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 substantial indirect financial benefits from a reduction in unpaid medical bills in collection. Using a nationally representative panel of 5 million credit records, we find that the health insurance expansion reduced households' unpaid medical bills in collection by $4.8 billion in its first two years. The policy also lowered delinquencies and personal bankruptcies, and improved credit scores. Using data on credit offers and pricing we document substantial improvements to availability and terms of credit as a result of the reform valued at $1 billion per year. Overall, we find that the financial benefits of Medicaid insurance double when considering these indirect benefits in addition to reduced out-of-pocket payments.

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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 Hamel et al. (2016), over half of non-elderly adults without insurance have difficulty paying 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. We start by making a basic theoretical point regarding the role of unpaid medical bills. 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 note that, although low-income uninsured individuals may only pay 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. This approach 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 simple framework 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 percent 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

[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.

that it contains information on individual credit obligations (trade lines). In particular, this 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 Medicaid expansion reduced the incidence of newly accrued medical debt by 30-40 percent, with a disproportionately greater effect for larger medical debts. On average, the reform led to a large annual decline in accrued medical debt of $47 per person, or $1,135 per treated person, which translates into an overall reduction of $4.8 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. Out findings also suggest that collection agencies are able to recover between 10-20% 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 percent. 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 gainst over 3 times larger than the average. We further find that the expansion led 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 $20 per person, or $488 per treated person. This translates into $1 billion in annual savings overall. This is slightly more than the reduc-

tion in out of pocket expenditures. Combining the direct effect of out-of-pocket payments with the indirect effects, and holding constant utilization of health care services, we find that the overall financial benefits of insurance is on the order of $0.65 per dollar of health care spending. This estimate is remarkably similar to our finding from an alternative revealed preference approach that suggests a benefit of $0.69 per dollar of health care spending.

Our paper contributes to three main literature. First, our findings add to a growing literature on the link between Medicaid and financial health (Finkelstein et al., 2012; Mazumder and Miller, 2015; Gross and Notowidigdo, 2011; Hu et al., 2016). In addition to providing new evidence of the effects on medical debt and measures of financial distress at the national level in a policy relevant context, we complement previous studies in at least two important ways. First, we view our paper as a systematic assessment of the financial consequences of unpaid medical bills. While previous studies have looked at the effects of Medicaid insurance on medical debt (Finkelstein et al., 2012), and measures of financial distress in different contexts, (Mazumder and Miller, 2015; Gross and Notowidigdo, 2011), the connection between unpaid bills and financial consequences has not been made very explicit. We combine novel data on credit offers and national data on medical and other types of debt to quantify the significance of this mechanism. Importantly, we are able to separately to contrast interest rate savings in dollars with changes in repayments to isolate the net consumer gains.

Second, our findings complement recent studies on the value of Medicaid (Finkelstein, Hendren and Luttmer, 2015) and the value of public insurance more generally (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. Nevertheless, as our data is particularly well suited to understanding financial outcomes, we extend the analysis of financial benefits by adding the gains 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. 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. Using the CCP,

we are able to quantify the amount of unpaid medical bills that go into collection and how they affect access and price of credit.

Finally, our evidence on bankruptcy filing contributes to the literature linking medical debt and insolvency. These studies have for the most part concluded that large medical bills explain between 17 and 62 percent of bankruptcies (Himmelstein et al., 2005, 2009; Dranove and Millenson, 2006). More recently, Dobkin et al. (2016) finds, based on data from southern California, that bankruptcy filings rise substantially in the year after a hospitalization. We use the natural experiment provided by Medicaid expansion to explore how the provision of health insurance can mitigate the need to file for bankruptcy protection. We contribute to this literature, by exploring plausibly exogenous variation in medical bills following the Medicaid expansion.

The remainder of this paper is organized as follows. In Section 8 we formalize the effects of paid and unpaid medical bills on consumer welfare. Our framework considers the traditional channel of reduced out-of-pocket payments and introduces the notion of an indirect *credit channel* that operates through access to more and cheaper credit. In Section 2 we provide an institutional overview, with an emphasis on the Medicaid expansion. In Section 3 we describe the data and lay out our difference-in-difference approach. We present our results of the reform's effects on medical debt and financial distress in Sections 5 and 6. In Section 7 we explore the impact of improved financial health on credit market outcomes and quantify the dollar value of this benefit. Finally, in Section 9 we combine results on direct and indirect effects and explore the overall financial benefits of insurance to consumers. 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 and their parents. 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").

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

The expansion primarily targets non-elderly adults without dependent children who otherwise would not qualify for Medicaid. Our estimated effects of the Medicaid expansion, therefore, predominantly reflect the effects for singles and couples without children.

[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.

[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.

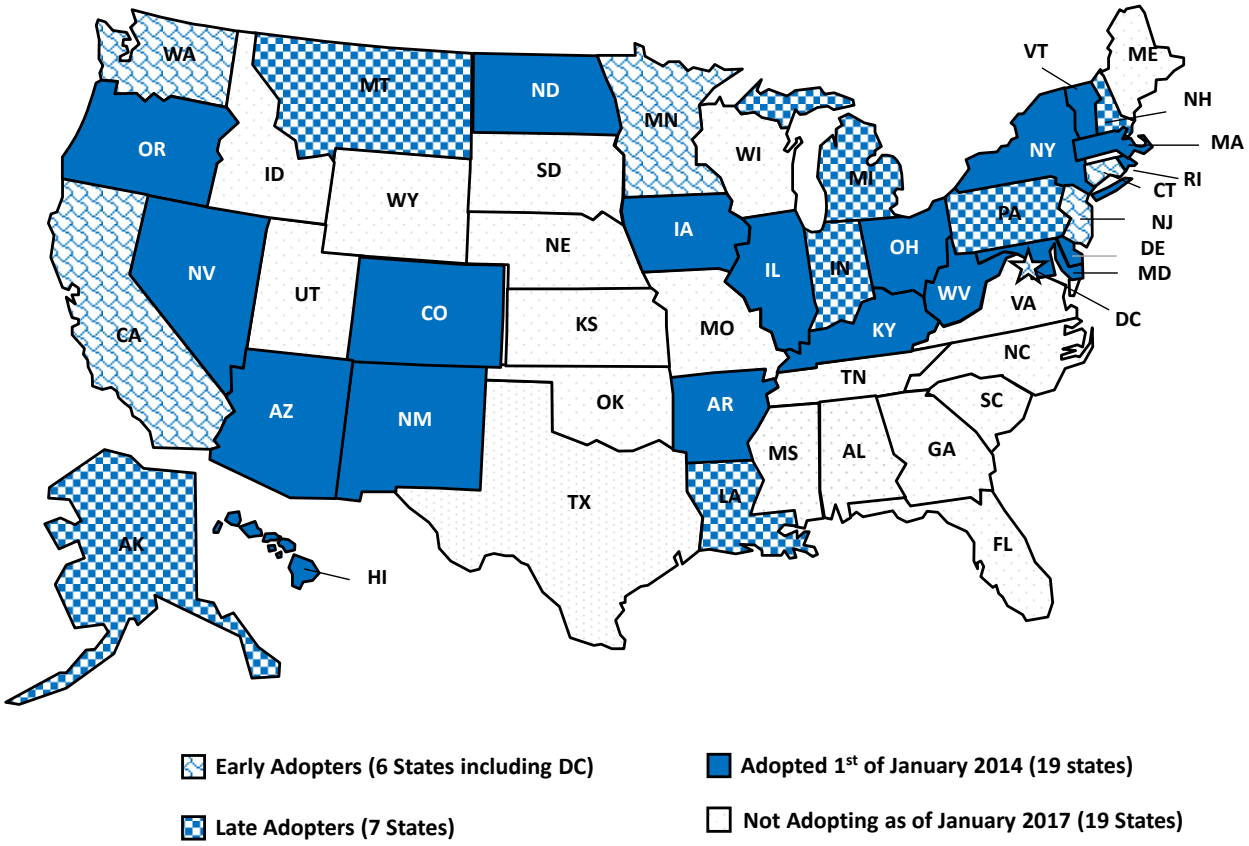

Figure 1: Medicaid Adoption Across States

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

2.2 Medical Bills, Medical Debt, and Out-of-Pocket Spending

A recent study from the Kaiser Family Foundation (KFF) (Hamel et al., 2016) notes that about a quarter of non-elderly adults in the U.S. report 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-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 collections agencies. Collections 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. Using observed changes in medical debt and uncompensated care following the Medicaid expansion, we estimate that about 40% of health care spending corresponds to "uninsured care", or "bad debt".[5] This implies that, netting out the 20% of health care costs uninsured adults pay out of pocket, about half of uncompensated care is treated by hospitals as "uninsured care" or "bad debts". This calculation is in line with estimates from the literature on uncompensated care. (Bachrach, Boozang and Lipson, 2015) find that the Medicaid expansion led to 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). We find an annual reduction in medical debt of about half this amount ($2.39 billion), which is consistent with the 20%/40%/40% split between out of pocket costs, bad debt, and charity care.

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 account-level information about sampled consumers' individual debt obligations (trade lines), including each account's opening date, current balance, and past payment history. While the CCP does not provide any information that would directly identify any of the consumers in the panel, such as names, addresses, or Social Security numbers, the credit records are linked overtime which allows us to study the evolution of debts for consumers in our sample.

Because the CCP provides information on individual trade lines, it is possible to determine which of the reported obligations represent new medical debts and the dates in which

[5] We discuss changes in medical debt in greater detail in the next subsection. Our calculation is as follows. We find a reduction in medical debt of about $1,100 per treated person, which corresponds to roughly 40% of total spending (Coughlin, 2014). Noting that 20% spending come from out-of-pocket spending, about 40% of medical spending remains as a pure discount or charity care.

they appeared on consumers' credit records. Specifically, we identify medical debts as those that were either directly reported by a medical provider or were reported by third-party debt collectors as being for unpaid medical bills.[6] We focus on the flow of new medical debts incurred each quarter because we believe this measure better reflects the effects of Medicaid expansion than would focusing on 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 (or other types of expenditures). Consequently, we exclude debts from paid medical bills in our definition of medical debt, though we evaluate the effects of Medicaid expansion on the overall debt position of households.

Like medical debt, we base our measures of financial distress on flows, which better depicts the timing of delinquency and bankruptcy decisions and allows 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 the previous quarter but are now 30 days past due (or worse). It could also include accounts that had been 30 days past due but during the quarter became 90 days past due.[7] In addition, the CCP contains information about bankruptcy filings, including the date the bankruptcy petition was filed and the chapter of bankruptcy. If more than one bankruptcy petition is filed, such as when a dismissed bankruptcy is almost immediately refiled or when a petitioner switches from Chapter 13 to Chapter 7, we observe separate information about each filing. This allows us to distinguish between pre- and post-reform filing decisions of individual consumers (Gross and Notowidigdo, 2011; Dobkin et al., 2016). We use bankruptcy filings during each quarter as an additional indicator of financial distress.

We restrict our sample to adults aged 18-64 in the 19 adopting (treatment) states and the 19 non-adopting (control) states (Figure 1). We focus on outcomes in the 10 quarters

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

[7]We considere 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.

before and 8 quarters following the expansion.[8] This covers the period 2011Q3 to 2015Q4, inclusive. 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. Lastly, often times there are significant lags between when debts are acquired and when they are reported to the NCRCs, 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. We then aggregate the data at the person-quarter level, yielding a baseline sample of about 2.7 million consumers (credit records) and 43 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 5 percent of consumers acquire a new medical debt each quarter. 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 falling by about 14 percent in adopting states. An average consumer with new medical debt accrues 1.7 new lines with an average value of about $1,200. Moreover, the number and value of new medical debts, among those who acquire them, is greater in non-adopting states and decreases following the implementation of the reform for adopting states.

The overall rate of new delinquencies in our sample is a little over 6 percent. It is slightly higher in non-adopting states and declines more following reform in adopting states. As might be expected, new bankruptcy are rare, occurring in about 16 out of each 10,000 records in a given quarter. Chapter 7 filings are more common than Chapter 13 filings.[9] New bankruptcy filings have been overall on the decline. Nevertheless, Chapter 7 filings decreased more rapidly in adopting states while Chapter 13 filings remained stable, a pattern suggesting that state bankruptcy laws may affect filing decisions.

[8] 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.

[9] In a very small number of cases, less than 0.01 percent of observations, consumers appear to have filed for both Chapter 7 and Chapter 13 in the same quarter.

