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ABSTRACT

An Examination of the Intracorrelation of Family Health Insurance*

A negative shock to one household member can have consequences for other household members. This paper demonstrates the extent of job lock and health insurance plan stemming from the unanticipated health shock of a child family member. In response to the shock, I estimate a 7 – 14 percent decreased likelihood of all family members leaving the current health insurance network and health plan. This is plausibly driven by reduced rates of job switching by the plan's primary policyholder. Furthermore, switching frictions stemming from the non-portability of health insurance products may contribute to the observed job and "health plan lock."

JEL Classification: I10, I12, J10, J20

Keywords: household, health shock, health insurance, job lock

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1 Introduction

Understanding the impact of individual-level shocks on the broader household is important in many settings. For example, it is important when considering the impacts of shocks to labor supply or wealth (e.g. Oreopoulos et al. (2008) and Lovenheim and Reynolds (2013)). In the context of health, the onset of an isolated, adverse event is an influential shock that can have far-reaching consequences on the broader family (e.g. Gertler and Gruber (2002), Dobkin et al. (2018)). Furthermore, given the prevalence of such adverse events, understanding their broader effects is important for society.[1] Yet, when examining the implications of health shocks on households, most studies typically focus on a limited set of outcomes among a subset of the household, such as the labor supply and earnings responses of working-age adults (e.g. Charles (1999), Fadlon and Nielsen (2015)). This paper expands upon this literature by examining how an acute adverse health shock experienced by one individual affects the health insurance outcomes of all family members. The issue merits serious consideration given that household-level linkages are defining features of the US health care system since health insurance is often tied to employment *and* bundled at the family level.[2] Further, in examining this question, this paper sheds light on the interplay between health status and employment decisions. In particular, this paper demonstrates that a health shock to one family member can amplify the job lock of another family member. This plausibly occurs because of the increased value of maintaining the current employer-sponsored health insurance network *and* health insurance plan following an emergency.

Relatively little is actually known about the effects of an adverse health shock on the entire household, with even less known about the impacts on health insurance outcomes of the entire family. However, given the structure of US health insurance markets where bundled family health insurance plans dominate, the potential spillover effects of a shock to the broader family are non-trivial for a large segment of society. For example, the Current Population Survey (2014 - 2018) indicates that approximately 58 percent of people 64 years of age or younger have employer-sponsored health insurance, with approximately 76 percent belonging to a family health plan. Also, given that investments in health likely have long term implications for socioeconomic status (e.g. Smith (2004) and Currie (2009)), it is critical to understand the factors influencing health insurance coverage and plan choices as both likely matter for health behaviors.

[1] According to the Centers for Disease Control and Prevention (CDC), in 2018, there were approximately 130 million emergency department visits, of which approximately 27 percent were due to injury (Centers for Disease Control and Prevention (2021)).)

[2] Examples of this include health plan enrollment decisions (e.g. enrolling in a health plan as a family vs. enrolling as an individual) Additional examples include the joint family deductible (for family-held health plans), whose responsibility is shared across all family members.

A-priori, the implications of a health shock on families' insurance outcomes are unclear. For example, one pathway by which a shock could operate is through interruptions to the labor supply of the primary insurance policyholder (Bradley et al. (2013)). In this case, a health shock experienced by the primary policyholder could disrupt continuous insurance coverage for the entire family. Alternatively, a health shock may provide new information about insurance plan quality or individual health status. This could result in higher (or lower) rates of health insurance plan switching (Handel (2013) and Strombom et al. (2002)) depending on the generosity of the family's current health plan.[3] Additionally, switching costs, in the form of product compatibility costs (Farrell and Klemperer (2007)) may make it more costly to change health insurance networks at the time of a health shock (e.g. due to the possible loss of an in-network health care provider). This, in turn, would inhibit the changing of health insurance networks and plans.

To address the research question, this study examines how an acute appendicitis emergency experienced by a child family member affects the subsequent health insurance network and plan choice for family members holding the same health insurance plan. This is achieved by using a *big* US medical claims data, consisting of individuals who hold private insurance through a large commercial insurer. In particular, this study addresses the research question by examining the evolution of dropout from the observed insurance network after the onset of acute appendicitis. The approach is novel in that it captures changes in health insurance plan choice by leveraging key features of the data: dropout is due either to switching one's health insurance plan to another insurance network (e.g. due to job changes or changes made during open and special enrollment periods) or to the complete loss of health insurance coverage (e.g. due to job loss). To be discussed later, by examining the health shock of a child, the effect of the latter route should be greatly minimized, allowing for a more precise identification of the drivers of the observed behaviors.

Acute appendicitis is an ideal emergency health shock to analyze because of the as-good-as-random nature with which the disease occurs (Bhangu et al. (2015)) and the immediacy with which the disease needs to be treated. Furthermore, the onset of this disease is isolated and transitory such that is extremely unlikely to concurrently occur within a family. Thus, this particular shock allows for the identification of family's responses to unanticipated, individual-level health shocks. Additionally, by focusing on emergencies experienced by children, the study is able to better home in on the possible mechanisms underlying the observed health insurance behaviors. This is because it is extremely unlikely for a child to be the primary policyholder of a family health insurance

[3]This response may be rooted in adverse selection/adverse retention (Altman et al. (1998); Cutler et al. (2010); Polyakova (2016).)

plan.[4] Therefore, their health shock should have limited effects on intermediate outcomes that could influence the observed response, such as changes to labor supply or household income.

To measure the impact of the emergency, I estimate stacked Difference-in-Difference models and compare the responses of family members exposed to appendicitis to a control group who are never exposed to an appendicitis emergency. The control group is constructed using a coarsened exact matching approach, where individuals exposed to an appendicitis health shock are paired with control individuals who enroll in the insurance network in the same month and year and who have a similar *tenure* profile, prior to the health shock. The idea here is that those who do not experience the emergency can be used to control for the natural rate of exit from the network that would have occurred in the absence of this health shock, while also accounting for the non-linear rate of dropout that varies over time spent in the data (i.e. tenure). This matching procedure allows for the establishment of a placebo emergency date and in doing so, creates a point-in-time benchmark to examine the natural rate of "churn" out of the insurance network in the absence of a health shock.[5] The same point-in-time benchmark is also used to examine whether households who stay in the insurance network choose to remain in the same health insurance plan after the health shock.

The results of the analysis indicate that the emergency health shock of a family member leads to *lower* rates of exit from one's current health insurance network and health plan.[6] Interestingly, this effect primarily manifests as lowered rates of job change by the primary policyholder of the health insurance plan. Furthermore, within three months of an emergency, families exposed to appendicitis are approximately 14 percent less likely to leave their current health plan, relative to the control group. After six months, families are 12 percent less likely to leave their current plan and after one year, this number is approximately 7 percent. Thus, exposure to the emergency decreases the likelihood of leaving the current health plan by 7 – 14 percent in the one year period after the emergency occurs.

Investigating the underlying mechanisms, I find evidence that switching costs may be a source for reduced health plan switching. In particular, switching frictions may

[4]For example, according to 2011-2013 American Community Survey estimates, approximately 53 percent of children, ages 6 through 17 had employer-sponsored health insurance (American-Fact-Finder (2019)). Additionally, the 2017 California Health Interview Survey found that approximately 50 percent of children, ages 0 - 17 years, have Employer-Sponsored Health Insurance (ESHI) (UCLA Center for Health Policy Research, Los Angeles, CA (2019)). Given the low rate of employment for this age group, ESHI must come from a family member/affiliate.

[5]This matching procedure is related to the matching techniques used by Miller (2017) and Fadlon and Nielsen (2019).

[6]The current health plan is defined as the health plan held at the time of the emergency.

stem from the bundling of health insurance products (Farrell and Klemperer (2007)), namely the bundling of *non-portable* health reimbursement accounts (HRA) with health insurance plans. This is because an HRA is tied to both a specific employer and typically to a specific health insurance plan. Thus, it may be costly to forefeit money in the HRA in times of high current, or anticipated, medical expenses. In support of this mechanism, families belonging to health plans that are paired with an HRA are much less likely to leave their current plan after the sudden health shock. This result stands in contrast to the relatively higher rates of exit among families whose health insurance plan is paired with a portable Health Savings Account (HSA). While this result does not exclusively rule out the presence of adverse selection or other sources of switching frictions, it does suggest that the non-portability of an HRA may make it costly to switch health plans *and* employers.

Furthermore, the effect of the emergency on dropout rates is nearly identical across all family members. In particular, the onset of the emergency leads to decreased exit from the health insurance network and plan (held at the time of the emergency) for both the person who experiences the emergency and their affiliated family. This suggests that health insurance plan decisions are jointly made at the family level.[7] While the joint nature of health plan decisions at the household-level is assumed in many settings (e.g. Bundorf et al. (2012)), the findings of this study suggest that when modeling health plan selection at the household level, the aggregation of individual family member's household health risk should also account for health risks stemming from transitory health shocks (and not just chronic diseases).

This paper contributes to three distinct strands of literature. First, it is one of a few studies that examines the effects of health shocks on the health care behaviors of families in a developed country setting. This could be due to the limited number of datasets that provide a sufficient level of detail to precisely measure these impacts. Instead, most studies analyzing health shocks typically focus on the employment outcomes of either the person who experiences the health shock or their spouse, earnings declines, or the health care spending associated with the event (e.g. Charles (1999); Bradley et al. (2007); Jeon and Pohl (2017)); García-Gómez et al. (2013); Fadlon and Nielsen (2015)). These studies typically find that own labor supply and spousal labor supply are affected by health shocks. The response may vary depending on if health insurance is held through a spousal policy (Bradley et al. (2007)) or if the person experiencing the shock is male or female (García-Gómez et al. (2013)).

[7] This is consistent with studies that have found high degrees of correlation in health-related behaviors across family members (Hamersma et al. (2019)). For example, Hamersma et al. (2019) find that that when parents become Medicaid eligible, their children are also more likely to become insured.

An exception to the above mentioned studies is recent work by Fadlon and Nielsen (2019) who examine the response of families to the emergency heart attack of a family member in Denmark. The authors find that the onset of family member's heart attack encourages other family members to engage in healthier behaviors, including increased uptake of preventative care. However, the specifics of the US health care system, such as the lack of universal coverage, the direct responsibility for medical expenses, and the prevalence of bundled family health insurance often tied to the employment of a household member, make it difficult to extrapolate results from countries with universal health insurance or those with limited/informal insurance markets. This is especially true when the outcome of consideration is whether or not all family members maintain continuous insurance coverage through the same health plan.

Second, this study also compliments the existing literature that examines health insurance plan choice (Handel (2013), Handel and Kolstad (2015), Polyakova (2016)). In particular, this study shows that acute, transitory health shocks may result in reduced health plan switching. The findings of this study also suggest that a distinct source for reduced plan mobility may be the bundling of non-portable health reimbursement arrangements with health insurance plans.

Third, by showing that the non-portability of health reimbursement arrangements may be a source of reduced health plan switching, and subsequently job switching, this analysis also demonstrates that the current structure of health insurance markets may still contribute to job lock. This remains the case even after laws meant to address this issue, such as the Health Insurance Portability and Accountability Act (HIPAA), were passed (Madrian (1994)) and also after the expansion of public health insurance options, such as the Affordable Care Act (Bailey and Dave (2019)).[8] Thus, the findings of this analysis contribute to the literature by showing that job lock can occur even in the case of isolated, transitory health shocks (Stroupe et al. (2001)) and that an additional source of job lock may stem from the non-portability of certain health plan products offered by employers.

Finally, by documenting the high degree of correlation in health plan choice among families after a health shock, the results inform our understanding of health insurance markets. In particular, the findings of this study are informative for understanding adverse selection, stemming from the sorting of *individuals* into health insurance plans based on their own realized health risk (Akerlof (1978), Rothschild and Stiglitz (1978), Cutler and Zeckhauser (1998)). This study shows that the high degree of correlation in plan choice among family members effectively results in a more balanced health insurance plan risk pool. In particular, healthier family members who tend to have lower health risk can

[8]For a more detailed discussion on the provisions of HIPAA, please see Lewin (1999).

effectively balance/offset the health risk associated with the sicker family members who recently experienced the health shock. This is an important consideration when examining the market inefficiencies associated with adverse selection.

The rest of this paper will proceed as follows. Section 2 discusses the Research Design while Section 3 discusses the Data. Section 4 discusses the Empirical Strategy. Section 5 presents the Results while Section 6 concludes.

2 Research Design

In this section, I discuss the quasi-experiment used to analyze the impact of health shocks. I also discuss features of the data and the additional considerations it necessitates, as well as the construction of the control group. A more detailed description of the data is found in Section 3.

2.1 Quasi-Experiment: Appendicitis

The central challenge in identifying the impact of health shocks on insurance coverage is in establishing a plausible counterfactual. In an ideal setting, one would compare families who are similar in their propensity to leave their health plan (i.e. due to job switching and health plan switching), but for the occurrence of the health shock. This could be achieved through a randomized control trial where individuals are "randomly assigned" a health shock or instead by focusing on a case setting in which the shocks are considered to be as-good-as random. In the latter scenario, the unobservable factors influencing dropout should be similar across the general population, facilitating the construction of a plausible control group.

Acute appendicitis meets the criteria of being an as-good-as-random health shock. This is because the causes and origins of this condition are not well understood (Baird et al. (2017) and its onset seems to occur with few discernible predictable risk factors.[9] As such, the observable characteristics across the families exposed to appendicitis and those who are not, should not systematically differ. This implies that the onset of this disease can be considered as essentially random in its occurrence and timing.

Furthermore, acute appendicitis is a condition that requires immediate medical attention. As such, its onset allows for the identification of families' responses to unanticipated

[9] There is a slightly higher rate of appendicitis in males versus females and the "peak incidence usually occurs in the second or third decade of life, and the disease is less common at both extremes of age" (Baird et al. (2017), p. 1278). Additionally, Golz et al. (2020) finds geo-spatial variation in the incidence of certain kinds of appendicitis (perforated appendicitis) in Washington state.

health shocks. Additionally, "acute appendicitis is one of the most common general surgical emergencies worldwide, with an estimated lifetime risk reported to be 7–8 percent" (Bhangu et al. (2015), p.1278). Thus, the results of this analysis are more likely to extrapolate to a broader group given its non-negligible rate of occurrence in the general population.

