I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 10917

Taking the CON out of Pennsylvania: Did Hip and Knee Replacement Patients Benefit?

Susan L. Averett
Sabrina Terrizzi
Yang Wang

JULY 2017

DISCUSSION PAPER SERIES

IZA DP No. 10917

Taking the CON out of Pennsylvania: Did Hip and Knee Replacement Patients Benefit?

Susan L. Averett
Lafayette College and IZA

Sabrina Terrizzi
Moravian College

Yang Wang
University of Wisconsin - Madison

JULY 2017

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Taking the CON out of Pennsylvania: Did Hip and Knee Replacement Patients Benefit?*

Policymakers and the general public have expressed increasing concern over rising health care costs. The Certificate-of-Need (CON) programs began at the federal level in 1974 to stem the increase in costs by limiting hospital expansion and acquisition of equipment. The federal requirement for CON programs ended in 1987; however, 37 states and DC still maintain various forms of CON programs. We examine the effect of the expiration of Pennsylvania's CON law on indicators of quality and cost of health care for patients undergoing hip and knee replacement surgery. We use the standard difference-in-differences method and the Synthetic Control method. Our preferred method indicates that the expiration had no statistically significant effect on our various measures of quality and cost.

JEL Classification: I18, I10

Keywords: certificate of need, knee and hip replacement, health care, cost, quality

Corresponding author:
Susan L. Averett
Department of Economics
Lafayette College
Easton, PA 18042
USA

E-mail: averetts@lafayette.edu

* The authors thank Scott Cunningham for generously providing Stata code for some of our analyses.

Introduction:

Health care costs and quality remain pressing issues for American policymakers and the general public. The US spends more on health care per capita (and as a percentage of GDP) than any other OECD country (OECD, 2015). Beginning in 1974, as a response to growing concerns about health care costs, many Certificate-of-Need (CON) laws were enacted across the nation as part of the federal "Health Planning Resources Development Act" of 1974.[1] A certificate of need is a legal document that is required before any acquisition, expansion, or creation of facilities are permitted. Originally, CON laws regulated the purchase of new equipment as well as the number of beds in hospitals and nursing homes. More recently, some states regulate outpatient facilities and long term care facilities. As of 2016, despite numerous changes in the past 30 years, more than half of the states (and the District of Columbia) retain some type of CON program, law, or agency.

In the post-Affordable Care Act environment, CON laws remain controversial (e.g. Weight and Elliott, 2013; Schencker, 2016). Those in favor of CON laws note that CON regulation increases access to care by making existing hospitals more profitable through decreased competition. A proliferation of competing hospitals that locate to serve well-insured, healthier patients may mean that rural, less wealthy populations lose their access to care. Further, the most profitable services (cardiac care, orthopedics and diagnostic imaging) subsidize the use of less profitable, but necessary services, such as emergency room care, mental health services, or chemical dependency provisions (Moran, 2015; Schencker, 2016). However, those opposed to

[1] See http://www.ncsl.org/research/health/con-certificate-of-need-state-laws.aspx for an up-to-date discussion and the history of state CON laws.

CON laws believe that limiting competition increases costs and decreases quality for patients (Schencker, 2016).

In this analysis, we use data from the Healthcare Cost and Utilization Project National Inpatient Survey (HCUP-NIS) for the years 1993 through 1999 to examine the effect of the expiration of Pennsylvania's CON law on a wide array of outcomes related to hip and knee replacement surgery. The CON regulations in PA were intended to regulate a variety of procedures within acute care and long-term care settings including hospitals, ambulatory centers, and nursing homes; and the goals of the CON program with respect to acute care were threefold: control costs; maintain high-quality service; and expand access to these services (Arnold and Mendelson, 1992). In 1996, PA's CON law expired as its lawmakers failed to act by a certain deadline (Moore, 1997; Longwell and Steele, 2011); that is, this policy change was not the result of an affirmative decision based on cost or quality concerns. This arguably exogenous policy change thus provides a natural experiment that allows us to identify the effect of the CON expiration in PA on quality and costs of health care.[2]

Most previous research related to CON laws has focused on the Medicare population affected by Acute Myocardial Infarction (AMI) because demand for AMI procedures is largely price inelastic, and it is one of the most profitable areas in medicine with costly expansions/duplications of its facilities (e.g. Ho, 2006; Ho and Ku-Goto, 2013).[3] However, it is unclear whether the conclusions concerning the effect of (expiration of) CON laws on outcomes related to AMI are generalizable to other areas in medicine or to other insurance types.

[2] While it is possible that permitting the law to expire was itself a deliberate act (and hence arguably not exogenous) we found no such evidence in our research. Furthermore, the CON laws in PA were reauthorized four years earlier in 1992 by General Assembly (Arnold and Mendelson, 1992).
[3] To our best knowledge, there are only two existing studies (Lorch et al., 2012 and Khanna et al., 2013) that analyzed a procedure or area of medicine other than cardiovascular-related procedures.

We make three important contributions to this literature. First, we examine the effect of the PA CON expiration for the patient population who undergo hip and knee replacement surgeries. We examine hip and knee replacement surgery because of its increasing importance to the US population and economy. Osteoarthritis is one of the ten most disabling diseases in developed countries ("Chronic Diseases and Health Promotion", n.d.). In the US, expenditures related to osteoarthritis and other non-traumatic joint disorders totaled $80.3 billion (AHRQ, 1) and affected 40 million people in 2014 (AHRQ, 2). Total knee arthroplasty is also one of the most common and costly surgical procedures performed (Cram et al., 2012). In addition, there has been a 161% increase in knee replacement surgeries among Medicare participants in the past 20 years (Lloyd, 2012). Total annual costs are approximately $5 billion and rising due to an increased demand primarily from the Medicare-eligible population (Lloyd, 2012). Hip replacement surgery has also increased in popularity in the US, and the US does more knee replacement surgeries per capita than any other OECD country (OECD, 2011). Surgeons perform approximately 280,000 hip replacement surgeries annually, at a cost of approximately $12 billion (Ostrow, 2011). Recent estimates suggest that more than one million total hip and total knee replacements are performed each year in the US, and as the population continues to age, these are expected to be the most common elective surgical procedures in the coming years (Kremers et al., 2015).

Second, we expand the patient population of interest to a wider age range, not just those over age 65. We also examine all potential insurance types including uninsured and self-pay patients, as these patient populations could be affected differently than the Medicare population.

Third, we contribute to the literature by being the first to examine the effects of changes in CON laws on various outcomes using the Synthetic Control (SC) method, in addition to the standard difference-in-differences (DD) method. Compared to the standard DD method, the SC method can help us identify a better counterfactual to the treatment group by assigning different weights to all the potential units in the control group according to their match with the treatment group. This method, using subsets of optimally chosen control units, is a generalization of the DD approach (Abadie et al., 2010).

