Intertemporal Substitution in Response to Non-Linear Health Insurance Contracts

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Abstract

Non-linear health insurance contracts featuring high deductibles followed by coinsurance rates have become increasingly popular. This work studies whether individuals in the modern U.S. healthcare system optimize spending by consuming elective healthcare at a lower price in the calendar year when the coinsurance arm of the plan is unexpectedly met, and then in the next year reducing elective healthcare consumption. To obtain a causal effect of reaching the coinsurance arm on healthcare consumption in the following year, I use a fuzzy regression discontinuity design comparing those with specific injuries on either side of the new year. Using claim-level data from large firms following privately insured individuals from 2010-2012, I show evidence suggesting there is intertemporal substitution in healthcare consumption. Local average treatment effects indicate that reaching the coinsurance arm in one year leads to $13,263 less healthcare consumed, $788 less paid out of pocket, and 7.4 fewer care dates in the following year. For those induced to consume more healthcare by reaching the coinsurance arm of their plan, I find that that for every dollar of healthcare consumed in the year the coinsurance arm is reached, roughly $0.37 less is consumed in the following year. Ignoring this intertemporal substitution would cause previous estimates using a single year to overstate the cost-saving benefits of high-deductible plans.

1. Introduction

In recent years, deductibles have become an increasingly common part of private health insurance plan structures, and the size of deductibles continues to rise. From 2010 to 2020, the number of employer-sponsored health insurance plans with a deductible over $1,000 for singles rose from 27% to 57%. Among plans with a deductible, the average deductible rose from $917 to $1,644 (Kaiser Family Foundation, 2020). These non-linear plans cause individuals to face very different prices if they meet their deductible during the year and different prices again when their deductible resets at the beginning of each calendar year. When individuals meet their deductible, most face a much lower price based on a coinsurance rate until the start of the next calendar year when the deductible resets.

It is possible that consumers optimize healthcare spending by attempting to consume more elective healthcare at a lower price in the calendar year when the coinsurance arm of the plan is met, and then in the next year avoiding relatively elective healthcare spending. However, little is known about how individuals respond to non-linear health insurance contracts across years in modern private health insurance plans. Across-year intertemporal substitution has been shown in other contexts including dental insurance (Cabral, 2016), and Medicare Part D (Einav et al., 2015). Lin & Sacks (2019) use the RAND Health Insurance Experiment to conclude that failing to account for intertemporal substitution could cause estimates to overstate savings from high deductible health insurance plans by 20% or more but suggest the importance of examining the topic in a modern setting where there are even more elective and preventative procedures available. This work fills this gap in the literature and suggests that for a group of consumers in modern private health insurance plans, estimates which fail to account for intertemporal substitution could lead researchers to overstate savings from deductible plans by 37% or more.

Within a single year, dynamic incentives, spot prices, and future prices all matter for healthcare consumption choices (Aron-Dine et al., 2015; Brot-Goldberg, 2017; Dalton et al., 2019; Guo & Zhang, 2019; Kowalski, 2016). If within year dynamic incentives are relevant for healthcare consumption decisions, it is likely that incentives across plan years are also important to consider (Klein et al., 2022). Guo & Zhang (2019) concludes that, relative to fully-forward looking behavior, the myopia of fathers in responding to nonlinear health insurance plans in the year of childbirth leads to a 21-24% decrease in annual medical spending. Brot-Goldberg (2017) exploits a firm switching from a free-healthcare to a high-deductible plan and estimates that the firm saved 11.8-13.8% on healthcare spending from switching. These works focus on a single plan year either for simplicity or due to data limitations; however, below I show that estimates using only a single year could overstate savings from high-deductible health insurance plans.

In this paper, I investigate whether individuals decrease their healthcare consumption in the year after unexpectedly meeting their deductible. A reduction in the following year suggests that individuals are not just increasing healthcare consumption in response to lower prices, but rather changing the timing or intertemporally substituting their healthcare consumption. For those induced to consume more healthcare by reaching the coinsurance arm of their plan, I find that for every dollar of healthcare consumed in the year the deductible is met, roughly $0.37 less is consumed in the following year.

I use the 2010-2012 IBM MarketScan Commercial Claims Database, which includes a detailed breakdown of individual claim payments and diagnosis and procedure codes. The data is extremely well-suited for this topic, as it follows privately insured individuals and their dependents through the healthcare system for three years. Further, the data includes individuals from a variety of large firms and private insurers, making it representative of a broader population than previous research using a single employer or insurer.

Using a fuzzy regression discontinuity design, I identify the effect of meeting a deductible in one year on healthcare consumption in the following year. I exploit the fact that most health insurance deductibles reset at the beginning of the calendar year by comparing those with a class of unexpected injuries, which would be unlikely to be strategically delayed, in late 2010 and early 2011. We would expect that those who suffer injuries near the end of a calendar year are similar to those who suffer injuries near the beginning of the subsequent year, except that the year in which their injury occurs changes the probability of them meeting their deductible in 2011. In turn, this variation allows for the identification of the effect of meeting a deductible in one year (2011) on healthcare consumption in the following year (2012), relative to meeting the deductible in the prior year (2010).

Using this strategy, I present evidence that there are individuals who substitute healthcare consumption across years to lower prices for elective care. Comparing those with similar injuries in late 2010 and early 2011, I find that those meeting their deductible in one year (2011) consume $13,263 less of healthcare and spend $788 less out of pocket in the following year (2012). For every dollar spent out of pocket in the year the deductible is met, by those induced to consume more healthcare when meeting their deductible in one year, $0.24 less is spent in the following year. I estimate this amounts to US consumers saving 1.5 billion dollars per year through intertemporal substitution.

To avoid concerns about the propensity to consume more medical care and more expensive medical care being related, I also examine care dates and find a decrease of 7.4 care dates in the year after meeting their deductible. To better understand in what areas individuals respond, I examine classes of elective and preventative healthcare. I find a marginally significant decrease of 12.3 percentage points in the probability of consuming any elective care and fail to detect any significant differences in the usage of any preventive care.

The remainder of the paper proceeds as follows. Section 2 provides relevant background on non-linear health insurance plans. Section 3 develops a theoretical model of intertemporal substitution in response to non-linear health insurance plans. Section 4 discusses the data. Section 5 describes the identification strategy, empirical model, and specification details. In Sections 6 and 7, respectively, I discuss the main results, and a variety of sensitivity analyses. I conclude in Section 8 with a discussion of my findings and their potential relevance to both the literature and insurance markets.

2. Background on Non-Linear Health Insurance Plans

First, I discuss the simple case of an individual with a non-linear (or high deductible) insurance plan[1], and then explain the relevant variations for family plans. The most common form a non-linear plan takes includes a deductible arm, coinsurance arm, and stoploss (or maximum out-of-pocket). The deductible arm is when at the beginning of the plan the consumer is responsible for the entirety of their healthcare costs. This can also be framed as a 100% coinsurance rate.

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[1] I use the term high-deductible plan broadly and do not tie it to the legal definition for Health Savings Account eligibility.

In reality, preventative care and prescriptions like an annual physical or contraception are often not included in the deductible and instead are subject to a copay or zero out-of-pocket cost. These exemptions make it less likely that effects will be observed among preventive care outcomes. As a simplification, I will not model copays, but will capture them in spending measures, which is common in the literature. Additionally, the Affordable Care Act (ACA) increased the number of services insurance plans must provide without consumer cost-sharing. However, despite these exceptions the majority of medical procedures and diagnostic tests are subject to the deductible.

Once the deductible is met by the insured paying for the entirety of their medical costs up to the deductible at the beginning of the plan year, the coinsurance arm is reached. In this section of the plan, the insured is only responsible for paying a certain percentage of their healthcare costs. If a consumer is within the coinsurance arm of their plan and has a 20% coinsurance rate, the out-of-pocket cost for a $500 scan would be $100. The range of the coinsurance arm in terms of total costs is usually much larger than the deductible arm.

Once a certain amount has been paid out of pocket (through the deductible, coinsurance, and copays), the stoploss or out-of-pocket maximum is met. After this stoploss is hit, the insured no longer contributes to the cost of healthcare and is fully insured.

While a single enrollee has a complex non-linear pricing scheme when facing the common deductible, coinsurance arm, and stoploss insurance plan structure, it can become even more complex for a family plan. Many plans include both individual and family deductibles, and out-of-pocket maximums. Most commonly the family deductible and stoploss are two to three times the individual deductible and stoploss.

Consider a family plan where each family member faces an individual deductible of $1,000 and a family deductible of $2,000. For a family of two this is equivalent to individual deductibles of $1,000, but it is not equivalent for larger families. For a larger family, the family deductible means that instead of an individual being guaranteed to pay a $1,000 deductible, they could pay a maximum of $1,000 before reaching the coinsurance arm. The coinsurance arm could be met by no family member meeting their individual deductible and instead multiple family members contributing a sum larger than the family deductible.

A single family member could still hit their individual deductible of $1,000 and then individually move to the coinsurance arm of the plan. Then the threshold for the other family members to reach the coinsurance arm is either $1,000 individually or summed among the other members. I study the effect of reaching the deductible by identifying individuals that reach the coinsurance arm of their plan by meeting either their individual or family deductible.

3. Theoretical Model

Coming soon to the next draft.

