Reducing Readmissions by Addressing the Social Determinants of Health

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Abstract

Hospital readmissions generate enormous costs and are the subject of increased scrutiny among U.S. lawmakers. The Affordable Care Act created the Community-Based Care Transitions Program (CCTP) to test models for improving care transitions after hospital discharge with the goal of reducing 30-day Medicare hospital readmission rates by 20 percent. Few of these demonstrations showed sustained reductions in readmission rates. In contrast to more traditional medically- focused programs, the Chicago Southland Coalition for Transition Care (CSCTC) utilized social workers solely to manage care transitions in an effort to address nonmedical obstacles to recovery. Using a difference-in-differences model and the census of Medicare discharges over the 2010-2015 period, we evaluate the impact of this program. We select as a comparison group hospitals in the Chicago area with similar pre-treatment trends in readmission rates and total discharges. Treatment-on-treated estimates indicate that the CSCTC program reduced 30, 60, and 90-day readmission rates by a statistically significant 14 percent or more of the sample mean, and reduced readmission costs an amount equal to CSCTC program cost. Effects are driven by black and Hispanic patients as well as those with dual eligibility for both Medicare and Medicaid.

Keywords: Medicare; Hospital Readmissions; CCTP
JEL:I13; I14; I3

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I. Introduction

In fiscal year 2017, there were over 11 million inpatient hospital discharges in the Medicare fee for service program, generating $135 billion in payments.[1] A large component of this spending was associated with unplanned hospital readmissions that occurred within 30 days of a discharge, which are often related to complications associated with the initial hospitalization. Jencks et al. (2009) estimate that 20 percent of Medicare discharges have an unplanned readmission within 30 days. Inflating their estimates to 2017 admissions, these readmissions cost Medicare about $23 billion that year.

In response, a number of programs have been legislated by the federal government or adopted by the Centers for Medicare and Medicaid Services (CMS) in an attempt to reduce readmissions and their associated costs. One such program was the Community-Based Care Transitions Program (CCTP) that was passed as part of the Affordable Care Act (ACA). CCTP was created to test models for improving care transitions after hospital discharge with the goal of reducing 30-day hospital readmission rates for Medicare patients by 20 percent.

A total of 101 Community Based Organizations (CBOs) were initially accepted as part of CCTP, and began serving patients as early as February 2012.[2] Overall, the results from CCTP were modest at best. Fifty-seven of the original contracts were not renewed because the interventions did not show progress towards meeting the targeted 20 percent reduction in readmissions. Contracts at 44 sites that showed some promise were extended past the original period. A consultant's report (Ruiz et al. 2017) about the impact of the program found that statistically significant reductions in

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[1] https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/CMSProgramStatistics/2017/2017_Utilization.html

[2] More information on the CCTP program is available at https://innovation.cms.gov/initiatives/CCTP/

readmissions were just as likely as statistically significant increases in readmission rates (seven versus eight sites, respectively).[3]

The programs that were part of the CCTP demonstration were quite varied in their design. Some relied on in-hospital or in-home visits, while others primarily used phone calls with patients to help with care transition. The composition of the workers who provided care also varied between nurses, nurse practitioners, hospital staff, or social workers. Despite the disappointing results of CCTP in general, it is useful to consider whether some variations of the program may have generated positive results. In this paper, we evaluate the impact of the Chicago Southland Coalition for Transition Care (CSCTC) program. This was one of the original CCTP sites administered in four Chicago hospitals starting in mid-2012. A local social service agency, Catholic Charities Chicago, directed the intervention and its service delivery was unique in that social workers were solely responsible for care transitions. Although CCTP sites used social workers in combination with registered nurses and licensed practical nurses in a majority of care transition programs, only a small fraction of the CCTP sites utilized social workers as the sole care transition coordinators (Econometrica 2014). Social workers are well positioned to assist patients with obstacles that might inhibit their recovery including difficulty scheduling and obtaining transportation for follow-up care, and confusion about post-discharge instructions. Additionally, the costs of employing social workers to conduct home visits is significantly lower than the cost of employing medical professionals.

[3] Though the consultant's report documented many cases where hospital readmissions did not decline following adoption of CCTP, its analysis simply compared overall readmission rates before program implementation with readmission rates for CCTP patients following the program. If cases were positively (negatively) selected, the authors overstate (understate) the benefits of the program. Without accounting for this selection, we cannot adequately assess the value of these programs.

Despite the wide variation in service delivery across CCTP sites, there have only been a few published papers that examine the impact of specific CCTP sites; we discuss these below. Given that the CSCTC model is both scalable and replicable, evaluating this program can inform future social programs and public policies aimed at reducing readmission rates.[4]

We quantify the impact of the CSCTC program using a difference-in-differences model where the comparison sample comprises large hospitals in the Chicago area that had the same pre-treatment monthly trends in both 30-day readmission rates and log total CCTP-eligible discharges between January 2010 and July 2012. The selection procedure identifies 18 Chicago hospitals with characteristics similar to our 4 treatment hospitals, and generates a comparison sample of hospital discharges that is roughly twice the size of the treatment group.

The data for the project are the universe of Medicare fee-for-service claims from the Chicago area. The CSCTC program had a fixed capacity per month and the eligible population of Medicare fee-for-service beneficiaries was declining over time. We therefore identify the program impacts within the difference-in-differences framework by using as an instrument for CSCTC service a variable that is zero in the pre-treatment period and is a monthly trend over time in the four treated hospitals after the intervention starts. This time-by-hospital interaction can be used as a first-stage measure for whether someone received services from CSCTC in a two-stage least-square model to estimate a treatment-on-the-treated effect. These models demonstrate that the program reduced 30-, 60-, and 90-day readmission rates by a large and statistically significant amount, of 14 percent or more of the sample mean. More importantly, we estimate that the program reduced the

[4] As the primary cost of the program is labor and the key inputs are performed outside the hospital, this model is eminently scalable. There is nothing unique about CC-Chicago or the four hospitals in this project that cannot be applied in another setting.

costs associated with 30-day readmissions on average by $364—and by even larger amounts for high-risk patients. CSCTC spent an average of $368 per person served, so our estimates indicate that the program potentially pays for itself.

The results demonstrate there is no definitive pattern in program effectiveness for readmission rates based on the severity of the case as measured by patient comorbidities: the program appears to reduce readmission rates by the same amount for more severe cases as it does for less severe cases. The estimates are, however, very different for the costs of readmission. In this case, the monetary savings from reduced readmissions is monotonically increasing in condition severity of the patient. This suggests that if the goal of a hospital is to reduce readmission rates, this could be achieved by administering a program like CSCTC to a broad base of patients. However, if the goal is to reduce the costs of readmissions, the program will generate larger returns if it is directed to patients with more serious conditions who exhibit a higher risk of readmission.

This paper contributes to the broader literature on how to reduce readmission rates in a vulnerable population, as well as a growing research focus within the medical community about how to ameliorate the impacts of a poor social environment on health (i.e., the social determinants of health). The impact of social environment on health is thought to be quite extensive. Daniel et al. (2018) outlined the official view of the American College of Physicians, stating that the "… set of forces and systems shaping the conditions of daily life… are responsible for most health inequalities." Galea et al. (2011) estimated that annual deaths in the United States attributable to low social support outnumbered the annual deaths due to lung cancer. Hospitals have also pushed for risk adjustment calculations to incorporate socioeconomic factors (Joynt Maddox et al. 2019), while the American Medical Association has charged that the hospitals themselves need to address social determinants of health in their care practices (Sullivan 2019). Despite these advances, most physicians feel they are not equipped to deal effectively with these issues. A 2011 Robert Wood

Johnson Foundation survey found that 80 percent of primary care physicians were not confident they could meet the social needs of their patients and that this hindered provision of quality care (Golden 2017). CSCTC's novel use of social workers and subsequent successful reduction of readmissions rates and costs suggest that future programs may benefit from a heavier emphasis on addressing social and economic factors that contribute to re-hospitalization.

II. Background

A. THE CHICAGO SOUTHLAND COALITION FOR TRANSITION CARE (CSCTC) PROGRAM

Beginning in July 2012, Catholic Charities of the Archdiocese of Chicago (CC-Chicago) operated a CCTP called the Chicago Southland Coalition for Transition Care (CSCTC). The program was a partnership with four hospitals that served 70 low-income zip codes in the Chicago Southland area. The CSCTC program began when a hospital consulting company approached CC-Chicago about implementing a care transition model based on the social determinants of health as part of the CCTP initiative. As the program utilized social workers delivering care transitions, CC-Chicago was interested and noted it had an existing partnership with four local hospitals. The consulting firm was enthusiastic about these four hospitals as all of them had very high readmission rates among their Medicare patients.[5] As a result, the selection of these four hospitals was due primarily to the care transition provider's prior relationships.

[5] Our contacts at CC-Chicago indicated the consulting firm had an interest in adding two additional hospitals in the Chicago area to the grant proposal but CC-Chicago had no on-going relationship with the hospitals and a partnership with these two hospitals was not pursued.

Under the CC-Chicago model, a social worker "coach" is assigned to each patient to help coordinate the patient's transition home following an inpatient stay. The CSCTC employs the Coleman Care Transition Intervention (CTI) model, an evidence-based care transition model focused on helping patients to (i) manage their health care, medications, and nutrition, (ii) communicate more effectively with physicians, and (iii) connect to community resources such as meal delivery, payment assistance for medication, and transportation (Coleman et al. 2006).

The original proposal was for CSCTC to provide care to patients with six conditions: acute myocardial infarction, heart failure, pneumonia, septicemia, renal failure and chronic obstructive pulmonary disease. The program was never this limited. Instead, the program offered services to a wide variety of patients. In the first year alone, the program provided care to patients in over 300 diagnosis related groups (DRGs). The 25 most frequent DRGs represent about 47 percent of patients served and the 50 most frequent represent 64 percent.

In contrast with traditional transition models that rely on health care providers such as nurses or a mix of social workers and medical professionals, the CSCTC employed only social workers to serve as hospital coaches. A review of the initial CCTP sites notes that 17 percent used medical professionals exclusively, 75 percent used a combination of medical and social workers, and only 9 percent used social workers exclusively (Econometrica, Inc. 2014). The public health community has grown increasingly concerned with the fact that social factors are major predictors of preventable readmissions, especially among Medicare recipients. Arbaje et al. (2008) found that living alone was associated with a 50 percent increase in 60-day readmission rates, and individuals lacking a high school diploma were 40 percent more likely to be readmitted than those with a high school education or more. Graham et al. (2009) show that minorities, recent immigrants, and seniors with limited English proficiency are especially vulnerable during periods of health care transition, and more likely to be readmitted after a hospital visit. These non-medical needs are difficult to

predict prior to discharge, and were largely unaddressed in many transitional care programs (Proctor et al. 2000; Altfeld et al. 2012; Altfeld Pavle et al. 2012).

Several qualitative studies suggest that social workers are especially well equipped to build additional social support mechanisms for the patients to rely on. A study of nurses and social workers who worked collaboratively in a hospice setting found that while nurses spent the majority of their time educating patients on various clinical procedures, social workers were strongly influenced by a patient's social situation (Black 2006). For example, social workers were much more likely to know whether the patients were living alone, and whether other family members were in regular contact. Addressing these relational questions helped the social workers to offer advice within the context of each patient's own personal situations. The social workers were also often able to incorporate family members into the support system. Holliman et al. (2003) found that even when both nurses and social workers take on similar discharge planning roles, social workers provide the bulk of the education and support tools to patients' caregivers after hospital discharge. These noted contrasts in the content of care delivered by nurses versus social workers will produce fundamentally different types of transitional programs, and different rates of efficacy are likely.

The CSCTC program was developed with the knowledge that many health events requiring hospital readmission are linked to ongoing unmet emotional, social, or logistical needs. After a hospital discharge, a lack of transportation to get to follow-up appointments, insufficient supply of nutritious food, difficulty obtaining or paying for prescriptions, or confusion about discharge instructions may increase an individual's risk of readmission. Because of their consciousness of the social and relational settings to which discharged patients were transitioning, social workers are particularly well positioned to assist patients with these obstacles. In addition to the guidance provided by social workers, CSCTC supplied patients with pharmacy support services through retail

pharmacy chains and also provided home-delivered meals. Between July 2012 and November 2015, the period of our analysis, CSCTC assisted over 16,000 patients.

The population served by the CSCTC hospitals lived on the south side of Chicago, an area that on average has lower incomes and poorer health outcomes than other parts of the city (Peek et al. 2012). Medicare recipients living on the south side are also likely to differ from those living in other parts of the Chicago region. To demonstrate this point, we compare zip code characteristics of CSCTC hospital patients with the rest of Chicago. Ninety-eight percent of patients from the CSCTC hospitals list a zip code in one of 15 Public Use Micro Area (PUMAs) to the south of downtown Chicago. We use the 2011-2015 five-year American Community Survey (Ruggles et al. 2019) to identify Medicare enrollees from these PUMAs not living in group quarters, and compare them to Medicare recipients living in the Chicago-metro area but not in the catchment area served by the CSCTC hospitals.[6]

[TABLE 1 ABOUT HERE]

We summarize demographic information for these groups in Table 1. In the first column of the table, we report the characteristics of Medicare recipients in the catchment area for the four CSCTC hospitals, and in column 2, we report data for those in the Chicago metro area but not in this catchment area. For reference, we also report data for Medicare recipients that live in metro areas for the country as whole but do not live in the catchment area (column 3). Compared to the rest of Chicago, the area served by CSCTC hospitals is generally more economically and socially disadvantaged. For example, the CSCTC areas show a much higher fraction of patients younger than

[6] This is an imperfect comparison to our sample, which is only traditional Medicare patients. The ACS only identifies whether someone is on Medicare and does not identify whether they are receiving services from Medicare Advantage or traditional Medicare.

65 years of age (14.5 percent vs. 11.6 percent), who receive Medicare because they are disabled. The CSCTC catchment area has three times the fraction of black, non-Hispanic residents but a smaller fraction who are other race, non-Hispanic, and a slightly smaller fraction Hispanic. Medicare recipients in the catchment area are substantially less likely to be married compared to the rest of Chicago (42.9 percent vs. 51.1 percent). Medicare recipients in the catchment area have about 7 percent lower Social Security income than the Medicare recipients in the rest of Chicago but have 20 percent lower family income. Poverty rates in the catchment area among Medicare recipients are 30 percent higher than in the rest of Chicago and 38 percent of Medicare recipients in the catchment area have incomes less than 200 percent of the federal poverty level.

