5,000). Our previous estimates suggest a medical debt reduction of about $920 per treated person, which corresponds to a raw bill of $\frac{\$920}{0.40} \approx \$2,300$. At $2,300 this ratios exceeds 44%. The calibration thus implies that restricting consideration to reductions in out-of-pocket payments may understate the effects on consumer welfare by a factor of $\frac{44\%}{20\%} = 2.2$.

Using the above calibrated factor of 2.2, an associated parameter of risk aversion of 3, and considering overall annual health care spending of $2,400 per uninsured non-elderly person

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[24]We find that medical debt is reduced by about $920 per treated person, which corresponds to roughly 40% of overall health care utilization. Adding 20% of out-of-pocket spending suggests that the remaining 40% is treated as charity care.

(see Section 2.2), we calculate out-of-pocket spending and implied compensating variation of \$480 and \$480 × 2.2 = \$1,056, respectively. This suggests an indirect benefit through the credit channel of \$1,056-\$480=\$576. These results are detailed in column 1 of Table 6.

Table 6: Overall Annual Financial Benefits

	Revealed Preference	Direct Approach
	(1)	(2)
Mean Effects		
Credit Channel (Indirect)	576	283
Out-of-Pocket (OOP) Spending (Direct)	480	480
Compensating Variation (CV)	1,056	763
Ratio: $\frac{CV}{OOP}$	2.2	1.6
Variance Effects		
Risk Premium (RP)	600	(600)
Risk Premium OOP Benchmark (RP OOP)	240	(240)
Ratio: $\frac{RP}{RP\,OOP}$	2.5	(2.5)
Total Benefit	1,656	1,363
Total Spending (Coughlin, 2014)	2,400	2,400
Ratio: Benefit/Spending	0.69	0.57

Risk averse consumers are also willing to pay a premium for a reduction in risk. We evaluate this risk premium based on equation (5) around average annual consumption of \$3,300 and consider a standard deviation in consumption of \$768 as in (Finkelstein, Hendren and Luttmer, 2015).[25] We need to make two adjustments to equation (5) to take the role of charity care into account. First, we replace the variance in the medical bill, $var(\epsilon_{MB})$, by the variance in non-charity care, $var(\epsilon_{MB}^{non-charity})$. Second, we need to adjust the out-of-pocket spending ratio $(1 - \bar{\tau})$ to express out-of-pocket spending relative to the bill amount that is not covered by charity care. Since only 60% of the medical bill is held against the patient (40% is charity care), we replace $(1 - \bar{\tau})$ by $(1 - \bar{\tau}_{non-charity}) = \frac{0.2}{0.6} = \frac{1}{3}$. To quantify the variance in non-charity care, we build on the observation that only one third of the non-charity care amount is paid out-of-pocket. Specifically, the variance in consumption then equals $(1-\bar{\tau}_{non-charity})^2 \times var(\epsilon_{MB}^{non-charity})$. Leveraging the observed variance in consumption allows us to pin down the variance in non-charity care. Solving for RP in the revised equation

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[25] The consumption level corresponds to income net of average out-of-pocket spending: \$3,800 − \$480 ≈ \$3,300.

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([5](#)), we find a risk premium of \$600, which exceeds the pure OOP benchmark, building on a revised equation [6](#), by a factor of 2.5 (column 2 of Table [6](#)). Combining the estimates, we find an overall annual financial benefit of \$1,656, about 69% of overall medical spending, which exceeds the out-of-pocket benchmark by a factor of 2.3.

9.2 Direct Approach

We benchmark our calibration to our direct estimates presented above. The estimated indirect benefits from reduced costs of credit equal $\frac{\$8.19+\$2.81+\$0.22+\$0.40}{0.041} = \frac{11.62}{0.041} = \$283$ per year (column 2 of Table [6](#)). Combined with the reduction in out-of-pocket spending, we calculate a compensating variation of \$763, which exceeds the out-of-pocket reduction by 60%. These findings are a bit smaller than the results from the revealed preference approach, which is sensible because the direct approach ignores other benefits from a reduction in unpaid bills such as reduced hassle costs with collection agencies, reduction in costs related to bankruptcy filing, and improved credit offer rates.

When compared to the overall reduction in medical debt, the estimated credit channel (indirect) benefit is valued at $\frac{\$11.62}{\$37} = \$0.31$ per dollar of reduced medical debt. Taking repayments of medical debt on the order of 8% into account (Table [5](#)), we find a total financial benefit of a reduction in unpaid medical bills of about $\$0.31 + \$0.08 \approx \$0.39$ per dollar of reduced medical debt. Unfortunately, our direct approach does not yield an estimate for the risk premium. Therefore, we borrow the corresponding estimates from the revealed preference approach to calculate an overall annual financial benefit of $\frac{\$1,363}{\$2,400} \approx 57\%$ of overall medical spending. This exceeds the out-of-pocket benchmark by a factor of 1.9.

9.3 Other Insurance Value

The above suggests that, absent changes in health care utilization, individuals may not be willing to buy Medicaid insurance even when offered at a fair premium.[26] This may be because of charity care and the option to not pay the medical bill, including the option to file bankruptcy, provide implicit insurance over of health care spending. Dividing the CV by overall medical spending, ignoring the risk premium, we find an effective price of only 40 cents per dollar, suggesting that perhaps charity care and default options insure about 60% of health care spending.

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[26]This finding is consistent with the results in (Finkelstein, Hendren and Luttmer, 2015) and (Finkelstein, Hendren and Shepard, 2017).

We revisit the role of charity care and medical debt in two thought experiments. In the first, we use the revealed preference approach to calculate the benefit-spending ratio in the absence of charity care, holding constant utilization and the proportion of the bill paid out of pocket (%20). Our model implies that $\frac{CV}{Medical\ Bill}$ now increases to 89%, or that the out-of-pocket spending would understate the CV by a factor of 89%/20%=4.45. The implied CV and risk premium equal $2,136 and $849, respectively. This leads to a total benefit of $2,136 + $849 = $2,985, which now exceeds overall health care spending by 24%.

In the second, we consider one possible mechanism for the net value of unpaid medical bills: the insurance value of bankruptcy protection. Medical debt can be discharged in bankruptcy proceedings (Mahoney, 2015) which may explain why patients value a one dollar reduction in medical debt at only 51 cents. However, we find that that subprime borrowers discharge on average only $860 per bankruptcy filing, see Table 7. Considering an annual reduction of about 25,000 bankruptcies, see Section B.4 for details, this can account for only about $860 × 25,000 = $21.5m in medical debt or 1% of the overall reduction in medical debt. However, we note that the marginal filers, who were affected by the Medicaid expansion, may hold considerably more medical debt. If so, the $21.5m estimate provides a very conservative estimate of the potential insurance value of bankruptcy protection.

Overall, this suggests that charity care is more important in explaining low valuations of health insurance than the option to default.

10   Conclusion

More than half of the uninsured in the U.S. report difficulties paying their medical bills and pay on average only about 20% of overall health care utilization out-of-pocket. If the residual 80% of utilization are provided as charity care, then the out-of-pocket payments provide a good estimate of the financial cost of health care utilization for the uninsured population. In practice, however, a large fraction of unpaid medical bills goes into collection, which may have profound negative effects on these individuals' financial health, through access to and terms of credit. This suggests that the incidence of unpaid medical bills (uncompensated care) at least partially falls on the low-income uninsured patients themselves, through an indirect credit channel.

In this paper, we quantify the financial benefits of health insurance, including the indirect benefits through the credit channel, in the context of the Medicaid expansion provision under the Affordable Care Act (ACA). Combining state-level variation between adopting and non-adopting Medicaid expansion states with a nationally representative panel of 5 million credit

reports, we find that the expansion reduced households' medical debt in collection by $3.4 billion in its first two years. This corresponds to an annual reduction of about $920 per treated person or about 40% of overall health care spending. We further find that the Medicaid expansion significantly reduced debt delinquencies and led to higher credit scores for consumers. Using data on loan pricing, we document that improved financial health led to better terms of credit for individuals in treated states. We then simulate a debt refinance given improved credit conditions and calculate annual interest rate savings of about $520 million, which is about 60% of the reduction in out-of-pocket spending. Overall, we find that the financial benefits of health insurance double when considering the indirect benefits of improved terms of credit in addition to reductions in out-of-pocket payments. Our estimates also suggest that beneficiaries value reductions in medical debt by about 40 cents per dollar in face value.

Finally, we find that uninsured patients pay effectively 32 to 44 cents per dollar of health care utilization, divided about equally between changes in direct out-of-pocket and indirect interest rate payments. This suggests that charity care and the ability to not pay medical bills (or borrow) effectively insures over 60% of health care spending. As a result, beneficiaries value Medicaid insurance only at about 65% of health care spending.

References

Bachrach, D, P Boozang, and M Lipson. 2015. "The impact of Medicaid expansion on uncompensated care costs: Early results and policy implications for states." *Princeton: Robert Wood Johnson Foundation.*

Brevoort, Kenneth P., and Michelle Kambara. 2015. "Are all collections equal? The Case of Medical Debt." *The Journal of Credit Risk*, 11(4).

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

Bureau, Consumer Financial Protection. 2015. "The Consumer Credit Card Market."

Cabral, Marika, and Mark R Cullen. 2016. "Estimating the Value of Public Insurance Using Complementary Private Insurance."

Coughlin, Teresa A. 2014. "Uncompensated care for the uninsured in 2013: A detailed examination."

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. 2016. "Impacts of the Affordable Care Act on health insurance coverage in Medicaid expansion and non-expansion states." National Bureau of Economic Research.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J Notowidigdo. 2016. "The Economic Consequences of Hospital Admissions." *Working Paper.*

Domowitz, Ian, and Robert L. Sartain. 1999. "Determinants of the Consumer Bankruptcy Decision." *Journal of Finance*, 54: 403–420.