4.1 Data

To address this question, I use the 2010-2012 IBM Truven Health MarketScan Commercial Database which is sourced from large companies and private health insurers across the United States. For this reason, this research is not representative of the U.S. population overall but of a select group of privately insured. However, because the dataset comes from a variety of employers and companies across the U.S., I am able to study a broader privately insured population than studies with data from a single employer or insurer.

The MarketScan database contains all insurance claims data for individuals and their spouse/dependents including inpatient, outpatient, and pharmaceutical claims. Each claim provides information on the total amount paid by the insurer and out-of-pocket payment categorized as payment towards the deductible, coinsurance, or copayment. I aggregate this claim-level information to the individual level for all analyses. The dataset also includes limited demographic information on the age and sex of all individuals.

Claims data is essential to this research because it allows me to observe in detail the spending, diagnoses, and procedures of individuals. The major limitation of this claims data is that I do not observe individuals without any claims in a year. However, any small claim within the year such as an influenza vaccine or prescription refill would lead to inclusion. To follow changes in healthcare consumption over time, I must limit my sample to those observed in my sample all three years. This means that the sample represents a group where the primary enrollee is linked to the same employer or private insurer for three consecutive years. I also exclude individuals under the age of 18 out of concern that guardians may be more altruistic towards their children and not be willing to delay their care, but I also show robustness to their inclusion in Appendix Table A1.

To select my sample of those with unexpected injuries, I use the class of plausibly exogenous injuries from Kowalski (2016) which were selected based on the fact that individuals that have the injury in their families do not spend more on their own medical care before the injuries occur. Those that have one of these injuries would make significant progress towards, if not meet, their deductible in the year that the injury occurs. Based on their selection, this class of injuries does not appear to be strategically timed in any manner.

In Table 1, I show the identifying injuries, their ICD-9 codes, and the counts overall and by year of injury. The most common identifying injury is sprains and strains of joints and adjacent muscles occurring in 34 percent of the sample. Other common injuries occurring in roughly ten percent of the sample include fractures, dislocations, open wounds, contusions, and complications of trauma.

Summary statistics of observed covariates overall and by injury year are displayed in Table 2. The summary statistics across the two sides of the discontinuity appear quite similar. The sample is 58% women, and the most common age range is 45-54. The mean individual deductible in 2011 is $608. Table 3 presents summary statistics of the 2012 outcomes overall. The mean of total spending is $11,631, while the 99^{th} percentile of total spending is $125,763. The out-of-pocket mean is $1,468, while the 99^{th} percentile, $7,121, is relatively smaller because out-of-pocket maximums exist on nearly all plans. The average number of care dates in 2012 is 16 with the majority being outpatient, while only 9% of individuals have an inpatient claim. In 2012, 31 and 60% have at least one elective or preventive claim observed, respectively.

We would expect those with the same injuries occurring a short time apart to be incredibly similar. However, when in the year the injury occurs determines how long the individual has to benefit from meeting their deductible and thus reaching the coinsurance arm of their plan. Therefore, an individual with an injury occurring in the end of the year would have little time to react from the increased likelihood of meeting their deductible, while an individual with the same injury in the beginning of the subsequent year could have twelve months to react to the increased likelihood of reaching their deductible. In Figure 1, I show the probability of reaching the coinsurance arm (i.e., meeting the deductible) by first date the injury is observed. The probabilities of reaching the coinsurance arm in 2011 for those with a 2010 or 2011 injury are 70.4 and 77.6, respectively (Table 4).

In my main specification, I focus on those with the first observed date of the injury occurring within 90 days of the 2010–2011-year change. This selection of a 90-day bandwidth is based on the average across outcomes for data-driven bandwidth selection methods following the procedures of Calonico, Cattaneo, and Titiunik (2014a, b, 2015b). I additionally show robustness to other bandwidths in Section 7.

4.2 Determining Deductible Amount

The major limitation of this dataset is that it does not include specific plan details such as the deductible or out-of-pocket maximum. But I am able to back out deductible amounts for over 90% of individuals through a few reasonable assumptions and data features that are very similar to the procedures used in Guo and Zhang (2019). First, I assume that all family members will have the same deductible and that the family deductible is two times the individual deductible.

I also have a plan key that identifies all individuals on the same insurance plan for a portion of the sample and assume that all individuals with the same plan key have the same deductible. Because deductibles are most often chosen at common increments, I assume that individual deductibles must be multiples of 25 and family deductibles must be multiples of 50.

For each individual and each family, I sum the deductible charges throughout each calendar year. If the individual sum of deductible charges is a multiple of 25 or the family sum is a multiple of 50, I consider that to be the most likely deductible. Then for each plan key, I consider the most common deductible amount to be the deductible for all with the plan key with the exception of zero. If the most common deductible amount is zero, I consider the deductible to be zero if greater than 90% of those on the plan have a deductible of zero. If not, then the second most common deductible on the plan is chosen. This is done because some plans have deductibles but offer many deductible exemptions for things like standard office visits.

For those with no plan key, I assume the deductible is the sum of deductible charges observed for the individual (family) if it is a multiple of 25 (50). If I still have not found a deductible amount for a family in 2011, then I use the deductible estimated for 2012 or 2010, respectively, since it is reasonable to assume that those enrolled at the same employer would enroll in similar plans across years. In my main analysis, I exclude those with a deductible of $100 or less as the instrument shows little validity for this group (Table 7).[2]

4.3.1 2012 Outcomes

[2] In Appendix Table A1, I show robustness to these exclusions and that similar conclusions would be drawn.

The primary outcome of interest is total healthcare spending in year $t+1$ (2012). Total spending is defined as the total amount spent by the insurance company and individual out of pocket on all healthcare claims (outpatient, inpatient, and pharmaceutical) in year $t+1$. To examine the spending most relevant to the healthcare consumer, I define the outcome total out-of-pocket spending on all healthcare claims (outpatient, inpatient, and pharmaceutical) in year $t+1$. Out-of-pocket spending is the sum of all payments by the individual towards the deductible, coinsurance, or copayments. To address concerns about the skewed distributions of these spending outcomes, I also examine both outcomes with natural log, $\ln(1+y_{it+1})$, and inverse hyperbolic sine, $arsinh(y_{it+1})$, transformations.

To avoid concerns about the propensity to consume more medical care and the propensity to consume more expensive medical care being related, I also examine total care dates. A count of dates rather than a count of services is used because it is often difficult to distinguish separate services in claims or they may be charged as a bundle of services. I define care dates as a count of the number of service dates in year $t+1$ that an individual has outpatient or inpatient claims.

To better understand in what areas individuals respond, I examine outpatient and inpatient care dates separately, and classes of elective and preventative healthcare. Outpatient and inpatient care dates are counts of the number of service dates in year $t+$

1 that an individual has outpatient or inpatient claims, respectively. The elective care dates outcome is a count of the number of dates in year $t+1$ with elective services being defined based on elective procedures defined using Berenson-Eggers Type of Service (BETOS) codes by Clemens and Gottlieb (2014) and also used by Guo and Zhang (2019). This class of elective services includes procedures such as cataract removal, joint replacement, colonoscopy, and minor skin procedures. The preventive care dates outcome is a count of the number of dates in year $t+1$ with preventative services being defined based on the Center of Medicare and Medicaid Services' list of preventive services. Examples of these preventive services include annual wellness visits, influenza vaccinations, and disease screenings. The full list of elective and preventive services is available in the Appendix. For outcomes that do not always occur and zeros are common (inpatient, elective, and preventive), I also examine the outcome as an indicator of any of that type of care consumed in the year.

Tables 2 and 3 present summary statistics on the year t+1 (2012) outcomes. Mean total healthcare spending and out-of-pocket spending in year $t+1$ are \$11,631 and \$1,468, respectively. The average number of care dates is 16.2 with outpatient and inpatient averages of 15.8 and 0.5. Only nine percent of the sample has any inpatient care while 31 and 60 percent have any elective or preventive care, respectively.

4.3.2 2011 Outcomes

To give an estimate of the tradeoff between elective spending in the year the deductible is met and the following year, I also will estimate the models for the outcomes in year t (2011). First, I separate the outcomes in year t into those that are related to the injury or not. For the total healthcare spending outcomes, I measure spending related to the injury as the totals from any claim that has one of the injury ICD-9 codes. I then also measure the complement, spending unrelated to the injury, which is the total of any charges in year t which does not have one of the injury ICD-9 codes. This is the cleanest measure of the outcomes related to injury or not that I have been able to develop from the data, but it is possible that the injury codes are not always used on claims for follow-up care. This would lead to an overestimate of the tradeoff of elective spending. To provide a range of the tradeoff in elective spending across years, I also measure all spending and care dates in year t, regardless of injury. These measures in year t contain the cost of treating the original injury for those with the first date the injury is observed in the beginning of year t. Follow-up care for these injuries could be contained in the measures for anyone in the sample. The true trade-off between elective care spending in the year the deductible is met and the subsequent year should lie between my estimates of spending with the injury codes and all spending.

In Table 4, I present averages of year t (2011) and year $t+1$ (2012) outcomes by the year of injury to show that the expected patterns are observed in the raw data. Year t

total spending is higher for those with an injury in year t comparing \$14,804 to \$11,761. Then in the following year average spending is lower for those with a year t injury relative to a year $t-1$ injury (\$11,526 to \$11,726).