In the final column of the table, we report characteristics of Medicare patients in metro areas from the rest of the country that are not in the CSCTC hospital catchment area. This group is less well off financially than Chicago metro residents but better off than Medicare patients in the CSCTC catchment area.

B. PREVIOUS LITERATURE ON CCTP AND TRANSITION PROGRAMS

Previous research has found limited evidence of an impact of CCTP on readmission rates. A broad evaluation of all CCTP sites did not find significantly lower readmission rates and inpatient Medicare expenditures at CCTP hospitals relative to non-CCTP hospitals in similar markets (Ruiz et al. 2017). Other studies documented small reductions in readmission rates at CCTP sites targeted at high risk patients (Jenq et al. 2016; Duncan et al. 2014). Studies evaluating other (non-CCTP) care transition intervention programs have found mixed evidence on their effectiveness (Feltner et al. 2014).

Studies on cost-effectiveness of social worker interventions in health for both CCTP and other programs uncovered evidence of significant cost savings for a variety of demographics and

countries (Steketee et al. 2017; Rizzo and Rowe 2016; Stauffer et al. 2011). The cost of the CSCTC program was approximately $368 dollars per person, which is roughly the median expense across all CCTP sites funded in the first year.[7] Relative to the cost of similar transition programs utilizing nurses, previous literature has not clearly demonstrated whether the use of social workers was more or less expensive.[8] This gap in knowledge may be partially due to the limited existence of programs emphasizing social worker intervention as well as the difference in the services provided by nursing professionals. It is important to note, however, that the CSCTC program used in-person visits with social workers as the key feature of the transition program. A similar visit by an RN or LPN would likely be more expensive though there is limited data to document this. For example, using data from the American Community Survey from 2013 to 2017, we calculate the average hourly wage of social workers in Chicago to be $23.89, which was considerably lower than the $34.74 average wage for RNs.[9] Assuming nurses and social workers require the same amount of time to provide transitional care services to each patient, the labor costs of a social-worker based program will be 40 percent less than a nurse-delivery service model.

Transition care models that rely on social workers offer a potentially effective way to address non-medical challenges facing the elderly following hospitalizations. The "Bridge Model" is one such program that has been associated with documented reductions in 30-day readmission rates. Bridge is a social worker-driven transitional care model that incorporates pre- and post-discharge

[7] Using data from Ruiz et al. (2017), we calculate the average cost of a CCTP intervention was $361 and the median was $364.

[8] A transition program based in Arizona using RNs and LPNs estimated the cost per person to be $360 per person (Logue and Drago 2013)

[9] Authors' calculations using data from Ruggles et al. (2019).

assessments and individualized post-discharge interventions.[10] Early evidence from a randomized control trial (RCT) at Rush University Hospital indicates that patients who participated in the Bridge program had statistically significant higher rates of follow-up appointments. Although the RCT showed no reduction in 30-day readmission (Altfeld et al. 2013), an analysis of non-experimental data by Boutwell et al. (2016) compared outcomes for Bridge participants and those without care transitions and found Bridge patients had 20 percent lower 30-day readmission. We note that this analysis only controls for selection on the observables and the quality of the comparison sample in this context is not clear.

C. OTHER CMS QUALITY IMPROVEMENT PROGRAMS

CCTP is among several recent policy efforts that have targeted unnecessary hospital readmissions in an effort to reduce health care spending. A complementary CMS program adopted around the same time as CCTP was the Hospital Readmission Reduction Program (HRRP), that financially penalized hospitals with higher than expected 30-day readmission rates for certain types of inpatient stays. Beginning in October 2012, HRRP targeted patients admitted for heart attack, heart failure, and pneumonia. The program expanded to include chronic obstructive pulmonary disease (COPD) and elective hip and knee replacement surgeries in 2014, and coronary artery bypass graft (CABG) surgery in 2016.[11] Readmission rates among Medicare patients declined following implementation of HRRP, while mortality rates remained stable (Zuckerman et al. 2016; Gupta 2017; Desai et al. 2016; Boccuti and Casillas 2017; Khera et al. 2018; Ody et al. 2019; Joshi et al.

[10] More information on the Bridge Model is available at https://transitionalcare.org/the-bridge-model/.

[11] More information about the HRRP is available at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.html.

2019). Gupta (2017) found that this reduction was driven in part by changes in hospital admitting behavior; other research has suggested that hospital up-coding contributed to lower calculated risk-adjusted readmission rates (Ibrahim et al. 2018).

Two other ACA initiatives targeted at quality of care improvement in hospitals could also have shifted readmission rates. The Hospital Value-Based Purchasing (VBP) Program, implemented in October 2012, adjusts hospital payments based on achievement of and improvement on quality of care metrics for Medicare patients, including mortality rates and surgical site infections.[12] Under the Hospital-Acquired Condition Reduction Program (HACRP), hospitals receive a score from CMS based on a composite Patient Safety Indicator and measures of 5 different types of healthcare-associated infections. Beginning in October 2014, hospitals in the lowest performing quartile of hospitals received a one percent reduction in payments, evaluated annually.[13] Given that these programs occurred during a similar time as CCTP, our analysis takes into account potential concurrent programs and policy changes.

III. Data

Our empirical analysis relies on patient-level administrative records provided by CC-Chicago and patient claims data from CMS.[14] The CMS data include all inpatient claims paid for Medicare fee-for-service (FFS) patients in the U.S. from 2010 to 2015. We observe information about each discharge including patient characteristics, date of discharge, diagnosis and procedure codes,

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[12] More information about the VBP Program is available at https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/Value-Based-Programs/HVBP/Hospital-Value-Based-Purchasing.html

[13] Information on the HACRP is available at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/HAC-Reduction-Program.html.

[14] CMS data were procured through the National Bureau of Economic Research.

diagnostic related group (DRG) codes, hospital, and payments made by Medicare and patients for an inpatient stay.

A list of all patients who obtained CSCTC services was supplied by the transition care provider, CC-Chicago. The CC-Chicago file includes the patient's gender, birthdate, discharge date, and the hospital of treatment associated with each CSCTC patient's discharge but does not contain the Medicare beneficiary identification reported in the Medicare FFS claims database. We match CSCTC enrollees to their corresponding claim in Medicare using a progressive algorithm on the discharge characteristics. Using this strategy, we are able to match 15,736 (74 percent) of all CSCTC enrollees. Many of the non-matches are due to keypunch errors in one of the data sets. We therefore create eight additional match IDs using alternative combinations of discharge characteristics in order to assign remaining unmatched CSCTC patients to the claims in the Medicare data. In all, our algorithm includes nine rounds of matching and we can match 82.7 percent of the CSCTC enrollees to Medicare claims information. Specific details on the matching strategy utilized are available in the Data Appendix.

In our analysis, we restrict the CMS sample to include only those discharges that would be eligible for a CSCTC visit, regardless of the period and hospital of discharge. This sample therefore contains only those discharged alive and discharged to home or home health care. The CSCTC program was not administered to people discharged to another hospital or a skilled nursing facility.

In addition to patient characteristics, we use the Medicare claims data to construct the key outcomes of interest for this study: readmission rates and associated costs. Readmissions are calculated at 7, 14, 30, 60, and 90 days post hospital discharge. Readmission can occur at any hospital in the Chicago area. As we have data through the end of 2015, our analysis of 30, 60, and 90-day readmission rates includes data through November, October, and September 2015, respectively. We also calculate readmission costs for any readmission starting within 30, 60, and 90

days of discharge. For example, if a readmission begins on day 29 after discharge and lasts 10 days, we include the costs of all 10 days in the calculation of readmission costs within 30 days. Nominal costs are converted to 2015 dollars using the Medical Care in U.S. City Average, All Urban Consumers (CPIMEDSL) version of the Consumer Price Index from the St. Louis Federal Reserve Economic Data (FRED).

IV. Methods

A. SELECTING COMPARISON HOSPITALS

The objective of our empirical strategy is to test whether the CSCTC program measurably reduced readmission rates, as well as whether the program reduced the expected costs of readmission. Our econometric model is a difference-in-differences specification, identified by the fact that only four hospitals in the greater Chicago area implemented the CSCTC program. We compare outcomes for patients at these four hospitals with those at nearby hospitals that display similar trends in readmissions rates and total Medicare fee-for-service discharges in the 30 months prior to the start of the program. When estimating the treatment effect with a difference-in-differences model, a necessary assumption is that in the absence of the intervention, the CSCTC and non-CSCTC hospitals would exhibit parallel trends in outcomes during the post treatment period. In order to maximize this likelihood, we select the comparison hospitals in the following way. We first restrict the data to only hospital visits that occurred from January 2010 to July 2012. Let Y_{iht} be an indicator for whether a patient i was readmitted within 30 days of her initial discharge date from hospital h in period t. There are M potential comparison hospitals in the Chicago area. We construct a sample that has the four hospitals plus one comparison hospital and fit the following model M times:

(1) $$y_{iht} = x_{iht}\beta + u_h + trend_t\delta + D_m trend_t \delta_m + \eta_{iht}$$

where x_{iht} is a vector of patient-level variables, u_h denotes hospital fixed effects, $trend_t$ is a linear monthly time trend, D_m is a dummy variable that identifies the possible comparison hospital, η_{iht} is a random error. The vector x_{iht} includes indicators for patient age, sex, and race (dummy variables for black non-Hispanic, other race non-Hispanic, and Hispanic; white non-Hispanic is the reference group), and a cubic in the patient's comorbidity index. The expected morbidity index used is the Charlson Comorbidity Index (CCI), which is calculated from hospital-reported ICD diagnosis codes (Charlson et al. 1987), using the Stata package *charlson*.[15] The CCI score reflects the cumulative increase in likelihood of one-year mortality due to the severity of the effect of comorbidities.[16] We select hospital *m* as a comparison hospital if we cannot reject the null that the trend for the potential comparison does not differ from the aggregate trend of the four treated hospitals, that is, if δ_m=0. We keep as a comparison sample all hospitals for which the coefficient on this trend generates a p-value greater than 0.1 (with standard errors clustered at the hospital level). Given this selection strategy, we believe the control sample to consistently represent the trends that CSCTC hospitals would have experienced in the post-period if there were no CCTP intervention.

Trends in admissions among traditional Medicare patients in the four treated hospitals fall steadily over the sample period as a result of large changes in the share of Medicare enrollees

[15] The *charlson* command can calculate the CCI using either ICD-9 or ICD-10 diagnostic codes. Our data includes both ICD-9 and ICD-10 classifications. We include up to 12 diagnostic codes for each patient.

[16] The comorbidity index (CCI) is a mapping between all available diagnostic codes and the overall mortality risk. The CCI takes into account the interactive effect of multiple diseases on a patient's expected mortality. A lower CCI indicates lower mortality risk. For example, a 65-year-old patient with no comorbidities has an estimated 10-year survival probability of 0.90. If the same 65-year-old presents with myocardial infarction (ICD9=125.2) and diabetes with chronic complications (ICD9=E10.2), the CCI rises to 5 with an expected 10-year survival probability of 0.21. This means that the CCI can help physicians determine if and how to treat a patient for each of the comorbidities.

participating in the Medicare Advantage program. We therefore re-estimate equation (1) at the hospital-month level for the *M* possible comparison hospitals using the natural log of eligible total traditional (i.e., fee-for-service) Medicare admissions as the outcome of interest. In these models, we drop the vector of individual characteristics.

The hospitals considered for the comparison group had at least 2,000 CSCTC-eligible, Medicare-covered discharges, defined as someone discharged alive to home or home health care, from January 2010 to June 2012: 79 hospitals met these criteria. The selection procedure described above produces 28 hospitals that have the same pre-treatment trends in hospital discharges, 56 with the same pre-treatment trends in 30-day readmissions, and a set of 18 comparison hospitals used in the analysis.

Basic monthly time-series information about the treatment and comparison samples are displayed in Figure 1. The black line reports raw counts of CCTP-eligible Medicare discharges, which declined rapidly over this period. The four combined treated hospitals had about 1,500 discharges per month at the start of 2010 but this falls consistently over time to around half that level by the end of 2015. The aggregate discharges in the 18 comparison hospitals are in gray and these number about 3,500 per month at the start and decline steadily as well. The black dotted line shows the number of discharges treated by the CSCTC by month. Note that once the program is established, about 350 patients are treated each month. As the total number of discharges are declining throughout this period, the fraction of discharges treated by CSCTC (the gray dashed line) is increasing throughout. We use this fact in specifying our difference-in-differences model below.

[FIGURE 1 ABOUT HERE]

B. OBTAINING A TREATMENT-ON-THE-TREATED ESTIMATE

Our goal is to estimate the impact of participating in the CSCTC program on readmission rates and costs. Given the structure of the data, the equation of interest can be specified by the following equation:

$$(2) \qquad y_{iht} = x_{iht}\beta + CSCTC_{iht}\alpha + u_h + \lambda_t + \varepsilon_{iht}$$

where y_{iht} denotes a hospital readmission or costs (total payments) for a readmission within 7, 14, 30, 60, or 90 days of patient *i*'s initial admission. The variable $CSCTC_{iht}$ is an indicator that equals 1 if the person is treated by the intervention, u_h and λ_t are hospital and year effects, respectively, and ε_{iht} is a random error. One challenge in this estimation is that we have little information about the decision criteria hospitals used to enroll individual patients in the CSCTC program. The provider running the program typically received lists of current inpatients from the hospital and would then contact the patients during their initial admission to the hospital. The agreement between the hospitals and the provider was that the hospital would enroll patients with high readmission chances, such as those with heart failure and acute myocardial infarction. However, we observe no consistent pattern in the claims data that enables us to predict definitively which patients were treated by the CSCTC intervention. OLS estimates for $\hat{\alpha}$ (which would be negative if the program were successful) would be biased downward if the hospitals were cherry picking the lowest risk patients for program participation and biased upward if they were sending the more difficult cases to the program. Likewise, patients could opt-out of using CSCTC services: if there were a pattern in this behavior, the OLS estimates of (2) would be biased as well. Additionally, during the period of analysis, the share of Medicare beneficiaries enrolled in Medicare Advantage increased. Because CSCTC program participation was limited to traditional Medicare enrollees, the likelihood of selection into the program was therefore increasing over time.

