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Spillover Theory: Unintended Consequences of Provisions in the Affordable Care Act

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Spillover Theory: Unintended Consequences of Provisions in the Affordable Care Act

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

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To my lovely fiancé:

Nicole

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Contents

Abstract

Objective: To examine spillovers from a federal policy, managed care market, and community perspective.

Data Sources/Study Setting: We studied spillovers from a federal policy and managed care market perspective using the Health Care Utilization Project's (HCUP) State Inpatient Database (SID), American Hospital Association (AHA) data, Interstudy Commercial Managed Care, and Area Health Resource File (AHRF). Medicare Advantage county-level payment schedules originate from CMS. We examined community uninsurance spillovers using 2011-2015 Medical Expenditure Panel Survey (MEPS), the Area Health Resource File (AHRF), and the Small Area Health Insurance Estimator (SAHIE).

Study Design: Ordinary Least Squares (OLS) and difference-in-difference regression analyses were used to examine a federal policy spillover on hospital readmissions. We used OLS and instrumental variable (IV) estimation to examined Medicare Advantage (MA) spillovers on Medicare fee-for-service (FFS) hospital readmissions. We used logistic regression to examine community uninsurance spillovers on the privately insured.

Principal Findings: After the HRRP, Medicare FFS saw a decrease in 30-day preventable condition- and all-cause readmissions. Medicare Advantage saw a positive spillover after the HRRP. MA market penetration has no effect on Medicare FFS hospital readmissions. High community uninsurance rates are associated with less access to behavioral health related outpatient/office-based and prescription utilization.

Conclusions: HRRP had a positive spillover on MA hospital all-cause readmissions. MA market penetration has no effect on Medicare FFS readmissions. High levels of community uninsurance are associated with poorer access to outpatient/office-based and prescription behavioral related services.

Chapter 1: Introduction

Overview and Structure of the Dissertation

SPILLOVER THEORY: UNINTENDED CONSEQUENCES OF PROVISIONS IN THE AFFORDABLE CARE ACT

By Robert Tyler Braun, Ph.D., M.S.

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

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This dissertation is comprised of three empirical papers surrounding one essential theme: spillovers. The three papers examined spillovers from three different perspectives: spillovers within hospitals, managed care spillovers, and spillovers on the community level. The main databases used in these papers are: (a) State Inpatient Databases (SIDs) from the Health Care Utilization Project (HCUP) and (b) the Medical Expenditure Panel Survey (MEPS) data. The SID contains detailed information on the diagnoses and conditions associated with the treatment of patients in a given hospital. The SID tracks the primary source of payment and basic demographic information. The MEPS is the most comprehensive source of nationally representative data on individual health care utilization, expenditures, and insurance coverage of the U.S. non-institutionalized population. The variables of interests in this dissertation include topics on quality of care outcomes such as 30-day preventable readmissions, access to behavioral health services, and other relevant ideas.

The first paper (Chapter 2) examines analytically and conceptually how the Hospital Readmissions Reduction Program (HRRP) may pressure not only how hospitals reduce readmissions for its intended population (Medicare fee-for-service), but also beneficiaries who have Medicare Advantage or private insurance. Conceptually, the HRRP creates an economic incentive for hospitals to reduce Medicare fee-for-service 30-day preventable readmissions or be fined if they do not meet standard benchmarks. As a result, hospitals must react to the HRRP by organizing and changing practice behaviors to reduce preventable readmissions. Under the assumption that hospitals and providers are unlikely to know a patient's payer status when he/she enters the hospital for a readmission, all patients receive the same care regardless of insurance status. As a result, adjustments in provider behavior to reduce Medicare fee-for-service readmissions will also be experienced by Medicare Advantage and privately insured plan holders. This is known as a spillover. Analytically, we examined this by isolating the HRRP on Medicare fee-for-service, Medicare Advantage, and privately insured preventable 30-day condition specific and all-cause readmissions.