Dranove, David, Craig Garthwaite, and Christopher Ody. 2016. "Uncompensated care decreased at hospitals in Medicaid expansion states but not at hospitals in nonexpansion states." *Health Affairs*, 35(8): 1471–1479.

Finkelstein, Amy. 2007. "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare." *The Quarterly Journal of Economics*, 122(1): 1–37.

Finkelstein, Amy, and Robin McKnight. 2008. "What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending." *Journal of public economics*, 92(7): 1644–1668.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer. 2015. "The value of Medicaid: Interpreting results from the Oregon Health Insurance Experiment."

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard. 2017. "Subsidizing health insurance for low-income adults: Evidence from Massachusetts." *NBER Working Paper.*

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, et al. 2012. "the Oregon Health Insurance Experiment: Evidence from the First Year." *Quarterly Journal of Economics*, 127(3).

Frean, Molly, Jonathan Gruber, and Benjamin D Sommers. 2016. "Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act." *NBER Working Paper.*

Fulford, Scott L, and Scott D Schuh. 2017. "Consumer revolving credit and debt over the life cycle and business cycle." *Federal Reserve Bank of Boston Working Paper.*

Garthwaite, Craig, Tal Gross, and Matthew J Notowidigdo. 2015. "Hospitals as insurers of last resort."

Gross, Tal, and Matthew J Notowidigdo. 2011. "Health insurance and the consumer bankruptcy decision: Evidence from expansions of Medicaid." *Journal of Public Economics*, 95(7): 767–778.

Hamel, Liz, Mira Norton, Karen Pollitz, Larry Levitt, Gary Claxton, and Mollyann Brodie. 2016. "The burden of medical debt: Results from the Kaiser Family Foundation." *New York Times medical bills survey.*

Hu, Luojia, Robert Kaestner, Bhashkar Mazumder, Sarah Miller, and Ashley Wong. 2016. "The effect of the Patient Protection and Affordable Care Act Medicaid expansions on financial well-being." *NBER Working Paper.*

Kaiser Family Foundation. 2012. "A Guide to the Supreme Court's Decision on the ACA's Medicaid Expansion." *http://kff.org/health-reform/issue-brief/a-guide-to-the-supreme-courts-decision/*, Accessed: 2015-03-25.

Kowalski, Amanda E. 2015. "What do longitudinal data on millions of hospital visits tell us about the value of public health insurance as a safety net for the young and privately insured?" *NBER Working Paper.*

Mahoney, Neale. 2015. "Bankruptcy as implicit health insurance." *The American Economic Review*, 105(2): 710–746.

Mazumder, Bhashkar, and Sarah Miller. 2016. "The effects of the Massachusetts health reform on household financial distress." *American Economic Journal: Economics Policy*, 8(3): 284–313.

Sojourner, Aaron, and Ezra Golberstein. 2017. "The ACAs Medicaid expansion and its effects onfFinancial wellbeing." *Working Paper*.

White, Michelle. 2006. *Bankruptcy and consumer behavior: Theory and US evidence.* Vol. 7, ch.

Zeckhauser, Richard. 1970. "Medical Insurance: A case study of the tradeoff between risk spreading and appropriate incentives." *Journal of Economic Theory*, 2(1): 10–26.

A   Collections, Debts, & Distress: An Event Study

In this section we discuss the relationship between medical collections and financial distress. In doing so we provide further detail on the analysis in Section 6. Our approach closely follows the event study methodology in Dobkin et al. (2016) which tracks how individuals' financial outcomes fare following a hospital admission. As we do not observe hospitalization, we replace the event of hospital admission with reporting of a large new medical collection ($1,000). Large new collections are likely associated with hospitalization for uninsured individuals.

There several differences between a hospital admission and a medical collection. For example, new collections are generally not reported for up to 180 days following services rendered. Moreover, not all hospital admissions result in patients having their unpaid medical bills sent to collections. However there are also similarities, especially when considering uninsured individuals. As such, in addition to illustrating the relationship between collections and distress, we benchmark our event study results to those in Dobkin et al. (2016).

We subset our sample to include only large collections, which likely result from hospital admissions. Each individual in our sample received at least one collection valued at more $1,000 prior to January 1, 2014. We then follow each of these individuals from six quarters prior to receiving the collection and for eight quarters, or two years, following the event. We use a non-parametric methodology similar to Dobkin et al. (2016) as follows:

$$y_{ict}^k = \alpha_c^k + \eta_t^k + \sum_{r=S}^{r=-2} \beta_r^k + \sum_{r=0}^{r=F} \beta_r^k + \epsilon_{ict}^k \tag{7}$$

where y_{ict}^k denotes the respective outcome k for record i in census tract c during year-quarter t, such as delinquency. As in equation 1, the specification includes tract fixed effects α_c^k and quarter-year fixed effects η_t^k. The key parameters of interest are the β^r, which are indicators for time relative to having a collection placed on the record. Outcomes are normalized to the end of the quarter just prior to a collection being placed on the account. All analyses allow for an arbitrary variance-covariance matrix at the Census Tract level.

Figure 12 plots the raw β_r^ks and their respective confidence intervals. The figure plots these for medical collection balances (left panel), serious delinquencies (middle panel), and credit scores (left panel) separately for individuals with base credit score < 620 and > 620, or subprime and prime borrowers, respectively. As shown in the figure, following a new collections, and by construction, individuals' collections balances increase substantially. Nevertheless, this increase in medical debt is long lasting, as the high level of medical collections
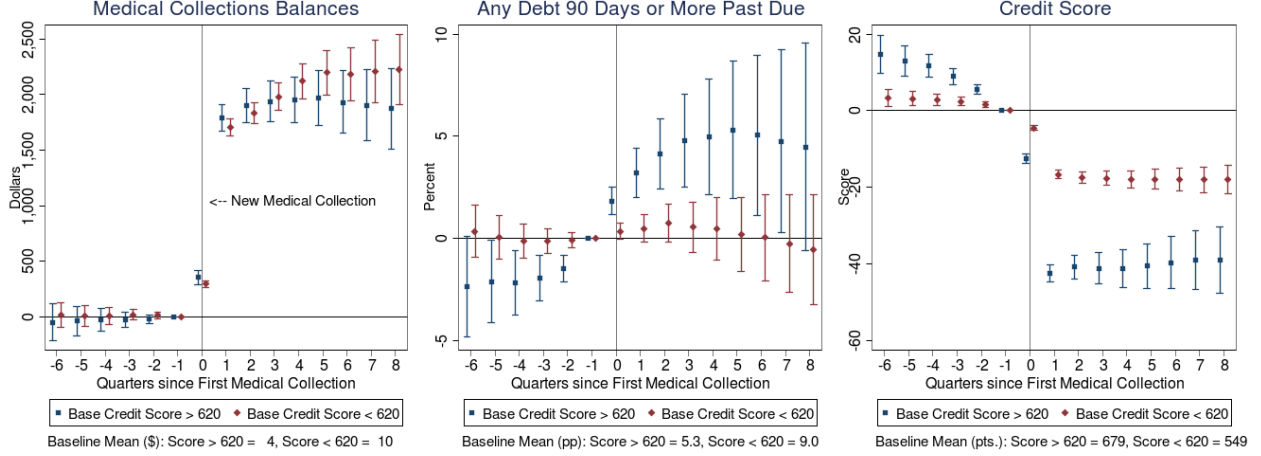
Figure 12: Event Study: Credit Worthiness (By Risk)

Notes: *The figure shows how 'healthy' individuals who receive a medical collection fair in the eight quarters (2 years) following the event. It does so along three dimensions: (1) Overall medical collections balances (left panel) (2) serious (90 day or more) delinquency (middle panel) (3) credit score (right panel). Serious delinquency is defined as the individual ever having become delinquent on a non-medical credit line, or debt, by that quarter. Data are from the CFPB's Consumer Credit Panel, which is described in detail in section 3. The figure includes only individuals who received large collections prior to January 1, 2014. Effects are as of the end of each quarter and are normalized to the quarter just prior to the first collection an individual receives on their record (the event). All regressions (Equation 7) include Census tract and year-quarter fixed effects. Confidence intervals in the figure are calculated using standard errors clustered at the Census tract level. For estimation details see appendix A.*

balances remains on individuals' accounts for at least 2 years after the first one is reported. This is true for both prime and subprime consumers. As might be expected, following a new medical collection, loan delinquency rates increase dramatically. However, in contrast to medical debt balances, there is a stronger surge in delinquency for prime borrowers. This is likely because prime borrowers' base levels of delinquency are low to begin with, whereas subprime borrowers are likely troubled by delinquencies prior to receiving a new medical collection. It follows that a new collection also dramatically reduces borrowers' credit scores, and that this effect is much greater among prime borrowers. As is shown in the figure, credit scores begin to fall prior to the collection, likely because the actual health event, and distress resulting from it, begin some time before a medical collection is placed on individuals' records. However, there is a substantial drop just after the first collection is reported which persists for several years following. This is likely a direct result of the new collections account, which is used by credit scoring companies to help predict future delinquencies.

