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THE ACA MEDICAID EXPANSION IN MICHIGAN AND FINANCIAL HEALTH

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**ABSTRACT**

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# The ACA Medicaid Expansion in Michigan and Financial Health

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## Abstract

This article examines the impact of the Affordable Care Act Medicaid expansion in Michigan, the Healthy Michigan Program (HMP), on the financial well-being of new Medicaid enrollees. Our analysis uses a dataset on credit reports matched to administrative data on HMP enrollment and use of health care services. We find that enrollment is associated with large improvements in several measures of financial health, including reductions in unpaid bills, medical bills, over limit credit card spending, delinquencies, and public records (such as evictions, judgments, and bankruptcies). These benefits are apparent across several subgroups, although individuals with greater medical need (such as those with chronic illnesses) experience the largest improvements.

## 1 Introduction

As part of the Affordable Care Act (ACA), the state of Michigan expanded Medicaid eligibility to those earning up to 138 percent of the Federal Poverty Level (FPL). Expanded eligibility became effective April of 2014 with the creation of the Healthy Michigan Plan (HMP). In the

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same year, similar expansions occurred in 29 states and the District of Columbia, although to date, many states have still not adopted the expansion (Dorn et al. (2014)).

A number of studies have shown that these expansions significantly increased enrollment in Medicaid and decreased the number of people without insurance<sup>1</sup> and affected the ability to access care, health care utilization, and the health of those gaining coverage.<sup>2</sup> However, fewer papers have explored the impact of this policy on financial well-being, despite the fact that one of the most important, intended consequences of the expansion of health insurance is to provide financial protection from losses associated with illness or injury.<sup>3</sup> Previous studies that have explored this topic (Hu et al. (2018), Brevoort et al. (2017) and Caswell and Waidmann (2017)) are limited because they do not observe the financial outcomes of individuals who actually enroll in Medicaid. Instead, these studies rely on changes in financial outcomes among samples that include only a fraction of people actually affected by the ACA Medicaid expansions; for example, a sample of people living in low-income zip codes or people living in counties with high rates of uninsured prior to the ACA Medicaid expansions. Therefore, to obtain the effect of gaining insurance through Medicaid expansion, these studies “back out” the effect of insurance coverage on financial outcomes by comparing the observed changes in financial outcomes to aggregate estimates of insurance coverage changes.

This indirect approach is not ideal, because Medicaid beneficiaries represent only a small fraction of the total sample used, and may be particularly under-represented in data about financial outcomes due to reporting issues (see, e.g., Brevoort et al. (2015)). This data limitation may be especially problematic when considering rare but policy-relevant outcomes such as evictions, bankruptcies, or wage garnishments, where aggregate analysis may lack adequate power.

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<sup>1</sup>See, for example, Courtemanche et al. (2017), Kaestner et al. (2017), Miller and Wherry (2017), and Freaux et al. (2017).

<sup>2</sup>For example, Wherry and Miller (2016), Miller and Wherry (2017), Sommers et al. (2015), Ghosh et al. (2017), Simon et al. (2017).

<sup>3</sup>See, e.g., Dobkin et al. (2018), Hu et al. (2018), Brevoort et al. (2017), Caswell and Waidmann (2017), Gross and Notowidigdo (2011), Finkelstein et al. (2012), Argys et al. (2017).

Furthermore, without knowing who in the data has actually received health insurance coverage (i.e., without an accurate measure of the “first stage”), it is difficult to correctly estimate the treatment effect of Medicaid on financial outcomes. Finally, the lack of linked data has prevented researchers from examining how gaining insurance affects those with poor health who are most likely to benefit from obtaining Medicaid. In sum, previous studies have provided an incomplete picture of the effects of the ACA Medicaid expansions on the financial well-being of those affected.

The only prior study to have access to financial information for those who obtained Medicaid was the Oregon Health Insurance Experiment (OHIE, Finkelstein et al. (2012)). Results from this study showed that gaining Medicaid significantly improved financial health. However, the sample sizes in the OHIE were relatively small, about 10,000 individuals gaining coverage, which limited the statistical power of the study, particularly with respect to relatively rare events such as bankruptcies or court judgments. In addition, the OHIE did not examine sub-groups within the Medicaid population, such as the chronically ill or near-poor, for whom benefits of health insurance are likely to differ.

This article reports novel evidence of the impact of Medicaid on financial outcomes. We analyze a new dataset that links administrative records on Medicaid enrollment, demographic characteristics, and use of health services to credit report data. To conduct our analysis, we leverage differences in the timing of Medicaid enrollment and examine changes in financial outcomes around the time of enrollment as compared to counterfactual trend. Using data that links credit report information to enrollment and health data allows us to: measure the effect of Medicaid on financial well-being for those actually affected; identify the effect of Medicaid for subgroups defined by illness burden; and study the effect of Medicaid on rare, but particularly salient, financial outcomes such as bankruptcies.

Our results show that gaining Medicaid substantially improves financial well-being. In par-

particular, we estimate that enrolling in Medicaid reduces the amount of medical bills in collections by \$515 (about 57% relative to the pre-ACA mean) and reduces the amount of debt past due that has not yet been sent to a third party collection agency of about \$233 (about 28%). We find significant reductions in the number of public records (such as evictions, bankruptcies, or wage garnishments), which falls by 0.07, or about 16%, and the number of bankruptcies, which falls by 0.01, or about 10%. In addition, we see that individuals are 16% less likely to overdraw their credit cards.

We also see evidence that enrollment in Medicaid is associated with improved access to credit markets and increased borrowing. We find that the probability that an enrollee has a credit score in the “subprime” range falls by about 2 percentage points, or about 3%, and in the “deep subprime” range by about 3 percentage points, or about 18%. We also see increases in average credit card debt of about 13 percent and increases in the amount of auto debt of about 21 percent. This increase in borrowing may reflect better access to credit markets, and is consistent with other research that finds that interest rates offered to low income individuals fall when Medicaid coverage expands (Brevoort et al. (2017)) and that Medicaid expansion reduces use of payday loans (Allen et al. (2017)).

In addition to looking at overall effects, our large sample enables us to examine heterogeneity in this effect across enrollee characteristics. We find larger effects on bills sent to third party collections and credit scores for enrollees with chronic illnesses (relative to those without) and among enrollees with a hospitalization or emergency department visit within the first 12 months of enrollment (relative to those with no such utilization). We also find stronger effects of the program on bills in collections among individuals for whom Medicaid is the only source of insurance. However, even among groups without apparent high health need, we see statistically significant benefits for many of the outcomes we examine. These results suggest that the financial benefits of Medicaid coverage are apparent across almost all subgroups of beneficiaries.

## 2 Background

The ACA resulted in one of the largest expansions of health insurance coverage since the 1960s, with some estimates indicating that over 20 million individuals gained insurance coverage since 2010 (Cohen et al. (2017)). While estimates differ, it is widely acknowledged that most of the increase in health insurance coverage associated with the ACA came from the Medicaid expansion; Frean et al. (2017) estimate this fraction to be about 60 percent. As part of the ACA, eligibility for Medicaid was expanded to include all individuals in households with incomes under 138 percent of the Federal Poverty Level. These eligibility expansions were made optional by a 2012 Supreme Court decision, and, to date, 33 states and DC have adopted these expansions.

The Healthy Michigan Plan (HMP) was passed by the Michigan legislature and signed by the governor in September 2013, and was implemented in April of 2014. HMP was approved through a Section 1115 waiver that allowed Michigan to make modifications to the traditional Medicaid program. Although it is similar to other Medicaid programs in terms of services covered, HMP has additional cost sharing requirements for enrollees with higher incomes. After 6 months of enrollment, enrollees from households with incomes between 100 and 138 percent of the FPL are required to pay a 2% contribution that is not to exceed of 5% of their income, but this can be reduced by completing a “health risk assessment” with a primary care provider. Fewer than 30 percent of enrollees are required to pay such a contribution, and, on average, the contribution amount is less than \$5 per month (Cliff et al. (2017)). Ayanian (2013) provides more details on the plan’s characteristics and cost sharing provisions.

Upon implementation there was rapid enrollment in HMP. The plan was advertised broadly through community organizations, hospital associations, and public health departments. Within the first 3 months, over 300,000 adults had enrolled in HMP, representing about 3.3 percent of

Michigan's total population and substantially exceeding enrollment expectations (Ayanian et al. (2014)).

As part of the state-sponsored evaluation of the expansion, researchers conducted a survey of HMP enrollees called Healthy Michigan Voices. The survey found that, in the 12 months prior to enrollment in HMP, approximately 45 percent of enrollees reported problems paying medical bills, and about 26 percent said that they had foregone necessary care due to concerns about costs, but that these measures fell after HMP enrollment (Goold and Kullgren (2018)). This is in line with similar survey evidence (e.g., Miller and Wherry (2017)), and indicates that an important effect of HMP could be the financial protection it offers individuals who are faced with illness or injury.

### **3 Data**

Data for this analysis comes from two sources. First, we used Medicaid administrative data that includes the month and year of HMP enrollment, income relative to FPL as determined at the time of enrollment, the number of emergency department visits and hospitalizations over the first 12 months enrollment, and a dichotomous flag indicating the presence of a diagnosis code for a chronic illness on any encounter in the first 12 months of HMP enrollment.<sup>4</sup> The administrative data includes all individuals who enrolled in HMP between April of 2014 and March of 2015. We excluded individuals who were enrolled in a different state program (e.g., the Adult Benefits Waiver program, which covered some services for adults in households with incomes under 35 percent of the FPL) in the year before their enrollment in HMP in order to focus on individuals transitioning from no insurance to HMP coverage.