We find that the expiration of the CON program in PA is not associated with any statistically or economically significant changes in our measures of quality and cost of health care for patients undergoing hip or knee replacement surgeries. These findings have important policy implications. Understanding the implications of regulations related to the provision of any services is necessary to craft policy measures that reduce expenditures while maintaining high standards of quality. Our analysis provides critical insight into the relative effectiveness of one such policy measure --- the (expiration of the) CON program, and helps states make decisions to retain their CON laws or let them expire.

Literature Review and Background on Hip and Knee Replacement

Beginning in 1964, state legislatures considered various forms of regulation as they attempted to stem rising health care costs, and NY became the first state to enact Certificate of Need (CON) regulation (Cauchi, 2011). In 1975, the Federal government mandated that all states institute CON programs, or lose federal health care funding (Longwell and Steele, 2011). The intention was to limit growing health care costs by regulating the number of beds in hospitals and nursing homes, thereby reducing excess capacity (Cauchi, 2011). Questioning the effectiveness in cost containment, the federal requirement for CON programs ended in 1987 (Longwell and

Steele, 2011). Currently, 37 states and the District of Columbia maintain various forms of CON programs.[4]

With the mandate and subsequent expiration of CON programs, researchers have attempted to identify the implications of these regulations on the number of procedures performed, quality of, cost of, and access to medical care (as measured by number of facilities). Early studies (e.g. Robinson et al., 2001; Ho, 2006; Popescu et al., 2006; Ross et al., 2007) used Ordinary Least Squares regression methods, which made causal inference challenging. Subsequent studies used state fixed effects to attempt to control for the potential endogeneity of CON laws (e.g. Grabowski et al. 2003 and Lorch et al., 2012). Most recently, researchers have taken advantage of the natural experiment afforded by states where their CON laws expire (e.g. Ho et al., 2009, Ho and Ku-Goto, 2013) to identify the causal effects of this regulation. Although some consensus appears to be rising, there is no general agreement of the effects of (the expiration of) these laws.

A wide variety of studies have been conducted assessing the effects of CON regulation on costs, quality, and the number of procedures. However, the evidence regarding these effects is mixed. In regards to cost, some studies have indicated that CON regulations can lower costs through mechanisms such as higher occupancy rates, reduced expenditures, and reduced acute care spending (Conover and Sloan, 1998; Devers et al., 2003; Hellinger, 2009; Yee et al., 2011; Rosko and Mutter, 2014), while others find neutral or negative associations with total per capital spending or procedural expenses (Conover and Sloan, 1998; Grabowski et al., 2003; Ross et al., 2007; Yee et al., 2011; Ho and Ku-Goto, 2013; Khanna et al., 2013).

[4] See http://mercatus.org/publication/40-years-certificate-need-laws-across-america or http://www.ncsl.org/research/health/con-certificate-of-need-state-laws.aspx for up-to-date lists of state CON laws. Also see http://mercatus.org/sites/default/files/Con-Map-Present.pdf for a map of those states with CON laws and http://www.ncsl.org/research/health/con-certificate-of-need-state-laws.aspx for a history of the laws.

Similarly, evidence on the effects of CON regulation on procedural rates is mixed, and varies by procedure. Popescu et al. (2006) and Ho et al. (2009) find decreases in procedural rates, while others find evidence of increases in volume and procedural availability (Ho, 2006; Popescu et al., 2006; Ross et al., 2007; Khanna et al., 2013). Surgeries may also be redistributed to higher-quality surgeons following changes in CON legislation (Cutler et al., 2010).

The existing literature finds little to no association between CON regulation and quality of health care. While Ho (2006) finds that the expiration of CON regulation is associated with very small reductions in inpatient mortality, most of the current analyses find no measurable difference in mortality rates between states with and without CON regulations (Robinson et al., 2001; Popescu et al., 2006; Ho, 2009; Lorch et al., 2012). There is some evidence that patients in states that eliminated CON regulations experience lower CABG mortality rates; however, this differential dissipates over time (Ho et al., 2009).

Despite the quantity of studies assessing the effects of CON regulation on costs, quality, the number of procedures performed, and access to care, there is no consensus on the effects of this regulation across a variety of outcomes. However, it is quite clear that effects vary across procedures (Ross et al., 2007; Lorch et al., 2012; Ho and Ku-Goto, 2013; Khanna et al., 2013). In this study, we explore procedures beyond those related to cardiovascular for the Medicare population. We examine a wider age range of patients with various payment methods, who undergo hip and knee replacement surgery, to assess the effects of CON expiration on important indicators of quality and costs of health care. We are the first researchers to provide empirical evidence on the effects of the expiration of CON laws on costs and quality of health care for patients undergoing these important procedures.

Methods

The first method we use is a standard DD estimator as follows:

(1) $$y_{ihst} = \alpha + Post_t\gamma_1 + CON_s\gamma_2 + \left(Post_t * CON_s\right)\gamma_3 + Z_{hst}\gamma_4 + X_{ihst}\beta + \delta_s + \theta_t + \varepsilon_{ihst}$$

where y_{ihts} indicates the outcome variables for individual *i* at hospital *h* in state *s* in year *t*. $Post_t$ is a binary variable indicating whether the CON law has expired; thus, it takes the value of one in the years after the CON expired in PA (1996). CON_s is a binary variable equal to one if the individual was observed in PA and zero if they were observed in a control state. Z_{hst} and X_{ihst} describe hospital and individual characteristics, respectively. Finally, δ_s is a time-invariant state fixed effect and θ_t is a year fixed effect. Because the expiration of the CON law only affects those patients in PA, γ_3 is the main parameter of interest and captures the effect of the CON expiration on patient-level outcomes in this framework.

The second method we use is the SC method. This method is particularly useful with single aggregate treatment units (Abadie et al., 2010), and is a generalization of the DD approach. Abadie et al. (2010, 2015) provide technical details of this approach; therefore, we focus on intuitively describing this method and its application to our case. In a straightforward DD approach, all of the control states get an equal weight and they may not represent the most appropriate comparison group for our treated sample. Contrastingly, using the SC approach we generate a control group using the weighted average of all potential control states. In this method, characteristics and outcome variables are matched between the treatment and control groups in the time period before the policy change. States with a better match with the treatment group are assigned a higher weight in the synthetic control group, while others are assigned a lower or even zero weight; all weights sum to one. This results in a better approximation of the counterfactual to the treatment group as compared to the standard DD method. It is therefore important to note that we do not necessarily expect the results from the DD and SC methods to be the same, as the control groups are identified using a preferred matching technique in the SC method. In the post-treatment period, the SC estimator measures the causal effect of the policy change as:

$$(2)\quad Y_{1T} - \sum_{s=2}^{s+1} w_s * Y_{st}$$

where Y_{st} is the outcome for unit *s* of *s*+1 state units (*s* states in the control group and one treatment state) at time *t*, and w_s is a vector of optimally chosen weights.