Figure 13 plots coefficients β_r^k for auto loan balances (left panel) and credit card utilization (right panel) for prime and subprime borrowers, respectively. From the figure we find that, as
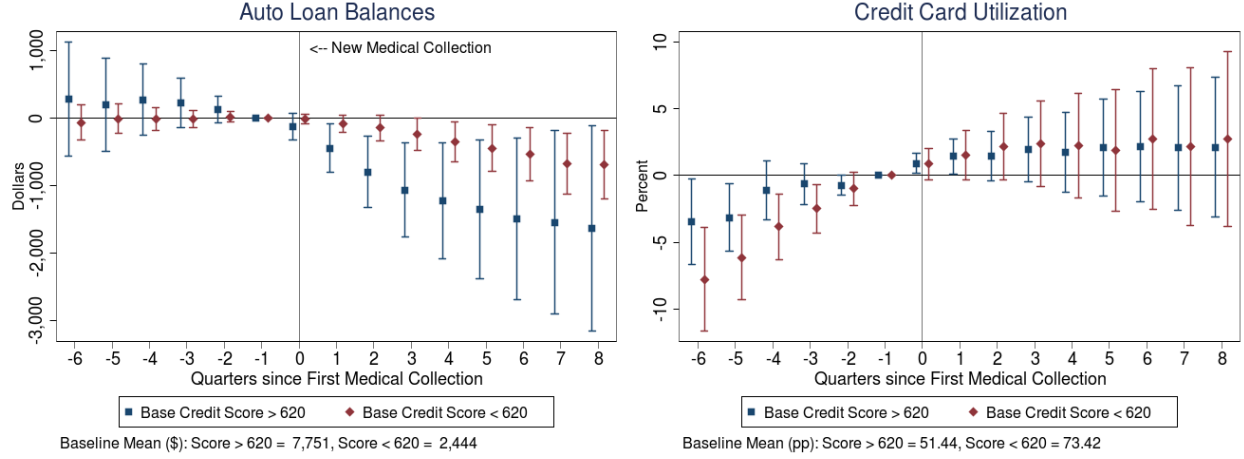
Figure 13: Event Study: Non-Medical Debt (By Risk)

Notes: *See notes in Figure 12.*

in Dobkin et al. (2016), auto loan balances decline following a new collection being reported. This is consistent with individuals having lower income and fewer borrowing options, being unable to either refinance their car loans or make new purchases. Two years following a collection, their balances are nearly $1,500, or about 20%, lower than just prior to the event. Consistent with this story, we find that credit card utilization increases in the quarters up to and for almost two years following the event. As large medical collections are spurred on by adverse health events, it is likely that individuals use unsecured credit lines to smooth out consumption during these bad times. Moreover, signaled financial distress likely restricts the availability of credit to these individuals, leading them to draw further into their already available credit.

In all, these figures suggest that individuals who have a large medical collection placed on their account become financial distressed in the two years following this event. This is signaled by their increased delinquency and significantly reduced credit scores. Moreover, this greater distress leads to poorer borrowing options, as indicated by their lower auto loan balances and increased credit card utilization rate.

B   Robustness and Empirical Appendix

B.1   Robustness: Other Collections & Federal Exchanges

Figure 14 plots trends in non-medical collections. To the extent that reduction in medical debt is driven by increased insurance rates reducing unpaid medical bills, trends in non-
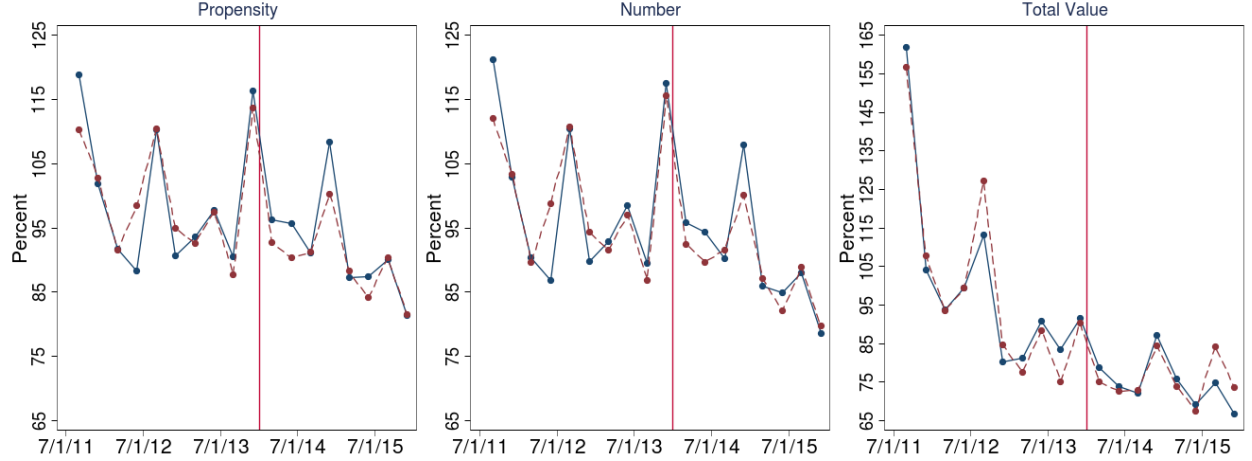
Figure 14: Trends in Newly Accrued Non-Medical Collections

Notes: *The figure shows trends in the incidence, frequency, and value of newly accrued non-medical collections. Data are from the CFPB's Consumer Credit Panel described in section 3. Trends are quarterly means of newly accrued non-medical collections for treament and control states, respectively, and are normalized by the pre reform mean for each group. Vertical lines highlight the implementation date of the expansion - January 1st, 2014.*

medical collections should not differ in treatment states relative to control following the reform. Indeed, we note no evidence of differences in trends of non-medical collections for treatment states relative to control following the reform. We conclude that there was no systematic change in overall collections activity driving the reduction in medical debt accruals. Rather, reductions in unpaid medical bills sent to collections are a result of newly-insured households not generating newly-unpaid medical bills following unexpected adverse health events.

Figure 15 plots trends in medical collections for states opening insurance exchanges using the federal platform. Other factors governing medical debt may be associated with the opening of the exchanges and, specifically, platform choice among states. To account for these factors, we subset our sample to include only states that adopted the federal platform. In other words, for these states, all individuals using the exchanges did so on the same platform.

We find that this pruning does not materially alter our results. For the most part, we see that medical collection declines dramatically in propensity, number, and volume across treatment and control states all of which opted to use the federal platform for the exchanges. Moreover, the magnitudes are quite similar when considered alongside the full sample.
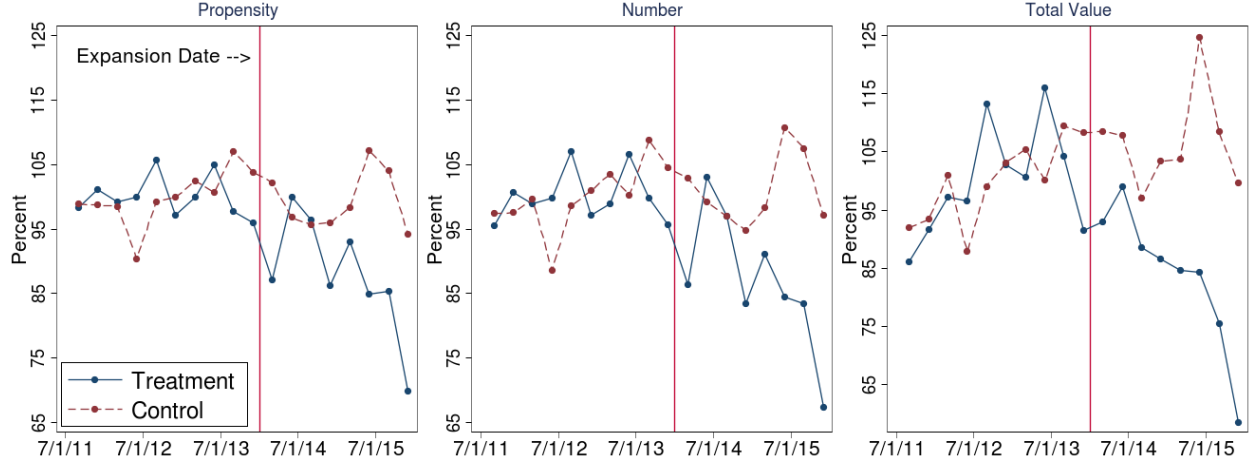
Figure 15: Newly Accrued Medical Debt for States Running Federal Exchanges

Notes: *The figure shows trends in the incidence, frequency, and value of accrued medical debt. Data are from the CFPB's Consumer Credit Panel described in section 3. Trends are quarterly means of newly accrued medical loans for treament and control states, respectively, and are normalized by the pre reform mean for each group. Vertical lines highlight the implementation date of the expansion - January 1st, 2014.*

B.2 Reductions in Credit Card Debt

Often individuals pay medical bills using their credit cards. This is true at a private doctor's office as well as in a hospital. Although we do not observe the source of debt on credit cards in the CCP, we may expect that the Medicaid expansion's effect on credit card debt may have flowed through a reduction in the payment of medical expenditures for newly insured individuals. Figure 16 plots trends in credit card balances for consumers in adopting (treatment) and non-adopting states (control). As shown in the top panel of the table, credit card balances on average declined by about 1.9% for individuals in treatment vs. control states in the two years following the reform. We interpret this decline as the overall per-person reduction after 4 quarters, the mid-point of the post-reform period, given that the negative effect on non-medical debt is gradually growing in magnitude over time. The Moreover, the bottom right panel of the table shows that this decrease was proportionally greater in poorer communities with higher Medicaid eligibility rates. The level reduction, however, was greater in richer communities, where it is likely that individuals had more generous credit lines from which to borrow to pay for medical services.