Second, data from TransUnion on consumer credit histories was matched with the Healthy

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<sup>4</sup>Chronic illnesses were defined using HCUP Chronic Condition Indicator software, see: Healthcare Cost and Utilization Project Chronic Condition Indicator for ICD-9-CM. Accessed 9/5/2017. Available at: <http://www.hcup-us.ahrq.gov/toolssoftware/chronic/chronic.jsp>.



Michigan administrative data using name, address, and social security number. TransUnion credit reports were observed twice per year, in January and July, starting with July 2011 and ending with January 2016, resulting in ten observation periods. Prior to providing the matched data to the researchers, all personally identifying information was removed. See the Appendix for additional details on the match process.

Table 1 compares characteristics across HMP enrollees who were and were not successfully matched to a credit record. Approximately 98 percent of HMP enrollees were matched; those who were not matched were disproportionately poorer, younger, and less likely to have a hospital or emergency department visit or a chronic illness within the first 12 months of enrollment. Our match rate is much higher than the 68.5 percent match rate reported in the OHIE, likely due to our inclusion of social security number as a match variable.

From the credit report information, we use the total amount of debt that has been sent by the original creditor to a third party collection agency. This debt could represent unpaid bills (such as a utility bill), or severely derogatory credit accounts (such as a credit card bill that is over 180 days late). Within third party collections, we also examine collections specifically for medical bills. We also look at debt on credit accounts that is 30 days or more past due but not yet sent to a collection agency. The total amount of debt on which a consumer is delinquent is the sum of the amount in collections and the amount past due but not yet in collections.

In addition, we evaluated the number of public records recorded on an individual's credit report. Public records include evictions, wage garnishments, and bankruptcies, as well as any law suits or other court judgments that could negatively effect an individual's credit worthiness. A subset of public records are bankruptcies, which we examine separately.

Another measure of delinquency that we use is the number of months a consumer is overdrawn on his or her credit card out of the last 12 months. While being overdrawn is not a measure of delinquency per se, it is a sign that the consumer is having difficulty spending less

than their card limit (and incurring fees as a result), and may be a precursor to delinquent behavior.

If health insurance coverage affects delinquencies, then it may also affect access to credit and borrowing. Medicaid coverage may lead individuals to experience improved access to credit markets, for example in the form of lower interest rates or higher credit card or loan approval rates. Indeed, Brevoort et al. (2017) find that when states expand Medicaid, individuals receive more favorable interest rate offers from credit card companies. This could encourage higher levels of borrowing. In contrast, if individuals are borrowing to pay for medical care, gaining Medicaid coverage may lead to a reduction in the need for such borrowing. The effect of Medicaid coverage on borrowing is therefore ambiguous.

Accordingly, we examine these aspects of consumer finances. To measure credit access, we examine an individual's Vantage 3.0 score, a commonly-used version of the credit score that is similar to a FICO score. Lenders use this score when evaluating whether to extend credit, and at what price, making it a convenient summary of access to credit markets and general creditworthiness. We examine the probability that an individual has a credit score in the "subprime" ( $\leq 600$ ) range, as well as in the "deep subprime" ( $< 500$ ) range, indicating that this individual would have a high expected default rate and therefore experience poor access to credit.<sup>5</sup> To examine the effect of Medicaid on borrowing, we examine two types of debt that are common in our sample population: credit card and auto loans.

Table 2 presents descriptive statistics from our matched sample. The top panel shows descriptive statistics related to the credit report outcomes we consider in this paper, and shows the averages for all enrollees, as well as for each subgroup, for the period before and after the individual enrolls in HMP. The bottom panel shows baseline characteristics that are either measured at enrollment (age at enrollment, gender, income relative to the FPL) or during the first

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<sup>5</sup>Our data use agreement with TransUnion prohibits us from using the credit score itself as an outcome.

12 months of enrollment (chronic illness status, hospitalizations, and ED visits).

These descriptive statistics show that HMP enrollees tend to be poor, in poor health, and in dire financial straits. Average household income upon enrollment in HMP is only about 39 percent of the FPL, which would be about \$7500 for a family of 3 or \$4400 for an individual in 2014. HMP enrollees also tend to be in poor health, with about 70 percent of enrollees having a chronic illness; the average number of hospitalizations in a year is 0.14 and number of ED visits in a year is about 1. Financially, HMP enrollees have high rates of delinquencies relative to their income, with about \$1839 on average owed to third party collectors (with \$906 related to medical bills) and an additional \$845 on average past due on open credit accounts. For comparison, among a random sample of credit reports, the average amount of bills in collection are \$1009 (with \$521 related to medical bills) and the amount past due is \$582 (Miller and Soo (2018)). About 64 percent of HMP enrollees have credit scores in the subprime range, with about 17 percent in the deep subprime range. In general, delinquencies appear to be worse among those with higher apparent health need. Among enrollees with a hospitalization or ED visit in the first year, collections were \$2591 prior to HMP enrollment, with \$1536 related to medical bills. Similarly, among those with a chronic illness, collections were \$2099, with \$1112 related to medical bills. We also show descriptive statistics for those for whom Medicaid is the primary or secondary payer. The latter group includes those with workers' compensation, employer sponsored health insurance, or stand-alone vision or dental plans. Those with Medicaid as a secondary payer are less poor, in better health and have better baseline financial health than those for whom Medicaid is the primary payer.

Notably, we see that financial well-being improves after enrolling in HMP. For example, among all enrollees, the total amount in collection declined by \$340 (18 percent) pre-to-post the HMP expansion. Similar pre-to-post changes are observed among other subgroups.

## 4 Empirical Approach

We conduct an event study analysis that examines changes in financial outcomes that occur around the time an individual enrolls in HMP. In our data, we observe the month in which an individual enrolls in the Healthy Michigan program and their credit report outcomes twice annually beginning in July of 2011. We must combine these two pieces of information to trace out monthly changes around the time of enrollment, relying on the fact that individuals enroll at different times relative to the calendar months in which we observe the credit data. For example, in order to identify the effect after one month of enrollment in the program, we must use individuals who enrolled exactly one month before we observe their credit reports; since we observe credit reports in January and July, the coefficient on the event study indicator for one month after enrollment is identified by individuals who enrolled in December or June.

We illustrate this with a brief example. First, consider the cohort who enrolled in May of 2014. The first credit report we observe for this cohort is July of 2011, which is 34 months prior to their enrollment. The last credit report we observe for this cohort is January of 2016, which is 20 months after their enrollment. The average medical collections for this cohort is plotted by calendar time in the first panel of Figure 3, with the months relative to enrollment (“event time”) displayed above each mean. We also include a linear trend to show how medical collections change around the time of enrollment.

The cohort who enrolled in August of 2014 is also observed for the same 10 calendar time periods; however, for this cohort, the July 2011 credit report corresponds to 37 months prior to enrollment, while the January 2016 credit report corresponds to 17 months post enrollment. Average medical bills in collection for this cohort are plotted in the second panel. Finally, we also plot the outcome for the cohort who enrolled in January of 2015 in panel 3 of Figure 3. For this cohort, we observe 42 months prior to enrollment but only 12 months after enrollment.

The final panel of Figure 3 subtracts the mean level of medical collections from each cohort and plots the residual against event time. The fact that each cohort began the program at a different time allows us to trace out changes relative to time of enrollment. Using only these three cohorts, we see that generally later event periods correspond with larger decreases in collections even if they refer to the same calendar month; for example, event months 12, 17, and 21 are all estimated using the credit reports observed in January of 2016. As we increase the number of cohorts, we are able to gain precision in our estimate of each event study coefficient, as multiple cohorts will contribute to the same event study coefficient; for example, the event study coefficient for event time 1 month after enrollment will be estimated using cohorts that enrolled in either June and December of 2014.

Our empirical approach is an event study design that takes advantage of variation in beneficiaries' enrollment date and the timing at which we observe credit reports. Specifically, we examine whether there were significant deviations in the trend of financial outcomes around the time an individual enrolls in HMP, similar to models used in, e.g., Dobkin et al. (2018), Blascak et al. (2016), and Gross et al. (2018). We estimate this model using the following regression specification:

$$Y_{ic\tau} = \alpha_c + \delta_\tau + \beta_m + \epsilon_{ic\tau} \quad (1)$$

where  $i$  refers to individual enrollees,  $\alpha_c$  refers to enrollment month fixed effects, and  $\tau$  refers to event time indicators. We also include indicators for the calendar month (January or July) to account for seasonality ( $\beta_m$ ). Our primary variables of interest are the fixed effects associated with each event period, denoted  $\delta_\tau$ , ranging from 39 months prior to enrollment to 21 months after enrollment, with  $\tau = 0$  denoting the month of enrollment. We use the month prior to enrollment ( $\tau = -1$ ) as our reference category.<sup>6</sup>

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<sup>6</sup>In order to identify cohort, month, event fixed effects, and a linear trend, we must group together some event

We estimate two versions of this model that account for linear pre-existing trends in event time.<sup>7</sup> For these specifications, the event study coefficients can be interpreted as the change in outcomes experienced by beneficiaries relative to a counterfactual linear trend. The first version estimates a linear trend in event time on the pre-enrollment data and removes this from the outcome variable in a first step, generating the predicted value of the outcome  $\tilde{Y}_{it}$ . This de-trended version of the outcome is then used in place of  $Y_{it}$  in equation (1).<sup>8</sup>

The second version estimates a variation on model (1) that imposes the linear pre-enrollment trend rather than estimate pre-enrollment fixed effects in the following way (similar to Gross et al. (2018)):

$$Y_{it} = \alpha_c + \beta_1\tau + \delta_\tau(\tau > 0) + \beta_m + \epsilon_{it}. \quad (2)$$

In this model, only post-enrollment fixed effects are included, as is a linear trend in event time ( $\tau$ ). We estimate all models using ordinary least squares and report heteroskedasticity-robust standard errors that are clustered at the individual level.