We can make inferences for the SC method using placebo or falsification tests. Specifically, we have more confidence in the estimated effect of the CON expiration on the outcome variables, if this effect remains large compared to what we find using each of the potential control states as a 'falsified' treatment state. Alternatively stated, our results are only convincing when the effect is large relative to the distribution of false effects generated from falsely assigning each of the potential control states as a 'treatment' state. The relevant component of this analysis is the ratio of the mean square prediction errors (MSPEs). The MSPE ratio is lower (higher) when the matching works well (not so well) in the post-treatment period compared to the MSPE in the pre-intervention period. We compare the MSPE ratio for PA to the MSPE ratios calculated for all the potential control states when each of the potential control states is used in a placebo/falsification test. We calculate the p-value by dividing the number of potential control states with a MSPE at least as high as that for PA by the total number of potential control states plus one (i.e., the number of potential control states plus the number of treatment states). This p-value indicates the statistical significance of the effect of the CON expiration on each outcome assessed. For example, if there are 12 potential control states and PA ranks 10th in the MSPE ratio among all 13 states then the p-value would be 10/13 = 0.7692.

Data

To conduct the analyses described above, we use data from the National Inpatient Survey (NIS), which is part of a family of databases developed for the Healthcare Cost and Utilization Project (HCUP). The NIS is particularly well-suited for our research as it is the largest all-payer inpatient health care database in the United States, and is often used to obtain national estimates of hospital inpatient stays. The NIS contains all discharge data from more than 1,000 short-term and non-Federal hospitals each year, which approximates a 20 percent stratified sample of US community hospitals. The NIS contains charge information on all patients, including individuals covered by Medicare, Medicaid, or private insurance, as well as those who are uninsured. It also contains information on the hospitals including their size, ownership, and the income level of the patient's zip code. Because hip and knee replacements were in-patient procedures during the time period of our study, our use of in-patient data for this analysis is appropriate. Further, as recently as 2014, CMS did not fund hip and knee replacement surgeries at outpatient facilities (Graham, 2016 and Meyer, 2016), providing additional support for our use of inpatient data for this analysis.

As explained earlier, we exploit the expiration of the CON laws in Pennsylvania in 1996 to identify the effects of CON laws on patient-level outcomes for those patients undergoing knee or hip replacement surgery. To create the analysis sample, we start with all patients in 1993, 1994, 1995, 1997, 1998 and 1999, which provides us with a before and after period of three years.

For those states without a CON law, most repealed their CON laws in the 1970s or 1980s, a period not covered in the HCUP NIS data that we use. The only two states that repealed their CON laws (or allowed them to expire) in the 1990s are Pennsylvania and North Dakota, the latter is not in our sample. Pennsylvania therefore is our treatment state. Our control states are those that had a CON law that regulated acute care services and did not change their CON laws/regulations during the period of our study. Also, these control states must have participated in the NIS in each of the years of our analysis because a balanced panel is required for the SC method. These control states are Connecticut, Florida, Iowa, Illinois, Massachusetts, Maryland, New Jersey, New York, Oregon, South Carolina and Washington. We limit our sample to people age 50 or older because they are most likely to obtain a total hip or knee replacement (Kremers et al., 2015).[5] This age range also allows us to examine a population outside of Medicare recipients, which has been the main population of interest in the literature.

We examine four outcome variables. Three of our outcome variables are indicators of quality: Hospital Acquired Condition (HAC), a binary variable indicating whether the patient experienced any of the complications from their surgery as identified by CMS[6]; mortality, a binary indicator for whether the patient died in the hospital; and Length of Stay (LOS) in days[7]. The fourth outcome variable, (the log of) the total charge for the hospitalization, is a measure of cost.[8] Each outcome has a slightly different sample size due to missing information for some patients.

The four outcome variables are summarized in Table 1. Both HAC and LOS have a downward trend across treatment and control states, which is consistent with the national trend

---

[5] We focus our analysis on those patients who had a hip or knee replacement as coded according to the HCUP clinical classification software as "152" or "153".
[6] CMS identifies the following complications from knee or hip replacement as HACs: http://www.hcup-us.ahrq.gov/datainnovations/clinicaldata/ExampleofUsingPOA-CMSHACsusingall-payerdata.jsp (last accessed 02/17/2017).
[7] LOS ranged from 0 to 3029 days but only 1 percent had an LOS in excess of 64 days so we trimmed our sample at that number. This yields a mean LOS of 7.75 days which is consistent with that reported by other researchers using data over the same time frame (e.g. Cram et al., 2012).
[8] Because we use the logarithm of the total charge and we control for year fixed effects in our model, we do not index the total charges to inflation.

for these procedures (Cram et al., 2012). The log of total charges has an upward and similar trend across both treatment and control states. Finally, the probability of dying in the hospital is decreasing in the control states, but remained steady in PA. These unadjusted means in Table 1 can also be used to calculate non-parametric DD estimates, which preview some of our parametric DD estimation results below. For example, though LOS declined over the same period for both treatment and control groups, the CON expiration was associated with an average of 0.7973 days increase in LOS for the patients in the treatment state ((4.8965 – 6.7454) – (5.0291 – 7.7476) = 0.8696) compared to the control states. This simple, unadjusted difference-in-differences calculation, though interesting and informative, does not give us an indication of statistical significance.

To account for the effects of other explanatory variables on the outcomes of interest, we also include two sets of covariates (Z_{hst} and X_{ihst} in Equation (1)) that describe the hospitals and the individuals, respectively. Table 2 presents the means of the control variables in the same format as Table 1. Many of the control variables are self-explanatory, but a few merit a more detailed explanation.[9] The Charlson index is an index of comorbidities; we calculate this using the diagnostic codes and software provided by HCUP. Higher values indicate more comorbid conditions. In the NIS, income is reported categorically as the quartile classification of the estimated median household income of residents in the patient's zip code (based on 1999 demographics)[10]. We follow the procedures in Hout (2004) to create a log of real income for each patient. If income is not reported, we set income equal to the mean income across all years

[9] We are unable to control for race or hospital ownership in our analysis because not all states collected this information during our sample period.
[10] See https://www.hcup-us.ahrq.gov/db/vars/zipinc_qrtl/nisnote.jsp (last accessed 05/26/2017) for a description of the income variable in the NIS.

for that zip code and control for missing income in our models. We also control for type of payment. Because of the age of our sample, Medicare is the dominant payment method, but we also find a sizeable patient population using private insurance. Medicaid, self-pay, and other payers together account for less than 7% of the sample. Our benchmark category is the uninsured. Payment types are mutually exclusive in HCUP. For hospitals, consistent with the literature, we control for their sizes and their teaching status.

Examining the characteristics of the patients and the hospitals reported in Table 2, we observe that patients from the treatment and the control groups have very similar characteristics whether it is before or after the CON expiration. Specifically, they share a similar gender ratio, average age, real income, and have very similar payment methods for their hip and knee surgery. The only visible difference in patients' characteristics comes from the Charlson comorbidity index, which was relatively lower for patients in the treatment group as compared to those in the control group before the policy change, but this index for both groups converged to approximately 0.5 after the policy change.

When we consider the hospital characteristics, we find that most hospitals were of medium size in the treatment state, but of large size in the control states, both before and after the policy change. Hospitals in the treatment state are more likely to be teaching hospitals.