Table 1: Summary Statistics

	All (1)		Pre (2)	Post (3)
New Medical Collections				
Receiving (p.p.)	4.72	*Not Adopting*	5.87	5.82
		Adopting	3.48	3.06
Average Number	1.66	*Not Adopting*	1.68	1.70
		Adopting	1.62	1.60
Average Value ($)	1,187	*Not Adopting*	1,229	1,317
		Adopting	1,041	956
Delinquency Rate (p.p.)				
Any	6.33	*Not Adopting*	6.55	6.47
		Adopting	6.19	5.98
Bankruptcy Filing Rate (p.p.)				
Any	0.16	*Not Adopting*	0.19	0.14
		Adopting	0.18	0.13
Chapter 7	0.11	*Not Adopting*	0.11	0.08
		Adopting	0.14	0.10
Chapter 13	0.06	*Not Adopting*	0.08	0.07
		Adopting	0.04	0.04
Consumer Risk				
Credit Score (Fico)	677	*Not Adopting*	667	671
		Adopting	683	688
Non-Medical Debt Obligations ($)				
Credit Cards	4,013	*Not Adopting*	3,702	3,871
		Adopting	4,323	4,296
Personal Loans	761	*Not Adopting*	777	909
		Adopting	614	733
Mortgages	51,034	*Not Adopting*	45,868	46,917
		Adopting	56,459	57,613
Auto Loans	5,702	*Not Adopting*	5,496	6,759
		Adopting	4,845	5,775
Records	2,724,784	*Not Adopting*	1,461,238	1,441,995
		Adopting	1,180,228	1,145,167
Observations	43,049,659	*Not Adopting*	13,309,290	10,712,450
		Adopting	10,605,020	8,422,899

Notes: *This table shows summary statistics of medical debt, non-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. Delinquencies and bankruptcies are new delinquencies or filings (flows) in that quarter. Non-medical debt obligations are counted the amount of debt outstanding at the end of the quarter. Mortgage debt includes first lien mortgages, closed-end home equity loans (junior liens), and home equity lines of credit.*

Lastly, table 1 shows summary statistics on consumers' credit risk profiles and non-medical debt obligations. Consumers' risk is measured by their Fico credit score as of the end of each quarter. An average consumers' credit score is 677, which is considered as Prime

for purposes of credit.[10] Note that, although credit scores went up on average following the reform, they increased more in adopting states. Looking at consumers' obligations, average credit card debt outstanding is approximately $4,000, nearly as large as average balances on outstanding auto loans ($5,700). Moreover, following the reform, credit card debt increases slightly in non-adopting states and falls in adopting states.[11] Although less common historically, personal loans, or unsecured installment loans, have grown in popularity in recent years. As shown in the table, average outstanding debt on these unsecured loans is roughly $760, or about 20 percent of outstanding credit card debt. As expected, by far the largest debt obligation on consumers' balance sheet is their mortgage. Average outstanding mortgage debt over this period was just over $51,000.

3.1.1 Medical Debt, Delinquencies, and Credit Scores

Uninsured care, or bad debt, is most commonly billed to consumers through third party collections and reported to the nationwide credit reporting companies (NCRCs). The existence of bad debts, or medical collections, on an individual's credit report can indicate a broader financial hardship, which can increase the likelihood of future delinquencies in debt repayment and even bankruptcy (Domowitz and Sartain, 1999; Himmelstein et al., 2005, 2009). Consequently, reporting of third party collections directly reduces consumers' credit scores, potentially making credit both less available and more expensive (Brevoort and Kambara, 2015).

Figure 2 illustrates the relationship between reported medical collections, serious delinquency, and credit scores. It does so using an event study approach, tracing 'healthy' individuals' medical debt balances (left panel), delinquency (middle panel), and credit score (right panel) following a reported collection. Outcomes are traced starting 6 quarters prior to the event (reported collection) and for 8 quarters, or 2 years, following.[12]

The figure suggests a strong relationship between reported collections, delinquencies, and credit scores. Upon receiving a new medical collection, an individual, by construction, experiences substantial increase in medical debt balances. However, these balances persist

[10] 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 percent of adults with such records, see Brevoort, Grimm and Kambara (2016).

[11] See appendix C for a more complete analysis of the effects of the reform on outstanding credit card debt.

[12] This approach is quite similar to that used in Dobkin et al. (2016), who look at credit outcomes following a hospitalization. In Appendix A we describe our methodology in greater detail and benchmark our results to theirs.

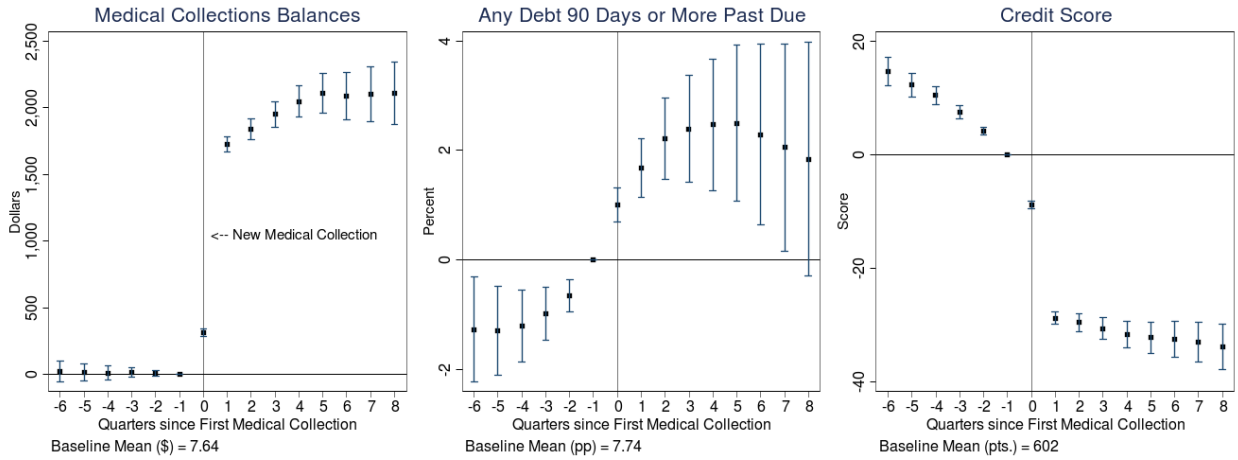

Figure 2: Medical Debt and Credit Worthiness: An Event Study

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 include Census tract and year-quarter fixed effects (Equation 13). Confidence intervals in the figure are calculated using standard errors clustered at the Census tract level. For estimation details see appendix A.*

for at least two years following the event, further indicating that a large proportion of 'bad debt' is not repaid for at least two years after it is first reported. Moreover, a new medical debt is associated with an increase in the probability of becoming seriously delinquent on other debts in subsequent quarters. Consistent with this, a newly reported medical debt leads to a significant drop in credit scores. In all, bad medical debts reported to NCRCs via third party collections agencies seemingly indicate future financial hardship, as measured by repayment delinquencies, and lead directly to significantly lower credit scores.[13]

3.2 Loan Offers and Pricing (Mintel and MyFico)

We further bring in data on loan offers and pricing to calculate potential supply side effects and dollar values of improved financial health. We focus on the four most common sources of debt for the medicaid population: (1) credit cards (2) personal loans (3) auto loans (4)

[13]In addition, leaving bills unpaid can garner substantial non-pecuniary costs as collectors can be aggressive in their efforts to get repayment. A discussion of these non-pecuniary costs is beyond the scope of this paper.

mortgages. We estimate changes in credit card and personal loan rates using data on direct mail pre-screened offers made lenders from *Mintel Comperemedia* (Mintel). The Mintel data are acquired via a nationally representative survey. Each month, approximately 2,000 participating household are asked to turn over all mail solicitations they received during the month.[14] Solicitations, including offers of credit, are then coded, appended to households' demographic information, and matched to individual recipients' credit records. The most popular and effective channel by which lenders advertise both credit cards and personal loans to consumers is through direct mail. As a result these data are well designed for exploring (1) whether consumers residing in the treatment states that expanded Medicaid were more or less likely to receive credit offers and, (2) how Medicaid expansion affected the interest rates on the offers they received.

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 nationally determined, make translating credit score ranges into lower interest rates less complicated. For example, all else equal consumers with scores between 620 and 639 may all receive the same interest rate from a given lender. We use publicly available information on interest rates published by Fair Isaac Corporation, the creator of the widely-used FICO score. 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. We measure potential interest rate effects of the policy by assigning each consumer the interest rate they would have qualified for in that quarter based on their credit score. This imputation implies that any changes in average rates arise directly from the changes in credit scores across treatment and control (Section 6.3).[15]

4 Empirical Strategy

Our empirical strategy uses the quasi natural experiment provided by states' option to expand Medicaid. We apply a difference-in-difference (DD) approach to identify the effects of the reform on medical debt accruals, the rate of flows into delinquency and the bankruptcy filing choice of consumers, the effect on borrowers' overall net debt positions, lenders' pricing and offers of credit to consumers. Our treatment is the Medicaid expansion. As a result, the treatment group comprises consumers in states that expanded their Medicaid programs

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

[15] The data on loan pricing used in this section come from http://www.myfico.com/credit-education/calculators/loan-savings-calculator on March 19, 2017. See Appendix D for details.

on January 1, 2014 and the control group comprises consumers in non-adopting states (See Figure 1).

We consider three 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 bankruptcy filings as well as subsequent improvements in consumers' credit risk. In each we use the following basic specification

$$y_{ict}^k = \alpha_c^k + \eta_t^k + \beta^k \cdot (Post_k \cdot Adopt_{s(c)}) + \epsilon_{ict}^k \tag{1}$$

Here, y_{ict}^k denotes the respective outcome k for record i 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. $Post_k$ and $Adopt_{s(c)}$ are indicator variables that turn on in the post-reform period and expansion states (census tracts), respectively. The key parameter of interest is β^k, which captures differential changes in the outcome variable between expansion and non-expansion census tracts before and after the reform.[16]

The majority of individuals in our sample were not eligible for the reform, and, given our data, we cannot differentiate those who are eligible from those who are ineligible. As a result, we interpret our Difference-in-Difference results as Intent-to-Treat (ITT) effects.

5 Direct Effects of Medicaid on Medical Debt

The Medicaid expansion substantially reduced medical debt burdens. Moreover, as nearly all medical debt ($>> 99\%$) accrues in the form of unpaid bills sent to collections rather than through planned expenditure, this reduction is largely driven by individuals who no longer get charged large medical bills because they are now covered by Medicaid.[17]

5.1 Average Effects

Figure 3 plots raw data trends in newly accrued medical collections for treatment and control states, respectively. In the Figure, the left panels show trends in the overall propensity to

[16]Following Bertrand, Duflo and Mullainathan (2003), we estimate one average treatment effect of the reform. Moreover, we allow for unobserved time-varying group effects at the census tract level. This implies the unobservables in the regression may not be iid and, by assumption, covary at the census tract level. We thus cluster the standard errors at the tract level to account for arbitrary correlation within a census tract and over time.

[17]For a broader discussion of medical collections see Brevoort and Kambara (2015).

receive a collection, the middle panels show the total number of collections credited to the record in a given quarter, and the right panels show the total value of new collections reported. As illustrated in the figure, two-years after the reform, the propensity to accrue new

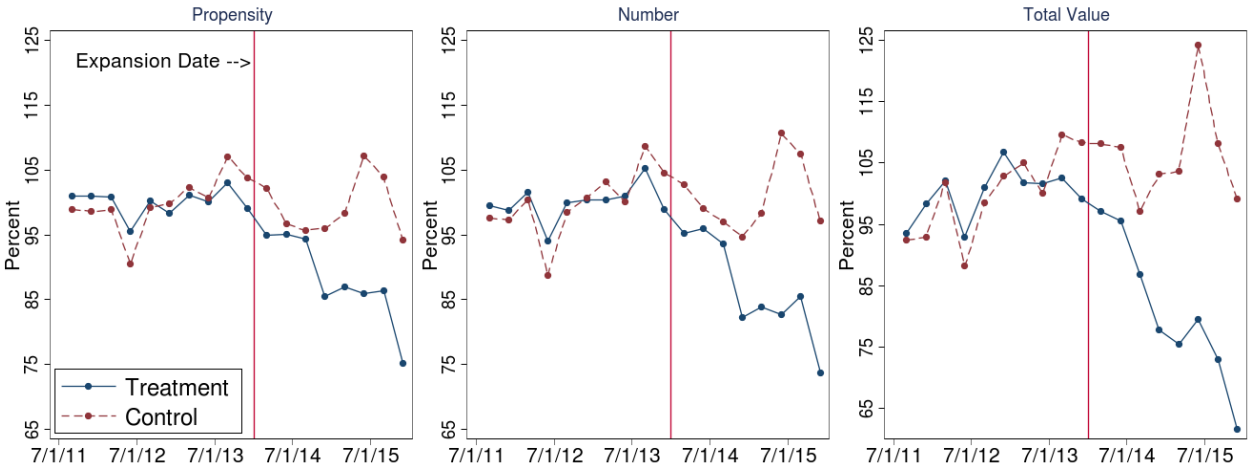

Figure 3: Trends in Newly Accrued Medical Debt

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.*

medical debt fell by 20 percent in treatment states relative to control states. These effects are on a similar order 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 note two important factors to rule out in identifying the underlying direct effects of the expansion on the accrual of medical debt. The first is that perhaps the expansion had a broader effect on collection activity, or that simply any reduction in medical collections are the result of changes in collections rules and/or activity across treatment and control states unrelated to the increase in insurance rates. When we repeat the above exercise using non-medical collections we find that in fact there was very little difference in non-medical collection activity between treatment and control states before and after the expansion. The second factor is the opening of the private exchanges, which occurred concurrently with the Medicaid expansion. Although the exchanges were rolled out in all states, some opted for state run exchanges while others decided to operate directly through the federal platform.