Under the assumption that the observed reduction in credit card debt resulting from to the expansion is entirely due to reduced out-of-pocket payment of medical bills, we calculate a reduction in out of pocket payments from reduced credit card debt to be $0.0186 \cdot \$4,026 = \$74.88$ per person, or approximately $3.8 billion.
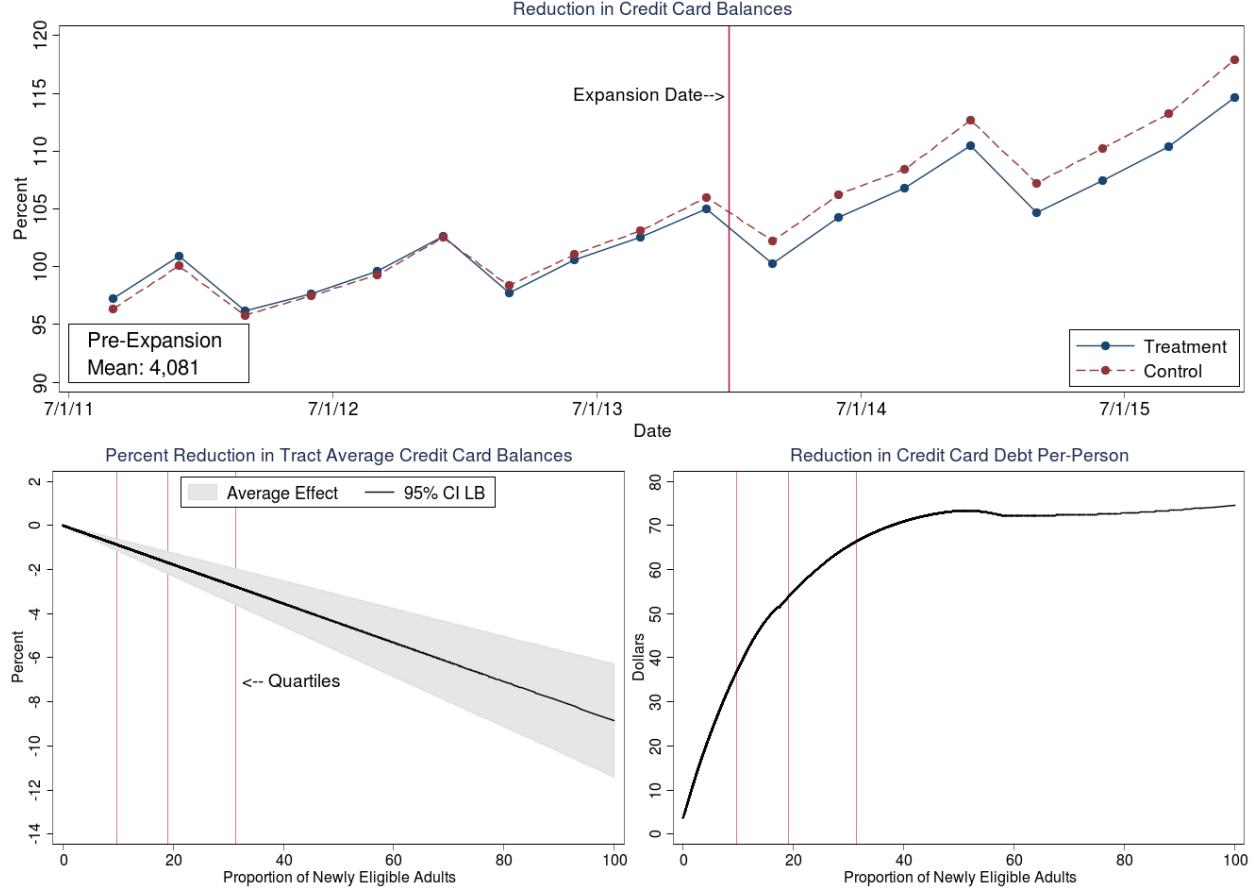
Figure 16: Effects of the Medicaid Expansion on Credit Card Balances

Notes: *The figure shows trends in the credit card balances. Data are from the CFPB's Consumer Credit Panel described in section 3. Trends are quarterly means in the level of credit card balances for treatment and control states, respectively, and are normalized by the pre-reform mean for each group. The vertical line in the top panel highlights the implementation date of the expansion - January 1st, 2014. Trends exclude extreme outliers ($\sim 95^{th} Pctl.$)in credit card balances, which are likely not affected by the reform. The DiD estimate is the from a regression of the log average balance in Census tract c in quarter t and includes Census tract and quarter year fixed effects. Standard errors are clustered at the tract level.*

B.3 Access to Credit

In this Section, we present evidence on the reform's effect on access to credit card debt and personal loans using the Mintel data. Figure 17 provides evidence on the share of adults that receives any new credit card offer in the given quarter. The left panel provides suggestive evidence for an increase in the offer rate in treatment states following the expansion. This is supported by the right panel, which provides analogous regression based evidence based on our primary empirical difference-in-difference specification.
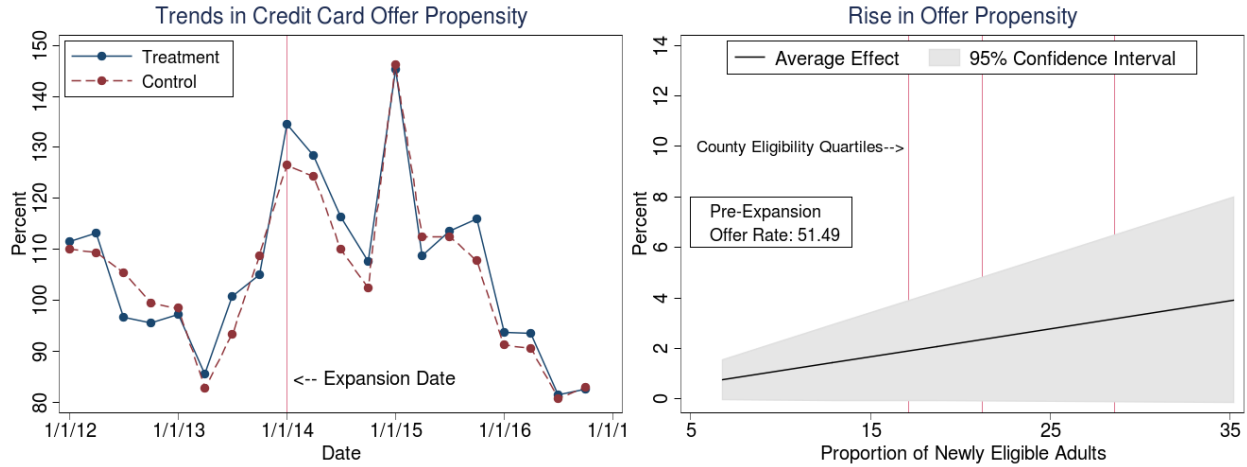
Figure 17: Effects of the Medicaid Expansion on Access to Credit Cards

Figure 18 presents the analogous results for personal loans. Here the evidence is mixed. While the left panel suggests an increase, the right panel suggests a decrease in offer rates.
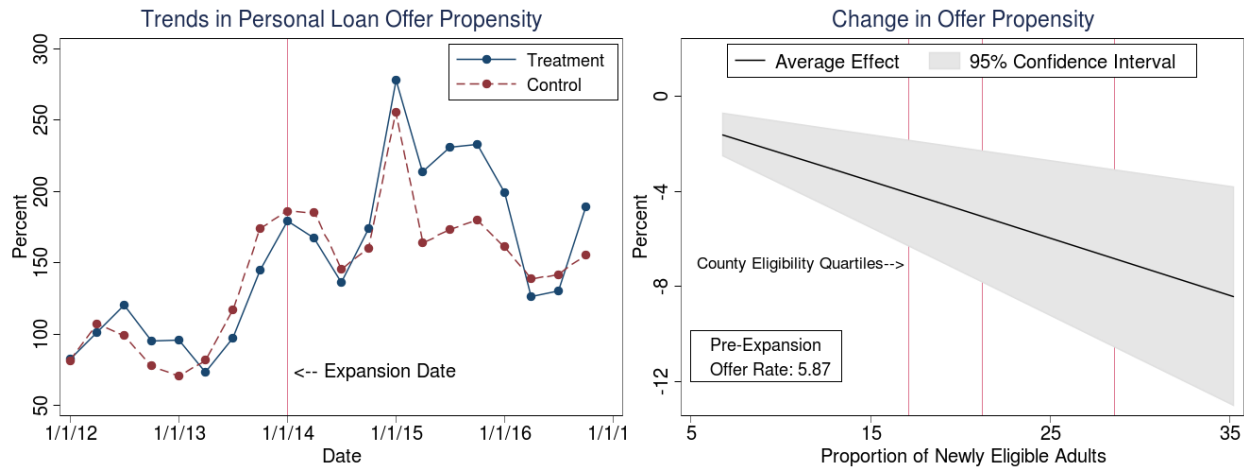

Figure 18: Effects of the Medicaid Expansion on Access to Personal Loans

Overall, we interpret these results as supportive evidence for an increase in access to credit because credit card debt is a common form of debt among poor households that benefit from the Medicaid expansions.

B.4 Bankruptcy

Another measure of financial distress, often discussed in the context of medical expenditures, is bankruptcy, or insolvency. In the U.S., individuals most commonly file for bankruptcy under Chapter 7 or Chapter 13, the former being about twice as common. Under Chapter 7, a filer can discharge nearly all debts. However, the filer is required to relinquish any of their non-exempt assets.[27] Once the debts have been discharged, the consumer is given a fresh start and not required to make any additional payments out of her future income. In contrast, Chapter 13 is geared towards consumers with wage incomes who are permitted to retain their assets but must enter into a repayment plan. Under repayment only a portion of debts are discharged. Chapter 13 bankruptcy has the additional requirement that creditors must receive at least as much from the repayment plan as they would have by liquidating the debtor's assets in a Chapter 7 bankruptcy.