5. Empirical Strategy

I use a fuzzy regression discontinuity design to identify the effect of meeting a deductible in one year on healthcare consumption in the following year. I exploit the fact that most health insurance deductibles reset at the beginning of the calendar year by comparing those with a class of unexpected injuries, which would be unlikely to be strategically delayed, in late 2010 and early 2011. We would expect that those who suffer injuries on either side of the calendar year charges are similar, except that the year in which their injury occurs changes the probability of them meeting their deductible in 2011. My model relies on this variation to identify the effect of meeting a deductible (*i.e.,* reaching the coinsurance arm) in one year (2011) on healthcare consumption in the following year (2012), relative to the effect of meeting the deductible in the previous year (2010).

5.1 First Stage

I implement the fuzzy regression discontinuity using a local linear regression with a bandwidth of 90 days and a rectangular kernel. I use an instrumental variables estimation framework (Imbens and Lemieux, 2008) where the first stage of the model is:

$$w_{it} = \gamma_0 + \gamma_1 Injury_{it} + \gamma_2\ Injury_{it-1} \times Date_{it-1} + \gamma_3\ Injury_{it} \times Date_{it} + \boldsymbol{\gamma_4 X'_{it}} + \upsilon_{it} \quad (1)$$

where w_{it} is an indicator for individual $\boldsymbol{i}$ reaching the coinsurance arm of their plan in year t. An individual could reach the coinsurance arm of their plan by either meeting their individual deductible or their family deductible. The year is indexed with $t-1$ for 2010 measures, t for 2011 measures, and $t+1$ for 2012 measures. The excluded instrument, $Injury_{it}$, is an indicator equaling one if the injury was first observed in year t (early 2011) and zero if in year $t-1$ (late 2010). The running variable is represented by $Date_{it-1}$ and $Date_{it}$ which range from 1-90 in years $\boldsymbol{t-1}$ and t, respectively. The interactions $Injury_{it-1} \times Date_{it-1}$ and $Injury_{it} \times Date_{it}$ between the running variable and what year the injury occurs allow the two sides of the discontinuity to have separate slopes.

The vector $\boldsymbol{X'_{it}}$ contains age, sex, individual deductible amount, and number of family members observed on the plan in ranges. Although there appear to be balance across the discontinuity in these observables (Figure 2), I include the deductible amount and number of family members because they are mechanical factors in predicting the likelihood of an individual reaching the coinsurance arm of the plan. I also show robustness to the exclusion of these covariates in Table 7.

Figure 1 shows a visual of the first-stage identification. Visually, the discontinuity is clear with little overlap across the year change in the probability of meeting the deductible. The first stage point estimate of γ_1 of 0.059 represents a roughly six percentage point increase at the discontinuity in the probability of an individual meeting their deductible in year t. The first stage meets all recent standards for power with a first stage F-statistic of 237.0.

To further support the validity of the research design, Figure 2 presents visualizations of the balance of covariates including the 2011 deductible, number of family members observed on the plan, birth year, and sex. They all show no major patterns or discontinuity at the cutoff supporting the validity of the design. Figure 3 shows the density of observations across first observed service date for injuries. There are clear weekly patterns in the frequencies and some variations that can be attributed to holidays. Seasonal variation in these injuries is also plausible since many of the injuries could be connected to risky behaviors. However, the density plot still appears relatively smooth across the discontinuity.

5.2 Second Stage

The second stage is as follows:

$$y_{it+1} = \beta_0 + \beta_1 w_{it} + \ \beta_2 Injury_{it-1} \times Date_{it-1} + \ \beta_3 \ Injury_{it} \times Date_{it} + \boldsymbol{\beta_4 X'_{it}} + \varepsilon_{it} \quad (2)$$

where y_{it+1}, is a healthcare consumption outcome in the year $t+1$. The second stage contains the same date-injury year interactions and covariates as the first stage. Here w_{it}, the indicator for reaching the coinsurance arm in year t is instrumented for by $Injury_{it}$, which is an indicator for having an injury in year t versus $t-1$. The estimates of β_1 are therefore identified by the discontinuities in the probability of reaching the coinsurance arm in year t at the year change.

6. Results and Discussion

6.1 2012 Outcomes

Table 5 presents estimates of β_1 based on Eqs. (1) and (2). Because injury date, $Date_{it}$, is discrete, all models report standard errors clustered by injury date following the inference procedure proposed by Lee and Card (2008). The first row has outcomes in the form of dollars spent or count of care dates, the second and third row presents the natural log and inverse hyperbolic sine of spending outcomes, and the fourth row presents outcomes as an indicator for the type of care occurring during the year.

In the first column, the outcome is total spending on healthcare in year $t+1$ and the point estimate of -13,263 implies that an individual meeting their deductible in the prior year is associated with a $13,263 decrease in total spending, relative to the effect of meeting the deductible in year $t-1$. This effect is large relative to the sample mean of $11,631 for total spending. In the second column, the point estimate for total out-of-pocket spending is -788. This implies that an individual meeting their deductible in the prior year is associated with a $788 decrease in out-of-pocket spending, relative to the effect of meeting the deductible in year $t-1$. The magnitude of this estimate is still large relative to the mean of $1,468, but not proportional to the total spending estimates because of the non-linear plan structure and out-of-pocket maximums.

To remove variations in costs as a factor, I examine total care dates in the third column. I estimate that meeting the deductible in the year prior leads to a decrease of 7.4 care dates relative to a mean of 16.2 care dates. The effect appears to be driven by decreases in both outpatient and inpatient care dates. When examining a class of elective care dates, the point estimates imply a 12.3 percentage point decrease in the probability of consuming any elective care in the year after the deductible is met, relative to a mean of 31 percent. In my main specification, I fail to detect any changes in preventive care dates. This result is suggestive that insurance company and public policy effort to exempt preventive care from consumer cost-sharing may successfully prevent decreases compared to other types of care.

To support the estimates of Table 5 visually, Figures 4 and 5 show the reduced-form relationship between the first date of service for the injury and outcomes. Despite being only the reduced form, the discontinuity in the expected direction is visually apparent.

6.2 2011 Outcomes

I use outcomes in the year the deductible is met to (1) verify that there is an observed increase in care in the year the deductible is met, and (2) estimate the tradeoff between spending across years. The first three rows of estimates in Table 6 contain the identifying injury for those with an injury in year t and potentially follow-up care for all individuals. The fourth and fifth rows decompose total spending based on whether an injury code is present on the charge. Overall, the point estimate for total spending is \$36,706 with the estimate for injury charges in year t being \$12,818 and for non-injury charges being \$23,887. Relative to the mean of total spending in year t of \$13,215, these estimates are large and economically significant increases in consumption.

Combining the year t overall estimates with those from year $t + 1$ implies that for those induced to consume more healthcare by meeting their deductible in one year, for every dollar of healthcare consumed in the year the deductible is met they consume \$0.37 less in the following year (\$13,263/\$36,706). Further, if we are interested in only the tradeoff between elective spending beyond that related to the injury, my estimates imply that for those induced to consume more healthcare by meeting their deductible in one year, for every dollar of elective care consumed in the year the deductible is met, they consume \$0.56 less in the following year (\$13,263/\$23,887). My preferred tradeoff to consider is the more conservative total spending measure because it is difficult to categorize what care is directly related to the injury as diagnosis and billing codes may vary. From the consumer's perspective, the out-of-pocket estimates imply that for those induced to consume more healthcare by meeting their deductible in one year, for every dollar spent out of pocket in the year the deductible is met \$0.24 less is spent in the following year (\$788/\$3,288).

Examining elective and preventive care dates, which are unrelated to the injury, provides insights into where the increases in elective spending are occurring. The point estimate for elective care dates of 1.96 relative to a mean in year t of 0.65 suggests that these elective procedures are a major channel where this spending occurs. Interestingly, there is a 37.1 percentage point increase in the probability of consuming any preventive care relative to a mean of 59.4 percent. This contrasts with failing to detect any significant effect on preventive care in year $t+1$. A possible explanation is that increased interaction with the healthcare system increases preventive care usage, but cost-sharing exemptions are effective at minimizing decreases in preventive care due to non-linear plans.

6.3 Back-of-the-Envelope Calculation of Economic Impact

To understand the scope of this intertemporal substitution, I conduct a back-of-the-envelope calculation of the cost savings to the privately insured in the U.S. from intertemporally substituting when consuming the average out-of-pocket cost using 2020 insurance rates. I calculate

$$150{,}000{,}000 \ * \ 0.57 \ * \ 0.83 \ * \ 0.24 \ * \$1{,}468 \ * \ 0.06 = \ \$1{,}500{,}143{,}328 \qquad (3)$$

where there are roughly 150 million employed workers in the US, 57% of workers are covered by employer-provided insurance, 83% then have a deductible, the out-of-pocket spending tradeoff found is \$0.24 less spent per dollar spent in the previous year, the average out-of-pocket is \$1,468, and roughly 6% of the population are compliers (KFF, 2020).[3] I find that U.S. consumers are saving at least \$1.5 billion per year through intertemporal substitution.