The second paper presents (Chapter 3) data on spillovers from a managed care market perspective. We studied how Medicare Advantage penetration affected quality of care for Medicare fee-for-service and Medicare Advantage patients. We used 30-day preventable condition specific and all-cause readmissions to gauge whether Medicare fee-for-service and Medicare Advantage hospital quality of care varied by Medicare Advantage penetration. Conceptually, when managed care is the dominant insurance at a hospital or provider's practice, the more influence it has on provider practice patterns. Since managed care selectively contracts, leverages a large integrated and coordinated network, and uses rigorous forms of utilization review to reduce utilization and costs, the expectation of fewer readmissions and higher quality of care for Medicare Advantage patients seems reasonable. Furthermore, greater Medicare Advantage penetration may also change the quality of care for Medicare fee-for-service patients because of managed care influence over provider practice patterns. Like previous studies, we isolated exogenous increases in Medicare Advantage enrollment and traced the effects of greater managed care penetration on hospital quality of care by using Center for Medicare and Medicaid Service (CMS) county-level Medicare Advantage payment schedule as an instrumental variable for Medicare Advantage penetration rates. We examined this instrumental variable and its association with preventable 30-day condition specific and all-cause readmissions.

Paper 3 (Chapter 4) examines spillovers from a community perspective. The objective of this paper was to investigate the effect of community uninsurance rates on access to behavioral health services for individuals with continuous employer-sponsored insurance. Spillover effects associated with community uninsured rates have been a major concern in the U.S. since the early 2000's. Conceptually, over the long-term, high-uninsured rates could negatively affect access to care for both the insured and uninsured due to the lack of community resources available to build provider capacity and thus increase health care access. Analytically, we examined adults with continuous employer-sponsored insurance who had mental health problems and we examined how greater community-level uninsured rates affected their access to behavioral health services. Behavioral health services are defined by whether a person had (1) a mental health related emergency department or inpatient encounter, (2) mental health related outpatient or office-based encounter, or (3) was prescribed a medication for a mental health related issue.

Contribution

The first paper contributes to present spillover literature by creating a formal spillover conceptual framework that does not exist in the current literature. This framework can be used for the HRRP policy and it applies to other studies examining the influence of federal and state policies on certain populations. Furthermore, this is the first study to examine spillovers of the HRRP by exclusively separating Medicare Advantage and private payers. Additionally, to our knowledge at this time, this study leverages data from more states than any other study examining the spillovers of the HRRP. Our results indicate similar conclusions as another study, but finds that hospitals may not be targeting condition-specific readmissions and individual payers, but instead are adjusting practice patterns to reduce all readmissions, regardless of payer status.

The second paper follows the analytical strategies and conceptual frameworks of several other studies. However, this paper contributes to the conceptual framework of how Medicare Advantage penetration may influence Medicare fee-for-service quality of care as it pertains to readmissions. Like similar studies, we find no evidence of Medicare Advantage penetration spillover on Medicare fee-for-service preventable readmission outcomes. In contrast to other studies, we find that Medicare Advantage penetration has little to no effect on Medicare Advantage readmissions. To our knowledge, we assert, regardless of the analytical approach used (ordinary least squares or instrumental variable estimation), that Medicare Advantage penetration has no affect on Medicare fee-for-service and Medicare Advantage preventable readmissions.

Lastly, the third paper contributes to community-level spillover research in several ways. This paper is the first known to examine the association of community-level uninsured rates and behavioral health access. Secondly, using a report from the Institute of Medicine in 2003 as the foundation of our conceptual framework, we attempt to reconcile why other community-level spillover studies have different results. We concluded that community-level spillover analyses should be thought of in one of two ways: the long-term or short-term. The conceptual framework in this paper attempts to distinguish the two perspectives by explaining that short-term expansions may generate negative spillovers, while long-term effects may lead to positive spillovers. Short-term increases in community uninsurance could lead to temporary decreases in access to care for those who were already insured, as the health system did not have time to meet increased demand. These negative spillovers will eventually dissipate over the long-term, as higher coverage rates of insurance increase community resources and help build provider capacity. Our analytical strategy attempted to look at spillovers over the long-term by using county-level and year fixed effects to look at community uninsurance rates and behavioral health access over the course of time. We found that high levels of community uninsurance—as compared to low levels of community uninsurance was associated with a lower probability of outpatient or office-based mental health related visits, and a lower probability of mental health related prescription utilization.