## 4.1 Endogenous enrollment timing

Our empirical approach assumes that there is no factor that affects financial outcomes among our sample that is correlated with the timing that an individual enrolls in Medicaid. This assumption could be violated if, for example, an individual enrolls in Medicaid as the result of a health shock; in that case, the timing of enrollment is correlated with the outcome variable and may generate a spurious relationship between Medicaid enrollment and the outcome. We

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study coefficients (see Borusyak and Jaravel (2017) for full discussion of underidentification in event study models). We group together all event time periods 39 months or more prior to enrollment, so that the indicator for  $\tau = -39$  is replaced with an indicator that event time is -39 or earlier (i.e.,  $\tau \leq -39$ ).

<sup>7</sup>We select a linear trend, rather than quadratic or higher order polynomial, because pre-trends in our data appeared to be approximately linear.

<sup>8</sup>A degrees of freedom correction is required due to this first stage; however, given our large sample sizes, this correction is not discernible for the number of significant digits we report.

believe the concern about endogenous enrollment is mitigated in our setting relative to other contexts. First, if individuals enroll because they experience a health or income shock, then this would result in a spurious *positive* relationship between Medicaid and financial distress. Instead, we find that Medicaid reduces financial distress. This suggests that, if anything, our results are too conservative. Second, over 30 percent of the individuals in our sample enrolled in the first month that HMP became available; see Figure 1, which presents a histogram of enrollment times. For these individuals, it is likely the timing of enrollment was driven by the policy change, rather than an individual-specific shock. We analyze this group separately and find similar effects as when we use the full sample. Although any fixed difference in characteristics across cohorts is accounted for by our cohort-specific fixed effect ( $\beta_c$ ), it is reassuring that characteristics are fairly similar across early and late enrollers, as reported in Figure 2. Finally, if we think that individuals first experience a health decline, and then opt to enroll in Medicaid as a consequence, we would see pre-existing trends in our outcome variables, especially those closely tied to medical bills. However, we find little evidence of pre-existing trends, with practically no evidence of any pre-trends for medical collections, as we describe in the subsequent section. This suggests that enrollment for this particular group made eligible by the ACA is unlikely to be caused by an unmeasured factor correlated with the outcome variable.

## 5 Results

### 5.1 Full HMP Population Results

We present the coefficients on the event study variables described in equation (1) in Figures 4 and 5. In these figures, the horizontal axis displays the month relative to enrollment, with the vertical dotted line indicating the enrollment month. The month prior to enrollment is our reference month and this coefficient is set equal to zero. For most outcomes related to delinquency, we see relatively little trends prior to enrollment in HMP, but observe divergence

around the time of enrollment. In all cases, we see reductions in measures of delinquency, and these effects appear to grow over time. In contrast, borrowing appears to increase around the time of enrollment after remaining relatively constant prior to enrollment. This change in trend is especially pronounced for auto borrowing, reported in panel (b) of Figure 5.

The estimates for selected event coefficients related to delinquency and creditworthiness are reported in Table 3. We report the effects observed 6 months after enrollment, 12 months after enrollment, and in the last post-enrollment month that we observe, 21 months after enrollment. The first column shows the effects for the model described in equation (1). The second column adds a pre-enrollment trend; these estimates match the event study figures. The third column reports the estimates from the model in equation (2). Across all three specifications, we see evidence that HMP enrollment substantially reduces the total amount of bills sent to third party collection agencies. By the end of the period we observe, we see that third party collections have fallen by between \$538 and \$676, or 29 to 37 percent relative to the average amount in collections before enrollment. Much of the reduction in third party collections appears to be driven by a reduction in medical bills being sent to collection; we observe reductions in medical collections of between \$384 and \$515, or 42 to 57 percent. We also see a reduction in the amount of debt past due on credit accounts (i.e., debt past due that has not yet been sent to a third party collection). Our estimates indicate that by the end of the period, HMP enrollment reduces the amount past due by about \$230, or 27 percent.

For some outcomes, the improvements in delinquencies (panels a through c in Figure 4) tend to emerge between 6 and 10 months after enrollment and grow larger over time. The lag in these effects may reflect the period between the time when care is used and when improvements in financial outcomes become apparent. It may also be due, in part, to new requirements for non-profit hospitals in the Affordable Care Act. In particular, Section 501(r) of the Internal Revenue Code placed new obligations on non-profit hospitals to determine patient eligibility for charity



care policies and to provide several rounds of notifications to patients before pursuing debt collection measures (see Nikpay and Ayanian (2015)).<sup>9</sup>

In addition to these reductions in delinquencies, we also see reductions in other measures of financial distress. The number of public records on an individual's credit report falls by between 0.05 and 0.07 by the end of our sample period (11 to 16 percent), and the number of bankruptcies on the credit report falls by about 0.01 (about 10 percent). We also observe a reduction in the number of months that an individual has overdrawn his or her credit card in the last 12 months of about 0.40 months, about 16 percent relative to the baseline mean of 2.5 months. Note that sample sizes are smaller for this final outcome because not all individuals in the sample have a credit card.

Because all individuals in our sample enrolled in HMP, these estimates can be directly interpreted as the treatment effect of Medicaid coverage. Our estimated effects on medical collections are smaller than those documented in Hu et al. (2018) and Brevoort et al. (2017), who estimate that Medicaid enrollment reduces medical collections by \$1140 and \$1236 respectively. However, the treatment effect estimates reported by these papers are sensitive to assumptions about Medicaid enrollment, which are not directly measured in the credit report samples that they use. Also, our estimates pertain only to enrollees in Michigan. Our estimates are similar to those reported in Finkelstein et al. (2012), who find that Medicaid enrollment reduces medical debt in collections by \$390 (relative to our estimate of \$515).

Table 4 displays the results on the effect of HMP on credit access and borrowing outcomes. The fraction of individuals who are classified as "subprime" falls by about 2 percentage points, or about 3 percent relative to the baseline mean. The fraction of those classified as "deep subprime" also falls about 2 percentage points, or 12 percent relative to the baseline mean. We also

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<sup>9</sup>The IRS required hospitals to file information on their compliance with these measures on their tax returns beginning in 2012, although this rule was not fully enforced (i.e., no hospitals actually lost non-profit status for failure to comply) until 2016.

see increases in both credit card and auto debt. Credit card debt increases by between \$22 and \$142, although these effects are not consistently statistically significant across specifications. Auto debt increases by between \$75 and \$134 after 12 months of enrollment and by between \$170 and \$309 by the end of the observation period. These observed increases in borrowing are consistent with results in other papers showing that the ACA Medicaid expansions improved interest rates offered to low income borrowers (Brevoort et al. (2017)). In addition, other research has shown that the ACA Medicaid expansions reduced the use of “alternative” lending products like payday loans (Allen et al. (2017)); the increase in borrowing through “traditional” lending products may represent substitution away from payday borrowers and towards traditional financial markets.

## **5.2 Subgroup Analyses**

We also conduct our analysis by subgroup based on observable characteristics of HMP recipients. We present these results graphically in Figures 6 - 8. For the sake of readability, these figures display only the post-enrollment coefficients.

Figure 6 compares the effect of HMP enrollment across individuals who did and did not have a hospitalization or ED visit in the first 12 months of enrollment in the HMP program. We find significantly stronger effects of HMP enrollment on collections and medical collections for the group with utilization during the first year. However, even among the group with no hospitalization or ED visit in the first year, we still detect statistically significant reductions in collections, albeit smaller in magnitude. There also is greater improvement in credit scores for some event months, as well as suggestive evidence that reductions in the months overdrawn on a credit card are larger among the group that was hospitalized or had an ED visit. Both groups experienced similar reductions in amount past due, public records, and bankruptcies. Increases in auto borrowing are similar across groups and increases in credit card borrowing

are, if anything, slightly larger in the group that was not hospitalized.

A similar pattern is apparent in Figure 7, which compares outcomes across individuals with and without a chronic illness recorded in their first 12 months of enrollment. The effects of HMP enrollment on collections is much stronger for the group with the chronic illness, and the reduction in public records, overdrawn on credit card, and fraction deep subprime also appear to be larger, although the differences across the two groups are not statistically significant. Other outcomes exhibit similar patterns across the two groups.

We also compare the results across individuals for whom HMP is the only payer to those who have some form of third party liability. Although we cannot characterize the type of third party liability, it is reasonable to expect that those with an insurance source beyond HMP may be less affected by HMP enrollment. We also note that those with a second source of insurance tend to be higher income, with fewer delinquencies and higher credit scores, which may also affect the impact of Medicaid enrollment on outcomes (see Table 2). The results presented in Figure 8 suggest that there was less of an effect on collections for those with insurance other than Medicaid, although there do appear to be effects on public records and amount past due. In contrast, those for whom Medicaid is the only payer see large reductions in collections, particularly medical collections.