To address these concerns, we estimate equation (2) with a two-stage least-squares (2SLS) procedure that generates consistent estimates by accounting for a patient's changing likelihood of program participation over time. We construct an instrument for CSCTC participation that exploits the fact that the probability that someone in a treatment hospital participated in the CSCTC program is growing steadily over time (Figure 1). We define $THOSP_h$ as a binary variable that equals 1 if a patient is from one of the four treated hospitals, $POSTTREND_t$ is a trend that equals zero through July 2012, then increases by 1 for every month after that. We then interact these terms to create an instrument for CSCTC program participation over time. Our first-stage regression would be of the form

$$(3) \qquad CSCTP_{iht} = x_{iht}\beta_1 + THOSP_h POSTTREND_t \alpha_1 + u_{1h} + \lambda_{1t} + \varepsilon_{1iht}$$

where all control variables in the equation are defined similarly to the terms in Equation (2). The accompanying reduced-form model that flows from equation (3) is specified by Equation (4):

$$(4) \qquad y_{iht} = x_{iht}\beta_2 + THOSP_h POSTTREND_t \alpha_2 + u_{2h} + \lambda_{2t} + \varepsilon_{2iht}.$$

Equation (4) estimates the intent-to-treat effect, that is, the aggregate difference in readmissions between participating and non-participating hospitals as the program ages. This reduced-form model will be free of any contamination due to either positive or adverse selection into CSCTC as long as our comparison hospitals provide an accurate representation if what would have happened in the absence of the intervention.

Given that this is an exactly-identified model, the 2SLS estimate for $\hat{\alpha}$ in equation (2) is simply $\hat{\alpha} = \hat{\alpha}_2 / \hat{\alpha}_1$. Panels of repeated cross sections such as what we use here tend to generate within-group correlation in errors. To correct for this, we cluster standard errors at the hospital-level in all models. Clustering at the group-level is generally sufficient when the number of panels is large

but we only have 22 hospitals in our analysis sample. In light of this, we also calculate p-values for tests of hypotheses using the wild bootstrap procedure of Cameron et al. (2008).

IV. Results

A. MAIN FINDINGS

The basic characteristics of CSCTC and comparison hospitals for the pre- and post-treatment periods are reported in Table 2. The CSCTC hospital population has slightly lower values for mean age and male share, but a higher mean CCI, both before and after the introduction of the program. The slightly lower comorbidity in the comparison group is driven by the fact that the comparison hospitals have a smaller fraction of cases where patients had a CCI of 3 or 4 and more cases where patients had scores of 2 or below. Despite this difference in case severity, the comparison hospitals have a slightly higher mean cost per admission. Prior to CSCTC, the 30-day readmission rates in the CSCTC hospitals were much higher. There are 30 months in the pre-CSCTC period so each comparison hospitals averages about 212 discharges per month, with the corresponding number for each of the 4 treatment hospitals being 379.

In the final two columns of Table 2, we report the characteristics of the two groups of patients who were hospitalized during the period that the CSCTC program was active in the four participating hospitals, which is July 2012 through November 2015. Samples in both groups of hospitals are getting older and riskier over time, as measured by the CCI. Despite this, readmission rates decline in both sectors, although the drop is larger in CSCTC hospitals.

[TABLE 2 ABOUT HERE]

We present the monthly time-series of the 30-day readmission rate for CSCTC hospitals and the comparison group in Figure 2, Panel A. As the comparison hospitals have 3 percentage point lower readmission rates than the treatment hospitals in the pre-treatment period, the left axis reports

rates for the treatment hospitals while the right axis is for the controls. Both axes are on a 20-point scale, but the left goes from 0.1 to 0.30 and the right is scaled from 0.07 to 0.27. Panel A indicates that that the comparison hospitals track outcomes well among treatment hospitals in the pre-CCTP period, but there is a growing difference between the two series in the post treatment period. Both groups show an aggregate decline in readmission rates in the post-2012 period, which may reflect the overall effort by hospitals to comply with HRRP and other policies adopted by CMS over the period.

Given the noise in the month-to-month readmission rates, we graph in Panel B of Figure 2 the difference in the two series, i.e., the average 30-day readmission rate for the treatment group minus that of the comparison group. In this graph, we fit linear time trends for the difference before and after the start of CCTP. Note that in the pre-treatment period there is no trend in the difference, which is consistent with the "parallel trends" assumption necessary for a quality comparison sample in a difference-in-differences model. Second, the difference in averages grows noticeably in the post-treatment period. This is consistent with Figure 1, which shows an increasing fraction of discharges in the four treated hospitals participating in CCTP. Fitting a line through the difference in the post-treatment period, we estimate that the difference declines by 0.00045 per month.

[FIGURE 2A and 2B ABOUT HERE]

In Table 3, we report the intention-to-treat (ITT) and the treatment-on-the-treated (TOT) results for the program. The first row presents estimates from the first-stage and ITT which are calculated by OLS. In column 1 of that row, we report the first-stage estimates where the outcome is whether someone enrolled in CSCTC and the key covariate is the instrument $THOSP_h x$ $TRENDINDEX_t$. For each regression, we report the regression coefficient, the standard errors

based on clustering at the hospital level, the p-value using that standard error for the null being zero, and the p-value using the wild bootstrap procedure.

The first-stage estimate indicates that the fraction of patients in treatment hospitals that use CSCTC increased by about 1.5 percentage points per month. The first-stage F-statistic from the model with clustered standard errors is in excess of 1000 so there are no finite sample concerns.

In the next five columns, we report the reduced-form ITT estimates. The left-hand side variables in these equations are readmission events 7, 14, 30, 60 and 90 days after discharge. The covariate of interest in this case is the coefficient on the $THOSP_h \times TRENDINDEX_t$ variable. Focusing on the 30-day readmission rate results first, these results suggest that each month, average readmission rates are falling by 0.049 percentage points which is virtually identical to what the simple graph in Figure 2, Panel B suggests. The p-value for this estimate is however just at 0.1. Looking from 14 to 90-day rates, three have p-values under 0.10 based on the wild-bootstrap procedure (7, 14, and 60-day) while the 30- and 90-day models have p-value at 0.1. In the next row of the table, we report the 2SLS estimates of the CSCTC variable using $THOSP_h \times TRENDINDEX_t$ as the instrument. Reading from 7 to 90 days, the effect size is increasing but the coefficients are a declining percent of the sample mean, representing 28, 19, 17, 15 and 14 percent reductions over the sample means. The results for 7 and 14 have a p-value based on the wild bootstrap under 0.05, while the other three models have p-values below 0.1.

[TABLE 3, 4 ABOUT HERE]

In Table 4, we report estimates of models similar to those in Table 3 but the outcome of interest is the cost to Medicare associated with readmissions. As we noted above, readmissions costs include any cost generated from a hospital admission starting within a fixed time after discharge: 7, 14, 30, 60, and 90 days. Since the IV strategy is the same as in Table 3, the first-stage estimate is unchanged and we do not report it again in Table 4. The TOT results convey a pattern of negative

coefficients consistent with the results on readmission rates, but with improved precision. Four of the 2SLS models have wild bootstrap p-values under 0.05 and in one case (the 30-day model), the p-value is 0.061. The estimates are monotonically increasing from 7 to 90 days, suggesting that the cost savings of the program are persistent and growing over time after a discharge. The 30-day results suggest that participation in CSCTC reduces costs associated with readmission by $364. Moving from 7 to 90-day costs, the percent reduction in readmission costs fall by 34, 29, 30, 30, and 27 percent of the sample mean, respectively.

The average cost per patient served in CSCTC was $368 and our estimate from Table 4 suggests that the cost savings within 30 days of discharge ($364) was nearly exactly this number. We cannot reject the null that the program generates savings equal to program costs, although these estimates have wide standard errors allowing for both cost savings and possible expenses. We return to this point in detail in the next section.

B. PATIENT RISK HETEROGENEITY

Next, we consider whether there is some heterogeneity in program effects based on patient severity. The most direct way to consider this is to estimate separate models based on the comorbidity index (CCI) of the patients. In Figure 3, we graph the readmission rate among all 19 hospitals in our analysis sample during the pre-CSCTC period (dark grey bars). Readmission rates are strongly correlated with the CCI. Those with CCI's of 0 or 1 have less than a 20 percent readmission rate while those with CCI's in excess of 5 have rates greater than 35 percent. Within our sample, the patient-weighted correlation coefficient between the CCI and the mean readmission rate by CCI is 0.97. Estimating the CSCTC treatment effects for specific CCIs is difficult because the CCI distribution is highly skewed and there are few patients with very large, risky values of the CCI in the sample. In Figure 3, the distribution of CCI scores is given by the solid black line,

showing that the vast majority of patients have CCIs of 0-2. Therefore, to have sufficient power to test the heterogeneity of the program, we group patients into broad CCI categories.

[FIGURE 3 ABOUT HERE]

To evaluate the heterogeneity of the program impact by underlying patient risk, we use three groups based on CCI values of 0-1, 2-3, and 4+. The readmission rates and distribution of values for these groups in the pre-CSCTC sample are given in Figure 4. Moving from lower to higher scores, these three groups represent 46.8, 35.0 and 18.2 percent of patients and have baseline readmission rates of 14, 22, and 29 percent, respectively.

[FIGURE 4 ABOUT HERE]

In Table 5, we present TOT estimates from 2SLS models similar to those in Tables 3 and 4 for readmission rates and costs of readmission based on CCI scores. To conserve space, we report estimates for only the 30, 60, and 90-day periods. These models have the same covariates as used in Tables 3 and 4 but in the models for samples with CCI scores of 0-1 and 2-3, we replace the cubic in CCI with a dummy for the CCI levels.

[TABLE 5 ABOUT HERE]

Table 5 displays the results for three post-discharge ranges (30, 60, and 90-day). There are two sets of columns: on the left are readmission rates and on the right are costs of readmissions. For each outcome, we present results for the three CCI groups: 0-1, 2-3 and 4+.

The results for readmissions show larger absolute and percent changes for the lowest and highest CCI groups. Readmissions effects, however, are limited by large standard errors. We cannot reject the null hypothesis that the absolute changes are different for pairwise comparisons between any of the follow-up readmission ranges. Looking at the p-values from the wild bootstrap procedure, we find statistically significant effects on 90-day readmission rates at the 0.05 level only for the highest comorbidity patient group (CCI=4+). The magnitudes of this effect for the highest

group is quite large, reducing readmission rates by 8.1 percentage points, or 28 percent. We generate a very similar pattern in results for the 60- and 90-day readmission rates with higher absolute and percent reductions for the lowest and highest readmission rates. Overall, the results suggest that the program is most effective in reducing readmissions rates for lower- and higher-risk cases. That said, for each period under consideration, the 95 percent confidence intervals overlap between models for the lowest and middle groups, and for the middle and highest risk groups. It does appear that the program works best for the higher risk groups but the results do not rule out equivalent effectiveness for patients at all risk levels.

Although the results are not monotonic moving across CCI groups in readmission rates, they are when looking at the effect of CSCTC participation on readmission costs. Here the results show a definitive pattern – there is greater savings per user for the riskier cases. Looking at 30-day readmission costs, the lowest to riskiest groups show a TOT savings of $254, $279, and $917, which are 34, 19, and 44 percent of their respective sample means. In general, the results for this outcome are also more precise with six of nine coefficients having p-values under 0.10 and four of nine having p-values under 0.05. The parameter for the highest group is also statistically different from the two less acute groups.

The cost estimates also indicate the program saves money for the highest risk group. Given program costs of $368/patient, in the 90-day model, the average cost savings are $1,203 (1571-368). The 95 percent confidence interval on this estimate is ($381, $2,025). The means cost savings for 30- and 60-day results for this group are $550 and $999, respectively, and the corresponding 95-percent confidence intervals for these values are ($256, $1,741) and (-$111, $1,210).[17]

[17] It is possible that the average cost of the program could increase with the CCI. Unfortunately, we have no data on specific case costs.

C. ROBUSTNESS TO SAMPLE AND COMPARISON GROUP SELECTION

In our robustness checks, we consider the extent to which our results may be confounded by coinciding programs, control group selection, or selective attrition from patient death. The July 2012 start of the CSCTC program coincided with implementation of HRRP, discussed above, which penalized hospitals with higher than expected readmission rates beginning in October 2012. The program targeted a set of conditions during the period of our analysis: heart attack, heart failure, and pneumonia, COPD, and hip and knee replacements. Our estimated CSCTC treatment effects may be biased upwards if the treatment hospitals were changing their procedures in additional ways to combat readmissions as a direct response to HRRP.

We re-estimate our main models excluding patients who were admitted for any of the diagnosis codes associated with these conditions. The results are shown in Table 6. Column 1 shows the baseline estimates from Table 3 and 4 for the 30-day readmission rates and readmission costs while column 2 shows the estimates from this revised model. The results in column 2 show that our estimates remain virtually unchanged even when we restrict our sample to conditions that were not directly targeted under the HRRP.[18]

[TABLE 6 ABOUT HERE]

Our main analysis uses as a comparison group 18 other hospitals in the Chicago area with similar pre-treatment trends in readmission rates and patient volume. To test whether our results are sensitive to this restricted control group, we estimate our main models using a comparison group

[18] All of the hospitals in our sample were subject to HRRP penalties at some point during the period of our analysis. The four CCTP (treatment) hospitals in our sample and 14 of the 18 comparison hospitals were subject to reimbursement penalties in all years of our analysis after the program was instated (2013-2015). Because the HRRP adjustment levels are mechanically correlated with our outcomes of interest, we cannot directly control for HRRP penalties in our analyses.

that includes all 83 hospitals in the Chicago region.[19] These results, shown in column 3, are slightly smaller in magnitude than our baseline estimates, but still meaningful and in most cases, statistically significant. These estimates indicate that selecting all hospitals in a comparison model would have understated the effectiveness of the program but would still point to a measurable impact.

As we noted above, 28 hospitals match the four treated hospitals in pre-treatment trends on Medicare discharges, and 56 match on pre-treatment trends in the 30-day readmission rate. Using the 56 that match on pre-treatment trends as the comparison group, the 2SLS estimates of the TOT (with standard errors clustered at the hospital-level) in the 30-day readmission rate and the 30-day cost of readmission models are -0.032 (0.015) and -$323 ($128), respectively. When we use only the 28 hospitals that match on the pre-treatment trends in Medicare discharges, the results are very different with the corresponding numbers being -0.011 (0.018) and -$303 ($154). In this case, matching on pre-treatment trends in readmission rates is crucial.