This may have resulted in a difference between treatment and control states not directly driven by the expansion. We test this by restricting the above analysis to states using federal platform to run their exchanges and find that the above effects are robust to this restriction. These robustness checks are shown in Appendix B. Overall, we conclude that the reduction in medical collections shown in Figure 3 is very likely due to newly insured individuals no longer receiving collections due to unpaid medical bills.

5.2 Distributional Effects

As is shown in Table 1, fewer than 5 percent of consumers incur new medical debt in any given quarter. It stands to reason that adverse health events among the uninsured are rare and expensive when they occur. With this in mind, we further consider the effects of the policy on the distribution of medical debt. This distributional analysis is illustrated in Figure 4. The top four panels highlight differences in the effects of the expansion on consumers' propensity to accrue large versus small unpaid medical bills. We plot trends in each of four successively larger value bins: (1) \$1-\$999, (2) \$1,000-\$9,999, (3) \$10,000-\$24,999, (4) >\$25,000. The bottom panels of the figure measure the average changes in Census Tract quantiles of medical debt flows. Specifically, for each quantile of medical debt q in Census Tract c and quarter t we estimate

$$ln(quantile)^q_{ct} = \alpha^q_c + \eta^q_t + \beta^q \cdot (Post \cdot Adopt_{s(c)}) + \epsilon^q_{ct} \tag{2}$$

We plot each β^q in equation 2, for $q \in [89, 99]$, along with its related 95% confidence interval, in the bottom left panel. The bottom right panel shows level effects by comparing Pre-reform average quantile q in treatment Tracts c (blue squares) to the average counterfactual quantile $q^{ctr} \equiv (1 + \beta^q) \cdot q$ (red circles).

As shown in the figure, the expansion was considerably more effective in reducing uninsured households' exposure to large medical bills. While the propensity to accrue unpaid medical bills smaller than \$1,000 decreased by a modest 2.5 percent, the likelihood of accruing medical bills in excess of \$1,000 fell by up to 40 percent, with the incidence of new debts in excess of \$25,000 falling by about 35 percent. 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 debts further supports the idea that in fact

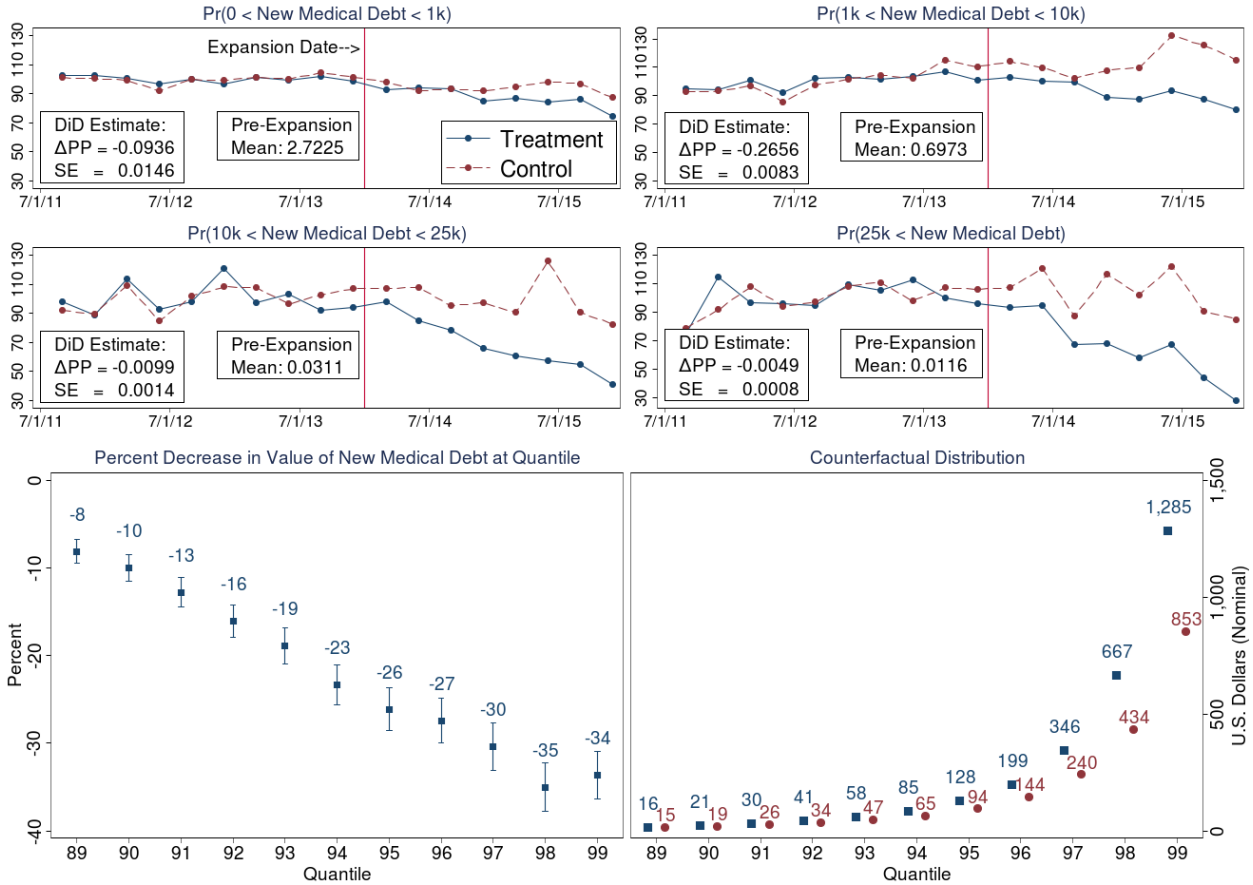

Figure 4: Distributional Effects of Expansion on Medical Collections

Notes: *The figure shows distributional effects of the reform on the accrual of medical debt. Data are from CFPB's CCP. The top four panels show trends in the propensity to accrue new medical collections by value category: (1) <$1,000, (2) $1,000-$10,000, (3) $10,000-$25,000, (4) >$25,000. 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. Difference-in-Difference coefficients are from regressions described in equation 1. The bottom left panel plots coefficients and 95% confidence intervals from DD regressions as described by equation 2. Regressions at the quantile are weighted using the proportion of adults in a Census Tracts newly eligible for Medicaid coverage. In all regressions, standard errors are clustered at the Census Tract level.*

fewer unpaid medical bills following the reform are the result of newly insured individuals no longer incurring large medical bills after treatment.

Because they are somewhat rare, expensive adverse health shocks denote relatively extreme 'right tail' events, a fact not well captured in the average treatment effect. As a result, we might expect the expansion to have greatest impact on the right tail of the accrued medical debt distribution. As shown in the bottom panels of the figure, even at the 89th percentile we find a modest 8 percentage point reduction in the Tract level quantile for

treatment relative to control.[18] This effect more than triples for the 98th and 99th percentiles to 35 and 34 percentage points, respectively. The dollar reductions (bottom right) further confirm our assertions that the reform in large part helped insure more individuals against rare and costly adverse health events. As shown in the figure, an average reduction of 8 percentage points at the 89th percentile, on a base of \$20 in average debt at the quantile, in effect translates to an modest savings of only \$2. Nevertheless, the savings become quite substantial past the 95th percentile. For the highest quantile, a 34 percentage point reduction translates into about \$430 of savings, or about 36% the average size of an unpaid medical bill in collections (Table 1).

5.3 Heterogeneous Effects Across Communities

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 be masking substantial heterogeneity in the impact of the policy across wealthier and more modest communities. We explore this heterogeneity by merging demographic data at the Census tract level from the American Community Survey (ACS) to identify communities (Census tracts) in which a greater proportion of the population was likely to be directly affected by the reform.[19] Using pre reform eligibility criteria by state for childless adults as of January 1, 2013 and the policies new eligibility benchmark of 138% of the federal poverty line (FPL), we calculate the proportion of adults in each Census tract that would be newly eligible for Medicaid following the expansion. We then extend our DD framework to allow the treatment effect to vary across communities with different marginally eligible population. Our heterogeneous treatment is incorporated into our DD framework as a triple difference in the following form

$$ln(\hat{\mathbb{E}}[Med.\ Col.])_{ct} = \alpha_c + \eta_t + \delta \cdot Pvrt \cdot Post + \beta \cdot Post \cdot Adopt + \gamma \cdot Post \cdot Adopt \cdot Pvrt + \epsilon_{ct} \quad (3)$$

in Census tract c and quarter t. The dependent variable ($ln(\hat{\mathbb{E}}[Med.\ Col.])_{ct}$) is the log of the mean value of the newly accrued medical debt in a tract-quarter, and $Pvrt \in [0, 1]$ denotes the proportion of adults newly eligible for Medicaid with the reform.

Figure 5 shows results of this heterogeneous effect. The left panel of the figure shows changes in the relative per-capita reduction in new medical debt due to the reform ($\%\Delta =$

[18] Although fewer than 5 percent 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.

[19] For this match we use the 2009-2013 ACS 5-year averages to calculate counts at the census tract level. We then match to the CCP using FIPS codes.

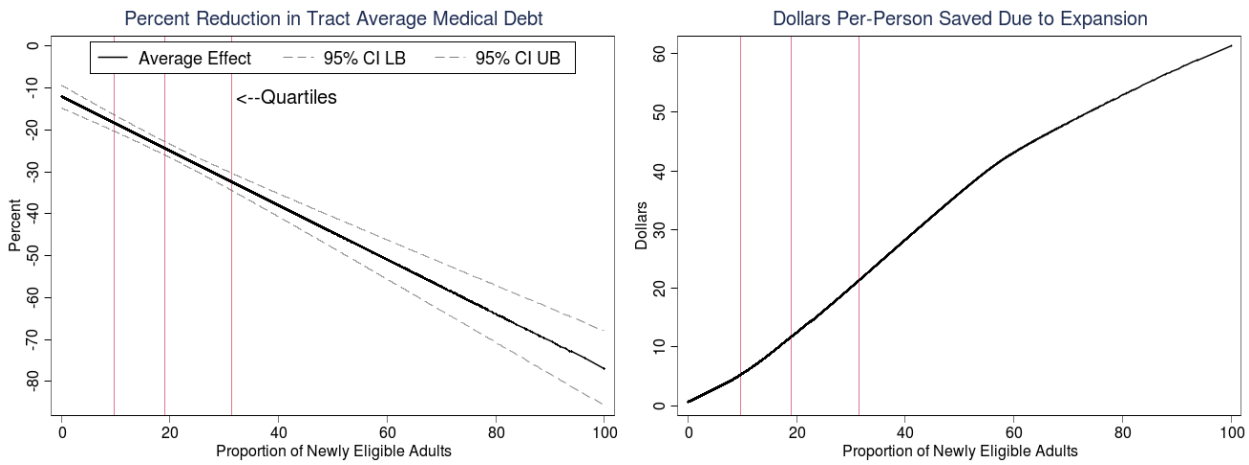

Figure 5: Changes in Non-Medical Debt

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 3 with related point-wise 95% confidence intervals. The effect for a given eligibility rate is defined as* $\%\Delta = \hat{\beta} + \hat{\gamma} \cdot Pvrt$. *Regressions are weighted using the number of newly eligible adults in the Tract. All standard errors are clustered at the Census tract level. The right panel of the figure plots average level effects defined as:* $\hat{\mathbb{E}}(Save)_{ct} = \%\Delta \cdot \hat{\mathbb{E}}[Med.\ Col.])_{ct}$. *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 (new) 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.*

$\hat{\beta} + \hat{\gamma} \cdot Pvrt$). The right panel of the figure shows average dollar-per-person savings due to the expansion($\hat{\mathbb{E}}(Save)_{ct} = \%\Delta \cdot \hat{\mathbb{E}}[Med.\ Col.])_{ct}$) and smoothed using a weighted local linear regression. In each panel, the vertical lines denote quartiles of the tract level eligibility rate distribution.[20]

As shown in the figure, the decrease in newly accrued debt is greater in Tracts with a larger proportion of newly eligible individuals. In Tracts with 12 percent of adults newly eligible (25th percentile), accrued medical debt per person-quarter decreased by approximately 20 percent, while that reduction was closer to 30 percent for tracts in with 30 percent of adults newly eligible (75th percentile). Similar to Figure 4 above, the level effects are also substantial. 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 \$20 dollars per person-quarter.

[20]The left most left line signifies the 25th percentile among census tracts (e.g. 25% of all census tracts have a lower poverty rate), the middle line the 50th percentile, and the vertical line furthest to the right the 75th percentile.