In Table 7, we provide summary statistics on the debt distribution of bankruptcy filers. About of third of bankruptcy filers hold medical debt, worth, on average, \$2,000. The average, however, masks substantial heterogeneity. The top 1% of filers with medical debt aim to discharge nearly twelve times that amount, or \$24,000, suggesting that medical debt may be an important contributor to bankruptcy filing. More generally, bankruptcy filers hold about twice as much unsecured non-medical debt as the average consumer (Table 1), with prime filers holding slightly more. This is expected, given that filers benefit from discharging unsecured debt. Conversely, we do not find clear evidence for differences in secured debt, such as mortgage loans or other non-mortgage debt, which is plausible, given that filers would also lose some underlying assets.

The previous comparison indicates a positive correlation between unsecured debt and bankruptcy filing. We now revisit this mechanism using the Medicaid expansion, which shields beneficiaries from accruing new unsecured medical debt. Figure 19 shows normalized trends in bankruptcy rates for consumers in treatment and control states around the time of the expansion. Each panel also shows results from a DD regression of the form

$$\mathbb{1}[AnyFiling]_{ict} = \alpha_c + \eta_t + \beta \cdot (Adopt \times Post) + \epsilon_{ict}. \tag{8}$$

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[27]Some debts may be ineligible to be discharged under Chapter 7. Most notably, student loans and taxes cannot be discharged without the debtor showing undue hardship. The size of the asset exemption varies across the states, the only part of bankruptcy law that is not uniform nationwide (White, 2006). Many states also have different exemptions for a debtor's principle residence and for other types of personal property. Secured debts may also be discharged if the debtor gives up the collateral securing the loan.

Table 7: Debt at Bankruptcy

	All	(Base Credit Score < 620)	(Base Credit Score > 620)
	(1)	(2)	(3)
Percent Filing with Medical Debt	33.32	40.93	13.63
Medical Debt at Filing			
Mean if Medical Debt >0	1,976	2,025	1,585
Median	550	569	392
75th Pctl.	1,553	1,614	1,023
90th Pctl.	3,919	4,142	2,785
99th Pctl.	23,413	23,385	24,844
Other Debt at Filing			
Credit Cards	8,171	7,149	10,905
Personal Loans	1,138	986	1,531
Auto Loans	4,874	4,197	6,628
Mortgages	48,194	41,832	64,651

Notes: *This table shows debt portfolios of individuals declaring bankruptcy. The data are from the CFPBs CCP and include only pre-expansion filings (before January 1, 2014) among those living in Medicaid expansion states (Figure 1). Debt figures include also debt that has been charged off by the lenders. Column 1 shows debt portfolios among all filers. Columns 2 and 3 show debt portfolios among subprime and prime filers, respectively.*

where α_c are Census tract fixed effects and η_t are quarter-year fixed effects.[28] Like our analysis of financial distress, we distinguish the effects of the policy for consumers with credit scores of 620 or above (left panel) or below 620 (right panel). As illustrated in the figure, the Medicaid expansion had little effect on the likelihood of filing for bankruptcy among consumers with baseline credit scores of 620 or higher. For this more resilient group, overall filing rates are low and do not seem influenced by the expansion. In contrast, among financially vulnerable consumers, with baseline credit score of less than 620, the Medicaid expansion reduced the quarterly rate of bankruptcy filings by a substantial 0.03 percentage points, or 8% of the pre-expansion mean. Given our sample frame, this translates into approximately 50,000 fewer bankruptcies over the first two post-reform years.[29]

To put our estimates into perspective, Mazumder and Miller (2016) find that the Massachusetts health reform reduced bankruptcy filing by 0.08 percentage points over two years

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[28]For the bankruptcy analysis we depart from the functional form in the main paper, Equation 1. This is because bankruptcies are somewhat rare and much lagged.

[29]The above are calculated from our sample and estimated coefficients as follows:

$$\Delta Bankruptcy = \underbrace{468,144}_{\text{\# of subprime Records in Treament States}} \times \underbrace{48}_{\text{pop. wgt.}} \times \underbrace{-0.000271}_{\Delta \text{ percentage points}} \times \underbrace{8}_{\text{post quarters}} \approx -48,717$$
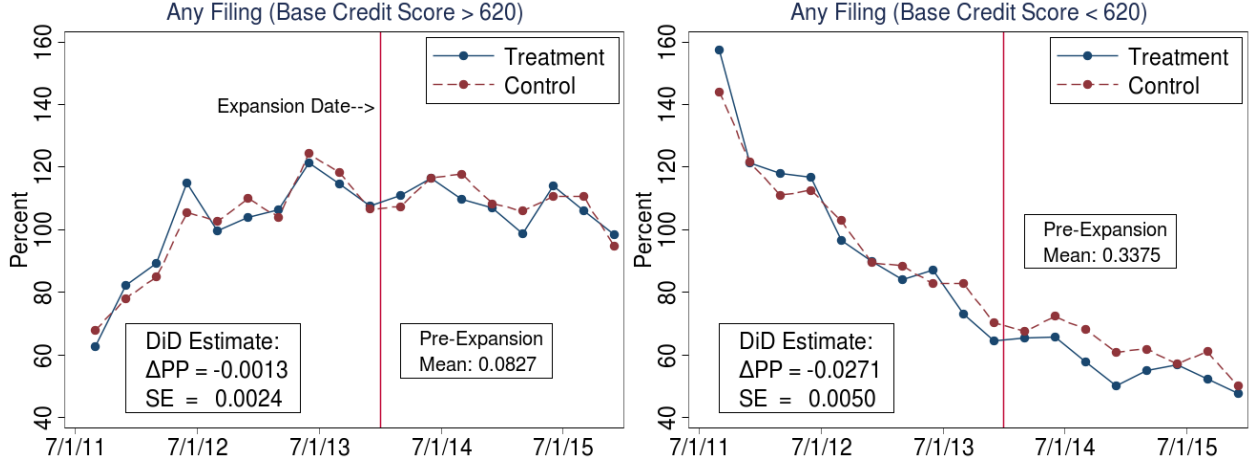
Figure 19: Effects of Medicaid Expansion on New Bankruptcy Filings

Notes: *The figure shows trends of bankruptcy rates among consumers for treament and control states, respectively. Trends are are normalized by the pre reform mean for each group. Bankruptcy is defined as a consumer having filed for Chapter 7 or Chapter 13 bankruptcy protection during a particular quarter. The left panel shows trends for consumers with a baseline credit score $\geq$ 620. The right panel shows respective filings for consumers with a baseline credit score < 620. Each panel also shows estimates from a DD regression as described in equation 1 in which $\mathbb{1}[Bankruptcy Filing]$ is the dependent variable. All standard errors are clustered at the Census tract level.*

per 1 percentage point increase in coverage among subprime borrowers. Our estimates are very similar in magnitude, suggesting a $8 \times 0.0255 = 0.2$ percentage point increase over two years, per 3-4 percentage point increase in coverage among subprime borrowers. This suggests a reduction of 0.05 to 0.067 percentage points over two years per 1 percentage point increase in coverage. Gross and Notowidigdo (2011) find that a 10 percentage point increase in insurance, resulting from Medicaid expansions, reduced bankruptcy filings by 8% overall. We find an 8% reduction for a 4 percentage point increase among subprime borrowers.

Overall, however, we find that medical debt plays an important role in individuals' bankruptcy decisions and that the expansion led to substantial reduction in bankruptcy. Moreover, this effect was more important for financially vulnerable consumers.

C   Calculations of Simulated Decline in Monthly Bills

As described in Section 7.2, we use offer data for credit cards and personal loans from Mintel Compremedia and rate sheet pricing data for auto loans and mortgages from MyFico to estimate how the interest rates available to consumers were affected by the Medicaid

expansion. In this section, we detail how we convert those interest rate changes into the savings in interest rate expenses that were available to consumers via a simulated refinancing.

First, note that a borrower i residing in Census tract c paying a monthly interest rate r_c (e.g. $\frac{APR}{12}$) with current balance $B_{i,0}$ and amortization period m (e.g. 12, 24 or 36 months) faces a monthly payment of

$$P_{i,c}(m, r_c, B_{i,0}) = B_{i,0} \cdot \frac{r_c \cdot (1+r_c)^m}{(1+r_c)^m - 1}. \tag{9}$$

As aforementioned (Section 7.2), our exercise simulates a debt refinancing as of the end of 2013Q4, just prior to the expansion. It follows that for each borrower we take B_0 to be their outstanding debt of that loan type as of that date. Moreover, in our calculations we assume fixed-payment loans with fixed interest and loan terms of 5-years for auto loans, 30-years for mortgages, and 3-years for credit cards and personal loans.[30] Because credit cards are revolving debt, they generally do not have fixed repayment terms or fixed payments. We use 3 years as an admittedly arbitrary estimate of how long it would take consumers to pay off their existing balances. Our results do not vary much if we reduce the payoff period to 1 year.

For unsecured loans, the scheduled monthly payments for a loan can overstate the expected cost to borrowers since some borrowers will fail to repay. A borrower who fails to repay an auto loan or mortgage loses the car or house backing the loan and is deprived of the flow of transportation and housing services those products provide. As a result, any money saved by not making payments will be at least partially offset by the loss of collateral. In contrast, unsecured borrowers do not surrender collateral when they default and are unlikely to face any directly offsetting expenses (though they do incur the costs of dealing with debt collectors and may have to pay higher costs for credit in the future).[31] For these borrowers, the stream of scheduled monthly payments likely overstates the cost of the loan. We therefore calculate an expected repayment amount for these loans as

$$\overline{P}_{i,c}(m, r_c, B_{i,0}, d_c) = (1 - d_c) \cdot P_c(m, r_c, B_{i,0}) + d_c \cdot 0 = (1 - d_c) \cdot P_c(m, r_c, B_{i,0}) \tag{10}$$

where d_c is the monthly default rate in tract c. We measure default d_c as the likelihood of having a new 90-day delinquency or worse during a month for a respective debt type

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[30]Specifically, mortgage rates are for a 30-year, fixed rate mortgage of $150,000 on a single-family owner-occupied property with a loan-to-value ratio of 80% and 1 point in origination fees. Auto rates are for a 60-month loan of between $10,000 and $20,000 for a new automobile.