It is possible that participation in CSCTC could impact mortality rates after a patient's initial hospitalization. If individuals are more likely to die due to participation in CSCTC, this could lead us to overstate the effect of CSCTC on readmission rates, as individuals who died would necessarily not have a readmission. We address this concern in two ways. First, we consider death after discharge as an outcome in all of our models. Specifically, we estimate a reduced-form similar to equation (4) using whether someone died within 30 days of a discharge as the outcome of interest. The mean for this outcome is 2.1 percent and the coefficient on the treatment index x CSCTC hospital indicator {wild bootstrap p-value} is 0.00002 {0.84}, so there no evidence of any impact on

[19] As we did when we selected comparison hospitals, we exclude hospitals with fewer than 2,000 hospital admission in total in the pre-treatment period. With the larger sample, the wild bootstrap p-value converges to the regular p-value.

mortality.[20] Second, we estimate our 2SLS specification on readmissions and costs, excluding individuals who died after being discharged from the hospital but had no readmission.[21] These results are presented column 4 of Table 6. In this analysis, the sample readmitted is the same as in the baseline so the sample mean of readmissions and sample mean costs of a readmission should increase slightly but the average cost of a readmission conditional on a readmission will be the same as the baseline numbers in column 1 of the table. Estimates shown in column 4 indicate that the estimates are not sensitive to this exclusion, so increased post-discharge mortality is not driving our findings.

As mentioned in Section II, the HVBP program was implemented in October 2012 and adjusted hospital reimbursements based on quality of care metrics. In column 5 of Table 6, we present estimates controlling for a hospital's percent reduction in payments under the HVBP program. Our main findings are robust to this inclusion, indicating that penalties due to the HVBP program are not driving the estimated reductions in readmission rates and costs among our treatment hospitals.

Beginning in January 2014, Illinois expanded Medicaid coverage to adults with incomes below 138 percent of the federal poverty level as part of the Affordable Care Act. This expansion could confound our estimated effects of CCTP if treatment and comparison hospitals in our sample were differentially affected by the increased Medicaid coverage. We address this in two ways. First, some Medicare beneficiaries were more likely to be eligible for both Medicare and Medicaid (i.e., dually eligible) under the Medicaid expansion. We therefore include a patient-level control for dual eligibility status to account for increased likelihood of dual eligibility among Medicare beneficiaries

[20] Results on post-discharge mortality are available upon request.

[21] If, for example, a person had a readmission on day 10 and died on day 20, they would still be in this sample.

over time (Table 6, column 6).[22] Second, we include a control for the hospital's annual number of Medicaid discharges from the American Hospital Association Annual Survey (Table 6, column 7). Our results are not sensitive to these inclusions, providing some evidence that the findings in this paper are not biased by being differential affected by the Medicaid expansion.

D. RESULTS FROM SYNTHETIC CONTROLS

An alternative to the evaluative model outlined above is the synthetic control method of Abadie et al. (2010). For a given series that is treated with an intervention after a fixed date, the procedure non-parametrically selects a synthetic control series that is a weighted average from a set of "donor" series that provides the best match to the pre-treatment trends for the treated group. The difference between the actual and the synthetic control series for a given time period in the post-treatment era is then taken as an estimate of the treatment effect for that observation. The synthetic control method is most useful when there is one series that is being treated, when there is a moderately sized donor pool available, and when the key outcome of interest is a reduced-form treatment effect.

The synthetic control method may not be ideal in the CSCTC setting for three reasons. First, the data is at the monthly level and such high frequency data is hard to match without including a large number of donor units, especially given the volatility in the series. Second, the key outcome of interest for us is the TOT parameter, which we can only obtain indirectly through the synthetic control method. Third, the monthly series is very volatile and hence we suspect that the

[22] We constructed the dual eligible status using monthly dual eligible indicators and Medicare entitlement codes from the Medicare Beneficiary Summary File.

standard methods to identify the estimated variance in synthetic controls estimates will show a great deal of imprecision on a month-to-month basis. We can potentially extract information that is more precise by putting some structure on how the reduced-form should change over time, as we do in the 2SLS model.

Despite these drawbacks, we estimate a model in the spirit of the synthetic control model for this sample and examine the reduced-form outcome for 30-day readmission rates and the costs from 30-day readmissions. To implement the procedure, we first aggregate the four treatment hospitals into one series for each outcome. Next, we use the set of 28 hospitals that matched the pre-treatment hospitals trends in traditional Medicare discharges. The noise in synthetic cohort estimates are assessed by randomly selecting series from the donor pool, generating a placebo synthetic control to compare against that series as if it were treated, and repeating the process many times to generate a distribution for the effect estimated for the actually treated unit. Synthetic cohort estimates from the real intervention that are statistically significant should be in the tails of this placebo distribution. We modify this process slightly and select four hospital from the donor pool at random, aggregate this data into one series, then estimate the placebo synthetic control group. We repeat this process 40 times.

In Figure 5, we report the 30-day readmission rate for the four treated hospitals and the synthetic controls. In Figure 6, we examine the precision of the estimates from Figure 5 by reporting in black the synthetic control estimate (treatment minus synthetic control), and in gray, the 40 different placebo estimates. In Figures 7 and 8, we report the corresponding numbers for the costs associated with readmissions that begins within 30 days of discharge.

Several points are notable about these graphs. First, the synthetic controls in the pre-period in both Figures 5 and 7 match reasonably well, but not nearly as well as some of the motivating examples for this method such as those described in Abadie et al. (2010). Second, in the early

months of the intervention, there is no noticeable difference in the series for the 30-day readmissions, but there is a sizable difference between the two in the final 24 months of the sample. Third, there is a noticeable and growing difference, on average, between the treatment group and synthetic controls for the costs associated with the synthetic controls. Fourth, the magnitudes suggested in the synthetic controls match closely with the treatment effect suggested by the reduced-form model in Tables 3 and 4. To demonstrate this point, we take the monthly estimates of the synthetic control treatment effect in the post-treatment period and regress this series on a trend term that equals 0 in the first month, 1 in the second, etc. This is analogous to the reduced-form difference-in-difference estimates outlined above. The coefficient (standard error) on the constant and the trend are 0.0134 (0.0066) and -0.00067 (0.00029) respectively, for 30-day readmission rates. The corresponding parameter values in the payment model are 101.6 (75.2) and -8.9 (3.4). Both of these models show very similar results to what we found in the reduced-form models presented in Tables 3 and 4. Finally, for the average month, the treatment effect from the synthetic control method in both Figures 5 and 7 are not precisely estimated, and most of the estimates are not in the extremes of the distribution. This was anticipated given the volatile nature of the discharge data over the study period.

[FIGURE 5, 6, 7, 8 ABOUT HERE]

E. WHAT POPULATIONS WERE MOST AFFECTED?

In order to better understand why CSCTC was effective and in what contexts this model is likely to produce similar results, we separate the sample into subgroups of the overall Medicare patient population. Racial and ethnic disparities in hospital readmission rates are well documented (Oronce, Shai, Shi 2015; Tsai, Orav, Joynt 2014; Rodriguez et al. 2011). Previous research has attributed these disparities in part to differences in access to adequate follow-up care among

minority populations (Joynt, Orav, and Jha 2011). Similarly, low-income patients may live in neighborhoods with limited access to outpatient services or have fewer resources to obtain these services. Some subsets of the population may also be more reliant on medical care to fill emotional and social needs, or may be more likely to return to the hospital when experiencing uncertainty or anxiety about their health. If this is the case, these populations could experience larger benefits from CSCTC than others. CSCTC served a population that was more likely to be black and Hispanic than other similar programs: 35 percent of CSCTC patients were black and 8 percent were Hispanic, compared to 14 percent black and 4 percent Hispanic in other CCTP sites (Econometrica 2014).

In Table 7, we estimate the impact of CCTP by separately considering its effect on white, non-Hispanic patients relative to black patients and Hispanic patients. Additionally, we consider patients who are more likely to be low-income by focusing on those that were dually eligible for both Medicaid and Medicare relative to those who were on Medicare but not eligible for Medicaid. We find that patients who were black or Hispanic, and those that were dually eligible experienced larger reductions in 30-day readmissions than other patients.

The effect of CSCTC on the 30-day readmission rate for blacks and Hispanics is a reduction of 5.9 percentage points (bootstrapped p-value of 0.06) which is 25 percent of the sample mean. The impact of CSCTC on white, non-Hispanic enrollees was virtually zero with only a 0.5 percentage point reduction (bootstrapped p-value of 0.824). The impact of CSCTC on readmission costs was also larger for blacks and Hispanics compared to white, non-Hispanic counterparts with $403.7 and $126.7 reductions, respectively. Neither estimate had a statistically significant bootstrapped p-value though blacks and Hispanics was nearly significant at the 10 percent level.

We see a similar story when we evaluate the effect of the CSCTC program on the dually eligible population compared to enrollees who are not dually eligible. Dually eligible individuals are typically from lower income households and are thought to be more vulnerable than patients who

are not dually eligible. Dually eligible individuals who were enrolled in CSCTC experienced an 8.7 percentage point reduction in 30-day readmissions (bootstrapped p-value of 0.001). This is 35 percent of the sample mean. Non-dually eligible individuals experienced decreases in 30-day readmissions of 1.6 percentage points but this was not statistically significant. The cost estimates show a larger spot estimate for Medicaid cost reductions among dually eligible than non-dually eligible, although the p-value for the dually eligible sample is just over the 0.1 threshold.

The estimates in Table 7 strongly suggest that CSCTC was most effective at reducing readmission rates and costs for minority and low-income populations. This may be because readmissions among these populations are disproportionately driven by social determinants of health, while readmissions of other patient populations are more likely to be driven by medical causes that cannot be offset by social supports. It is also possible that the differential effect is due to Catholic Charities Chicago being particularly skilled at working with at-risk populations, social workers being more experienced with caring for disadvantaged groups, or some combination of factors.

F. CAN OTHER WITHIN-HOSPITAL REFORMS EXPLAIN THE RESULTS?

The four treatment hospitals adopted the CCTP program at a time of heightened concern about hospital readmissions in the Medicare program due to the HRRP penalties. All four hospitals in the treatment group were slated for reduced reimbursements under HRRP and all had some of the highest readmission rates within the target DRGs in the state. From our discussions with the service provider it became clear that the CSCTC program was the primary intervention these four hospitals used to address their HRRP penalties. Three of the four hospitals were struggling financially. Two closed their doors after the CSCTC program ended and another was acquired by a

local hospital chain. The fact that the program was offered free of charge was attractive to the hospitals in the treatment group.

Notwithstanding, we cannot definitively rule out the possibility that hospitals instituted other system-wide changes to reduce readmissions that may drive the estimated effects Tables 3 and 4. To examine this point, we first report in Figure 9 the monthly time series in 30-day readmission rates for CCTP (i.e., treated) and non-CCTP Medicare patients in the four treatment hospitals during the post-CCTP period. The figure illustrates that the readmission rates for non-CCTP patients are increasing steadily in the post-treatment period, while the results for the CCTP patients show a steadily declining rate. At the end of the period, the treated patients have 25 percent lower readmission rates than those not treated. These results indicate that some other overall hospital-wide change is not driving the results.

[FIGURE 9, 10 ABOUT HERE]

Changing patient composition between the treatment and control groups may also influence readmission rates in Figure 9. In Table 8, we report descriptive statistics for CCTP and non-CCTP patients in the post-treatment period for the four treatment hospitals. In the final column, we report the difference in the means and the standard error on these differences. In all cases, the differences are statistically significant but small in magnitude. CCTP patients are older, more likely to be female, and have a lower comorbidity index (CCI). However, this difference in CCI between the two groups is small, at about 6 percent.

To investigate the comorbidity differences in more detail, in Figure 10, we graph the CCI in the post-treatment period for those matched to the CCTP program and those not. Two observations are of note. First, both groups show increasing average comorbidities; therefore, the declines we observe in the 30-day readmission rate for the treatment group in Figure 9 is not driven

by improved health. Second, there is a growing gap between the two groups with the patients not treated by CCTP having more comorbidities. However, as previously noted, this difference is small.

VI. Discussion and Conclusion

This analysis offers encouraging news for CCTP in general, and the CSCTC model in particular. We find that the CSCTC program reduced 30-day readmissions by about 17 percent, which is close to CMS's 20 percent target under the CCTP initiative. Not only is the CSCTC model effective, but it also reduced costs. The average cost per person of CSCTC was only $368, but 30-day readmission costs fall by an average of the same amount for each program recipient.[23] Moreover, our results also indicate that the program was particularly effective at reducing costs for the highest risk patients: for these patients, there is evidence that the program pays for itself through reduced costs.

We do not have data that allow us to identify the exact mechanism by which the program was able to reduce readmissions. On this, we can only speculate. The Bridge program mentioned above also relied on social workers to reduce hospital readmissions; an RCT of that intervention demonstrated that Bridge patients had substantially higher attendance rates with their primary care provider after discharge than those not assisted by a care transition. As we note in section II, part of the goal of social work is to enhance connections with a larger social network of family, friends, and providers. If social workers are able to identify non-medical patient needs that impact recovery, they may be able to expand patient contact with other resources and social service organizations, which could lead to improved outcomes.

[23] The 95% confidence interval around our estimated $512 reduction in readmission costs ranges from $182 to $841, so we cannot reject the null that the cost savings are the same as the program costs.

The CSCTC program was designed on the premise that some preventable readmissions have a social rather than a medical etiology. As CSCTC was one of the few initiatives to exclusively use social workers for care transitions, our results suggest that this is an avenue for future investigation. Rigorous research understanding the economic contributions of social work on health outcomes is limited as most studies focus on programs utilizing nurses as the primary form of transitional care (Steketee et al. 2017). Filling this void is critical for understanding potential efficiency gains in this sector. A direct comparison between the impact of nurse versus social worker care in transition programs has never been explored, but a randomized control trial evaluating this comparison would be worth investment. An attractive feature of the program is that it is at the mean price for other CCTP programs. Although Medicare does allow billing for transition care—only medical providers are eligible for reimbursement—services delivered by social workers are not eligible for reimbursement. Our work suggests that CMS should revisit this restriction.