5.4 Medical Debt and Consumer Payments

We use the coefficients from equation 3 to calculate the total amount of new medical debt not accrued due to the reform in the first 8 quarters following the expansion. These aggregate effects are presented in the top panel of Table 2. As shown in the table, the policy led to a $2.4

Table 2: 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 ($)	46.53	12.42	28.97	61.57	128.65
Total ($Billions)	2.39	0.26	0.41	0.59	0.88
Proportion of New Medical Collections Repaid (p.p)					
After One Year					
Repaid	7.86	9.55	8.79	8.80	5.99
Repaid or Removed	36.67	33.90	35.20	37.35	37.94
After Two Years					
Repaid	9.03	10.55	10.12	10.27	6.90
Repaid or Removed	51.46	48.07	49.49	52.40	53.01
Annual Decrease in Per Person Expected Medical Debt Payment ($)					
After One Year					
Lower Bound	3.66	1.19	2.55	5.42	7.71
Upper Bound	17.06	4.21	10.20	23.00	48.41
After Two Years					
Lower Bound	4.20	1.31	2.93	6.32	8.88
Upper Bound	23.94	5.97	14.34	32.26	68.20
CCP Population 18-64 (Millions)	51.34	20.87	14.10	9.56	6.82

Notes: This table presents estimates of annual per-capita average reduction in medical debt, repayment rates, and total accrued savings using estimates from equation 3. Our aggregate dollar measure is calculated as follows: $TotDollars = 4 \cdot Pop_c \cdot \%\Delta_c$. 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 bound of out of pocket savings is defined as $\%\Delta_c \cdot \%Repaid$. The upper bound of out of pocket savings is defined as $\%\Delta_c \cdot \%(Repaid\ or\ Removed)$. The CCP Population is calculated by multiplying the number of records in 2013Q4 by 48, the sampling rate of the data (Section 3).

billion annual reduction in unpaid medical bills. About 40 percent of this decline ($\sim$ $900) came from individuals living in the poorest communities, where per-capita reductions ($\sim$ $130) were nearly three times the average ($\sim$ $46.53). Overall, our results show that, perhaps

as intended, the program was progressive, investing heavily in low income neighborhoods and less so in wealthy communities.

The majority of unpaid medical bills sent to collections are never repaid. As a result, fewer accrued medical debts do not necessarily translate directly into a reduction in consumer payments. The middle of panel of Table 2 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 we have no information regarding the repayment status of removed collections we form bounds on repayment rates. The lower bound of repayment 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 percent of newly accrued debt is repaid within one year of appearing on an individual's credit report, and 9 percent within two years. About half of newly accrued debt is removed entirely from the credit record within two years, the majority of which within one year. Although the proportion of medical debt repaid is lower in poorer communities, the proportion of debt repaid or removed is higher. In the richest communities about 11 percent of debt is repaid and 48 percent is repaid or removed. In the poorest communities that proportion declines to 7 and 53 percent, respectively.

In the bottom panel of the Table 2 we combine 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 \$4 and \$20. Despite lower repayment rates, the largest reductions came from the poorest communities, for whom the decline was between 5 and 12 times larger than for the richest communities.

Table 2 also allows us to compare 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 \$46.53 reduction in medical debt per person and quarter. Dividing this point estimate by an estimated coverage gain of 4.1 percentage points from Medicaid expansion we calculate a debt reduction of $-\frac{\$46.53}{0.041} = -\$1,135$ 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 \$568. 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 DD 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.

Relatedly, Garthwaite, Gross and Notowidigdo (2015) find that each additional uninsured person costs a local hospital about \$900 annually in uncompensated care. As discussed in the institutional detail section, hospitals provide only 60% of uncompensated care. On the other hand, only about 50% of uncompensated care may contribute to bad (medical) debt. This suggests that an uninsured person adds medical debt worth $\frac{\$900}{0.6} \times 0.5 = \$750$ per year. Considering that about 20% of medical debt is paid by consumers in our sample, we find an annual reduction in medical debt of about $(1 - 0.2) \times \$1,135 = \$908$ per newly insured person, which exceeds the former estimate by only 20 percent.

6 Indirect Effect of Medicaid on Financial Health

Health insurance can affect the financial health of households for reasons that go beyond the direct effects that insurance has on the accrual of unpaid medical bills. Consumers facing significant uninsured medical bills or pharmaceutical costs, even if they are able to pay those expenses or fail to do so altogether (Table 2), will have fewer financial resources available to meet their other expenses and/or face worsening credit conditions. Such households can struggle to pay their non-medical bills, resulting in financial distress or insolvency.

6.1 Repayment Delinquencies

Consumers in financial distress are more likely to miss payments on their outstanding loans. As a result, credit delinquency rates are commonly used indicators of financial distress. Using the payment history for each account in the CCP, we determine whether each consumer became 30 or more days past due on any of their accounts during the quarter, which is our measure of delinquency. Isolating flows into delinquency, rather than focusing on the contemporaneous payment status of all outstanding accounts, allows us to focus on episodes

of worsening distress. We use the resulting delinquency rate to explore whether Medicaid expansion reduced the likelihood of financial distress.

The top panel of figure 6 shows the normalized delinquency rates each quarter that prevailed for the treatment and control groups over the sample period. While the trends for both groups were similar during the pre-expansion period, delinquency rates trended notably lower after expansion in states that expanded Medicaid. Using our DD approach (equation 1), we find that Medicaid expansion reduced delinquency rates in the treatment group by 0.14 percentage points, or 2 percent of the pre-expansion mean.

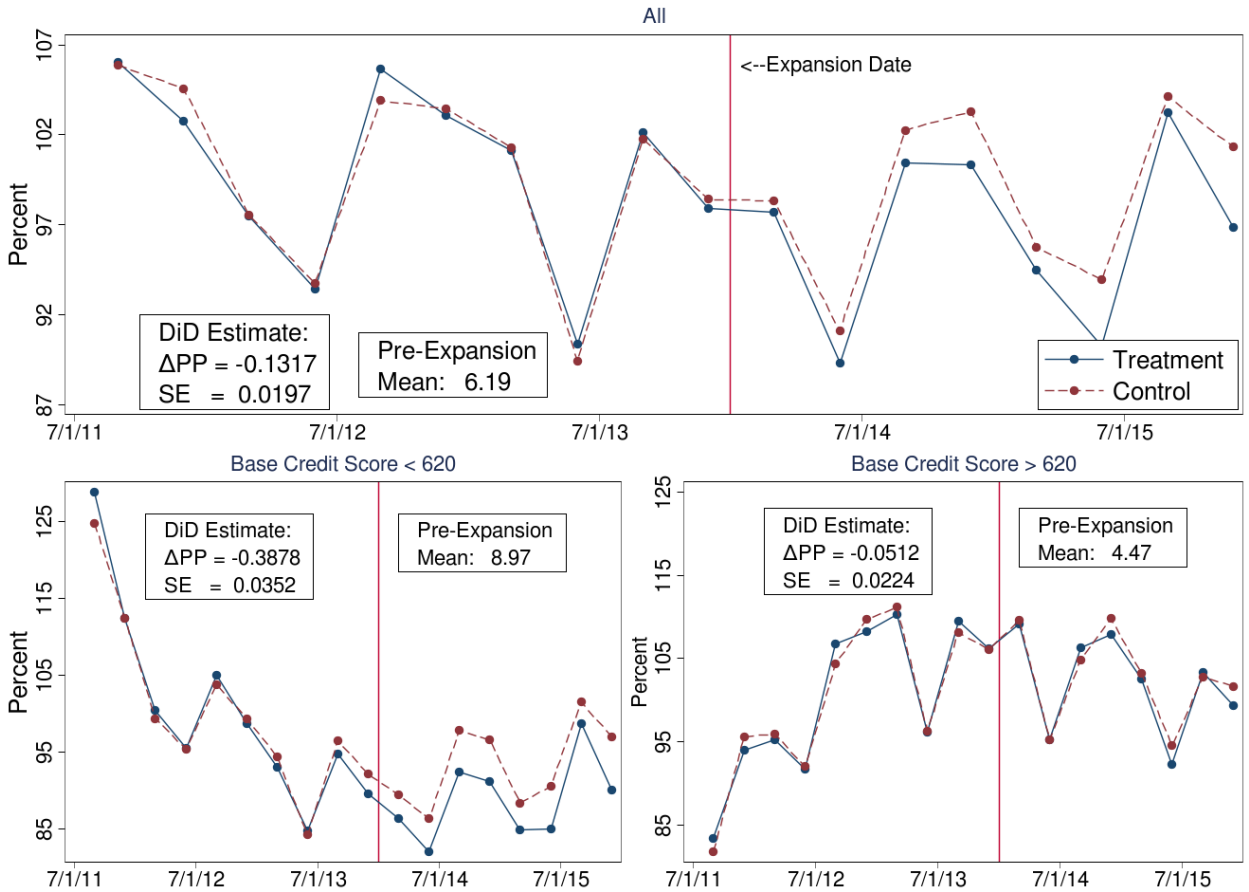

Figure 6: Effects of Medicaid Expansion on New Loan Delinquencies

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 top panel shows trends for all consumers in the data and the bottom panel shows delinquency rates for subprime and prime consumers, defined as of the first quarter in analysis the period, respectively. Estimates from the DD regression described in equation 1 are provided. All standard errors are clustered at the Census tract level.*

The reduction in delinquency in the treatment states may mask significant heterogeneity in Medicaid expansion's effects on financial distress. Uninsured medical expenses should only cause financial distress when consumers lack sufficient financial resources. So the reductions in delinquency should be larger for consumers with fewer financial resources, who should, therefore, be more susceptible to financial distress and who may benefit more from Medicaid expansion. Information about the income and assets of consumers in the sample would provide a good measure of the ability of consumers to withstand the expense shocks that accompany an adverse health event. However, the CCP does not contain such information. Instead, we use each consumer's credit score, which is a measure lenders use to predict the likelihood that a consumer will become delinquent on credit obligations in the future, as an indicator of financial fragility and the likelihood of benefiting from Medicaid expansion. Specifically, we divide the sample into two groups based on *baseline* scores: consumers with scores below 620 (*subprime*) and with scores of 620 or above (*prime*) in the beginning of the sample period.

Subprime consumers are more likely to be positively affected by Medicaid expansion for several reasons. First, their low scores suggest that they have experienced financial distress in the past (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 indicates 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 more likely to have subprime credit scores. Third, the declines in the incidence of medical debt observed in section 5 were concentrated among subprime consumers.

The bottom panels of figure 6 show delinquency rates around the time of Medicaid expansion for subprime and prime consumers respectively. While the DD estimates suggest that Medicaid expansion reduced delinquency rates for both groups, the effects were substantially larger for subprime consumers. Among subprime consumers, delinquency rates declined by 0.39 percentage points, or 4 percent of the pre-reform mean. For prime consumers, the decline is substantially smaller, about 1 percent of the pre-reform mean.

6.2 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, as outlined in Table 1. Under Chapter 7, a filer can discharge nearly all debts. However, the filer is required

to relinquish any of their non-exempt assets.[21] 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 3, 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,

Table 3: Debt at Bankruptcy

	All	(Base Credit Score < 620)	(Base Credit Score > 620)
	(1)	(2)	(3)
Percent Filing with Medical Debt	32.87	40.58	13.41
Medical Debt at Filing			
Mean if Medical Debt >0	1,980	2,117	1,698
Median	556	578	387
75th Pctl.	1,559	1,632	1,032
90th Pctl.	3,954	4,148	2,820
99th Pctl.	23,927	23,385	24,844
Other Debt at Filing			
Credit Cards	8,360	7,351	10,905
Personal Loans	1,169	1,002	1,592
Auto Loans	4,853	4,173	6,567
Mortgages	48,557	42,258	64,451

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 expanding (treatment) 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.*

however, masks substantial heterogeneity. The top 1 percent of filers with medical debt look 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

[21] 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.

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 give that filers would also loose some of of their 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 7 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 in equation 1. Like our analysis of consumer delinquency, we distinguish the effects of the policy for consumers with credit scores of 620 or above (left panel) or below 620 (right panel). We discuss differences in bankruptcy filing by chapter in the Online Appendix.

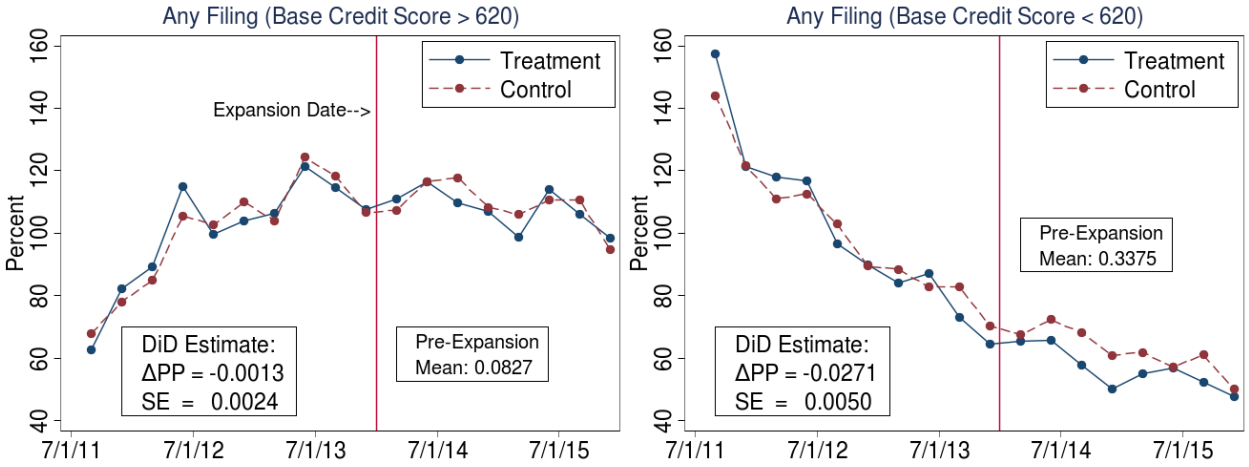

Figure 7: Effects of Medicaid Expansion on New Bankruptcy Filings

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.*

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 more vulnerable consumers, with baseline credit score $<$ 620, the Medicaid expansion reduced the quarterly rate of bankruptcy filings by a substantial

0.03 percentage points, or 8 percent of the pre-expansion mean. Given our sample frame, this translates into approximately 50,000 fewer bankruptcies over the first two post-reform years.[22]

To put our estimates into perspective, Mazumder and Miller (2016) find that Massachusetts health reform reduced bankruptcy filing by 0.08 percentage points over two years 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 percent overall. We find a 8 percent reduction for a 4 percentage point increase when looking at 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.

