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Two Essays on Econometric Modelling of Consumer Demand for Health Insurance and Financial Impact of Rural Hospital Closures

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ABSTRACT

TWO ESSAYS ON ECONOMETRIC MODELLING OF CONSUMER DEMAND FOR HEALTH INSURANCE AND FINANCIAL IMPACT OF RURAL HOSPITAL CLOSURES.

BY

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While distinct in their particular theme, the following two essays all have one unified goal. Their collective goal is to provide accurate estimates for important policy topics useful for policymakers and researchers. The first essay revisits the RAND HIE using a new matching method to address the potential insurance plan endogeneity. The resulting analysis finds small changes in demand elasticity for medical care but statistically significant improvement in smoking rates at the study exit. The second essay looks at the financial health impacts of rural hospital closures.

Keywords: matching, hospital closure, health insurance, financial health, event study, Equifax, debt, and health economics.

TWO ESSAYS ON ECONOMETRIC MODELLING OF CONSUMER DEMAND FOR HEALTH INSURANCE AND FINANCIAL IMPACT OF RURAL HOSPITAL CLOSURES

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

To my loving family, especially my incredible wife Jessica Henson, whose unwavering support, boundless love, and endless patience have been the foundation upon which I have built this dissertation. I am eternally grateful for her presence in my life and all the sacrifices she has made to help me achieve my dreams. Additionally, I would like to thank my mother for always being there when I needed her and for all her time helping take care of our children.

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Chapter 1 Revisiting the RAND HIE with Nonbipartite Matching

1.1 Introduction

Matching techniques have become an increasingly important tool for researchers looking at counterfactual or causal models. Established literature exists for matching with two groups, *aka* bipartite matching. The matching literature for several groups, *aka* nonbipartite matching, is starting to develop in the field of statistics but has not been introduced to the area of economics. This paper presents the first use of a nonbipartite matching method to analyze the effect of health insurance on health care expenditures and outcomes.

This paper applies an optimal nonbipartite matching method to address the potential refusal bias in the RAND Health Insurance Experiment (RAND HIE). In looking at the literature on potential bias in the RAND HIE, only one other paper has taken a serious look at the fee-for-service (FFS) experiment (Aron-Dine et al., 2013). This paper takes a different approach from the previous paper by using nonbipartite matching to balance the pre-treatment covariates of health at the individual level to determine if better balance changes the medical expenditures or the health outcomes.

The results show that, on average, the individuals removed by nonbipartite matching had higher medical expenditures and were poorer, less educated, older, and less unhealthy. The results indicate that nonbipartite matching strengthened the assumption of ignorability. The replications of (Aron-Dine et al., 2013) showed that some models were misspecified and can result in a dramatic difference in the elasticities in their paper. The free care plan showed better outcomes for the amount of smoking at study exit. After matching, the general health index had a statistically significant effect on ECG abnormality and joint pain.

1.2 Literature Review

The foundational work on matching is summarized in (D. Rubin, 2006) and provides an essential perspective on matching methodology. In particular, it is discussed that most large observational studies will produce estimators with small sampling variance, and the potential for estimators to be susceptible to bias is the primary concern for researchers. One solution presented was to form a causal framework for the source and potential direction of the bias, then attempt to apply matching to reduce the potential bias. The main objective of all matching methods is to balance the data so that control and treatment groups have independent variables from the same joint distribution (Morgan & Winship, 2007).[1]

The use of matching methods to analyze the effect of selection bias between observational and randomized studies is well developed (Cochran S. P., 1965; Cook & Steiner, 2010; Rosenbaum, 2010). In a recent experiment, a group of participants was sorted into groups either with a randomized or observational group setup (where treatment could be selected) to determine the effectiveness of matching in removing the selection bias with matching (Cook & Steiner, 2010; D. B. Rubin, 2008; Shadish et al.,

[1] For readers interested in a more comprehensive understanding of matching methods (Morgan & Winship, 2007) provides a deeper analysis than can be presented in this paper and summarizes a majority of the papers on matching.

2008). This literature found that if participants are selected into a treatment group, motivational measures for selection or refusal of treatment can remove bias if matching is done using the correct pre-treatment measures.

A significant development in matching methods was optimal matching (Rosenbaum, 1989). Optimal matching was created to solve the problem that nearest available matching can generate suboptimal matches. The suboptimal matches would occur when the order in which matched pairs are decided minimizes the difference between each pair but does not minimize the overall average difference between all pairs. An optimal matching method searches through all possible matching orders to find the smallest average difference between all pairs. Using optimal matching in studies with an unbalanced number of control and treatment cases can show the largest improvements (Hansen, 2004).

A study with one control group and several treatment groups makes using two-way matching more complicated to implement (Imbens, 2000). A researcher could use a series of two-way matches between the one control group and each treatment group or across all groups. The problem with this approach is that it requires having to estimate separate propensity scores for each two-way comparison and is computationally not feasible with many different treatment levels. A new and growing body of literature on optimal nonbipartite matching has used more complex algorithms to find the optimal matched pairs across all groups (Greevy et al., 2004; Lu et al., 2001, 2011b).

The RAND Health Insurance Experiment (HIE), started in 1974, has been extensively examined and researched. The study was an excellent example of a well-executed pseudorandomized study and gave a detailed picture of how copayment rates or out-of-pocket expenditures affect health care spending and outcomes (Manning et al., 1987; Newhouse & Group, 1993). The study's main results showed that the elasticities for medical care were nonzero for all medical care at approximately -0.12 and -0.17 for outpatient care. This makes families' response to cost-sharing, not a trivial policy matter. A second important finding was that the health outcomes of the average person in the free care plan showed no significant benefit compared to the cost-sharing plans[2]. The RAND HIE debated the validity of the assertion of a true random assignment (Newhouse et al., 2008; Nyman, 2007). The different insurance plans had different refusal rates, but in defense of the study, the original authors asserted that all participants were offered large enough monetary incentives to hold the participants harmless from a randomly assigned plan. This paper takes a second look at the main results using nonbipartite matching to remove the potential bias from the differences in refusal rates.

There has only been one paper that takes a detailed second look at the results of the RAND HIE and the potential questions about its validity (Aron-Dine et al., 2013). It looked at the potential threats to validity from differences in failure to report utilization across plans, non-random assignment of families across plans, and differences in refusal and attrition rates across plans. The authors concluded the original assertion that healthcare spending responds to out-of-pocket costs and is not affected by the threats to validity. The paper does contain several methodological mistakes. In cleaning the original data, their final dataset still contained several participants from the HMO

[2] Benefits did exist for the sub group of poor individuals with high blood pressure and correctable vision problems.

experimental group. The econometric methodology fails to follow the extensive literature on 5nrolment health expenditures and costs with non-normal distributions and heterogeneity (Duan, 1983; Jones M, 2010; Manning, 1998; Manning et al., 2005; Manning & Mullahy, 1999; Mullahy, 1997)[3]. This brings into question some of the inherently nonlinear predictions using linear estimation methods. My paper addresses several of the weakness of (Aron-Dine et al., 2013) to determine if the models are misspecified and if results differed if it was modeled appropriately.

This paper addresses some of the weaknesses of the current literature on testing the validity of the RAND HIE and takes a slightly different approach. It provides the first attempt to address the potential bias in health expenditures with a causal framework using nonbipartite matching, and it is the first known attempt to re-examine the health outcomes of the RAND HIE for potential bias. The data section will provide an overview of the cleaning process necessary to obtain a dataset close to the original dataset (Manning et al., 1987). The methods section will provide a causal framework for the pre-treatment variables used in nonbipartite matching and a brief overview of nonbipartite matching. The results section shows the differences in expenditures between the original results, the results of the current literature, and my proposed econometric modeling. It also looks at the difference in health outcomes between the original dataset and the matched dataset.

[3] In a 2011 personal correspondence with Dr. Willard Manning on the most appropriate way to model the RAND HIE with current econometrics techniques. The appropriate econometric methodology to test and determine the appropriate model differs from the method used in (Aron-Dine et al., 2013). It was also mentioned that the original four part model used in (Manning et al., 1987) would not be used today, but was used at the time because of the limited computational power and memory.

1.3 Data

To create the necessary data for this paper, I needed to start with the public files of the RAND HIE to collect all the necessary health outcomes. The original dataset from (Manning et al., 1987) had 5,809 persons and 20,190 person-years. This dataset is the ideal case for comparing to the original work. In (Deb & Trivedi, 2002), Dr. Manning provided the identification variables for the FFS group examined in the original paper[4]. This dataset had some minor coding errors related to site and person identifiers. The errors stem from the alphanumeric identifiers and sites. The unique identifier has a letter defining the original site. The dataset also had a variable identifying the baseline site of residence. These were not the same in a few cases, which was corrected by inspecting the data for the correct identifier. The correction allowed a match between the original dataset and the open-access files. The results were reasonably close and contained 5807 persons and 20180 person-years.

In (Aron-Dine et al., 2013), the published dataset from the JEP website has 5915 persons and 20203 person-years. The additional individuals in the dataset had come from the HMO experimental group and were assigned to the free care plan. Double-checking with the original dataset revealed that these people did not switch from HMO to an FFS plan at any point in the study. These individuals remained after the top spenders were removed from the free care plan to use the sharp bounds method. Thus, both results are based on incorrect data.

[4] This dataset can be obtained in the materials of the textbook (Cameron & Trivedi, 2005), which cites (Deb & Trivedi, 2002) as the original source of the data. There were also some original variables provided such as the imputed general health index.

Table 1.1

Dataset Compared to Original Dataset

Plan	Current Dataset [a]	Original Dataset [a]
Free	6817	6822
25 percent	4065	4065
50 percent	1401	1401
95 percent	3274	3727
Individual Deductible	4173	4175
Total	20180	20190

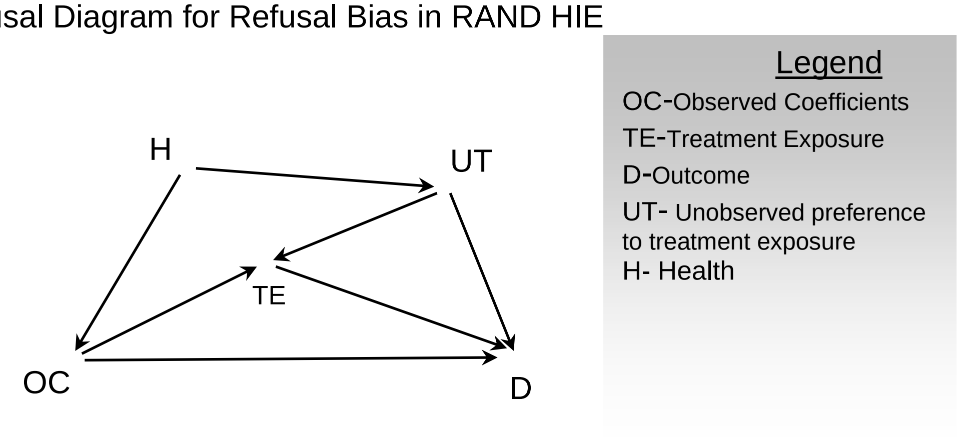
Notes.
[a] Person-years

1.4 Methods

The implicit assumptions of this paper are strong ignorability after matching, common support, and Stable Unit Treatment Value Assumption (SUTVA). The effect being estimated is the Average Treatment effect for the Treated (ATT) before matching. After matching, the effect is the Average Treatment effect for the Treated (ATT) within the area of common support created by nonbipartite matching. Directed Acyclic Graphs (DAGs) help portray a problem such as a refusal bias or confounding in a causal framework (Hernan et al., 2004). A DAG is a graphical representation of a causal question that uses nodes to show variables and arrows for causal effects (Pearl, 2009).

Figure 1.1

Causal Diagram for Refusal Bias in RAND HIE



The identification strategy is based on the DAG in Figure 1.1. The RAND HIE assigned families to different health insurance plans. The different plans are different treatment exposures (TE) in Figure 1.1. The researchers knew that the participants would have demographic, family, economic, and health characteristics that effect both the TE and the outcome (D). This makes the observable pre-treatment covariates (OC) display confounding by effecting both D directly and indirectly through the treatment exposure. This causes the total association between TE and D not to be equal to the causal effect $TE \rightarrow D$. The RAND HIE handled the confounding by balancing some pre-treatment covariates during the random assignment and included observed covariates in the econometric model. The resulting causal effect of $OC \rightarrow TE \rightarrow D$ should be a consistent and unbiased estimator[5].

The nonresponse by either refusal or attrition creates another confounder and makes the treatment assignment nonignorable. In Figure 1.1, the unobserved preference to treatment exposure (UT) confounds the casual effect of $TE \rightarrow D$. In the case of the RAND HIE, it is the refusal and attrition of health insurance plans. In (Manning et al., 1995), the authors noted that the balance of health across plans was one potential threat to validity[6]. The proposed solution is to use matching to balance the covariates related to health (H) and minimize the effect of the path from $UT \rightarrow TE$. This allows a more robust assertion of the assumption of ignorable treatment assignment. In

[5] This statement ignores the other potential issues discussed further in the paper.

[6] The authors also noted the free care plan had much lower refusal rates at 6% compared to 23% in the 95% coinsurance plan. This would indicate the situation in Figure 1.1 with the presence of UT as reasonable assertion.

this scenario, the refusal to higher cost-sharing plans generates an imbalanced pool of participants across plans with respect to health. A regression model (with the general health index at enrolment as the dependent variable and plan dummies as the independent variables) is used to check for a potential imbalance in the health index being correlated with treatment exposure[7].

The randomization in the RAND HIE used the finite selection model to improve the balance of pre-treatment variables across the 12 treatment groups (Morris, 1979). The mean value of a family unit was balanced using 24 weighted variables (Morton & Rolph, 2000)[8]. The method provides a set amount of balance given a set amount of computational time, but it cannot provide the maximum amount of balance.

The variables used for nonbipartite matching are listed in Table 1.5. The variables used are slightly different from those used by the RAND HIE. The individual-level variables are used in the matching process instead of the average value for a family unit. The reason behind using individual-level variables is that the decision to accept a health insurance plan will not be a democratic process, with the median preference being the dominate choice. Thus, it appears best to remain agnostic to the functional form of the decision-making process and use the individual-level information.

Optimal nonbipartite matching minimizes the total distance among all combinations of matched pairs (Lu et al., 2011a). The distance used in the distance

[7] The regression uses family identity for cluster robust errors.

[8] The variables used were annual physician visits, self-reported health status, income, family size, age, education of male (head of household), education of female (head of household), maximum wage rate, proportion of family experiencing pain, proportion of family experiencing worry, health insurance status at start, number of heads of household, race, proportion of females in family, AFDC recipient, employed head of household, nonwage income, location, annual hospital admissions, and a constant term.

matrix is the squared difference in the estimated propensity score. The perfect matchings are found with Derig's shortest augmentation path algorithm (Derigs, 1988). The free care, 25% coinsurance, 50% coinsurance, 95% coinsurance, and individual-deductible plan are set to prevent matching within the same plan. The matching removes the sample participants with the highest distance among all possible matched pairs. The removal of worst matches is gone at 1% intervals and was stopped after 8% of the original sample had been removed.

Health expenditures and outcomes in the RAND HIE have a causal effect that can be very model-dependent (Duan, 1983; Manning et al., 1987). Matched sampling has the additional benefit of working as a nonparametric preprocessing method to reduce model dependence on the parametric form of analysis (Ho et al., 2007). This is accomplished by only using pre-treatment variables related to health in the matching process to reduce the model's dependence on the functional form of health. A higher imbalance of one variable at the cost for a lower imbalance of all other variables is one potential downside to using matching with preprocessing. This paper does not claim that any one variable used in matching is more important to balance. Thus, the standard difference in the sample means across all plan pairings relative to the free care plan is presented in Appendix 1.3[9]. The standardized difference is used to compare the quality of balance across variables[10]. Figure 1.2 below summarises the information in Appendix

[9] The author believes the nonbipartite matching method does a good job of reducing the overall. It is left to the reader to review each possible pair combination for brevity reasons.

[10] An unstandardized difference can be informative with variables such as age, because it can be more informative to look at the difference in age by year instead of difference in age by standard deviations. A standardized difference is used to make comparison across all variable easier to interpret.

1.3 and 1.4 by creating a heat map of the improvement in the balance of variables across plans.

Figure 1.2
Heat Map of Standardized Difference in Sample Means

1st plan co-pay		0%	0%	0%	0%
Compared to		25%	50%	95%	100%
Covariates	Took physician exam	0.553	-0.693	-0.97	-1.833
	Black	1.141	-3.308	1.776	-2.071
	Income	-2.887	2.1	-2.171	-1.769
	Age	0.448	1.765	-1.582	0.013
	Female	0.708	0.833	-0.508	-0.979
	Education level	-4.602	-3.495	-4.474	-2.163
	Family size	-1.385	-5.224	-2.97	-1.565
	Mental health index	0.838	2.963	2.121	0.437
	Number of chronic diseases	3.908	2.829	2.766	0.071
	Child (age<18)	-1.226	-0.183	-0.274	-0.979
	General health index	-3.154	-5.266	-0.551	-1.836
	Income not missing	2.786	-3.337	0.378	1.712
	General health index	-2.593	-4.129	2.389	-1.5
	General health index not missing	-0.292	-1.414	0.213	-0.316

The final matched samples will now be the participants under the region of common support. The differences in the remaining matched pairs and the discarded participants provide an informative way to analyze the potential problems with common support. If the discarded participants were sicker and older than the remaining pairs, the randomized assignment (of the finite selection model by average pre-treatment values in a family unit) still left health imbalanced for individuals. If the discarded participants were healthy or healthier than the remaining participants, it could indicate that the plans were balanced across families and individuals. The results section will present a comparison of discarded and remaining matched pairs.

The results of (Aron-Dine et al., 2013) were replicated with the original code and data of the authors published by The Journal of Economic Perspectives.[11]

$$y_{i,t} = \delta_p + \tau_t + \gamma_{l,m} + \varepsilon_{i,t}$$

The econometric models contained either level expenditures or logged expenditures as the primary dependent variable (y). The independent variables were plan (δ), year (τ), site-by-starting-month (γ), and fixed effects. The model clustered the errors by family (i) because the random assignment was done by family. The model specification contains no constant to ensure all plans can be used simultaneously without causing the problem of multicollinearity.

In order to establish a comparison, I estimate arc-elasticities by average coinsurance rate to compare to the original RAND HIE study to show a good starting point to compare results across studies with different methods. Next, the replication will check the specifications with the RESET test (Jones et al., 2007) because there is an excellent reason to doubt using a simple linear regression with the RAND HIE data. The normality of skewness and kurtosis were tested (D'Agostino et al., 1990) to determine if the dependent variables could be considered normal or log-normal (with a constant). The models related to the sensitivity of elasticity to cost sharing and the sensitivity of medical expenditures are looked at with the original and GLM models. The results related to sensitivity from threats to validity will be examined with the original and GLM models.[12]

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[11] The replication of the results for (Aron-Dine et al., 2013) were not the initial intention of this paper. It was only done as the econometric models kept failing the specifications tests. The paper displayed a great depth and breadth of knowledge regarding the possible concerns to validity.

[12] The data used is not the original authors is modified to match the cleaned dataset described in the data section.

The replication of the sharp bounds of the treatment effect (Lee, 2009) will not be presented in this analysis because there are concerns with the consistency of the bounding estimator. The nonbipartite matching method will replace the sharp bounds and adjustment for pre-treatment covariates used in (Aron-Dine et al., 2013). A replication of controlling for pre-randomized covariates is also not undertaken. The primary reason is that this model suffers from severe misspecification and slight overfitting from using 86 independent variables.

The health expenditures model for total medical, inpatient, and outpatient spending will have the same functional form but use a generalized linear model (GLM). A GLM has a link function (between the mean and the linear predictor) and a family function (between the mean and variance on the original scale) (Mihaylova et al., 2010). The GLM provides a more flexible framework than the standard OLS specification by obtaining estimates of $E(Y|x)$ without dealing with heteroskedastic smearing[13].

The data was used to determine the correct link and family function (Deb et al., 2014). The link function is determined using a Box-Cox test to determine the relationship between the mean and the linear predictor. The family function was determined using a GLM family test to determine the variance structure. The final models were all checked for misspecification using Pregibon’s link test. The testing showed a link function of log for total medical, inpatient, and outpatient spending. The family of gamma was most appropriate for total medical inpatient spending, and a family

[13] The original four-part model from (Manning et al., 1987) was examined along with GLM version of the four-part model. It is not presented here for brevity. The model does well at estimating the medical expenditures.

function of poisson best estimated the outpatient spending[14]. All GLM models used bootstrapped cluster-robust standard errors to handle the skewness in the data[15].

The model was determined by the same strategy as the one used for medical expenditures in the estimation of the elasticity of coinsurance. All the models concerning elasticity were found to have a log link function and a family function of gamma. It should not be surprising that the link function was a log for estimating elasticities.

The health outcomes use an ordered probit for categorical variables and ordinary least squares (OLS) regression for the continuous variables. The models were tested for misspecification using the RESET test, and the health outcomes with successful models are presented below[16]. The econometric model is

$$Y^*_{i,t+1} = \beta_0 + \beta_1 Site_{i,t} + \beta_2 Plan_{i,p} + \beta_3 Y_{i,t} + \beta_4 X_{i,t} + \varepsilon_i$$

It models the health status at the exit $Y^*_{i,t+1}$ as the dependent variable. The independent variables are site fixed-effects, plan dummies, health status at the beginning, and demographic and health covariates at the beginning. The health outcomes examined were physical activity, joint pain, ECG abnormalities, shortness of breath, current smoking amount, self-reported health status, body mass index, systolic blood pressure, and cholesterol.

[14] A typical concern with poisson is the mean must equal the variance. The econometric models use clustered robust standard errors which relax the assumption of equivalence. A good review of this property can be seen at http://blog.stata.com/2011/08/22/use-poisson-rather-than-regress-tell-a-friend/.

[15] The errors are clustered by family identifier and bootstrapped for 500 replications.

[16] The models for diastolic blood pressure and glucose failed the RESET test.

1.5 Results

The general health index was correlated with a plan assignment at the 5% level for the 50% copay plan relative to the free care plan. The coefficient indicated that a 50% copay plan was predictive of having better health relative to the free care plan. This could indicate that the potential concern for the nonignorable treatment assignment presented in Figure 1 is somewhat justified. Given an assumption that health insurance decisions would be made by individuals over the age of 18, this group provides a more striking result[17]. The general health index was correlated with plan assignment at the 1% level for the 50% copay plan and at the 10% level for both the 25% copay and 95% copay plan. The coefficients for the 25%, 50%, and 95% plans all displayed having better health relative to the free care plan.