2.2 Assumptions and Background for Control Group

A key feature of the dataset used in this analysis is that the majority of individuals have commercial, employer-sponsored health insurance (ESHI). This means that the reason for exit from the insurance network will likely be driven by two factors: 1) job switching/job loss and 2) switching health insurance plans, specifically into the health plan of a different insurance network.[10] The assumption that insurance network exit and plan changes can be largely contributed to job changes is based on evidence that individuals tend to be inert in changing health plans (Handel (2013)). Additionally, Cunningham and Kohn (2000) show that a major reason for changes to health plans are job changes - among those who changed health plans over a one year period, nearly 70 percent did so either because they changed employers or their current employer changed the plan offerings.

A necessary assumption in constructing an appropriate counterfactual for the appendicitis group is that there exists an identifiable comparison group that is similar in its propensity to exit the insurance network due to job switching and health plan switching, in the absence of a health shock. Given the evidence of inertia in health plan choice, discussed above, it is plausible that the latter condition can be achieved when comparing the appendicitis group and a hypothetical control group, particularly in a setting where the health shock is considered to be exogenous.

To achieve, ex-ante, comparability in the job switching rates, this analysis constructs a control group from individuals who have been in the insurance network for a similar amount of time before the appendicitis group's emergency date (i.e. they have a similar tenure) and who join a network health plan in the same year and month. The assumption underlying this approach for selecting eligible controls is that: 1) since there are low rates of within-job health plan switching (Handel (2013)), tenure at the job is a good proxy for insurance network tenure and 2) the rate of network exit due to job switching is likely a non-linear function of the time period in which a job is joined (Oreopoulos et al. (2012)) and the amount of time already spent at the job (Copeland (2019), US Department of

[10]Changes to insurance networks and plans can occur during open enrollment periods or due to *Qualifying life events*. The latter are events that if experienced by an individual, allow individuals to change their health insurance network/plan outside of an open enrollment period, are also a possible reason for insurance network and plan switching. This will be further discussed in the Results section.

Labor (2018)). Thus, individuals who are at similar points in their job cycle are more likely to have similar rates of exit from the insurance network.

In support of the non-linearity of exit over time spent in the network (i.e. tenure), Figure 3a depicts the Kaplan-Meier survival curve for a sample of individuals who are not exposed to appendicitis. Similarly, Figure 3b depicts the distinct Kaplan-Meier survival curves for a sample of individuals who are not exposed to appendicitis, stratified by the years in which they joined the data.[11] Both figures depict the share of the people who still belong to a health plan within the insurance network (i.e. have "survived" in the data) at any given point in time, t. Of interest is the slope of the graphs. The slope, at a given time t, indicates the rate of exit for those who have survived up until that point. As shown, there is a higher rate of exit for smaller values of t, whereas there is a lower rate of exit at higher values of t. These figures suggest that the rate of network exit is non-linear in time and that the rate of exit may vary by an individual's start-month and start-year in the data.

In short, the analysis assumes that the exit rate of families exposed to appendicitis can be approximated by the exit rate of families who are defined as belonging to the same cohort, but who themselves were not exposed to a health shock. A cohort is defined as individuals who join the dataset in the same year and month and who have survived in the data at least as long as the families exposed to appendicitis at the time of the appendicitis health shock. To be discussed in the next section, the control group will be constructed from the above described eligible cohort. Further, the control group will ultimately consist of households with two adults and at least one child to ensure comparability in family structure across the appendicitis group and control group.

2.3 Construction of the Control Group

The construction of the control group is achieved through a coarsened exact matching approach. Specifically, this analysis matches both the *distribution* of pre-emergency tenure and the initial month-year (month $\times$ year) of insurance network enrollment of the appendicitis group.

To construct the control group, the analysis begins by selecting individuals who have never been exposed, directly or indirectly, to appendicitis during their time in the insurance network/tenure with the insurer, and who have a similar family structure as treatment group individuals (to be defined in the Data Section). The candidate control sample is then limited to individuals who are similar to the reference individual in the

[11] The join dates and days of total tenure are chosen for illustrative purposes; the general conclusions still hold if these are varied.

treatment group, where this reference person is the individual who directly experiences the appendicitis emergency. Similarity is defined as: 1) joining the sample in the same year and month and 2) having at least as many days of total continuous tenure before the emergency date of the paired treatment individual.[12]

A cross-pairing for every possible appendicitis group and eligible control combination is then formed such that the two previously mentioned requirements are met. Up to fifty of the cross-pairing matches are then selected at random and the emergency date of the treated reference individual is assigned to the paired control individual.[13] This assigned date is the *placebo emergency* date for the control group individuals, but for the purposes of the analysis, will be referred to as the emergency date. Finally, control families are identified as the control individual matched in the cross-pairing along with any other individual who shares the same insurance policy on the placebo emergency date.

The emergency date assigned to the control group serves as an event-time benchmark from which to examine the outcome of interest. This approach is similar to that of Fadlon and Nielsen (2019), Miller (2017) and Jeon and Pohl (2017) who establish pseudo-event dates among eligible controls as a means for constructing counterfactuals in dynamic difference-in-difference and event-study frameworks. Further, in this analysis setting, the control group is constructed such that the pre-emergency tenure *distribution* and the initial enrollment month-year of the appendicitis group is matched, rather than just the mean of these characteristics. This is evident in the histogram displayed in Figure 1, which shows the very similar distributions of tenure held before the emergency date for the appendicitis and control groups, respectively.

3 Data Description

Data consists of information on medical claims for commercially insured individuals who have both health and prescription insurance coverage administered by a single payer. Data were obtained from Optum's Clinformatics Data Mart Database.[14] The dataset spans the period from January 2003 to June 2019 and includes certain demographic information typically captured by insurers, such as state of residence, age, and gender of individuals.

[12] In practice, the latter condition requires that $floor(\frac{T^C}{365}) \geq ceiling(\frac{T^T}{365})$, where T^C is the total days of tenure held by a control individual and T^T is the number of days of tenure held before the onset of the appendicitis emergency for the treated individual (i.e. the pre-emergency tenure).

[13] The number of cross-pairings matches used is varied and tested in the Robustness Checks Section. Additionally, a control individual/family can be used as a match more than once across different emergency dates and for different treatment families.

[14] *Optum* refers to Optum©'s de-identified Clinformatics® Data Mart Database. Optum©'s Clinformatics® Data Mart (CDM) is a statistically de-identified database of administrative health claims for members of a large national managed care company affiliated with Optum.

The data includes the medical claims records for individuals with Medicare Advantage plans but does not include individuals who have Medicaid or traditional Medicare. As a testament to the size of the data, there are approximately 16 million individuals observed in the data in 2018.

3.1 Analysis Sample: Appendicitis and Control Groups

The focus of this analysis is on health shocks stemming from the onset of acute appendicitis. To construct the appendicitis treatment group, I make several restrictions. First, the appendicitis sample is limited to individuals who: 1) experience their first diagnosis of non-fatal acute appendicitis and 2) are admitted to an emergency room or hospital for emergency or urgent reasons.

Furthermore, the individual experiencing the health shock must be a child, where a child is defined as an individual younger than 16 years of age at the time of the emergency.[15] Family units are then identified for these individuals where a family is defined as a group of two or more individuals who are linked together by a shared health plan subscriber number on the date of the emergency (i.e. these individuals are covered by the same health plan policy). Of note, the age threshold is chosen so as to minimize the likelihood of dropout owing to life transitions that may occur around 18 years of age, such as college attendance. Also, since the primary policyholder of the health plan cannot be identified in the data, this approach avoids the challenges that occur when trying to identify the mechanisms underlying the response to adult emergencies.[16]

Common restrictions are made for both the treatment and control groups. These restrictions include that families must consist of two adult heads and one at least one child and families must not experience an emergency admission or hospitalization within one year prior to the emergency date.[17] The former is done in order to narrow in on the possible mechanisms influencing the insurance decisions observed in the data.[18] For example, since marital status is unknown, in households observed to have one adult, it

[15] Acute appendicitis incidents are captured by identifying International Classification of Diseases (ICD) codes that begin with either 540 (ICD-9) or K35 (ICD-10). Further, Current Procedural Terminology (CPT) Codes of 44950, 44960, and 44970 are used to identify individuals who have had an appendectomy.

[16] These challenges are namely that, the effect of the health shock (e.g. the sign of the treatment effect) will likely vary depending on whether or not it is the primary policyholder who experiences the health shock, as discussed in Bradley et al. (2007).

[17] For the treatment group, this restriction is relaxed to allow for the inclusion of individuals/families where there is an observed emergency admission up to one day prior to the date of the appendicitis emergency. This allows for the inclusion of individuals who present to health care providers with problematic health before actually being diagnosed with appendicitis.

[18] It is ideal to observe the behavior of all members in the household; as such, a family structure is picked that best allows for that identification, since one cannot observe marital status/relationship status in the data.

is not possible to determine if families drop out to join the health plan of an unobserved family member. Thus, focusing on two adult households allows for better homing in on mechanisms behind the switching/non-switching of health plans. The latter restriction is made to ensure that the responses captured after the appendicitis emergency truly stem from that emergency and not a different health shock.

Second, the age of all family members is restricted to being below 63 years. This restriction is made in order to minimize the probability of drop out due to non-emergency reasons such as retirement or Medicare eligibility (at age 65). Third, the sample is limited to families in which all individuals have at least one year of insurance coverage (through the insurance network) prior to the emergency. This allows for the examination of pre-trends along non-insurance outcomes. Thus, emergencies must occur between January 2004 and May 2018, ensuring that there is one year of pre- and post-emergency data available for observation.

Table 1 shows that the treatment and control groups have very similar demographic characteristics. The average family consists of slightly fewer than five individuals, where the average across individuals in both groups ranges between 25 - 26 years. The sample is roughly evenly split along gender, although there are more males in the treatment groups (approximately 53 percent), consistent with the fact that the disease tends to have a slightly higher incidence in males (Craig and Brenner (2020)). Also, the pre-emergency tenure is quite similar across both the treatment and controls groups at approximately 1279 days (3.5 years) and 1198 days (3.3 years), respectively.

Importantly, general health, as proxied by the one-year Charlson comorbidity score (Charlson et al. (1987)) is highly similar across both groups.[19] Specifically, the share of individuals in both groups having zero comorbid conditions prior to the emergency is approximately 92 percent. The comparability of this statistic across both groups is consistent with the nature of appendicitis, whose determinants are still not well understood. Further, this statistic substantiates the plausibility that when focusing on an appendicitis shock, the treatment and control groups are likely to be comparable on health status. This matters, if, for example, individuals vary in their rates of job exit or health insurance plan exit by health status or health risk.

The majority of individuals in the treatment group live in the South (40 percent), followed by the Midwest (25 percent), with the fewest individuals living in the East. These shares are roughly the same in the control group. Additionally, the most common health plan held by the treatment group is a Point-of-Service (POS) plan, which is a hybrid between a health maintenance organization (HMO) and a Preferred Provider Organization

[19]The look back period used to compute the Charlson comorbidity score is one year before the emergency.

(PPO) plan. This plan is held by approximately 72 percent of individuals in the treatment group. The next most commonly held plan is the Exclusive Provider Organization (EPO) health plans, which are also similar to a hybrid of a PPO and HMO plan, then HMO plans, followed by PPO plans. The ordered prevalence of health plan type is similar to the control group where the POS plans are the most prevalent, followed by EPO, HMO and PPO plans, respectively.

Lastly, the appendicitis emergency tends to be expensive. The average medical costs incurred by families on the day of the emergency are approximately \$1600. This stands in contrast to the average family-level expenses of approximately \$116 spent in the year prior to the emergency.

4 Empirical Strategy

To examine the effects of an emergency on insurance coverage and other outcomes, the following stacked Difference-in-Difference model is estimated.

$$Y_{it} = \alpha + \sum_{k=-12, k\neq -1}^{11} \rho_k D_{it}^k + \sum_{k=-12, k\neq -1}^{11} \beta_k D_{it}^k \times T_i + \gamma T_i + X_i' \delta + \phi_t + \epsilon_{it} \qquad (1)$$

Y_{it} represents the outcome of interest, which is insurance network exit/dropout. It takes the value of one if an individual maintains continuous insurance coverage through the insurance network over the entire interval (i.e. there is no dropout), where each interval is approximately 30 days long; it is zero, otherwise.[20]

Time is normalized to event-time, such that t represents intervals until/since an emergency occurs ($t = 0$). D_{it}^k takes the value of one when an individual is observed k intervals since the emergency (placebo emergency); it is zero otherwise.[21] T_i represents treatment. It is a binary variable taking the value one if an individual belongs to a family that experiences an emergency; it takes the value of zero if an individual belongs to the control group.

The model focuses on a two year event window - one year before and one year after the emergency. Thus, $t \in [-12, 11]$. This is done because the effect of a health shock

[20]The focus is on rolling 30 day windows since an emergency, with the last interval being 35 days long. This is done because people are unlikely to make job/health plan decisions based on calendar months and instead make decisions based on time since an emergency. Thus, using this rolling window allows one to better capture the immediate effects of the emergency since emergencies can occur in the middle or end of the month.

[21]$D_{it}^k = \mathbb{1}(t = e_i + k)$, where $\mathbb{1}(\cdot)$ is the indicator function and e_i is the date where an individual is exposed to an emergency.

is likely largest closest to the emergency date (Dobkin et al. (2018)). As mentioned, the observations and outcomes of interest are also aggregated over roughly 30 day intervals and may be interpreted as *monthly* responses.

The parameters of interest in this model are the β_k. For each k, β_k gives the effect of exposure to an emergency on the probability of exiting the network (as compared to the control group), in the k^{th} interval since the emergency, relative to the interval right before the emergency (i.e. when $t = -1$). The ρ_k parameter estimates provide a benchmark for the natural rate of exit in the absence of an actual emergency. This benchmark is used to interpret the economic importance of the β estimates.

In order to interpret the β coefficients as the causal effect of experiencing an emergency on the outcomes of interest, two key assumptions are necessary. The first is that the parallel trends assumption must be valid. In other words, in the absence of an emergency, the emergency sample would have trended similarly in the outcome to the control group. Given that the control group is also limited to having insurance for at least one year prior to the placebo emergency and that there is a general overlap in demographic characteristics as presented in Table 1, this is plausible. Furthermore, in the next section, I compare the stability of pre-emergency medical spending, the number of medical claims made and the number of medical visits to help substantiate the validity of the parallel trends assumption.