6.3 Credit Scores

The reductions in medical debt and delinquency that accompanied Medicaid expansion may have additional benefits for consumers in the form of higher credit scores. New credit delinquencies will lower the credit scores of borrowers and, since credit scores are pervasively used in credit underwriting and pricing, will increase their likelihood of being denied credit or increase the interest rates they pay for the credit they obtain. A lower rate of new delinquencies should thus translate into higher credit scores for consumers.

Figure 8 shows effects of the medicaid expansion on consumers' credit scores. The left panel shows the normalized credit score trends for consumers in the treatment and control states over the sample period and the related difference-in-difference estimate. The middle panel shows these trends only for consumers with baseline credit scores below 620. From the figure, the treatment and control groups exhibit similar credit score patterns for prime and subprime consumers during the pre-expansion period and both appear to show some separation after Medicaid expansion. We find that Medicaid expansion increased the credit

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

$$\Delta Bankruptcy = \underbrace{468,144}_{\#\ of\ subprime\ Records\ in\ Treament\ States} \times \underbrace{48}_{pop.\ wgt.} \times \underbrace{-0.000271}_{\Delta\ percentage\ points} \times \underbrace{8}_{post\ quarters} \approx -48,717$$

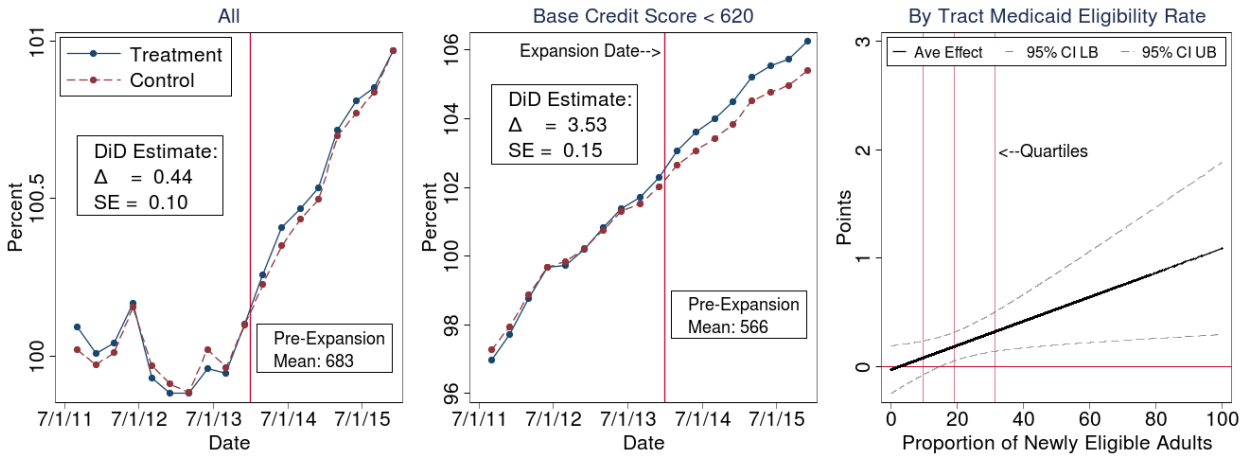

Figure 8: Effects of Medicaid Expansion on Credit Scores

Notes: *The left and middle panels of the figure show normalized trends in the credit scores of consumers in treament and control states, respectively. The credit score used is as of the end of each quarter. It also shows estimates from a DD regression as described in equation 1 in which the credit score is the dependent variable. The right panel shows heterogeneous treatment effects across tracts with varying eligibility rates as in equation 3. All standard errors are clustered at the Census Tract level.*

scores on average by 0.44 points relative to a pre-expansion mean of 683 points. Congruent with effects on delinquency and bankruptcy, this separation is substantially more pronounced among financially more vulnerable consumers.

The right hand panel of the figure shows how this treatment effect differs across census tracts with varying eligibility rates. To the extent that the Medicaid expansion is the driving factor behind this documented effect, we expect a larger treatment in Census Tracts with higher Medicaid eligibility rates. As shown in the figure, the treatment effect is zero in Tracts with low eligibility rates and quite substantially larger, and statistically significant in tracts with higher eligibility rates. Specifically, among poorer communities, in which eligibility rates are high, the treatment effect is nearly three times larger than that overall (right panel of Figure 8).

In Figure 9 we explore the effect of the policy across the credit score distribution. Like in Figure 4, we estimate equation 2 over the entire distribution of credit scores. As discussed above, the effects of the policy on medical debt and financial distress are larger for financially more vulnerable consumers. We would therefore expect the resulting score increases to be concentrated in the lower tail of the score distribution. As shown in the figure, Medicaid expansion improved credit scores more at the bottom of the distribution, with the largest effects at the bottom quartile of the distribution. Consistent with above results on financial distress, the results suggest that credit scores increased significantly as a result of the reform.

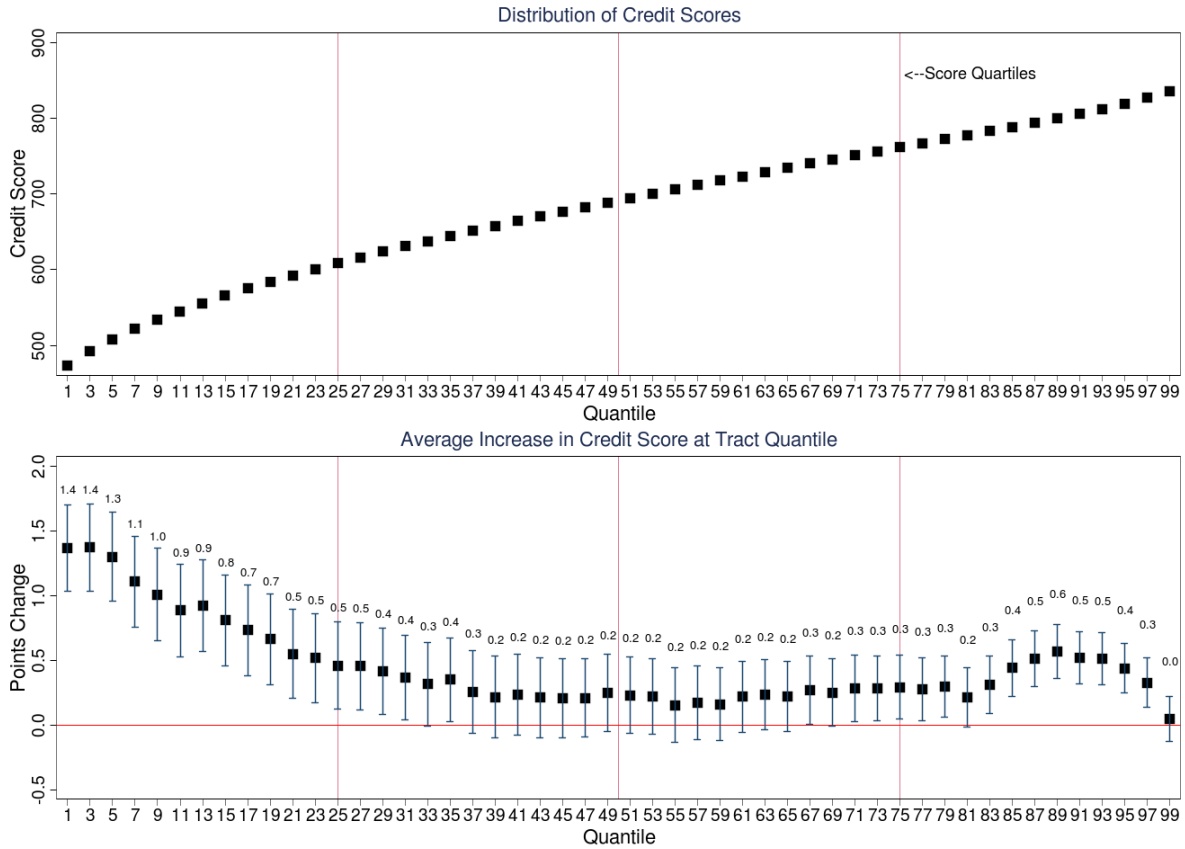

Figure 9: Effects of Medicaid Expansion on Credit Scores

Notes: *The figure shows distributional effects of the reform on individual credit scores. The top panel shows the distribution of credit scores among individuals in treatment states, measured as the average quantile in each Tract, prior to the reform. The bottom left panel plots coefficients and 95% confidence intervals from DD regressions as described by equation 2. All standard errors are clustered at the Census tract level.*

Moreover, those increases were most felt in communities with higher Medicaid eligibility rates as well as among individuals who were likely already financially distressed.

7 Pricing and Availability of Credit

Consumer with improved financial health are more likely to be offered more credit and on better terms. It stands to reason that improvements in the financial health of consumers stemming from the policy might translate into greater access to cheaper credit. In this section we explore the extent to which terms of credit offered to consumers improved following the reform. Specifically we look at such effects on 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 then calculate how changes in credit terms might translate into lower monthly payments (savings) by simulating a debt refinance under the new credit terms.

7.1 Changes in Availability and Terms of Credit

Table 4 shows the effects of the Medicaid Expansion on the availability and pricing of credit to consumers. For this we use data from Mintel and MyFico as described above (Section

Table 4: Medicaid Expansion and Credit Supply

	Mintel Comperemedia				MyFico (Imputed)	
	Credit Cards		Personal Loans		Auto Loans	Mortages
	Pr(Receive)	Interest Rate	Pr(Receive)	Interest Rate	Interest Rate	Interest Rate
	(1)	(2)	(3)	(4)	(5)	(6)
DiD	0.0153	-0.5825	-0.0405	-1.0821	-0.0075	-0.0024
	(0.0110)	(0.2000)	(0.0111)	(0.2883)	(0.0046)	(0.0005)
Pre-Expansion Mean	0.67	15.19	0.1100	8.8800	7.3311	4.2003
R^2	0.0047	0.0445	0.0250	0.0702	0.0003	0.0000
Observations	91,558	44,922	91,558	6,942	35,789,890	25,995,823

Notes: *The table shows DD regressions of credit offers to consumers. In columns (1)-(4) the data come from Mintel Comperemedia which is a nationwide household survey of mail out credit offers. The data are monthly cross sections of a nationally representative sample of households. The data from columns (5)-(6) are pulled from the Fair Isaac corporation's MyFico webpage (see Appendix). Columns 1 and 3 show DD results of linear probability regressions in which the dependent variable takes the value 1 if an individual receives a credit card or personal loan offer, respectively, and 0 otherwise. Columns 2, 4, 5, and 6 show DD results of OLS regressions in which the dependent variable is the price. In columns (2) and (4) only pre-screened offers are included, or those which, by law, contain a pre-screen opt out disclosure. This means lenders use potential customers' credit reports prior to making an offer and that individuals receive a strong signal of the offer being honored upon take up. Mintel regressions (Columns (1)-(4)) are weighted by the average mail volume received in a county over the period. All regressions include County (Columns (1)-(4)) or Tract (Columns (5)-(6)) FE, and month-year FE. Standard errors are clustered at the County (Columns (1)-(4)) or Tract (Columns (5),(6)) level.*

3). We apply the same DD approach specified in equation (1). Given the reduced sample size, we control for effects at the County rather than the Tract level for regressions using the Mintel data.

The DD coefficient estimates in the table are largely consistent with increased credit supply for consumers in states that expanded Medicaid, relative to the supply available in states that did not. The likelihood of receiving solicitations in the treatment states increased by 1.5 percentage points, or about 3 percent, for credit cards and decreased by 4 percentage points or by 30 percent for personal loans. While the decline in personal loan solicitations may seem counter-intuitive, it is not necessarily inconsistent with greater credit availability.

Unlike credit cards, personal loans tend to be used by consumers with lower credit scores. To the extent that consumer credit scores have increased and financial distress decreased in treatment states, lenders may have viewed the environment as less fruitful for personal loan solicitations.