As the primary input into the production process is the time of the social worker and most of the time was spent in the home of the patient, the model is easily scalable. There is nothing unique about the model that would not allow it to be replicated in another context. A still unanswered question is whether the results of the CSCTC can be reproduced in another set of hospitals, but we believe this is likely among hospitals with reasonably diverse patient populations. The external validity of this intervention is enhanced by three factors. First, the treated hospitals had high readmission rates, a characteristic of many hospitals. In the first five years of HRRP, 64 to 79 percent of hospitals were subject to penalties for high readmission rates.[24] Second, the program was provided to a very broad set of patients. As we noted above, over 300 DRGs were treated with

[24] https://www.kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/

this CCTP intervention in the first year alone. Third, our models suggest that the program worked for cases with low, medium, and high levels of comorbidities.

In contrast, a common concern with demonstration projects in general, and RCTs in particular, is that results tend not to reproduce well on a larger scale (Deaton and Cartwright 2018). One unique feature of CSTSC was the pre-existing relationship between Catholic Charities and the four participating hospitals; this characteristic may have been central to effective service delivery and is clearly challenging to replicate. Another factor that could counteract the program's impact in a broader context is that, as we indicate in Table 1, the population served by the intervention is poorer than the average Medicare patient, and more likely to be black or Hispanic. Our subsample analysis indicates that the program is especially well suited to these patient populations. Although we do not rule out an impact for higher income patients, our data suggest wealthier patients or white patients on average will not see as much benefit from a CCTP-type service

At the same time, there are likely populations that are actually too disadvantaged to benefit from a relatively low-cost intervention such as CSCTC, and may require a more intensive intervention. In another program designed to reduce readmissions, hospitals in Camden, NJ worked in partnership with both registered nurses and social workers to manage patients' post-discharge care and support (Finkelstein et al. 2020). Notably, this program was not limited to Medicare patients (nearly three quarters of patients were under the age of 65), but they were severely disadvantaged with only 5 percent employed and 74 percent reporting a serious mental health diagnosis. The researchers found that the post-discharge program was not effective in reducing readmissions among this population. CSCTC served a much different population that, while disadvantaged, was closer to the typical Medicare population in an urban setting. Also, as we have noted, other interventions that utilized a hybrid of medical professionals and social workers did not appear to achieve significant reductions in hospital readmission rates.

Moving forward, the potential for models like CSCTC to impact particular groups of Medicare patients will depend on the objectives of hospital administrators and policymakers. We find suggestive evidence that the program more easily reduces readmission rates for less complicated cases (i.e., those with a CCI of one or less), as well as for black, Hispanic, and dually eligible patients. If the goal is to reduce 30-day readmissions, directing resources to patients with lower medical risk, minorities, or dually eligible patients would seem to be prudent. In contrast, if the goal is to reduce costs, focusing on cases with higher medical risk is preferred. Here, the money savings are much larger given the much higher readmission costs for these patients. Furthermore, looking beyond the 30-day readmission window at longer time horizons may yield additional savings.

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Figure 1
Monthly Admissions in Medicare FFS, CSCTC Programs and Comparison Group Hospitals, January 2010 – November 2015

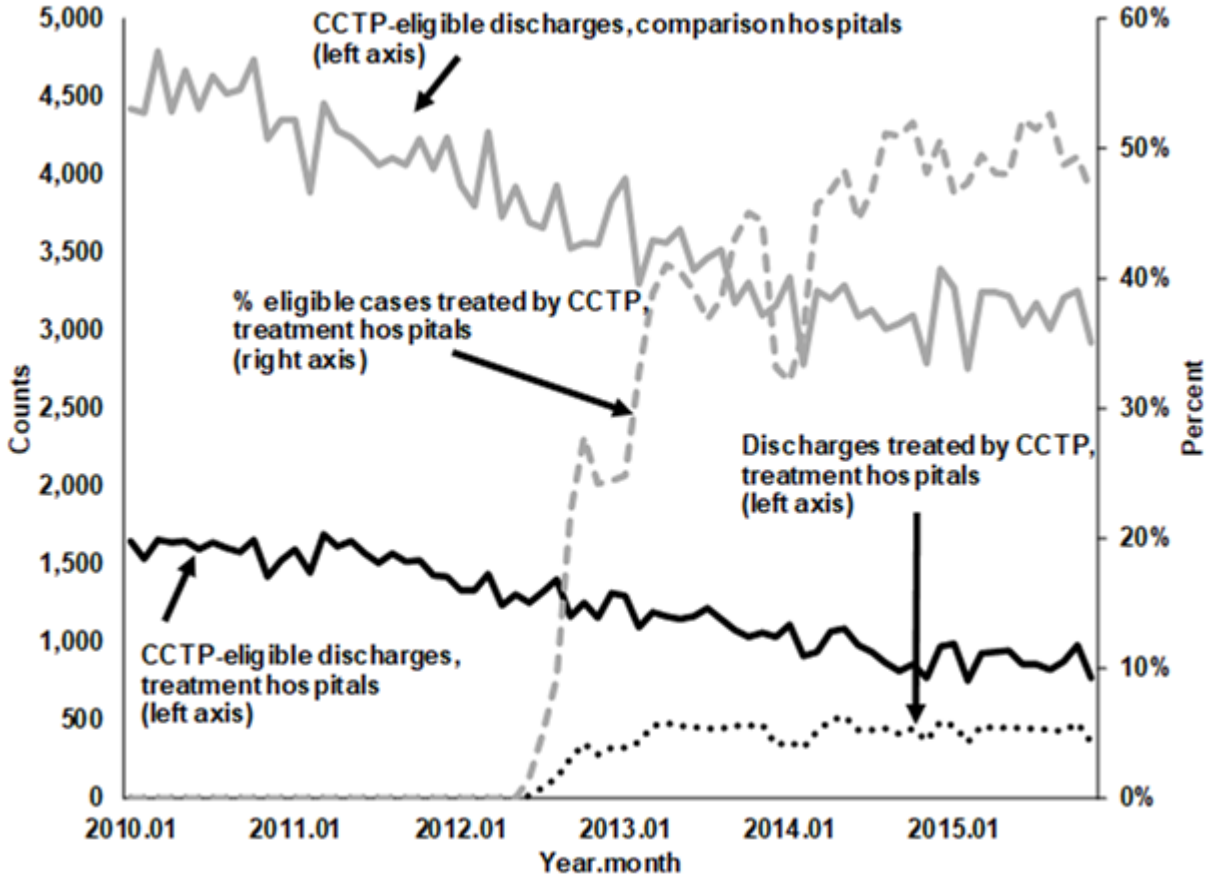

Figure 2
Average Monthly 30-Day Readmission Rate and Differences
CSCTC Programs and Comparison Group Hospitals, January 2010 – November 2015

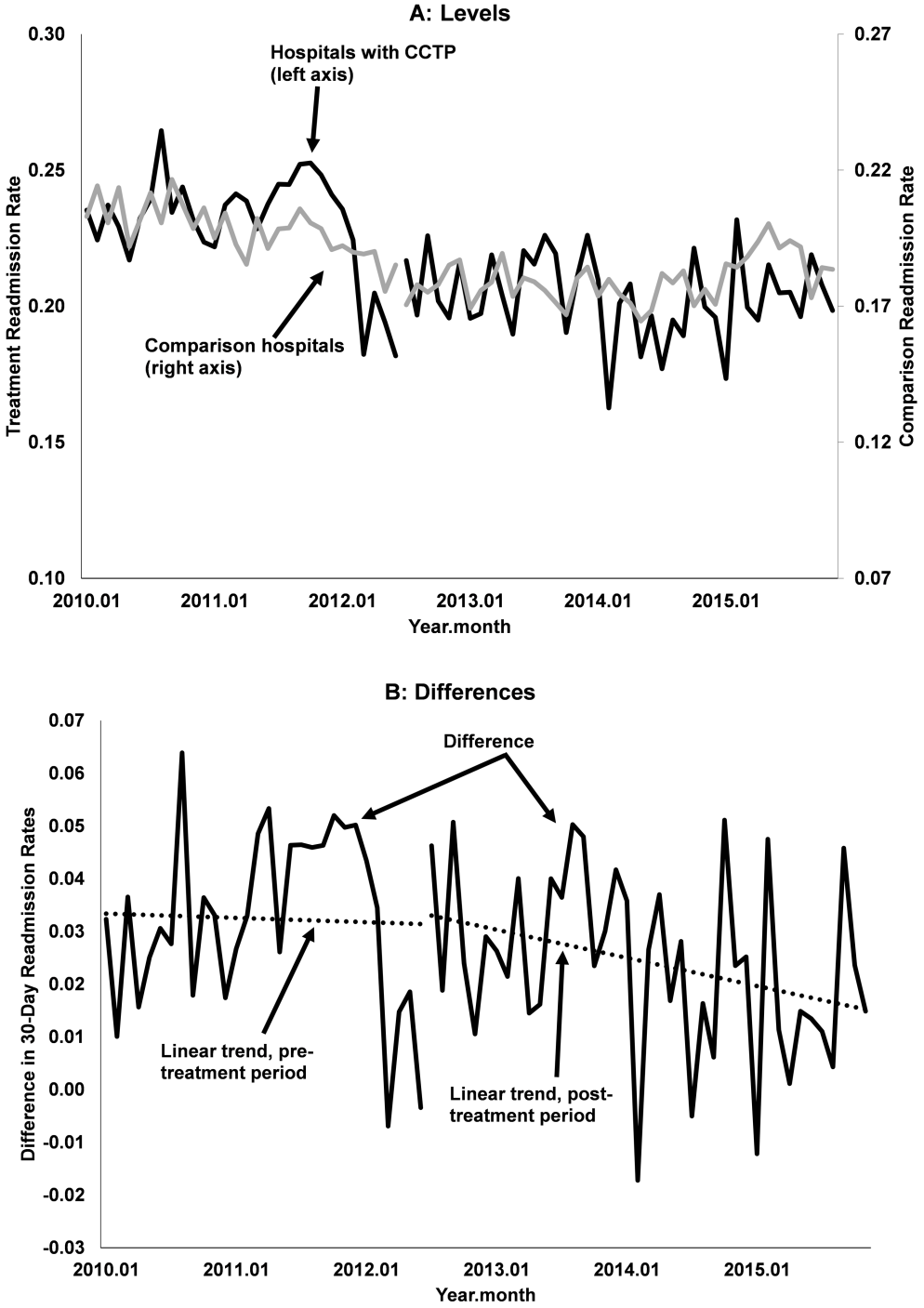

Figure 3
30-Day Readmission Rates in Pre-CSCTC Period by CCI and
Share of Analysis Sample by CCI

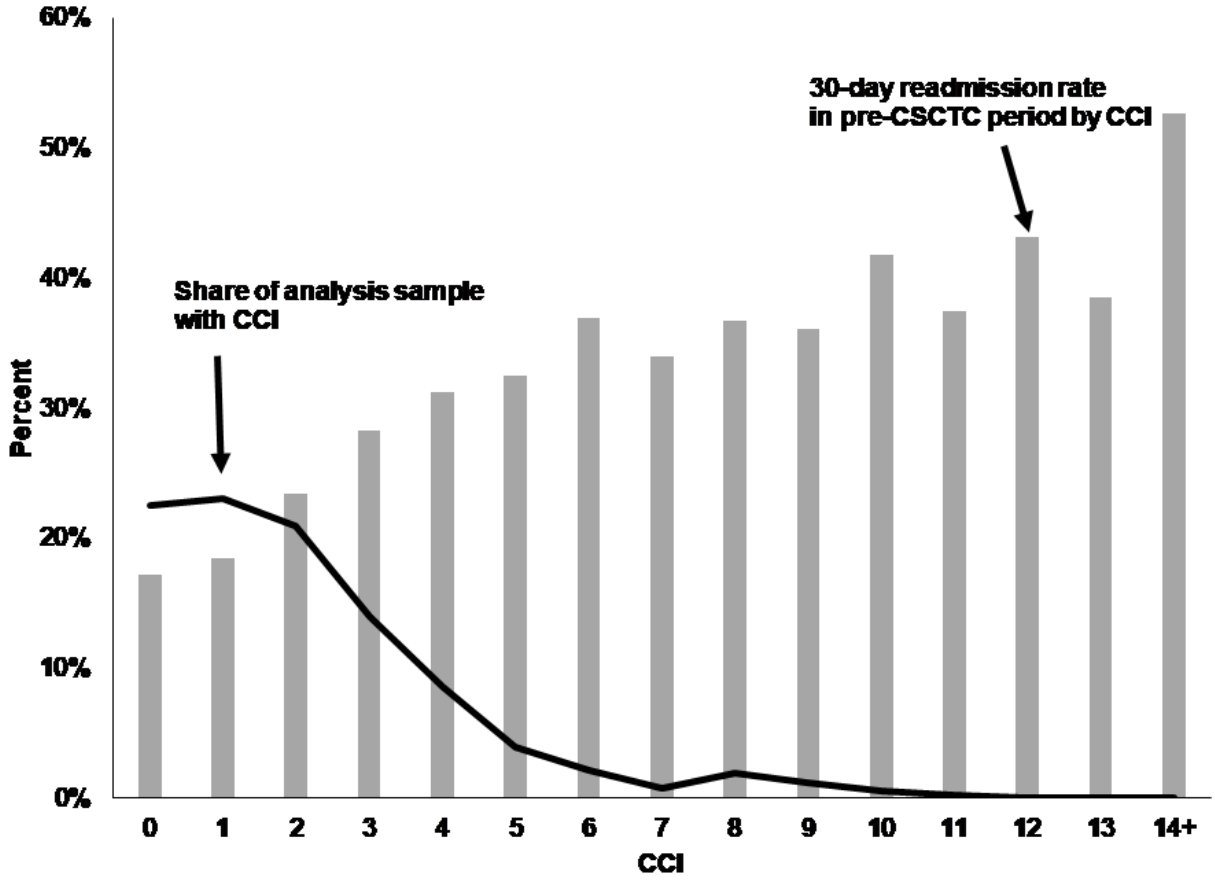

Figure 4
30-Day Readmission Rates in Pre-CSCTC Period by CCI Groupings and
Share of Analysis Sample by CCI Groupings