Similarly, I estimate what savings health insurance companies are not receiving that single year estimates would suggest. I calculate

$$150{,}000{,}000 \ * \ 0.57 \ * \ 0.83 \ * \ 0.37 \ * \$11{,}631 \ * \ 0.06 = \$18{,}323{,}744{,}913 \tag{4}$$

where there are roughly 150 million employed workers in the US, 57% of workers are covered by employer-provided insurance, 83% then have a deductible, the total spending tradeoff found is \$0.37 less spent per dollar consumed in the previous year, the average of total spending is \$11,631, and roughly 6% of the population are compliers (KFF, 2020). Thus, I find that that estimates using only a single year would overestimate the savings of high-deductible plans by \$18.3 billion.

Further, if intertemporal substitution extends beyond the year after the deductible is met, all of these estimates will underestimate the true effect. It seems plausible that

[3] While there should be standard errors on all the terms of the calculation, some are unpublished, so I am unable to provide a confidence interval.

intertemporal substitution would extend beyond a single year as some types of care could be strategically timed across multiple years and some individuals may expect to meet their deductible only every few years Additionally, the size of deductibles has continued to grow over time which would likely lead to both increased rates and magnitudes of intertemporal substitution. Thus, these results are a conservative estimate of the economic impact of intertemporal substitution.

7. Sensitivity, Robustness, Placebo, and Heterogeneity Analyses

7.1 Placebo Tests and Heterogeneity by Deductible Amount

In Figure 6, I show reduced form plots of 2011 and 2012 total spending for the main sample and then for those that are excluded from the sample because they have no deductible. Those with no deductible are a placebo test in the sense that we would expect to see a mechanical difference in 2011 and no change in 2012 spending because the group has no deductible. The 2011 total spending plots look very similar across groups, while the 2012 total spending plots, show different patterns as expected. For those with a deductible greater than $100 there is a noticeable decrease in total spending at the discontinuity as expected, while for those without a deductible, there is an increase in 2012 total spending at the discontinuity of a much smaller magnitude. The fact that the placebo test of those without a deductible is of the opposite sign shows that the identification is coming solely from those with deductibles and is strong evidence in support of the identification strategy's validity.

In Table 7, I conduct a heterogeneity analysis stratifying by deductible amount. But the first group of those with a deductible that is less than or equal to $100 serve as a placebo test because a deductible that small is much less likely to induce these behavioral responses across years. I find no significant results for this group and the instrument is weak with a first-stage F-statistic of 0.17.

The second through fifth columns of Table 7 presents the results from the main sample stratified by deductible amount. As would be predicted, results are of the largest magnitude for deductibles of $300-999. These individuals are likely the most likely to only meet their deductible in some years leading to a substituting care across years. Those with smaller deductibles are more likely to reach the coinsurance arm of their plan consistently. Similarly, those with a larger deductible are less likely to meet their deductible often or from the injury. Sample size limitations make it difficult to comment on deductibles greater than $1000.

7.2 Sensitivity/Robustness

In my main specifications, I include covariates to address concerns about observables which may impact the likelihood of an individual meeting their deductible. I show robustness to this choice in Table 8 where the covariates in the vector $\boldsymbol{X}'_{it}$ (age, sex, individual deductible amount, and number of family members observed on the plan in ranges) are excluded. Overall, results appear quite similar with estimates having slightly larger magnitudes making the main specification a conservative estimate. Specifically, the estimates without covariates for total and out-of-pocket spending of -15,085 and -925 are very close to the corresponding estimates with covariates of -13,263 and -788.

Due to lack of plan information, I assume that the family deductible is twice the individual deductible meaning it is only relevant for families with more than two individuals enrolled. To show robustness to this assumption, I show results stratified by the number of observed family members enrolled in Table 9. Point estimates are similar and of a larger magnitude for those with one or two family members observed on the plan. Since the family deductible is not relevant for these individuals, assumptions about the family deductible are not driving results.

To address concerns about individuals strategically shifting treatment around the year change, I run two donut regression discontinuities with bandwidths of 7 and 14 days (Table 10). These specifications also address potential concerns about the uniqueness of injuries during the winter holiday season. These estimates are quite similar to the main specification with a slightly larger magnitude for the point estimates. Similarly, Table 11 shows variations in bandwidth of 45, 60, and 75 days compared to the main specification of 90 days. Point estimates are all of the same sign and similar magnitudes, but standard errors vary across these bandwidths.

8. Conclusion

In this work, I show that intertemporal substitution across years in response to non-linear health insurance plans exists in the modern U.S. healthcare context. This finding is especially important as high-deductible health insurance plans have become increasingly common, and many estimates of the cost savings of high deductibles come from single year data sources. Using claims data following privately insured individuals over three years, I find that every dollar of healthcare consumed in the year the coinsurance arm is reached, roughly $0.37 less is consumed in the following year for those induced to consume more care by meeting their deductible. The local average treatment effects indicate that reaching the coinsurance arm in one year leads to $13,263 less healthcare consumed and $788 fewer paid out of pocket in the following year. Ignoring this intertemporal substitution would cause many previous estimates using a single year to overstate the cost-saving benefits of high-deductible plans.

These results align with the conclusions of Lin and Sacks (2019), based on a simulation using the RAND Health Insurance Experiment, that failing to account for intertemporal substitution could cause estimates to overstate cost savings from high deductible plans by more than 20 percent. While my fuzzy regression discontinuity produces a local average treatment effect with strong internal validity, it does not immediately translate to total cost estimates for the entire population. To understand the scope of this intertemporal substitution, I conduct a back-of-the-envelope calculation of and find that U.S. consumers are saving at least \$1.5 billion per year through intertemporal substitution. Further, single year estimates would overstate the national savings from high-deductible plans by at least \$18.3 billion emphasizing the importance of the results that ignoring across-year intertemporal substitution would cause many previous estimates using a single year to overstate the cost-saving benefits of high-deductible plans.