Using nonbipartite matching for removing 4% of individuals reduced the predictive power of the 50% coinsurance, and it became statistically insignificant at the 10% level. The over 18 age-group showed similar results with the 50% coinsurance plan and was only statistically significant at the 10% level, and the other plan became statistically insignificant. The remaining results will be shown with 4% of the participants removed using 4% nonbipartite matching[18].

The summary statistics of the remaining participants compared to the removed participants is informative. The 4% matched data showed that the dropped participants

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[17] This could be caused by and anchoring effect (Kahneman, 2011) of viewing other health insurance needs relative oneself. It is also know from experimental literature that altruistic or other-regarding preference is observed in about half of experimental subjects depending on the monetary threshold (Cox, 2004).

[18] The matching results after 5% of participants were removed by nonbipartite matching started showed weaker model specification. The other reason for only presenting the 4% matches is the results tables become cluttered.

were poorer, older, less healthy, less educated, and came from larger families. The differences in medical-expenditure outcomes showed that the dropped participants had lower rates of positive total medical and outpatient spending but a 4.7% higher rate of positive inpatient medical spending. The dropped participants spent 1.8 times more on total medical spending, 1.04 times more on outpatient medical spending, and 2.19 times more on inpatient medical spending.

The resulting arc elasticities in Table 1.2 show a decent approximation to the original results using the average coinsurance rates

Table 1.2
Arc Elasticities for Types of Care by Average Coinsurance Rates

Range of Coinsurance Variation	Range of Average Coinsurance Variation	All Care	Outpatient Care
Panel A. Original Estimates			
0-25%	0-16	0.10	0.13
25-95%	16-31	0.14	0.21
Panel B. Recreation of Baseline Estimates			
0-25%		0.10	0.13
25-95%		0.17	0.23
Panel C. After 4% Matching			
0-25%		0.08	0.12
25-95%		0.19	0.23
Panel D. Estimates from Aron-Dine et al.			
0-25%	N/A	N/A	N/A
25-95%	N/A	0.039	N/A

In replicating the results of (Aron-Dine et al., 2013), it was essential to determine if the log transformation $ln(spending + 1)$ used produced a log-normal distribution. The log transformation with a constant of one failed to be a log-normal distribution with regards to skewness. The log transformation of total medical spending had an optimal skewness-reducing constant of 8.22, and outpatient spending had 14.8 as the optimal skewness-reducing constant. Inpatient spending did not have an optimal skewness-reducing constant, and skewness could only be reduced to 2.85 with a constant close to zero. The total medical and outpatient spending was log-normal with regard to skewness using the correct constant, but none of the expenditures could be made log-normal with regard to kurtosis.

The RESET test indicated misspecification in most of the regression models. The GLM models are considered correctly specified using Pregibon's link test. Table 1.3a and 1.3b shows the results for the replication of the difference between plan for total medical and outpatient spending in both levels and logs. The second row of each panel shows the sensitivity of estimates to differences across plans in reporting medical spending. The difference in underreporting for the 95% coinsurance plan is around 8 percent higher than for the free care plan (Newhouse and Rogers, 1985).

Table 1.3a

Sensitivity of total expenditures to model dependence and underreporting [a]

	Total Spending			
	OLS		GLM	
	Spending in $	Spending in logs	Spending in $	Spending in logs
95% Coinsurance plan vs. Free Care				
Baseline model	-847.6 (119.3)	-1.382 (0.0958)	-875.46 (0.077)	-0.533 (0.0727)
Corrected for underreporting	-788.5 (123.1)	-1.314 (0.0974)	-814.24 (0.068)	-0.472 (0.0691)
25% Coinsurance plan vs. Free Care				
Baseline model	-650.4 (152.0)	-0.748 (0.0955)	-632.18 (0.091)	-0.397 (0.0870)
Corrected for underreporting	-647.2 (154.6)	-0.734 (0.0961)	-628.88 (0.085)	-0.382 (0.0885)
95% Coinsurance plan vs. 25% Coinsurance plan				
Baseline model	-197.2 (159.8)	-0.634 (0.120)	-243.28 (0.099)	-0.136 (0.0995)
Corrected for underreporting	-141.3 (164.0)	-0.580 (0.122)	-185.37 (0.096)	-0.0900 (0.0988)

Notes: [a] The robust clustered standard errors are in parentheses

Table 1.3b

Sensitivity of outpatient expenditures to model dependence and underreporting [a]

	Outpatient Spending			
	OLS		GLM	
	Spending in $	Spending in logs	Spending in $	Spending in logs
95% Coinsurance plan vs. Free Care				
Baseline model	-631.1 (50.34)	-1.361 (0.0929)	-618.96 (0.053)	-0.627 (0.0548)
Corrected for underreporting	-584.0 (54.92)	-1.299 (0.0946)	-571.11 (0.059)	-0.535 (0.0568)
25% Coinsurance plan vs. Free Care				
Baseline model	-421.8 (61.92)	-0.720 (0.0928)	-406.45 (0.061)	-0.387 (0.0629)
Corrected for underreporting	-419.9 (65.25)	-0.707 (0.0936)	-403.94 (0.060)	-0.367 (0.0606)
95% Coinsurance plan vs. 25% Coinsurance plan				
Baseline model	-209.3 (60.90)	-0.641 (0.117)	-212.50 (0.074)	-0.240 (0.0746)
Corrected for underreporting	-164.1 (66.10)	-0.592 (0.118)	-167.17 (0.070)	-0.168 (0.0782)

Notes: [a] The robust clustered standard errors are in parentheses

The difference in the OLS and GLM model is significant in predicting the actual expenditures. The difference in the data between the 95% and 25% plans for inflation-adjusted outpatient expenditures was -212.50 (in 2011 dollars). This is the same as the predicted inflation-adjusted outpatient expenditure provided by the GLM model. The other GLM predictions for baseline expenditures are much closer to value in the data than the OLS models of expenditures. The inaccuracy in the OLS estimate causes the difference between baseline and corrected for underreporting to be 4% lower than the GLM estimates. The standard errors were smaller in the GLM model, which in some cases the rejection of the null of no differences between plans will be rejected at the 10% level for the OLS model and at the 5% level for the GLM. The results for the same analysis with 4% of participants removed with matching are presented in Appendix 1.5. The results show that the GLM model predictions more closely approximate the data[19].

The original RAND HIE had elasticity estimates of the coinsurance rate in the range of -0.1 to -0.2. The replicated results in Table 1.4 of (Aron-Dine et al., 2013) show baseline elasticities that are too large with pairwise OLS regression and too small with pairwise arc elasticities. Pregibon’s link test indicated that the Gaussian distribution with the link of log was misspecified. The pairwise GLM model produces elasticities of -0.162 for all plans except the free care plan, and -0.156 for all plans except the free care and individual deductible plan. These estimates are perfectly in line with the RAND HIE original elasticity estimates

[19] A more thorough analysis of individual plan difference were not presented in this paper, but can ask for upon request. It is more intuitive to look at the elasticity results in Table 3 for the general trend on the effect of coinsurance with regards to medical expenditures.

Table 1.4
Elasticities of Total Medical Spending using various price measures [a,b]

Baseline	Coinsurance rate			
	Arc elasticity		Elasticity	
Baseline	(Aron-Dine et al, 2013)	(Manning et al, 1987)	OLS (Aron-Dine et al, 2013)	GLM
All plans	-0.095 (0.062)		NA	NA
All plans besides Free Care	-0.039 (0.120)		-0.524 (0.082)	-0.141 (0.074)
All plans besides Free Care and Individual Deductible	-0.039 (0.103)	(-0.14)	-0.538 (0.084)	-0.156 (0.077)
After Matching [c]	Arc elasticity		Elasticity OLS	Elasticity GLM
All plans	-0.103 (0.276)		NA	NA
All plans besides Free Care	-0.179 (0.464)		-0.525 (0.083)	-0.162 (0.071)
All plans besides Free Care and Individual Deductible	-0.087 (0.096)		-0.537 (0.085)	-0.137 (0.077)

Notes.
[a] For a more detailed explanation of the plans and methodology refer to (Aron-Dine et al., 2013).
[b] A full list of the pairwise arc elasticities before and after matching are listed in appendix 6 and 7.
[c] The results are after matching removed 4% of the sample.

After matching, the pairwise arc elasticity estimates were much closer to the original RAND HIE elasticity estimates. This is an excellent example of the ability of nonbipartite matching to reduce model dependence in estimating arc elasticities. In (Aron-Dine et al., 2013), the smaller elasticities for baseline results were attributed to the use levels for estimating treatment effects. This reduction in model dependence on the functional form can be seen in the significant convergence to estimates of the GLM model. The pairwise GLM elasticity model (after matching) was again correctly specified by the link test. Comparing the GLM estimates before and after matching indicates that the removed participants were more price inelastic and would be less sensitive to price changes. The elasticity estimates from pairwise OLS regression showed no significant change before and after matching.

The following results look at the changes in health outcomes at the exit from the RAND HIE. The analysis is concerned with any changes in the effect of the coinsurance rate or the general health index. The general health index before matching was not statistically significant in predicting joint pain or ECG abnormalities at the exit. After matching had removed 5% of the sample, the general health index was statistically significant at the 5% level for predicting ECG abnormalities at the exit and at the 10% level for predicting joint pain at the exit. Before matching, the free care plan and the 95% coinsurance rate plan showed no difference in the amount of smoking at the exit. After matching had removed 4% of the sample, the plans were statistically different. The direction of the coefficients indicated that the free care plan was more likely to have less smoking at the exit, and the 95% coinsurance plan was more likely to have more smoking at the exit.

1.6 Discussion

Using optimal nonbipartite matching along with a causal framework for addressing potential refusal bias can benefit researchers looking at complex experiments without a simple one-control and one-treatment design. The improvement in the estimates of the arc elasticities shows another benefit of using the optimal nonbipartite matching method to model dependence in a dataset, regardless of the concerns related to refusal bias. The use of matching did reduce the potential for pre-treatment health being predictive of plan assignment while only losing 4% of the sample. It is an acceptable trade-off if the assumption of ignorability is strengthened in the process. The modeling of medical expenditure data requires careful consideration of the data-generating process. If researchers intend to use simple OLS on logged dependent variables of medical expenditure, then it should be standard practice to report a misspecification test to reassure readers that the results are robust to a certain level. The results in (Aron-Dine et al., 2013) suffer from misspecification, and the elasticity of the coinsurance rate was 3.7 times more elastic than the correctly specified GLM model. Did the RAND HIE's main expenditure and health outcome results change after using matching to control for imbalance and bias? Yes, some of the results are slightly different, but the magnitude of the changes is not likely to make a significant difference to the average participant in the study. In looking to future areas of research, the significant difference in characteristics of the participants removed by matching could indicate that the results for subgroups might be more pronounced. Regarding health outcomes, some participants had no information about the health outcomes at enrollment. Restricting the matches to participants who had information on health outcomes at enrolment could allow for better balance and potentially different results. Finally, testing with simulated data could benefit the causal framework presented to address refusal bias. This would help determine the degree to which the identification strategy presented can reduce the proposed potential bias.

Chapter 2 The Relationship between Rural Hospital Closures and Consumer Financial Debt

2.1 Introduction

Rural hospital closures in the United States have become a growing concern in recent years. Between January 2008 and August 2016, 118 rural hospitals closed, potentially impacting rural communities.[20] These impacts include decreased access to emergency care, primary care, and healthcare providers and negative impacts on personal financial health, economic development, and local government spending. This paper focuses on the impact of rural hospital closures on consumer financial health, specifically financial debt.

In addition to healthcare production, hospitals provide other economic benefits for the community. Therefore, the closure of a hospital has the potential to impact the community in several ways. Firstly, there are direct employment effects. According to Germack et al. (2019), rural hospital closures have led to an average annual reduction of 9.2% in the supply of physicians at the county-level. Additionally, specialized hospital staff, such as specialized nurses or physician assistants, are more likely to leave the local economy, export their highly specialized skills, and receive higher average wages (Germack et al., 2019). The loss of the hospital and any high-income tax-base workers also has implications for economic development and the stability of local government revenue.

[20] According to the North Carolina Rural Health Research Program. There were also 129 closures since 2005, which implies the closures are occurring at an increasing rate. 10.875 vs. 8.4 hospital closures per year (2018 to 2010 vs 2009 to 2005). The methods of determining a rural hospital closure is discussed in the Data section.

One method of capturing the impact of the hospital on the community is by examining the impact of the closure on financial health. The hospital closure could impact the community’s financial health in various ways. First, there is the loss of income for individuals and firms that rely on the hospital as an employer, purchaser of goods and services, or as an entity that generates traffic to the community. In addition, the loss of the hospital could increase the cost of obtaining health care. Hospital closures are associated with increased travel distance and costs, reduced quality of care, and increased mortality rates for elderly patients (Kralewski & Carter, 1992, Becker & Petersen, 2015, Hatfield & McWilliams, 2016). Elderly people in rural areas with hospital closures and longer travel distances have more prominent declines in healthcare utilization among elderly Medicare beneficiaries(Cai & Kuo, 2019). Furthermore, creditors might not be inclined to extend credit if the perceived risk of default increases from the hospital closure. Potential causes of higher perceived default risks include declining income, falling home prices, and higher local unemployment rates.

The data used in identifying hospital closures comes from several sources, including government data from the Centers for Medicare & Medicaid Services (CMS), data from the North Carolina Rural Health Research Program at the University of North Carolina, and public data from various newspaper articles to ensure hospitals were permanently closed between 2005 and 2016. The final list of hospital closures only includes emergency care short-term hospitals (explain what that is). The financial data comes from the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP) dataset, which is an anonymous 5% random sample of the United States population with a credit history. This individual-level data is updated quarterly and contains financial information for accounts such as auto debt, mortgage debt, and credit card debt.

The two methods used in this paper will be a difference-in-difference (DID) approach and an event study to examine hospital closures' dynamic effect over time. Both methods use individual fixed effects along with year-by-quarter interacted fixed effects. The outcome variables are examined over several different age groups as people use debt early in life to smooth consumption and pay off the debt later in life when income levels peak but before retirement. The analysis looks at two geographic levels County and Hospital Service Areas (HAS). An HSA is a geographic area in which a hospital provides medical care. The HSA area was reassembled using zipcode level information.

To our knowledge, only one other paper investigates the relationship between consumer financial health and rural hospital closures (Alexander & Richards, 2021) and finds little to no effect on aggregate county-level consumer financial health. This research, which explores individual level data, suggests that rural hospital closures have a statistically significant and negative impact on consumers' financial health, leading to increases in the consumers' amount of severely delinquent debt. The treatment effects of a rural hospital closure on severely delinquent debt are more prominent within the hospital service area (HSA) than at the county level.

2.2 Literature Review

When looking at how a hospital closure would affect a local economy, it is helpful to look at the literature on the general effects of a firm closure on the local economy.

2.2.1 Non-Hospital Closures effects

One of the earliest works looking at the impact of firm closures on the local economy considered the case of the closure of a major electrical equipment producer (Cole, 1987). They estimated the net impact of the closure in the first year to be 1,808 job losses, $37.5 million in lost wages, and $17.5 million in lost government.

The literature on the impact of military base closures on the local economy has shown mixed results. One paper looking at military base closures from 1970 to 2000 (Hooker & Knetter, 2001) found no significant impact on job-loss and per-capita income. Military personnel contractions between 1988 to 2000 (Zou 2017) analyzed with a synthetic control method found decreases number of civilian job, number of private business establishments, and landowner rents. Military base closures are different from hospital closures in that the Office of Economic Adjustment (OEA) provides technical and financial assistance to the affected communities by military base closures. The literature mentions this as a potential reason for minimal impacts from military base closures.

The firm closure literature has also examined the effect of the coal boom and bust in the 1970s and 1980s (Black et al., 2005). Mining wages grew more during the boom than non-mining wages, while mining and non-mining wages declined by around 9% during the bust of the coal industry. Consequently, the poverty rate, which had declined substantially during the coal boom, grew significantly during the coal bust. This spillover effect on the local economy is relevant to the impact of hospitals on the local economy. Plant closures between 1986 and 2002 in Denmark were linked to higher mortality and hospitalization rates (Browning & Heinesen, 2011) Other research found that mass layoffs are linked to lower employment prospects and persistent wage loss (Gathmann et al., 2014).

2.2.2 General Job Displacement Effects

Another area of the literature that is relevant focuses on earning losses and other financial impacts due to job displacement. Job displacement has a statistically significant and lasting negative impact on the long-term wage earnings of displaced workers (Ruhm, 1991). These long-term earning losses impact workers in all industries and earning losses were on average 25% of pre-displacement earnings for high-tenure workers (Jacobson et al., 1993). In the case of mass layoffs, the earning losses from job displacement were around 32% to 33% initially and 12% to 15% earning losses after six years (Couch & Placzek, 2010). It would be reasonable to assume that hospital closures would have lasting impacts on direct and indirect labor, especially in rural areas as hospitals can be a sizeable per-capita employer.

It is reasonable to assume that job displacement and adverse economic shocks would negatively impact consumers financial health in ways besides earnings. Unsecured debt has been shown to increase for households in the second and third deciles of assets in response to unemployment-induced earning losses (Sullivan, 2008). This implies that some individuals use the credit market to smooth consumption, while others are unaffected or may have limited access to such markets. Furthermore, Banerjee & Canals-Cerdab, (2012) found that an economic downturn and increased unemployment resulted in an increased probability of transition into delinquency and default.

An unemployment spell increases the likelihood of bankruptcy for ages younger than 48 (citation?). Layoffs in manufacturing are 40% more likely to result in bankruptcy than non-manufacturing job layoffs. The proposed reason layoffs affect manufacturing jobs more severely is that having specialized human capital creates a negative incentive to switch to other sectors of the economy (Keys, 2018). While manufacturing and healthcare are different and distinct industries, they are similar in those employees in both industries generally have high levels of specialization. Given the higher level of specialization among hospital employees, it is reasonable to assume that hospital employees would sell their homes quickly to move to new employment or go bankrupt from the loss of income during the transition to new employment. The resulting fall in home prices would cause a change in locals' marginal propensity to consume, which would lower aggregate demand(Aladangady, 2017).

2.2.3 Reasons for Hospital Closures

One of the earliest works on the determinants of hospital closures found that size-adjusted hospital occupancy, occupancy rates, chain affiliation, MediCal patient proportions, complex patient care mixture, and crowded areas were all statistically significant in predicting hospital survival (Mobley & Frech, 1994). The form of ownership has also been shown to affect the likelihood of hospital closure, with for-profit hospitals being more responsive to demand and secular nonprofit hospitals being least responsive (Hansmann et al., 2003). State regulations to lower costs are another reason hospitals could close. However, state regulations have been shown to have little effect on controlling hospital costs (Antel et al., 1995; Sloan, 1981). The urban hospitals that close tend to be higher cost and less efficient. Harrison (2007) found that higher average length of stay was an indication of inefficiency and associated with closure and higher local market competition was associated with a higher probability of exiting the market.

Harrison (2007) uses a competing risk hazard model to examine hospital closures. She found the statistically significant factors for closures were the number of beds, number of Medicaid inpatient days, number of Medicare inpatient days, length of stay, for-profit status, urban status, and the number of hospital beds relative to the market area.

The closure of trauma centers has been shown to be influenced by similar factors, including profit margin, better than average reimbursement from Medicare, minority population share, and penetration of health maintenance organizations (Shen et al., 2009). The factors associated with Emergency Department closures are slightly different and include safety-net status, for-profit ownership, low-profit margins, the proportion of residents in poverty, and local market competition (Hsia et al., 2011).

When looking at the ACA Medicaid expansion effect on hospital financial performance and closure rates, the main results were hospitals in expansion states were 84% less likely to close than in non-expansion states (Lindrooth et al., 2018). Other factors affecting closure were similar to the previous literature on hospital closure.

(Holmes et al., 2017) found similar results of Medicaid expansion when examining the impact on inpatient services.

2.2.4 Effect of Hospital Closures on Local Economy

The effect of rural hospital closures on local economies have shown mixed results. Some papers found no significant effect (Hart et al., 1994) (Pearson, 2002) (Ona et al., 2007). While others (Holmes et al., 2006; Probst et al., 1999) have found some significant effects on per-capita income and unemployment by taking a different approach than the typical I/O analysis[21]. The most recent paper (Holmes et al., 2006) examined hospital closures between 1990 and 2000 and found that a community with a sole hospital closure had a 4% decrease in per-capita income, but no long-run effect on communities with alternative sources of hospital care[22]. They note that random shocks to a community's local economic health might impact the rural hospital's viability. The log per-capita income decreased by 0.9% and unemployment increased by 0.3%. A more recent attempt using a DID model with propensity score matching (Manlove & Whitacre, 2017) looked at 76 hospital closures' economic impact between 2010 and 2014. They found statistically significant increases in the poverty level and

[21] A typical I/O analysis normally looks at the change in employment of both direct and indirect job. In simplest terms, the typical I/O approach estimates the direct and indirect job losses from a hospital closure no longer purchasing inputs from the local economy and the loss of the money multiplier effect from no output produced by a close hospital. This make the I/O analysis sensitive to the data used in determining purchasing patterns, which is typically averaged of the entire U.S. population.

[22] They dismissed the I/O analysis approach to hospital closures in favor of a multivariate regression approach for four reasons. First, I/O analysis does not provide a measure of precision in the estimation. Second, the inputs are based on national purchasing trends and not local purchasing trends when estimating the economic multiplier. Third, the approach uses aggregate measures such as total income measure instead of per-capita income. Finally, an I/O analysis approach treats the county as an isolated economy and ignores market area considerations, leading to biased estimation.

unemployment rate, while finding statistically significant decreases in median income, median rent, and working at home. Regarding health outcomes, hospital closures are associated with increased mortality rates from heart attacks and motor vehicle accidents (Bertoli & Grembi, 2017; Buchmueller et al., 2006). Additionally, hospital closures were associated with increased travel distance and costs, reduction in the quality of care, and increased mortality rates for elderly patients (Kralewski & Carter, 1992, Becker & Petersen, 2015, Hatfield & McWilliams, 2016).

According to several studies, hospital closures can devastate small and rural communities. The closure of hospitals can lead to a decline in economic activity in the surrounding areas, resulting in job losses and reduced consumer spending. For example, a study by (Radey and Abraham, 2010) found that hospital closures in small communities led to declining local employment and income. Furthermore, hospital closures can result in reduced access to healthcare services for residents, particularly those who are elderly or low-income, leading to poorer health outcomes. In addition, (Courtemanche et al., 2019) found that rural hospital closures were associated with increased mortality rates in affected areas. The closure of hospitals can also have a ripple effect on other healthcare providers, leading to increased demand for services at remaining hospitals and clinics, which can strain their resources. Hospital closures can have negative economic and health consequences for communities, particularly those already economically vulnerable.