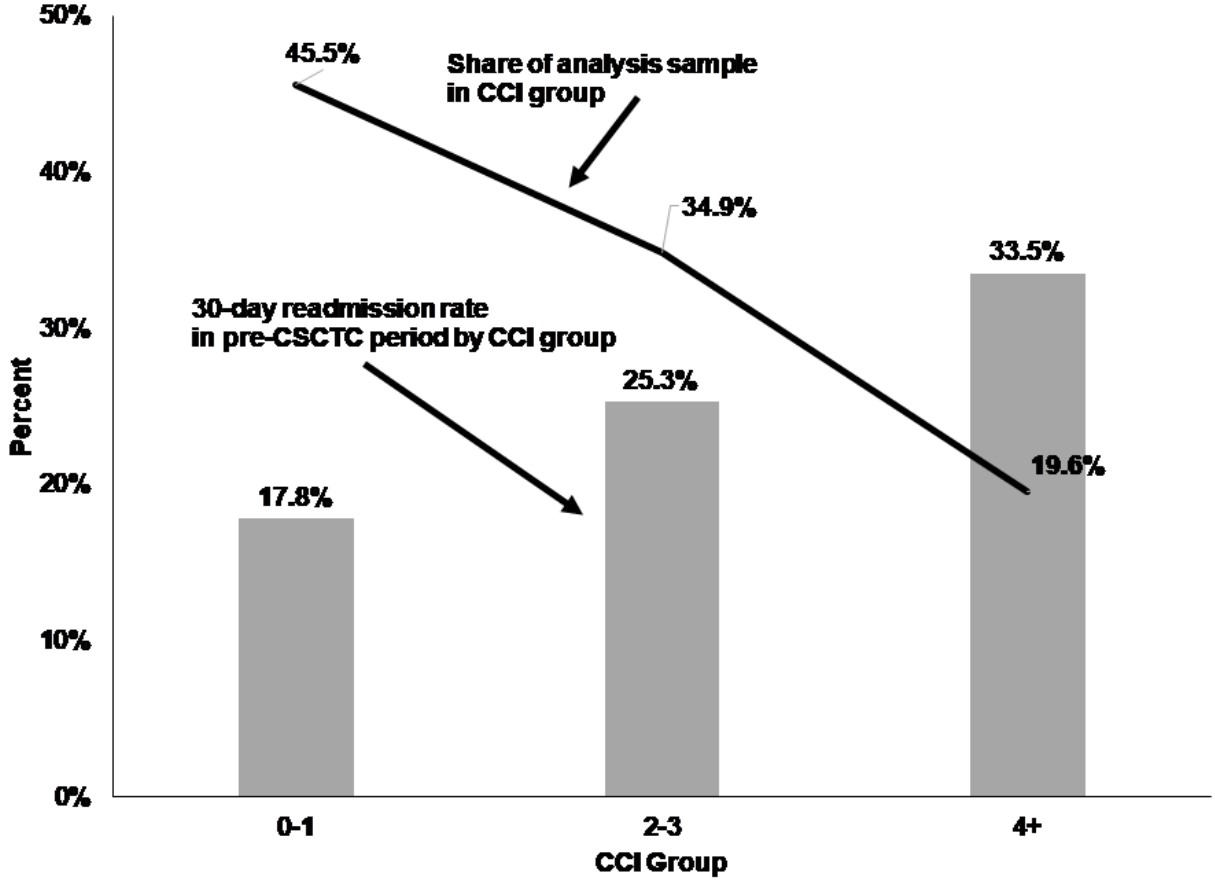

Figure 5
30-Day Readmission Rates, Treatment Hospitals and Synthetic Controls

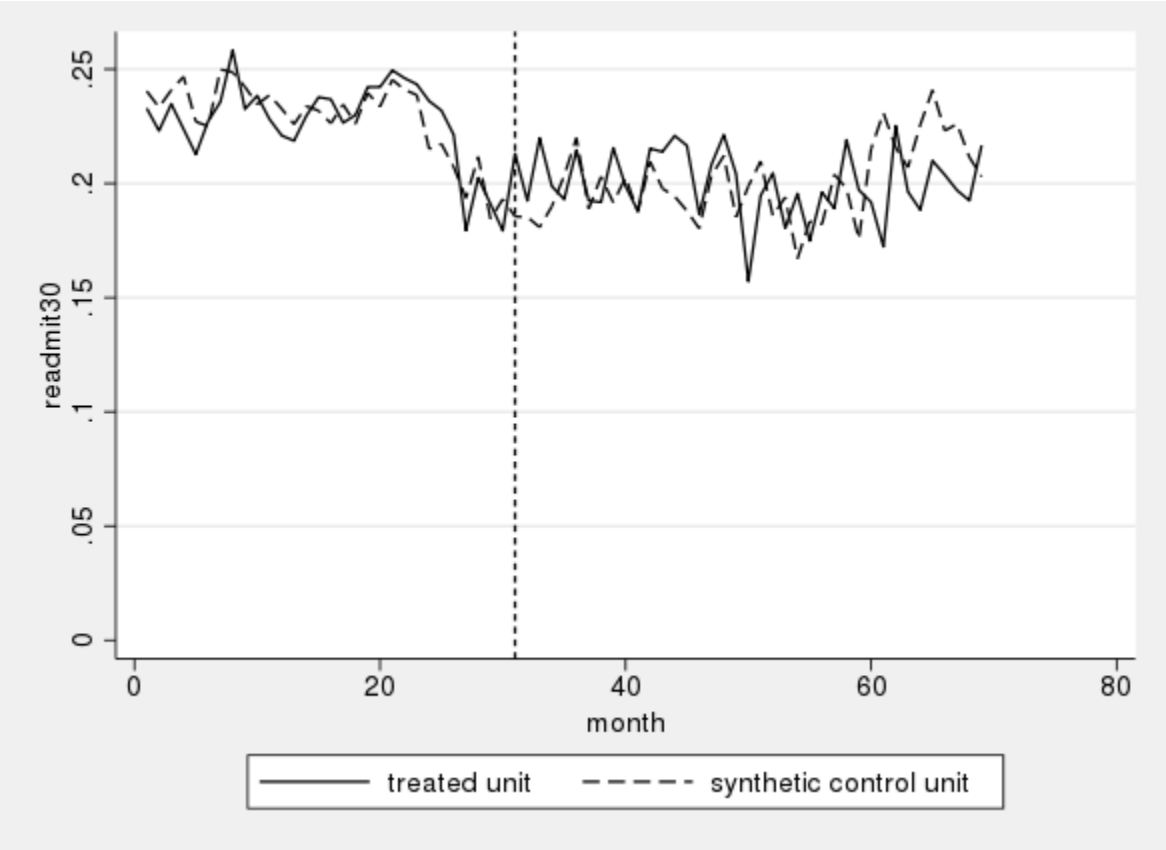

Figure 6
Differences Between in 30-Day Readmission Rates for Treated Hospitals
and Synthetic Controls, Plus Placebo Treatment Effects

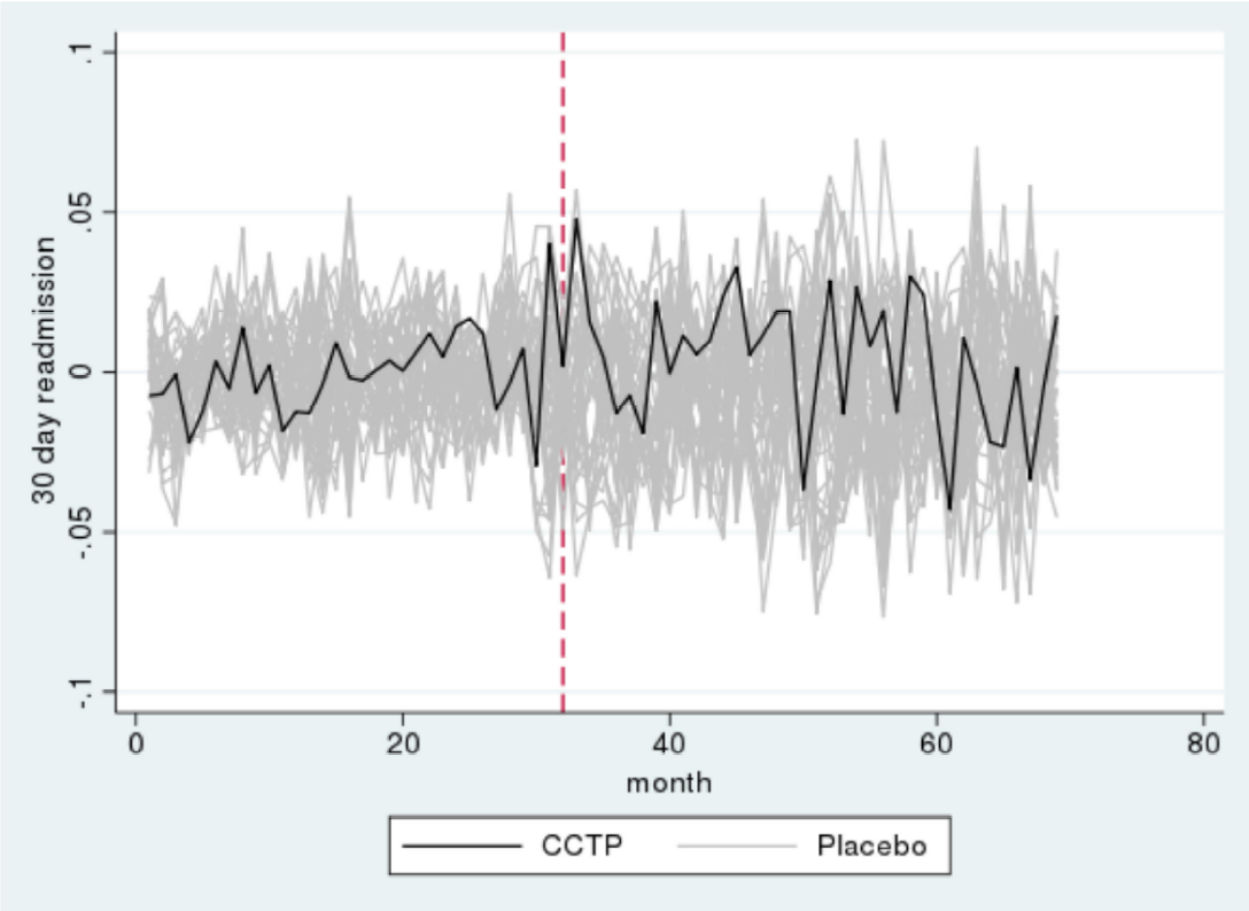

Figure 7
Costs from 30-Day Readmissions, Treatment Hospitals and Synthetic Controls

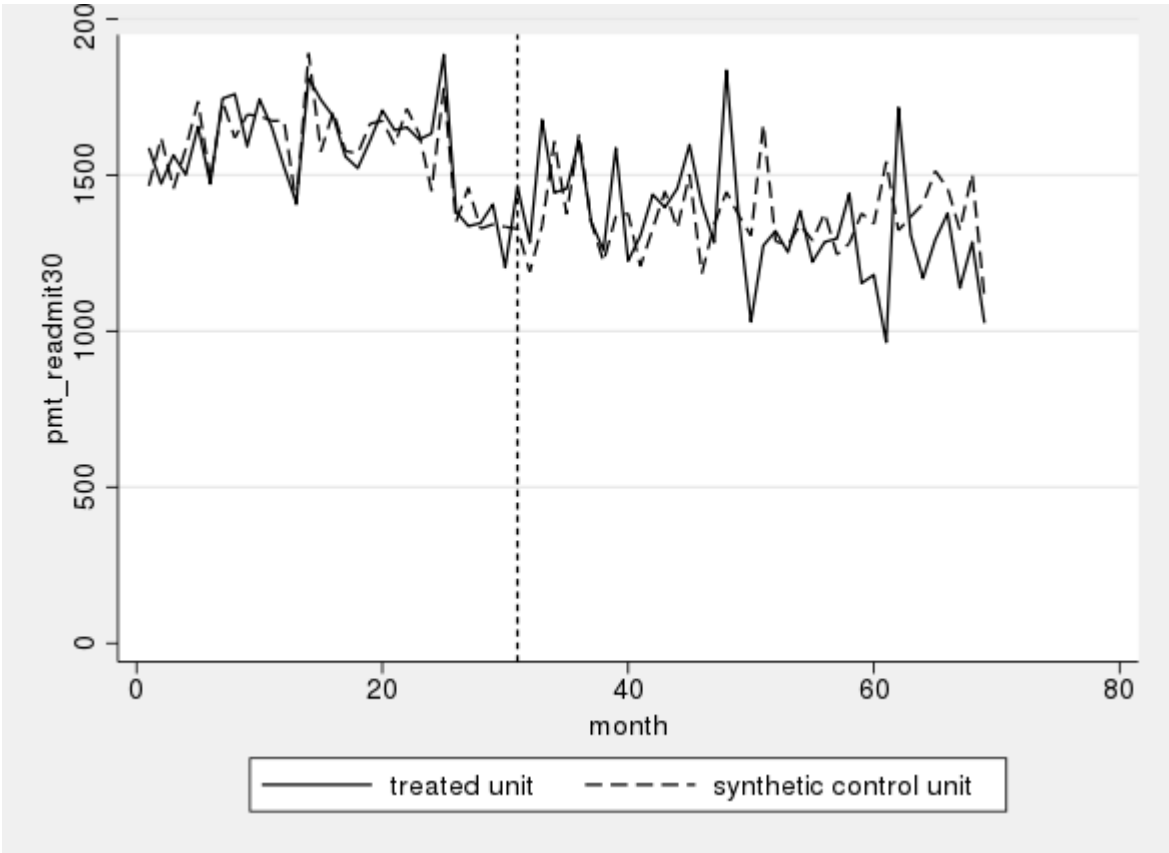

Figure 8
Differences in Costs of 30-Day Readmissions for Treated Hospitals
and Synthetic Controls, Plus Placebo Treatment Effects