The effects for credit cards and personal loans are consistent with increased credit availability across all three products, our results suggest that the interest rates decreased in treatment states relative to the control states for both credit products. Quoted interest rates were 58 basis points, or 4 percent, lower for credit cards and 108 basis points, or 12 percent, lower for personal loans. We also not small changes in interest rates available for Auto loans and Mortgages. Although mechanical, we believe these provide 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 supply and pricing of credit (Table 4) to calculate the potential dollar value of improved financial health by simulating a refinancing of debt held by consumers in treatment states under new credit terms.[23] We restrict our population individuals living in treatment states and consider a refinancing of their debt just prior to the expension, e.g. December 2013. In our simulation, we 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 D.

Table 5 shows the results from our simulation exercise. The top row shows per person annual savings using our Intent-to-Treat estimates from Table 4. The bottom row shows total effects, in millions of dollars, which are calculated by multiplying the per person effect by the CCP Population (2). As shown in the table, savings to consumers are substantial, accounting for about 40 percent of the per person reduction in medical debt (Table 2). Moreover, savings on unsecured loans, and in particular credit cards dominate the total

[23] We acknowledge that while credit score increases will have option value for all consumers, any lower interest rates that result will only tangibly benefit those consumers who take out loans. We therefore interpret these as potential savings that would result if the borrowers in our data refinanced their actual outstanding balances.

Table 5: Annual Savings From Medicaid Expansion

	Credit Cards (1)	Personal Loans (2)	Auto Loans (3)	Mortgages (4)	Total
Per Person ($)	14.33	3.79	0.38	1.27	19.77
Total ($ Millions)	735.65	194.64	19.50	65.02	1014.81

Notes: *Notes* The table shows results from simulations of consumer savings using Intent-to-Treat estimates in Table 4. The table shows per person effects and total effects. Total effects are calculated using the CCP Population (Table 2). See Appendix D for further details.

effect. Simulated savings for credit cards and personal loans add up to about $18, or ∼95 percent of the total. This is consistent with results from Table 3, which shows that the most at risk individuals carry a disproportionate amount of unsecured debt, which can be discharged at bankruptcy. 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.

Our calculated savings are rough estimates of the magnitude of the potential savings to borrowers and may be biased higher or lower for a few different reasons. First, they are based on realized score changes, in the case of automobile and mortgage loans, which are based on Intent-to-Treat effects. Only a portion of these consumers, however, will experience an adverse medical event that could trigger financial distress. For the remainder, we would not expect significant changes to their credit scores from Medicaid coverage. As a result, the actual score changes were likely much higher for some borrowers and closer to zero for the others. Because of the nonlinearity in the relationship between scores and interest rates, we expect our average effects to understate the savings that would actually result.

Second, in these estimations we have assumed that prime and subprime consumers have an equal likelihood of being newly enrolled in Medicaid (both groups are assumed to have a 4.1 percent probability); however, we expect that the likelihood of being enrolled is much larger for consumers with subprime scores and lower for consumers with prime scores. Since the per-capita savings are larger for subprime consumers, this assumption of an equal enrollment rate likely underestimates the potential savings to borrowers that resulted. However, it is also true that most of the outstanding debt is held by borrowers with prime credit scores and to the extent we are over weighting prime borrowers by assuming the same 4.1 percent treatment, our estimate may overstate the aggregate savings.

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 partial payments of medical bills provide information on the disutility of higher debt levels (Section 5.4).

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

$$U = g(c) - h(D) \tag{4}$$

with $g'(\cdot) > 0, g''(\cdot) < 0$ and $h'(\cdot) > 0, h''(\cdot) > 0$. Consumers' marginal utility of consumption is decreasing while their marginal disutility of medical debt is increasing.[24] 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.

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:

$$\max_{0 \leq b \leq \epsilon_{MB}} g(Y - (\epsilon_{MB} - b)) - h(\bar{D} + b) \tag{5}$$

[24] These properties imply that consumers choose to repay a positive portion of their medical bills, a fact corroborated by the data (5.4).

where in optimality

$$F(\epsilon_{MB}, b) = g'(Y - (\epsilon_{MB} - b^*)) - h'(\bar{D} + b^*) = 0 \ . \tag{6}$$

Applying the implicit function theorem, it follows that

$$\begin{aligned} \frac{\partial F(\epsilon_{MB}, b)}{\partial \epsilon_{MB}} \Delta\epsilon_{MB} + \frac{\partial F(\epsilon_{MB}, b)}{\partial b} \Delta b &= -g'' \Delta\epsilon_{MB} + \Big[g'' - h''\Big] \Delta b = 0 \\ \iff \frac{\Delta b}{\Delta \epsilon_{MB}} &= \frac{g''(Y - \epsilon_{MB} + b^*)}{g''(Y - \epsilon_{MB} + b^*) - h''(\bar{D} + b^*)} \in [0, 1] \end{aligned} \tag{7}$$

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

$$b^* = \tau(\epsilon_{MB}) \cdot \epsilon_{MB} \ \Rightarrow \ \frac{\Delta b}{\Delta \epsilon_{MB}} = \tau'(\epsilon_{MB})\epsilon_{MB} + \tau(\epsilon_{MB}). \tag{8}$$

Equations 6, 7, and 8 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.

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 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,

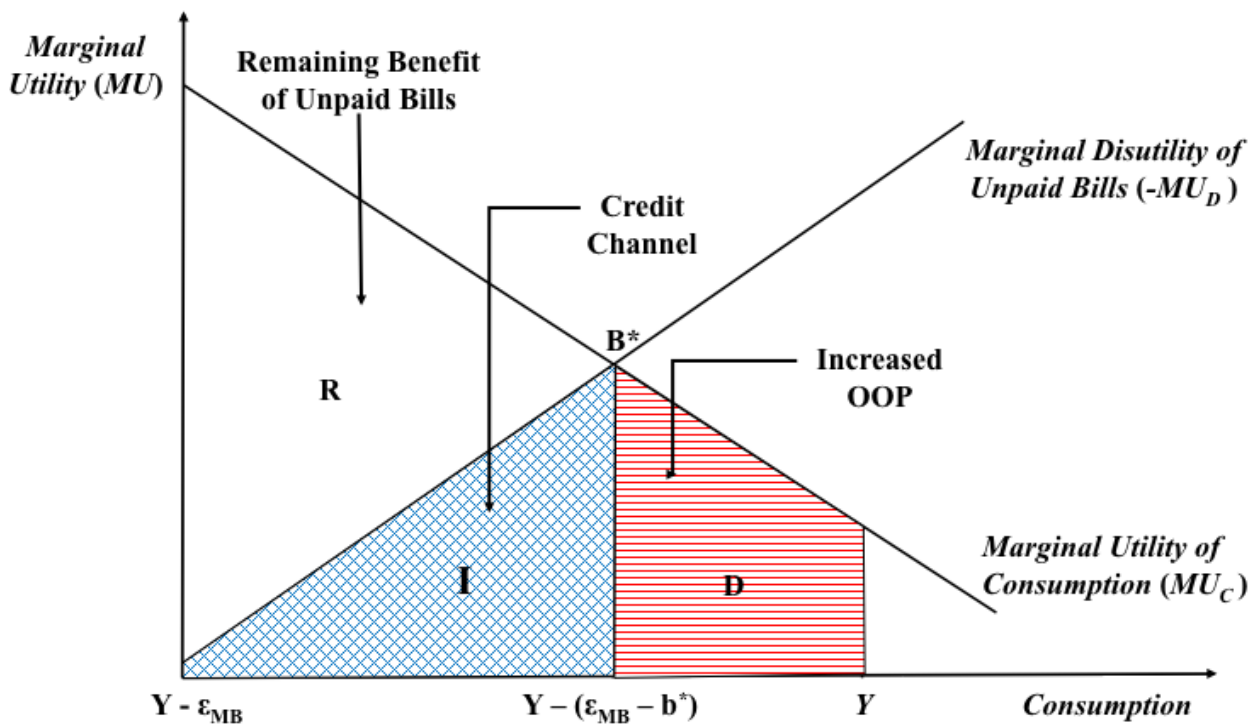

Figure 10: Welfare Benefits of Mean Reduction: Example

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 I 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 capture the overall utility loss from the 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 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

$$\begin{aligned} u_0 &= g(Y - (1 - \tau(\epsilon_{MB}))\epsilon_{MB}) - h(\bar{D} + \tau(\epsilon_{MB})\epsilon_{MB}) \\ u_0 &= g(Y - dc) - h(\bar{D} - dd) \end{aligned} \tag{9}$$

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 9 as

$$\int_{Y-CV}^{Y-(1-\tau(\epsilon_{MB}))\epsilon_{MB}} g'(x)dx = \int_{\bar{D}}^{\bar{D}+\tau(\epsilon_{MB})\epsilon_{MB}} h'(x)dx\ . \tag{10}$$

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.[25]

8.2.2 Local Approximation of CV and Comparative Statics

To provide intuition for the magnitude and the comparative statics of the CV, we maintain the simplifications from the graphical analysis. Specifically, we use a linear approximation to the marginal utility function around b^* and assume that the fraction of unpaid bills is "locally" constant: $\tau(\epsilon_{MB}) = \bar{\tau}$. This allows us to describe the CV as stated by the following proposition, see the Online Appendix for the proof.

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*

[25] The lower bound is achieved if the right had side of equation (10) equals zero. The upper bound is achieved if $-\int_{\bar{D}}^{\bar{D}+\tau(\epsilon_{MB})\epsilon_{MB}} h'(x)dx \geq \int_{Y-\epsilon_{MB}}^{Y-(1-\tau(\epsilon_{MB}))\epsilon_{MB}} g'(x)dx$.

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}.[26] More specifically, the CV is decreasing in the curvature 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.

[26] 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.

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 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.

8.3.1 Variance Reduction with Unpaid Medical Bills

Using the implicit function theorem and the first order condition, we replace the first and second derivative of $h(\cdot)$ and yield[27]

$$\begin{aligned} U(\epsilon_{MB}, \bar{\epsilon}_{MB}) &= g(Y-(1-\bar{\tau})\cdot\bar{\epsilon}_{MB}) - h(\bar{D}+\bar{\tau}\cdot\bar{\epsilon}_{MB}) \\ &- g'(Y-(1-\bar{\tau})\cdot\bar{\epsilon}_{MB})(\epsilon_{MB}-\bar{\epsilon}_{MB}) \\ &+ \frac{1}{2}\cdot(1-\bar{\tau})\cdot g''(Y-(1-\bar{\tau})\cdot\bar{\epsilon}_{MB})(\epsilon_{MB}-\bar{\epsilon}_{MB})^2 \ . \end{aligned} \tag{11}$$

The risk premium, RP can be written as

$$EU = g(Y-(1-\bar{\tau})\cdot\bar{\epsilon}_{MB} - RP) - h(\bar{D}+\bar{\tau}\cdot\bar{\epsilon}_{MB}) \ , \tag{12}$$

where $EU = \int U(\epsilon_{MB}, \bar{\epsilon_{MB}})dG$, denotes expected utility. Finally, we have

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

8.3.2 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

[27] See the Appendix Section for details.

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

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

Like for 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.

9 Overall Effects of Medicaid on Financial Health

In this last section, we quantify the overall effect of the Medicaid expansion in two complementary ways. In the first we use a calibrated version of the theoretical model (Section 8). We call this the *revealed preference approach*. In the second we use effects implied by our empirical results. We call this 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 40% of medical bills go as charity care, such that individuals are only held responsible $1-\alpha_{charity}=0.6$ of medical bills. We also assume that patients pay 20% of the original medical bill out-of-pocket.

In Figure 11, we plot the ratio of the implied compensating variation (CV) and 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 60% for small bills to $1-\bar{\tau}=0.2$ for large bills. Moreover, the decrease is $\frac{CV}{Medical\ Bill}$ is convex and more pronounced for more risk averse consumers. Evaluated at $\theta=3$, this ratio exceeds 50% (30%) for medical bills worth less than \$1,000 (\$5,000). Our previous estimates suggest a medical debt reduction of about \$1,100 per treated person, which corresponds to a raw bill of $\frac{\$1,100}{0.40}\approx\$2,500$. At \$2,500 this ratios exceeds 44%. The calibration thus implies that restricting consideration

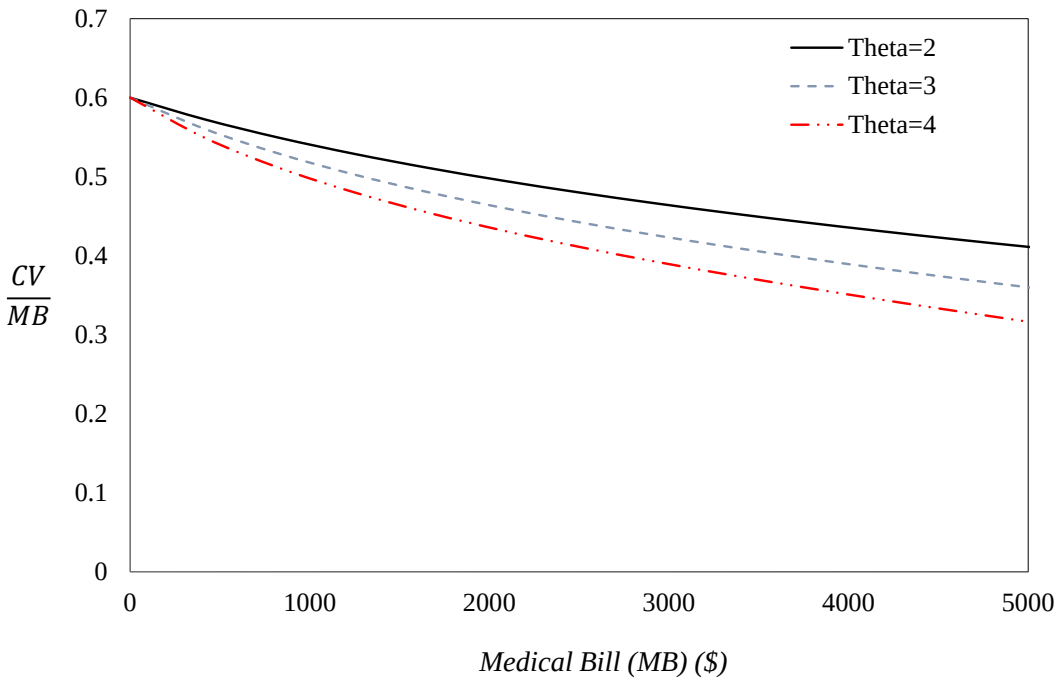

Figure 11: Compensating Variation/Medical Bill by Medical Bill

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 (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 (Section 2), we calculate out of pocket spending and implied compensating variation of \$480 and $\$480 \times 2.2 = \$1,056$, respectively. This suggests that an indirect benefit through the credit channel of \$1,056-\$480=\$576. These results are detailed in column 1 of Table 6.