When examining how urban hospital closures would affect the remaining hospitals' operating efficiency in the local market (Lindrooth et al., 2003), closed hospitals were found to be less efficient at baseline (2 years before closure), and local competitors saw a decrease in costs due to an increase in inpatient admissions and emergency room visits. Thus, it appears that hospital closures in urban areas can improve the community's welfare, in contrast to what is observed in rural areas. To account for any potential spillover effect of hospital closure on other local hospitals' performance, a matching approach using distance was employed to avoid such effects.

2.3 Data

The data section is divided into hospital closure data and financial credit data.

2.3.1 Hospital Closure Data

The information on hospital closures and conversions comes from several sources. Information on the location (address level), type of service, closure, conversions, and other important characteristics of hospitals (beds, etc.) was obtained from the Centers for Medicare & Medicaid Services Provider of Services (CMS POS) data. The CMS POS data is then combined with the CMS Healthcare Cost Reporting Information System (HCRIS), which provides information on revenue, cost, wages, number of employees, and a second closure variable. The North Carolina Rural Health Research Program at the University of North Carolina has compiled a list of hospital closures that occurred from 2005 to the present, which was combined with the first two datasets to provide more detailed information on closures, closure timing, and conversions. Additionally, another dataset of hospital closures used in this paper, covering the period from 2008 to 2016, was obtained via Lindrooth et al., 2018[23]. Finally, the potential rural hospital closure list is checked using internet searches for news articles confirming the closure date and if the hospital closure became a permanent closure during the panel from 2005 to 2016.[24] The choice of permanent closure provides the most straightforward treatment effect on the local economy from a hospital closure as it is unclear from the literature how a hospital conversion to a different type of medical facility would impact the local economy. The final list of hospitals only includes emergency care short-term hospitals.

This analysis focuses on rural hospitals at both the county and hospital service areas (HSA) levels. The 2013 CDC urban-rural classification is used to identify rural counties and the rural-urban commuting area (RUCA) from the United States Department of Agriculture is used to identify rural zip codes. The HSA is a collection of zip codes, so determining how to classify an HSA was determined by having zero zip codes considered urban. This classification method resulted in 62 counties and 66 HSA's affected by hospital closures in rural areas. The controls in hospital closures cases are taken from counties or HSAs with at least one active short-term hospital.

[23] Dr. Lindrooth kindly provided the cleaned hospital closure data that has been updated from the original paper.The data was previously hand-checked, and included for a secondary checks on hospital closures, hospital closure timing, and hospital conversions.

[24] In the event that no news articles could be found on a provider and the other sources of data were consistent in closure status and date, then remaining two checks were to look for the same street address existing in years after closure within the datasets and to look at the address using google maps to determine if another facility was placed in approximately the same location.

2.3.2 Financial Credit Data

The credit data for 2005-2016 is obtained from the Federal Reserve Bank of New York's Consumer Credit Panel/Equifax (CCP) dataset, which is an anonymous 5% random sample of the United States population with a credit history and a social security number on file. There is a large amount of information on debt in the CCP dataset. In this paper, the focus in on delinquency in overall debt as well as in mortgage, revolving, and auto.

2.3.3 Financial Variable Terminology

A revolving account has a debt with variable debt payment amounts (credit card). An open account has debt that requires full payment each time a statement is received, typically monthly, and an example would be a charge card. An installment account has debt that has payments in fixed installments. A typical example is a 30-year fixed-rate mortgage. The term tradeline describes an account with a line of credit such as a credit card, car loan, car lease, or mortgage. In this paper, the terms mortgage, revolving, and auto is made up of several different tradeline accounts. The composition of the debt terms is described below.

The descendent tradelines are aggregated to the simpler terms that have similar tradelines in each group. For example, mortgage debt includes revolving home equity line of credit (HELOC) accounts, first mortgage accounts, and second mortgage accounts. These accounts are similar in that they involve either obtaining credit to purchase a home or using the equity in a home to obtain credit. In the case of revolving accounts, each tradeline represents access to a credit account, but are owned by different industries such as retail department stores, credit unions, banks, or financial institutions. The revolving debt represents credit cards, secured credit cards, charge cards, and other small consumer finance loans less than $20,000. The auto debt is composed of automobile loans, which can be either financed through banks and other financial institutes or through auto financing.

If any tradeline account becomes 90 days or more past due on payment, it is considered to be in serious delinquency or to be a severely delinquent account. It can have a serious negative impact on a consumer’s credit report, and thus, their ability to borrow in the future (Perlmeter, 2018) The Equifax Risk Score is a number that ranges from 280 to 850, with higher scores implying a lower credit risk for lenders. The Equifax Risk Score is based on an algorithm and predicts the probability of severe delinquency in the next 24 months.

The other concerns for financial health are foreclosures and bankruptcies. A bankruptcy in particular can severely restrict a consumer’s ability to borrow from the credit market and the court process may take months or even years to finish. Most negative credit information will stay on a credit report for up to 7 years but a bankruptcy can remain on a credit report for up to 10 years.

2.3.4 Final Consumer Panel

The hospital closure data is merged with the CCP by county and HSA. The sample includes individuals over age 26, who are not eligible to be covered by their parent’s insurance, and under age 75, due to concern over identification of mortality in the CCP. The data is provided quarterly, and includes the years 2005 through 2016. A consumer must be in the panel for at least four quarters without gaps to avoid potential concerns of fraud. Consumers with severely delinquent status or bankruptcy six quarters before the start of entering the panel are dropped to focus on the financial consequences of the hospital closure. Individuals with severe delinquency cannot smooth consumption and take on debt, thus potentially understating the impact of the closure. In the event of bankruptcy, the consumer's remaining observations are removed because their ability to obtain new credit is limited. Only individuals who do not move during the panel are included in the final analysis to avoid migration in and out of the treatment area. This step is done for both the county and HSA analysis creating two datasets. Given the large sample size in the CCP, a 20% random sample of the remaining consumers from both the county and HSA is utilized due to computational limitations. The final sample size is listed in table 2.1.

TABLE 2.1
Final Sample Sizes Of Individuals By Area Type

	County	HSA
Total	166,727	156,197
Treated	8,332	6,186
Controls	158,395	150,011

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax

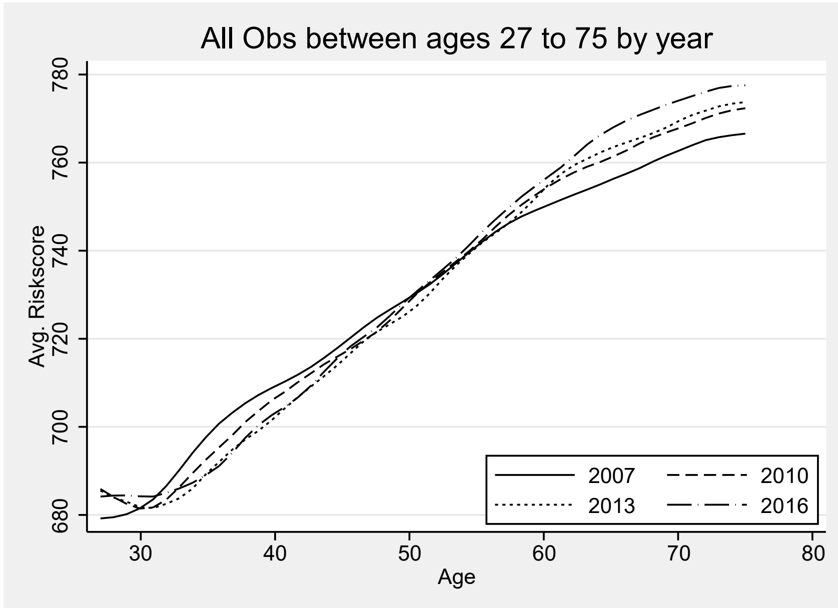
2.3.5 Financial Debt Characteristics

There are certain aspects of the financial credit data that are informative and thus, helps to understand this paper's methods and results. Examining the median Equifax Risk Score for consumers with at least one open account of each type of debt provides an idea of how restrictive the credit market is with each type of debt.

The following graphs are calculated at the county-level and HSA-level with quarterly values, with similar results.[25] The graphs are kernel-weighted local polynomial regressions and can be viewed as a moving average. The graphs have the years 2007, 2010, 2013, and 2016. 2007 is the first year presented as the requirement to remove the first six quarters of bankruptcy, and severely delinquent debt would skew the graphs. In Figure 2.1, individuals have a Equifax Risk Score that increases with age regardless of the year chosen. It is reasonable to assume that older consumers have longer credit histories and have paid down a larger portion of their total debt, which contributed to the increase in Equifax Risk Scores.

Figure 2.1

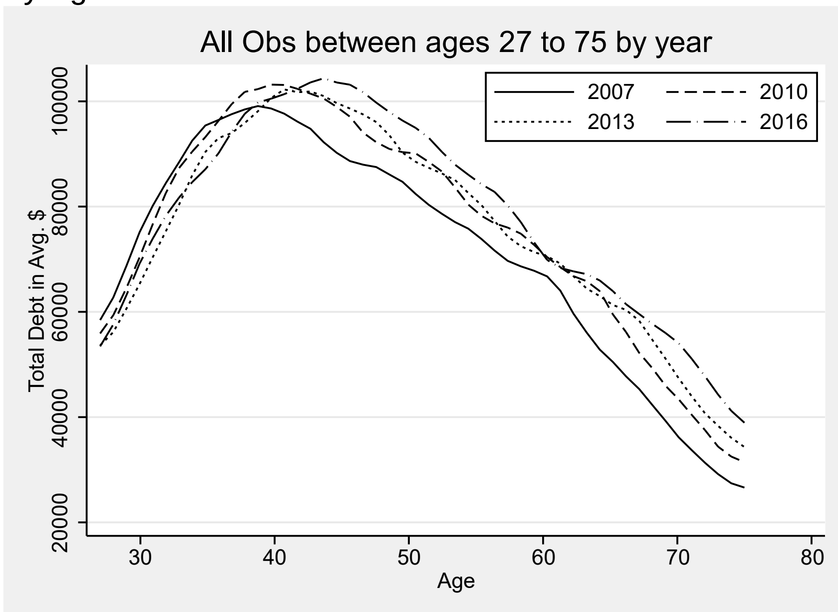
Average County-level Quarterly Equifax Risk Score by Age.



Source: *Federal Reserve Bank of New York Consumer Credit Panel/Equifax*

Figure 2.2 represents the average total amount of debt for consumers across the lifecycle, ages 27-75, given that they have positive debt levels. The graph shows that consumers at age 27 start with around $55,000 to $60,000 in debt. The consumers accumulate debt from age 27 until a peak of approximately $100,000 between ages 40-45. The amount of debt continues to decline after the peak until age 75, which is the last observed in the panel.

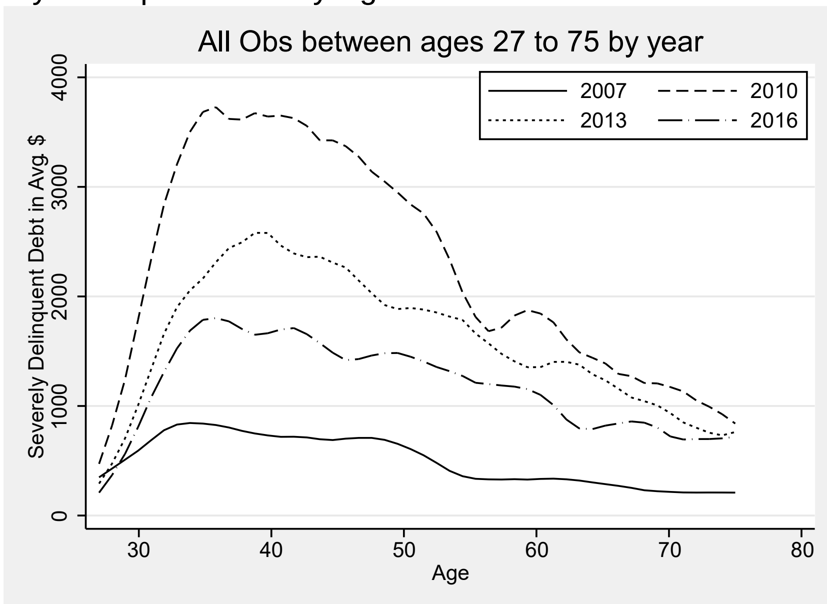
Figure 2.2
Average Debt by Age and Year



Source: *Federal Reserve Bank of New York Consumer Credit Panel/Equifax*

Figure 2.3 represents consumers' average amount of severely delinquent debt for consumers with positive debt levels between ages 27 and 75. The Great Recession of 2008 is apparent in the graph, with low levels of severely delinquent debt in 2007 and a significant increase by 2010 and subsequent decreases in 2013 and 2016. The Figure 2.2 shows that consumers at age 27 have an average of between $300 to $500 in severely delinquent debt. On average, consumers' severely delinquent debt increases at age 27 until it peaks around ages 35-40. The amount of severely delinquent debt declines from the peak until age 75, the last observed age.

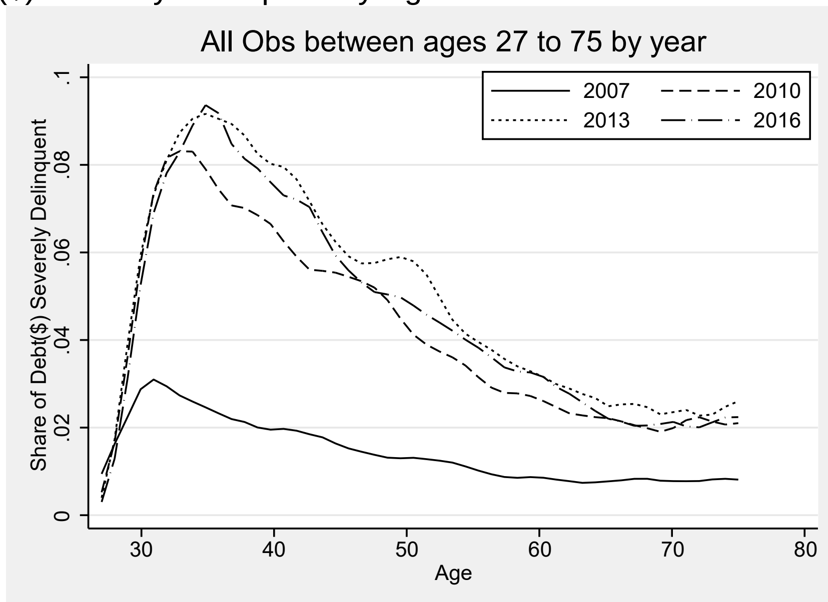
Figure 2.3
Average Severely Delinquent Debt by Age



Source: *Federal Reserve Bank of New York Consumer Credit Panel/Equifax*

Figure 2.4 represents the share of consumers' debt that is severely delinquent debt for consumers with positive debt levels between ages 27 and 75. This can be considered more representative and less prone to outliers than the amount of severely delinquent debt. The Great Recession of 2008 is apparent in the graph, with low levels of severely delinquent debt in 2007 with around 3% of the share of debt being severely delinquent and a significant increase by 2010 and later years to around 9%. Figure 2.4 shows that consumers between 30 and 40 have the highest share of debt severely delinquent. The trend after the peak declines until around age 70, when the share of debt severely delinquent stays constant.

Figure 2.4
Share of Debt($) Severely Delinquent by Age



Source: *Federal Reserve Bank of New York Consumer Credit Panel/Equifax*

The summary statistics for the 20% random sample is in Appendix B, Table B.1. The average person has 4.75 accounts, or tradelines, with an average of 0.876 accounts in severe delinquency. This represents just under 3% of all accounts in delinquency, on average. The average person holds almost $60,000 in debt, with an average of $982 in delinquency. Thus, the average individual has 2.5% of their debt in delinquency. The average Equifax Risk Score is 734.

The summary statistics by treatment status are presented in Appendix B, Table B.3. Generally, the treated have slightly fewer accounts and a lower amount of debt than the control group, but a slightly higher share of their accounts and their debt in severe delinquency. The treated group, with an average of 722, has a lower Equifax Risk Score than the control group.

2.4 Methods

The analysis of the effects of rural hospital closures on consumers' financial health will mainly consist of two main estimation methods. The two methods used in this paper will be a difference-in-difference (DID) approach and an event study to examine hospital closures' dynamic effect over time.

Each outcome variable is estimated using several different age groups. The age groups will capture how individuals at retirement age with Medicare are impacted differently from working-age individuals. This effect is captured using ages 27-64 and ages 65-75. The second set of age groups was designed from the financial debt characteristics in section 3.2.3. All model looks at the following five age groups: 27-44, 27-64, 27-75, 45-64, and 65-75.

Another concern is that individuals with lower Equifax Risk scores might be particularly at risk of being impacted by a rural hospital closure since they are already more credit constrained. In addition to the age group, the data is divided into groups based on Equifax Risk Scores, using the structure found Argys et al.(2017). All models use the following Equifax Risk Score groups: 280-659, 660-739, 740-850, and 280-850. Instead of estimating separate models for each Equifax Risk Score group, an overall model with all individuals in the sample is run as one model. The other models interact with a categorical variable for the three Equifax Risk Score groups (280-659, 660-739, 740-850) with the variable of interest. The categorical variable uses the highest Equifax Risk Score group (740-850) as the base variable.

2.4.1 Difference-in-Difference

The DID approach was originally conceived to address the cholera epidemics in London (Snow, 1855). There was a significant decline in cholera cases in the areas, with cleaner water coming from further upstream. The study provided simple and effective solutions for preventing cholera by hand washing and boiling water for drinking and culinary purposes.[26]

Recent papers on hospital closures and the effect of hospital closures use the DID approach (Friedman et al., 2016; Lindrooth et al., 2018; Manlove & Whitacre, 2017). The literature on the effect of closures does present reasons to avoid I/O analysis (Holmes et al., 2006). The main issues are the lack of precision and the use of national purchasing trends instead of local purchasing trends in estimating the jobs multiplier.

The generalized DID method is used for analysis as the treatment event occurs at different times. The inclusion of individual fixed effects removes the treatment dummy, as typically seen in the standard model. Including year and quarter interacted fixed effects removes the typical post dummy as typically seen in the standard model. This leaves the generalized DID model with only a treatment post variable, which is named $ClosurePost$ in the following model.

The Generalized DID model:

[26] In-depth analysis of the DID approach (Angrist & Krueger, 1999; Angrist & Pischke, 2009; Cameron & Trivedi, 2005; Morgan & Winship, 2007) are good references. A useful reference for DID practices with in health policy use (Wing et al., 2018).

$$y_{iq} = \beta_0 + \alpha_i + Year_y * Qtr_q + \beta_1 ClosurePost_{iq} + \varepsilon_{iq}$$

y_{iq} is the financial outcome of individual i in quarter q. β_1 is the effect of interest, it is the DID causal effect of hospital closure on the financial outcome y. $ClosurePost_{iq}$ equals one if a permanent hospital closure has occurred. Since individuals cannot move during the panel, the geographic subscript is omitted. The tables in the results section will identify individuals grouped by either county or hospital service area.

The generalized DID model is modified by interacting $ClosurePost_{iq}$ with the Equifax Risk Score categories $Riskcat_{iq}$. This interaction will be represented by the new variable $RiskDID_{iq}$ Furthermore, it will use superscripts to indicate the risk categories and treatment status. The Equifax Risk Score groups will be referred to as Risk Category 1 280-659), Risk Category 2 (660-739), and Risk Category 3 (740-850). $RiskDID_{iq}^{0r1}$ takes the value of 1 if the individual is a control case with a Risk Category 1 and 0 if it is a control case with a Risk Category 3. $RiskDID_{iq}^{0r2}$ takes the value of 1 if the individual is a control case with a Risk Category 2 and 0 if it is a control case with a Risk Category 3. $RiskDID_{iq}^{1r1}$ takes the value of 1 if an individual is a post-treatment case with a Risk Category 1 and 0 if it is a control case with a Risk Category 3. $RiskDID_{iq}^{1r2}$ takes the value of 1 if an individual is a post-treatment case with a Risk Category 2 and 0 if it is a control case with a Risk Category 3. $RiskDID_{iq}^{1r3}$ takes the value of 1 if an individual is a post-treatment case with a Risk Category 3 and 0 if it is a control case with a Risk Category 3 .

The Generalized DID model with Equifax Risk Score Categories:

$$y_{iq} = \beta_0 + \alpha_i + Year_y * Qtr_q + \beta_1 RiskDID_{iq}^{0r1} + \beta_2 RiskDID_{iq}^{0r2} + \beta_3 RiskDID_{iq}^{1r1} + \beta_4 RiskDID_{iq}^{1r2} + \beta_1 RiskDID_{iq}^{1r3} + \varepsilon_{iq}$$

In this model β_1 can be interpreted as the difference outcomes between control individuals with Risk Category 1 relative to control individuals with Risk Category 3. β_2 can be interpreted as the difference outcomes between control individuals with Risk Category 2 relative to control individuals with Risk Category 3. β_3 can be interpreted as the difference outcomes between treated individuals with Risk Category 1 relative to control individuals with Risk Category 3. β_4 can be interpreted as the difference outcomes between treated individuals with Risk Category 2 relative to control individuals with Risk Category 3. β_5 can be interpreted as the difference outcomes between treated individuals with Risk Category 3 relative to control individuals with Risk Category 3. An important comparison is a difference between β_1 and β_3 which is the difference in the effect of a hospital closure on the individual with Risk Category 1.

2.4.2 Event Study

The event study model allows for different effects of hospital closures in the periods before and after the hospital closure has occurred.

The Event Study model is as follows:

$$y_{iq} = \beta_0 + \alpha_i + Year_y * Qtr_q + \beta_{21-} ClosurePost_{iq} + \sum_{j=-20}^{j=20} \beta_j \, ClosurePost_{iq} + \beta_{21+} ClosurePost_{iq} + \varepsilon_{iq}$$

It is similar to the generalized DID model but with time period dummies. The coefficient β_{21-} captures all quarters that are lagged 21 quarters or more from the time of the closure. The coefficient β_{21+} captures all quarters that are led 21 quarters or more from the time of the closure. The omitted time period is the period of closure. A second model interacts with each of the time dummies with the Equifax Risk Score categories to obtain an idea of the dynamic of a hospital closure.