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Tables and Figures

Figure 1. Probability of Reaching Coinsurance Arm (Meeting Deductible) in 2011

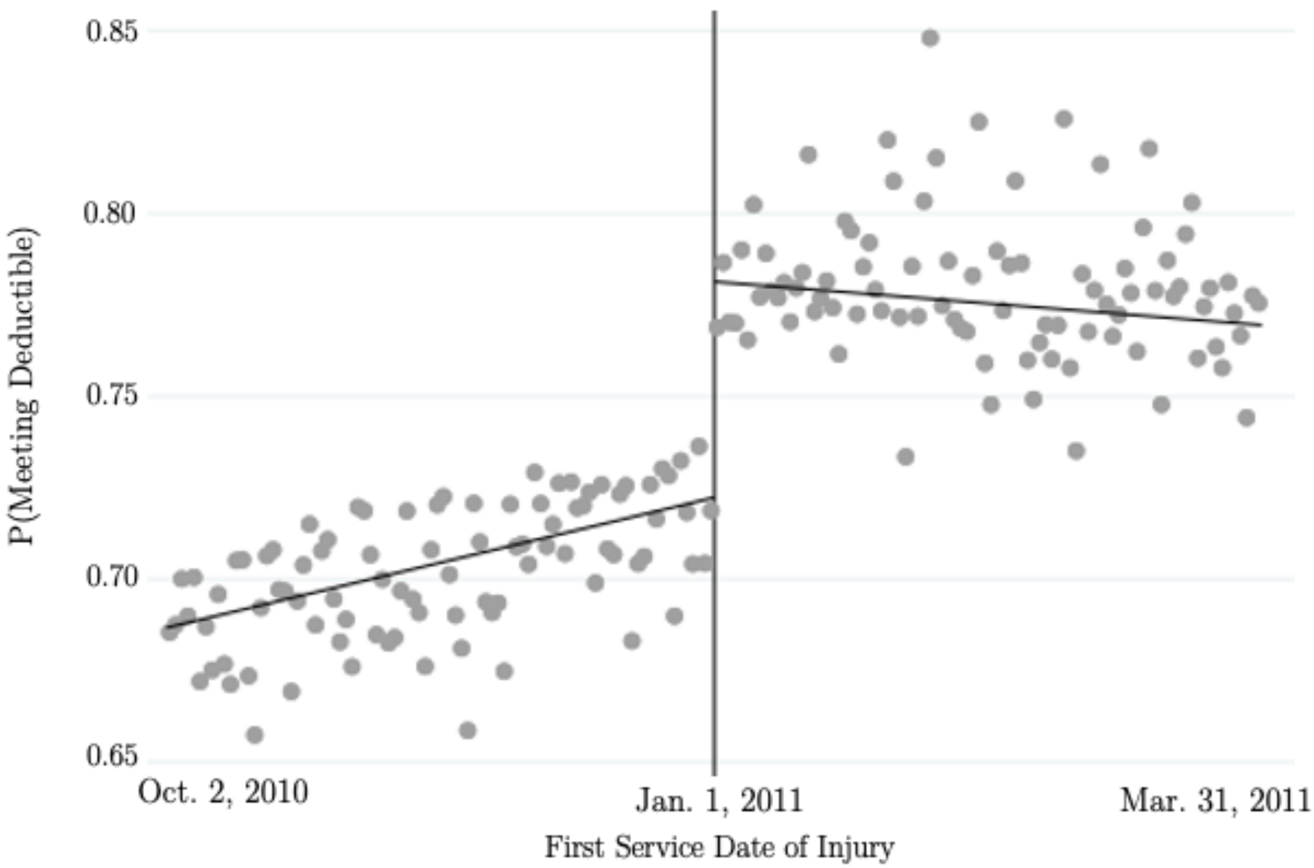


Figure 2. Balance Tests

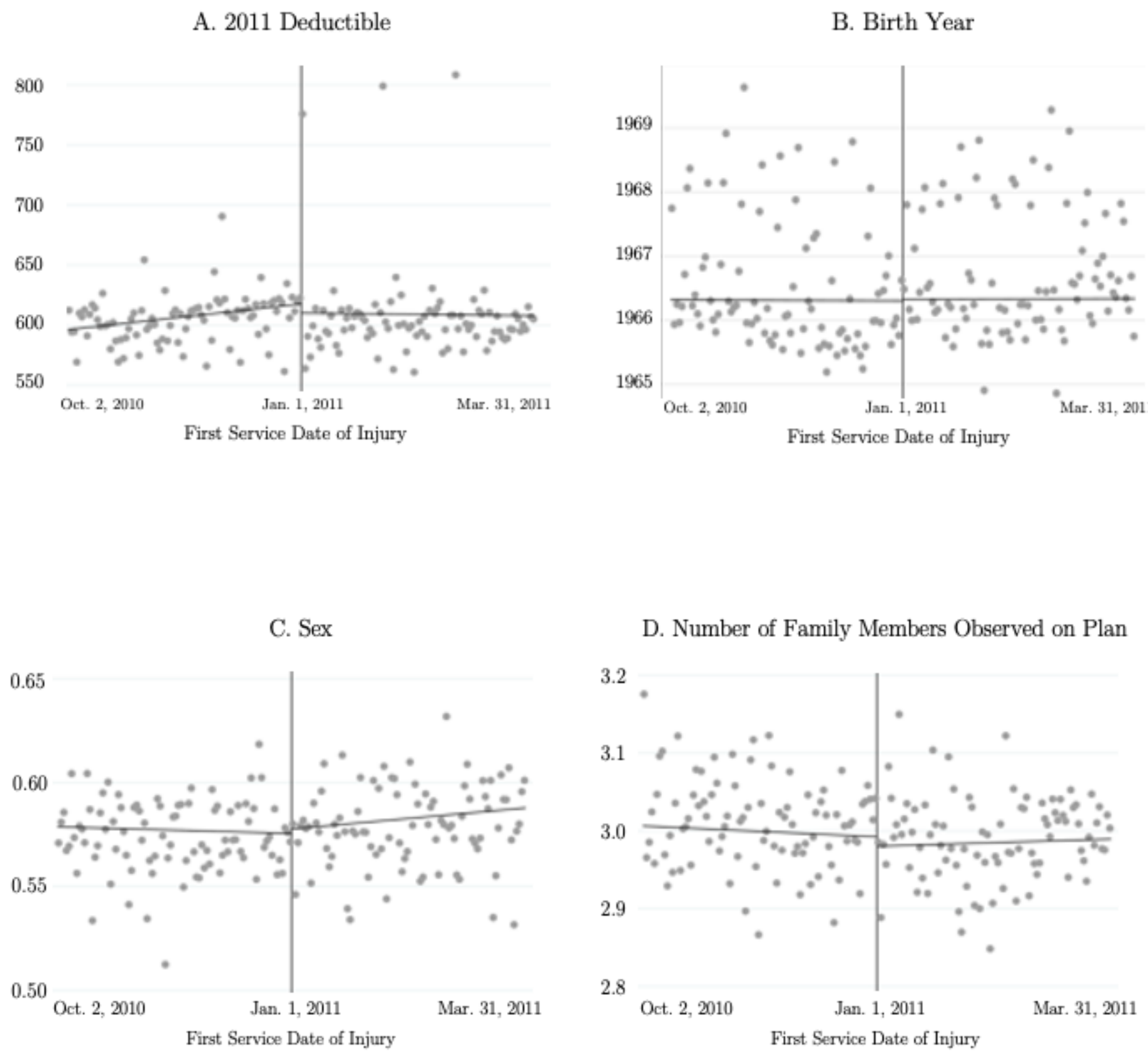


Figure 3. Number of Individuals Observed by First Service Date of Injury

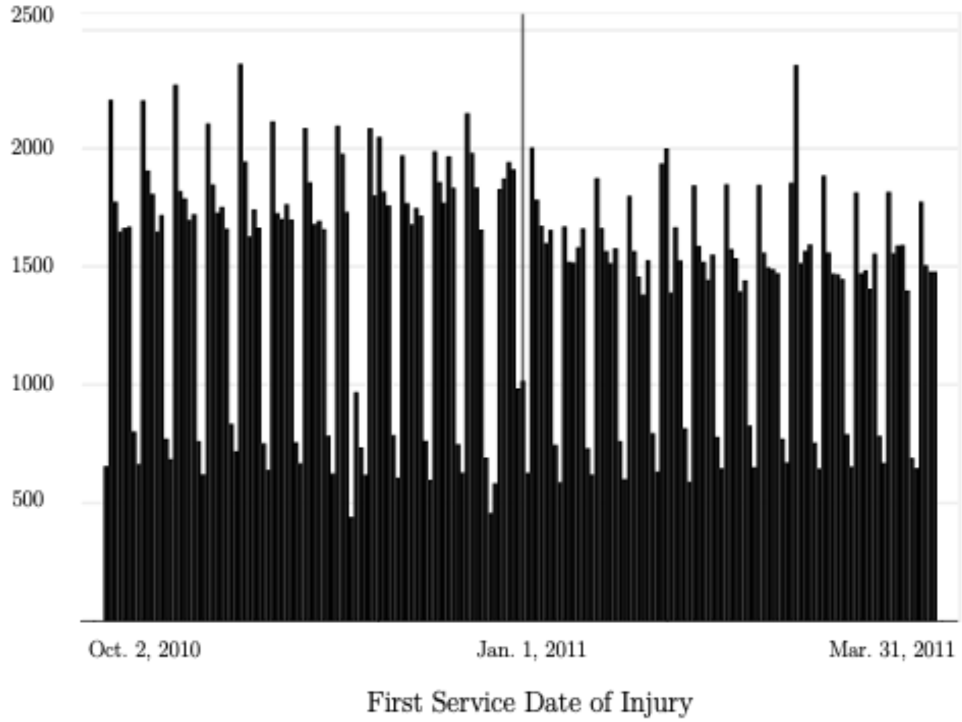
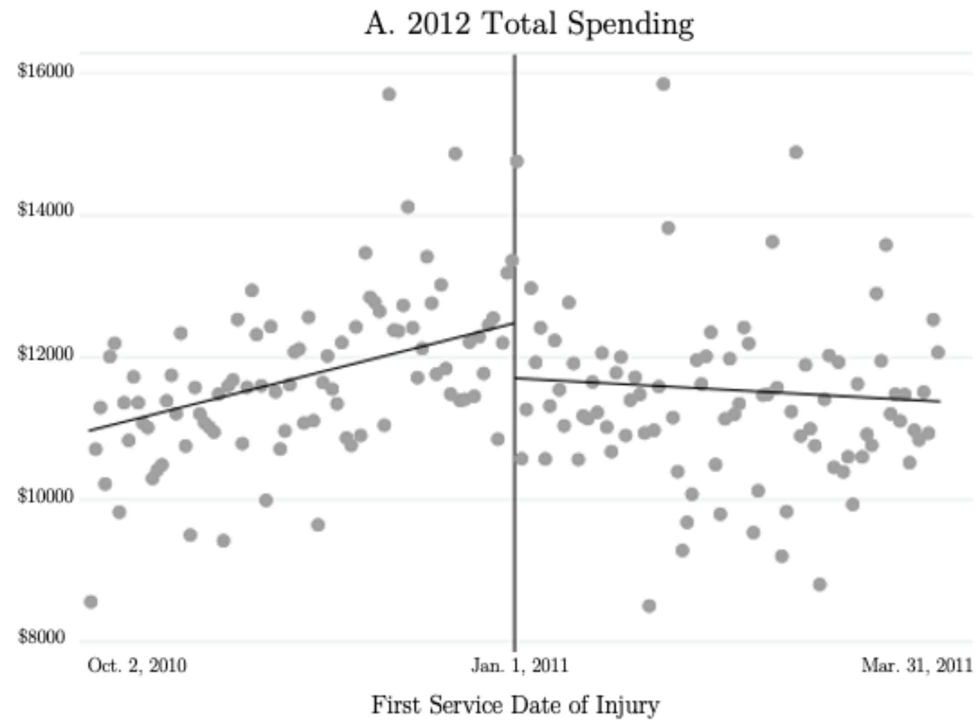