Results

Difference in Differences Method

Table 3 presents an estimation of Equation (1) without any covariates; this provides a baseline for comparison. As expected, the first row is identical to the DD estimates calculated from the means shown in Table 1. This baseline regression shows that the CON expiration statistically significantly increased patients' probabilities of having a hospital acquired condition, dying in the hospital, and their length of stay at the hospital, but it did not have any significant effect on their total charges.

We next conduct our DD estimations controlling for all covariates, and these results are presented in Table 4. With the inclusion of our covariates we find that the probability of obtaining a hospital acquired condition is no longer statistically significant and the probability of dying remains significant only at the 10 percent level. All standard errors are clustered by state.

The key assumption for any DD strategy is that the outcomes in the treatment and the control group would follow the same time trend in the absence of the treatment. Even though there is no test for this assumption because we cannot observe the counterfactual for the treated state, we would be concerned if PA already displayed significantly different trends in quality or cost measures from the control states *prior* to the expiration of the CON law. In that instance, we would not be able to conclusively assign the observed changes in quality or cost to the expiration of the CON law itself.

To check this pre-trend assumption, we estimate the DD model with interactions between our treatment group and each of the years before the policy change, the full set of covariates previously described, and year and state fixed effects. If those interaction terms between the treatment state and the pre-policy years are insignificant, then pre-treatment trends are unlikely to be driving our results and would not cause concern. However, if the difference in pre-policy trends indeed exists, then we would be less confident in our DD estimates.

The results shown in Table 5 provide clear evidence of the existence of different pre-treatment trends in our outcome variables between the treatment and control groups. For all four outcome variables, at least one of the interaction terms is statistically significant, and those statistically significant interaction terms tend to be of greater magnitude than the DD estimates of interest. While controlling for these trends, we find the CON expiration in PA had a statistically significant effect on mortality and length of stay: the expiration reduced mortality rates by 0.15 percentage points (.0015/.0092=16.3%) and increased length of stay by 0.3065 days (.3065/6.7454=4.54%). Notice that the result on mortality has changed sign, and the result on length of stay is much smaller in magnitude, as compared to the DD estimations without interaction terms.

Because of the evidence supporting differential pre-treatment trends between our treatment and control states in this standard DD method, we report the results using the SC method, which constructs the synthetic control group by finding the best match in the outcome and control variables between the treatment and the control groups before the policy change.

Synthetic Control Method

For each outcome variable, a weighted average of the potential control states becomes the synthetic control group, and the weights are listed in Table 6. These four outcome variables require different weights for each potential control state. For example, Oregon has the largest weight in the synthetic control group for HAC and Mortality, but Illinois and Maryland have the largest share for LOS and Charge, respectively. This difference is as expected, and is an improvement over the standard DD method, which cannot account for this variation in the combinatorial pattern of potential control states.

Table 7 clearly shows that PA, our treatment state, is very similar to the synthetic control group in the outcome variables and the covariates before the policy change. This close approximation is the main benefit of the SC method, which adjusts the weights of potential control states to construct an optimal control group. This provides confidence that our results using the SC method yield valid conclusions regarding the effects of CON expiration on our outcome variables. A comparison between this table and Table 2, which compares the covariates between PA and all states in the control group used by the standard DD method, further confirms that the synthetic control group provides a better match across all covariates.

Figures 1 through 4 show the trends in the outcome variables for PA and the synthetic control groups for our sample period. The figures indicate that the model fits fairly well in the pre-treatment period for all four outcome variables, and does not appear to diverge significantly in the post-treatment period for HAC, Mortality, and LOS. There appears to be a divergence in the post-treatment period for total charge, but the graph does not tell us whether the divergence is statistically significant.

Table 8 shows the point estimates of the effects of the CON expiration on our outcome variables and their statistical significance using the SC method. The point estimates are the differences in outcome variables between PA and the synthetic control states averaged over the post-treatment period. The corresponding p-values, shown in the second column of the same table, are determined using the placebo/falsification tests described in the Methodology section.[11]

Clearly, as shown in Table 8, we cannot reject the null hypothesis that the CON expiration has no effect on HAC, Mortality, LOS, or Charge. That is, the SC method shows that the CON expiration in PA had no statistically significant effect on important measures of quality and cost of health care for patients undergoing hip and knee replacement surgeries in PA relative to those in the synthetic control group.

[11] Histograms showing the ranking of pre/post MSPE are available upon request.

Conclusion

In this paper, we examine the effect of the expiration of Pennsylvania's CON law on indicators of quality and cost of health care. Our paper is the first to focus on knee and hip replacement surgeries — two procedures that have expanded greatly, have contributed increasingly to growing health care costs, and have not been well studied in the literature. We are also the first in this literature to use the SC method, in addition to the standard DD method, to estimate the effects of CON (de)regulation.

We find that the expiration of the CON law had no statistically significant effect on HACs, LOSs, mortality, or total charges for patients undergoing hip and knee replacement surgeries. As we noted in the Literature Review section, empirical evidence on the effects of CON (de)regulation on cost and quality of health care has been mixed. Our study, by focusing on patients who underwent hip and knee replacement surgeries and encompassing a larger age range than most previous studies, provides important new evidence on the effects of CON (de)regulation and on the generalizability of conclusions previously drawn across procedures and patient populations. Our findings provide additional information for consideration by policymakers in states which still have, and might consider repealing CON legislation. We find no adverse or positive effects on this specific patient population as a result of this expiration. We are the first researchers to provide empirical evidence on the effects of (the expiration of) CON laws on costs and quality of health care for this important patient population.

Although hip and knee replacements were in-patient procedures during the time period of our study, they are increasingly performed at ambulatory surgical centers (ASCs), and specialty orthopedic hospitals are the largest type of specialty hospital (Cram, 2007). Proliferation of these hospitals is controversial because CON laws in some states regulate the presence of ASCs and there is concern that ASCs will selectively treat more profitable, less complicated, and well-insured patients (Stratmann and Koopman, 2016). However, the existence of CON laws could limit competition further, thereby exacerbating a reported supply-side shortage of arthroplasty surgeons (Fehrig et al., 2010). An important area for future research would be to consider the effect of CON laws at outcomes in these centers.

References:

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, *105*(490), 493-505.

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. American Journal of Political Science, 59(2), 495-510.

Agency for Healthcare Research and Quality (AHRQ 1). Medical Expenditures Panel Survey Custom Table: Total Expenses and Percent Distribution for Selected Conditions by Type of Service, United States, 2014. https://meps.ahrq.gov/data_stats/quick_tables_results.jsp?component=1&subcomponent=0&tableSeries=2&year=-1&SearchMethod=1&Action=Search (Last Accessed 02/17/2017).

Agency for Healthcare Research and Quality (AHRQ 2). Medical Expenditures Panel Survey Custom Table: Number of People with Care for Selected Conditions by Type of Service: United States, 2014. https://meps.ahrq.gov/data_stats/tables_compendia_hh_interactive.jsp?_SERVICE=MEPSSocket0&_PROGRAM=MEPSPGM.TC.SAS&File=HCFY2014&Table=HCFY2014_CNDXP_A&_Debug= (Last Accessed March 2,, 2017).