2.5 Results

2.5.1 DID General and Equifax Risk Score Category Group Results

The simple DID model results show that rural hospital closures significantly impact consumer finances. The general results are listed in Appendix table B.6. For the model with all age groups; there was general support for an overall increase in the share of accounts and share of debt in severely delinquent debt for all tradeline, mortgage, and revolving accounts. In addition, as shown in Appendix Table B.7, rural hospital closures are associated with an increase in foreclosures. The general outcome is that individuals in the treated group have poorer financial outcomes relative to the control group.

The DID results at the HSA level are in Table B.15 and have some similarities with the county-level results. The all-age group model for all tradelines were more statistically significant for increases in the amount of debt in severe delinquency. However, the share of accounts in severe delinquency, the share of debt in severe delinquency, and the number of accounts in severe delinquency became statistically insignificant for the HSA-level results.

The all tradelines model for ages 27 to 54 had the share of accounts in severe delinquency become more statistically significant in the opposite direction, indicating negative effects on severely delinquent debt. The share of debt in severe delinquency and the number of accounts in severe delinquency showed statistically significant and negative effects in the HSA-level results compared to no statistically significant results in the county-level model. The amount of debt in severe delinquency was statistically significant at the 1% level in both models with negative outcomes.

The all tradelines model for ages 55 to 64 was similar in general, except that amount of debt in severe delinquency was strongly statistically significant and had a positive effect in the HSA-level model compared to no statistically significant results from the county-level model. The all tradelines model for ages 55 to 64 became statistically insignificant for the amount of debt in severe delinquency and statistically significant for the number of accounts in severe delinquency with a negative outcome.

The mortgage tradeline model for all ages had the share of accounts and the share of debt in severe delinquency become statistically insignificant. The increase in the number of accounts in severe delinquency was less statistically significant, while the increase in the amount of debt in severe delinquency switched to statistically significant in the HSA-level model, and the amount was larger in magnitude. The mortgage tradeline model for ages 27 to 54 stayed statistically significant, and both the county-level and HSA-level models show negative outcomes for all four measures. The mortgage tradeline model for ages 55 to 64 was unchanged, with no statistical significance for all four measures. The mortgage tradeline model for ages 65 to 74 had no statistically significant results for the share of accounts and the share of debt in severe delinquency for the county-level and HSA-level models. The number of accounts in severe delinquency was statistically significant, with a slightly positive outcome in the

HSA-level model, while the county-level model was not statistically significant. The amount of debt in severe delinquency was statically insignificant for the HSA-level model.

The auto tradeline model for all ages and ages 27 to 54 was statistically insignificant at the HSA-level compared to statistically significant with positive outcomes at the county-level. The auto tradeline model for ages 55 to 64 had the share of account in severe delinquency as statistically insignificant in the HSA-level model, with the same results as the county-level model. The share of debt severely delinquent because statistically significant, with a slightly positive outcome at the HSA-level compared to no statistically significant results at the county-level. The number of accounts in severe delinquency results was the same for both HSA-level and county-level models, with a slightly positive outcome and statistical significance. The amount of debt in severe delinquency was statistically significant, with positive outcomes at the HSA-level, while the county-level model showed no statistical significance. The auto tradeline model for ages 65 to 74 showed statistically significant negative outcomes for all four measures at the HSA-level, while the county-level results were statistically insignificant for all four measures.

The revolving tradeline model for all ages was statistically significant, with a negative outcome for the amount of debt in severe delinquency in the HSA-level and county-level models. The share of accounts in severe delinquency was a statistically significant and positive outcome at the HSA-level, while the county-level result was a statistically significant negative outcome. The share of debt in severe delinquency was statistically insignificant at the HSA-level, while the county-level result was a statistically significant negative outcome. The number of accounts in severe delinquency was statistically significant, with a positive outcome at the HSA-level, while the county-level result was statistically insignificant.

The revolving tradeline model for ages 27 to 54 was statistically significant for the share of debt and amount of debt in severe delinquency, with negative outcomes for both the HSA-level and county-level models. The number of accounts in severe delinquency was statistically insignificant for both HSA-level and county-level results. The share of accounts in severe delinquency was statistically significant, with negative outcomes at the HSA-level, while the county-level result was statistically insignificant. The revolving tradeline model for ages 55 to 64 had statistically insignificant results for both the share of accounts and the share of debt in severe delinquency at the HSA-level and county-level models. The number of accounts in severe delinquency was statistically significant, with a positive outcome for both HSA-level and county-level models. The amount of debt in severe delinquency was statistically significant, with a positive outcome for the HSA-level model, while the county-level results were statistically insignificant. The revolving tradeline model for ages 65 to 74 was statistically insignificant for all four measures at the HSA-level, while the county-level results showed that only the amount of debt was statistically significant with a positive outcome.

It can be informative to see how the DID results are impacted differently by Equifax Risk Score categories. The Equifax Risk Score categories are described in detail in Table B.9 and are separated into three groups, as discussed above and shown in Table B. 9. In general, as shown in Appendix B, Tables B.10-B.14, individuals in Risk

Category 1 had poorer financial health outcomes across all four measures of severe delinquency (share of accounts and debt, number of accounts, and amount of debt), foreclosure, and bankruptcy than the individuals in the control group in Risk Category 3. Furthermore, the effect is larger for the treated Risk Category 1 than the control Risk Category 1 across all debt categories and all age groups. This suggests that the impact of hospital closures is felt more strongly in the already financially vulnerable group.

2.5.2 Event Study General and Age Group Results

The Event Study results for all severe delinquency outcomes and all ages are presented in Appendix C. Figures C.1 - C.5. While not as statistically strong as the Difference-in-Difference results, the event studies provide insight into the timing of the delinquencies, suggesting the largest impact occurs approximately two years after the hospital closure. Interestingly, the event study analysis shows the most significant results for the 65-74-year-old age group. There is strong evidence that the revolving and, to a lesser degree, the mortgage accounts for the older age groups were significantly impacted by the hospital closure. This suggests that the increased cost of access to medical care may be a major contributor to the decline in their financial health.

2.6 Conclusion

In conclusion, this paper has examined the impact of rural hospital closures on consumer financial health, focusing on the effects of hospital closures on severe delinquent debt. The findings of this study suggest that rural hospital closures have significant negative impacts on consumer financial health, particularly for those in the low Equifax Risk Score category and those aged 65 to 75. The negative impacts for 65 to 74 include both increases in severely delinquent debt and foreclosure rates. The results of the difference-in-difference and event study methods provide insight into the timing and severity of these impacts, indicating that it may take time for the additional cost of healthcare to translate into severe delinquency for some groups.

These results have important implications for policymakers and healthcare providers, as they suggest that hospital closures not only lead to decreased access to healthcare but also have far-reaching economic impacts on rural communities. Moreover, as these events can lead to increased mortality rates (Argys et al., 2016), efforts to prevent hospital closures and support the financial stability of rural hospitals may provide additional measures to protect the health and well-being of rural residents.

Future research may consider the impacts of hospital closures on other economic factors, including employment and income levels, and how these impacts interact with consumer financial health. Additionally, further investigation into potential policy solutions and interventions to support rural hospitals' financial stability and access to healthcare may be warranted. Overall, this study contributes to the growing body of research on the impact of hospital closures on rural communities and highlights the need for continued attention and support for rural healthcare systems.

Appendices

Appendix A. Chapter 1 Supplemental Tables and Figures

Table A.1
Matching variables

Variable Name	Description	Type
Age	Age at enrolment	Continuous
Income	Family income	Continuous
Female	Dummy for female	Discrete
Black	Dummy for race	Discrete
Educdec	Education of decision maker	Continuous
Child	Current age less than 18	Discrete
Num	Family size	Continuous
MHI	Baseline mental health index	Continuous
Xghindx	Imputed general health index	Continuous
Xghindx2	(Xghindx)^2	Continuous
Disea	Count of chronic diseases	Continuous
Tookphys	Took baseline physical exam	Discrete
Ghinnm	General health index not missing	Discrete
Afairnm	Income not missing	Discrete

Table A.2
Standardized Difference in Sample Before Matching

1st plan co-pay		0%	0%	0%	0%
Compared to		**25%**	**50%**	**95%**	**100%**
Covariates	Tookphys	9.111	10.331	8.353	5.567
	black	2.076	8.273	5.814	3.496
	income	5.010	12.056	7.192	8.409
	age	0.749	0.223	1.822	3.247
	female	1.828	1.551	3.648	3.773
	educdec	9.203	9.293	6.956	4.630
	num	7.815	13.097	4.760	19.035
	mhi	1.055	0.480	7.878	5.364
	disea	6.860	4.806	4.891	4.717
	child	1.936	1.363	0.719	7.910
	xghindx	7.446	10.637	1.639	2.244
	afairnm	1.560	20.226	0.160	4.889
	xghindx2	6.374	7.042	0.030	1.549
	ghinnm	7.848	46.816	15.107	14.424

Table A.3
Standardized Difference in Sample after 4% removed

1st plan co-pay		**0%**	**0%**		**0%**	**0%**
Compared to		**25%**	**50%**		**95%**	**100%**
Covariates	Tookphys	9.664	9.638		7.383	3.734
	black	3.217	4.965		7.590	1.425
	income	2.123	14.156		5.021	6.640
	age	1.197	1.988		0.240	3.260
	female	2.536	2.384		3.140	2.794
	educdec	4.601	5.798		2.482	2.467
	num	6.430	7.873		1.790	17.470
	mhi	1.893	3.443		9.999	5.801
	Disea	10.768	7.635		7.657	4.788
	child	0.710	1.180		0.445	6.931
	xghindx	4.292	5.371		1.088	0.408
	afairnm	4.346	16.889		0.538	6.601
	xghindx2	3.781	2.913		2.419	0.049
	ghinnm	7.556	45.402		15.320	14.108

Table A.4
Pairwise Arc Elasticity of Total Spending before Matching

Plans [a]	25% Coinsurance	Mixed Coinsurance	50% Coinsurance	Individual Deductible	95% Coinsurance
Free Care	-0.181 (0.043)	-0.091 (0.052)	-0.149 (0.074)	-0.119 (0.035)	-0.235 (0.039)
25% Coinsurance		0.749 (0.519)	0.098 (0.263)	0.159 (0.122)	-0.097 (0.094)
Mixed Coinsurance			-0.264 (0.370)	-0.100 (0.191)	-0.295 (0.120)
50% Coinsurance				.4272574 (1.122)	-0.288 (0.253)
Individual Deductbile					-0.488 (0.190)

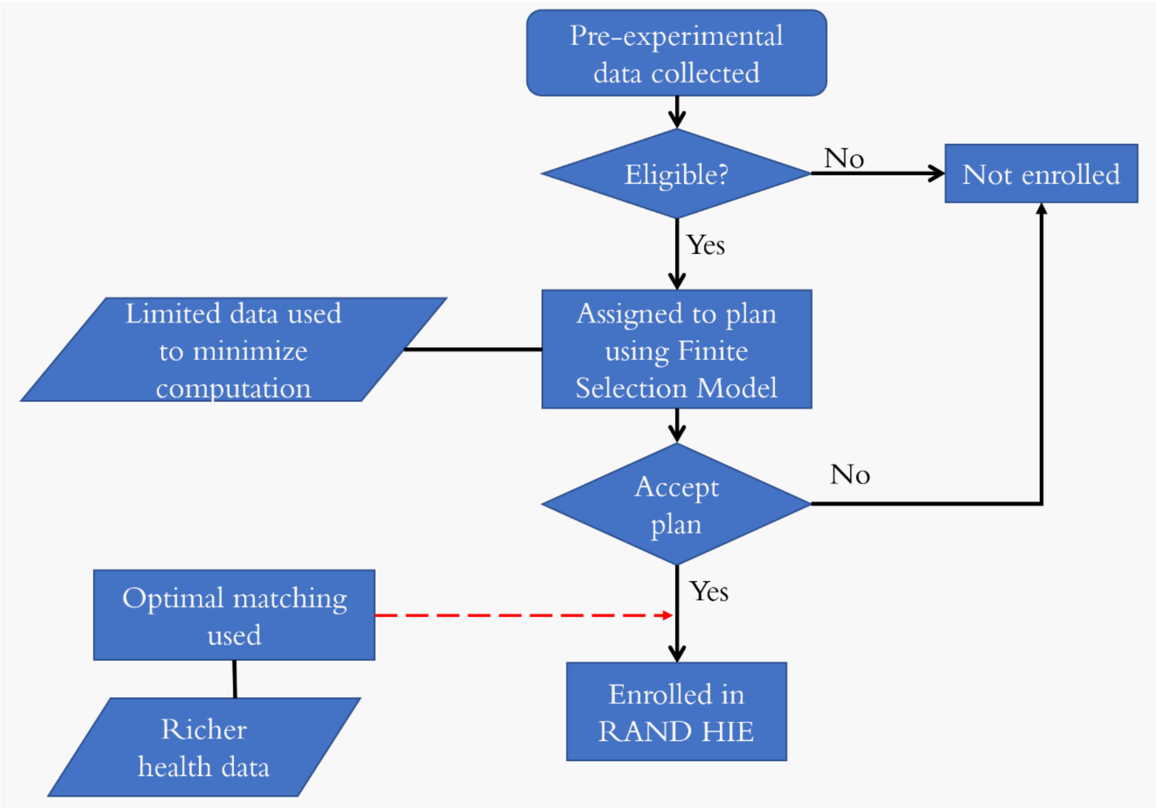
Notes:
[a] For a more detailed explanation of the plans and methodology refer to (Aron-Dine et al., 2013).

Table A.5
Pairwise Arc Elasticity of Total Spending after Matching [b]

Plans [a]	25% Coinsurance	Mixed Coinsurance	50% Coinsurance	Individual Deductible	95% Coinsurance
Free Care	0.068 (0.061)	0.032 (0.091)	-0.071 (0.055)	-0.152 (0.302)	0.046 (0.053)
25% Coinsurance		-0.305 (0.725)	-0.416 (0.173)	-0.552 (0.741)	-0.039 (0.086)
Mixed Coinsurance			-0.462 (0.373)	-0.592 (0.762)	0.029 (0.167)
50% Coinsurance				-1.153 (4.435)	0.375 (0.157)
Individual Deductbile					0.805 (1.189)

Notes:
[a] For a more detailed explanation of the plans and methodology refer to (Aron-Dine et al., 2013).
[b] The results are after matching removed 4% of the sample.

Figure A.1
Outline of Matching Solution



Appendix B. Chapter 2 Supplemental Tables

Table B.1

Summary Statistics: County 20% Random Sample

N= 371,283	N× T	Quarterly Mean	Std. Dev.
Count of Tradelines			
Total	5723219	4.61	4.19
Auto	5723219	.399	.667
Mortgage	5723219	.524	.778
Revolving	5723219	1.89	2.55
Count of Severely Delinquent Tradelines			
Total	5723219	.0781	.497
Auto	5723219	.00593	.082
Mortgage	5723219	.00404	.0709
Revolving	5723219	.0337	.316
Share of Accounts Severely Delinquent			
Total	5723219	.0236	.132
Auto	5723219	.00483	.0668
Mortgage	5723219	.00315	.054
Revolving	5723219	.0122	.103
Amount of Debt in Dollars			
Total	5723219	52520	106464
Auto	5723219	5120	11128
Mortgage	5723219	38762	90171
Revolving	5723219	8110	24266
Amount of Severely Delinquent Debt in Dollars			
Total	5723219	751	12288
Auto	5723219	44.7	792
Mortgage	5723219	421	11548
Revolving	5723219	346	4226
Share of Debt Amount Severely Delinquent			
Total	5723219	.0221	.136
Auto	5723219	.00471	.0666
Mortgage	5723219	.00316	.0547
Revolving	5723219	.0213	.137
Payments (Quarterly)			
Total	4433476	1425	49220
Mortgage	2196421	1393	57412
Auto	1791137	599	29910
Revolving	3613723	328	13447
Other			
Equifax Risk Score	5187236	733	86.1
Age	5723219	52.7	13.3
New Bankruptcy	5723219	.000756	.0275
New Foreclosure	5723219	.000384	.0196

SOURCE: FEDERAL RESERVE BANK OF NEW YORK CONSUMER CREDIT PANEL/EQUIFAX, CMS, AND THE NORTH CAROLINA RURAL HEALTH PROGRAM.

Table B.2

Summary Statistics HSA 20% Random Sample

N= 234,236	$N \times T$	Mean	Std. Dev.
Count of Tradelines			
Total	5418032	4.63	4.19
Auto	5418032	.398	.667
Mortgage	5418032	.529	.78
Revolving	5418032	1.89	2.56
Count of Severely Delinquent Tradelines			
Total	5418032	.0764	.495
Auto	5418032	.00548	.078
Mortgage	5418032	.00428	.0742
Revolving	5418032	.0327	.309
Share of Accounts Severely Delinquent			
Total	5418032	.0228	.129
Auto	5418032	.00452	.0648
Mortgage	5418032	.0033	.0552
Revolving	5418032	.0119	.101
Amount of Debt in Dollars			
Total	5418032	53386	105001
Auto	5418032	5122	11226
Mortgage	5418032	39570	91623
Revolving	5418032	8220	25085
Amount of Severely Delinquent Debt in Dollars			
Total	5418032	774	13221
Auto	5418032	40.6	759
Mortgage	5418032	446	12205
Revolving	5418032	355	4636
Share of Debt Amount Severely Delinquent			
Total	5418032	.0215	.134
Auto	5418032	.00441	.0645
Mortgage	5418032	.00332	.0561
Revolving	5418032	.0207	.136
Payments (Quarterly)			
Total	4215746	1351	38980
Mortgage	2092304	1282	43452
Auto	1693690	544	18838
Revolving	3437543	328	12553
Other			
Equifax Risk Score	4912768	734	85.5
Age	5418032	52.7	13.2
New Bankruptcy	5418032	.000774	.0278
New Foreclosure	5418032	.000396	.0199

Table B.3
Summary Statistics Control, Treatment, and Pre-Treatment at County-Level

	Control		Treatment		Pre-Treatment	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Count of Tradelines						
Total	4.62	4.19	4.5	4.24	4.93	4.31
Auto	.399	.667	.399	.67	.432	.689
Mortgage	.526	.779	.481	.764	.529	.784
Revolving	1.89	2.55	1.93	2.6	2.21	2.77
Count of Severely Delinquent Tradelines						
Total	.0773	.495	.0925	.529	.0829	.494
Auto	.0059	.0818	.0065	.0861	.0051	.0734
Mortgage	.00404	.071	.00405	.0701	.0032	.0648
Revolving	.033	.313	.0475	.38	.0478	.388
Share of Accounts Severely Delinquent						
Total	.0233	.131	.0285	.146	.0256	.138
Auto	.00481	.0668	.00512	.0683	.00433	.0636
Mortgage	.00315	.054	.00322	.055	.00241	.0472
Revolving	.0119	.102	.0166	.12	.016	.118
Amount of Debt in Dollars						
Total	52763	107276	47752	88943	50913	89990
Auto	5109	11110	5350	11478	5588	11217
Mortgage	38994	90800	34210	76665	35933	75114
Revolving	8116	23636	8002	34349	9126	42445
Amount of Severely Delinquent Debt in Dollars						
Total	754	12418	692	9400	574	8943
Auto	44.3	788	51.7	869	44.3	831
Mortgage	425	11681	344	8522	285	8129
Revolving	345	4241	362	3935	331	3786
Share of Debt Amount Severely Delinquent						
Total	.0219	.135	.026	.147	.0234	.14
Auto	.00469	.0665	.00504	.0685	.00434	.0641
Mortgage	.00316	.0547	.0032	.0552	.00235	.047
Revolving	.021	.137	.0266	.154	.0254	.15
Payments (Quarterly)						
Total	1432	50170	1279	23016	1358	30921
Mortgage	1410	58734	1018	3224	1002	2778
Auto	601	30659	544	872	536	839
Revolving	327	13741	341	4376	323	1826
Other						
Equifax Risk Score	733	85.9	727	89.5	725	87.9
Age	52.7	13.2	52.8	13.4	51	12.2
New Bankruptcy	.000759	.0275	.000705	.0265	.0000717	.00847
New Foreclosure	.000386	.0196	.000335	.0183	.000294	.0171
N	355,903		19,635		19,635	

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Table B.4

Summary Statistics Control, Treatment, and Pre-Treatment at HSA-Level

	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Count of Tradelines						
Total	4.64	4.19	4.41	4.23	4.83	4.25
Auto	.398	.667	.4	.675	.446	.705
Mortgage	.531	.78	.47	.787	.525	.811
Revolving	1.89	2.55	1.91	2.58	2.15	2.72
Count of Severely Delinquent Tradelines						
Total	.0761	.494	.0861	.51	.0793	.465
Auto	.0054	.0774	.00743	.0914	.00735	.0899
Mortgage	.00429	.074	.0039	.0794	.0033	.0694
Revolving	.0323	.307	.043	.356	.0469	.38
Share of Accounts Severely Delinquent						
Total	.0227	.129	.0265	.139	.0239	.13
Auto	.00447	.0644	.00598	.074	.00587	.073
Mortgage	.00332	.0554	.00278	.0502	.00241	.0465
Revolving	.0117	.101	.0153	.115	.0158	.117
Amount of Debt in Dollars						
Total	53626	105626	47193	87103	49940	86632
Auto	5114	11221	5333	11369	5721	11211
Mortgage	39795	92169	33751	75935	35171	73885
Revolving	8247	24640	7546	34642	8516	45528
Amount of Severely Delinquent Debt in Dollars						
Total	777	13324	701	10213	607	9262
Auto	39.8	749	60.2	973	58.5	927
Mortgage	450	12297	349	9512	304	8664
Revolving	355	4650	363	4261	306	3803
Share of Debt Amount Severely Delinquent						
Total	.0214	.134	.0248	.143	.0222	.134
Auto	.00436	.0642	.00583	.0738	.00576	.0729
Mortgage	.00334	.0563	.00284	.0515	.0026	.0494
Revolving	.0205	.135	.0246	.148	.0234	.143
Payments (Quarterly)						
Total	1353	39371	1287	26463	1230	5781
Mortgage	1285	43630	1210	37967	1043	4599
Auto	544	19197	557	871	558	900
Revolving	329	12766	318	3247	327	4121
Other						
Equifax Risk Score	734	85.3	726	88.7	722	88.2
Age	52.7	13.2	52.8	13.4	50.8	12.3
New Bankruptcy	.000777	.0279	.000708	.0266	.000069	.00831
New Foreclosure	.0004	.02	.000297	.0172	.000345	.0186
N	224,967		9,269		9,269	

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Table B.5

Difference in Difference Treatment Effects of Hospital Closure on Severely Deliquent at County-Level for Various Age Groups.