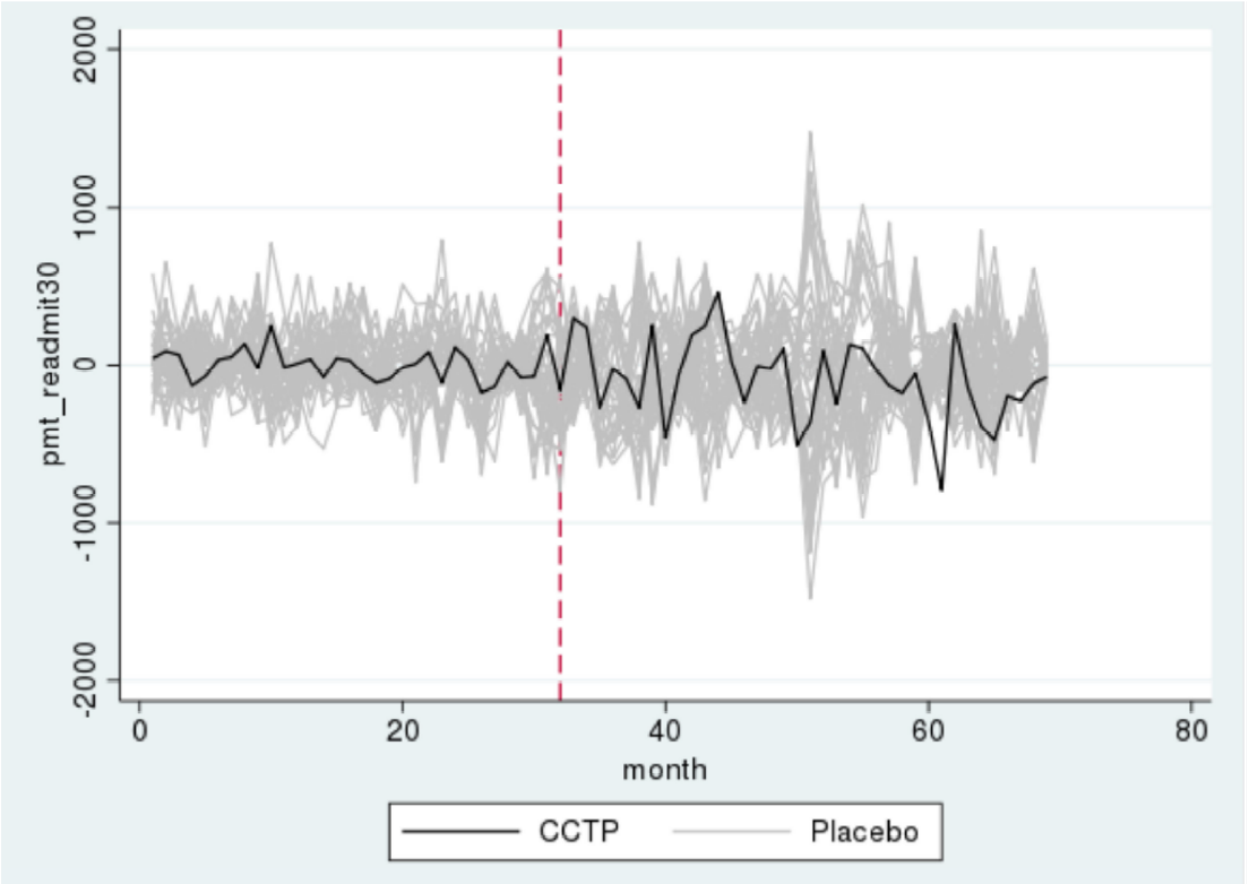

Figure 9
30-Day Readmission Rate in Four Treatment Hospitals,
By CSCTC and non-CSCTC Discharges, Post-CCTP Period

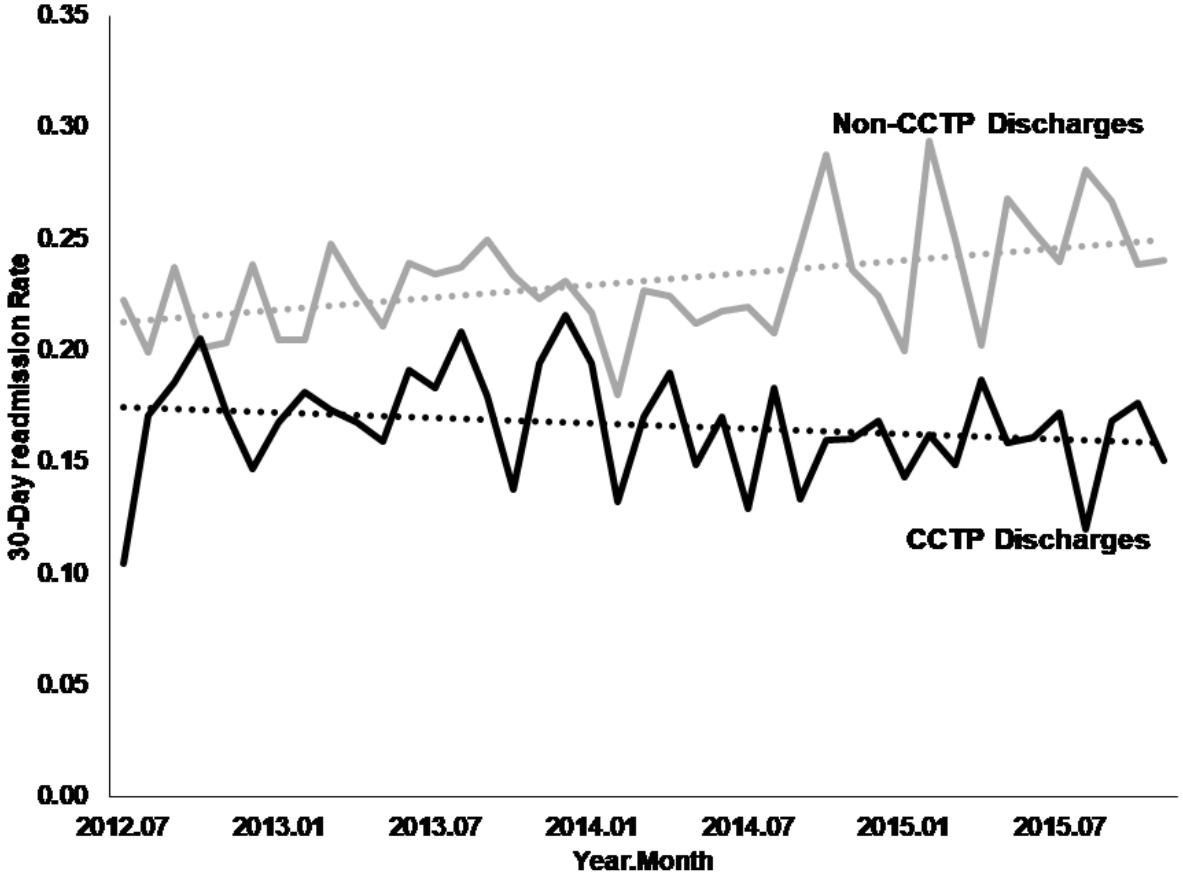

Figure 10
Average Charlson Comorbidity Index in Four Treatment Hospitals,
By CSCTC and non-CSCTC Discharges, Post-CCTP Period

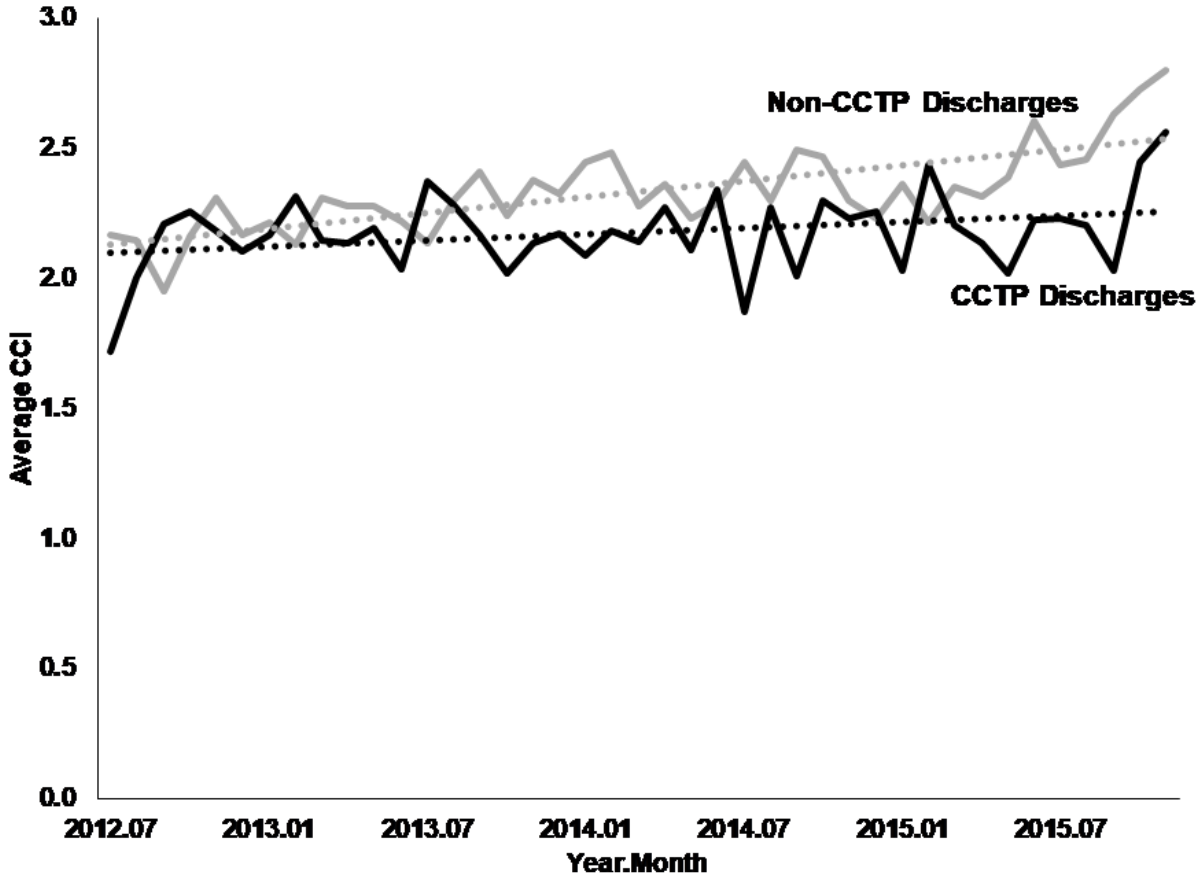

Table 1
Demographic Characteristics of Medicare Recipients in Catchment Area of CSCTC Hospitals, 2011-2015 Five-Year American Community Survey

Variable	CSCTC catchment area	Chicago metro area, not in catchment area	Rest of country in Metro areas, not in catchment area
Average age	71.5	72.1	71.5
% under 65	14.5	11.6	13.7
Average age | age≥65	74.9	74.6	74.7
% female	57.8	56.4	55.9
% black, non-Hispanic	35.3	11.7	10.7
% other race, non-Hispanic	2.9	6.3	5.9
% Hispanic	8.1	9.0	9.4
% married	42.9	51.1	51.1
Average Social Security income ($)	11,254	12,160	11,721
Average family income ($)	56,543	70,960	65,401
% ≤ 100% Federal poverty level	13.5	10.2	11.5
% ≤ 200% Federal poverty level	38.1	30.3	33.0
Sample size	15,066	46,544	1,949,840

Table 2
Descriptive Statistics for Analysis Sample

	Pre-CSCTC Period 1/1/2010-06/30/2012		Post-CSCTC Period 07/01/2012-11/30/2015	
Variable	CSCTC Hospitals	Comparison Hospitals	CSCTC Hospitals	Comparison Hospitals
Avg. age	70.8	72.4	71.4	72.35
	(13.99)	(13.08)	(13.86)	(12.80)
Fraction ≥ 65 years of age	0.761	0.812	0.774	0.814
	(0.426)	(0.39)	(0.418)	(0.388)
Fraction Female	0.580	0.555	0.591	0.548
	(0.494)	(0.497)	(0.492)	(0.498)
Avg. CCI	2.031	1.976	2.254	2.128
	(1.969)	(1.970	(2.037)	(2.027)
Fraction CCI ≤ 2	0.682	0.702	0.633	0.664
	(0.466)	(0.45)	(0.482)	(0.472)
Fraction CCI 3-4	0.229	0.209	0.259	0.232
	(0.420)	(0.407)	(0.438)	(0.422)
Fraction CCI ≥ 5	0.089	0.089	0.108	0.104
	(0.285)	(0.285)	(0.311)	(0.306)
Avg. cost of admission ($)	8,171	8,968	7,906	8,845
	(6,653)	(8,399)	(6,072)	(8,485)
30-day readmission rate	0.232	0.199	0.204	0.179
	(0.422)	(0.399)	(0.403)	(0.384)
Avg. cost of 30-day readmission[a]	1,455	1,265	1,194	1,113
($)	(4,450)	(4,586)	(3,749)	(4,423)
Avg. cost of 30-day readmission	6,280	6,368	5,854	6,206
($),	(7,427)	(8,565)	(6,452)	(8,798)
given a readmission				
Fraction admissions with CSCTC	0	0	0.391	0
			(0.488)	
Observations	45,522	127,443	42,245	132,889

Standard deviations in parentheses.

[a] This value is zero for patients that do not have a 30-day readmission rate.

Table 3
Intention-to-Treat and Treatment-on-Treated Estimates, Impact of CSCTC on Readmissions Rates

	Dependent Variable					
		Readmission rates within:				
Covariate	Enrolled in CSCTC	7-days	14-days	30-days	60-days	90-days
	1st-stage	ITT (Reduced-forms)				
Treat index x	0.01543	-0.00029	-0.00034	-0.00049	-0.00067	-0.00074
CSCTC hospital	(0.00048)	(0.00013)	(0.00013)	(0.00025)	(0.00033)	(0.00035)
	[0.000]	[0.037]	[0.017]	[0.068]	[0.054]	[0.045]
	{0.0000}	{0.0501}	{0.0180}	{0.1001}	{0.0891}	{0.1071}
		TOT (2SLS)				
Enrolled in CSCTC		-0.0192	-0.0229	-0.0328	-0.04403	-0.04791
		(0.00808)	(0.00831)	(0.0159)	(0.01976)	(0.02028)
		[0.017]	[0.006]	[0.039]	[0.026]	[0.018]
		{0.0360}	{0.0160}	{0.0691}	{0.0641}	{0.0891}
Observations		350,099	350,099	350,099	346,408	342,179
Sample mean		0.068	0.118	0.196	0.286	0.346

Standard errors in parentheses. Standard errors are calculated allowing arbitrary correlation in the errors across observations within the same hospital. The numbers in square brackets are p-values from these standard errors, and the numbers in curly brackets are p-values from the wild bootstrap of Cameron et al. (2008). Other covariates in the regression include month x year effects, hospital effects, a dummy for female, dummies for ages in five-year intervals, and a cubic term in the CCI.