Arnold, J. & Mendelson D. (1992). Evaluation of the Pennsylvania Certificate of Need Program. LEWIN-ICF.

Cauchi, Richard. (2011) "Certificate of Need: State Health Laws and Programs." NLCS.org. http://www.ncsl.org/research/health/con-certificate-of-need-state-laws.aspx#Program (Last accessed 02/17/2017).

"Chronic Diseases and Health Promotion", n.d. World Health Organization. http://www.who.int/chp/topics/rheumatic/en/

Conover, Christopher J., and Frank A. Sloan. "Does removing Certificate-of-Need regulations lead to a surge in health care spending?." *Journal of Health Politics, Policy and Law* 23, no. 3 (1998): 455-481.

Cram, P., Lu, X., Kates, S. L., Singh, J. A., Li, Y., & Wolf, B. R. (2012). Total knee arthroplasty volume, utilization, and outcomes among Medicare beneficiaries, 1991-2010. *JAMA*, *308*(12), 1227-1236.

Cram, Peter, Mary S. Vaughan-Sarrazin, Brian Wolf, Jeffrey N. Katz, and Gary E. Rosenthal. "A comparison of total hip and knee replacement in specialty and general hospitals." J Bone Joint Surg Am 89, no. 8 (2007): 1675-1684.

Cutler, David M., Robert S. Huckman, and Jonathan T. Kolstad. Input constraints and the efficiency of entry: lessons from cardiac surgery. *American Economic Journal: Economic Policy* 2, no. 1 (2010): 51-76.

Devers, Kelly J., Linda R. Brewster, and Lawrence P. Casalino. "Changes in hospital competitive strategy: a new medical arms race?" *Health services research* 38, no. 1p2 (2003): 447-469.

Fehring, T.K., Odum, S.M., Troyer, J.L., Iorio, R., Kurtz, S.M. and Lau, E.C., (2010). Joint replacement access in 2016: a supply side crisis. The Journal of arthroplasty, 25(8), pp.1175-1181.

Grabowski, David C., Robert L. Ohsfeldt, and Michael A. Morrisey. "The effects of CON repeal on Medicaid nursing home and long-term care expenditures." (2003): *Inquiry,* 40(2), 146-57.

Graham, M. (2016) "Are you prepared for the shift to outpatient total knee replacement?" https://www.sg2.com/health-care-intelligence-blog/2016/10/prepared-shift-outpatient-total-knee-replacement/ (Last accessed 05/30/2017).

Hellinger, Fred J. "The effect of certificate-of-need laws on hospital beds and healthcare expenditures: an empirical analysis." *The American journal of managed care* 15, no. 10 (2009): 737-744.

Ho, Vivian. "Does certificate of need affect cardiac outcomes and costs?" *International Journal of Health Care Finance and Economics* 6, no. 4 (2006): 300-324.

Ho, V., Ku□Goto, M. H., & Jollis, J. G. (2009). Certificate of need (CON) for cardiac care: controversy over the contributions of CON. *Health services research*, *44*(2p1), 483-500.

Ho, Vivian, and Meei-Hsiang Ku-Goto. "State deregulation and Medicare costs for acute cardiac care." *Medical Care Research and Review* 70, no. 2 (2013): 185-205.

Hout, M. (2004). *Getting the most out of the GSS income measures*. National Opinion Research Center.

Husted, H., Hansen, H. C., Holm, G., Bach-Dal, C., Rud, K., Andersen, K. L., & Kehlet, H. (2010). What determines length of stay after total hip and knee arthroplasty? A nationwide study in Denmark. *Archives of orthopaedic and trauma surgery*, *130*(2), 263-268.

Khanna, Abhinav, Jim C. Hu, Xiangmei Gu, Paul L. Nguyen, Stuart Lipsitz, and Ganesh S. Palapattu. "Certificate of need programs, intensity modulated radiation therapy use and the cost of prostate cancer care." *The Journal of urology* 189, no. 1 (2013): 75-79.

Kremers, H. M., Larson, D. R., Crowson, C. S., Kremers, W. K., Washington, R. E., Steiner, C. A., ... & Berry, D. J. (2015). Prevalence of total hip and knee replacement in the United States. *J Bone Joint Surg Am*, *97*(17), 1386-1397.

Lloyd, Janice. (2012) "Knee replacements on the increase among older adults." Usatoday.com. http://usatoday30.usatoday.com/news/nation/story/2012/09/25/knee-replacements-on-the-increase-among-older-adults/57841616/1. (Last Accessed 02/17/2017).

Longwell, Carol Brayshaw, and James T. Steele Jr. "Rise and Fall of Certificate of Need in Pennsylvania: An Experiment in Health Care Planning and the Role of the Commonwealth Court, The." *Widener LJ* 21 (2011): 185.

Lorch, S. A., P. Maheshwari, and O. Even-Shoshan. "The impact of certificate of need programs on neonatal intensive care units." *Journal of Perinatology* 32, no. 1 (2012): 39-44.

Meyer, H. (2016) "Replacing Joints Faster, Cheaper, and Better?" http://www.modernhealthcare.com/article/20160604/MAGAZINE/306049986 (Last access 05/30/2017).

Moore, J. D., Jr. (1997, August 11). Focus report: CON survival struggle: Certificate of Need: Gone in many states but not dead yet. Modern Healthcare, 27(32), 32-33, 36.

Moran, Patrick. "Should Minnesota Reinstate a Certificate of Need Program for Health Care Capital Expenditures?." (2015).

OECD. "Health at a Glance 2015: OECD Indicators". http://www.oecd.org/unitedstates/Health-at-a-Glance-2015-Key-Findings-UNITED-STATES.pdf (Last accessed June 6, 2017).

OECD. "Why is health spending in the United States so high?". 2011. http://www.oecd.org/unitedstates/49084355.pdf (Last accessed 02/17/2017).

Ostrow, Nicole. (2011) "Hip-Replacement Patients' Readmissions Rise with Shorter Stays, Study Says." Bloomberg.com. http://www.bloomberg.com/news/2011-04-19/hip-replacements-spur-quicker-hospital-discharges-while-more-return-trips.html. (Last Accessed June 10, 2014).

Popescu, Ioana, Mary S. Vaughan-Sarrazin, and Gary E. Rosenthal. "Certificate of need regulations and use of coronary revascularization after acute myocardial infarction." *Jama* 295, no. 18 (2006): 2141-2147.

Robinson, Jamie L., David B. Nash, Elizabeth Moxey, and John P. O'Connor. "Certificate of need and the quality of cardiac surgery." *American Journal of Medical Quality* 16, no. 5 (2001): 155-160.

Rosko, Michael D., and Ryan L. Mutter. "The Association of Hospital Cost-Inefficiency With Certificate-of-Need Regulation." *Medical Care Research and Review* (2014): 1077558713519167.