Age group	Share of Accounts in SD	Share of Debt($) SD	Number of Accounts in SD	Amount of Debt($) in SD
		Panel A: All Trades		
All	0.0034***	0.0031***	0.0143***	109.0*
	(4.34)	(3.79)	(4.82)	(1.85)
27 to 54	-0.0027*	-0.0020	-0.0053	366.8***
	(-1.89)	(-1.35)	(-0.91)	(3.60)
55 to 64	-0.0011	-0.0015	-0.0115***	-25.62
	(-1.07)	(-1.41)	(-2.75)	(-0.40)
65 to 74	-0.0010	-0.0012	0.0036	267.4**
	(-1.01)	(-1.11)	(1.05)	(2.04)
		Panel B: Mortgage		
All	0.0020***	0.0020***	0.0021***	48.63
	(5.83)	(5.87)	(4.70)	(0.90)
27 to 54	0.0019***	0.0020***	0.0018**	237.9**
	(3.13)	(3.10)	(2.29)	(2.57)
55 to 64	0.0003	0.0004	0.0003	-8.325
	(0.64)	(0.71)	(0.44)	(-0.16)
65 to 74	0.0001	0.0001	0.0004	300.0**
	(0.11)	(0.14)	(0.77)	(2.34)
		Panel C: Auto		
All	-0.0012***	-0.0013***	-0.0009*	-10.19*
	(-3.10)	(-3.19)	(-1.77)	(-1.95)
27 to 54	-0.0056***	-0.0054***	-0.0067***	-36.44***
	(-6.60)	(-6.41)	(-6.58)	(-3.58)
55 to 64	-0.0006	0.0001	-0.0022***	4.490
	(-0.90)	(0.09)	(-2.84)	(0.49)
65 to 74	-0.0000	0.0001	0.0002	5.196
	(-0.07)	(0.18)	(0.24)	(1.01)
		Panel D: Revolving		
All	0.0011*	0.0016*	0.0015	40.38*
	(1.70)	(1.90)	(0.70)	(1.71)
27 to 54	-0.0010	0.0031**	-0.0032	224.8***
	(-0.81)	(1.98)	(-0.81)	(5.45)
55 to 64	-0.0003	-0.0012	-0.0163***	-15.15
	(-0.35)	(-1.04)	(-4.71)	(-0.35)
65 to 74	-0.0004	-0.0005	-0.0016	-76.07*
	(-0.51)	(-0.50)	(-0.77)	(-1.89)

Notes. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=278,014 for all ages, N=106,162 for ages 27 to 54, N=83,195 for ages 55 to 64, and N=65,255 for ages 65 to 74.

Table B.6
Difference in Difference Treatment Effects of Hospital Closure on Foreclosure, Bankruptcy, and Payments at the County-Level Across Age Groups.

Age Group	New Foreclosure	New Bankruptcy	Total Account Payments	Auto Account Payments	Mortgage Account Payments	Revolving Account Payments
All	0.0004***	0.0002	-152.0	36.61***	12.86	4.527
	(2.77)	(1.27)	(-0.84)	(4.03)	(0.41)	(0.16)
27 to 54	0.0003	0.0008**	-34.31	41.65***	82.00*	32.32
	(1.19)	(2.15)	(-0.07)	(3.02)	(1.81)	(0.58)
55 to 64	0.0001	-0.0004	-591.5***	33.49***	-455.0**	-50.25***
	(0.04)	(-1.30)	(-3.66)	(2.71)	(-2.30)	(-2.74)
65 to 74	0.0002	-0.0002	56.55	51.29***	239.9	-4.551
	(0.77)	(-0.69)	(0.65)	(2.94)	(1.28)	(-0.14)

Notes. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. Payment categories are estimated for individuals with positive levels of debt in the same categories. Number of Observation is available in the Appendix

Table B.7
Observation Counts for Difference in Difference Treatment Effects of Hospital Closure on Foreclosure, Bankruptcy, and Payments at the County-Level Across Age Groups.

Age Group	New Foreclosure	New Bankruptcy	Total Account Payments	Auto Account Payments	Mortgage Account Payments	Revolving Account Payments
All	278014	278014	210634	86521	98064	170172
27 to 54	106162	106162	80796	38458	43120	64584
55 to 64	83195	83195	65499	26242	29910	53044
65 to 74	65255	65255	45962	14312	14681	37713

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Table B.8
Equifax Risk Category

Equifax Risk Score Category	Equifax Risk Score (R) Range
R1	<660
R2	660<=R<740
R3	>=740

Table B.9

Difference in Difference Treatment Effect of Hospital Closures on Share of Debt($) Severely Delinquent Debt With Equifax Risk Score Categories At County-Level:

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
			Panel A: All Trades Share of Debt($) Severely Delinquent		
All	0.0677***	0.0093***	0.130***	0.0075***	-0.0140***
	(54.61)	(9.20)	(93.39)	(6.01)	(-15.79)
27 to 54	0.0574***	0.00892***	0.102***	-0.00218	-0.0248***
	(26.67)	(4.72)	(44.10)	(-1.00)	(-14.34)
55 to 64	0.0169***	-0.000671	0.0717***	-0.00310**	-0.0128***
	(8.05)	(-0.42)	(37.02)	(-1.98)	(-10.98)
65 to 74	0.0525***	0.00438**	0.109***	0.00425***	-0.00822***
	(21.71)	(2.51)	(49.73)	(2.58)	(-7.04)
			Panel B: Mortgage Share of Debt($) Severely Delinquent		
All	0.00876***	-0.000306	0.0207***	0.000378	-0.000686*
	(16.33)	(-0.70)	(34.24)	(0.70)	(-1.79)
27 to 54	0.00982***	-0.00170**	0.0167***	0.000531	-0.00115
	(10.50)	(-2.07)	(16.65)	(0.56)	(-1.52)
55 to 64	0.00542***	-0.000534	0.0142***	0.000995	-0.00166***
	(5.09)	(-0.65)	(14.40)	(1.25)	(-2.82)
65 to 74	0.0114***	-0.00255***	0.00968***	0.000316	-0.000313
	(10.56)	(-3.26)	(9.87)	(0.43)	(-0.60)
			Panel C: Auto Share of Debt($) Severely Delinquent		
All	0.00747***	0.000110	0.0182***	-0.000959	-0.00506***
	(12.02)	(0.22)	(26.11)	(-1.53)	(-11.36)
27 to 54	0.0118***	0.00324***	0.0140***	-0.00215*	-0.00982***
	(9.45)	(2.95)	(10.45)	(-1.69)	(-9.76)
55 to 64	-0.00743***	0.000115	0.0211***	-0.00165*	-0.00528***
	(-5.98)	(0.12)	(18.35)	(-1.78)	(-7.65)
65 to 74	0.00384***	-0.00390***	0.0146***	-0.000695	-0.00193***
	(3.13)	(-4.41)	(13.09)	(-0.83)	(-3.26)
			Panel D: Revolving Share of Debt($) Severely Delinquent		
All	0.0779***	0.00426***	0.128***	0.00265**	-0.0124***
	(59.40)	(4.00)	(86.55)	(2.01)	(-13.25)
27 to 54	0.0540***	0.000476	-0.0205***	0.105***	-0.00623***
	(23.92)	(0.24)	(-11.30)	(43.47)	(-2.71)
55 to 64	0.0279***	-0.00133	0.0762***	-0.00262	-0.0113***
	(12.66)	(-0.79)	(37.42)	(-1.59)	(-9.20)
65 to 74	0.0434***	0.00240	0.106***	0.00137	-0.00775***
	(18.57)	(1.42)	(49.70)	(0.86)	(-6.87)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=278,014 for all ages, N=106,162 for ages 27 to 54, N=83,195 for ages 55 to 64, and N=65,255 for ages 65 to 74.

Table B.10

Difference in Difference Treatment Effect of Hospital Closures on Share of Accounts Severely Delinquent Debt With Equifax Risk Score Categories At County-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
Panel A: All Trades Share of Accounts Severely Delinquent					
All	0.0668***	0.0082***	0.136***	0.005***	-0.0151***
	(56.22)	(8.46)	(101.61)	(4.16)	(-17.75)
27 to 54	0.0546***	0.0077***	0.102***	-0.0066***	-0.0267***
	(26.72)	(4.28)	(46.71)	(-3.15)	(-16.20)
55 to 64	0.0153***	-0.0033**	0.0733***	-0.0033**	-0.0135***
	(7.75)	(-2.15)	(40.24)	(-2.21)	(-12.34)
65 to 74	0.04***	0.0016	0.0979***	0.0017	-0.0082***
	(18.32)	(1.03)	(49.43)	(1.15)	(-7.79)
Panel B: Mortgage Share of Accounts Severely Delinquent					
All	0.0085***	-0.0003	0.0202***	0.0004	-0.0007*
	(15.93)	(-0.75)	(33.63)	(0.79)	(-1.77)
27 to 54	0.0089***	-0.0014*	0.0163***	0.0004	-0.0012*
	(9.85)	(-1.69)	(16.74)	(0.45)	(-1.70)
55 to 64	0.0053***	-0.0008	0.0139***	0.0009	-0.0017***
	(5.07)	(-0.99)	(14.29)	(1.17)	(-2.98)
65 to 74	0.0108***	-0.0024***	0.0095***	0.0002	-0.0004
	(10.13)	(-3.16)	(9.84)	(0.34)	(-0.68)
Panel C: Auto Share of Accounts Severely Delinquent					
All	0.0072***	0.0001	0.0186***	-0.001	-0.0052***
	(11.65)	(0.24)	(26.79)	(-1.58)	(-11.70)
27 to 54	0.0117***	0.0031***	0.0137***	-0.0023*	-0.01***
	(9.36)	(2.82)	(10.23)	(-1.82)	(-9.97)
55 to 64	-0.0066***	0	0.0214***	-0.002**	-0.006***
	(-5.19)	(0.01)	(18.23)	(-2.10)	(-8.56)
65 to 74	0.004***	-0.0039***	0.0147***	-0.0008	-0.0021***
	(3.22)	(-4.39)	(13.11)	(-0.97)	(-3.50)
Panel D: Revolving Share of Accounts Severely Delinquent					
All	0.0378***	0.0035***	0.0697***	0.0022**	-0.0077***
	(36.15)	(4.05)	(59.24)	(2.05)	(-10.29)
27 to 54	0.0357***	0.0046***	0.058***	-0.0027	-0.0121***
	(19.40)	(2.86)	(29.41)	(-1.42)	(-8.18)
55 to 64	0.0058***	-0.0005	0.0387***	-0.0017	-0.0069***
	(3.21)	(-0.35)	(23.40)	(-1.25)	(-6.95)
65 to 74	0.0122***	-0.0031**	0.0498***	-0.0018	-0.0054***
	(6.50)	(-2.28)	(29.20)	(-1.40)	(-5.94)

Notes. C represents the Control group and T represents the Treated groupObservations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=278,014 for all ages, N=106,162 for ages 27 to 54, N=83,195 for ages 55 to 64, and N=65,255 for ages 65 to 74.

Table B.11

Difference in Difference Treatment Effect of Hospital Closures on Amount of Debt($) Severely Delinquent Debt With Equifax Risk Categories At County-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
		Panel A: All Trades Amount of Debt($) Severely Delinquent			
All	3078.9***	46.28	4621.7***	-64.47	-273.8***
	(33.22)	(0.61)	(44.35)	(-0.69)	(-4.12)
27 to 54	3240.9***	-206	4092.6***	392.5***	-111.1
	(21.69)	(-1.57)	(25.56)	(2.58)	(-0.92)
55 to 64	1765.2***	-99.1	2841.6***	-17.03	-282***
	(13.74)	(-1.01)	(23.96)	(-0.18)	(-3.96)
65 to 74	2215.2***	-705.9***	3903.8***	105.5	-21.1
	(7.46)	(-3.29)	(14.48)	(0.52)	(-0.15)
		Panel B: Mortgage Amount of Debt($) Severely Delinquent			
All	1801.2***	72.39	2547.7***	-41.07	-121.7**
	(21.10)	(1.04)	(26.55)	(-0.48)	(-1.99)
27 to 54	2264.7***	-161.7	2274.7***	441.5***	123.1
	(16.61)	(-1.35)	(15.57)	(3.18)	(1.12)
55 to 64	813.8***	-37.41	957.7***	76.31	-73.71
	(7.51)	(-0.45)	(9.58)	(0.95)	(-1.23)
65 to 74	1107.2***	-706***	2000.8***	117.6	109.5
	(3.81)	(-3.36)	(7.58)	(0.59)	(0.78)
		Panel C: Auto Amount of Debt($) Severely Delinquent			
All	94.43***	3.058	210.5***	-7.306	-49.4***
	(11.48)	(0.46)	(22.76)	(-0.88)	(-8.39)
27 to 54	103.1***	33.89**	174.3***	-19.45	-89.67***
	(6.87)	(2.57)	(10.84)	(-1.27)	(-7.42)
55 to 64	-48.63***	-2.027	239.1***	-24.47*	-46.15***
	(-2.64)	(-0.14)	(14.06)	(-1.78)	(-4.51)
65 to 74	38.05***	-41.01***	142.1***	-6.863	-13.55**
	(3.28)	(-4.90)	(13.50)	(-0.87)	(-2.42)
		Panel D: Revolving Amount of Debt($) Severely Delinquent			
All	1947.1***	-66.6**	2405.5***	-25.28	-91.92***
	(52.86)	(-2.22)	(58.08)	(-0.68)	(-3.48)
27 to 54	1450.3***	-116**	2206.5***	31.18	-84.75*
	(24.03)	(-2.19)	(34.13)	(0.51)	(-1.74)
55 to 64	1523.2***	-111.1*	2164.6***	-71.79	-165.2***
	(17.54)	(-1.67)	(27.00)	(-1.11)	(-3.43)
65 to 74	1797.1***	68.02	2803.7***	-51.22	-184.6***
	(19.92)	(1.04)	(34.21)	(-0.83)	(-4.24)

Notes. C represents the Control group and T represents the Treated groupObservations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=278,014 for all ages, N=106,162 for ages 27 to 54, N=83,195 for ages 55 to 64, and N=65,255 for ages 65 to 74.

Table B.12
Difference in Difference Treatment Effect of Hospital Closures on Number of Accounts Severely Delinquent Debt With Risk Categories At County-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
Panel A: All Trades Number of Accounts Severely Delinquent					
All	0.254***	0.0055	0.45***	0.0016	-0.037***
	(55.47)	(1.49)	(87.44)	(0.35)	(-11.28)
27 to 54	0.196***	-0.0036	0.343***	-0.0412***	-0.0809***
	(23.01)	(-0.48)	(37.62)	(-4.75)	(-11.81)
55 to 64	0.112***	-0.012*	0.272***	-0.0199***	-0.0477***
	(13.45)	(-1.87)	(35.26)	(-3.19)	(-10.29)
65 to 74	0.127***	-0.0052	0.356***	0.0016	-0.0237***
	(16.92)	(-0.95)	(52.12)	(0.31)	(-6.53)
Panel B: Mortgage Number of Accounts Severely Delinquent					
All	0.0131***	0	0.0257***	0.0008	-0.0009*
	(19.18)	(-0.02)	(33.37)	(1.15)	(-1.75)
27 to 54	0.0145***	-0.001	0.0212***	0.0007	-0.0014
	(12.67)	(-0.96)	(17.30)	(0.64)	(-1.50)
55 to 64	0.0089***	-0.0007	0.0158***	0.0012	-0.0016**
	(7.30)	(-0.77)	(14.08)	(1.37)	(-2.35)
65 to 74	0.0143***	-0.0032***	0.0138***	0.0005	-0.0002
	(11.56)	(-3.58)	(12.28)	(0.59)	(-0.27)
Panel C: Auto Number of Accounts Severely Delinquent					
All	0.0066***	-0.0003	0.0254***	-0.0018**	-0.0068***
	(8.48)	(-0.43)	(28.90)	(-2.31)	(-12.11)
27 to 54	0.0124***	0.0041***	0.0172***	-0.0038**	-0.0127***
	(8.21)	(3.08)	(10.61)	(-2.46)	(-10.46)
55 to 64	-0.0051***	-0.0003	0.0233***	-0.0035***	-0.0082***
	(-3.31)	(-0.29)	(16.50)	(-3.06)	(-9.62)
65 to 74	0.0015	-0.0045***	0.0179***	-0.0011	-0.0026***
	(1.10)	(-4.48)	(14.11)	(-1.20)	(-3.85)
Panel D: Revolving Number of Accounts Severely Delinquent					
All	0.111***	0.0129***	0.189***	0.0063*	-0.02***
	(33.75)	(4.82)	(51.11)	(1.89)	(-8.49)
27 to 54	0.108***	0.0135***	0.165***	-0.0058	-0.0328***
	(18.33)	(2.61)	(26.23)	(-0.96)	(-6.93)
55 to 64	0.0289***	-0.0017	0.0874***	-0.0175***	-0.0318***
	(4.15)	(-0.32)	(13.58)	(-3.37)	(-8.22)
65 to 74	0.0292***	-0.008**	0.126***	-0.0096***	-0.0133***
	(6.14)	(-2.34)	(29.08)	(-2.96)	(-5.81)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Sources: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=278,014 for all ages, N=106,162 for ages 27 to 54, N=83,195 for ages 55 to 64, and N=65,255 for ages 65 to 74.

Table B.13

Difference in Difference Treatment Effect of Hospital Closures on Foreclosures and Bankruptcy With Risk Categories At County-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
			Panel A: New Foreclosures		
All	0.0013***	-0.0001	0.0025***	0.0001	0.0001
	(6.59)	(-0.50)	(10.99)	(0.73)	(0.95)
27 to 54	0.0017***	-0.0001	0.0024***	0.0001	0.0001
	(4.50)	(-0.37)	(5.96)	(0.26)	(0.17)
55 to 64	0.0005	0	0.0013***	0.0002	-0.0002
	(1.30)	(-0.11)	(3.46)	(0.49)	(-0.88)
65 to 74	0.002***	-0.0002	0.0021***	0.0003	0.0001
	(3.86)	(-0.44)	(4.50)	(0.73)	(0.55)
			Panel B: New Bankruptcy		
All	0.0017***	0.0003	0.0071***	-0.001***	-0.0009***
	(6.06)	(1.46)	(22.32)	(-3.35)	(-4.55)
27 to 54	0.002***	-0.0001	0.0068***	-0.0007	-0.0009**
	(3.80)	(-0.22)	(12.02)	(-1.24)	(-2.15)
55 to 64	0.0018***	0.0004	0.004***	0.0002	-0.001***
	(3.14)	(0.87)	(7.66)	(0.44)	(-3.00)
65 to 74	0.0025***	0.0004	0.0062***	0.001**	-0.0008***
	(4.10)	(0.95)	(11.27)	(2.48)	(-2.90)

Notes: C represents the Control group and T represents the Treated groupObservations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.14

Difference in Difference Treatment Effects of Hospital Closure on Severely Deliquent at HSA-Level for Various Age Groups.

Age group	Share of Accounts in SD	Share of Debt($) SD	Number of Accounts in SD	Amount of Debt($) in SD
		Panel A: All Trades		
All	0.0008	0.0013	-0.0006	242.6***
	(0.95)	(1.35)	(-0.18)	(3.16)
27 to 54	0.0038**	0.0039**	0.018***	432.5***
	(2.53)	(2.45)	(2.71)	(3.52)
55 to 64	-0.0019	-0.0011	-0.0206***	-301.1***
	(-1.33)	(-0.76)	(-3.72)	(-3.28)
65 to 74	-0.0000	-0.0004	0.0061*	49.31
	(-0.04)	(-0.34)	(1.77)	(0.60)
		Panel B: Mortgage		
All	0.0005	0.0006	0.0010*	238.4***
	(1.42)	(1.51)	(1.74)	(3.29)
27 to 54	0.0023***	0.0028***	0.0027***	301.9***
	(3.40)	(3.99)	(3.51)	(2.64)
55 to 64	-0.0002	-0.0001	-0.0006	-122.1
	(-0.40)	(-0.18)	(-0.81)	(-1.54)
65 to 74	-0.0011	-0.0010	-0.0016**	30.51
	(-1.64)	(-1.56)	(-2.27)	(0.40)
		Panel C: Auto		
All	-0.0006	-0.0005	-0.0002	0.555
	(-1.13)	(-1.06)	(-0.39)	(0.08)
27 to 54	0.0006	0.0006	0.0004	-7.452
	(0.62)	(0.70)	(0.34)	(-0.69)
55 to 64	-0.0011	-0.0013*	-0.0026***	-47.32***
	(-1.48)	(-1.79)	(-2.62)	(-4.38)
65 to 74	0.0019***	0.0021***	0.0018***	25.81***
	(3.64)	(4.13)	(2.99)	(4.16)
		Panel D: Revolving		
All	-0.0024***	-0.0002	-0.0086***	71.75**
	(-3.15)	(-0.18)	(-3.70)	(2.44)
27 to 54	0.0033***	0.0100***	0.0058	170.2***
	(2.58)	(6.21)	(1.41)	(3.84)
55 to 64	-0.0007	-0.0013	-0.0071*	-198.1***
	(-0.62)	(-0.86)	(-1.79)	(-3.46)
65 to 74	0.00011	0.00018	-0.0027	-47.88
	(0.14)	(0.17)	(-1.46)	(-1.09)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.15
Difference in Difference Treatment Effects of Hospital Closure on Foreclosure, Bankruptcy, and Payments at the HSA-Level Across Age Groups.

Age Group	New Foreclosure	New Bankruptcy	Total Account Payments	Auto Account Payments	Mortgage Account Payments	Revolving Account Payments
All	0.0000516	0.00000155	241.8	8.031	-94.57***	916.8*
	(0.37)	(0.01)	(0.98)	(0.77)	(-2.90)	(1.75)
27 to 54	0.000309	0.00120***	-26.97	56.08***	85.79	67.53***
	(1.13)	(3.16)	(-0.28)	(3.05)	(1.61)	(2.68)
55 to 64	0.000292	0.000291	1874.8**	-9.606	-33.11	5097.2**
	(1.19)	(0.80)	(2.05)	(-0.53)	(-1.18)	(2.53)
65 to 74	0.000184	0.0000721	46.49	69.25**	-6.412	-114.7
	(0.75)	(0.26)	(0.73)	(2.15)	(-0.14)	(-1.40)

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Table B.16
Observations Counts for Difference in Difference Treatment Effects of Hospital Closure on Foreclosure, Bankruptcy, and Payments at the HSA-Level Across Age Groups.