Table 4
Intention-to-Treat and Treatment-on-Treated Estimates, Impact of CSCTC on Costs ($) from Readmissions

	Dependent variable: Costs generated from readmissions within:				
Covariate	7-days	14-days	30-days	60-days	90-days
	ITT (Reduced-form)				
Treat index x CSCTC hospital	-2.63	-3.13	-5.48	-8.32	-9.18
	(0.72)	(1.08)	(2.16)	(2.94)	(3.20)
	[0.001]	[0.008]	[0.019]	[0.010]	[0.009]
	{0.0240}	{0.0340}	{0.0741}	{0.0621}	{0.0430}
	TOT (2SLS)				
Enrolled in CSCTC	-173	-207	-364	-539	-580
	(42)	(66)	(133)	(174)	(187)
	[0.000]	[0.002]	[0.006]	[0.002]	[0.002]
	{0.0090}	{0.0230}	{0.0621}	{0.0440}	{0.0280}
Observations	350,099	350,099	350,099	346,408	342,179
Sample mean	405	723	1,223	1,787	2,140
Sample means | a readmission	5,964	6,140	6,233	6,244	6,184

Each regression has 299,768 observations. Standard errors in parentheses. Standard errors are calculated allowing arbitrary correlation in the errors across observations within the same hospital. The numbers in square brackets are p-values from these standard errors, and the numbers in curly brackets are p-values from the wild bootstrap of Cameron et al.(2008). Other covariates in the regression include month x year effects, hospital effects, a dummy for female, dummies for ages in five-year intervals, and a cubic term in the CCI.

Table 5
Heterogeneity in the Treatment-on-Treated Estimates based on CCI,
Impact of CSCTC on Readmissions and Costs of Readmission

	Treatment on Treated (standard error) [p-value]					
	Readmission rates			Costs of readmission ($)		
Covariate	CCI=0,1	CCI=2,3	CCI=4+	CCI=0,1	CCI=2,3	CCI=4+
			30-day			
Enrolled in CSCTC	-0.0337	-0.00947	-0.0809	-254.5	-278.8	-917.6
	(0.0214)	(0.0164)	(0.0246)	(136.7)	(148.2)	(337.4)
	[0.114]	[0.564]	[0.001]	[0.063]	[0.060]	[0.007]
	{0.2873}	{0.6296}	{0.0370}	{0.1622}	{0.1632}	{0.0521}
Mean of dep. var.	0.144	0.215	0.293	740	1,421	2,082
Mean costs | readmission				5,138	6,601	7,093
Sample size	163,718	122,592	63,789	163,718	122,592	63,789
			60-day			
Enrolled in CSCTC	-0.0448	-0.0289	-0.0866	-358.2	-502.3	-1366.8
	(0.0170)	(0.0210)	(0.0331)	(107.3)	(221.7)	(378.9)
	[0.008]	[0.169]	[0.009]	[0.001]	[0.023]	[0.000]
	{0.0220}	{0.2392}	{0.1131}	{0.0170}	{0.1051}	{0.0360}
Mean of dep. var.	0.210	0.315	0.422	1,086	2,072	2,996
Mean costs | readmission				5,166	6,578	7,095
Sample size	163,718	122,592	63,789	163,718	122,592	63,789
			90-day			
Enrolled in CSCTC	-0.0482	-0.0422	-0.0799	-324.9	-548.4	-1571.0
	(0.0147)	(0.0217)	(0.0372)	(115.5)	(244.7)	(419.2)
	[0.001]	[0.052]	[0.032]	[0.005]	[0.025]	[0.000]
	{0.0270}	{0.1632}	{0.1522}	{0.0350}	{0.0801}	{0.0210}
Mean of dep. var.	0.258	0.380	0.498	1,319	2,464	3,525
Mean costs | readmission				5,118	6,486	7,084
Sample size	163,718	122,592	63,789	163,718	122,592	63,789

Standard errors in parentheses. Standard errors are calculated allowing arbitrary correlation in the errors across observations within the same hospital. The numbers in square brackets are p-values from these standard errors, and the numbers in curly brackets are p-values from the wild bootstrap of Cameron et al. (2008). Other covariates in the regression include month x year effects, hospital effects, a dummy for female, dummies for ages in five-year intervals, and dummies for the CCI.

Table 6
Robustness tests for Treatment-on-Treated Estimates,
Impact of CSCTP on 30-day Readmissions and Costs of Readmission

Covariate	Baseline estimates Tables 3 and 4	Delete conditions impacted by HRRP	Use all hospitals in Chicago area as a control group	Remove fatalities within 30 days of discharge	Control for HVBP penalty	Control for dual eligible status	Control for hospital Medicaid discharges
	A. 30-day readmission rates						
Enrolled in CSCTP	-0.0328	-0.0333	-0.0279	-0.0328	-0.0304	-0.0336	-0.0348
	(0.0159)	(0.0154)	(0.0152)	(0.0164)	(0.0136)	(0.0155)	(0.0163)
	[0.039]	[0.030]	[0.066]	[0.046]	[0.025]	[0.030]	[0.033]]
	{0.0691}	{0.0671}		{0.0911}	{0.0561}	{0.0601}	{0.0561}
Sample mean	0.196	0.200	0.201	0.198	0.196	0.196	0.196
	B. Costs ($) of 30-day readmissions						
	-364	-371	-346	-365	-337.1	-365.0	-366.6
	(133)	(134)	(97)	(138)	(107.7)	(131.7)	(137.0)
	[0.006]	[0.006]	[0.000]	0.008	[0.002]	[0.006]	[0.007]
	{0.0621}	{0.0390}		{0.0721}	{0.0621}	{0.0631}	{0.0551}
Sample mean	1,223	1,251	1,462	1,234	1,223	1,224	$1,230
Sample means | a readmission	6,233	6,254	7,260	6,233	6,233	6,238	$6,258
Observations	350,099	296,373	1,254,303	346,900	350,099	348,015	339,217

Standard errors in parentheses. Standard errors are calculated allowing arbitrary correlation in the errors across observations within the same hospital. The numbers in square brackets are p-values from these standard errors, and the numbers in curly brackets are p-values from the wild bootstrap of Cameron et al. (2008). Excluded conditions in model (2) include heart attack, heart failure, and pneumonia, COPD, and hip and knee replacements. In model (3) we do not do the Wild Bootstrap as there are 83 hospitals in the sample. Other covariates in the regression include month x year effects, hospital effects, a dummy for female, dummies for ages in five-year intervals, and a cubic term in the CCI.

Table 7

Heterogeneity in Treatment-on-Treated Estimates,
Impact of CSCTP on 30-day Readmissions and Costs of Readmission

Covariate	White, non-Hispanics	Blacks and Hispanics	Dually eligible	Not Dually Eligible
	A. 30-day readmission rates			
Enrolled in CSCTP	0.0050	-0.0594	-0.0867	-0.0156
	(0.0166)	(0.0201)	(0.0169)	(0.0149)
	[0.765]	[0.008]	[0.000]	[0.302]
	{0.824}	{0.060}	{0.001}	[0.416]
Sample mean	0.182	0.233	0.246	0.179
	B. Costs ($) of 30-Day readmissions			
Enrolled in CSCTP	-126.7	-403.7	-388.2	-347.4
	(150.4)	(190.6)	(235.4)	(153.6)
	[0.409]	[0.046]	[0.113]	[0.034]
	{0.519]	{0.116}	{0.166}	{0.083}
Sample mean	1,084	1,556	1,646	1,080
Sample means | a readmission	5,966	6,692	6,694	6,023
Observations	233,681	102,378	88,659	259,356

Standard errors in parentheses. Standard errors are calculated allowing arbitrary correlation in the errors across observations within the same hospital. The numbers in square brackets are p-values from these standard errors, and the numbers in curly brackets are p-values from the wild bootstrap of Cameron et al. (2008). Other covariates in the regression include month x year effects, hospital effects, a dummy for female, dummies for ages in five-year intervals, and a cubic term in the CCI.

Table 8
Descriptive Statistics for Post-CCTP Period for CSCTC Hospitals

Variable	Matched to CSCTC Claim	Not matched	t-test (standard error)
Avg. age	73.2	70.2	23.0
	(12.2)	(14.7)	(0.13)
Fraction ≥ 65 years of age	0.83	0.74	20.8
	(0.38)	(0.44)	(0.0040)
Fraction Female	0.61	0.58	4.76
	(0.49)	(0.49)	(0.0049)
Avg. CCI	2.18	2.30	-5.70
	(1.97)	(2.08)	(0.020)
Fraction CCI ≤ 2	0.65	0.62	7.51
	(0.48)	(0.49)	(0.0048)
Fraction CCI 3-4	0.25	0.27	-4.42
	(0.43)	(0.44)	(0.0043)
Fraction CCI ≥ 5	0.098	0.11	-5.48
	(0.30)	(0.32)	(0.0031)
Avg. cost of admission ($)	8,083	7,793	4.85
	(5,861)	(6,200)	(59.8)
30-day readmission rate	0.17	0.23	-15.3
	(0.37)	(0.42)	(0.0039)
Avg. cost of 30-day readmission[a] ($)	938	1,359	-11.7
	(3,331)	(3,986)	(35.9)
Avg. cost of 30-day readmission ($), given a readmission	5,595	5,976	-2.58
	(6,337)	(6,502)	(147.5)
Observations	16,497	25,748	42,245

Standard deviations in parentheses. The t-test is for the null hypothesis that the means are the same across the two samples.

[a] This value is zero for patients that do not have a 30-day readmission rate.

Data Appendix: Matching Algorithm

A list of all patients who obtained CSCTC services was supplied by the transition care provider, CC-Chicago. These data include information about each CSCTC patient's discharge including the patient's gender, birthdate, discharge date, and the hospital where the patient was admitted, but do not contain the Medicare beneficiary identification reported in the Medicare FFS claims database. To match CSCTC enrollees with their corresponding claim in Medicare, we used a progressive algorithm based on discharge characteristics.

First, we created a restrictive match identification string variable that combined several discharge characteristics in a fixed order. This string is a concatenation of patient gender, hospital ID, month of birth, day of birth, year of birth, month of discharge, day of discharge, and year of discharge. Take, for example, a patient discharge record with the following characteristics:

Gender	Female
Hospital ID	1
Month of Birth	05
Day of Birth	16
Year of Birth	1977
Month of Discharge	05
Day of Discharge	21
Year of Discharge	2013

For this patient, the matching algorithm would create an identifier string variable of "F10516197705212013." We construct this variable in both the CSCTC and Medicare claims data and merge the two datasets using the constructed identifier. The match identifier uniquely identifies all CSCTC enrollees and only failed to uniquely identify 94 claims in the Medicare claims data. Duplicate identification observations that are not uniquely identified in the Medicare claims were randomly deleted so that only one observation for each non-unique ID remained Using this ID, we were able to match 15,736 (74 percent) of all CSCTC enrollees.

Given the nature of the data, many CSCTC enrollees may not match to Medicare claims due to keypunch errors in one of the data sets. For instance, the month of birth could be inverted and "01" (January) could become "10" (October), resulting in a non-match between the two datasets. To account for this, in a subsequent rounds of matching, we created match IDs using alternative combinations of discharge characteristics where we omit some characteristics that were most likely to have been affected by keystroke errors. Using these additional matching IDs, we performed eight further rounds of matching where we excluded any patients that been matched in a previous round. For each subsequent round of matching, we used the same strategy as with the matching ID from the first round of matching, but adjusted the matching ID in both datasets to omit certain characteristics from the constructed string concatenation. Later rounds excluded multiple characteristics from the string concatenation that showed higher evidence of keystroke error in earlier rounds. Details for each matching round are provided below.

- Round 1: Matching ID is string concatenation of gender, hospital ID, month of birth, day of birth, year of birth, month of discharge, day of discharge, and year of discharge (all characteristics used). This round matches 15,736 CSCTC patients to Medicare claims.
- Round 2: Matching ID is a string concatenation of hospital ID, month of birth, day of birth, year of birth, month of discharge, day of discharge, and year of discharge (gender is omitted). This round matches 99 CSCTC patients to Medicare claims.
- Round 3: Matching ID is string concatenation of gender, hospital ID, month of birth, day of birth, year of birth, month of discharge, and year of discharge (day of discharge omitted). This round matches 743 CSCTC patients to Medicare claims.
- Round 4: Matching ID is string concatenation of gender, hospital ID, month of birth, year of birth, month of discharge, day of discharge, and year of discharge (day of birth omitted). This round matches 213 CSCTC patients to Medicare claims.

- Round 5: Matching ID is string concatenation of gender, hospital ID, month of birth, day of birth, year of birth, day of discharge, and year of discharge (month of discharge omitted). This round matches 49 CSCTC patients to Medicare claims.
- Round 6: Matching ID is string concatenation of gender, hospital ID, day of birth, year of birth, month of discharge, day of discharge, and year of discharge (month of birth omitted). This round matches 36 CSCTC patients to Medicare claims.
- Round 7: Matching ID is string concatenation of gender, month of birth, day of birth, year of birth, month of discharge, day of discharge, and year of discharge (hospital ID omitted). This round matches 22 CSCTC patients to Medicare claims.
- Round 8: Matching ID is string concatenation of gender, hospital ID, month of birth, year of birth, month of discharge, and year of discharge (day of birth and day of discharge omitted). This round matches 549 CSCTC patients to Medicare claims.
- Round 9: Matching ID is string concatenation of hospital ID, month of birth, year of birth, month of discharge, and year of discharge (gender, day of birth, and day of discharge omitted). This round matches 549 CSCTC patients to Medicare claims.

At the end of 9 matching rounds, we successfully matched 82.7 percent of the CSCTC enrollees to Medicare claims information. We experimented with additional rounds of matching where we further excluded characteristics from the string concatenation of the matching ID. This resulted in a greater degree of non-uniqueness in the matching ID and subsequently higher levels of matching error. Given this, we did not match beyond the nine rounds as described above.