Finally, we separately examine the group of beneficiaries who enrolled the first month of the program. These beneficiaries likely enrolled due to the policy change rather than, for example, a health shock. The results are presented in Table 5 and Figure 9. By the end of the sample period, the results for most outcomes look similar in this sample relative to what we uncover when we use the entire sample. We also find similar, though somewhat larger, effects in earlier months for collections, medical collections, public records, bankruptcies, subprime and deep subprime outcomes. However, we do note that there is a longer lag before we observe an effect on the amount of debt past due; we do not observe statistically significant changes in this outcome

until 21 months after enrollment. Similarly, we do not see significant increases in auto or credit card borrowing until 15 and 21 months after enrollment respectively.

## **6 Discussion**

Our study provides the first evidence on the impact of the ACA Medicaid expansion using data that actually links participants to financial outcomes at the individual level. We see that enrollment in Michigan’s Medicaid expansion plan, HMP, is associated with improvements across a broad swath of financial measures. We found large reductions in the amount of debt sent to third party collectors (particularly medical debt), in the amount of debt that is past due, in the number of public records and bankruptcies, and in the propensity of enrollees to go over their credit card limits. Our effects are large when compared to the sample mean and appear to grow larger over time.

Our large sample also allows us to examine subgroups within the HMP population. We find that groups with higher apparent medical need experienced larger effects, particularly for measures related to third party collections. However, we also detected meaningful improvements on financial outcomes across all subgroups examined. Medicaid enrollment appears to have salutary effects on financial outcomes even among Medicaid recipients who are apparently healthier and have greater financial resources.

This study has several limitations. First, we are limited to only one state: Michigan. The impact of the ACA Medicaid expansion may be different in other states depending on demographic composition, existing social programs, or other factors. Second, our study period only allowed us to observe financial outcomes through 21 months following enrollment. Given that the improvement in financial outcomes appears to become larger over time, we may underestimate the true impact due to our limited sample period. However, despite these limitations, our study provides important new information on the role of Medicaid in providing financial

protections to low-income individuals.

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## **A Appendix. Further Details on the TransUnion Match and Matching Procedure**

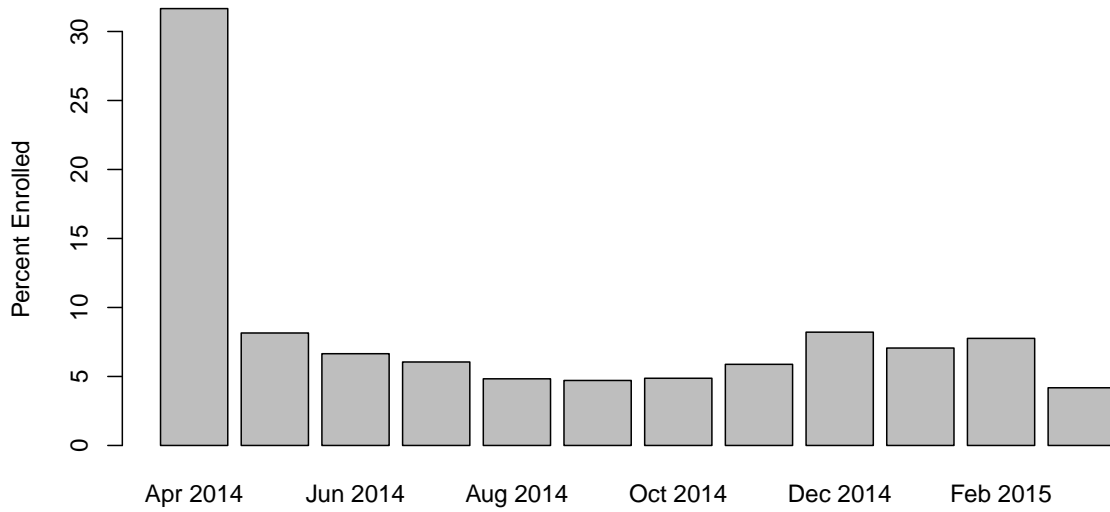
To conduct this analysis, a dataset was created to match individual-level data for Healthy Michigan Plan enrollees to their credit reports at TransUnion. The match was conducted using social security number, name, and address. Over 98 percent of all Healthy Michigan Plan enrollees were matched to a credit report. Those who were not matched were excluded from the study.

In order to preserve the confidentiality of HMP enrollees identities, the matching process utilized a double blind matching procedure as follows: an administrative associate of the Michigan Department of Health and Human Services extracted identifying information on HMP enrollees (name, address, and social security number). They appended to this dataset a randomly selected sample of approximately 1 million Michigan residents drawn from an unrelated state health database to serve as “masking” observations. Because social security number is not included in this database, these masking observations were assigned randomly-selected but valid social security numbers with group codes (first three digits) selected to match the distribution of group codes among the HMP population. These were inserted into the dataset in random order. To this, they appended an anonymized study ID code. This file (Dataset 1) was then provided to TransUnion. As a result of the masking observations included in the input file, TransUnion was unable to distinguish which observations were associated with HMP enrollees and which observations were generated for the purposes of masking. Simultaneously, the administrative associate of the Michigan Department of Health and Human Services extracted and de-identified information on HMP enrollees (enrollment date, FPL on record at the time of initial HMP enrollment, number of emergency department visits and hospitalizations in the first 12 months of enrollment, and the presence of a diagnosis code for a chronic illness on any encounter in the first 12 months of enrollment, , the presence of any third-party liability

during the first 12 months of HMP enrollment, and any pre-HMP Medicaid enrollment). The anonymized study ID was appended to this file (Dataset 2). Dataset 2 was provided to the researchers. Finally, TransUnion extracted credit report information and merged this information with Dataset 1. Then, TransUnion removed all personally identifying information, resulting in a de-identified file, Dataset 3, and provided this file to the researchers. Using the anonymized study ID code, the researchers merged Dataset 3 and Dataset 2, resulting in the final analytic dataset.

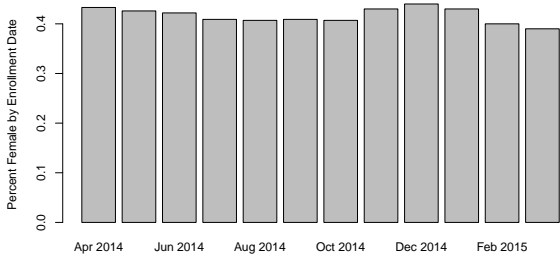
Table A3 compares the characteristics of those who were and were not matched to a credit report. All differences in characteristics across the matched and unmatched samples are statistically significant at the 1% level. In our sample, 322,305 were matched to a credit report and 3,717 were not, resulting in a match rate of 98.8%. Those unmatched tended to be younger, with an average age of 36.99, relative to the average age in the matched sample, 38.78. This discrepancy in age is consistent with analysis of those without credit reports conducted by the CFPB (Brevoort et al. (2015)), who find that age is strongly predictive of having a credit report. Unmatched individuals were also from much lower income households, with average income relative to the FPL at 22.4% for unmatched individuals and 38.92% for matched individuals. The unmatched sample has fewer inpatient discharges (0.09 vs. 0.14 in the matched sample) and ED visits (0.59 vs 0.96 in the matched sample) during the baseline year and is less likely to be diagnosed with a chronic illness (62% vs. 70% in the matched sample). Those in the unmatched sample are less likely to be female (42% female in unmatched sample vs 52% female in matched sample).

Figure 1: Histogram of Enrollment Times

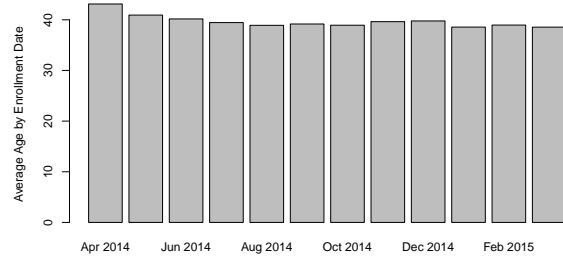


This figure displays the distribution of enrollment times for individuals included in the analysis. Source: authors' calculations from Healthy Michigan administrative data.