Figure 4. Reduced Form Plots for Spending Outcomes



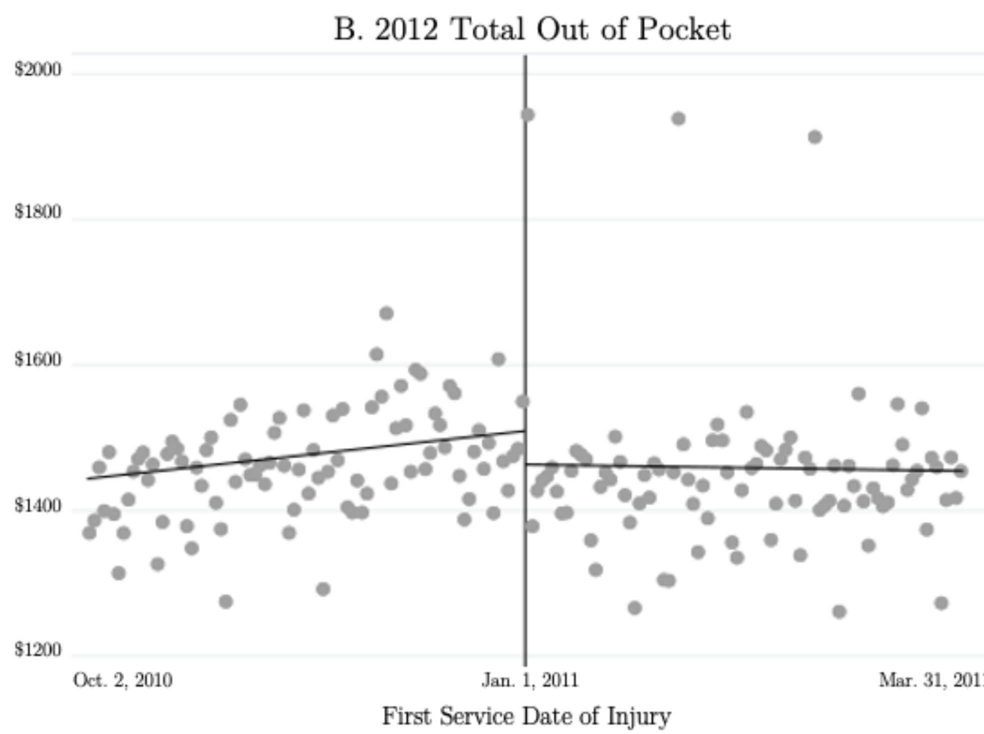


Figure 5. Reduced Form Plots for Care Date Outcomes

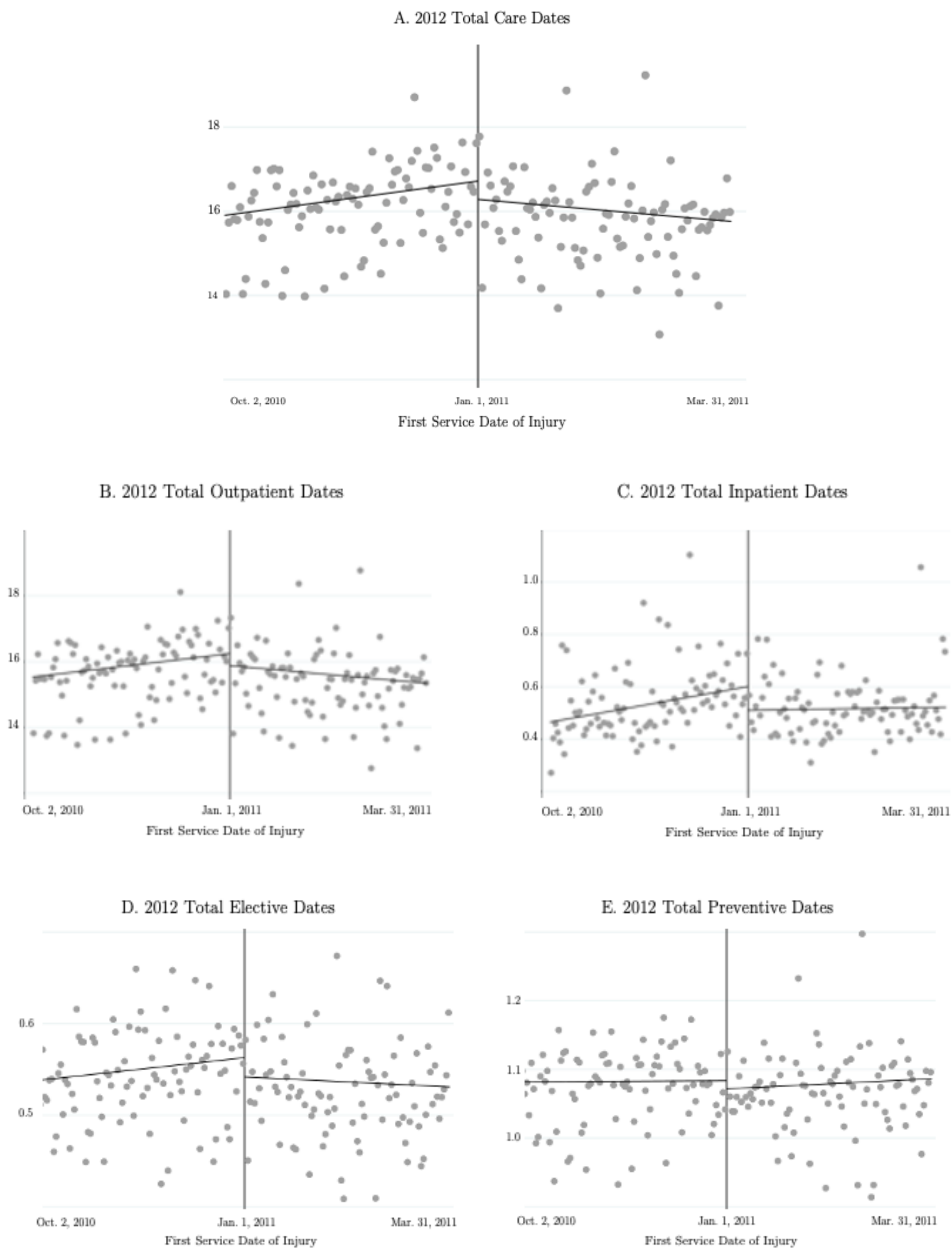


Figure 6. Reduced-Form Plot Placebo Test

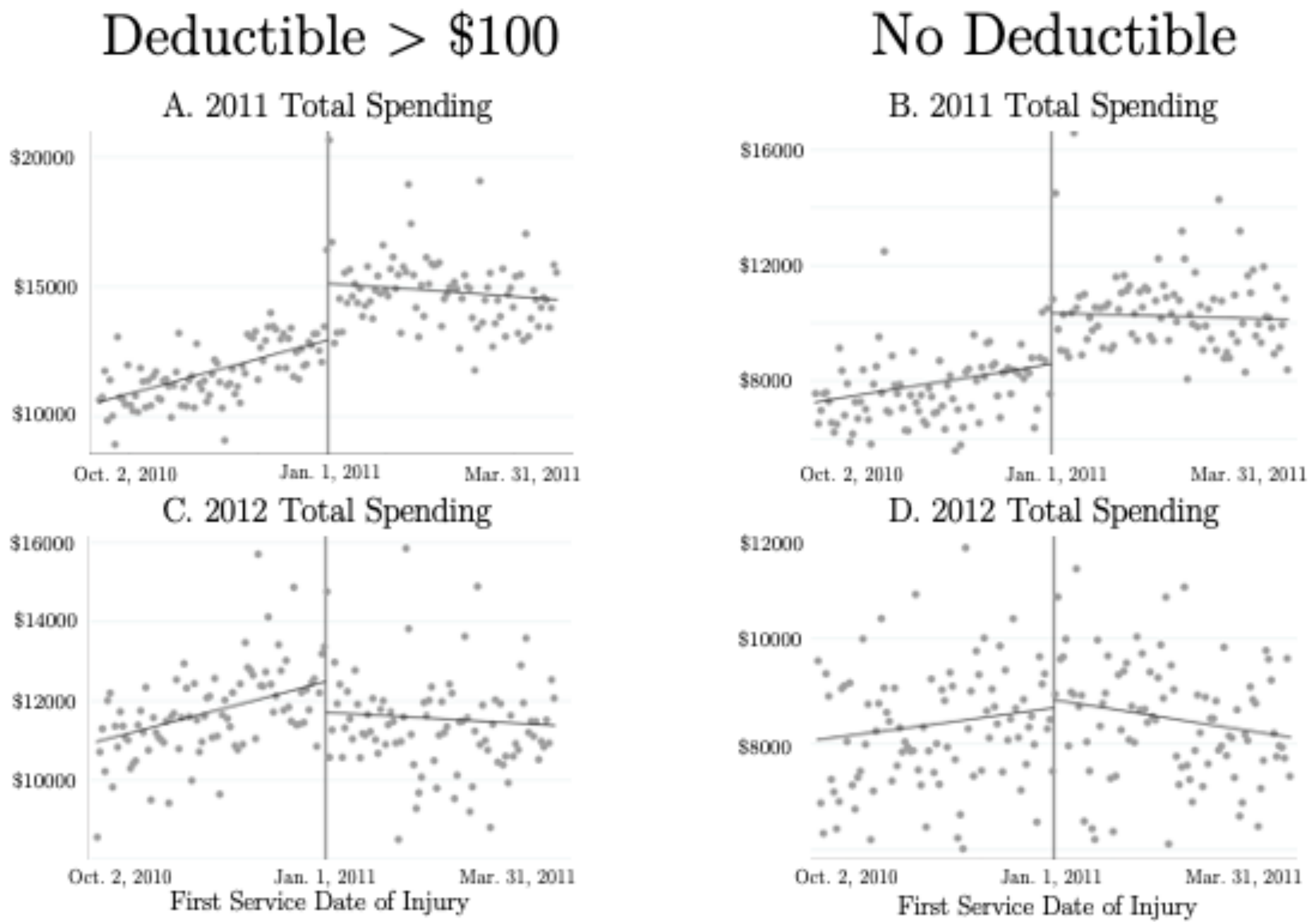


Table 1. Identifying Injuries in Sample, Overall and By Year of Injury

Injuries from Kowalski (2016)	ICD-9	Total Injuries (Percent)	Late 2010 Injuries (Percent)	Early 2011 Injuries (Percent)
Entire Sample		254,902 (100)	133,069 (100)	121,833 (100)
Fractures	800-829	23,847 (9.4)	12,187 (9.2)	11,660 (9.6)
Dislocation	830-839	24,742 (9.7)	13,509 (10.2)	11,233 (9.2)
Sprains and Strains of Joints and Adjacent Muscles	840-849	87,431 (34.3)	44,608 (33.5)	42,823 (35.1)
Intracranial Injuries, Excluding Skull Fractures	850-859	4,334 (1.7)	2,099 (1.6)	2,235 (1.8)
Internal Injury of Thorax, Abdomen, and Pelvis	860-869	0 (0.0)	0 (0.0)	0 (0.0)
Open Wounds	870-899	25,453 (10.0)	13,749 (10.3)	11,704 (9.6)
Injury to Blood Vessels	900-904	267 (0.1)	131 (0.1)	136 (0.1)
Late Effects of Injuries, Poisonings, Toxic Effects, and Other External	905-909	1,018 (0.4)	609 (0.5)	409 (0.3)
Superficial Injuries	910-919	13,535 (5.3)	7,748 (5.8)	5,787 (4.7)
Contusion with Intact Skin Surface	920-924	23,908 (9.4)	12,256 (9.2)	11,652 (9.6)
Crushing Injuries	925-929	675 (0.3)	383 (0.3)	292 (0.2)
Foreign Body Injuries	930-939	5,031 (2.0)	2,685 (2.0)	2,346 (1.9)
Burns	940-949	2,346 (0.9)	1,268 (1.0)	1,078 (0.9)
Injuries to Nerves and Spinal Cord	950-957	1,165 (0.5)	651 (0.5)	514 (0.4)
Complications of Trauma	958-959	32,188 (12.6)	15,882 (11.9)	16,306 (13.4)
Poisoning by Drugs, Medicinal and Biological Substances	960-979	2,254 (0.9)	1,117 (0.8)	1,137 (0.9)
Toxic Effects of Substances Chiefly Nonmedicinal and Other External	980-995	17,729 (7.0)	9,177 (6.9)	8,552 (7.0)
Complications of Surgical and Medical Care, Not Elsewhere Classified	996-999	16,789 (6.6)	8,469 (6.4)	8,320 (6.8)

Table 2. Covariate Summary Statistics, Overall and By Year of Injury

	Overall	2010 Injury	2011 Injury		Overall	2010 Injury	2011 Injury
2011 Deductible (in USD)				Sex			
Mean	607.9	606.8	609.1	Male	42.0	42.3	41.7
101-199	6.9	6.7	7.0	Female	58.0	57.7	58.3
200-299	18.6	18.8	18.3	Age (in 2010)			
300-399	20.0	20.2	19.9	18-34	24.7	24.4	25.0
400-499	6.6	6.5	6.7	35-44	24.6	24.5	24.8
500-749	22.0	22.1	21.8	45-54	33.0	33.3	32.6
750-999	5.3	5.2	5.4	55-64	17.7	17.9	17.6
1000-1249	9.7	9.5	9.9	Number of Family Members Enrolled			
1250-1499	3.3	3.1	3.5	1	20.0	19.5	20.6
1500-1749	4.3	4.3	4.2	2	23.6	24.0	23.3
1750-1999	0.4	0.5	0.4	3	18.1	18.2	18.0
2000-2499	1.2	1.2	1.1	4	22.7	22.8	22.7
2500-2999	0.6	0.6	0.6	5-6	13.4	13.4	13.4
3000-4999	1.1	1.2	1.1	7-8	1.7	1.7	1.7
5000-10000	0.0	0.0	0.0	≥ 9	0.4	0.4	0.4

Table 3. Summary Statistics of Year $t+1$ (2012) Outcomes

2012 Outcomes	Mean	SD	P1	P25	P50	P75	P99
Total Spending	11631	32495	52	1368	3867	10403	125763
Out of Pocket	1468	1900	0	383	958	2038	7121
Care Dates	16.17	19.43	0	5	10	21	88
Outpatient	15.75	18.39	0	5	10	20	83
Inpatient	0.53	3.64	0	0	0	0	11