Chapter 2: The Medicare Hospital Readmissions Reduction Program: Spillovers Into the Private Insurance Market

Abstract

Objective: To explore spillover effects of the Hospital Readmissions Reduction Program (HRRP) on hospital Medicare Advantage and privately insured beneficiaries.

Data Sources/Study Setting: Health Care Utilization Project's (HCUP) State Inpatient Database (SID) administrative claims data to calculate condition-specific thirty-day preventable readmissions. American Hospital Association (AHA) data, Interstudy Commercial Managed Care, and Area Health Resource File (AHRF) were used to determine hospital, managed care, and county-level characteristics.

Study Design: Ordinary Least Squares and difference-in-difference regression analyses were used to estimate the effect of the HRRP on Medicare and the spillover effect on Medicare Advantage and private insurance condition-specific and all-cause thirty-day preventable readmissions. Findings were compared across payer type.

Principal Findings: Overall, hospitals experienced a significant 1.73% and 3.11% decrease in Medicare congestive heart failure (CHF) and pneumonia (PN) thirty-day preventable readmissions compared to the privately insured after the HRRP, respectively. There were no differences between Medicare FFS and Medicare Advantage for condition-specific targeted readmissions. Hospitals displayed a 1% decrease in Medicare FFS and Medicare Advantage all-cause readmissions after the HRRP, suggesting a positive spillover. There was no spillover for private insurance.

Conclusions: In general, the HRRP may have created a positive spillover for Medicare Advantage and hospitals may be reducing readmissions through a comprehensive approach.

Introduction

Preventing avoidable readmissions on Medicare represents an opportunity to improve patient quality of care and outcomes, and bends the medical cost curve (Jencks, Williams, and Coleman 2009; Medpac Commission 2007). Under the Affordable Care Act (ACA), the U.S. Congress developed new financial incentives and penalties to increase health care system performance. Medicare's Hospital Readmission Reduction Program (HRRP) designates the reduction of avoidable readmissions as a target for health care cost savings and authorizes the Center for Medicare and Medicaid Services (CMS) to lower payments to hospitals with high risk-standardized rates of 30-day readmissions. The U.S. Congress implemented this policy as a response to control the costs associated with Medicare readmissions. Hospitals could be penalized up to 2% in the first year of the policy and 3% in the second and subsequent years by CMS withholding Medicare inpatient payments. Penalty readmission thresholds are calculated by retrospectively examining a hospital's past three years of readmission claims data prior to HRRP. Penalties vary by hospital and are executed relative to staying under the expected calculated threshold. Hospitals that exceed the threshold are penalized by a reduction in payments across all Medicare admissions, not just those that resulted in readmissions. The HRRP started penalizing hospitals for excess preventable readmission for Congestive Heart Failure (CHF), Pneumonia (PN), and Acute Myocardial Infarction (AMI) in October of 2012. Targeted readmission conditions were expanded in 2015 to include chronic obstructive pulmonary disease (COPD) and total knee and hip replacement. According to one study, in the third year of the HRRP, 78% of hospitals were penalized for excess readmissions, totaling $428 million (Boccuti and Casillas 2015).

Recent studies found reductions in Medicare readmission rates during the HRRP implementation period for targeted conditions (Demiralp, He, and Koenig 2017; Zuckerman et al. 2016; Carey and Lin 2015; Barrett et al. 2015). A study conducted by Desai et al. (2016) found hospitals penalized by the HRRP had greater reductions in targeted readmissions than those not penalized. Another study found hospitals that were poorest performing pre-HRRP had the greatest reduction of HRRP related readmissions (Wasfy et al. 2016).