Risk averse consumers are also willing to pay a premium for a reduction in risk. We evaluate this risk premium based on equation (13) around average annual consumption of \$3,300 and consider a standard deviation in consumption of \$768 as in (Finkelstein, Hendren and Luttmer, 2015).[28] We replace the variance in the medical bill, $var(Medical\ Bill)$, by the variance in non-charity care, $var([Medical\ Bill]_{non-charity})$ (60% of total bill) and adjust the out-of-pocket ratio. If out-of-pocket spending accounts for 20% of the full bill, then it accounts for $\bar{\tau}_{non-charity} = \frac{0.2}{0.6} = \frac{1}{3}$ of non-charity care. We then calculate the risk premium noting that variance in consumption equals $(1-\bar{\tau}_{non-charity})^2 \times var([Medical\ Bill]_{non-charity})$. We find a risk premium of \$600, which exceeds the pure OOP benchmark by a factor of 2.5

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

Table 6: Overall Annual Financial Benefits

	Revealed Preference (1)	Direct Approach (2)
Mean Effects		
Credit Channel (Indirect)	576	482
Out-of-Pocket (OOP) Spending (Direct)	480	480
Compensating Variation (CV)	1,056	962
Ratio: $\frac{CV}{OOP}$	2.2	2.0
Variance Effects		
Risk Premium (RP)	600	(600)
Rick Premium OOP Benchmark (RP OOP)	240	(240)
Ratio: $\frac{RP}{RP\ OOP}$	2.5	(2.5)
Total Benefit	1,656	1,562
Total Spending (Coughlin, 2014)	2,400	2,400
Ratio: Benefit/Spending	0.69	0.65

(column 2 of Table 6). Combining the estimates, we find an overall annual financial benefit of \$1,656, about 69% of overall medical spending.

9.2 Direct Approach

We benchmark our calibration to direct estimates presented above. Combining the benefits of reductions in costs of credit, our dollar value of improved financial health, we find annual benefits from a reduction in unpaid medical bills of $\frac{\$14.33+\$3.79+\$0.38+\$1.27}{0.041} = \frac{19.77}{0.041} = \$483$ (column 2 of Table 6). Combined with the reduction in out-of-pocket spending we calculate a compensating variation of \$962, which exceeds the out-of-pocket reduction by a factor of 2. These findings are remarkably similar to the results from the numerical exercise. The estimates are only slightly smaller despite the fact the direct approach ignores other benefits from a reduction in unpaid bills such as reduced hassle costs with collection agencies or a reduction in costs related to bankruptcy filing.

When compared to the overall reduction in medical debt, the estimated credit channel (indirect) benefit is valued at $\frac{\$19.77}{\$46.53} = \$0.43$ per dollar of reduced medical debt. Taking repayments of medical debt on the order of 8% into account (Table 2), we find a total financial benefit of a reduction in unpaid medical bills of about $\$0.43 + \$0.08 \approx \$0.51$ 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 $\frac{\$1,562}{\$2,400} \approx 65\%$ of overall medical spending.

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. This may be because 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.

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 3. Considering an annual reduction of about 25,000 bankruptcies, this can account for only about $\$860 \times 25,000 = \$21.5m$ 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.

10 Conclusion

Over half of the uninsured in the U.S. face 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 individual's financial health. It stands to reason that the financial cost of health care utilization may be substantially larger when taking into account these indirect *credit channel* effects. Conversely, the overall financial benefits of health insurance may largely exceed the implied reductions in out-of-pocket spending.

In this paper, we quantify the financial benefits of health insurance 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 $4.8 billion in its first two years. This corresponds to an annual reduction of about $1,100 per treated person or about 40% of overall health care spending. We further find that the Medicaid expansion significantly decreased debt delinquencies and personal bankruptcies, leading 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 $1 billion, which is slightly larger than the reduction in out-of-pocket spending. This implies that restricting attention to out of pocket payments may understate benefits by more than half. Finally, our estimates also suggest that beneficiaries value reductions in medical debt by about 51 cents per dollar in face value.

Overall we find that uninsured patients pay effectively 40 cents per dollar of health care utilization, divided about equally into changes in direct out-of-pocket and indirect interest rate payments. This suggests that charity care and the option 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, when taking the value of risk protection into account.

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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 3.1.1. Our approach closely follows the event study methodology in Dobkin et al. (2016) which tracks how individual's 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 some for of 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 6 quarter prior to receiving the collection and for 8 quarters, or 2 years, following the event. We use a non-parametric methodology similar to Dobkin et al. (2016) as follows:

$$y_{ict}^k = \alpha_c^k + \eta_t^k + \sum_{r=S}^{r=-2} \beta_r^k + \sum_{r=0}^{r=F} \beta_r^k + \epsilon_{ict}^k \tag{13}$$

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 collections 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

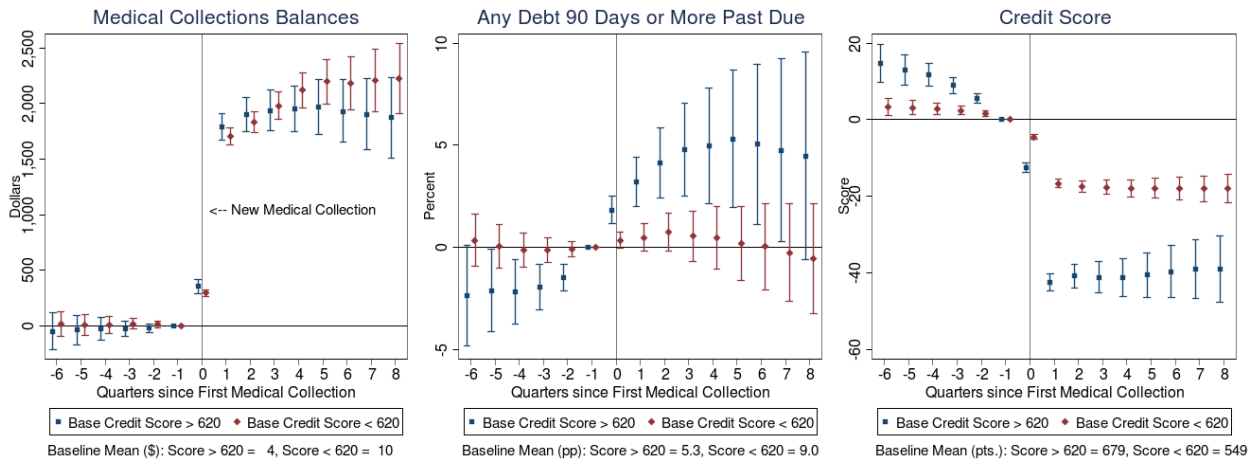

Figure 12: Trends in Newly Accrued Non-Medical Collections

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 13) 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 in delinquencies troubles 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

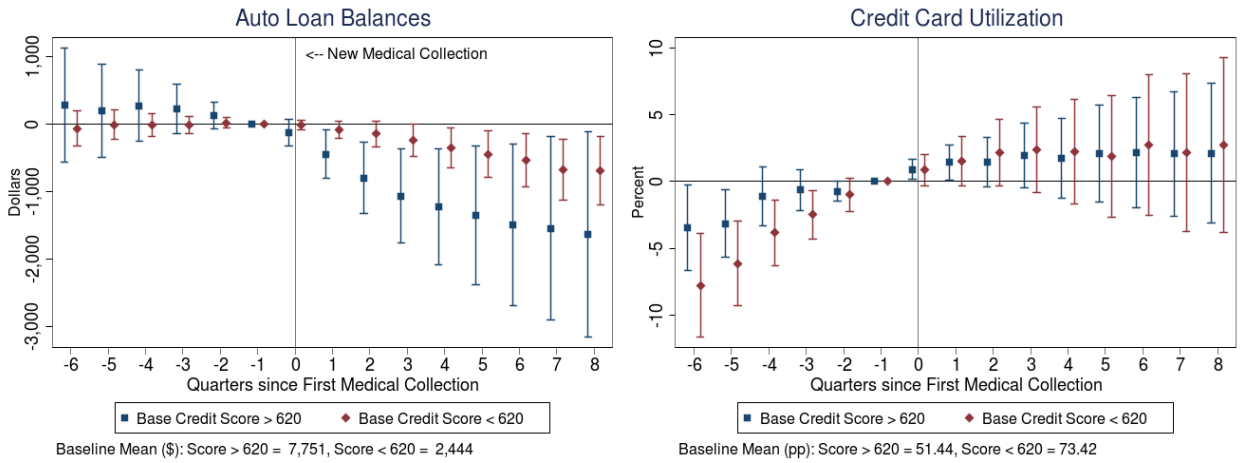

Figure 13: Trends in Newly Accrued Non-Medical Collections

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 percent, 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: 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-medical collections should not differ in treatment states relative to control following the

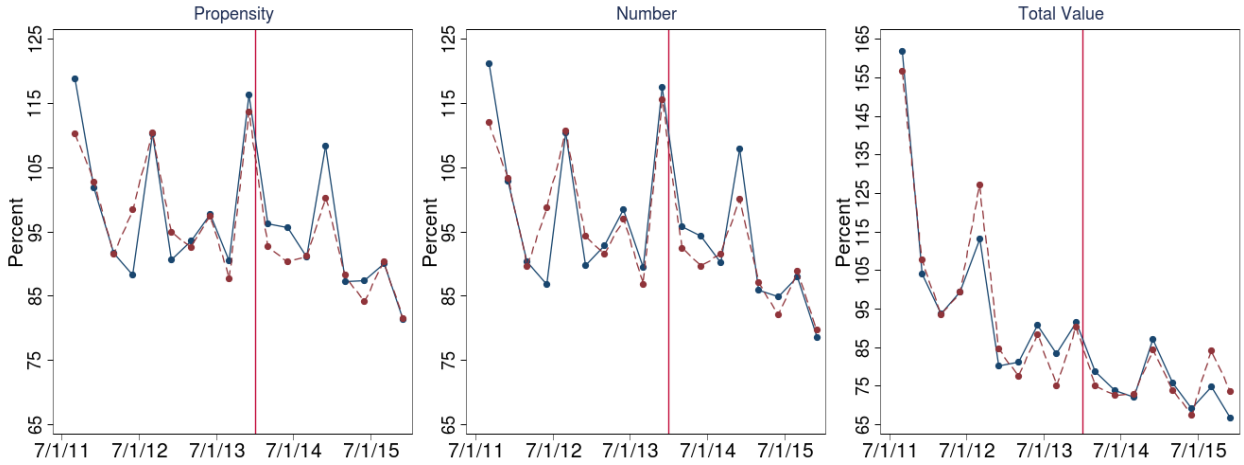

Figure 14: Trends in Newly Accrued Non-Medical Collections

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.*

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 were no systematic change in overall collections activity driving the reduction in medical debt accruals. Rather, reductions in unpaid medical bill 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 whom opted to use the federal platform for the exchanges. Moreover, the magnitudes are quite similar when considered against the full sample.