Elective	0.54	1.47	0	0	0	1	5
Preventive	1.08	1.31	0	0	1	2	5
$\mathbf{1}$(Inpatient>0)	0.09	0.28	0	0	0	0	1
$\mathbf{1}$(Elective>0)	0.31	0.46	0	0	0	1	1
$\mathbf{1}$(Preventive>0)	0.60	0.49	0	0	1	1	1

Table 4. Means of Outcomes Overall and by Year of Injury

2011 Outcomes (y_{it})	Overall	2010 Injury	2011 Injury	2012 Outcomes (y_{it+1})	Overall	2010 Injury	2011 Injury
Probability of Meeting Deductible	73.83	70.42	77.55				
Total Spending	13,215	11,761	14,804	Total Spending	11,631	11,726	11,526
Out of Pocket	1,583	1,461	1,717	Out of Pocket	1,468	1,474	1,461
Care Dates	19.08	18.02	20.23	Care Dates	16.17	16.32	16.01
Outpatient	18.52	17.57	19.57	Outpatient	15.75	15.89	15.60
Inpatient	0.69	0.56	0.83	Inpatient	0.52	0.53	0.52
Elective	0.65	0.59	0.72	Elective	0.54	0.55	0.53
Preventive	1.08	1.07	1.08	Preventive	1.08	1.08	1.08
$\mathbf{1}$(Inpatient>0)	0.110	0.096	0.126	$\mathbf{1}$(Inpatient>0)	0.087	0.087	0.087
$\mathbf{1}$(Elective>0)	0.375	0.337	0.416	$\mathbf{1}$(Elective>0)	0.309	0.313	0.305
$\mathbf{1}$(Preventive>0)	0.594	0.594	0.595	$\mathbf{1}$(Preventive>0)	0.603	0.603	0.604

Table 5. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$

Outcome Form	Total Spending	Total Out of Pocket	Total Care Dates	Outpatient Care Dates	Inpatient Care Dates	Elective Care Dates	Preventive Care Dates
y_{it+1}	-13,263***	-788.4**	-7.39**	-6.19*	-1.56***	-0.36*	-0.20
	(5,005)	(367.5)	(3.50)	(3.29)	(0.59)	(0.19)	(0.18)
$\ln(1+y_{it+1})$	-0.503*	-0.559**	-	-	-	-	-
	(0.276)	(0.235)					
$arsinh(y_{it+1})$	-0.504*	-0.577**	-	-	-	-	-
	(0.277)	(0.277)					
$\mathbf{1}(y_{it+1}>0)$	-	-	-	-	-0.0863**	-0.123*	-0.0667
					(0.042)	(0.064)	(0.059)
N	254,902	254,902	254,902	254,902	254,902	254,902	254,902
$Mean\ of\ y_{it+1}$	11,631	1,468	16.17	15.8	0.52	0.54	1.08
$SD\ of\ y_{it+1}$	32,495	1,900	19.42	18.4	3.64	1.47	1.31

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2). All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 6. Effect of Meeting Deductible in Year t on Year t Outcomes Relative to Meeting Deductible in Year $t-1$

Outcome Form	Total Spending	Total Out of Pocket	Total Care Dates	Outpatient Care Dates	Inpatient Care Dates	Elective Care Dates	Preventive Care Dates
y_{it}	36,706***	3,288***	23.09***	21.46***	2.159***	1.962***	0.122
	(5,938)	(263.5)	(3.838)	(3.654)	(0.686)	(0.277)	(0.216)
$\ln(1+y_{it})$	4.896***	4.423***	-	-	-	-	-
	(0.344)	(0.212)					
$arsinh(y_{it})$	4.905***	4.502***	-	-	-	-	-
	(0.345)	(0.216)					
$\mathbf{1}(y_{it}>0)$	-	-	-	-	0.486***	1.544***	0.371***
					(0.0372)	(0.104)	(0.0427)
y_{it} *on Injury*	12,818**	-	-	-	-	-	-
	(5,297)						
y_{it} *Not on Injury*	23,887***	-	-	-	-	-	-
	(1,918)						
N	254,902	254,902	254,902	254,902	254,902	254,902	254,902
Mean of y_{it}	13,215	1,583	19.08	18.52	0.691	0.651	1.075
SD of y_{it}	32,861	1900	20.4	19.12	4.187	1.450	1.343

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) with year $\boldsymbol{t}$ (2011) outcomes. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 7. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$ by Deductible Amount