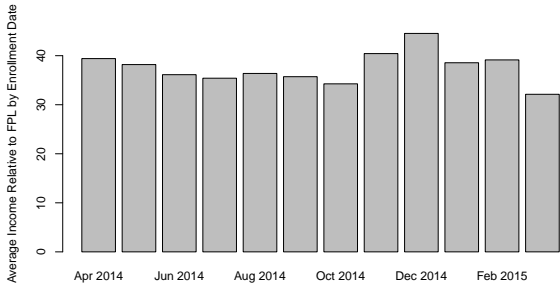
Figure 2: Characteristics by Enrollment Times



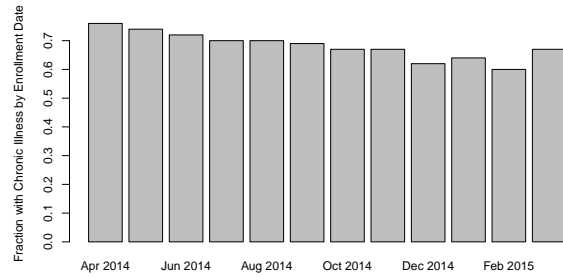
(a) Fraction Female



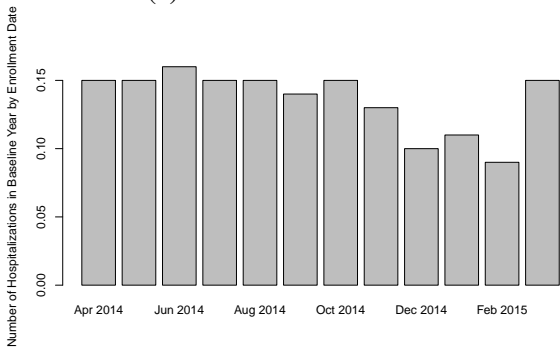
(b) Age



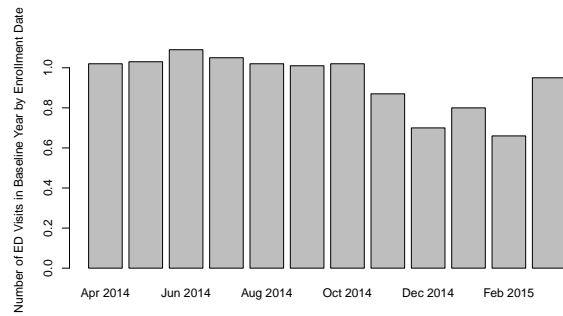
(c) Income Relative to FPL



(d) Chronic Illness



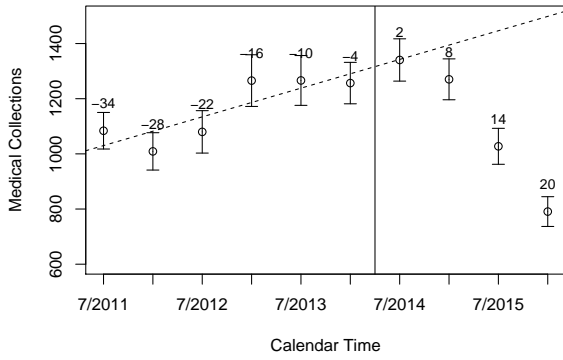
(e) Hospitalizations



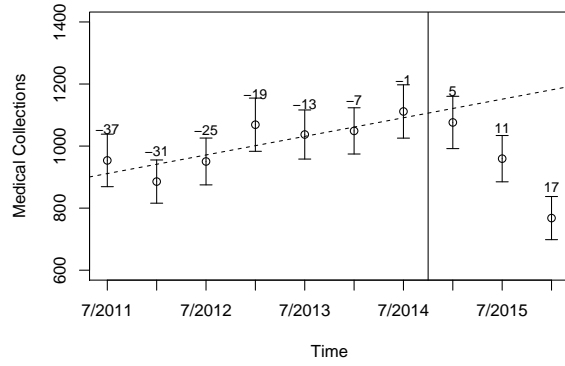
(f) ED Visits

This figure displays the characteristics of enrollees based on enrollment times for individuals included in the analysis. Source: authors' calculations from Healthy Michigan administrative data.

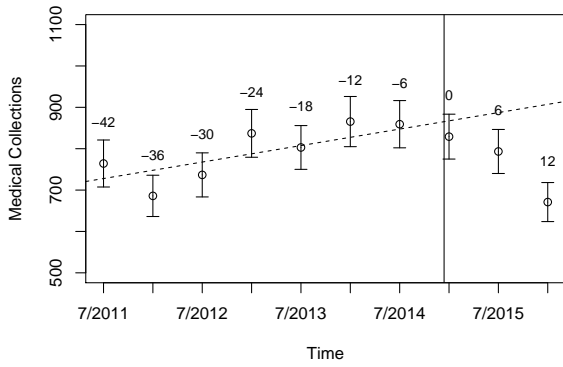
Figure 3: Event Study Construction Example



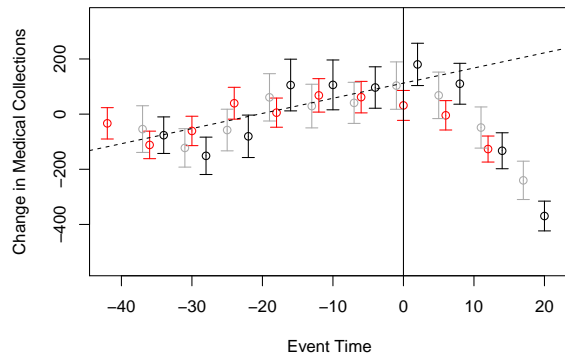
(a) May Cohort



(b) August Cohort



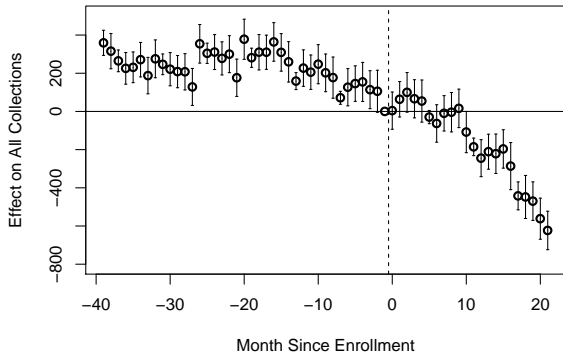
(c) January Cohort



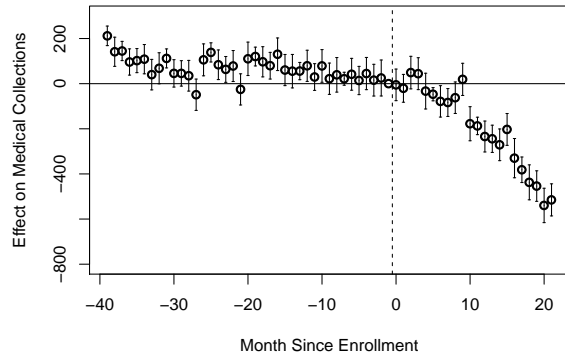
(d) Three Cohorts Combined

Figure depicts means and 95 percent confidence intervals for medical collections for three enrollment cohorts, with the vertical line indicating the date enrolled. The first three panels show these values relative to calendar time on the x-axis. The third panel shows the May (black), August (grey) and January (red) enrollment cohorts plotted against event time on the x-axis.

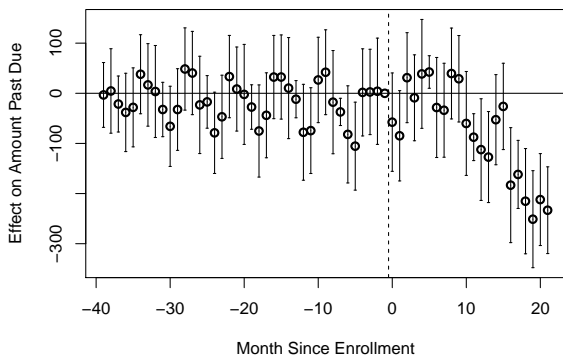
Figure 4: Event Study Coefficients: Delinquency Outcomes



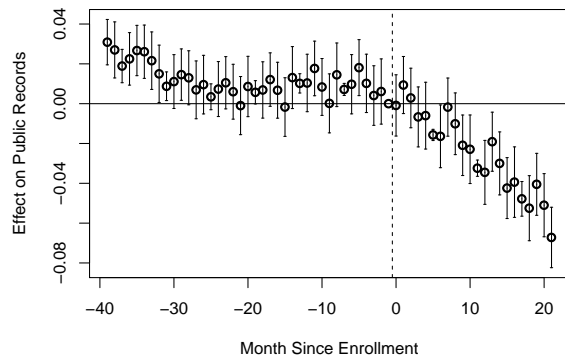
(a) All Collections



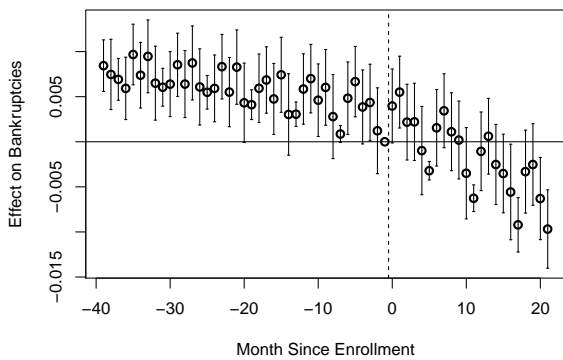
(b) Medical Collections



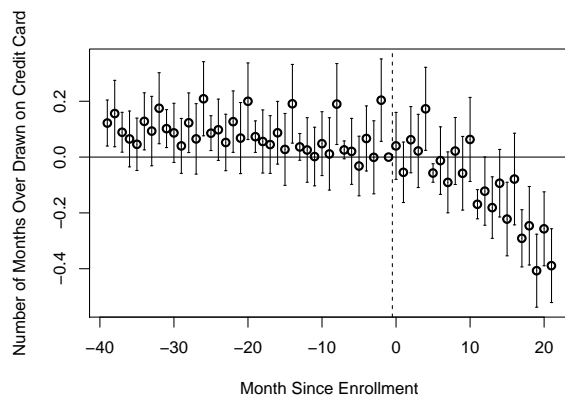
(c) Credit Market Amount Past Due



(d) Public Records



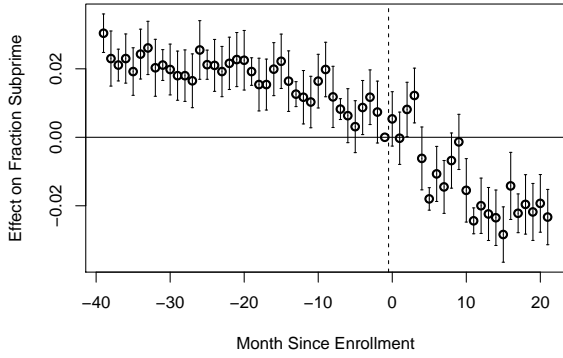
(e) Bankruptcies



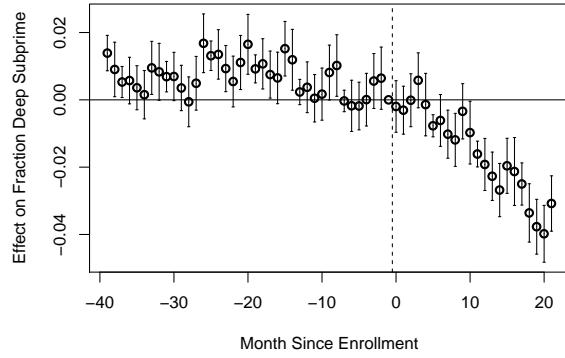
(f) Months Overdrawn on CC

Vertical line indicates month of enrollment in Medicaid. Event study conducted at the month level. These figures present coefficients and 95 percent confidence intervals estimated from a model that includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend estimated in the pre-HMP period.