[31]While lenders can seek wage garnishments or other ways of compelling payment from unsecured borrowers, these options are not commonly pursued.

(e.g. credit card or personal loan). Following 90 day delinquencies, the probability of ever repaying a loan is nearly zero. Borrowers who become 30 days or more delinquent are much more likely to return to repayment. We then estimate the effects of the policy on default rates for consumers in each debt category separately using our baseline specification (Equation 1) in which the dependent variable is $y_{ict}^k = \mathbb{1}[\text{New Delinquency}]_{ict}^k$ with $k \in$ {Credit Card, Personal Loan}. These estimates are shown in Table 8. Since our specification

Table 8: 90 Day Delinquency For Credit Cards and Personal Loans

	Coefficient	Std. Error	Delinquency Rate (Quarterly)	Delinquency Rate (Monthly)
	(1)	(2)	(3)	(4)
Credit Cards	-0.00182515	0.00086205	0.01135771	0.00378590
Personal Loan	-0.00028142	0.00114327	0.00068417	0.00002281

Notes: *This table shows effects of the Expansion on new 90 day or more delinquencies for credit cards and personal loans. Each regression is estimated using Equation 1. Standard errors are clustered by Tract. Columns 3 and 4 display the pre-reform means at the quarterly and monthly level, respectively.*

provides estimates for quarterly flows into delinquency (q_c), we approximate the monthly default rate as $d_c \approx \frac{q_c}{3}$.[32]

For the completion of the exercise, we must define *baseline* and *refinanced* rates and delinquencies for each of the four loan categories. Because we do not observe borrowers' individual interest rates, we assume borrowers residing in Census tract c face as their baseline the prevalent, or average, rate in their respective tract. For auto loans and mortages, expected interest rates are imputed directly into the CCP. As a result, we set borrowers' baseline rate for these products as the average imputed (monthly) rate for the respective product in their respective tract c prior to the expansion. Credit card and personal loan rates entail a further complication as they are not directly imputed in the CCP. For these products, we must take the extra step of using the Mintel data to predict a tract level interest rate for treated counties prior to the expansion as a function of county eligibility. Our estimating equations and subsequent estimates are

$$\bar{r}_{baseline,c}^{\text{CC}} = \frac{1}{12}(r_0^{CC} + r_1^{CC} \times ER_c) = \frac{1}{12}(14.41 + 6.18 \times ER_c) \tag{11}$$

$$\bar{r}_{baseline,c}^{\text{PL}} = \frac{1}{12}(r_0^{PL} + r_1^{PL} \times ER_c) = \frac{1}{12}(6.27 + 15.88 \times ER_c) \tag{12}$$

---

[32] Assuming independent in delinquency over months we have $\frac{q_c}{3} = \hat{m}(1 - \hat{m})^2$ whereby $\hat{m} < m$ so our simplification in fact modestly understates net savings.

where ER_c is the proportion of newly Medicaid eligible adults (Section 3).[33] We then impute these predicted rates by tract into the CCP and define the baseline interest rate for these product as this newly imputed rate. Note that we divide by 12 to transform APRs into monthly rates, under the assumption of monthly compounding. Delinquencies are directly observed in the CCP. Consequently, we set as the baseline the delinquency rate in each tract

$$\overline{d}^k_{baseline,c} = \frac{1}{3} \cdot \overline{q}^k_{baseline,c}$$

for $k \in \{CC, PL\}$.

To determine *refinanced* rates and delinquencies, we predict counterfactuals of each using the difference in difference estimates (Figures 7, 8, and 9) as follows

$$\overline{r}^\ell_{refinanced,c} = \overline{r}^\ell_{baseline,c} + \frac{1}{12} \times \beta^\ell \times ER_c \tag{13}$$

for $\ell \in \{CC, PL, AUT, MTG\}$. Again, β^ℓ is the key difference-in-difference coefficient from equation (1). Note that we divide the DiD estimate by 12 to transform our estimated APR reduction into a monthly interest rate decline. Similarly for delinquencies, we calculate

$$\overline{d}^k_{refinanced,c} = \overline{d}^k_{baseline,c} + \frac{1}{3} \times \beta^k \times ER_c \tag{14}$$

for $k \in \{CC, PL\}$. Finally we define expected annual savings (ASV) to be the sum of expected monthly savings as follows

$$ASV_{i,c} = 12 \times [\overline{P}_{i,c}(m^\ell, \overline{r}^\ell_{baseline,c}, B^\ell_{i,0}, \overline{d}^k_{baseline,c}) - \overline{P}_{i,c}(m^\ell, \overline{r}^\ell_{refinanced,c}, B^\ell_{i,0}, \overline{d}^k_{refinanced,c})] \tag{15}$$

for ℓ and k as shown above.

In our simulations we calculate an average per-person annual savings. As aforementioned, these Intent-to-Treat effects on rate savings are generated using slightly different methods for the secured and unsecured loans. For our estimates on secured products, we use the entire sample. Our estimates for the unsecured products, however, were estimated conditional on receiving a credit offer. We have no information on the correlation between receiving an offer and Medicaid eligibility. Absent this information, we assume independence between these receiving an offer and Medicaid enrollment and treat our estimates as Intent-to-Treat similar to the case for secured loans. There is another interpretation of this approach.

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[33]Specifically, we regress the pre-reform interest rates on the proportion of newly eligible adults at the county level. The two numbers in brackets denote the intercept and slope estimate of the underlying regression model.

Suppose there is non-zero correlation between Medicaid enrollment and the propensity to receive credit offers. Nevertheless, all individuals with improved credit scores still qualify for new loans at an equally lower rate, were they to seek them out. This interpretation assumes zero correlation between Medicaid enrollment and eligibility for lower rates, which is a weaker and quite plausible condition. Finally, we simulate aggregate potential savings by multiplying our per person effects with the CCP Population in 2013Q4 similar to Table 5.

D Details on the Consumer Welfare Analysis

We assume that consumers have existing medical debt $\bar{D}$ and decide on the optimal amount of new medical bills $0 \leq b \leq \epsilon_{MB}$ that go unpaid, trading off utility from consumption and disutility from medical debt. Conditional on a realized medical bill, ϵ_{MB}, consumers maximize:

$$\max_{0 \leq b \leq \epsilon_{MB}} g(Y - (\epsilon_{MB} - b)) - h(\bar{D} + b)$$

where in optimality

$$F(\epsilon_{MB}, b) = g'(Y - (\epsilon_{MB} - b^*)) - h'(\bar{D} + b^*) = 0 . \tag{16}$$

Applying the implicit function theorem, it follows that

$$\frac{\partial F(\epsilon_{MB}, b)}{\partial \epsilon_{MB}} \Delta \epsilon_{MB} + \frac{\partial F(\epsilon_{MB}, b)}{\partial b} \Delta b = -g'' \Delta \epsilon_{MB} + \left[g'' - h'' \right] \Delta b = 0$$

$$\iff \frac{\Delta b}{\Delta \epsilon_{MB}} = \frac{g''(Y - \epsilon_{MB} + b^*)}{g''(Y - \epsilon_{MB} + b^*) - h''(\bar{D} + b^*)} \in [0, 1] \tag{17}$$

where we normalize $b^*(\epsilon_{MB} = 0) = 0$. It follows that a fraction $\tau(\epsilon_{MB}) \in [0, 1]$ of new medical bills remains unpaid and becomes medical debt with

$$b^* = \tau(\epsilon_{MB}) \cdot \epsilon_{MB} \Rightarrow \frac{\Delta b}{\Delta \epsilon_{MB}} = \tau'(\epsilon_{MB}) \epsilon_{MB} + \tau(\epsilon_{MB}). \tag{18}$$

Equations 16, 17, and 18 allow us to express (locally) the first and second derivative of $h(D)$ in terms of $g'(c)$, $g''(c)$, and $\tau(\epsilon_{MB})$. We return to this observation below.

D.1 Details on Compensating Variation

To gauge the transfer gain from insurance, in dollars, we quantify the compensating variation (CV) As outlined above, we assume that the demand for medical care is price inelastic. Then, if consumers do not have the option to leave bills unpaid (e.g. borrow), we trivially have

$$CV = e(p_0, u_0) - e(p_1, u_0) = e(\epsilon_{MB}, u_0) - e(0, u_0) = Y - (Y - \epsilon_{MB}) = \epsilon_{MB}$$

where $e(\cdot)$ denotes the expenditure function. If consumers can leave bills unpaid, then we have to take the substitution patterns between consumption and unpaid bills into account. The compensating variation is implicitly defined by

$$
\begin{aligned}
u_0 &= g(Y - (1 - \tau(\epsilon_{MB}))\epsilon_{MB}) - h(\bar{D} + \tau(\epsilon_{MB})\epsilon_{MB}) \\
u_0 &= g(Y - dc) - h(\bar{D} - dd)
\end{aligned}
\tag{19}
$$

with

$$CV = dc - dd \geq [1 - \tau(\epsilon_{MB})] \cdot \epsilon_{MB}.$$

It follows that dc and dd correspond to the optimal reductions in consumption and unpaid bills (medical debt) if the income is reduced by CV. Under the assumption that consumers cannot take out medical debt to finance consumption, absent a new medical bill, we also have that $dd \geq 0$. The first order condition combined with, $g''(\cdot) < 0$, and $h''(\cdot) > 0$ imply that $g'(Y - dc) - h'(\bar{D}) > 0$ if $dc \geq (1 - \tau(\epsilon_{MB}))\epsilon_{MB}$. Therefore, individuals will not be willing reduce consumption in exchange for fewer unpaid bills. Hence, they optimally choose $dd = 0$, $dc = CV$. Consequently, we can rewrite the equation 19 as

$$\int_{Y-CV}^{Y-(1-\tau(\epsilon_{MB}))\epsilon_{MB}} g'(x)dx = \int_{\bar{D}}^{\bar{D}+\tau(\epsilon_{MB})\epsilon_{MB}} h'(x)dx \ . \tag{20}$$

In the context of Figure 10, $Y-CV$ corresponds to the point on the horizontal axis such that the corresponding area underneath MU_C bounded by $Y-CV$ from the left and $Y-(\epsilon_{MB}-b^*)$ from the right equals the blue area (I). It is evident from here that the CV is bounded from below by $(1 - \tau(\epsilon_{MB}))\epsilon_{MB}$ and by the entire bill ϵ_{MB} from above.[34]

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[34]The lower bound is achieved if the right had side of equation (20) equals zero. The upper bound is achieved if $-\int_{\bar{D}}^{\bar{D}+\tau(\epsilon_{MB})\epsilon_{MB}} h'(x)dx \geq \int_{Y-\epsilon_{MB}}^{Y-(1-\tau(\epsilon_{MB}))\epsilon_{MB}} g'(x)dx$.