Age Group	New Foreclosure	New Bankruptcy	Total Account Payments	Auto Account Payments	Mortgage Account Payments	Revolving Account Payments
All	202059	202059	151970	62934	121877	70257
27 to 54	101753	101753	76500	37557	40706	59918
55 to 64	55600	55600	43397	17616	20022	35011
65 to 74	47489	47489	33923	10090	10905	27584

Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Table B.17

Difference in Difference Treatment Effect of Hospital Closures on Share of Debt($) Severely Delinquent Debt With Risk Categories At HSA-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
			Panel A: All Trades Share of Debt($) Severely Delinquent		
All	0.0738***	0.01***	0.134***	0.0065***	-0.0166***
	(51.86)	(8.74)	(83.45)	(4.55)	(-16.09)
27 to 54	0.0644***	0.0107***	0.117***	0.0027	-0.0225***
	(28.86)	(5.33)	(48.77)	(1.15)	(-12.16)
55 to 64	0.0529***	-0.0013	0.092***	0.0065***	-0.0141***
	(18.90)	(-0.61)	(36.17)	(3.10)	(-8.75)
65 to 74	0.043***	0.0003	0.0972***	0.002	-0.0079***
	(15.00)	(0.15)	(40.76)	(1.10)	(-6.50)
			Panel B: Mortgage Share of Debt($) Severely Delinquent		
All	0.0103***	-0.0003	0.0144***	0.0003	-0.0007
	(17.38)	(-0.58)	(21.69)	(0.44)	(-1.63)
27 to 54	0.0074***	-0.0034***	0.0177***	-0.0002	-0.0022***
	(7.39)	(-3.74)	(16.40)	(-0.18)	(-2.65)
55 to 64	0.0066***	0.001	0.0153***	-0.0001	-0.002***
	(5.63)	(1.09)	(14.38)	(-0.11)	(-2.90)
65 to 74	0.0164***	-0.0009	0.018***	-0.0001	-0.0021***
	(10.03)	(-0.86)	(13.29)	(-0.14)	(-3.03)
			Panel C: Auto Share of Debt($) Severely Delinquent		
All	0.0093***	0.0018***	0.0224***	0.0005	-0.0047***
	(12.10)	(2.85)	(25.85)	(0.67)	(-8.41)
27 to 54	0.0085***	0.0031***	0.0226***	0.0021	-0.0069***
	(6.63)	(2.67)	(16.38)	(1.59)	(-6.50)
55 to 64	0.012***	-0.0009	0.0166***	-0.0009	-0.0033***
	(8.21)	(-0.78)	(12.49)	(-0.81)	(-3.93)
65 to 74	0.0024*	-0.0023***	0.0166***	0.0016**	0.0003
	(1.87)	(-2.84)	(15.38)	(2.00)	(0.47)
			Panel D: Revolving Share of Debt($) Severely Delinquent		
All	0.0789***	0.0028**	0.128***	-0.0004	-0.0159***
	(52.78)	(2.28)	(76.26)	(-0.26)	(-14.72)
27 to 54	0.0585***	-0.0004	0.119***	-0.0016	-0.0173***
	(25.62)	(-0.20)	(48.29)	(-0.68)	(-9.16)
55 to 64	0.048***	-0.0064***	0.0869***	0.001	-0.0142***
	(15.93)	(-2.72)	(31.70)	(0.44)	(-8.19)
65 to 74	0.0321***	0.0013	0.0837***	0.0009	-0.0061***
	(12.00)	(0.76)	(37.59)	(0.52)	(-5.36)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.18

Difference in Difference Treatment Effect of Hospital Closures on Share of Accounts Severely Delinquent Debt With Risk Categories At HSA-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
Panel A: All Trades Share of Accounts Severely Delinquent					
All	0.0705***	0.0076***	0.133***	0.0038***	-0.0179***
	(52.34)	(6.97)	(87.50)	(2.82)	(-18.35)
27 to 54	0.0588***	0.0098***	0.118***	-0.0019	-0.0243***
	(27.84)	(5.17)	(51.64)	(-0.85)	(-13.87)
55 to 64	0.0536***	-0.0008	0.0947***	0.005**	-0.0151***
	(20.04)	(-0.39)	(38.94)	(2.46)	(-9.79)
65 to 74	0.0387***	0.0009	0.0864***	0.0046***	-0.0071***
	(15.46)	(0.54)	(41.53)	(2.94)	(-6.64)
Panel B: Mortgage Share of Accounts Severely Delinquent					
All	0.0095***	-0.0003	0.0145***	-0.0001	-0.0009**
	(16.59)	(-0.74)	(22.48)	(-0.23)	(-2.23)
27 to 54	0.0067***	-0.003***	0.0166***	-0.0008	-0.0025***
	(6.86)	(-3.47)	(15.80)	(-0.76)	(-3.09)
55 to 64	0.0076***	0.0008	0.0155***	-0.0002	-0.002***
	(6.39)	(0.91)	(14.35)	(-0.24)	(-2.92)
65 to 74	0.015***	-0.0007	0.0184***	-0.0004	-0.0023***
	(9.20)	(-0.72)	(13.56)	(-0.37)	(-3.24)
Panel C: Auto Share of Accounts Severely Delinquent					
All	0.0094***	0.0018***	0.023***	0.0005	-0.0049***
	(12.15)	(2.95)	(26.52)	(0.64)	(-8.76)
27 to 54	0.0084***	0.003***	0.0226***	0.0021	-0.0071***
	(6.54)	(2.59)	(16.35)	(1.55)	(-6.68)
55 to 64	0.0128***	-0.0013	0.017***	-0.0007	-0.0031***
	(8.80)	(-1.16)	(12.91)	(-0.62)	(-3.67)
65 to 74	0.0028**	-0.0023***	0.0162***	0.0014*	0.0001
	(2.19)	(-2.76)	(15.05)	(1.75)	(0.10)
Panel D: Revolving Share of Accounts Severely Delinquent					
All	0.0375***	0.0038***	0.0633***	-0.002*	-0.0107***
	(31.88)	(4.00)	(47.85)	(-1.72)	(-12.52)
27 to 54	0.034***	0.0046***	0.066***	-0.0022	-0.0107***
	(18.50)	(2.77)	(33.33)	(-1.17)	(-7.02)
55 to 64	0.0259***	-0.0028	0.0441***	0.0025	-0.0075***
	(11.32)	(-1.55)	(21.21)	(1.48)	(-5.65)
65 to 74	0.0187***	-0.0029**	0.0386***	0.0021*	-0.0037***
	(9.59)	(-2.33)	(23.84)	(1.70)	(-4.44)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.19

Difference in Difference Treatment Effect of Hospital Closures on Amount of Debt($) Severely Delinquent Debt With Risk Categories At HSA-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
Panel A: All Trades Amount of Debt($) Severely Delinquent					
All	3281.7***	119	4909.9***	147.2	-170.8**
	(27.44)	(1.23)	(36.48)	(1.23)	(-1.97)
27 to 54	2781.8***	-435.2***	4508.1***	46.79	-474.8***
	(15.68)	(-2.73)	(23.54)	(0.25)	(-3.23)
55 to 64	2335.1***	67.61	2985.7***	-285.4**	-538***
	(13.01)	(0.48)	(18.29)	(-2.12)	(-5.20)
65 to 74	2002.6***	-255.2*	3670.1***	-129	-201.4**
	(9.63)	(-1.94)	(21.21)	(-1.00)	(-2.27)
Panel B: Mortgage Amount of Debt($) Severely Delinquent					
All	1979.1***	128.7	2707.1***	214*	106.7
	(17.45)	(1.40)	(21.21)	(1.88)	(1.30)
27 to 54	1914***	-329.9**	2614.5***	186.3	-112.6
	(11.56)	(-2.22)	(14.63)	(1.08)	(-0.82)
55 to 64	950.9***	157.8	1424.2***	-197.5*	-200**
	(6.10)	(1.30)	(10.04)	(-1.68)	(-2.22)
65 to 74	1389.8***	-209.5*	2042.4***	-59.93	-103.6
	(7.12)	(-1.70)	(12.57)	(-0.50)	(-1.25)
Panel C: Auto Amount of Debt($) Severely Delinquent					
All	102.1***	3.918	254***	-1.535	-46.66***
	(9.53)	(0.45)	(21.06)	(-0.14)	(-6.01)
27 to 54	63.08***	23.6*	231.6***	-19.46	-97.08***
	(4.01)	(1.67)	(13.63)	(-1.19)	(-7.45)
55 to 64	191.9***	-7.947	123.6***	-36.2**	-50.74***
	(9.04)	(-0.48)	(6.40)	(-2.27)	(-4.14)
65 to 74	40.85***	-16.06	186.5***	27.93***	7.116
	(2.60)	(-1.62)	(14.25)	(2.87)	(1.06)
Panel D: Revolving Amount of Debt($) Severely Delinquent					
All	1954.6***	-72.92**	2809.2***	-38.15	-192***
	(42.93)	(-1.98)	(54.83)	(-0.84)	(-5.82)
27 to 54	1566.3***	-190.3***	2348***	-86.42	-232.7***
	(24.65)	(-3.33)	(34.25)	(-1.31)	(-4.42)
55 to 64	2557.2***	-114.7	2406.5***	23.63	-347.3***
	(22.98)	(-1.32)	(23.77)	(0.28)	(-5.41)
65 to 74	776.1***	38.1	2267.6***	-256.2***	-180.9***
	(7.02)	(0.55)	(24.64)	(-3.74)	(-3.84)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.20

Difference in Difference Treatment Effect of Hospital Closures on Number of Accounts Severely Delinquent Debt With Risk Categories At HSA-Level

Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
Panel A: All Trades Number of Accounts Severely Delinquent					
All	0.244***	0.0055	0.428***	-0.0123**	-0.0567***
	(46.75)	(1.31)	(72.86)	(-2.36)	(-15.01)
27 to 54	0.19***	-0.0125	0.4***	-0.0366***	-0.0857***
	(20.48)	(-1.51)	(40.00)	(-3.81)	(-11.18)
55 to 64	0.226***	-0.0127	0.317***	-0.0029	-0.0594***
	(21.21)	(-1.53)	(32.70)	(-0.36)	(-9.67)
65 to 74	0.111***	-0.0115**	0.28***	0.0097*	-0.0183***
	(13.06)	(-2.14)	(39.54)	(1.84)	(-5.05)
Panel B: Mortgage Number of Accounts Severely Delinquent					
All	0.0161***	0.0006	0.0231***	0.0003	-0.0007
	(17.69)	(0.75)	(22.52)	(0.33)	(-1.03)
27 to 54	0.0092***	-0.0029***	0.0199***	-0.0007	-0.0023**
	(8.24)	(-2.91)	(16.61)	(-0.58)	(-2.47)
55 to 64	0.0112***	0.0013	0.0203***	-0.0006	-0.0027***
	(7.49)	(1.11)	(14.88)	(-0.51)	(-3.06)
65 to 74	0.019***	-0.0008	0.0196***	-0.001	-0.0026***
	(10.65)	(-0.71)	(13.22)	(-0.91)	(-3.46)
Panel C: Auto Number of Accounts Severely Delinquent					
All	0.0105***	0.0018**	0.0298***	0	-0.006***
	(11.02)	(2.34)	(27.92)	(-0.02)	(-8.78)
27 to 54	0.0082***	0.003**	0.028***	0.0002	-0.0099***
	(5.16)	(2.09)	(16.35)	(0.14)	(-7.53)
55 to 64	0.015***	-0.0011	0.0181***	-0.0022	-0.0046***
	(7.80)	(-0.70)	(10.38)	(-1.53)	(-4.11)
65 to 74	0.0021	-0.0027***	0.0176***	0.0012	-0.0003
	(1.40)	(-2.78)	(13.93)	(1.24)	(-0.45)
Panel D: Revolving Number of Accounts Severely Delinquent					
All	0.103***	0.0105***	0.153***	-0.0069*	-0.0258***
	(28.20)	(3.56)	(37.37)	(-1.88)	(-9.78)
27 to 54	0.107***	0.0131**	0.179***	-0.0059	-0.0269***
	(18.07)	(2.46)	(27.99)	(-0.95)	(-5.48)
55 to 64	0.0406***	-0.0066	0.0934***	-0.0029	-0.0252***
	(5.24)	(-1.10)	(13.26)	(-0.49)	(-5.64)
65 to 74	0.0507***	-0.0054*	0.0872***	0.0016	-0.0106***
	(10.69)	(-1.80)	(22.10)	(0.55)	(-5.25)

Notes. C represents the Control group and T represents the Treated group. Observations are the number of individuals multiplied by the number of quarterly periods. Model includes State, Year, Quarter, and Person fixed effects. Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program. N=202,059 for all ages, N=101,753 for ages 27 to 54, N=55,600 for ages 55 to 64, and N=47,489 for ages 65 to 74.

Table B.21
Difference in Difference Treatment Effect of Hospital Closures on Foreclosures and Bankruptcy With Risk Categories At HSA-Level

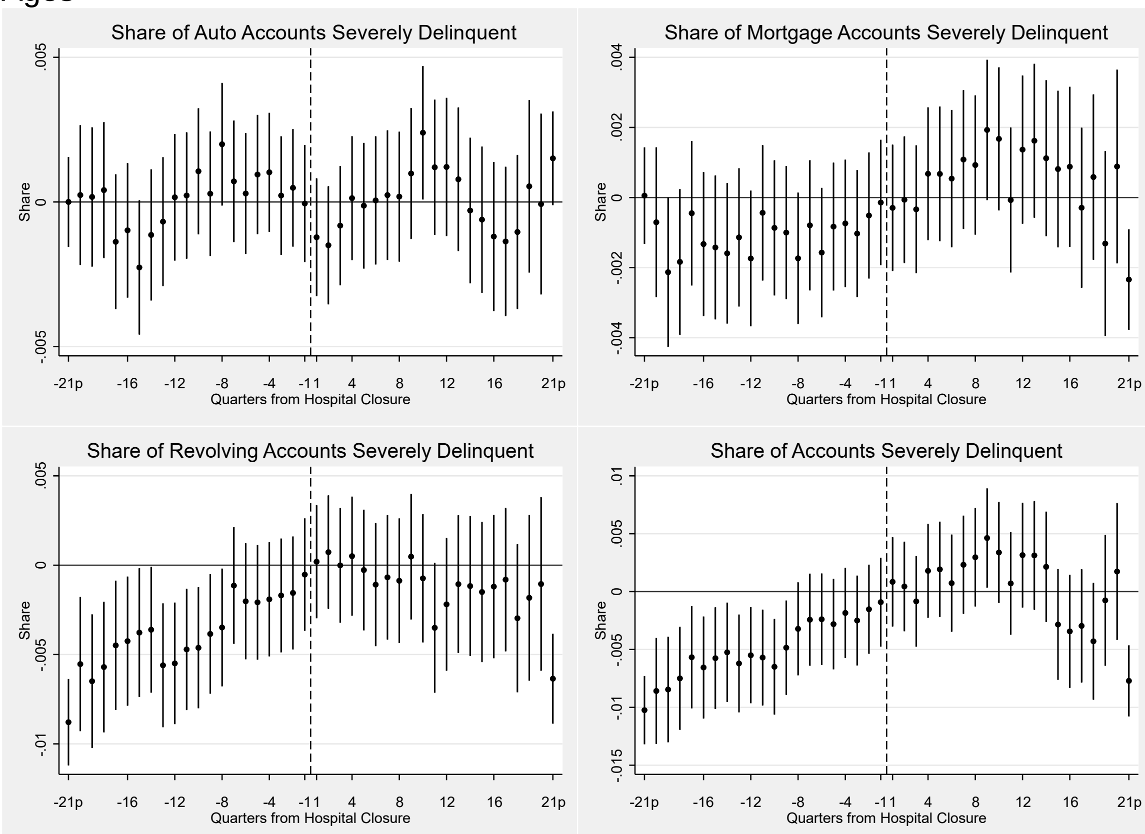
Age group	CR1 relative to $CR3$	$CR2$ relative to CR3	$TR1$ relative to C$R3$	$TR2$ relative to CR3	TR3 relative to CR3
			Panel A: New Foreclosures		
All	0.0013***	0	0.0013***	0	0.0001
	(6.12)	(-0.25)	(5.23)	(0.21)	(0.34)
27 to 54	0.0016***	-0.0002	0.0025***	0	-0.0001
	(3.92)	(-0.68)	(5.90)	(-0.09)	(-0.34)
55 to 64	0.0007	-0.0003	0.002***	0.0001	0
	(1.36)	(-0.87)	(4.50)	(0.40)	(-0.07)
65 to 74	0.0005	-0.0001	0.0032***	-0.0003	0
	(0.77)	(-0.30)	(6.23)	(-0.68)	(-0.15)
			Panel B: New Bankruptcy		
All	0.0016***	0.0004	0.0063***	-0.0006*	-0.0012***
	(4.87)	(1.39)	(16.78)	(-1.82)	(-4.87)
27 to 54	0.0018***	0.0002	0.0074***	-0.0001	-0.0008*
	(3.21)	(0.32)	(12.42)	(-0.20)	(-1.81)
55 to 64	0.002***	0.0003	0.0062***	0.0002	-0.0005
	(2.83)	(0.50)	(9.45)	(0.44)	(-1.30)
65 to 74	0.0032***	0.0011**	0.0078***	0.0009**	-0.0004
	(4.46)	(2.35)	(13.05)	(2.10)	(-1.42)

Source: C represents the Control group and T represents the Treated group. Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Appendix C. Chapter 2 Supplemental Figures

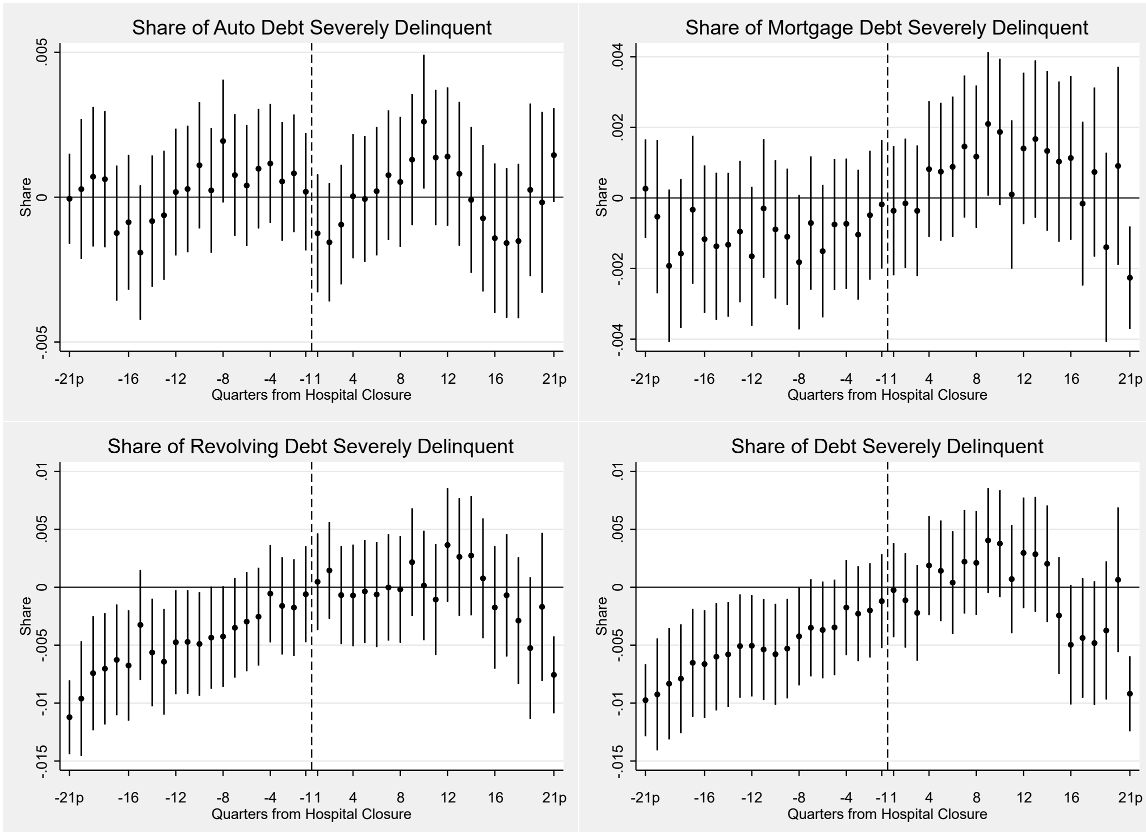
Figure C.1

Event Study for Share of Accounts Severely Delinquent Debt at the County-Level for All Ages



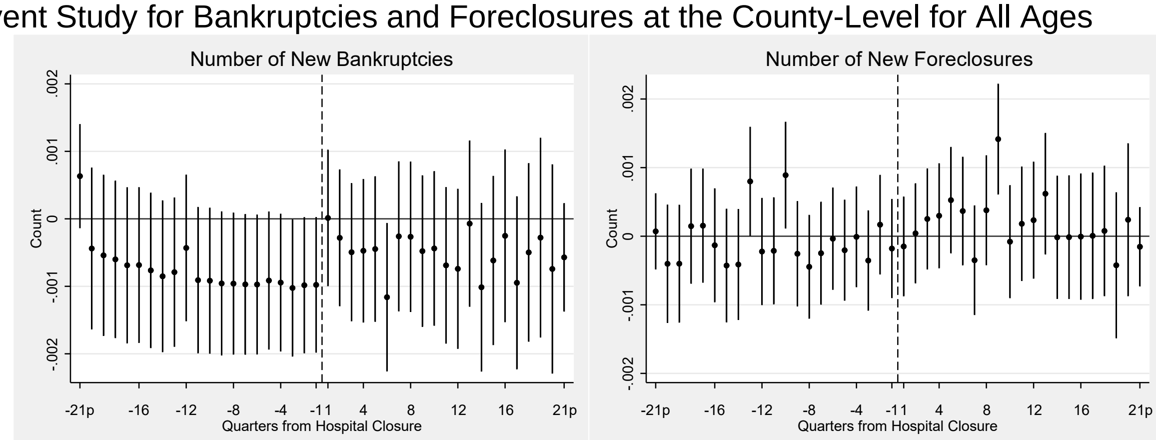
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.2
Event Study for Share of Debt($) Severely Delinquent Debt at the County-Level for All Ages