The second necessary assumption is that, conditional on observable characteristics, the timing of the emergency is as-good-as-random. This is a very plausible assumption given the nature of appendicitis. In support of this assumption, Figure 4 shows the average number of claims and spending made on each day leading up to the emergency for individuals experiencing appendicitis. It clearly demonstrates that there is little medical activity except on the day of the emergency (i.e. $t = 0$) and on the day immediately preceding the emergency.

X represents a vector of covariates. This vector includes gender; the month the emergency occurs; the year the emergency occurs; the type of health plan held at the time of the emergency (e.g. PPO; HMO; EPO); whether the plan has an "add-on" account such as a Health Reimbursement Account or a plan that comes with a Health Savings Account; the state of residence at the time of the emergency; the days of tenure held before the emergency (i.e. pre-emergency tenure) and the family size at the time of the emergency (i.e. the number of family members observed under the health plan). The covariates also include a categorical variable indicating the Charlson comorbidity index of an individual (Charlson et al. (1987)). This is included as a proxy for health as it measures the one year comorbidity risk of individuals. Additionally, calendar month and calendar year fixed effects are included.

5 Results

5.1 Parallel Trends

Before presenting the regression results, the validity of the parallel trends assumption is examined. This is done by estimating Equation 1 in the time periods leading up to the emergency (i.e. $t \in [-12, -1]$) across several medical utilization outcomes: medical spending/costs, number of claims made, and number of medical visits made over roughly 30 day periods.[22]

Given the increase in utilization in the day leading up to the emergency, as shown in Figure 4, $t = -2$ is used to represent the reference time period. Since medical utilization will likely vary depending on if one experiences the appendicitis emergency directly or not, I estimate Equation 1 separately for those individuals who directly experience the emergency (i.e. the affected) and for those individuals that are indirectly exposed due to family affiliation (i.e. the unaffected), comparing each group to the control group.

Figures 5 and 6 presents these results. They show that across all outcomes, medical utilization trend quite similarly before the onset of an emergency across all groups. The notable exception to this are the number of claims and visits made by the affected emergency group in the 30 day period preceding the emergency (i.e. when $t = -1$). However, as noted, this increase likely stems from medical utilization changes in the day leading up to the emergency.

5.2 Main Results - Insurance Network Changes

The main results are presented in Table 2, which reports the coefficient estimates of ρ and β from Equation 1. Estimates of ρ capture general trends in insurance coverage dropout (i.e. leaving the health insurance network) while β captures the added effect of an appendicitis emergency on the likelihood of leaving the insurance network. These results are also graphically presented in Figure 7a. By construction, in the intervals leading up to the emergency (i.e. when $t \in [-12, -1]$), there is no difference in the dropout rates across the emergency sample and control group.

The coefficient estimates in Table 2 indicate that an appendicitis emergency results in an overall *reduced* likelihood of leaving the insurance network. Within two months of an emergency, treatment families have a 1.1 percentage point higher probability of remaining in the insurance network. This represents an approximately 12 percent lower rate of exit

[22]Patient spending is equal to the sum of the deductible, co-insurance, and co-pay amounts paid by the patient for any health care received. Prices for these amounts are deflated to 2015 prices.

from the network.[23] Furthermore, this effect persists over time. Six months after an emergency, families exposed to the appendicitis emergency have a 1.7 percentage point higher probability of remaining in the insurance network; this represents a 12 percent lower likelihood of exiting the health insurance network. Further, within one year of the emergency, families exposed to appendicitis experience an exit rate that is approximately 2 percentage points lower, corresponding to a 7 percent lower likelihood of exiting the insurance network.

5.3 Health Plan Switching

I also examine the rate of within-insurance network health plan switching after the appendicitis health shock. In tandem with the results from section 5.2 which show reduced network exit after the appendicitis emergency; if individuals remain in the same health insurance plan after the emergency (conditional on remaining in the network), then the appendicitis emergency results in both reduced network exit and health plan switching.[24]

To determine the rate of health plan switching after the emergency, I calculate the share of treatment and control group members who switch from one network plan to another, conditional on continuing to remain insured through the insurance network for at least one year after the emergency.[25] This time frame is chosen as it provides a sufficient window of observation for families experiencing emergencies across the different calendar months to have had at least one open enrollment window in which to make changes to their health plans.

The plan switching shares are presented in Figure 8. While descriptive, the figure shows that there is relatively little plan switching for those who remain insured through the insurance network, which is consistent with the prior literature (e.g. Handel (2013)). For instance, conditional on remaining insured through the network 12 months after an emergency, 95.6 and 95.5 percent of the treatment and control groups maintain the same health insurance plan, respectively.[26] Thus, these results imply that the health emergency

[23] The rate of exit for the control group is ρ and the rate of exit for the treatment group is captured by $\beta + \rho$. The magnitude of interest is $\frac{\beta}{\rho} - 1$, which represents the change in the rate of network exit due to the appendicitis emergency.

[24] This insight can be shown through an application of Baye's rule: $P(A) = \frac{P(A|B) \times P(B)}{P(B|A)}$. Let A be the event that a family switches health plans within the network within one year and let B be the event that a family stays in the network for at least one year. Then, for the treatment (T) and control group (C), because $P(B|A)^T = P(B|A)^C = 1$ and $P(A|B)^T \approx P(A|B)^C$ (to be discussed), then $P(A)^T < P(A)^C$ since $P(B)^T < P(B)^C$.

[25] The analysis proxies for health plan switching by examining changes in the family's insurance policy number. Also, identification of within-network health plan switching is possible even if there is a job change by the primary policyholder, so long as the family elects a plan in the same insurance network after the job change.

[26] If considering a window of three months, these numbers are approximately 99 percent for both

results in reduced health plan switching. This is because of the reduced insurance network exit that occurs after the health shock coupled with the near identical rates of plan switching conditional on remaining in the network.

5.4 Correlation in Family Insurance Coverage

Given that health insurance is often bundled at the family level, I examine the degree of correlation in insurance coverage across family members after the health shock. This examination is informative for understanding how individual health shocks manifest into family spillovers. To determine this, Equation 1 is re-estimated where the "treatment" group is now defined as the family members directly experiencing the emergency and the "control" group are the family members who are exposed to appendicitis through family affiliation. Table 3 presents the coefficient estimates of β, which are also graphically displayed in Figure 7b. As shown in the figure, the average rate of network exit is essentially identical across family members in the periods after an emergency.

This finding illustrates that there is a high degree of correlation and persistence in health insurance plan choice within a family unit. Furthermore, these results document one form that family spillovers may take after an individual family member's health shock. A-priori, it is unclear whether this harms or benefits family members. There may be medium/longer-run household welfare losses from reduced health plan switching if there are welfare-improving plans that are being passed over (Handel (2013)) and families remain locked in to their plans. Alternatively, the high degree of correlation in insurance coverage could mitigate the effects of health insurance plan sorting on perceived health risk. This is because more healthy family members are also likely to stay in the health plan, which may help balance the risk pool within an insurance plan. In turn, this could affect health plan premiums or the availability of certain health insurance plan offerings through an employer.

5.5 How does the reduced plan switching occur?

In this subsection, I investigate how plan switching can manifest from either job changes of the primary policyholder or during open enrollment periods.

the treatment and control groups, conditional on remaining insured for at least three months after the emergency. The corresponding number for six months after an emergency, is approximately 98 percent for both treatment and control groups.

5.5.1 Changing Jobs

The results indicate that families are less likely to switch health insurance networks and plans after a health shock. Given the data structure and evidence from the literature, this is likely due either to: 1) reduced rates of job change by the primary policyholder of the health plan and/or 2) lower rates of health insurance plan switching, by the primary policyholder, when outside options are made available.

To understand the occurrence of reduced job switching, I leverage the fact that during the calendar months falling into Quarter-1 through Quarter-3, individuals are typically barred from making changes to their health plans outside of open enrollment periods. During open enrollment periods, which typically occur between October and December of a given year, individuals can change their insurance network and health plan. The network and plan selections will typically be realized in January of the subsequent calendar year. However, network and plan changes can occur outside of an open-enrollment window if an individual (or their partner) changes jobs such that the current health plan option is lost or for specific reasons determined by the Internal Revenue Service code. That is, individuals can only change their network and health plans during a non-open-enrollment period if they experience a qualifying life event (e.g. marriage, divorce, birth of a child, move to a different county), which then allows them to change their network and plan during a special enrollment period.[27]

If the appendicitis emergency does not differentially impact dropout stemming from non-job related qualifying life events, then lowered dropout during the non-open enrollment months is most likely due to lowered rates of job change by the primary policyholder. This is plausible given the evidence that leaving a job is the primary reason that individuals typically change their health insurance plan and network. For example, evidence from Cunningham and Kohn (2000) suggests that among those who changed health plans over a one year period, nearly 70 percent did so either because they changed employers or their current employer changed the health plan offerings.

To examine if job change rates are affected by the health shock, I analyze insurance network dropout across the treatment and control groups by calendar month of the emergency. Specifically, I re-estimate Equation 1 separately for each calendar month in which an emergency occurs. The results are presented in Figures 10 and 11 and trace out the effects of the health shock for emergencies occurring in calendar months January through November.[28] The findings indicate that in the months after an emergency, when the open enrollment option is not likely to be present, dropout rates from the insurance network are

[27] More examples of qualifying life events can be found at healthcare.gov (2020).

[28] December is not included since the $t = 0$ time period includes dropout in January since the time interval is a rolling 30 day period from the initial emergency date.

lower among the families exposed to the appendicitis health shock. For example, among families experiencing an emergency in February, within three to ten months of the emergency, the dropout rates are lower among the families exposed to the appendicitis health shock. In general, the standard errors for the β coefficient estimates are larger when examining the month-by-month response, which likely stems from the smaller within-month sample sizes. However, the generally positive coefficient estimates are still illustrative and suggest that the person who is the primary policyholder of the health plan is less likely to switch jobs as a result of a family member's health shock. As a result, the family unit remains insured through the same network and plan.

5.5.2 Open Enrollment Periods

In order to understand the importance of active health insurance decisions made during open enrollment periods, I examine insurance network dropout around the month when new health plan elections typically take into effect: January. In particular, I analyze the effect of the health shock on the decision to remain insured through the health insurance network during the open enrollment period following the appendicitis emergency. This is done by comparing the January coefficient estimates of β to a *projected* January coefficient estimate of β. The latter estimate is meant to capture the effect of the health shock on network dropout in the absence of open enrollment. Underlying this analysis is the assumption that in the absence of open enrollment (OE), β only changes over time due to differential rates in insurance network exit stemming from job changes. This can be described as:

$$\beta^{month+1} = \begin{cases} \beta^{month} + \delta_t, & month \in [Jan - Nov] \\ \beta^{month} + \delta_t + \theta, & month = Dec \end{cases}$$

For the case of January, this implies that $\beta^{Jan} = \beta^{Dec} + \delta_t + \theta$, where θ represents the effect of open enrollment and δ_t represents the difference in the share who exit the network due to job-switching across the treatment and control group at time t. Thus, $\theta = \beta^{Jan} - \beta^{Dec} - \delta_t$, where θ captures the effect of the health shock on the differential rate of insurance network exit during the open enrollment period, across the treatment and control groups.

To empirically determine the open enrollment effect (θ), I estimate δ_t using the average change in the β coefficient estimates, ranging from one to three months prior to January. These periods are chosen because the most recent growth in β may be most informative for its shorter-term evolution. I then compute the projected dropout rate for January in the absence of open enrollment, where $\widehat{\beta^{Jan}} = \beta^{Dec} + \widehat{\delta_t}$. If $\beta^{Jan} \geq \widehat{\beta^{Jan}}$, this suggests that families exposed to the health shock are more likely to remain in the same insurance network, and subsequently health plan, even when outside health plan options are presented during the open enrollment window. Alternatively, if it is lower, this suggests that during open enrollment, families exposed to a health shock are more likely to exit the insurance network than control families.

A challenge with this approach is that in order to examine dropout in calendar-month January, individuals must remain insured (in the network) through December, which may result in the examination of a selected sample. Secondly, it is difficult to determine the true counterfactual dropout rate differential in the absence of open enrollment. Thus, this analysis is viewed as primarily descriptive. However, it may still inform our understanding of whether health shocks promote or inhibit exit from one's current health insurance network and health plan once the opportunity presents.

Figures 12 and 13 present these comparisons using the prior one-month average change in β to compute $\widehat{\beta^{Jan}}$.[29] The evidence is mixed. In some months (i.e. emergencies occurring in April, July, August, October, November), $\beta^{Jan} \geq \widehat{\beta^{Jan}}$. However, in the other months this difference is less than zero. This mixed finding is robust to the alternative imputations, including assuming that there is zero growth β between December and January as well as setting the growth differential between December to January to that experienced between November and December. Taken together, there is little support for lowered dropout due to changes made during open enrollment periods. Instead, it appears that the lowered rate of network dropout is primarily driven by reduced rates of job change by the primary policyholder.

5.6 Mechanisms

To examine the mechanisms underlying the insurance plan behavior, this analysis focuses on a well-defined and observable feature of health plans. Specifically, I focus on whether a health plan is associated with a portable "savings" account or not. This feature is defined in the data and across health plans, and allows for a dimension upon which to examine heterogeneous responses.

Health insurance plans can have additional add-on "savings" accounts, which can be used to pay for qualifying medical expenses. These accounts can take the form of either a Health Reimbursement Arrangement (HRA) or a Health Savings Account (HSA), and are usually paired with a high-deductible health insurance plan. Both employers and employees can contribute to an HSA account, while contributions to the HRA account

[29]The one-month average change is chosen as this leaves the greatest number of months for analysis. For emergencies occurring in November, I assume that δ_t is zero since there are no prior months upon which to determine the change in the size of β estimates.

are exclusively made by the employer (Tax Policy Center (2020)).[30]

A key feature of HRA accounts is that they are employer funded and are generally not portable across health plans nor employers. For example, if an employee switches from a high deductible health plan to a non-high deductible health plan, the money held in the HRA would typically be lost. Similarly, if an employee switches employers, the money held in the HRA would likely be lost as well. Thus, I examine whether the non-portability of health-associated savings accounts, disincentivize plan switching. This could occur if high current medical expenses and/or anticipated medical expenses make it more costly to forfeit the money held in an HRA.