Ross, Joseph S., Vivian Ho, Yongfei Wang, Stephen S. Cha, Andrew J. Epstein, Frederick A. Masoudi, Brahmajee K. Nallamothu, and Harlan M. Krumholz. "Certificate of need regulation and cardiac catheterization appropriateness after acute myocardial infarction." *Circulation* 115, no. 8 (2007): 1012-1019.

Schencker, Lisa, 2016. State certificate-of-need laws weather persistent attacks. Modern healthcare, 46(4), p.12.

Stratmann, Thomas and Christopher Koopman. (2016). "The Impact of Certificate-of-Need Laws on Community Hospitals and Ambulatory Surgery Centers". Available at:

http://mercatus.org/sites/default/files/The-Impact-of-Certificate.pdf. Last accessed 02/17/2017.

Weight, C.J. and Elliott, S.P., 2013. “The Impotent Certificate of Need.” The Journal of urology, 189(1), pp.12-13.

WHO, 2016. http://www.who.int/chp/topics/rheumatic/en/ Accessed 6/6/2017.

Yee, Tracy, Lucy B. Stark, Amelia M. Bond, and Emily Carrier. *Health Care Certificate-of-need Laws: Policy Or Politics?* National Institute for Health Care Reform, 2011.

Figure 1: Matching of PA and Synthetic PA for HAC

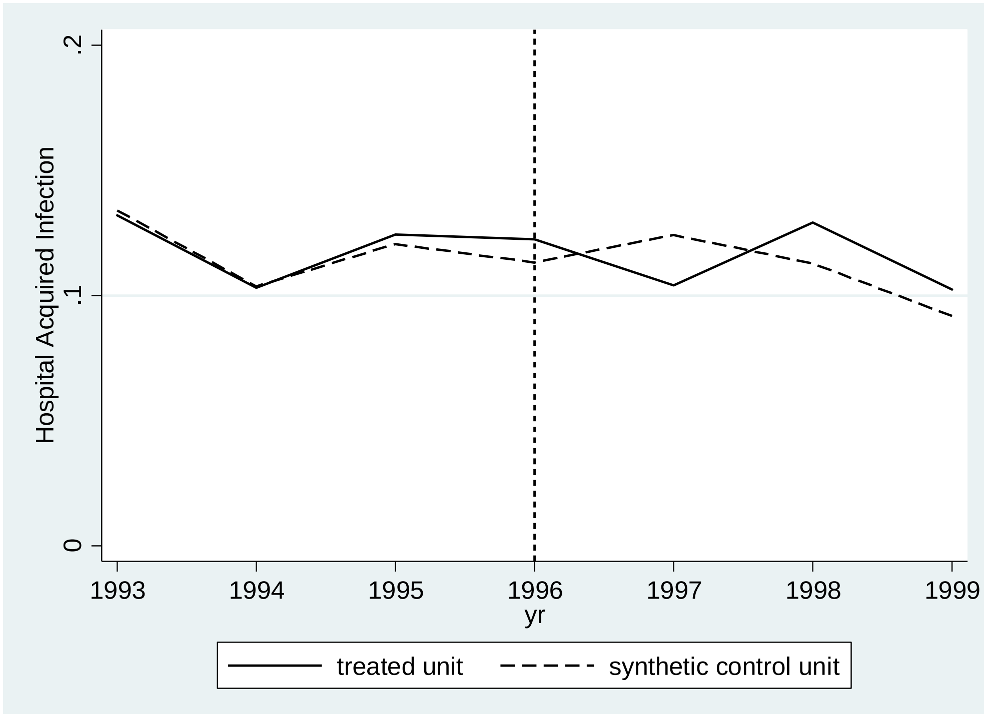

Figure 2: Matching of PA and Synthetic PA for LOS

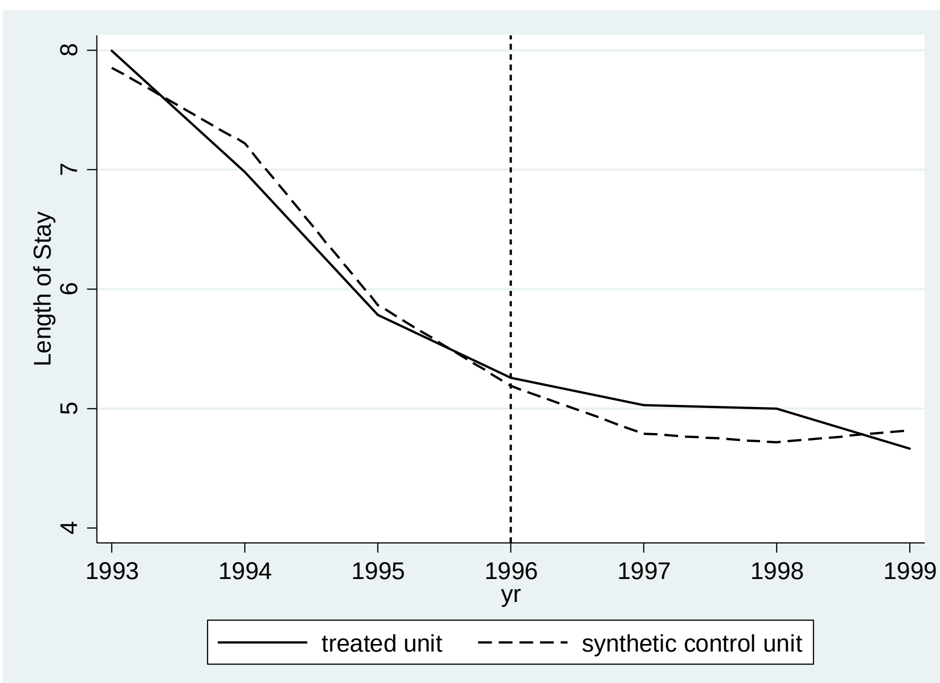

Figure 3: Matching of PA and Synthetic PA for Mortality

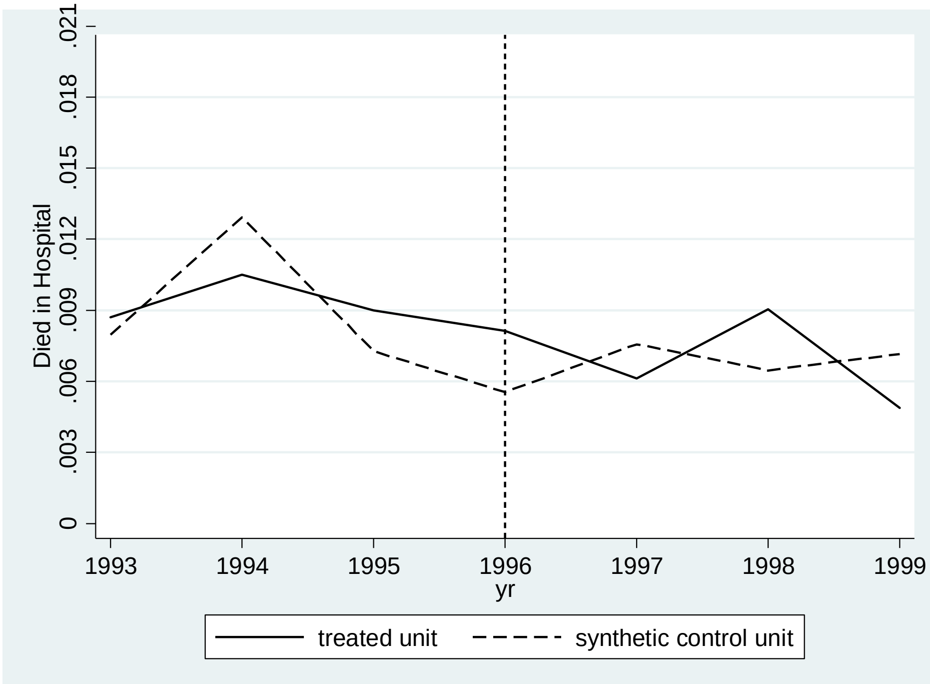

Figure 4: Matching of PA and Synthetic PA for Charge

Table 1: Means of Outcome Variables by Treatment Status, Traditional DD

Variable	Treated, Before	Treated, After	Control, Before	Control, After
Hospital acquired condition	.1194	.1106	.1513	.1247
	(.3243)	(.3137)	(.3583)	(.3304)
Died in hospital	.0092	.0065	.0125	.0072
	(.0957)	(.0806)	(.1112)	(.0845)
Length of Stay (days)	6.7454	4.8965	7.7476	5.0291
	(4.3362)	(2.9776)	(5.3857)	(3.2706)
Log total charges	9.8227	9.8384	9.8711	9.8808
	(.7353)	(.451)	(.4403)	(.4377)
Total Charges ($)	22148.69	20977.62	21518.49	21529.67
	(13581.01)	(13079.66)	(12946.34)	(11502.05)
Observations	36441	21439	306337	159397

Standard deviations in parentheses. Pennsylvania is the treatment state, other states in HCUP NIS are control states. After refers to 1997, 1998 and 1999.

Table 2: Means of Control Variables by Treatment Status

Variable	Treated, Before	Treated, After	Control, Before	Control, After
Charlson Index	.4518	.5409	.5333	.5195
	(.8563)	(.9048)	(.9737)	(.9125)
Male	.3552	.5376	.352	.5419
	(.4786)	(.4986)	(.4776)	(.4982)
Age years	71.4369	71.342	72.3609	71.958
	(8.8118)	(9.3465)	(8.9968)	(9.3958)
Small hospital	.1696	.1976	.1024	.1444
	(.3753)	(.3982)	(.3032)	(.3515)
Medium hospital	.4412	.4263	.2912	.2691
	(.4965)	(.4945)	(.4543)	(.4435)
Large hospital	.3892	.3761	.6064	.5865
	(.4876)	(.4844)	(.4885)	(.4925)
Log of real income	9.7675	9.8084	9.776	9.8507
	(.5173)	(.389)	(.4948)	(.3764)
Income missing	.0254	.0271	.0493	.0469
	(.1574)	(.1625)	(.2165)	(.2114)
Teaching hospital	.5179	.5263	.305	.4001
	(.4997)	(.4993)	(.4604)	(.4899)
Medicare	.7265	.6503	.774	.7321