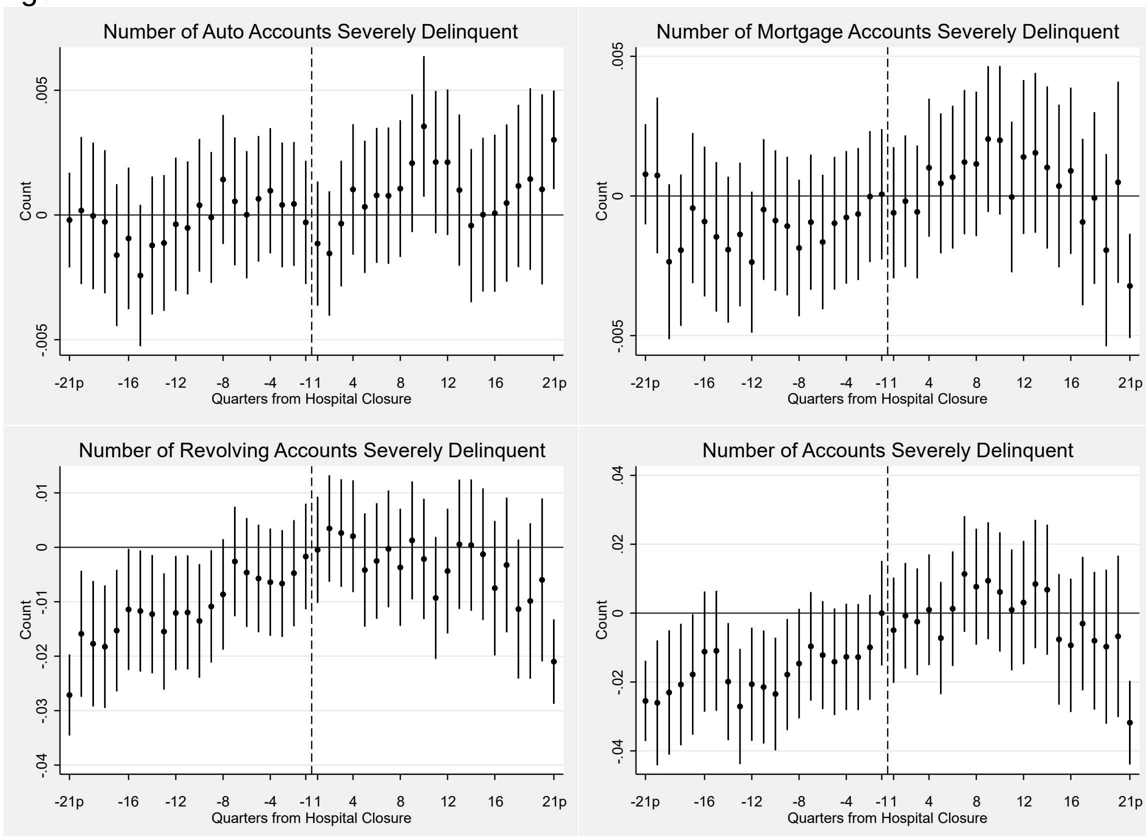
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.3
Event Study for Bankruptcies and Foreclosures at the County-Level for All Ages



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

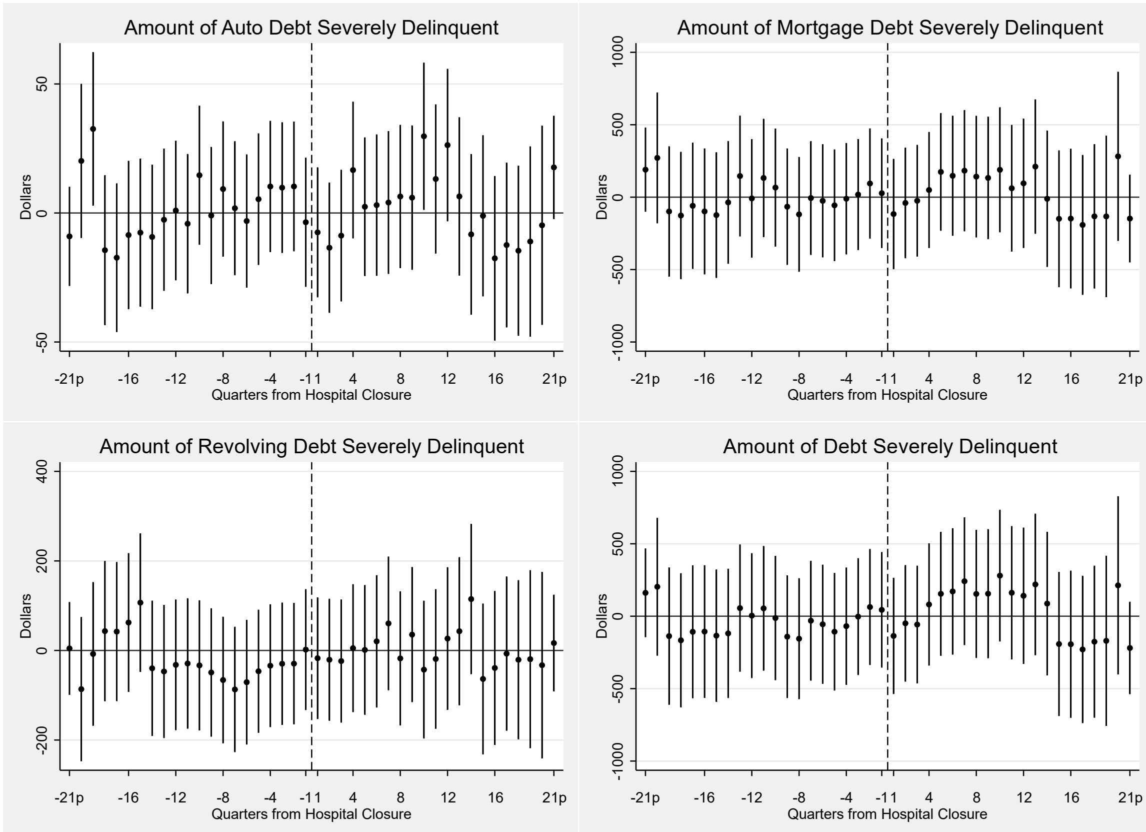
Figure C.4
Event Study for Number of Accounts Severely Delinquent Debt at the County-Level for All Ages



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.5

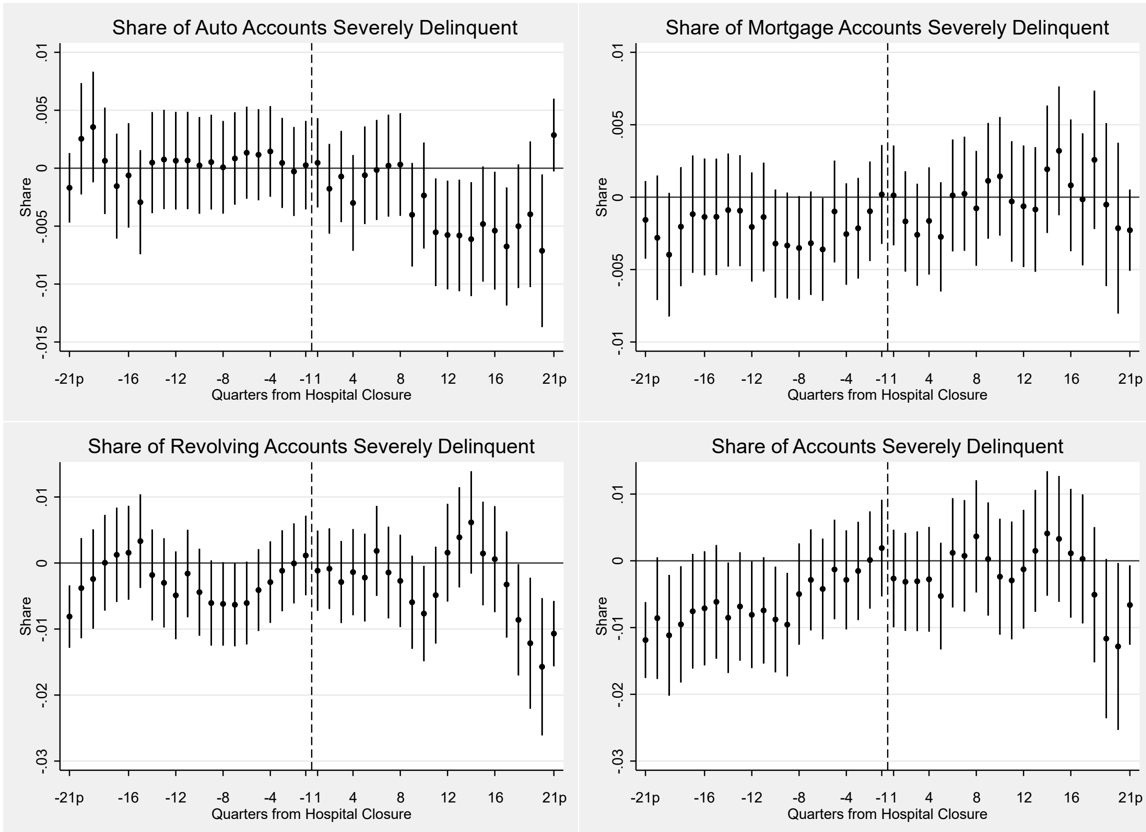
Event Study for Amount of Debt($) Severely Delinquent Debt at the County-Level for All Ages



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

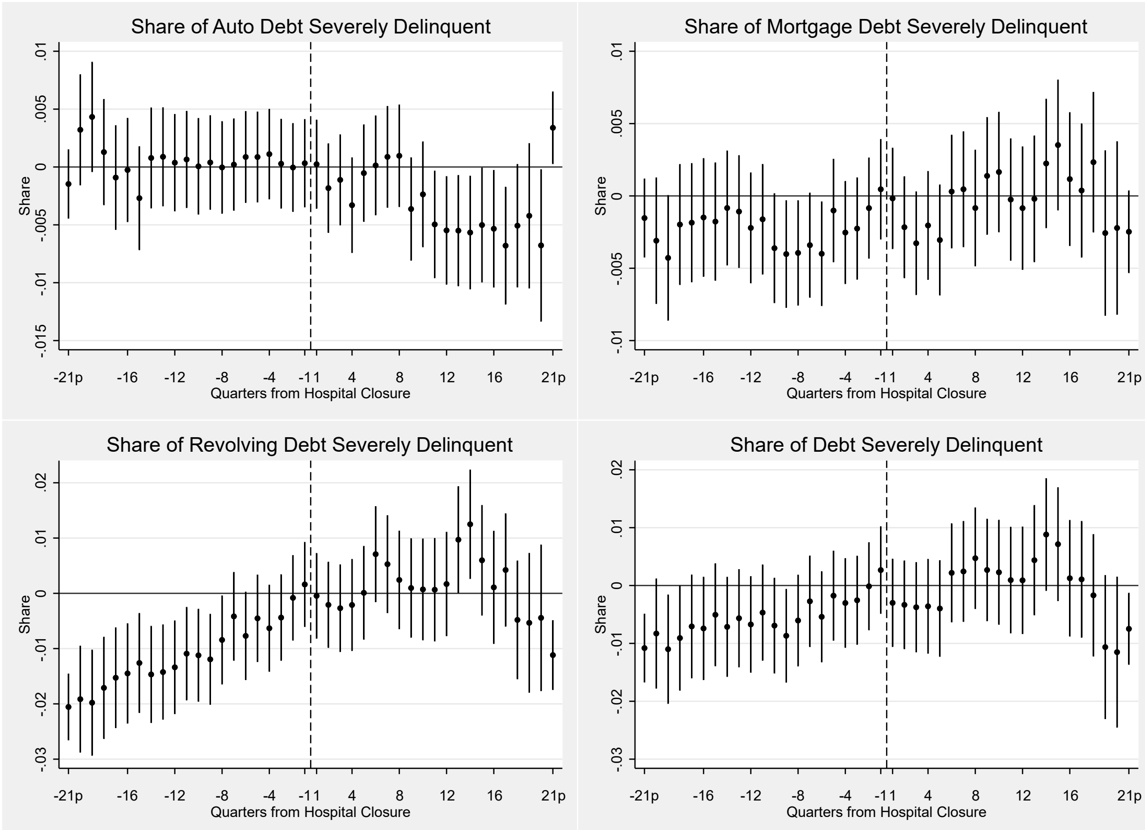
Figure C.6

Event Study for Share of Accounts Severely Delinquent Debt at the County-Level for Ages 27 to 54



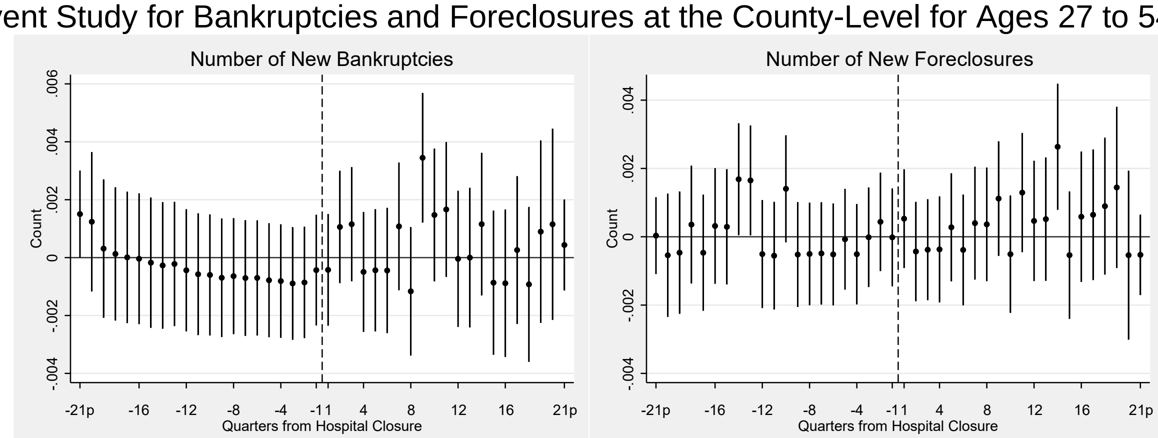
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.7
Event Study for Share of Debt($) Severely Delinquent Debt at the County-Level for Ages 27 to 54



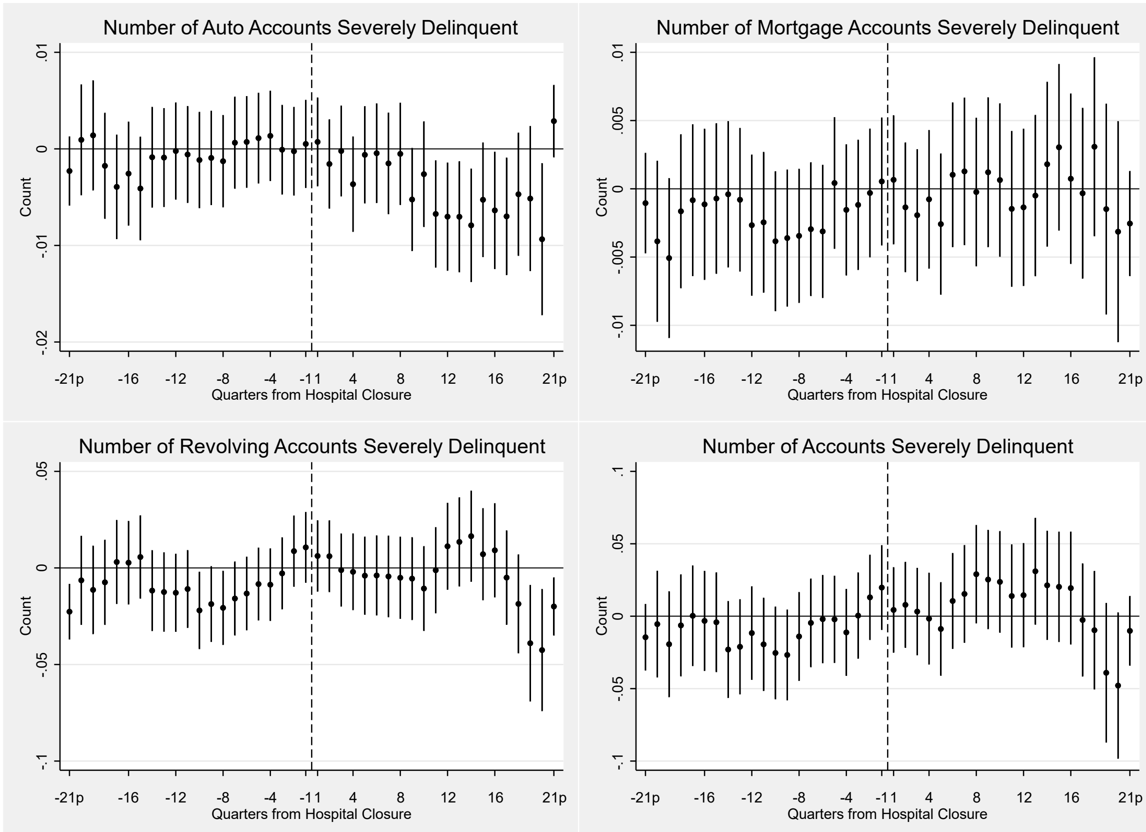
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.8
Event Study for Bankruptcies and Foreclosures at the County-Level for Ages 27 to 54



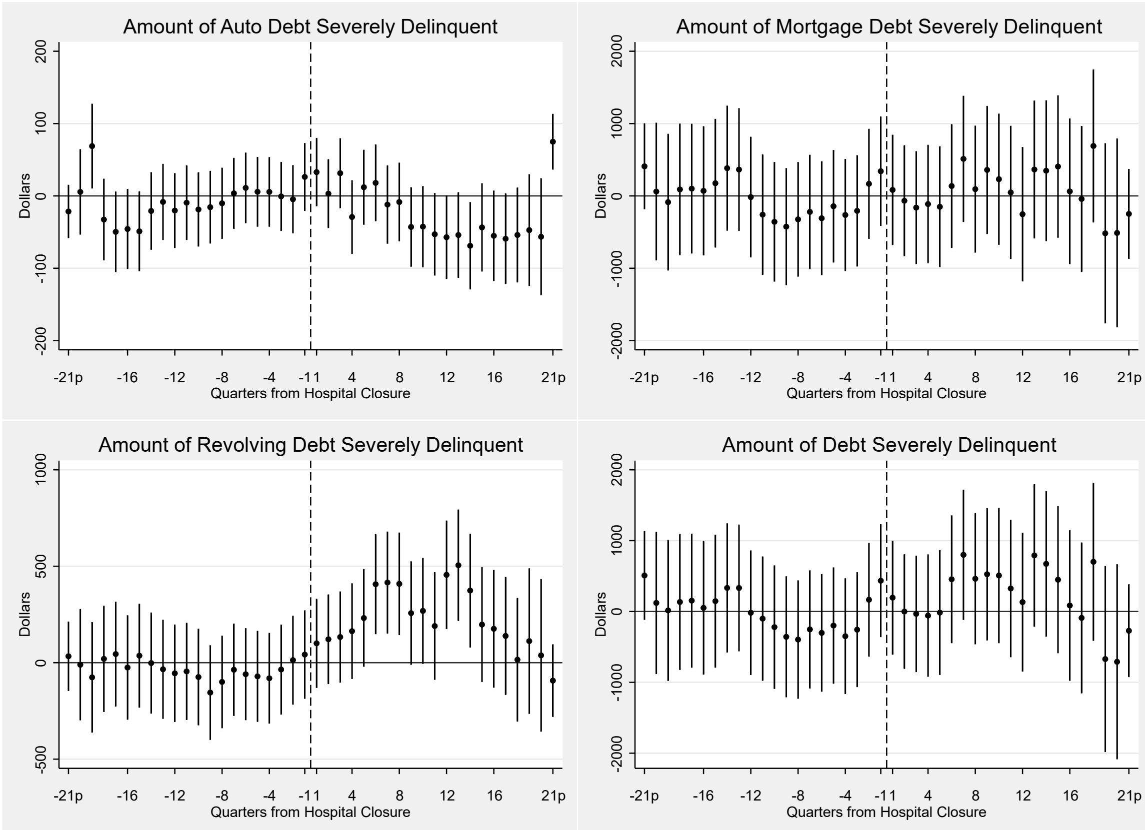
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.9
Event Study for Number of Accounts Severely Delinquent Debt at the County-Level for Ages 27 to 54



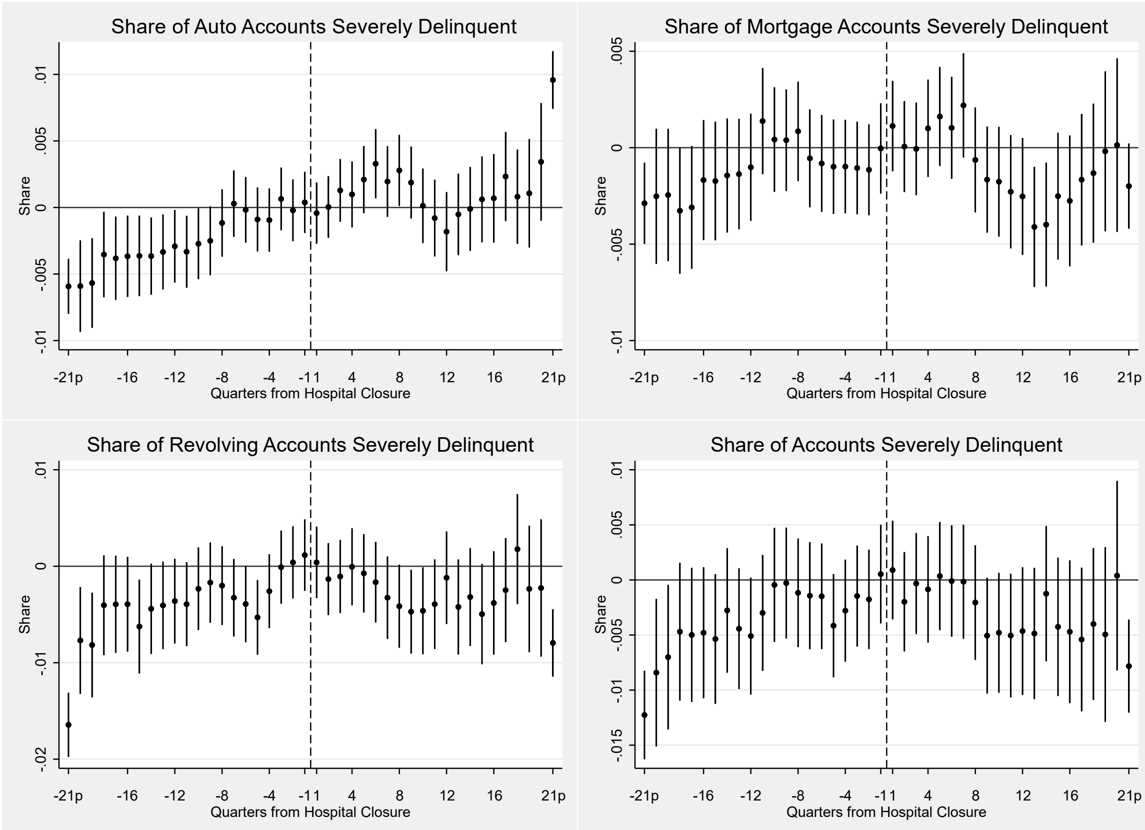
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.10
Event Study for Amount of Debt($) Severely Delinquent Debt at the County-Level for Ages 27 to 54