	Deductible (d)				
2012 *Outcome* (y_{it+1})	$0 < \text{d} \leq 100$	$100 < \text{d} < 300$	$300 \leq \text{d} < 500$	$500 \leq \text{d} < 1000$	$1000 \leq \text{d} < 10000$
Total Spending	-342,356	-7,004	-18,791**	-15,106**	-9,222
	(878,255)	(9,629)	(8,970)	(7,498)	(15,000)
Total Out of Pocket	-18,383	-644.3	-294.9	-1,788***	148.8
	(47,906)	(465.1)	(357.1)	(596.0)	(1,195)
Total Care Dates	-76.56	-1.561	-6.719	-14.19***	-2.410
	(234.5)	(6.255)	(4.870)	(5.240)	(8.845)
Outpatient Care Dates	-26.37	-0.605	-5.138	-12.75***	-1.919
	(130.7)	(5.971)	(4.575)	(4.854)	(8.252)
Inpatient Care Dates	-61.27	-1.248	-1.890**	-1.887**	-0.839
	(150.8)	(1.268)	(0.889)	(0.896)	(1.488)
Elective Care Dates	-0.0106	0.0699	-0.190	-0.579**	-0.665
	(11.12)	(0.485)	(0.383)	(0.263)	(0.509)
Preventive Care Dates	-8.509	0.164	-0.249	-0.389	-0.132
	(22.02)	(0.329)	(0.364)	(0.260)	(0.0987)
Sample Size	27,538	64,822	67,919	69,492	52,669
First-stage coefficient	0.004	0.048	0.058	0.073	0.054
First-stage F-statistics	0.17	43.33	93.48	91.48	50.69

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) stratified by deductible amount. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 8. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$ without Covariates

Outcome Form	Total Spending	Total Out of Pocket	Total Care Dates	Outpatient Care Dates	Inpatient Care Dates	Elective Care Dates	Preventive Care Dates
y_{it+1}	-15,085***	-925.2**	-8.954**	-3.822	-1.594***	-0.486**	-0.356*
	(5,133)	(463.9)	(3.822)	(3.640)	(0.578)	(0.203)	(0.209)
$\ln(1+y_{it+1})$	-0.712**	-0.709**					
	(0.322)	(0.309)					
$1(y_{it+1}>0)$					-0.0880**	-0.185**	-0.130*
					(0.0418)	(0.0718)	(0.0728)
Mean of y_{it+1}	11,631	1,468	16.17	15.8	0.52	0.54	1.08
SD of y_{it+1}	32,495	1,900	19.42	18.4	3.64	1.47	1.31

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) without covariates (deductible amount, number of family members observed on plan, age, sex). All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 9. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$ by Number of Family Members Observed on Plan

	Number of Family Members Observed on Plan		
2012 *Outcome* (y_{it+1})	1-2	3-4	≥ 5
Total Spending	-18,762***	-5,424	-12,603
	(6,221)	(8,241)	(10,279)
Total Out of Pocket	-844.9*	-754.6	-721.6
	(434.5)	(571.1)	(564.7)
Total Care Dates	-11.23**	-4.094	-1.523
	(4.395)	(5.164)	(6.888)
Outpatient Care Dates	-9.909**	-3.713	1.100
	(4.212)	(4.827)	(6.370)
Inpatient Care Dates	-1.782**	-0.494	-3.209**
	(0.765)	(0.885)	(1.297)
Elective Care Dates	-0.676***	0.0273	-0.163
	(0.245)	(0.371)	(0.475)
Preventive Care Dates	-0.520**	0.165	0.0568
	(0.213)	(0.364)	(0.351)
Sample Size	111,247	104,121	39,534
First-stage coefficient	0.070	0.049	0.056
First-stage F-statistics	125.68	71.33	47.00

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) stratified by number of family members observed on the plan. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 10. Donut Hole Specification of Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$

	Donut Hole Length in Each Year	
2012 *Outcome* (y_{it+1})	7 days	14 days
Total Spending	-17,300***	-22,092***
	(5,877)	(7,060)
Total Out of Pocket	-1,176***	-1,524***
	(404.2)	(471.8)
Total Care Dates	-8.973**	-14.38***
	(4.115)	(4.765)
Outpatient Care Dates	-7.386*	-12.44***
	(3.948)	(4.535)
Inpatient Care Dates	-2.051***	-2.400***
	(0.637)	(0.719)
Elective Care Dates	-0.351	-0.699***
	(0.238)	(0.268)
Preventive Care Dates	-0.297	-0.312
	(0.213)	(0.279)
Sample Size	234,965	215,995
First-stage coefficient	0.058	0.059
First-stage F-statistics	191.46	118.51

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) with donut holes of 7 and 14 days. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Table 11. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$ with Varying Bandwidths

	Bandwidth			
2012 *Outcome* (y_{it+1})	45 days	60 days	75 days	90 days
Total Spending	-8,942	-12,917**	-11,537**	-13,263***
	(7,109)	(6,360)	(5,376)	(5,005)
Total Out of Pocket	-437.5	-815.3*	-638.2	-788.4**
	(536.6)	(485.2)	(399.9)	(367.5)
Total Care Dates	-4.92	-9.22*	-6.33	-7.39**
	(5.04)	(4.76)	(3.87)	(3.50)
Outpatient Care Dates	-4.30	-8.11*	-5.32	-6.19*
	(4.72)	(4.51)	(3.66)	(3.29)
Inpatient Care Dates	-0.96	-1.50**	-1.37**	-1.56***
	(0.89)	(0.71)	(0.61)	(0.59)
Elective Care Dates	-0.17	-0.24	-0.26	-0.36*
	(0.28)	(0.23)	(0.21)	(0.19)
Preventive Care Dates	-0.04	-0.16	-0.16	-0.20
	(0.26)	(0.24)	(0.21)	(0.18)
Sample Size	125,677	169,353	213,145	254,902
First-stage coefficient	0.056	0.059	0.059	0.054
First-stage F-statistics	97.27	146.18	201.89	211.81

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) with varying bandwidth lengths. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.

Appendix

- Count of Elective Care Dates in 2012 is a count of the number of elective service dates in 2012 with elective services being defined based on elective procedures defined using Berenson-Eggers Type of Service (BETOS) codes by Clemens and Gottlieb (2014) and also used by Guo and Zhang (2019).
    - List of BETOS codes used: P2A: Major procedure, cardiovascular – CABG, P2C: Major procedure, cardiovascular – thrombo-endarterectomy, P2D: Major procedure, cardiovascular – coronary angioplasty (PTCA) P3B: Major procedure, orthopedic – hip replacement, P3C: Major procedure, orthopedic – knee replacement, P4B: Eye procedure – cataract removal/lens insertion, P5A: Ambulatory procedures – skin • P5B: Ambulatory procedures – musculoskeletal, P6A: Minor procedures – skin, P6B: Minor procedures – musculoskeletal, P8A: Endoscopy – arthroscopy, P8B: Endoscopy – upper gastrointestinal, P8C: Endoscopy – sigmoidoscopy, P8D: Endoscopy – colonoscopy, P8E: Endoscopy – cystoscopy, P8F: Endoscopy – bronchoscopy, P8G: Endoscopy – laparoscopic cholecystectomy, P8H: Endoscopy – laryngoscopy, I4A: Imaging/procedure – heart including cardiac catheter
- Count of Preventive Care Dates in 2012 is a count of the number of preventative service dates in 2012 with preventative services being defined based on the Center of Medicare and Medicaid Services' list of preventive services.
    - Preventive Service Categories include: Alcohol Misuse Screening & Counseling, Annual Wellness Visit, Bone Mass Measurements, Cardiovascular Disease Screening Tests, Cervical Cancer Screening, Colorectal Cancer Screening, Counseling to Prevent Tobacco Use, Depression Screening, Diabetes Screening, Diabetes Self-Management Training, Flu Shot & Administration, Glaucoma Screening, Hepatitis B Screening, Hepatitis B Shot & Administration, Hepatitis C Screening, HIV screening, IBT for Cardiovascular Disease, IBT for Obesity, Initial Preventive Physical Exam, Ling Cancer Screening, STI Screening & HIBC to Prevent STIs, Screening Pelvic Exams, Ultrasound AAA Screening

Appendix Table A1. Effect of Meeting Deductible in Year t on Year $t+1$ Outcomes Relative to the Effect of Meeting Deductible in Year $t-1$ without Sample Exclusions

	Group Included along with Main Sample	
2012 *Outcome* (y_{it+1})	Under 18	Deductible < 100
Total Spending	-9,888***	-15,270***
	(3,748)	(5,426)
Total Out of Pocket	-476.0*	-892.6**
	(261.5)	(399.3)
Total Care Dates	-4.74**	-7.79**
	(2.42)	(3.65)
Outpatient Care Dates	-3.79*	-6.28*
	(2.30)	(3.42)
Inpatient Care Dates	-1.21***	-1.94***
	(0.40)	(0.63)
Elective Care Dates	-0.27*	-0.36*
	(0.15)	(0.21)
Preventive Care Dates	-0.13	-0.25
	(0.12)	(0.19)
Sample Size	375,739	282,440
First-stage coefficient	0.063	0.054
First-stage F-statistics	370.35	211.81

Note: Each coefficient is estimated from a single regression and represents β_1 in Eq. (2) with varying observations included. All standard errors are clustered at the first service date of the injury. *p<0.10, **p<0.05, ***p<0.10.