To address this question, I re-estimate Equation 1 separately across families who, prior to the appendicitis emergency, belong to a health plan paired with an HRA or a health plan paired with an HSA. These groups are likely to be similar, in the absence of the health shock since both are likely to belong to a high-deductible health plan. As a result, they will face similar financial expenses associated with the health shock, where the expense might influence the network exit decision (e.g. if families are liquidity constrained, the money held in the add-on accounts may be costly to forfeit).

The results are presented in Table 4 and Figure 6. Among families exposed to the appendicitis health shock, those who belong to the HRA plan at the time of the emergency are much less likely to leave the insurance network after the emergency than those belonging to a plan with an HSA. For example, within 30 days of the health shock, families enrolled in an HRA have an approximately 1.5 percentage point higher probability of remaining in the insurance network. This corresponds to an approximately 67 percent reduced likelihood of exiting the network compared to control group families enrolled in an HRA. After 12 months, this number is approximately 3.3 percentage points (14 percent). These findings stand in contrast to those of control group families, where the difference in network exit rates across families holding an HRA vs. an HSA is essentially identical, over time, as observed in Figure 6. The differential insurance network retention rates observed across individuals with HRAs versus HSAs, among families exposed to appendicitis, is especially interesting given that both groups incur similar average patient expenses for the emergency (approximately \$2500-\$2800). This implies that differential expenses associated with the appendicitis emergency do not drive these results. Additionally, similar to the results presented in section 5.3, those who hold HRAs and HSAs at the time of the emergency exhibit little within-network plan switching conditional on remaining insured through the network for at least one year.

[30]The characteristics of enrollees across the three health plans are shown in Table 6. They are quite similar across age, family size and gender shares. However, HRA and HSA groups tend to be in the data longer than health plans with no paired account. Additionally, HSA enrollees tend to be slightly healthier, on average, as indicated by the higher share of individuals who have a zero comorbidity score.

While these results are suggestive, they show that a distinct source for reduced health network and health plan switching may be the bundling of health insurance products (i.e. a health insurance plan and a non-portable paired "savings" account). Specifically, it may be more costly for families to forfeit money held in an HRA particularly when faced with high current medical expenses or if anticipating higher medical expenses in the future. This finding is consistent with Farrell and Klemperer (2007) who discuss product bundling, and the associated pecuniary costs, as a source for reduced switching across consumer products. It is also consistent with Lamiraud and Stadelmann (2020) who show that lower priced supplementary health care products, paired with basic health insurance, are associated with lower switching across Swiss health insurance plans.

Thus, while an appendicitis health shock may result in reduced health insurance network and health plan mobility, certain features of health insurance products, such as non-portable HRAs may amplify this response. As shown, this may result in a form of health plan lock, where people are more likely to stay in their health plan after a health shock, *and* job, since these health plans are often tied to a specific employer.

5.7 Robustness Checks

To examine the robustness of the results, I re-estimate Equation 1 using a subset of the data that trims outlier families who have fewer than the 5th percentile (p5) and greater than the 95th percentile (p95) of matched control families. This is done because of heterogeneity in the number of corresponding matches for each treatment family, that tends to be correlated with the pre-emergency tenure of the treatment family. Thus, by examining the p5-p95 subset, this should limit the scope of potential biases caused by the overrepresentation of control families with lower pre-emergency tenure. This procedure results in 337 fewer treatment families and 8,954 fewer control families in the analysis.

The results of this analysis are presented in Table 5. These results are highly comparable to the main results in Table 2, suggesting that the main results appropriately capture the effects of the appendicitis health shock on insurance coverage outcomes.

6 Conclusion

This study examines the consequences of an individual-level adverse health shock on families' health insurance outcomes. This is achieved by examining how the onset of acute appendicitis among a child family member affects health insurance plan decisions for families who belong to a large, national health insurer. Using a constructed control group and stacked difference-in-difference estimation, this study finds that the onset of acute appendicitis leads families to reduce their likelihood of switching health plans between 7 – 14 percent within one year of the emergency. Additionally, health plan switching rates are near identical across all family members exposed to the emergency. This plausibly manifests as reduced rates of job switching by the primary policyholder of the health insurance plan.

The results of this study demonstrate a specific form that family spillovers may take in response to the acute, transitory health shock of a family member. These findings have important policy implications. In particular, the high degree of correlation in plan choice among family members, in the periods after a health shock, is an important finding in light of long-standing evidence of sorting into health plans based on health risk type (i.e. adverse selection). These results show that, under certain scenarios, the high degree of correlation in plan choice among family members may partially alleviate concerns about the sorting of individuals into health plans based on their health risk. This is because healthy family members continue to stay in the same health plan, which can offset the riskier health profile of the sicker family member.

Furthermore, this study finds that one source for reduced health plan switching may be the non-portability of certain health plan products that are paired with health insurance plans. In particular, the non-portability of a health reimbursement arrangements (HRAs) may make health plan switching more costly at the time of an expensive health shock. This finding suggests that certain characteristics of the current health insurance market can contribute to "health plan lock," which, in turn, likely affects job mobility. This is an important consideration given that policies meant to affect job lock, such as the Health Insurance Portability and Accountability Act (HIPAA), were passed in the mid-1990s.

Taken together, the findings of this study show that that adverse health events impact not only the individual who experiences the emergency, but also their affiliated family. As such, this study shows that it is important to examine the entire household in order to understand the full implications of adverse health events. Furthermore, the results can provide insight on how the current health insurance market structure, which bundles health insurance at the family level, may affect the efficient functioning of both health insurance and labor markets.

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Table 1: Summary Statistics

	Treatment (1)	*Control* (2)
Average age	25.60	25.31
Average family size	4.80	4.75
Pre-emergency tenure	1279.03	1197.87
Share Male (%)	53.1	50.6
Share w/Charlson Comorbidity Score = 0	92.00	91.74
Share HMO (%)	11.44	13.06
Share PPO (%)	4.85	5.01
Share POS (%)	71.65	69.95
Share EPO (%)	11.90	11.77
Share East Coast (%)	11.56	10.93
Share Midwest (%)	25.46	25.28
Share South (%)	40.02	40.85
Share West Coast (%)	22.76	22.39
Share directly experiencing emergency (%)	21.81	-
Day-of-Emergency Spending	$1613.42	-
Number of Individuals	21,246	605,517

Note: This table reports summary statistics for the individuals exposed to an appendicitis health shock (column 1) and the control group (column 2) at the time of the emergency (placebo emergency). Regions are defined by state groupings according to the US Census Bureau Census Regions (Census Bureau (2020)).

Table 2: Main Regression Estimates - Effect of Appendicitis Emergency on Insurance Coverage

	Full Interval Coverage		
	Main	No Cov	F.e.
	(1)	(2)	(3)
General effect (rel. to -1), ρ_k			
Intervals since emergency			
0	-0.027***	-0.027***	-0.027***
	(0.000)	(0.000)	(0.000)
1	-0.051***	-0.051***	-0.051***
	(0.001)	(0.001)	(0.001)
2	-0.075***	-0.075***	-0.075***
	(0.001)	(0.001)	(0.001)
3	-0.099***	-0.099***	-0.099***
	(0.001)	(0.001)	(0.001)
4	-0.123***	-0.123***	-0.123***
	(0.001)	(0.001)	(0.001)
5	-0.144***	-0.144***	-0.144***
	(0.001)	(0.001)	(0.001)
6	-0.168***	-0.168***	-0.168***
	(0.001)	(0.001)	(0.001)
7	-0.189***	-0.189***	-0.189***
	(0.001)	(0.001)	(0.001)
8	-0.210***	-0.210***	-0.210***
	(0.001)	(0.001)	(0.001)
9	-0.230***	-0.230***	-0.230***
	(0.001)	(0.001)	(0.001)
10	-0.249***	-0.249***	-0.249***
	(0.001)	(0.001)	(0.001)
11	-0.269***	-0.269***	-0.269***
	(0.001)	(0.001)	(0.001)
Added effect of treatment (rel. to -1), β_k			
Intervals since emergency			
0	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
1	0.006*	0.006*	0.006*
	(0.003)	(0.003)	(0.003)
2	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)
3	0.010**	0.010**	0.010**
	(0.004)	(0.004)	(0.004)
4	0.015***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)
5	0.017***	0.017***	0.017***
	(0.005)	(0.005)	(0.005)
6	0.016***	0.016***	0.016***
	(0.005)	(0.005)	(0.005)
7	0.017***	0.017***	0.017***
	(0.006)	(0.006)	(0.006)
8	0.021***	0.021***	0.021***
	(0.006)	(0.006)	(0.006)
9	0.019***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)
10	0.020***	0.020***	0.020***
	(0.006)	(0.006)	(0.006)
11	0.020***	0.020***	0.020***
	(0.007)	(0.007)	(0.007)
Number of individuals	590,613	590,613	590,613

1: Data consists of medical claims data pooled from 2003-2019.
2: General effect estimates represent coefficient estimates of ρ, while Added effect of treatment estimates represent coefficient estimates of β from Equation (1). By construction, the difference in coverage is constrained to be 0 between comparison groups when $k \in [-12, -1]$. *Treatment* takes the value of one if an individual belongs to families who are actually exposed to an emergency and is zero if they belong to the control group. Each interval represents an approximately 30 day rolling window since the emergency.
3: Column 1 include all demographic covariates while columns 2 excludes covariates. Column 3 presents results from a fixed-effect estimation estimated at the individual, (patient-id) level. All results presented are OLS estimates.
4: Standard errors are clustered at the family-id level– 139,029 clusters.
5: Level of statistical significance: ***1%; **5%; *10%.

Table 3: Main Regression Estimates - Subgroup Effect of an Emergency on Insurance Coverage

	Full Interval Coverage Directly Affected vs. Indirectly Affected (1)
General effect (rel. to -1), ρ_k	
Intervals since emergency	
0	-0.025***
	(0.002)
1	-0.045***
	(0.003)
2	-0.064***
	(0.004)
3	-0.090***
	(0.004)
4	-0.108***
	(0.005)
5	-0.129***
	(0.005)
6	-0.153***
	(0.005)
7	-0.174***
	(0.006)
8	-0.190***
	(0.006)
9	-0.212***
	(0.006)
10	-0.230***
	(0.006)
11	-0.251***
	(0.006)
Added effect of treatment (rel. to -1), β_k	
Intervals since emergency	
0	0.002**
	(0.001)
1	0.001
	(0.001)
2	0.002
	(0.001)
3	0.004***
	(0.001)
4	0.004***
	(0.002)
5	0.005***
	(0.002)
6	0.006***
	(0.002)
7	0.006***
	(0.002)
8	0.006***
	(0.002)
9	0.006***
	(0.002)
10	0.005***
	(0.002)
11	0.006***
	(0.002)
Number of individuals	21,246

1: Data consists of medical claims data pooled from 2003-2019. The data is limited to treatment group individuals.
2: General effect estimates represent coefficient estimates of ρ, while Added effect of treatment estimates represent coefficient estimates of β from Equation (1). By construction, the difference in coverage is constrained to be 0 between comparison groups when $k \in [-12, -1]$. $Treatment$ takes the value of one if an individual experiences the emergency themselves (i.e. the individual is affected) and is zero if they have a family member who experiences the emergency (i.e. the individual is unaffected). Each interval represents an approximately 30 day rolling window since the emergency.
3: Column 1 includes all demographic covariates. All results presented are OLS estimates.
4: Standard errors are clustered at the family-id level– 4,602 clusters.
5: Level of statistical significance: ***1%; **5%; *10%.

Table 4: Insurance Coverage Estimates Comparing Plans with HRA vs. HSA

	Full Interval Coverage	
	HRA vs. HSA (Treatment Group) (1)	HRA vs. HSA (Control Group) (2)
General effect (rel. to -1), ρ_k		
Intervals since emergency		
0	-0.022***	-0.025***
	(0.003)	(0.001)
1	-0.051***	-0.045***
	(0.004)	(0.001)
2	-0.065***	-0.066***
	(0.004)	(0.001)
3	-0.087***	-0.088***
	(0.005)	(0.001)
4	-0.097***	-0.110***
	(0.005)	(0.001)
5	-0.113***	-0.132***
	(0.005)	(0.001)
6	-0.142***	-0.152***
	(0.006)	(0.001)
7	-0.155***	-0.174***
	(0.006)	(0.001)
8	-0.171***	-0.192***
	(0.006)	(0.001)
9	-0.195***	-0.212***
	(0.007)	(0.001)
10	-0.212***	-0.231***
	(0.007)	(0.001)
11	-0.232***	-0.251***
	(0.007)	(0.002)
Added effect of treatment (rel. to -1), β_k		
Intervals since emergency		
0	0.015***	-0.002**
	(0.003)	(0.001)
1	0.030***	-0.003**
	(0.005)	(0.001)
2	0.030***	-0.003**
	(0.007)	(0.001)
3	0.030***	0.001
	(0.008)	(0.002)
4	0.018**	-0.002
	(0.009)	(0.002)
5	0.019**	0.002
	(0.010)	(0.002)
6	0.024**	-0.003
	(0.010)	(0.002)
7	0.004	-0.001
	(0.011)	(0.002)
8	0.012	-0.004*
	(0.012)	(0.002)
9	0.016	0.000
	(0.012)	(0.002)
10	0.026**	0.000
	(0.013)	(0.003)
11	0.033**	0.000
	(0.013)	(0.003)
Number of individuals	4,774	122,717

1: Data consists of medical claims data pooled from 2003-2019 for treatment and control groups. Regressions are separately estimated by health plan type, prior to the emergency (placebo emergency).
2: General effect estimates represent coefficient estimates of ρ, while Added effect of treatment estimates represent coefficient estimates of β from Equation (1). By construction, the difference in coverage is constrained to be 0 between comparison groups when $k \in [-12, -1]$. The $Treatment$ dummy takes the value of one if an individual belongs to a health plan paired with a Health Reimbursement Arrangement (HRA) and is zero if they belong to a health plan paired with a Health Savings Account (HSA). Estimates are performed separately for families exposed to the health shock and for families not exposed. Each interval represents an approximately 30 day rolling window since the emergency.
3: Standard errors are clustered at the family-id level– 1,026 and 28,558 clusters, respectively.
4: Level of statistical significance: ***1%; **5%; *10%.