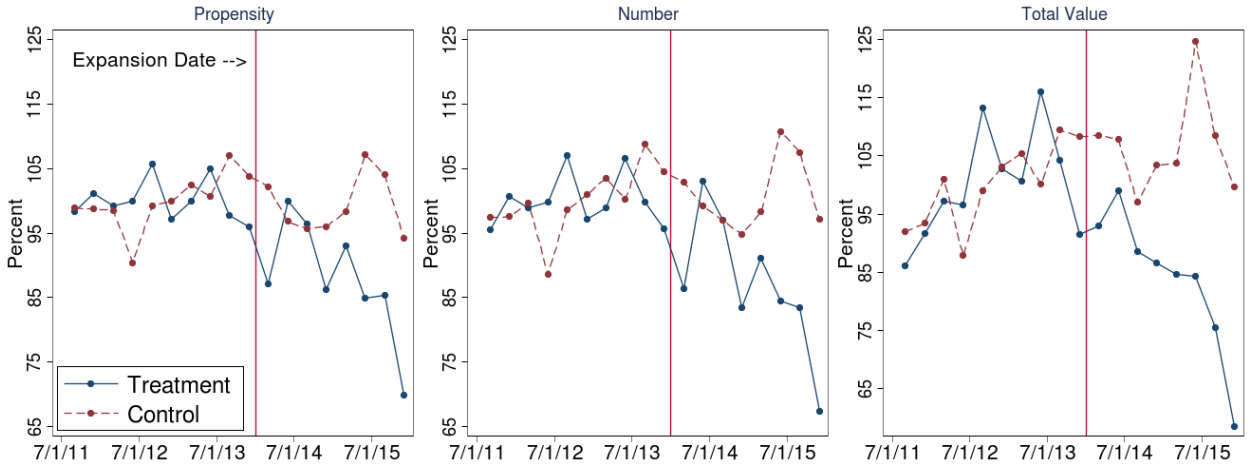

Figure 15: Newly Accrued Medical Debt for States Running Federal Exchanges

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.*

C 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 percent for individuals in treatment vs. control states in the two years following the reform. Which 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 likely 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 a reduction the 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.

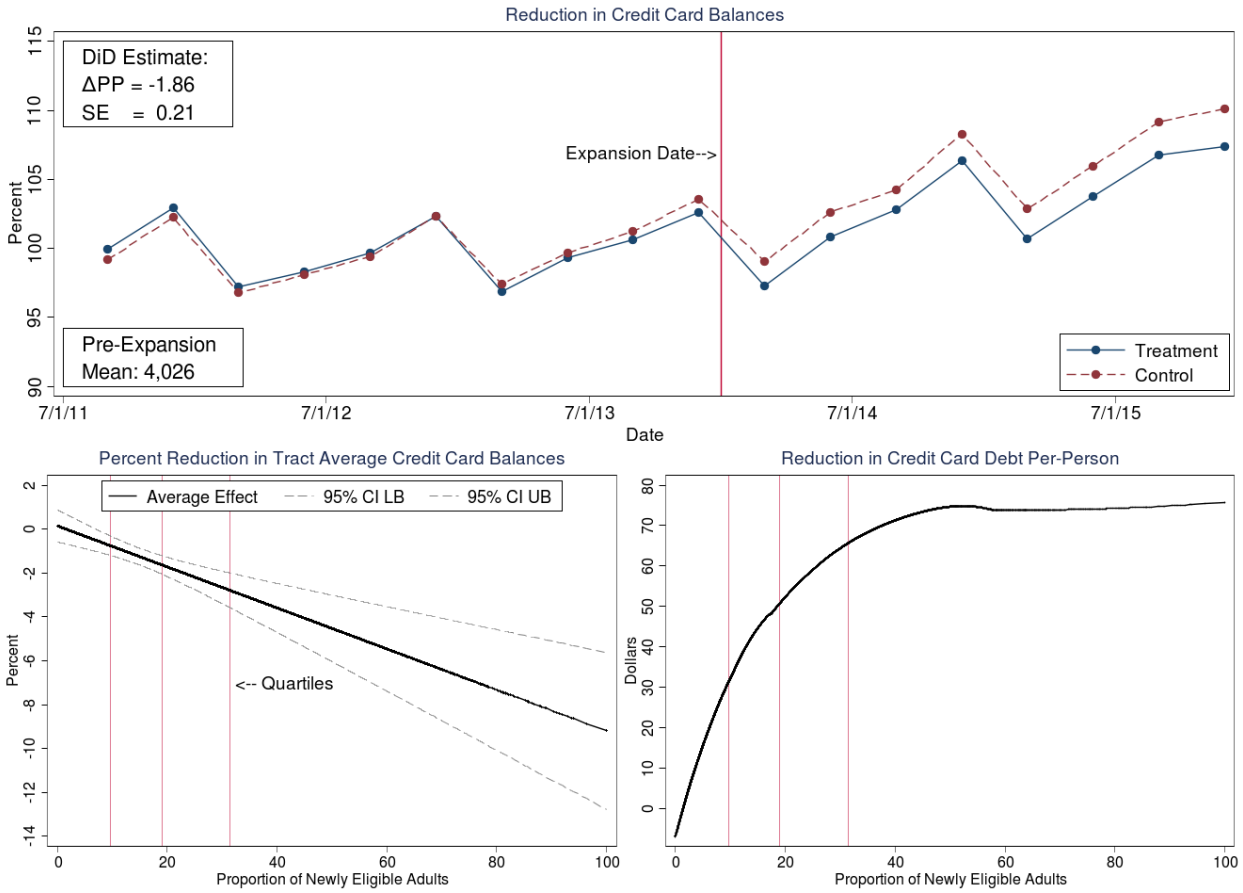

Figure 16: Effects of the Medicaid Expansion on Credit Card Balances

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 treament and control states, respectively, and are normalized by the pre-reform mean for each group. The vertical line in the top panel highlight 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.*

D Calculations of Simulated Decline in Monthly Bills

As described in Section 7.2, we use interest rate data for auto loans and mortgages from FICO and for credit cards and personal loans from Mintel Compremedia to estimate how the interest rates available to consumers in the treatment states were affected by Medicaid expansion. In this section, we detail how we converted those interest rate changes into the resulting savings in interest rate expenses that were available to consumers.

For each of the four products, we assume that consumers could have refinanced their existing balances at the average interest rate over the pre-expansion period covered by our

data (the "baseline" interest rate). Based on this assumption, we calculate the required monthly payment (P_m) to refinance balances from 2013Q4, the quarter immediately before Medicaid expansion, as

$$P_m = B_0 \cdot \frac{r \cdot (1+r)^m}{(1+r)^m - 1} \tag{14}$$

where B_0 represents the current balance, r is the monthly interest rate (e.g. $\frac{APR}{12}$), and m is the amortization period (e.g. 12, 24 or 36 months). 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.[29]

The scheduled monthly payments for a loan can overstate the expected cost to borrowers of unsecured loans since some borrowers will default. 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).[30] For these borrowers, the stream of scheduled monthly payments likely overstates the cost of the loan. We calculate the expected repayment amount as

$$\mathbb{E}[P_m] = (1-d) \cdot P_m + d \cdot 0 = (1-d) \cdot P_m \tag{15}$$

where d is the monthly default rate. Since our DiD estimates are for quarterly flows into default (q), we approximate the monthly default rate as $d \approx \frac{q}{3}$.[31] We measure default as the likelihood of having a new 90-day delinquency or worse during a month.[32] We estimate default rates for debtors in each debt category separately. These estimates are shown in Table 7. We define annual savings as $Savings = 12 \times \mathbb{E}_{basline} - \mathbb{E}_{refinance}$. Because we do

[29]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 percent 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. Moreover, 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, or 12 months.

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

[31]Under a independence assumption we have $\frac{q}{3} = \hat{m}(1-\hat{m})^2$ whereby $\hat{m} < m$ so we are in fact modestly understating the net savings.

[32]Following 90 day delinquencies the probability of ever repaying a loan is nearly zero. Borrowers who become 30 day or delinquent are much more likely to return to repayment.

Table 7: Rate Sheets & Delinquency By Product

Rate Sheets for Auto Loans and Mortgages						
	(1)	(2)	(3)	(4)	(5)	(5)
			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

Delinquency Rates By Product						
	Estimation Results		Delinquency Rates			
			Baseline		Simulated	
	Coefficient	Std. Error	Quarterly (q)	Monthly (d)	Quarterly (q)	Monthly (d)
Credit Cards	-0.0003407	0.0001452	0.0128010	0.0042670	0.0124603	0.0041534
Personal Loan	-0.0004008	0.0002083	0.0066177	0.0022059	0.0062169	0.0020723
Auto Loan	0.0000025	0.0000534	0.0026334	0.0008778	0.0026359	0.0008763
Mortgage	-0.0000410	0.0000265	0.0035294	0.0011764	0.0034884	0.0011628

Notes: *This table shows rate sheets and the probability of becoming 90 days or more past due on a debt obligation by type of debt. Rate sheets are from the Fair Isaac Corporation's (FICO) MyFico web page (http://www.myfico.com/credit-education/calculators/loan-savings-calculator). Rate sheets represent aggregated pricing across national lenders. For auto loans and mortgages, consumers with credit scores below the bottom price tiers are excluded from calculations, as they are not eligible for any refinancing. Delinquencies are calculated using the CCP and include only individuals holding balances on a particular product. Each regression includes time and Tract fixed effects (Equation 1). Standard errors are clustered by Tract.*

not observe individual interest rates in the data, we set $r_{baseline}$ as the pre-expansion average interest rate offered to borrowers in adopting states. It follows that the counterfactual interest rate $r_{refinance} = r_{baseline} + \beta_r^{DD}$ (Table 4). Similarly, for unsecured loans, $d_{baseline}$ is the expansion delinquency rate in adopting states and $d_{refinance} = d_{baseline} + \beta_d^{DD}$ (Table 7).

In our simulations we calculate an average per-person annual savings. As aforementioned, these Intent-to-Treat effects 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. Suppose there is non-zero correlation between Medicaid enrollment and the propensity to receive credit offers. Nevertheless, all individuals with improved credit score still qualify for new loans at an equally lower rate, were they to seek them out. This interpretation assumes zero cor-

relation between Medicaid enrollment and eligibility for lower rates, which is a weaker and quite plausible condition. Finally, we simulate aggregate potential savings that result by multiplying our per person effects with the CCP Population in 2013Q4 (Table 2).

E Proofs

E.1 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. 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 (10) as:

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

Simplifying terms, we have

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

and

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

Finally, we have

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

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.

Next, we 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 $\Big[\phi+\bar{\tau}\epsilon_{MB}\Big]^2>\Big(\sqrt{\cdot}\Big)^2$. So we have

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

which establishes the second part of the proposition.

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

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

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

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

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

$$
\begin{aligned}
\frac{dCV}{d\bar{\tau}} &\geq -\epsilon_{MB} * \Big[2 - \frac{\sqrt{\Big[\phi + (\bar{\tau} - \frac{1}{2})\epsilon_{MB}\Big]^2} + \sqrt{\Big[\phi(\cdot) + \bar{\tau} * \epsilon_{MB}\Big]^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}}\Big] \\
&= -\epsilon_{MB} * \Big[2 - \frac{\phi + (\bar{\tau} - \frac{1}{2})\epsilon_{MB} + \phi(\cdot) + \bar{\tau} * \epsilon_{MB}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}}\Big] \\
&= -\epsilon_{MB} * \Big[2 - 2\frac{\sqrt{(\phi(\cdot) + (\bar{\tau} - \frac{1}{4})\epsilon_{MB})^2}}{\sqrt{\phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2}}\Big].
\end{aligned}
$$

Finally, we show that

$$
\begin{aligned}
(\phi(\cdot) + (\bar{\tau} - \frac{1}{4})\epsilon_{MB})^2 &< \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2 \\
\leftrightarrow \phi(\cdot)^2 + 2\phi(\cdot)(\bar{\tau} - \frac{1}{4})\epsilon_{MB} + (\bar{\tau} - \frac{1}{4})^2\epsilon_{MB}^2 &< \phi(\cdot)^2 + 2\bar{\tau}\phi(\cdot)\epsilon_{MB} - \bar{\tau}(1-\bar{\tau})\epsilon_{MB}^2 \\
\leftrightarrow -\frac{1}{2}\phi(\cdot)\epsilon_{MB} + \frac{1}{2}\bar{\tau}\epsilon_{MB}^2 + \frac{1}{16}\epsilon_{MB}^2 &< 0 \\
\leftrightarrow \phi(\cdot) > (\bar{\tau} + \frac{1}{8})\epsilon_{MB} & \\
\leftrightarrow \epsilon_{MB} < \frac{\phi(\cdot)}{\bar{\tau} + \frac{1}{8}} &
\end{aligned}
$$

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

Finally, we turn to

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

Here we have

$$
\begin{aligned}
d\frac{CV}{\epsilon_{MB}}/d\epsilon_{MB} &= -\Big[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon_{MB}^2}\Big] + 2 * \frac{\Big[\frac{\phi(\cdot)}{\epsilon_{MB}} + \bar{\tau}\Big]}{2 * \sqrt{\cdot}}\Big[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon_{MB}^2}\Big] \\
&= -\Big[\frac{\frac{d\phi(\cdot)}{d\epsilon_{MB}} - \phi(\cdot)}{\epsilon_{MB}^2}\Big] * \Big[1 - \frac{\sqrt{\Big[\frac{\phi(\cdot)}{\epsilon_{MB}} + \bar{\tau}\Big]^2}}{\sqrt{\cdot}}\Big].
\end{aligned}
$$

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

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

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.

E.2 Details on Effects of Variance Reduction

The second order Taylor expansion yields:

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

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:

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

Finally, expected utility is given by:

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

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

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

Hence we have

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