Other recent studies examined the relationship between the HRRP and spillovers through investigation of nontargeted conditions, hospital length of stay, and its effects on payers other than Medicare fee-for-service (Carey and Lin 2015; Zuckerman et al. 2016; Mellor, Daly, and Smith 2017; Demiralp, He, and Koenig 2017; Desai et al. 2016). Carey and Lin (2015) found an estimated 1-percentage point decrease in nontargeted readmissions for the state of New York. Furthermore, Zuckerman and authors (2016) reported a 2-percentage-point reduction from a nationwide sample in nontargeted conditions after the HRRP implementation. Demirlap, He, and Koeing (2017) reported that hospitals in California and Florida with the largest reductions in targeted Medicare readmissions experienced higher reductions in nontargeted Medicare readmissions and the HRRP had no spillover on non-Medicare patients. Mellor, Daly, and Smith (2016) found no changes in AMI-related length of stays for hospitals in Virginia after the HRRP. Desai et al. (2016) found decreases in nontargeted readmissions by variation in hospital performance. While these findings suggest mixed evidence of spillovers associated with the HRRP, more research is needed to better understand the extent of such spillovers and the full effects of the HRRP.

This study contributes to prior literature on the effects of HRRP in several ways. First, while prior literature investigated the effect of HRRP on the non-Medicare population in one or two states, this study used claims data from five different states located in different regions of the U.S. in an attempt to make findings more generalizable. Second, other studies failed to disentangle HRRP's spillover by type of insurance; this work examined readmission changes in Medicare FFS, private payers, and Medicare Advantage separately, and then jointly tested the effects of the HRRP between these payers. Fourth, we presented a formal conceptual framework, which offered a foundation for considering the design features of the HRRP, as well as factors that influenced how hospitals responded to incentives and whether the HRRP was successful in reaching its stated goals. The framework can also be used to guide discussions about the design and implementation of existing spillover research and those in development and to define a structured agenda for evaluating spillover theory, with the explicit goal of developing knowledge to improve the understanding of spillovers in health care delivery.

Conceptual Framework

This formal spillover conceptual framework for this study revolved around several key assumptions—incentive (i.e., revenue potential of the HRRP penalty, improving quality of care), predisposing (i.e., hospital characteristics), and enabling factors (i.e., patient factors) that drove the incentive by medical providers to improve patient quality of care (Dudley et al. 1998; Frølich et al. 2007; Dranove and White 1998; Dranove et al. 2003). Not only were these factors associated with direct patient outcomes, they could contribute to spillovers as well. In past studies, researchers examined how policy actions designed to affect one payer type unintentionally affected other payer types (i.e., spillover effects). However, there is a shortage of evidence as to how federal government financial pressures and payment reductions in relation to readmissions spill over into several insurance markets.

Spillovers can be either positive or negative. Moreover, there could be no spillover at all. A positive spillover indicates that the HRRP induces hospitals to respond by adjusting quality of care (readmissions) not only for Medicare patients but also for other (private or Medicare Advantage) payer markets. To the extent that hospitals do not differentiate care between patients, all types of payers should see a similar reduction in readmissions and increase in quality of care. In the context of HRRP, a positive spillover indicates that hospitals respond by adjusting care for Medicare and to some degree for other payer markets. If the HRRP creates a positive spillover, then based on the aforementioned example and previous research findings, both types of payers should have a lower risk of readmission after the HRRP.

In contrast, a negative spillover is a possible outcome. This takes place when hospitals differentiate patients by payer and provide different levels of care or focus only on improving areas of care that by measure and incentive of the HRRP, while ignoring a subsample of necessary services and patients. This results in variations in quality of care across patients in the same hospital due to time and resource constraints and profitability of a patient. If a negative spillover takes place, a hospital can divert resources originally in use by one payer and redirect them to another payer (Dranove and White 1998). In this example, assuming hospitals have a fixed budget, more time and resources are shifted away from private payers or Medicare Advantage and allocated to Medicare FFS for increased discharge planning, patient education, and follow-ups to care, which would result in a lower quality of care to private payers or Medicare Advantage and a higher risk of readmission. This suggests that hospitals with the largest reductions in Medicare readmissions would have smaller or no reductions in privately insured readmissions. However, evidence of this negative resource and effort allocation spillover is mixed (Demiralp, He, and Koenig 2017; Carey and Lin 2015).