Table 5: Main Regression Estimates - p5 – p95 Subgroup Effect of an Emergency on Insurance Coverage

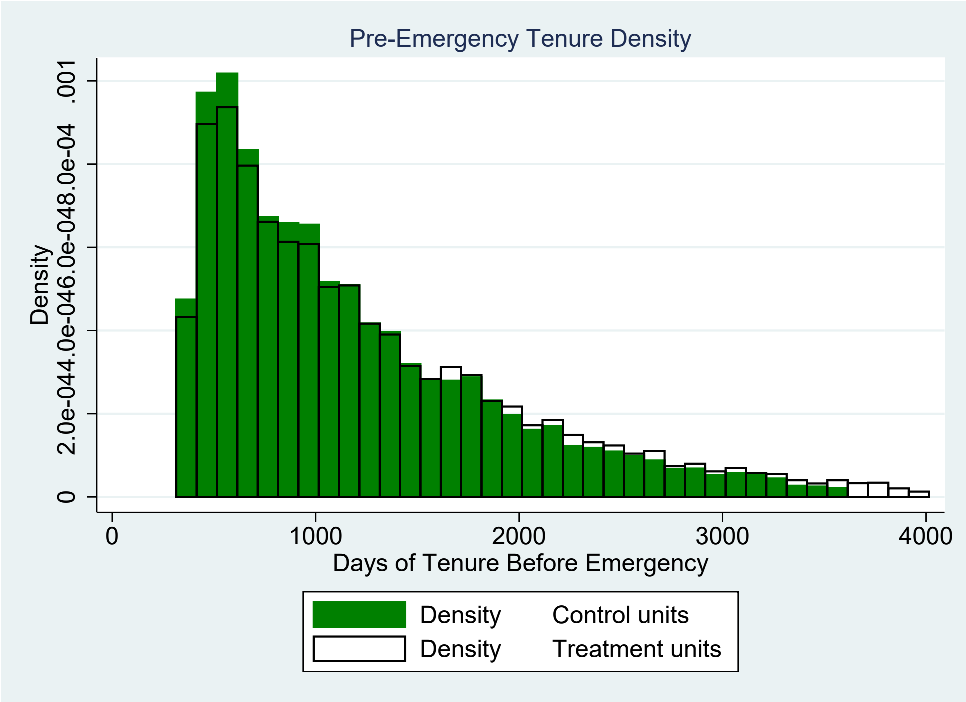
	Full Interval Coverage
	Main
	(1)
General effect (rel. to -1), ρ_k	
Intervals since emergency	
0	-0.027***
	(0.000)
1	-0.051***
	(0.001)
2	-0.075***
	(0.001)
3	-0.099***
	(0.001)
4	-0.123***
	(0.001)
5	-0.144***
	(0.001)
6	-0.168***
	(0.001)
7	-0.189***
	(0.001)
8	-0.210***
	(0.001)
9	-0.230***
	(0.001)
10	-0.249***
	(0.001)
11	-0.270***
	(0.001)
Added effect of treatment (rel. to -1), β_k	
Intervals since emergency	
0	0.003
	(0.002)
1	0.007**
	(0.003)
2	0.012***
	(0.004)
3	0.010**
	(0.004)
4	0.016***
	(0.005)
5	0.017***
	(0.005)
6	0.017***
	(0.006)
7	0.017***
	(0.006)
8	0.022***
	(0.006)
9	0.020***
	(0.006)
10	0.021***
	(0.007)
11	0.021***
	(0.007)
Number of individuals	553,481

1: Data consists of medical claims data pooled from 2003-2019. The data is limited to individuals in treatment families whose number of matched control families fall between p5-p95 of available control families, as well as the the individuals associated with these control families.
2: General effect estimates represent coefficient estimates of ρ, while Added effect of treatment estimates represent coefficient estimates of β from Equation (1). By construction, the difference in coverage is constrained to be 0 between comparison groups when $k \in [-12, -1]$. *Treatment* takes the value of one if an individual belongs to a family exposed to appendicitis and zero if they belong to the control group. Each interval represents an approximately 30 day rolling window since the emergency.
3: Column 1 includes all demographic covariates. All results presented are OLS estimates.
4: Standard errors are clustered at the family-id level– 129,780 clusters.
5: Level of statistical significance: ***1%; **5%; *10%.

Table 6: Data Summary by Health Plan Type

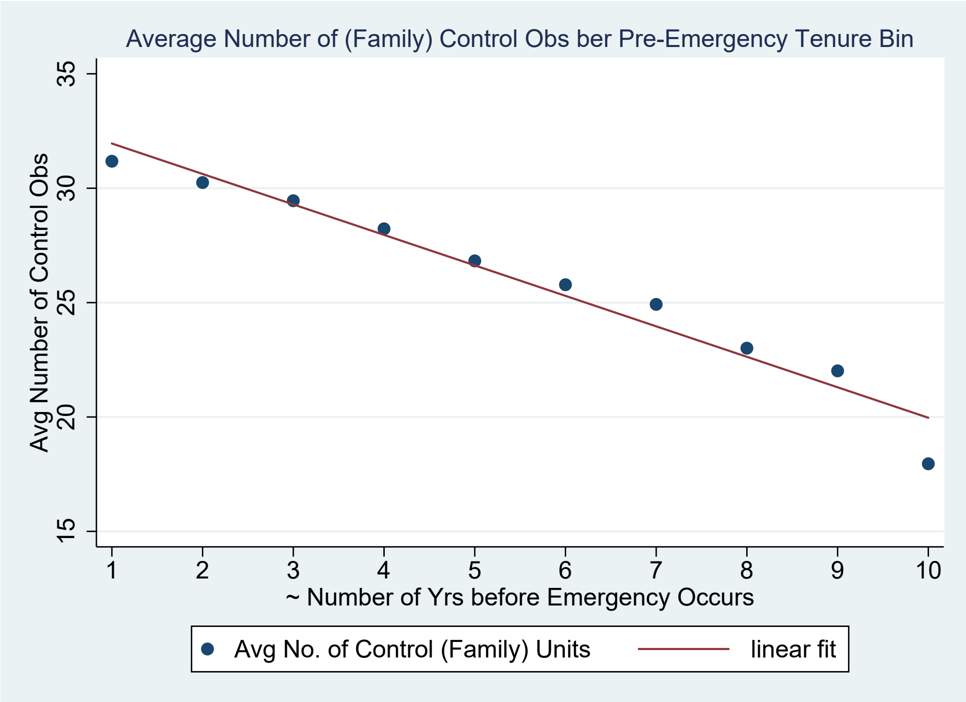
HRA + health plan	Treatment	Control
Average age	26.38	25.75
Average family size	4.70	4.71
Pre-emergency tenure	1395.81	1286.13
Share Male (%)	52.90	50.73
Share w/Charlson Comorbidity Score = 0	92.42	92.02
Share HMO (%)	0.00	0.31
Share PPO (%)	2.69	5.20
Share POS (%)	93.84	90.60
Share EPO (%)	3.47	3.89
Share East Coast (%)	9.14	7.39
Share Midwest (%)	25.57	26.14
Share South (%)	48.16	48.81
Share West Coast (%)	17.14	17.60
Share directly experiencing emergency (%)	22.24	-
Day-of-Emergency Spending	$2556.40	-
Number of Individuals	1,412	43,981
HSA + health plan	Treatment	Control
Average age	25.39	25.23
Average family size	4.99	4.85
Pre-emergency tenure	1380.03	1270.68
Share Male (%)	52.29	50.60
Share w/Charlson Comorbidity Score = 0	94.59	94.16
Share HMO (%)	1.25	1.39
Share PPO (%)	1.10	1.76
Share POS (%)	94.62	94.22
Share EPO (%)	3.03	2.63
Share East Coast (%)	8.39	9.25
Share Midwest (%)	32.78	34.74
Share South (%)	30.55	32.62
Share West Coast (%)	28.29	23.34
Share directly experiencing emergency (%)	21.21	-
Day-of-Emergency Spending	$2807.00	-
Number of Individuals	3,362	85,877
Only health plan	Treatment	Control
Average age	25.58	25.30
Average family size	4.80	4.73
Pre-emergency tenure	1253.60	1180.92
Share Male (%)	53.31	50.67
Share w/Charlson Comorbidity Score = 0	91.63	91.23
Share HMO (%)	9.95	12.19
Share PPO (%)	6.10	5.67
Share POS (%)	68.68	67.18
Share EPO (%)	15.24	14.93
Share East Coast (%)	13.06	12.15
Share Midwest (%)	20.09	20.89
Share South (%)	43.39	42.45
Share West Coast (%)	23.19	23.81
Share directly experiencing emergency (%)	21.89	-
Day-of-Emergency Spending	$1266.57	-
Number of Individuals	15,598	450,426

Figure 1: Pre-emergency Tenure Distributions of Treatment and Control Groups



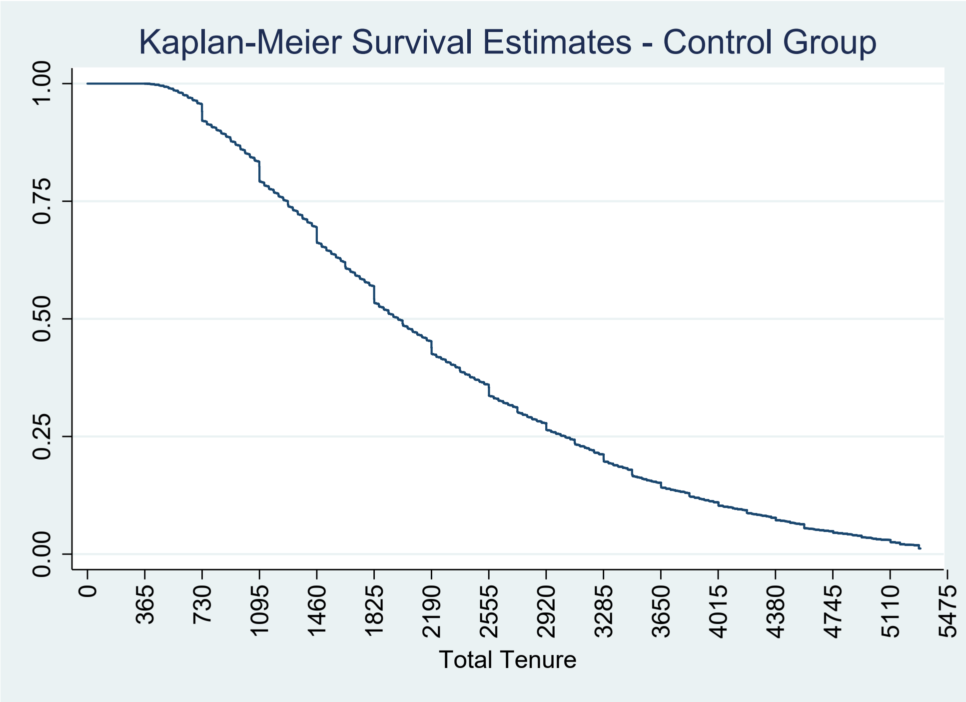
This figure presents the pre-emergency tenure distributions for the treatment and control groups. The distribution reflects the tenure for all family members belonging to the treatment and control group. Note, observations falling above the 99^{th} percentile of tenure are dropped in order to preserve anonymity.

Figure 2: Average Number of Available Controls by Treatment Family Tenure



This figures presents the average number of control families available to a treatment family, based on the number of days of pre-emergency tenure held by the treated families.

Figure 3: Kaplan-Meier Survival Curves



(b) *Kaplan-Meier Survival Curve - by Start-Cohort*

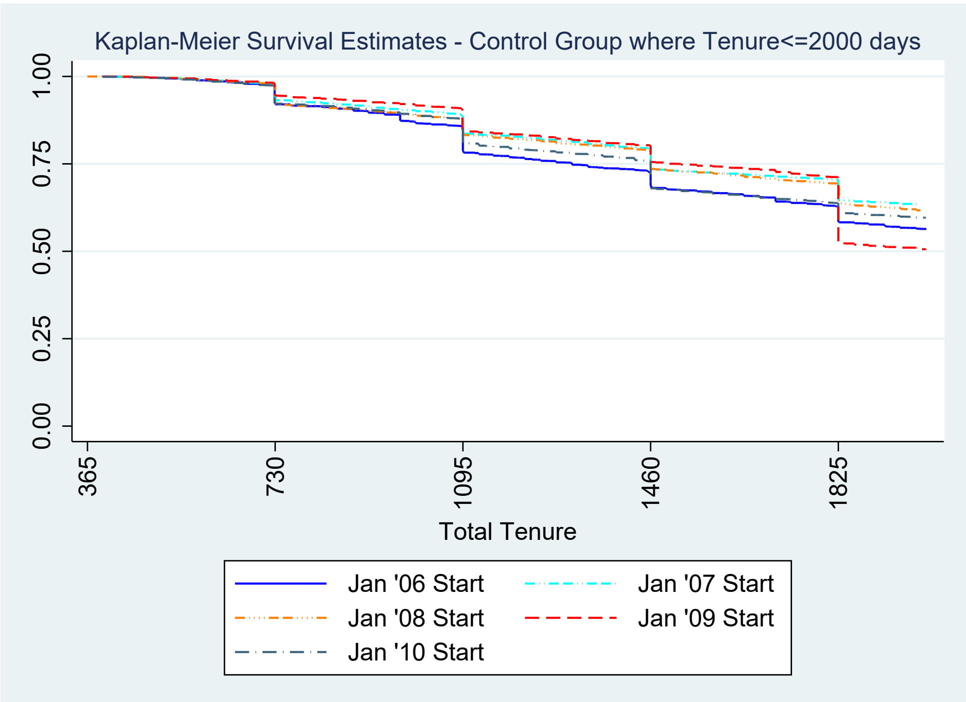
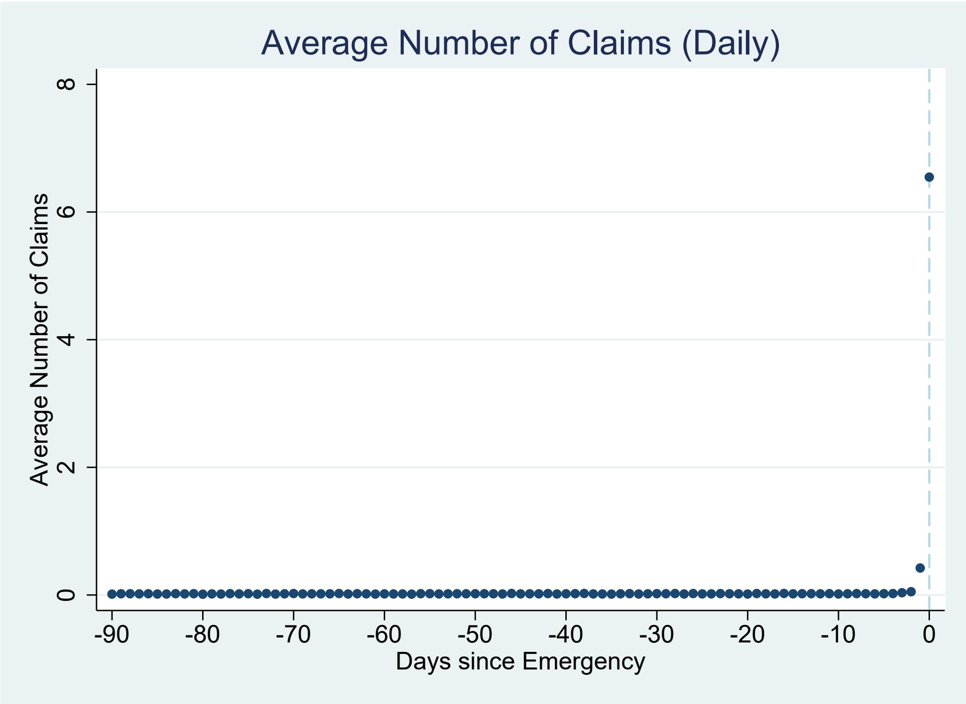