	(.4457)	(.4769)	(.4183)	(.4429)
Medicaid	.0154	.0123	.0145	.0154
	(.1233)	(.1103)	(.1197)	(.1232)
Private insurance	.2081	.2889	.1795	.2232
	(.4059)	(.4532)	(.3838)	(.4164)
Self pay	.0047	.0035	.0098	.0076
	(.0685)	(.0587)	(.0986)	(.0868)
Other payer	.0448	.0444	.0221	.0217
	(.2068)	(.2059)	(.1471)	(.1457)
Observations	36441	21439	306337	159397

Standard deviations in parentheses

Table 3: Unadjusted Difference-in-Differences Estimates of Con Repeal

VARIABLES	Hospital Acquired condition	Died	Length of Stay	Log of total charges
PA x Post 1996	0.0178***	0.0026***	0.8697**	0.0060
	(0.0040)	(0.0008)	(0.3061)	(0.0137)
PA	-0.0319**	-0.0033**	-1.0023*	-0.0483
	(0.0121)	(0.0012)	(0.4708)	(0.0730)
post 1996	-0.0266***	-0.0053***	-2.7186***	0.0097
	(0.0040)	(0.0008)	(0.3061)	(0.0137)
Constant	0.1513***	0.0125***	7.7476***	9.8711***
	(0.0121)	(0.0012)	(0.4708)	(0.0730)
Observations	523,226	521,603	522,689	522,207
R-squared	0.0018	0.0006	0.0691	0.0011

Standard errors clustered by state in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Difference-in-Differences Estimates of Con Repeal

VARIABLES	Hospital Acquired condition	Died	Length of Stay	Log of total charges
PA x Post 1996	0.0021	0.0010*	0.7380**	0.0134
	(0.0041)	(0.0005)	(0.2961)	(0.0131)
PA	-0.0068**	-0.0002	-1.7607***	-0.0386**
	(0.0027)	(0.0004)	(0.1090)	(0.0175)
post 1996	-0.0210***	-0.0043***	-3.7969***	0.0393
	(0.0054)	(0.0010)	(0.3639)	(0.0240)
Charlson Index	0.0472***	0.0130***	0.8942***	0.0491***
	(0.0030)	(0.0016)	(0.1132)	(0.0054)
Male	-0.0352***	0.0027***	-0.1090*	0.0193***
	(0.0041)	(0.0005)	(0.0536)	(0.0021)
Age years	0.0130***	0.0009***	0.0670***	-0.0017*
	(0.0008)	(0.0001)	(0.0113)	(0.0008)
Small hospital	0.0295**	0.0002	-0.1776	-0.0121
	(0.0100)	(0.0003)	(0.1989)	(0.0347)
Medium hospital	0.0197**	0.0006	-0.0773	0.0318
	(0.0078)	(0.0004)	(0.1938)	(0.0444)
Log of real income	-0.0025	-0.0012*	-0.2455***	0.0030
	(0.0048)	(0.0006)	(0.0569)	(0.0168)
Income missing	-0.0041	0.0016	0.0811	-0.0346*
	(0.0039)	(0.0011)	(0.0957)	(0.0172)
Teaching hospital	-0.0458***	-0.0006	0.1986	0.1292**
	(0.0053)	(0.0005)	(0.2221)	(0.0425)
Medicare	-0.0875**	0.0097**	0.9728**	0.2660**
	(0.0345)	(0.0043)	(0.4006)	(0.0874)
Medicaid	0.0359	0.0158***	2.8655***	0.3445***
	(0.0331)	(0.0046)	(0.5154)	(0.0850)
Private insurance	-0.0168	0.0153***	1.0758**	0.2699**
	(0.0344)	(0.0042)	(0.3556)	(0.0895)
Self pay	0.0153	0.0130**	1.4241**	0.2582**
	(0.0463)	(0.0057)	(0.5723)	(0.0928)
Other payer	-0.0113	0.0134***	1.0839**	0.2680**
	(0.0290)	(0.0039)	(0.4116)	(0.0932)
Constant	-0.6965***	-0.0617***	5.7556***	9.5648***
	(0.0784)	(0.0034)	(1.0733)	(0.2267)
Observations	522,148	520,525	521,612	521,129
R-squared	0.1335	0.0240	0.2104	0.1630

Standard errors clustered by state in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Benchmark categories are individuals who are females admitted to a large non-teaching hospital whose primary payer was unknown. Models include state and year fixed-effects.