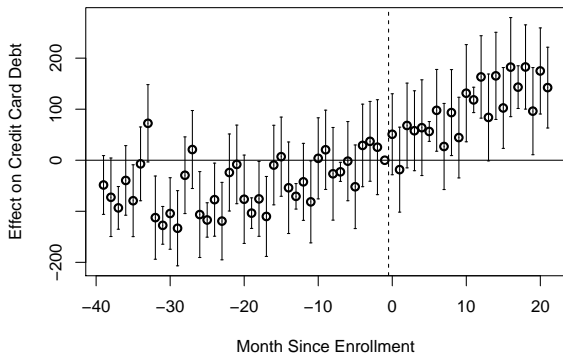
Figure 5: Event Study Coefficients: Access to and Use of Credit



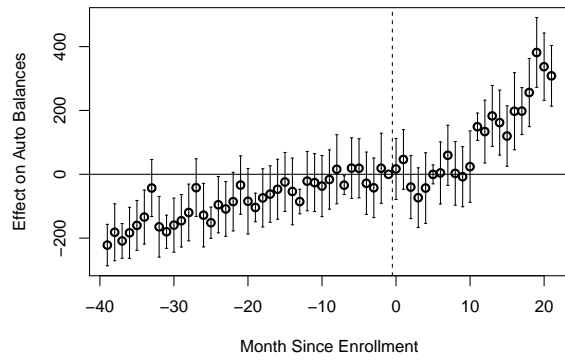
(a) Subprime



(b) Deep Subprime



(c) Credit Card Borrowing



(d) Auto Borrowing

Vertical line indicates month of enrollment in Medicaid. Event study conducted at the month level. These figures present coefficients and 95 percent confidence intervals estimated from a model that includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend estimated in the pre-HMP period.



Figure 6: Hospitalized/ED (Black) vs no hospitalization/ED (red)

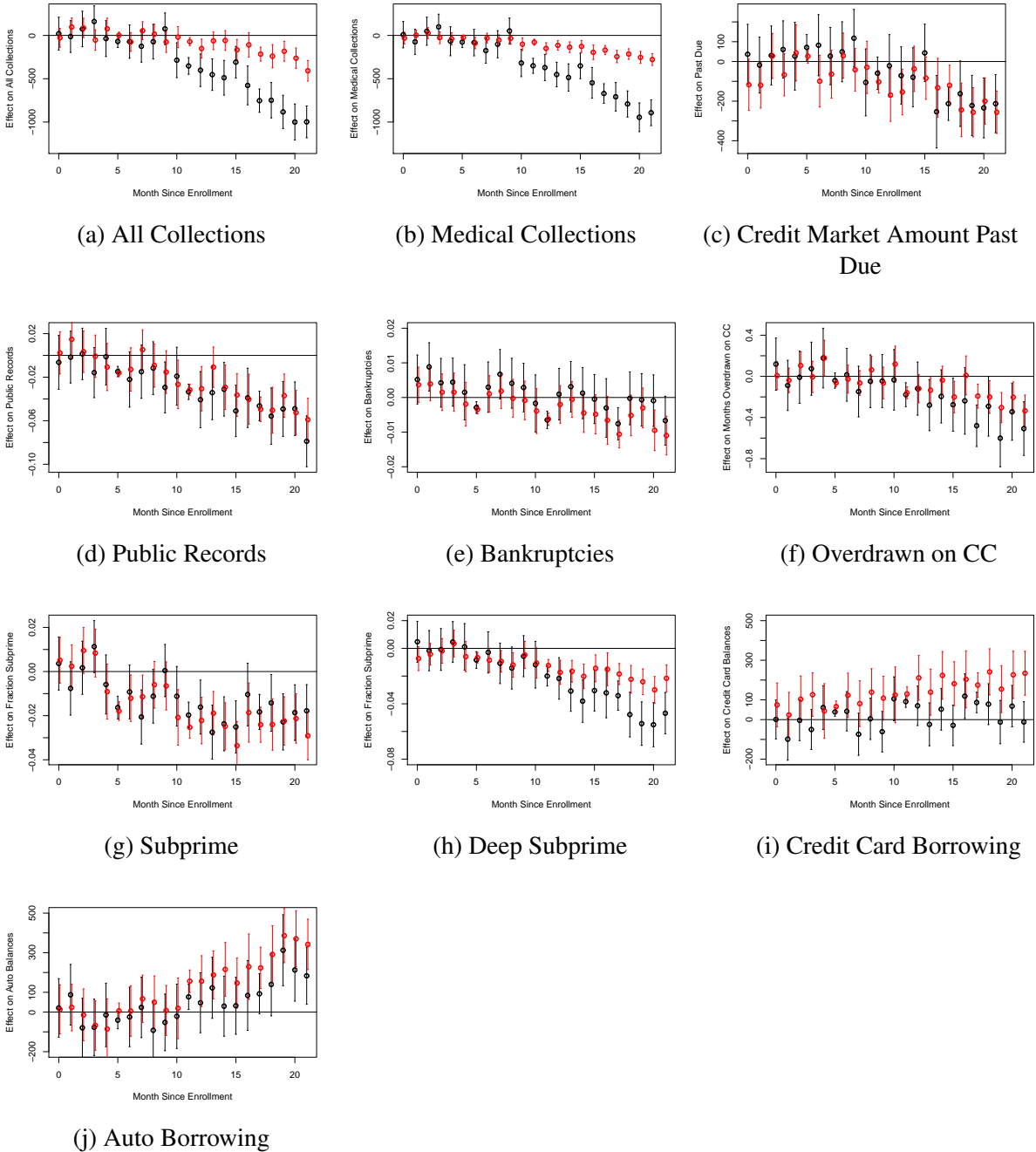


Figure depicts event study coefficients and 95 percent confidence intervals for post-enrollment time periods across a sample that had a hospitalization or ED visit in the baseline year (black line) relative to the sample without a hospitalization or ED visit in baseline year (red line). Model includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend.

Figure 7: Chronic Illness (Black) vs no Chronic Illness (red)