D.2 Proposition 1

The specific value of CV depends on the shape of both marginal utility functions. Unfortunately, it is difficult to calibrate $h'(\cdot)$ directly. However, we can combine the first order condition and the result from the implicit function theorem with observed out-of-pocket payments to approximate the marginal disutility of medical debt in terms of the marginal utility of consumption. We start with the case $h''(\cdot) > 0$ and turn to the case $h''(\cdot) = 0$ below. Specifically, we propose a local linear approximation of the marginal disutility of debt around the optimal borrowing decision:

$$
\begin{aligned}
h'(\bar{D} + x) &= h'(\bar{D} + \tau(\epsilon_{MB})\epsilon_{MB}) + h''(\bar{D} + \tau(\epsilon_{MB})\epsilon_{MB}) * (x - \tau(\epsilon_{MB})\epsilon_{MB}) \\
&= g'(Y - (1 - \tau(\epsilon_{MB}))\epsilon_{MB}) - \frac{1 - \tau'(\epsilon_{MB})\epsilon_{MB} - \tau(\epsilon_{MB})}{\tau'(\epsilon_{MB})\epsilon_{MB} + \tau(\epsilon_{MB})} \\
&\quad * g''(Y - (1 - \tau(\epsilon_{MB}))\epsilon_{MB}) * (x - \tau(\epsilon_{MB})\epsilon_{MB}),
\end{aligned}
$$

where the second equality uses the first order condition and the implicit function theorem. Similarly, using a local linear approximation around $g'(\cdot)$ and assuming that locally a constant fraction of medical bills is unpaid $\tau(\epsilon_{MB}) = \bar{\tau}$, we can rewrite equation (20) as:

$$
\begin{aligned}
&g'(Y - (1 - \bar{\tau})\epsilon_{MB})\Big[CV - (1 - \bar{\tau})\epsilon_{MB}\Big] \\
+\ &g''(Y - (1 - \bar{\tau})\epsilon_{MB}) \int_{Y - CV}^{Y - (1 - \bar{\tau})\epsilon_{MB}} (x - (Y - (1 - \bar{\tau})\epsilon_{MB}))dx \\
=\ &g'(Y - (1 - \bar{\tau})\epsilon_{MB}) * \bar{\tau}\epsilon_{MB} - \frac{1 - \bar{\tau}}{\bar{\tau}} * g''(Y - (1 - \bar{\tau})\epsilon_{MB}) \int_{\bar{D}}^{\bar{D} + \bar{\tau}\epsilon_{MB}} (x - (\bar{D} + \bar{\tau}\epsilon_{MB}))dx .
\end{aligned}
$$

Simplifying terms, we have

$$
\begin{aligned}
&g'(Y - (1 - \bar{\tau})\epsilon_{MB})\Big[CV - (1 - \bar{\tau})\epsilon_{MB}\Big] - g''(Y - (1 - \bar{\tau})\epsilon_{MB}) \int_{0}^{CV - (1 - \bar{\tau})\epsilon_{MB}} x\,dx \\
=\ &g'(Y - (1 - \bar{\tau})\epsilon_{MB}) * \bar{\tau}\epsilon_{MB} + \frac{1 - \bar{\tau}}{\bar{\tau}} * g''(Y - (1 - \bar{\tau})\epsilon_{MB}) \int_{0}^{\bar{\tau}\epsilon_{MB}} x\,dx .
\end{aligned}
$$

and

$$
\begin{aligned}
&g'(Y - (1 - \bar{\tau})\epsilon_{MB})\Big[CV - \epsilon_{MB}\Big] - \frac{1}{2}g''(Y - (1 - \bar{\tau})\epsilon_{MB})\Big[CV - (1 - \bar{\tau})\epsilon_{MB}\Big]^2 \\
=\ &\frac{1 - \bar{\tau}}{2 * \bar{\tau}} * g''(Y - (1 - \bar{\tau})\epsilon_{MB})\Big[\bar{\tau}\epsilon_{MB}\Big]^2 .
\end{aligned}
$$

Finally, we have

$$CV = \frac{\left[-g'(\cdot) - (1 - \bar{\tau})\epsilon_{MB}g''(\cdot)\right] + \sqrt{g'(\cdot)^2 - 2\bar{\tau}g'(\cdot)g''(\cdot)\epsilon_{MB} - \bar{\tau}g''(\cdot)^2\epsilon_{MB}^2(1 - \bar{\tau})}}{-g''(\cdot)}.$$

Let $\phi(\cdot) = -\frac{g'(\cdot)}{g''(\cdot)}$, then we have

$$CV = -\phi(\cdot) + (1 - \bar{\tau})\epsilon_{MB} + \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon_{MB}^2},$$

which establishes the first part of the proposition.

Case $h''(\cdot) = 0$: Before we turn to the comparative statics, we establish that the CV discussed above provides a lower bound for the case $h''(\cdot) = 0$. Simplifying the former derivation we now have,

$$g'(Y - (1 - \bar{\tau})\epsilon_{MB})\left[CV - \epsilon_{MB}\right] - \frac{1}{2}g''(Y - (1 - \bar{\tau})\epsilon_{MB})\left[CV - (1 - \bar{\tau})\epsilon_{MB}\right]^2 = 0.$$

This implies the following compensating variation:

$$\begin{aligned} CV^* &= -\phi(\cdot) + (1 - \bar{\tau})\epsilon_{MB} + \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB}} \\ &\geq -\phi(\cdot) + (1 - \bar{\tau})\epsilon_{MB} + \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon_{MB}^2}, \end{aligned}$$

where the second row replicates the CV derived above.

Comparative statics: We now turn to the comparative statics. We first show that $\frac{dCV}{d\phi(\cdot)} > 0$. Taking the first derivative, we have

$$\frac{dCV}{d\phi(\cdot)} = -1 + \frac{\phi + \bar{\tau}\epsilon_{MB}}{\sqrt{\cdot}}.$$

Now we show that $\left[\phi + \bar{\tau}\epsilon_{MB}\right]^2 > \left(\sqrt{\cdot}\right)^2$. So we have

$$\begin{aligned} \left[\phi + \bar{\tau}\epsilon_{MB}\right]^2 &> \left(\sqrt{\cdot}\right)^2 \\ \phi(\cdot)^2 + 2\bar{\tau}\epsilon_{MB}\phi(\cdot) + \bar{\tau}^2\epsilon_{MB}^2 &> \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon_{MB}^2 \\ \leftrightarrow 0 &> -\bar{\tau}\epsilon_{MB}^2, \end{aligned}$$

which establishes the second part of the proposition.

Next we show that $\frac{dCV}{d\bar{\tau}} < 0$. Taking the first derivative, we have

$$
\begin{aligned}
\frac{dCV}{d\bar{\tau}} &= -\epsilon_{MB} + \frac{1}{2 * \sqrt{\cdot}}\left[2\phi(\cdot)\epsilon_{MB} - \epsilon_{MB}^2 + 2\bar{\tau}\epsilon_{MB}^2\right] - \frac{d\phi(\cdot)}{d\bar{\tau}} + \frac{1}{2 * \sqrt{\cdot}}\left[2\phi(\cdot)\frac{d\phi(\cdot)}{d\bar{\tau}} + 2\epsilon_{MB}\bar{\tau}\frac{d\phi(\cdot)}{d\bar{\tau}}\right] \\[2mm]
&= -\epsilon_{MB}\underbrace{\left[1 - \frac{\sqrt{\left[\phi + (\bar{\tau}-\frac{1}{2})\epsilon_{MB}\right]^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}}\right]}_{A} \\[2mm]
&\quad - \underbrace{\frac{d\phi(\cdot)}{d\bar{\tau}}\left[1 - \frac{\sqrt{(\phi(\cdot)+\bar{\tau}*\epsilon_{MB})^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}}\right]}_{B}
\end{aligned}
$$

First, we note that $\sqrt{\left[\phi + (\bar{\tau}-\frac{1}{2})\epsilon_{MB}\right]^2} < \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}$, which implies that term A is greater than 0. Hence, we have

$$
\begin{aligned}
\left[\phi + (\bar{\tau}-\frac{1}{2})\epsilon_{MB}\right]^2 &< \left(\sqrt{\cdot}\right)^2 \\[2mm]
\phi(\cdot)^2 + 2(\bar{\tau}-\frac{1}{2})\epsilon_{MB}\phi(\cdot) + (\bar{\tau}-\frac{1}{2})^2\epsilon_{MB}^2 &< \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2 \\[2mm]
\leftrightarrow -\phi(\cdot)\epsilon_{MB} + [\bar{\tau}^2 - \bar{\tau} + \frac{1}{4}]\epsilon_{MB}^2 &< [\bar{\tau}^2 - \bar{\tau}]\epsilon_{MB}^2 \\[2mm]
\leftrightarrow \frac{\epsilon_{MB}^2}{4} &< \phi(\cdot)\epsilon_{MB} \\[2mm]
\leftrightarrow \epsilon_{MB} &< 4\phi(\cdot) \ .
\end{aligned}
$$

which is true if $\epsilon_{MB} < min\{\frac{\phi(\cdot)}{\bar{\tau}+\frac{1}{8}}, 4\phi(\cdot)\}$ as required in the proposition.