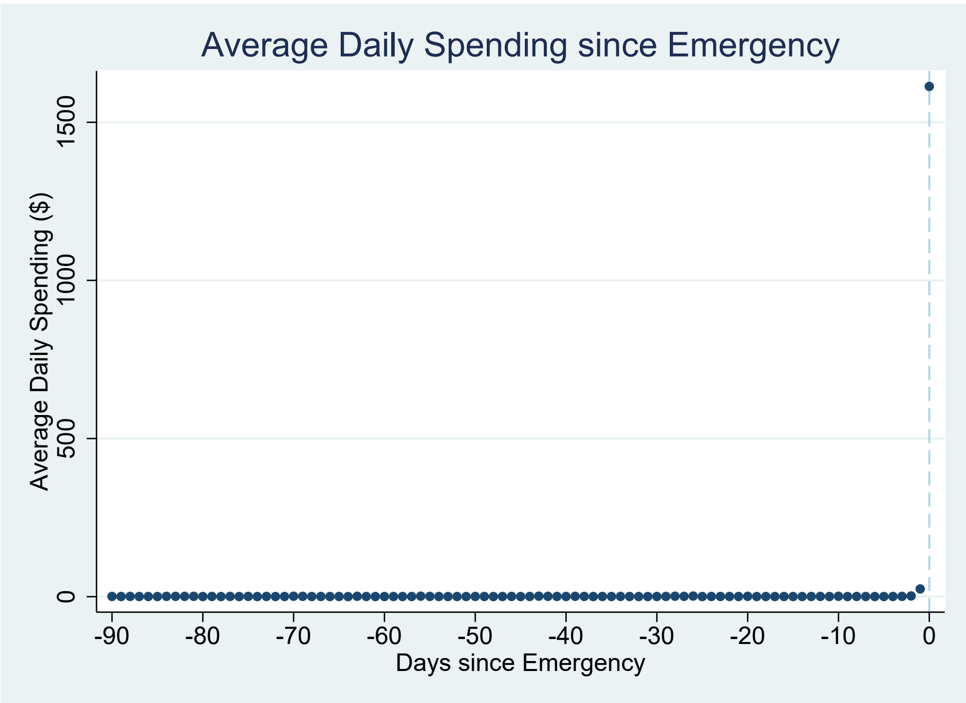
Figure 3a presents the Kaplan-Meier survival curves for all eligible controls. Figure 3b presents this curve for five distinct cohorts where the total tenure is less than or equal to 2000 days. Note, observations falling above the 99^{th} percentile of tenure are dropped in order to preserve anonymity.

Figure 4: 90 Day Medical Outcomes for Directly Affected Individuals

(a) Number Claims: - 90 to 0 Day Range



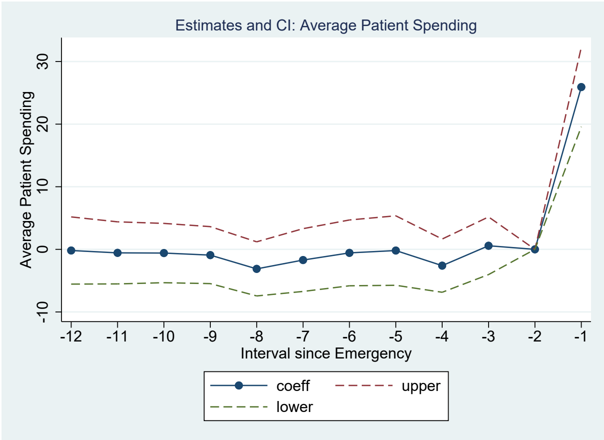
(b) Spending: -90 to 0 Day Range



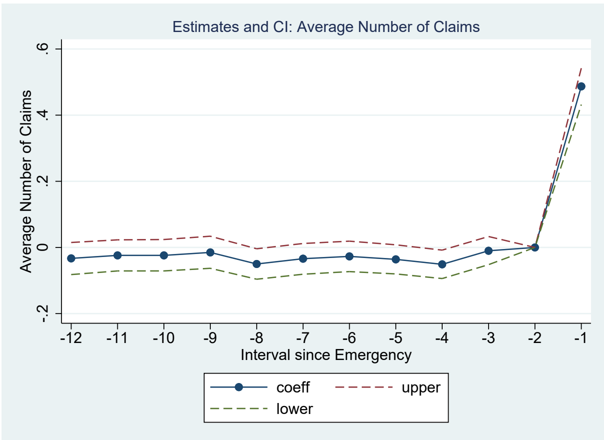
This figure presents the average daily medical spending and average number of medical claims made on a daily basis 90 days to 0 days before the appendicitis emergency. The sample is limited to individuals who directly experience the appendicitis emergency and who have insurance coverage for at least one year prior to the emergency.

Figure 5: Pre-trends in Medical Outcomes - Directly Affected Individuals

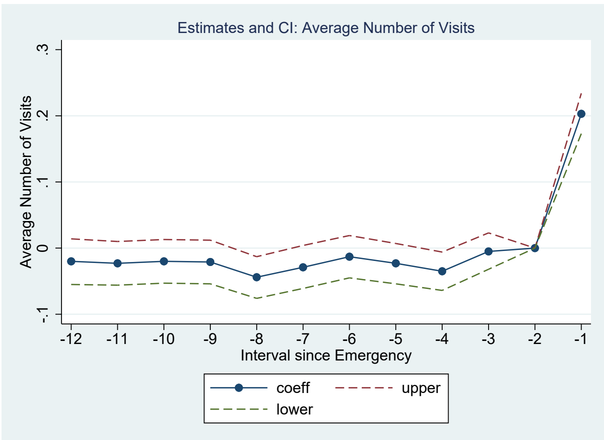
(a) Spending



(b) Number of Claims



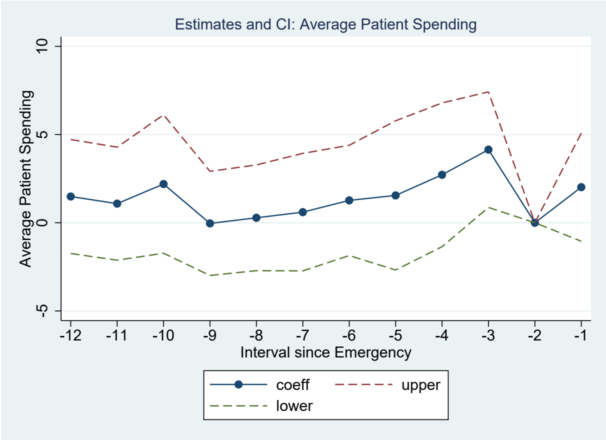
(c) Number of Visits



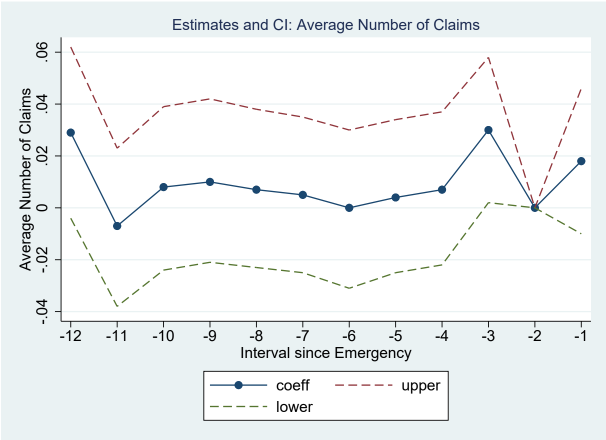
This figure presents estimates of β from the estimation of Equation 1 where the reference time period is $t = -2$, in the one year prior to the emergency. The outcomes are medical utilization outcomes for directly affected treatment individuals and all control group individuals who have at least one year of insurance coverage prior to an emergency. emergency.

Figure 6: Pre-trends in Medical Outcomes - Indirectly Affected Individuals

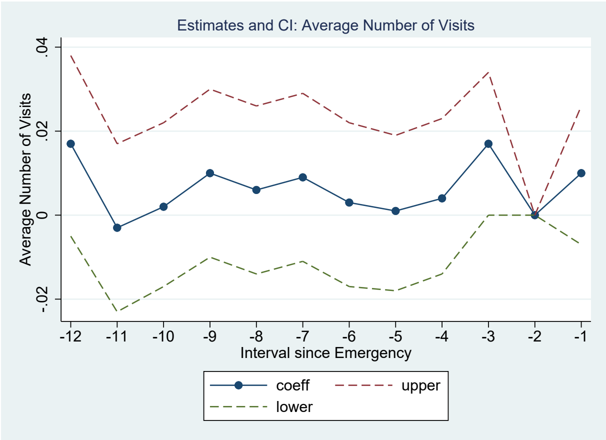
(a) Spending



(b) Number of Claims



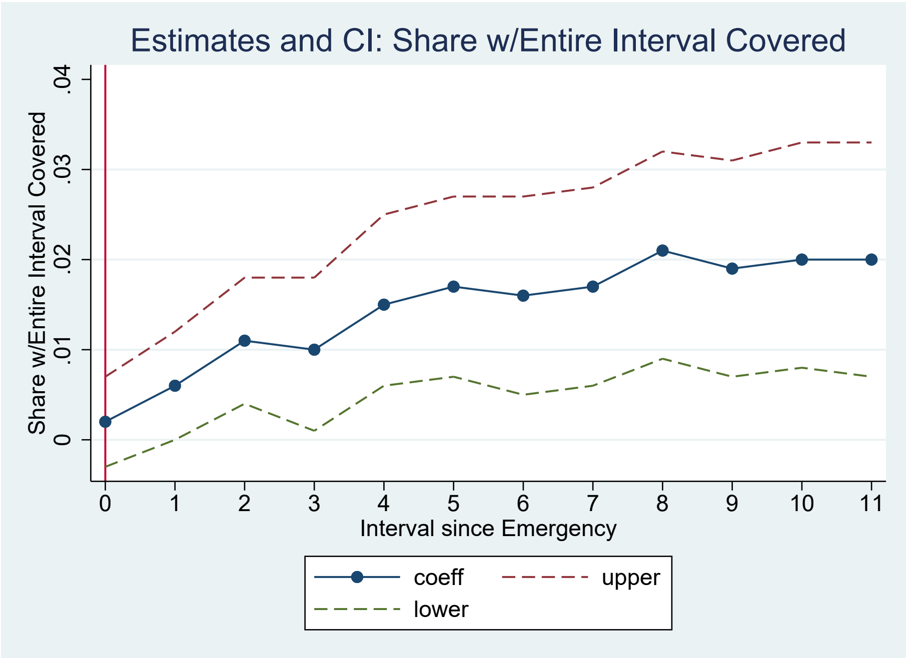
(c) Number of Visits



This figure presents estimates of β from the estimation of Equation 1 where the reference time period is $t = -2$, in the one year prior to the emergency. The outcomes are medical utilization outcomes for indirectly affected treatment individuals and all control group individuals who have at least one year of insurance coverage prior to an emergency.