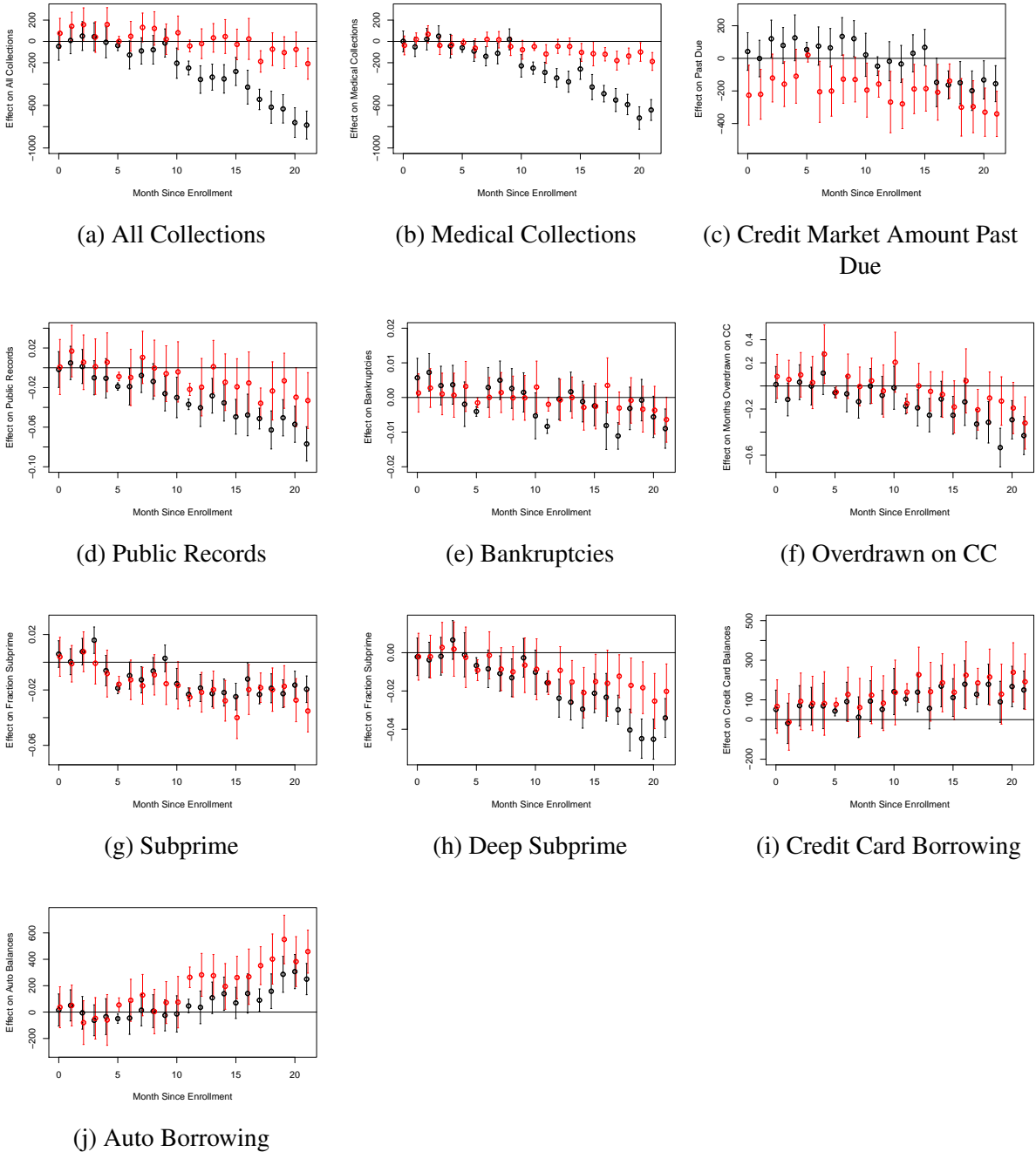


Figure depicts event study coefficients and 95 percent confidence intervals for post-enrollment time periods across a sample that had a chronic illness recorded in the baseline year (black line) relative to the sample without chronic illness in baseline year (red line). Model includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend.

Figure 8: Medicaid Only Payer (Black) vs Medicaid Secondary Payer (red)

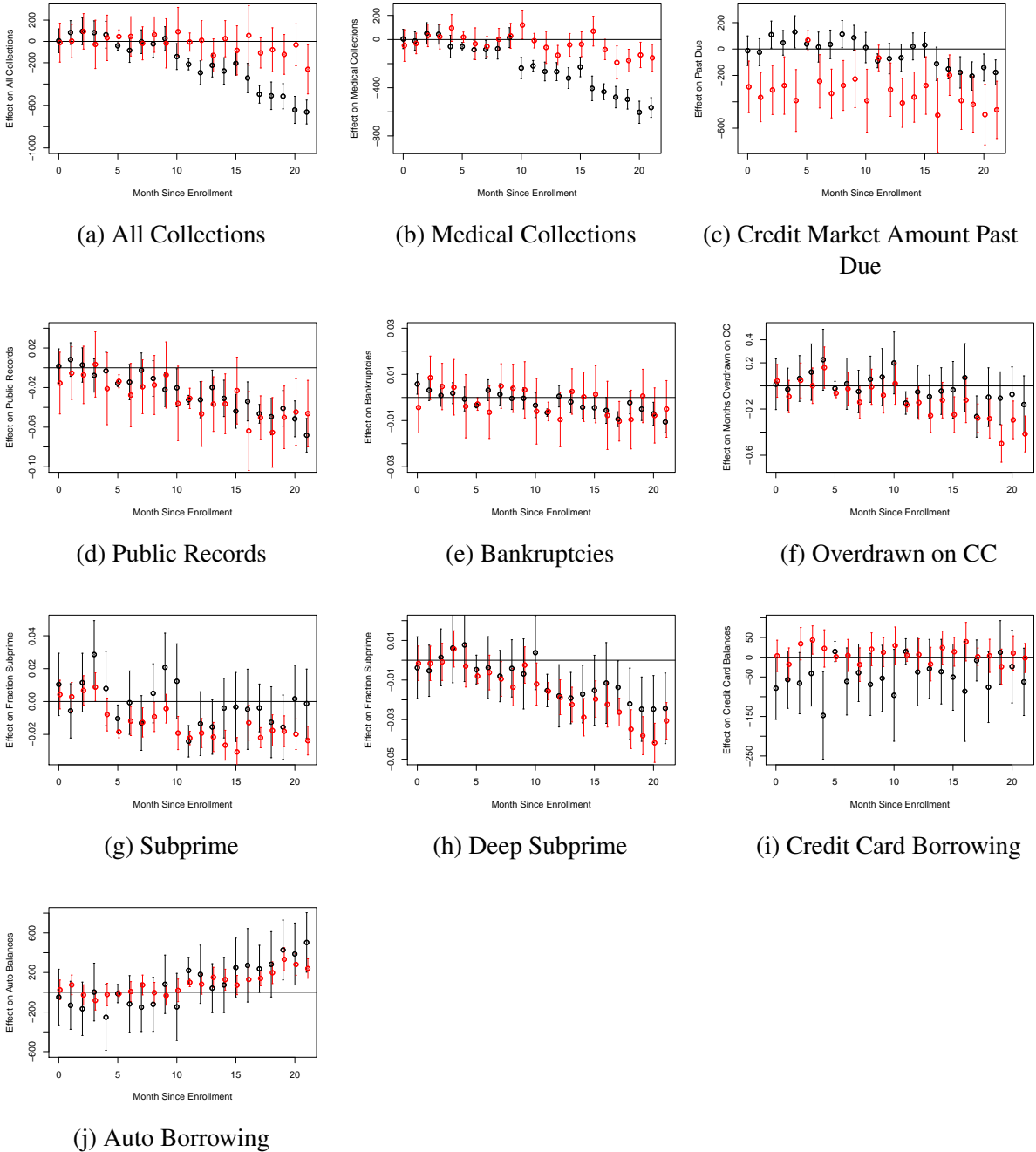
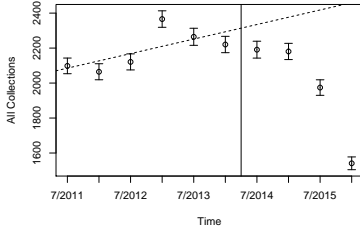
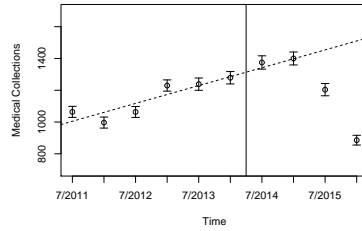


Figure depicts event study coefficients and 95 percent confidence intervals for post-enrollment time periods across a sample with third party liability (red line) and without third party liability (black line). Model includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend.

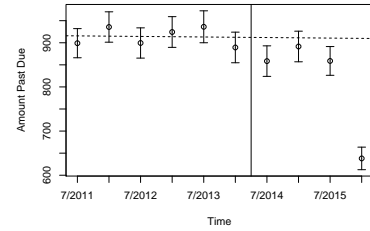
Figure 9: First Enrollment Cohort



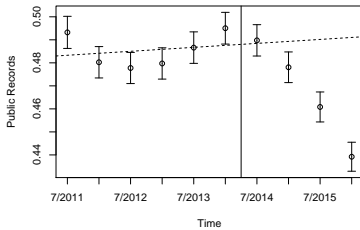
(a) All Collections



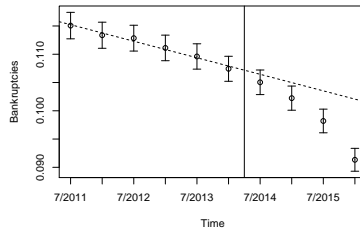
(b) Medical Collections



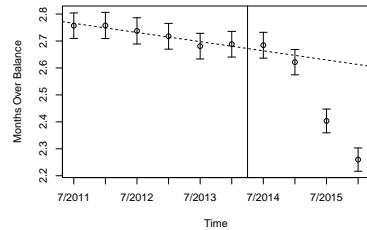
(c) Credit Market Amount Past Due



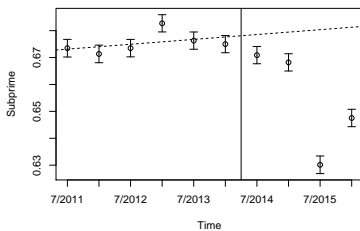
(d) Public Records



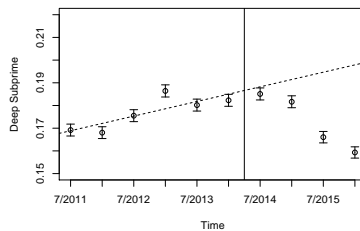
(e) Bankruptcies



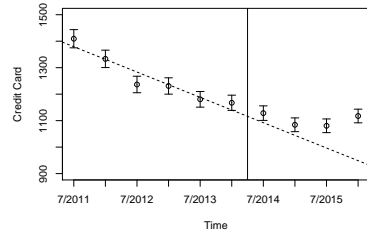
(f) Overdrawn on CC



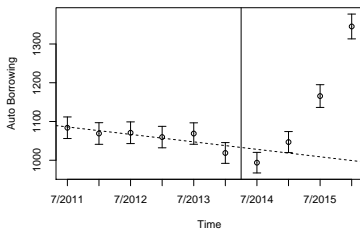
(g) Subprime



(h) Deep Subprime



(i) Credit Card Borrowing



(j) Auto Borrowing

Figure depicts event study coefficients and 95 percent confidence intervals for post-enrollment time periods across a sample with third party liability (red line) and without third party liability (black line). Model includes event time indicator variables, month x year enrollment cohort fixed effects, calendar month fixed effects (to account for seasonality), and a linear time trend.