Second, we have that $\sqrt{(\phi(\cdot)+\bar{\tau}*\epsilon_{MB})^2} \geq \sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}$, which implies that $sign(B) = sign(-\frac{d\phi(\cdot)}{d\bar{\tau}})$. Here, we have

$$
\frac{d\phi(\cdot)}{d\bar{\tau}} = -\frac{d\frac{g'(\cdot)}{g''(\cdot)}}{d\bar{\tau}} = -\frac{g''(\cdot)^2\epsilon_{MB} - \epsilon_{MB}g'''(\cdot)g'(\cdot)}{g''(\cdot)^2}.
$$

If $\frac{g'''(\cdot)g'(\cdot)}{g''(\cdot)^2} \leq 2$ then $\frac{d\phi(\cdot)}{d\bar{\tau}} \leq \epsilon_{MB}$. Then we have

$$\frac{dCV}{d\bar{\tau}} \geq -\epsilon_{MB} * \left[2 - \frac{\sqrt{\left[\phi + (\bar{\tau} - \frac{1}{2})\epsilon_{MB}\right]^2} + \sqrt{\left[\phi(\cdot) + \bar{\tau} * \epsilon_{MB}\right]^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon^2_{MB}}}\right]$$

$$= -\epsilon_{MB} * \left[2 - \frac{\phi + (\bar{\tau} - \frac{1}{2})\epsilon_{MB} + \phi(\cdot) + \bar{\tau} * \epsilon_{MB}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon^2_{MB}}}\right]$$

$$= -\epsilon_{MB} * \left[2 - 2\frac{\sqrt{(\phi(\cdot) + (\bar{\tau} - \frac{1}{4})\epsilon_{MB})^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon^2_{MB}}}\right].$$

Finally, we show that

$$(\phi(\cdot) + (\bar{\tau} - \frac{1}{4})\epsilon_{MB})^2 < \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon^2_{MB}$$

$$\leftrightarrow \phi(\cdot)^2 + 2\phi(\cdot)(\bar{\tau} - \frac{1}{4})\epsilon_{MB} + (\bar{\tau} - \frac{1}{4})^2\epsilon^2_{MB} < \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1 - \bar{\tau})\epsilon^2_{MB}$$

$$\leftrightarrow -\frac{1}{2}\phi(\cdot)\epsilon_{MB} + \frac{1}{2}\bar{\tau}\epsilon^2_{MB} + \frac{1}{16}\epsilon^2_{MB} < 0$$

$$\leftrightarrow \phi(\cdot) > (\bar{\tau} + \frac{1}{8})\epsilon_{MB}$$

$$\leftrightarrow \epsilon_{MB} < \frac{\phi(\cdot)}{\bar{\tau} + \frac{1}{8}}$$

which is true if $\epsilon_{MB} < min\{\frac{\phi(\cdot)}{\bar{\tau} + \frac{1}{8}}, 4\phi(\cdot)\}$ as required in the proposition. This establishes the third part of the proposition.

Finally, we turn to

$$\frac{CV}{\epsilon} = -\frac{\phi(\cdot)}{\epsilon_{MB}} + (1 - \bar{\tau}) + \sqrt{\frac{\phi(\cdot)^2}{\epsilon^2_{MB}} + 2\frac{\bar{\tau}\phi(\cdot)}{\epsilon_{MB}} - \bar{\tau}(1 - \bar{\tau})}$$

Here we have

$$d\frac{CV}{\epsilon_{MB}}/d\epsilon_{MB} = -\left[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon^2_{MB}}\right] + 2 * \frac{\left[\frac{\phi(\cdot)}{\epsilon_{MB}} + \bar{\tau}\right]}{2 * \sqrt{\cdot}}\left[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon^2_{MB}}\right]$$

$$= -\left[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon^2_{MB}}\right] * \left[1 - \frac{\sqrt{\left[\frac{\phi(\cdot)}{\epsilon_{MB}} + \bar{\tau}\right]^2}}{\sqrt{\cdot}}\right].$$

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Since $\sqrt{\left[\frac{\phi(\cdot)}{\epsilon_{MB}} + \bar{\tau}\right]^2} \geq \sqrt{\cdot}$, the second factor is smaller than zero. Hence the sign of the effect equals the sign of $\left[\frac{\frac{d\phi(\cdot)}{d\epsilon} - \phi(\cdot)}{\epsilon_{MB}^2}\right]$.

We have

$$
\begin{aligned}
\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot) &= -(1 - \bar{\tau})\left[\frac{g''(\cdot)^2 - g'''(\cdot)g'(\cdot)}{g''(\cdot)^2}\right] - \phi(\cdot) \\
&< -(1 - \bar{\tau}) + \phi + (1 - \bar{\tau}) - \phi(\cdot) = 0,
\end{aligned}
$$

where the second line uses $\frac{g'''(\cdot)g'(\cdot)}{g''(\cdot)^2} \leq 1 + \frac{\phi(\cdot)}{1 - \bar{\tau}}$. This establishes the last part of the proposition.

D.3   Details on Effects of Variance Reduction

The second order Taylor expansion yields:

$$
\begin{aligned}
U(\epsilon_{MB}, \epsilon_{\bar{M}B}) &= g(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) - h(\bar{D} + \bar{\tau} * \epsilon_{\bar{M}B}) \\
&- \left[(1 - \bar{\tau}) * g'(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) + \bar{\tau} * h'(\bar{D} + \bar{\tau} * \epsilon_{\bar{M}B})\right](\epsilon_{MB} - \epsilon_{\bar{M}B}) \\
&+ \frac{1}{2}\left[(1 - \bar{\tau})^2 g''(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) - \bar{\tau}^2 * h''(\bar{D} + \bar{\tau} * \epsilon_{\bar{M}B})\right](\epsilon_{MB} - \epsilon_{\bar{M}B})^2 \, .
\end{aligned}
$$

The first order condition and the condition from the implicit function theorem allow us to replace the derivatives of $h(\cdot)$ with derivatives of $g(\cdot)$ as follows:

$$
\begin{aligned}
U(\epsilon_{MB}, \bar{\epsilon}) &= g(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) - h(\bar{D} + \bar{\tau} * \epsilon_{\bar{M}B}) \\
&- g'(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B})(\epsilon_{MB} - \epsilon_{\bar{M}B}) \\
&+ \frac{1}{2} * (1 - \bar{\tau}) * g''(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B})(\epsilon_{MB} - \epsilon_{\bar{M}B})^2 \, .
\end{aligned}
$$

Finally, expected utility is given by:

$$
EU = \int U(\epsilon, \epsilon_{\bar{M}B}) dG
$$

and the risk premium, RP, is implicitly given by:

$$
EU = g(Y - (1 - \tau) * \epsilon_{\bar{M}B} - RP) - h(\bar{D} + \tau * \epsilon_{\bar{M}B}) \, .
$$

Hence we have

$$
\begin{aligned}
& g(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) - g(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B} - RP) \\
= \ & -\frac{1}{2} * (1 - \tau) * g''(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) \int (\epsilon_{MB} - \epsilon_{\bar{M}B})^2 dG \\
= \ & -\frac{1}{2} * (1 - \bar{\tau}) * g''(Y - (1 - \bar{\tau}) * \epsilon_{\bar{M}B}) * var(\epsilon_{MB}) \ .
\end{aligned}
$$

D.4 Pure Out-Of-Pocket Benchmark

Conversely, had we ignored the impact of unpaid medical bills, we could have applied a second order Taylor approximation around $U^{oop} = g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB})$. This would deliver:

$$
\begin{aligned}
U^{oop}(\epsilon_{MB}, \bar{\epsilon}_{MB}) \ = \ & g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) \\
- \ & (1 - \bar{\tau}) \cdot g'(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB})(\epsilon_{MB} - \bar{\epsilon}_{MB}) \\
+ \ & \frac{1}{2}(1 - \bar{\tau})^2 g''(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB})(\epsilon_{MB} - \bar{\epsilon}_{MB})^2 .
\end{aligned}
$$

Compared to the case also considering unpaid medical bills, the first and the second order term are now each smaller by a factor of $\frac{1}{1-\bar{\tau}}$. The implied risk premium ignoring the impact of unpaid medical bills RP^{oop} is then

$$
\begin{aligned}
& g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) - g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB} - RP) \\
= \ & \frac{1}{1 - \bar{\tau}} \cdot \Big[g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB}) - g(Y - (1 - \bar{\tau}) \cdot \bar{\epsilon}_{MB} - RP^{oop}) \Big].
\end{aligned}
$$

It follows that

$$
RP^{oop} < RP < \frac{1}{1 - \bar{\tau}} \cdot RP^{oop} \ .
$$

As with the mean reduction, this suggests that considering unpaid medical bills can increase the risk premium by factor of $\frac{1}{1-\bar{\tau}}$. We quantify the risk premium in a numerical example in Section 9.