Table 5: Difference-in-Differences Estimates of Con Repeal controlling for pre-trends

VARIABLES	Hospital Acquired condition	Died	Length of Stay	Log of total charges
PA x Post 1996	-0.0050	-0.0015***	0.3065**	-0.0134
	(0.0033)	(0.0004)	(0.1332)	(0.0101)
PA	0.0003	0.0024***	-1.3223***	-0.0110
	(0.0034)	(0.0004)	(0.0820)	(0.0224)
Post 1996	-0.0210***	-0.0041***	-3.7762***	0.0462**
	(0.0055)	(0.0010)	(0.3623)	(0.0199)
Charlson Index	0.0472***	0.0130***	0.8925***	0.0494***
	(0.0030)	(0.0016)	(0.1128)	(0.0054)
Male	-0.0352***	0.0027***	-0.1086*	0.0192***
	(0.0041)	(0.0005)	(0.0535)	(0.0021)
Age years	0.0130***	0.0009***	0.0670***	-0.0017*
	(0.0008)	(0.0001)	(0.0113)	(0.0008)
Small hospital	0.0295**	0.0002	-0.1804	-0.0114
	(0.0100)	(0.0003)	(0.1978)	(0.0350)
Medium hospital	0.0198**	0.0007	-0.0677	0.0309
	(0.0078)	(0.0004)	(0.1943)	(0.0440)
Log of real income	-0.0025	-0.0011*	-0.2430***	0.0034
	(0.0048)	(0.0006)	(0.0570)	(0.0170)
Income missing	-0.0041	0.0016	0.0818	-0.0342*
	(0.0039)	(0.0011)	(0.0961)	(0.0172)
Teaching hospital	-0.0458***	-0.0005	0.2108	0.1291**
	(0.0053)	(0.0005)	(0.2208)	(0.0427)
Medicare	-0.0878**	0.0093**	0.9220*	0.2511***
	(0.0343)	(0.0042)	(0.4253)	(0.0718)
Medicaid	0.0355	0.0154***	2.8048***	0.3282***
	(0.0329)	(0.0045)	(0.5429)	(0.0686)
Private insurance	-0.0171	0.0150***	1.0246**	0.2548***
	(0.0341)	(0.0041)	(0.3803)	(0.0738)
Self pay	0.0150	0.0126**	1.3710**	0.2427***
	(0.0460)	(0.0056)	(0.5894)	(0.0779)
Other payer	-0.0116	0.0131***	1.0363**	0.2514***
	(0.0288)	(0.0038)	(0.4361)	(0.0770)
PA x 1993	-0.0074*	-0.0008	-0.1969	0.0463***
	(0.0037)	(0.0008)	(0.2257)	(0.0123)
PA x 1994	-0.0112**	-0.0067***	-0.9616***	0.0126
	(0.0036)	(0.0010)	(0.2898)	(0.0222)
PA x 1995	-0.0064***	-0.0005	-0.3407***	-0.2469***
	(0.0015)	(0.0004)	(0.0994)	(0.0105)
Constant	-0.6963***	-0.0618***	5.7448***	9.5691***
	(0.0785)	(0.0033)	(1.0650)	(0.2252)
Observations	522,148	520,525	521,612	521,129
R-squared	0.1335	0.0240	0.2108	0.1662

Standard errors clustered by state in parentheses

*** p<0.01, ** p<0.05, * p<0.1. . Benchmark categories are individuals who are females admitted to a large non-teaching hospital whose primary payer was unknown. Models include state and year fixed-effects.

Table 6: Weights for Synthetic Control Groups by Outcome Variable

State ID	State	HAC	Mortality	LOS	Charges
4	Connecticut	0.136	0.310	0.000	0.427
5	Florida	0.000	0.000	0.000	0.000
8	Iowa	0.000	0.000	0.027	0.000
9	Illinois	0.000	0.029	0.721	0.022
11	Massachusetts	0.000	0.000	0.000	0.000
12	Maryland	0.043	0.000	0.000	0.477
15	New Jersey	0.000	0.000	0.000	0.000
16	New York	0.103	0.010	0.000	0.040
17	Oregon	0.658	0.651	0.000	0.035
19	South Carolina	0.060	0.000	0.000	0.000
23	Washington	0.000	0.000	0.252	0.000

Table 7: Means of Covariates and Outcome Variables Across Treatment and Synthetic Control Groups

	HAC		Died		LOS		Ln(charges)	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Charlson Index	0.4492	0.4640	0.4492	0.4740	0.4492	0.4333	0.4492	0.5909
Male	0.3538	0.3571	0.3538	0.3598	0.3538	0.3510	0.3538	0.3426
Age years	71.42	72.12	71.42	72.25	71.42	72.09	71.42	71.92
Small Hospital	0.1669	0.1661	0.1669	0.1776	0.1669	0.1600	0.1669	0.1915
Medium Hosp.	0.4420	0.3373	0.4420	0.4312	0.4420	0.3144	0.4420	0.5260
Large Hosp.	0.3911	0.4965	0.3911	0.3912	0.3911	0.5256	0.3911	0.2835
Log real income	9.7702	9.6101	9.7702	9.6924	9.7702	9.8325	9.7702	10.0968
Income missing	0.0252	0.0293	0.0252	0.0244	0.0252	0.0202	0.0252	0.0344
Teaching hosp.	0.5178	0.2536	0.5178	0.3016	0.5178	0.4376	0.5178	0.4904
Medicare	0.7333	0.7697	0.7333	0.7742	0.7333	0.7342	0.7333	0.7602
Medicaid	0.0158	0.0175	0.0158	0.0157	0.0158	0.0158	0.0158	0.0160
Private Ins.	0.2013	0.1643	0.2013	0.1648	0.2013	0.2176	0.2013	0.1986
Self pay	0.0049	0.0050	0.0049	0.0038	0.0049	0.0156	0.0049	0.0057
Other payer	0.0442	0.0435	0.0442	0.0415	0.0442	0.0168	0.0442	0.0204
Dependent var.	0.1198	0.1194	0.0094	0.0094	6.9214	6.9812	9.7906	9.8003

Table 8: Point Estimates and P-values using Synthetic Control Method

Outcome	Coefficient	P-value
Hospital acquired condition	-0.0004	0.5375
Mortality	-0.0010	0.3077
Length of Stay	0.1484	0.6923
Ln(Charges)	0.1867	0.5385