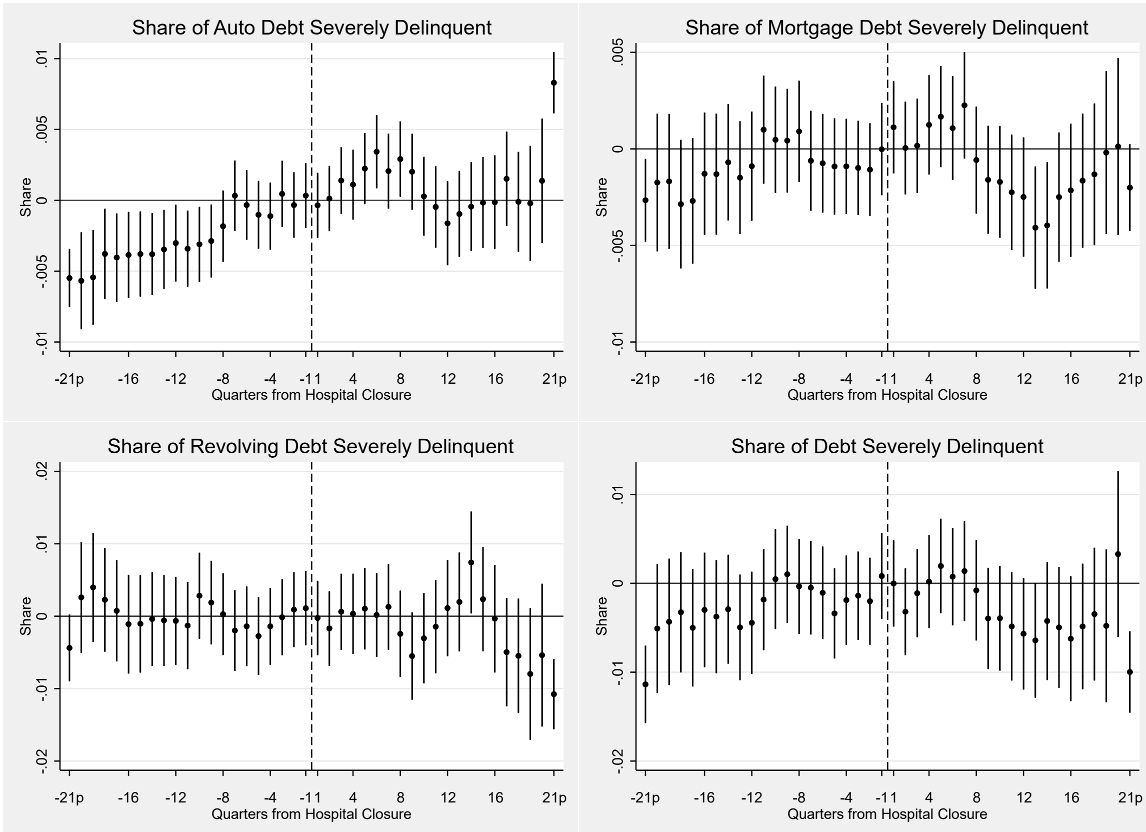
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.11
Event Study for Share of Accounts Severely Delinquent Debt at the County-Level for Ages 55 to 64



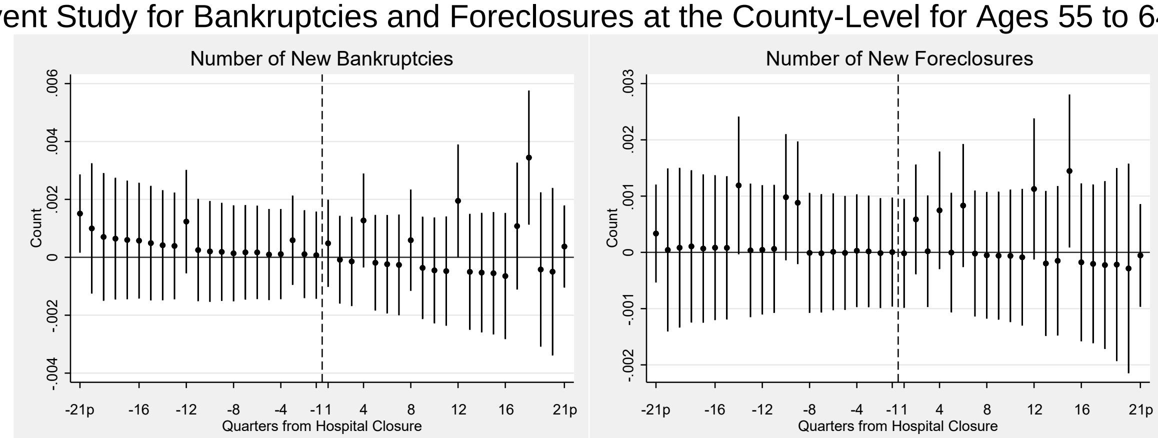
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.12
Event Study for Share of Debt($) Severely Delinquent Debt at the County-Level for Ages 55 to 64



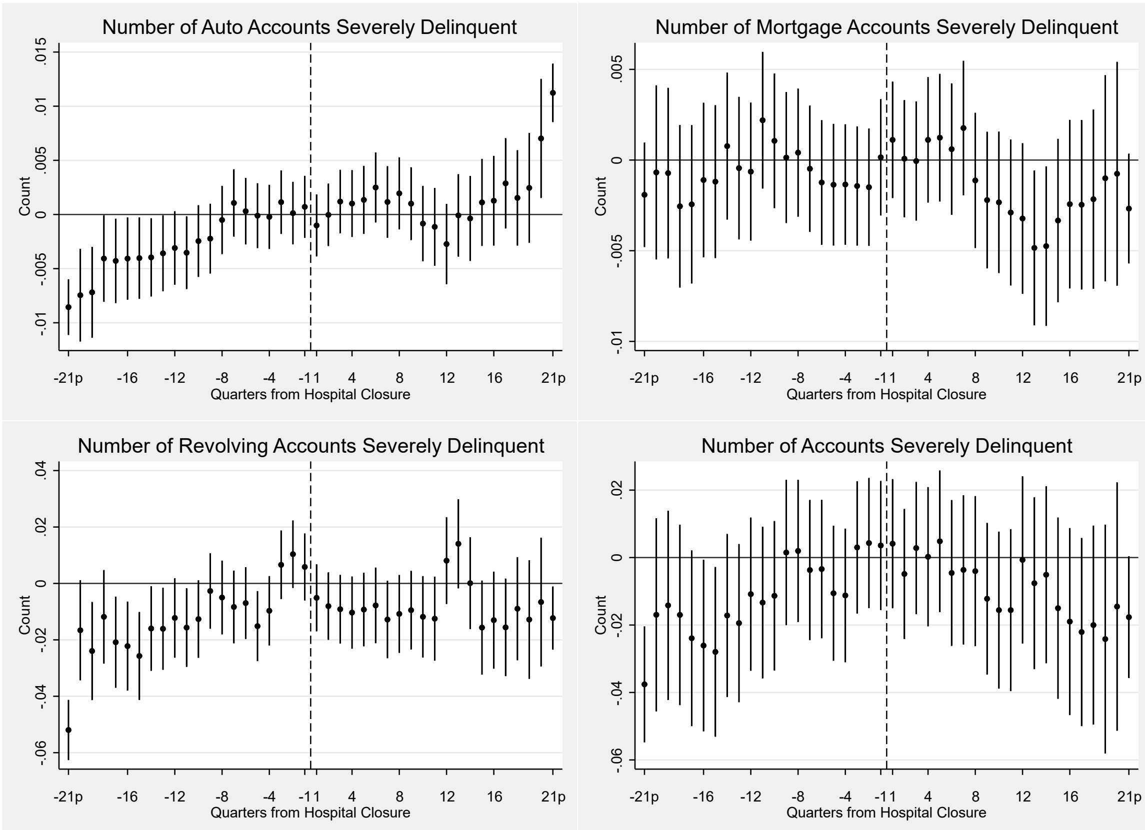
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.13
Event Study for Bankruptcies and Foreclosures at the County-Level for Ages 55 to 64



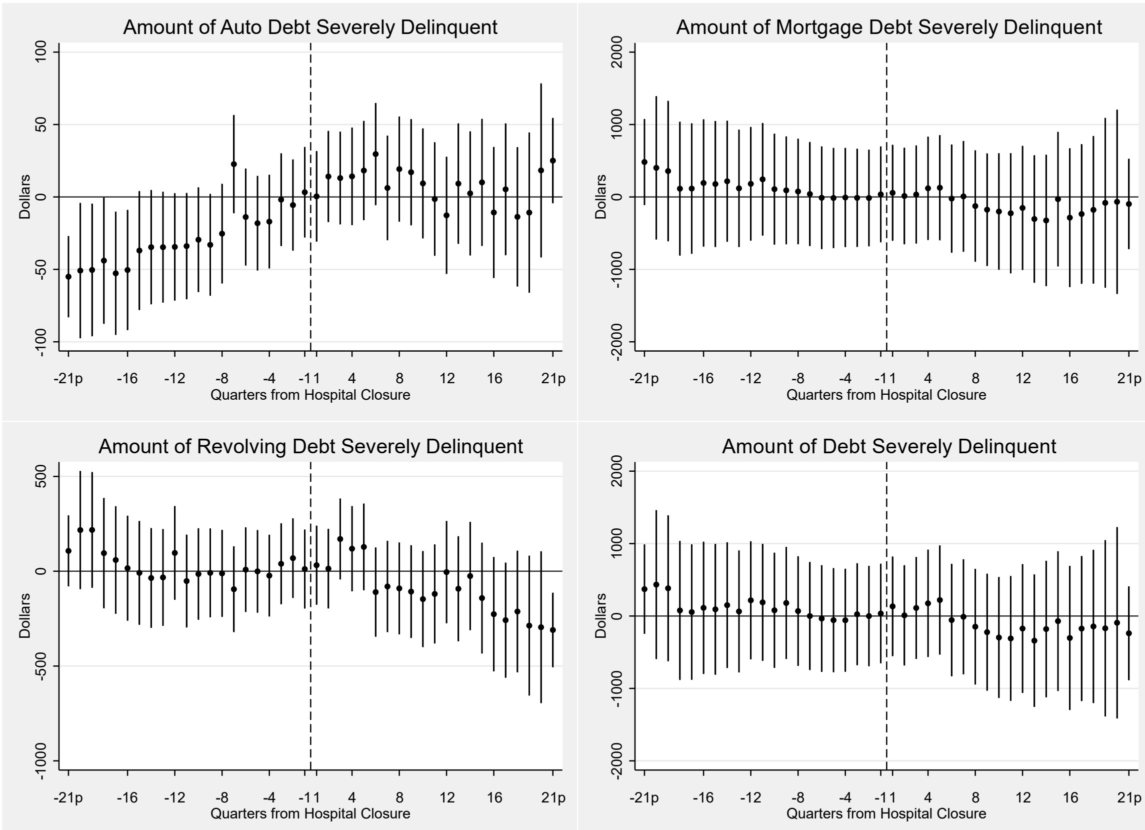
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.14
Event Study for Number of Accounts Severely Delinquent Debt at the County-Level for Ages 55 to 64



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

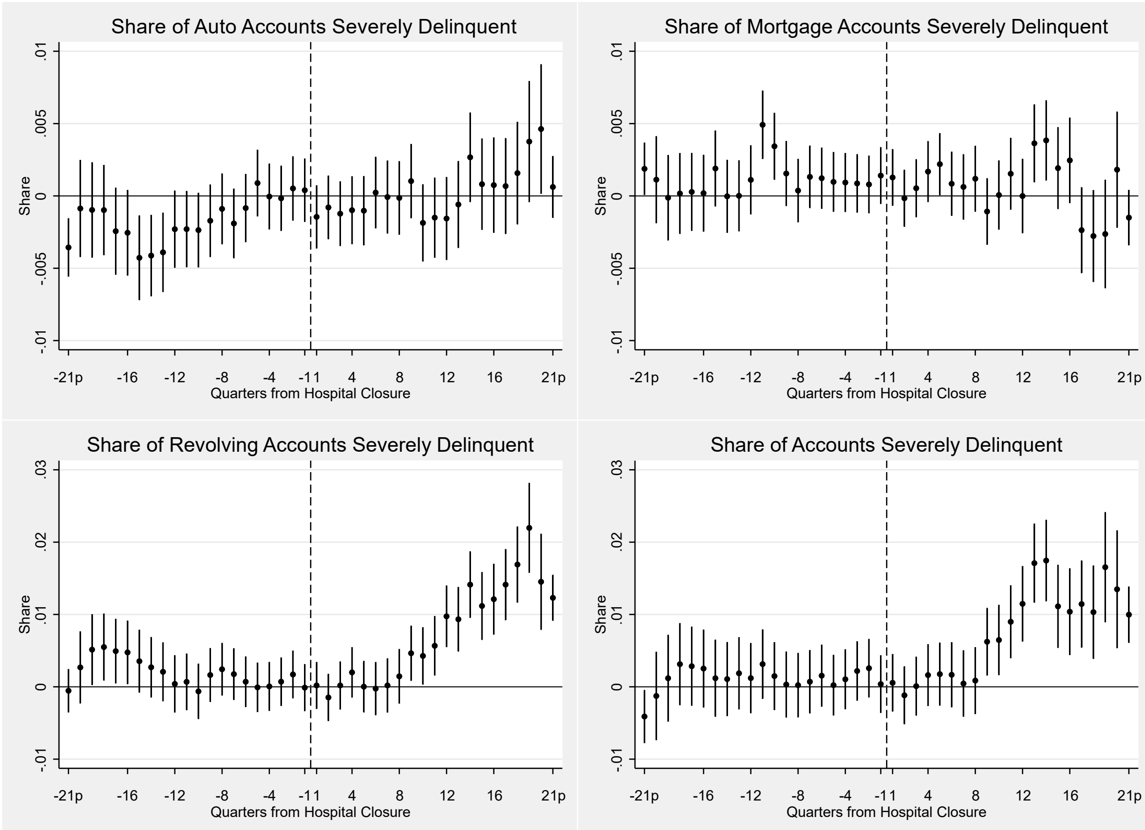
Figure C.15
Event Study for Amount of Debt($) Severely Delinquent Debt at the County-Level for Ages 55 to 64



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.16

Event Study for Share of Accounts Severely Delinquent Debt at the County-Level for Ages 65 to 74

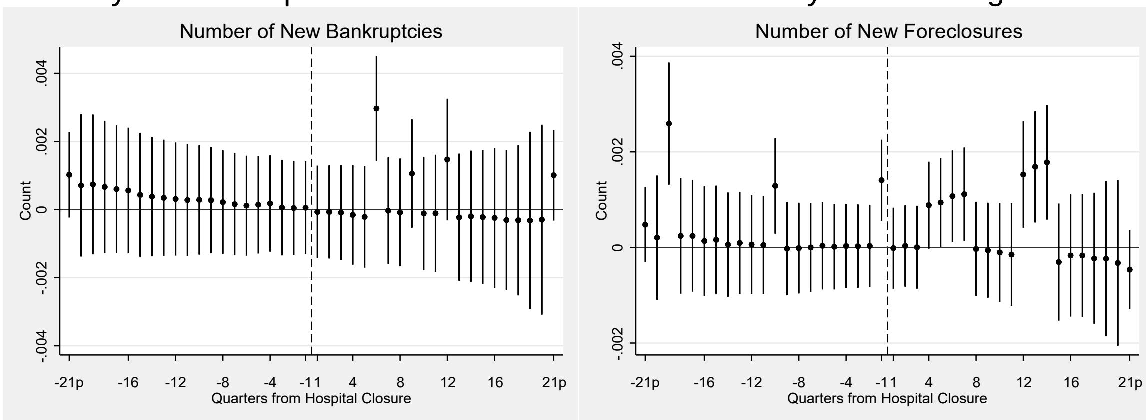


Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.17
Event Study for Share of Debt($) Severely Delinquent Debt at the County-Level for Ages 65 to 74

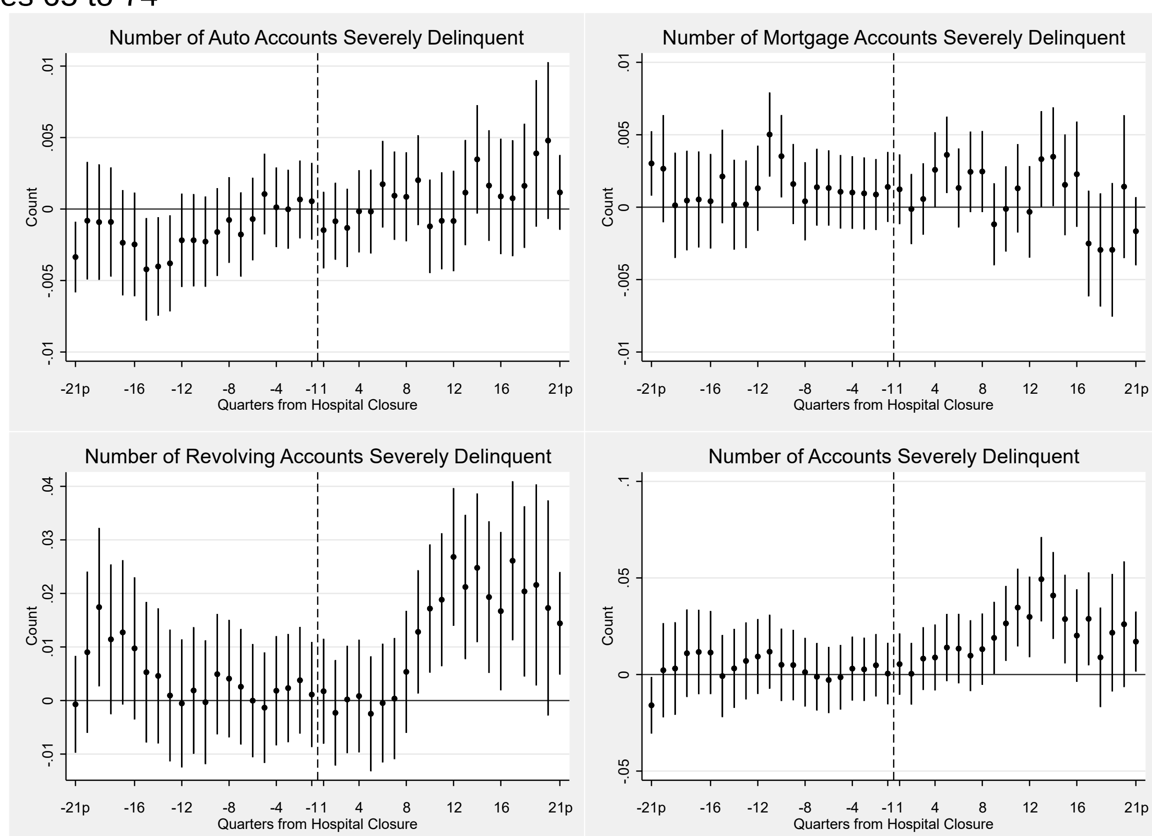
Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.18
Event Study for Bankruptcies and Foreclosures at the County-Level for Ages 65 to 74



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

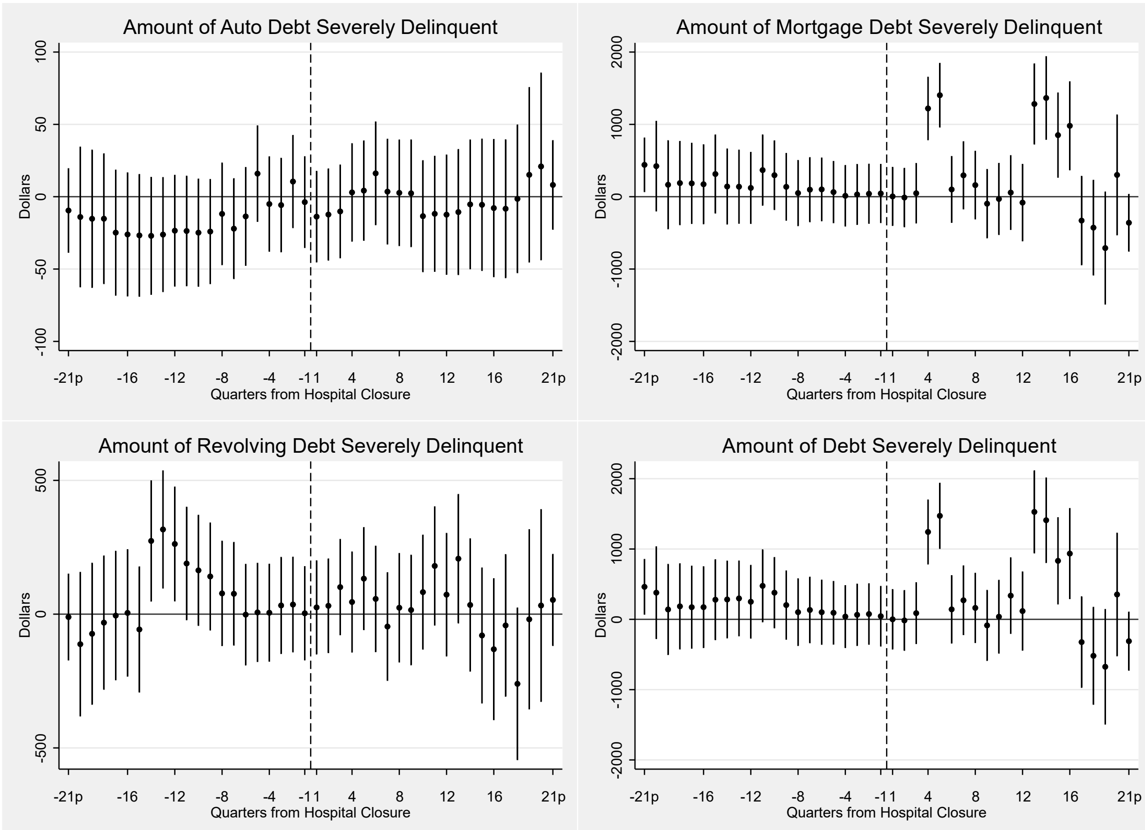
Figure C.19
Event Study for Number of Accounts Severely Delinquent Debt at the County-Level for Ages 65 to 74



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

Figure C.20

Event Study for Amount of Debt($) Severely Delinquent Debt at the County-Level for Ages 65 to 74



Source: Federal Reserve Bank of New York Consumer Credit Panel/Equifax, CMS, and the North Carolina Rural Health Program

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