Figure 7: Estimates of β

(a) Main Results: Estimates of β



(b) Directly Affected vs. Indirectly Affected

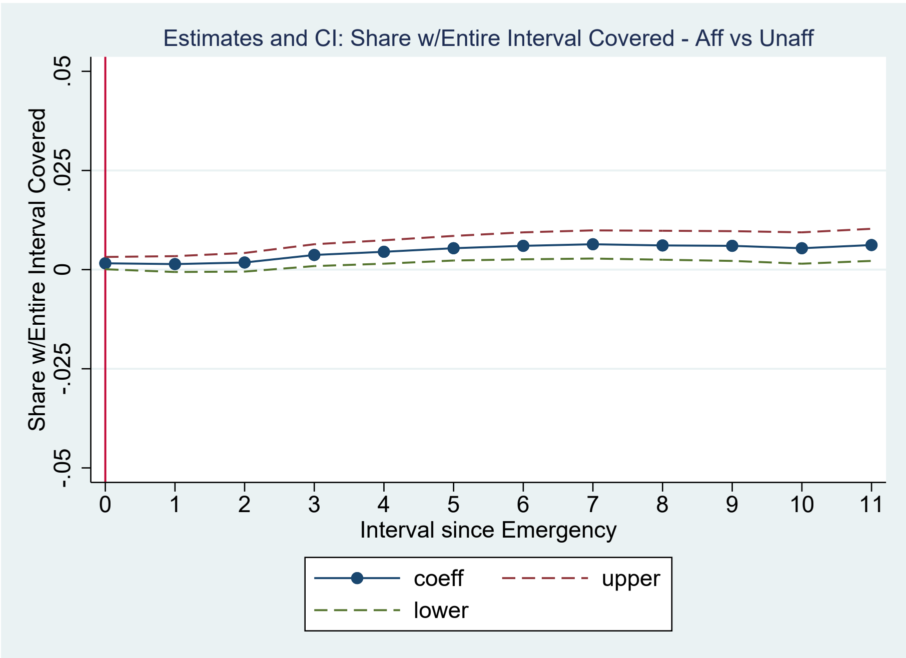
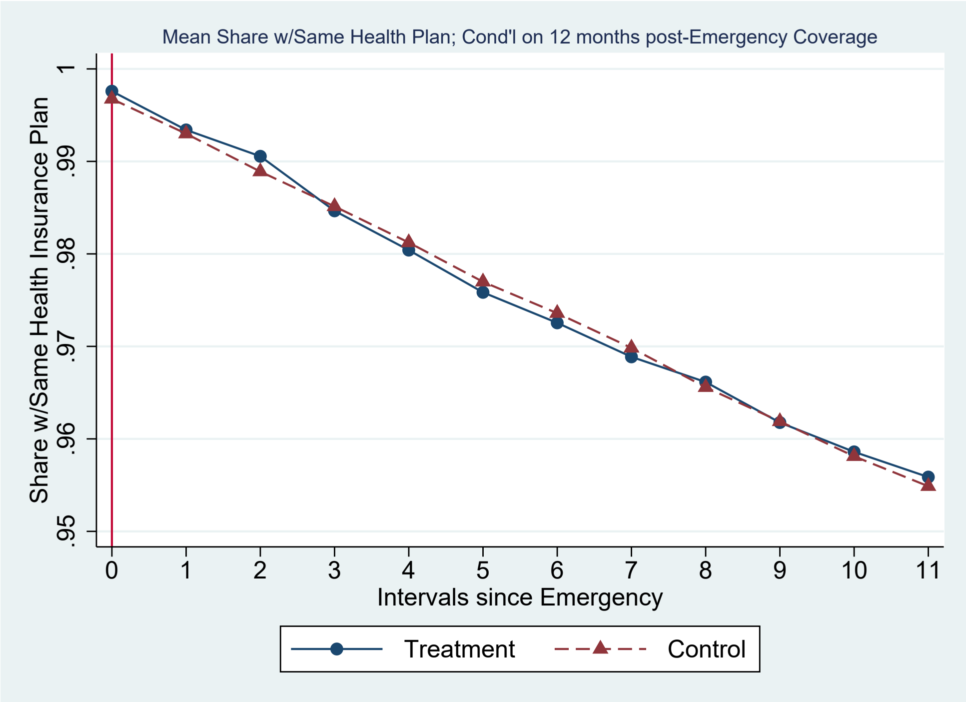


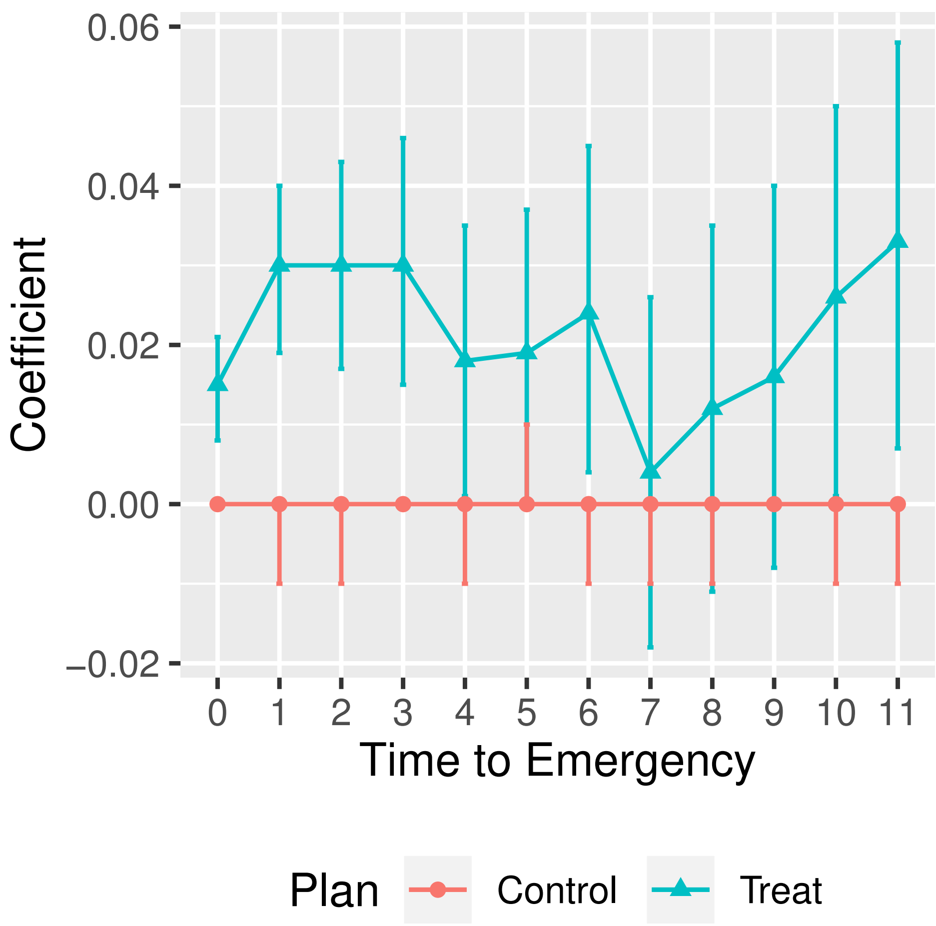
Figure 7b presents estimates of β from Equation (1) where treatment is defined as belonging to a family experiencing an appendicitis emergency. The examined outcome is a binary variable taking the value one if an individual has insurance coverage (through the insurance network) over the time interval considered and is zero, otherwise. The sample is limited to those with insurance coverage for at least one year prior to the emergency. Figure 7b presents estimates of β from Equation (1) where treatment takes the value one if an individual directly experiences the appendicitis emergency and zero if they are indirectly exposed through family affiliation. The sample is limited to treatment group individuals.

Figure 8: Within-Insurer Network Health Plan Switching



This figure presents the share of individuals who switch health insurance plans, conditional on remaining insured through the insurance network, at least 12 months after the emergency.

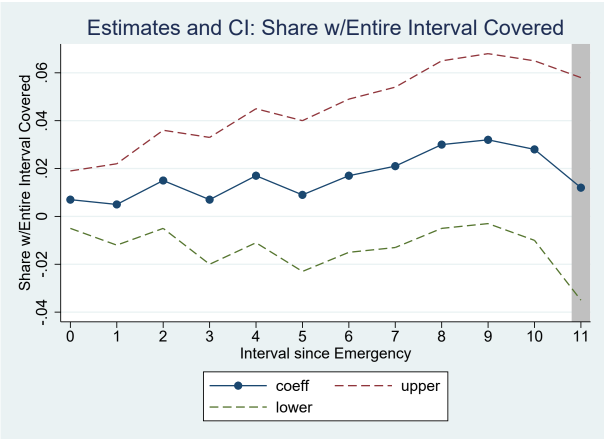
Figure 9: Event Study Estimates of β: HRA vs. HSA



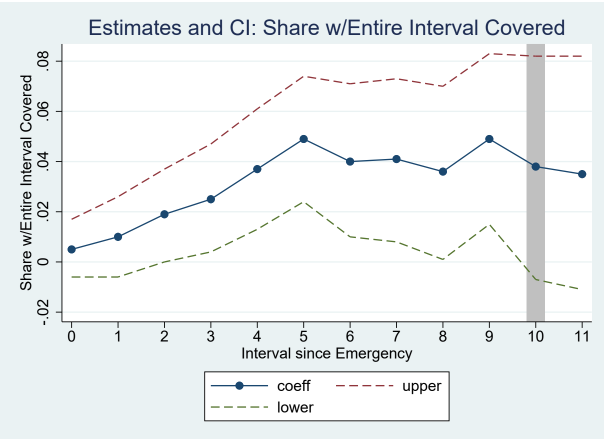
This figure presents estimates of β in each time period since an emergency, along with estimates of the 95 percent confidence interval, from Equation (1). Estimations are performed separately by treatment/control group and compare families belonging to health plans with a Health Reimbursement Arrangement (HRA) vs. health plans with a Health Savings Account (HSA).

Figure 10: Estimates of β by Month of Emergency: January - June

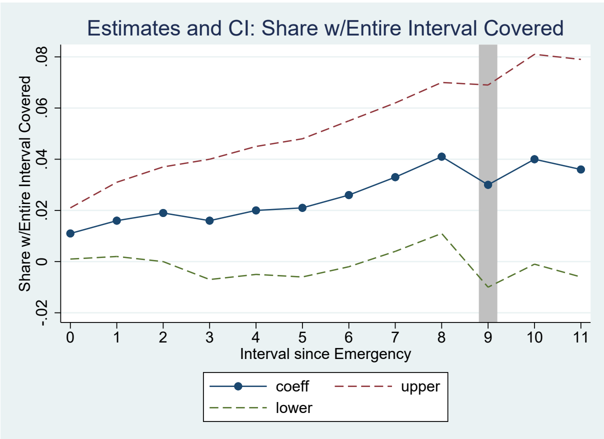
(a) January



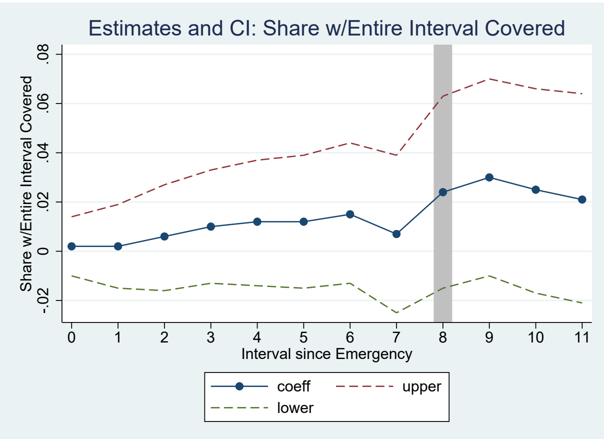
(b) February



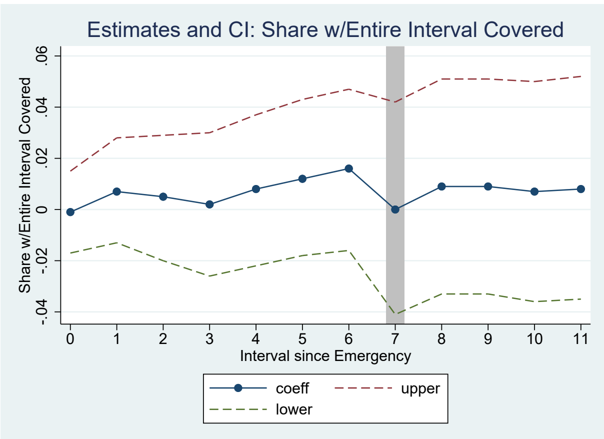
(c) March



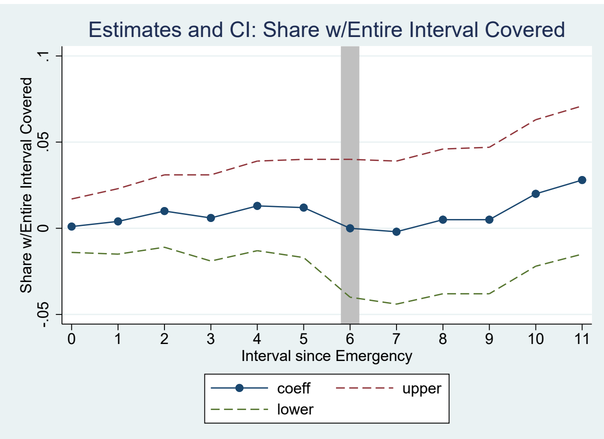
(d) April



(e) May



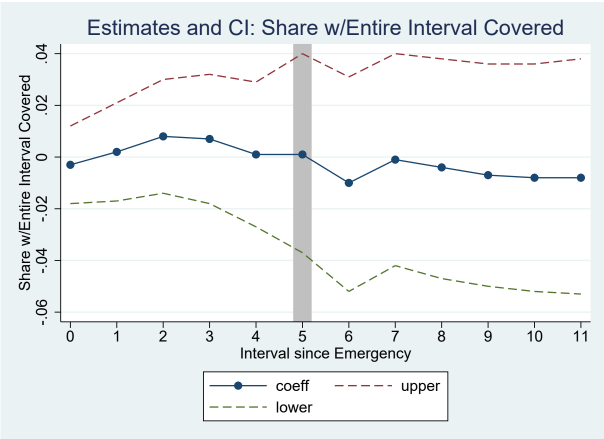
(f) June



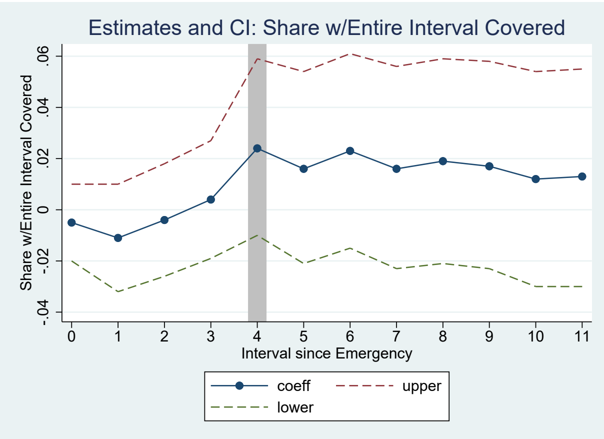
This figure presents estimates of β in each interval since the emergency using Equation (1). Estimation is performed separately by the month of the emergency. Treatment is defined as belonging to a family experiencing an appendicitis emergency. The examined outcome is a binary variable taking the value one if an individual has insurance coverage (through the insurance network) over the interval time period considered and is zero, otherwise. The sample is limited to individuals who have health insurance through the network for at least one year before an emergency.