Table 1: Comparison of matched and unmatched samples

	Un-Matched	Matched
Age	36.99 (14.72)	38.78 (12.37)
Gender=Female	42%	57%
Inpatient Discharges	0.09 (0.42)	0.14 (0.66)
ED Visits	0.59 (1.49)	0.96 (2.66)
Chronic Illness Flag=1	62%	70%
Income as Percent of FPL	22.43 (40.07)	38.92 (47.09)
N	3,717	322,305

This table presents descriptive statistics for HMP enrollees that were not matched (column 1) and matched (column 2) to a TransUnion credit report. Standard deviations are in parentheses.

Table 2: Descriptive Statistics

	All Enrollees		Enrollees with Hospitalization or ED Visit in First Year		Enrollees with Chronic Illness in First Year		Medicaid Only Payer		Medicaid Secondary Payer	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
All Collections	1839.14	1489.76	2591.26	2284.78	2099.21	1755.46	1984.73	1587.66	1141.75	968.9
Medical Collections	906.88	850.87	1536.24	1511.37	1112.56	1074.46	981.98	923.26	447.64	465.83
Amount Past Due	845.13	710.47	892.06	795.44	885.22	750.92	873.79	718.21	707.85	669.29
Fraction Subprime	0.64	0.63	0.78	0.78	0.66	0.65	0.69	0.67	0.44	0.43
Fraction Deep Subprime	0.17	0.17	0.23	0.24	0.18	0.18	0.18	0.18	0.10	0.11
# Public Records	0.44	0.39	0.47	0.42	0.48	0.43	0.44	0.38	0.41	0.4
# Bankruptcies	0.1	0.08	0.09	0.08	0.11	0.09	0.09	0.08	0.13	0.11
Months Over Limit on Credit Card	2.52	2.39	3.26	3.12	2.62	2.48	2.75	2.56	1.86	1.88
Credit card borrowing	1099.32	1347.32	877.42	704.5	1386	1071.38	1181.61	940	2141.13	1946.89
Auto borrowing	1323.76	1382.41	1138.69	1089.39	1429.85	1250.79	1178.57	1110.25	2358.86	2459.64
Baseline characteristics:										
Age at Enrollment	38.78			38.02		40.82		38.78		38.77
Female	0.57			0.59		0.54		0.59		0.48
Income Relative to FPL (%)	38.92			31.39		37.67		36.26		51.61
Chronic Illness=1	0.70			0.90		1		0.73		0.59
Hospitalization	0.14			0.34		0.19		0.15		0.07
ED Visits	0.96			2.35		1.28		1.05		0.48
# Individuals	322,305			130,814		227,008		267,704		54,601

Note: Table displays summary statistics. Within our sample, 98.7% of HMP enrollees were matched to a credit report. Financial outcomes are presented for both pre- and post-HMP enrollment. These time periods are defined relative to the individual's enrollment month. Note that the variables "months over limit on credit cards," "subprime" and "deep subprime" are not defined for all individuals. Baseline sample characteristics for Healthy Michigan Plan Enrollees are presented in the bottom panel.

Table 3: Results: Delinquency Outcomes

	All Collections			Medical Collections			Amount Past Due		
6 Month Effect	-34.52 (49.02)	-62.99 (49.02)	-211.3*** (23.89)	-34.96 (34.77)	-78.50** (34.77)	-100.4*** (18.54)	-27.62 (49.88)	-28.32 (49.88)	55.36*** (20.63)
12 Month Effect	-187.9*** (48.42)	-244.8*** (48.42)	-372.4*** (24.86)	-147.2*** (34.24)	-234.2*** (34.24)	-242.5*** (18.75)	-110.9** (50.68)	-112.3** (50.68)	-24.71 (24.09)
21 Month Effect	-537.9*** (50.38)	-623.3*** (50.38)	-675.5*** (22.16)	-384.4*** (35.55)	-515.0*** (35.55)	-438.3*** (16.86)	-231.1*** (43.25)	-233.2*** (43.25)	-231.7*** (17.06)
Linear time trend		X	X		X	X		X	X
Pre-Enrollment Event	X	X		X	X		X	X	
Variables Included									
N	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466
	Public Records			Bankruptcies			Months Overdrawn on Credit Card		
6 Month Effect	-0.0115 (0.00788)	-0.0164** (0.00788)	-0.0160*** (0.00294)	0.00127 (0.00212)	0.00155 (0.00212)	-0.000512 (0.000907)	-0.0114 (0.0605)	-0.0126 (0.0605)	-0.0707** (0.0288)
12 Month Effect	-0.0247*** (0.00803)	-0.0345*** (0.00803)	-0.0313*** (0.00335)	-0.00163 (0.00218)	-0.00106 (0.00218)	-0.00230** (0.00105)	-0.120** (0.061)	-0.122** (0.061)	-0.177*** (0.032)
21 Month Effect	-0.0524*** (0.0076)	-0.0672*** (0.0076)	-0.0537*** (0.0025)	-0.0105*** (0.0022)	-0.00968*** (0.0022)	-0.0116*** (0.0008)	-0.385*** (0.066)	-0.389*** (0.066)	-0.420*** (0.021)
Linear time trend		X	X		X	X		X	X
Pre-Enrollment Event	X	X		X	X		X	X	
Variables Included									
N	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466

Note: Table displays estimates of equations (1) and (2). Robust standard errors clustered at the individual level are reported in parentheses. Significance levels: \*=10 percent, \*\*=5 percent, \*\*\*=1 percent.

Table 4: Results: Credit Access and Borrowing Outcomes

	Subprime			Deep Subprime		
6 Month Effect	-0.0087** (0.004)	-0.011*** (0.004)	-0.019*** (0.002)	-0.003 (0.004)	-0.006 (0.004)	0.003* (0.002)
12 Month Effect	-0.016*** (0.004)	-0.020*** (0.004)	-0.026*** (0.002)	-0.0122*** (0.004)	-0.0192*** (0.004)	-0.00625*** (0.002)
21 Month Effect	-0.017*** (0.004)	-0.023*** (0.004)	-0.030*** (0.001)	-0.020*** (0.004)	-0.031*** (0.004)	-0.018*** (0.001)
Linear time trend		X	X		X	X
Pre-Enrollment Event	X	X		X	X	
Variables Included						
N	3,002,331	3,002,331	3,002,331	3,002,331	3,002,331	3,002,331
	Credit Card			Auto		
6 Month Effect	57.78 (40.05)	97.77** (40.05)	123.7*** (15.99)	4.294 (48.61)	-6.019 (48.61)	-28.28 (22.83)
12 Month Effect	83.25** (40.35)	163.2*** (40.35)	183.1*** (17.60)	133.8*** (49.19)	113.1** (49.19)	74.50*** (25.70)
21 Month Effect	22.28 (39.57)	142.3*** (39.57)	78.67*** (13.92)	308.5*** (47.56)	277.6*** (47.56)	169.6*** (18.78)
Linear time trend		X	X		X	X
Pre-Enrollment Event	X	X		X	X	
Variables Included						
N	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466	3,187,466

Note: Table displays estimates of equations (1) and (2). Robust standard errors clustered at the individual level are reported in parentheses. Significance levels: \*=10 percent, \*\*= 5 percent, \*\*\*=1 percent.



Table 5: Results: First Enrollment Cohort Only

	All Collections	Medical Collections	Amount Past Due	Public Records	Bankruptcies	Months Overdrawn On Credit Card
3 Month Effect	-118.62*** (19.68)	-64.83*** (16.44)	8.71 (11.68)	-0.026*** (0.001)	-0.003*** (0.001)	-0.012 (0.014)
9 Month Effect	-99.18*** (19.31)	25.08 (17.30)	18.35 (11.32)	-0.025*** (0.001)	-0.004*** (0.0005)	-0.056*** (0.016)
15 Month Effect	-372.96*** (24.58)	-304.81*** (20.82)	14.81 (14.38)	-0.063*** (0.002)	-0.009*** (0.001)	-0.27*** (0.021)
21 Month Effect	-747.24*** (20.69)	-533.67*** (16.92)	-234.04*** (14.20)	-0.072*** (0.002)	-0.014*** (0.001)	-0.39*** (0.022)
Linear time trend	X	X	X	X	X	X
Pre-Enrollment Event Variables Included	X	X	X	X	X	X
N	1,020,431	1,020,431	1,020,431	1,020,431	1,020,431	391,101
	Subprime	Deep Subprime	Credit Card	Auto		
3 Month Effect	-0.01*** (0.001)	-0.005*** (0.001)	-35.61*** (11.68)	-56.51*** (8.80)		
9 Month Effect	-0.01*** (0.001)	-0.007*** (0.001)	-4.61 (8.71)	18.12 (11.19)		
15 Month Effect	-0.05*** (0.002)	-0.031*** (0.002)	-5.04 (11.51)	118.17*** (15.71)		
21 Month Effect	-0.034*** (0.001)	-0.036*** (0.001)	110.64*** (11.01)	323.77*** (15.75)		
Linear time trend	X	X	X	X		
Pre-Enrollment Event Variables Included	X	X	X	X		
N	967,248	967,248	1,020,431	1,020,431		

Note: Table displays estimates of equations (1) and (2). Robust standard errors clustered at the individual level are reported in parentheses. Significance levels: \*=10 percent, \*\*= 5 percent, \*\*\*=1 percent.