Figure 11: Estimates of β by Month in which Emergency Occurs: July - December

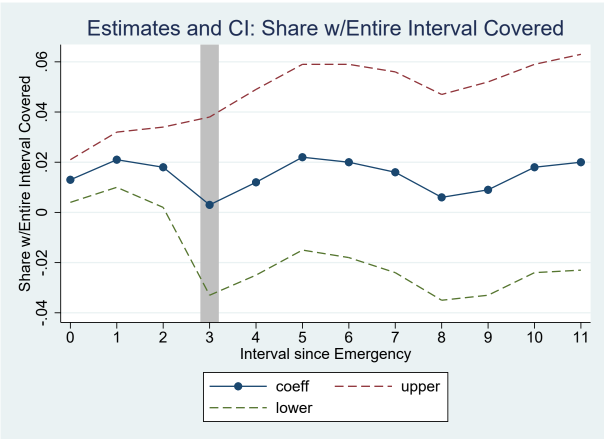
(a) July



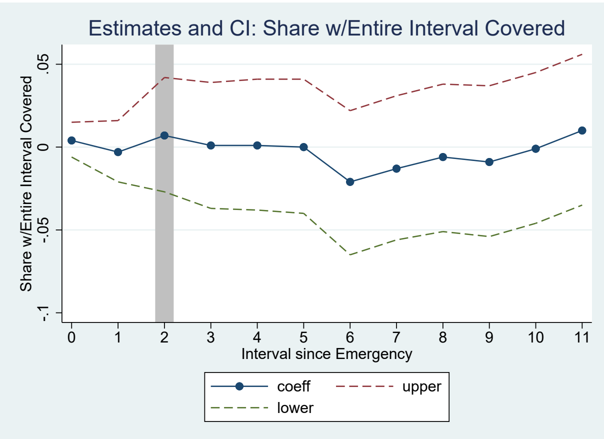
(b) August



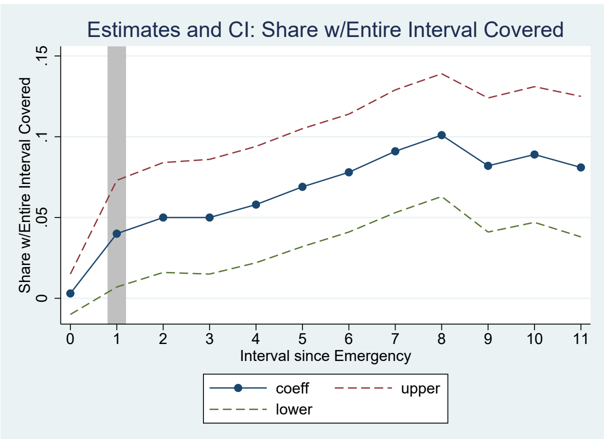
(c) September



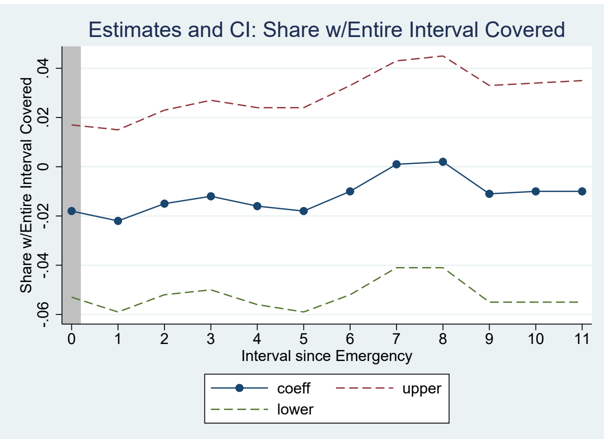
(d) October



(e) Nov



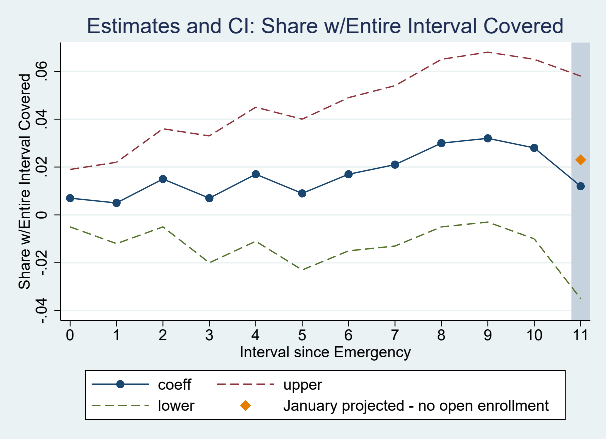
(f) December



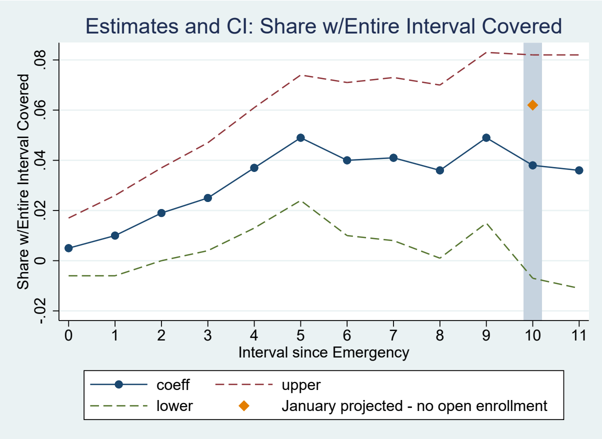
This figure presents estimates of β in each interval since the emergency using Equation (1). Estimation is performed separately by the month of the emergency. Treatment is defined as belonging to a family experiencing an appendicitis emergency. The examined outcome is a binary variable taking the value one if an individual has insurance coverage (through the insurance network) over the interval time period considered and is zero, otherwise. The sample is limited to individuals who have health insurance through the network for at least one year before an emergency.

Figure 12: Computed Estimates of $\widehat{\beta_{Jan}}$ vs. β^{Jan} by Month of Emergency: January - June

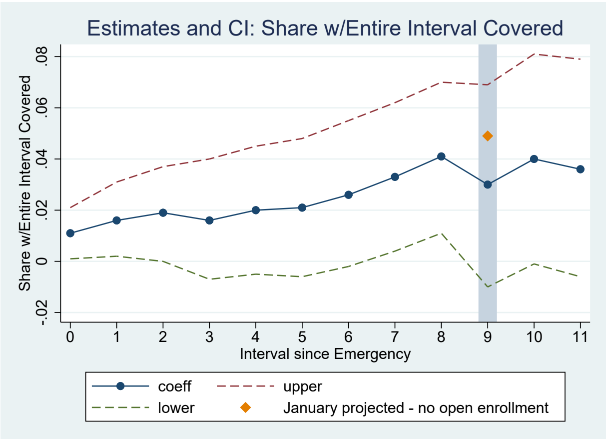
(a) January



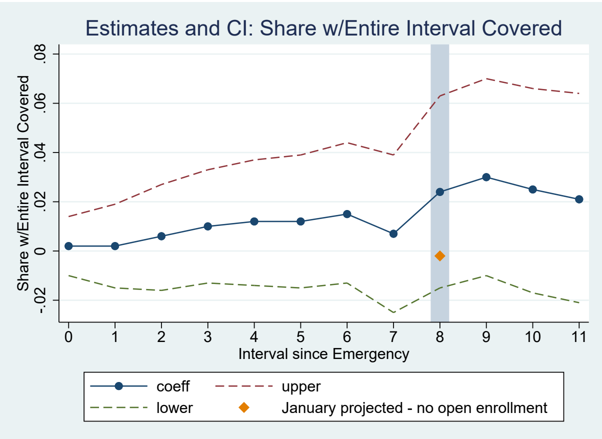
(b) February



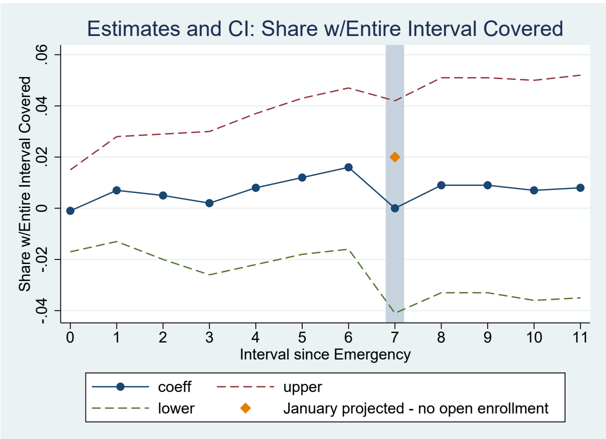
(c) March



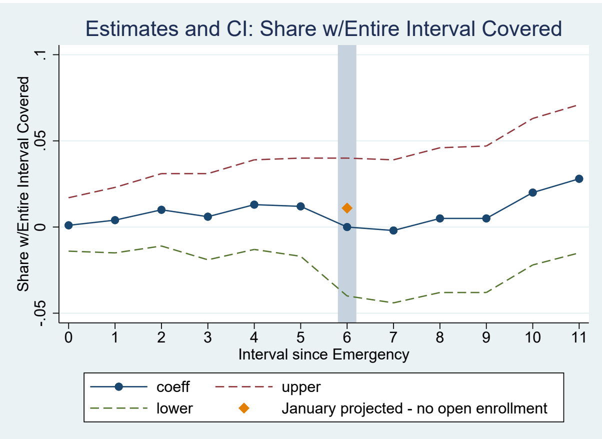
(d) April



(e) May



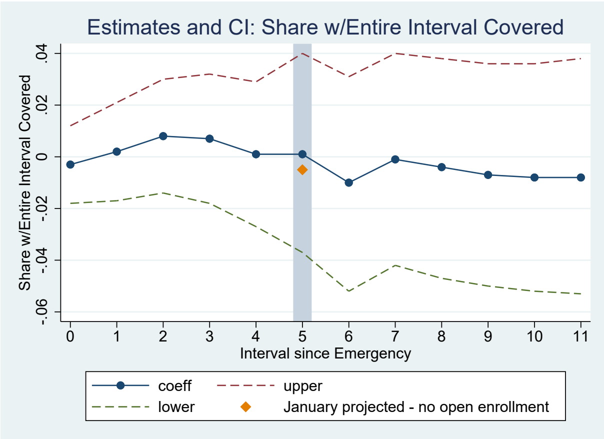
(f) June



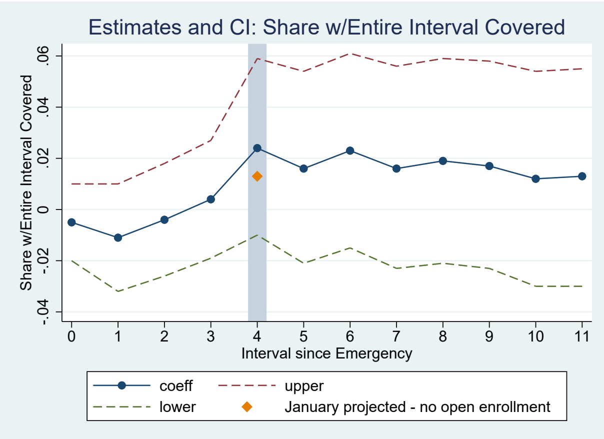
This figure presents estimates of β from Equation (1) in each interval since an emergency, alongside computed estimates of the projected January-specific treatment effect in the absence of open enrollment (i.e. $\widehat{\beta^{Jan}}$). This is estimated separately by the month of the emergency. Treatment is defined as belonging to a family experiencing an appendicitis emergency. The examined outcome is a binary variable taking the value one if an individual has insurance coverage (through the insurance network) over the time interval considered and is zero, otherwise. The sample is limited to individuals who have health insurance through the network for at least one year before an emergency.

Figure 13: Computed Estimates of $\widehat{\beta_{Jan}}$ vs. β^{Jan} by Month of Emergency: July - November

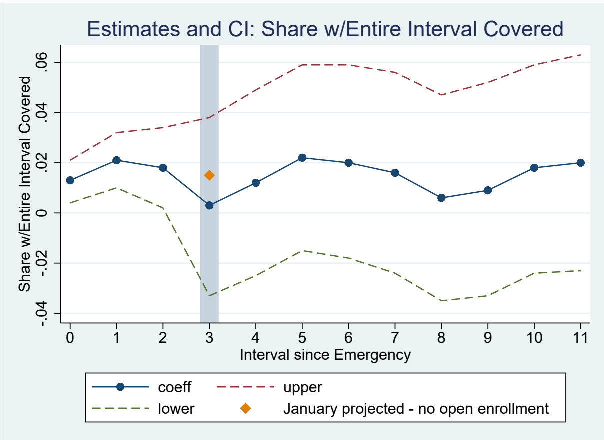
(a) July



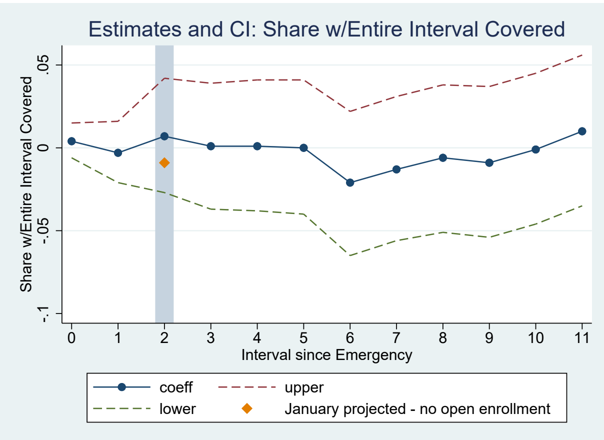
(b) August



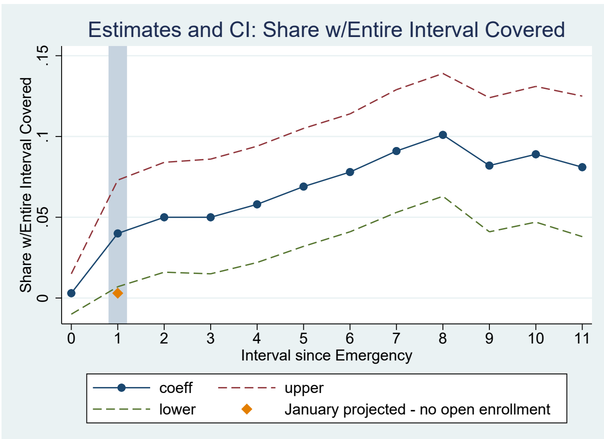
(c) September



(d) October



(e) November



This figure presents estimates of β from Equation (1) in each interval since an emergency, alongside computed estimates of the projected January-specific treatment effect in the absence of open enrollment (i.e. $\widehat{\beta^{Jan}}$). This is estimated separately by the month of the emergency. Treatment is defined as belonging to a family experiencing an appendicitis emergency. The examined outcome is a binary variable taking the value one if an individual has insurance coverage (through the insurance network) over the time interval considered and is zero, otherwise. The sample is limited to individuals who have health insurance through the network for at least one year before an emergency.