The overarching theme to the conceptual framework in Figure 1 is that the HRRP financial incentives of the policy/penalty or other factors drive hospitals to reduce readmissions. Since hospitals must respond to the HRRP by reforming care structures or processes to reduce Medicare readmissions, privately insured or Medicare Advantage patients may experience the same improvement in preventable readmissions. If the quality of care a Medicare FFS, privately insured, and Medicare Advantage patient receives is the same, there should be no statistical difference in the rate change between Medicare, privately insured, and Medicare Advantage preventable readmissions (Dranove and White 1998). The identification strategy assumes that financial penalties of the HRRP, which are based on readmissions (quality performance) for Medicare patients only, are reflected in quality of care received by all patients. This is a reasonable assumption because many, if not all, hospitals' responses to the HRRP financial penalties likely require improvements that affect all patients; it is probably not feasible for hospitals to specifically target Medicare FFS patients for quality improvement activities (medical staff are unlikely aware of payer status). Even if targeting were possible, it would be considered dangerous to patients and highly unethical. Therefore, resources are unlikely to shift away from private payers and care related to readmissions resembles a public good (Ryan and Blustein 2011; Dranove and White 1998; Chen et al. 2010). We expected that due to the HRRP, hospitals and providers would change practice behavior to reduce readmissions, and that they did not discriminate by payer status. Therefore, we hypothesized:

H1: Medicare FFS will see a decrease in condition-specific and all-cause readmissions after the HRRP.

H2: Medicare Advantage will see a decrease in condition-specific and all-cause readmissions after the HRRP

H3: Private payers will see a decrease in condition-specific and all-cause readmissions after the HRRP.

Methods

Data Source and Sample Population Overview

The primary data used in the analyses came from the Health Care Utilization Project's State Inpatient Databases (HCUP). The databases contain detailed information on the diagnoses and conditions associated with index admissions/readmissions; the treatments received for the universe of patients in a given state; primary source of payment; and basic demographic information such as age, gender, and race/ethnicity. The analyses were limited to the following states for the years 2009–2013: California, Florida, Iowa, Massachusetts, and New York because they differentiated between Medicare fee-for-service and other types of insurance payment. The study sample consisted of all urban general hospitals that operated between 2009 and 2013.

To measure the capacity and availability of medical and hospital resources, we derived the county-level commercial managed care penetration rates from the Interstudy managed care enrollment dataset. County-level household income, and the percentage insured came from the Area Health Resource File (AHRF). We used the American Hospital Association (AHA) annual surveys to measure hospital characteristics and to calculate hospital competition.

We excluded the year 2011 from the analytical sample, as it coincided with the implementation of various components of the ACA and the anticipation of HRRP. Omitting 2011 allowed observation of the full effects of the HRRP—specifically, any partial responses after the ACA passage but before the penalties went into full effect (Mellor, Daly, and Smith 2017). We then selected hospital discharges: Medicare FFS and Advantage patients 65 years or older, and privately insured patients between the ages of 45 and 64. We followed details in the construction of readmission rates found in the technical reports prepared by CMS (CMS 2014). Furthermore, individuals who died during admission, dual-eligible Medicare patients, and those who had a planned readmission were excluded. We also excluded hospitals that had fewer than 30 discharges (Chen et al. 2010).

Outcome: Targeted Readmissions

Dependent variables are presented in rates. There were fifteen outcome variables (three for each type of readmission): CHF, PN, and AMI Medicare FFS readmission rates; CHF, PN, and AMI Medicare Advantage readmission rates; CHF, PN, and AMI private preventable readmission rates; and the difference between the Medicare and private preventable readmission rates. The difference in the preventable readmission rate was between Medicare and Medicare Advantage or private payer patients. A preventable readmission was considered a 30-day preventable readmission for individuals hospitalized at a short-stay acute care hospital and experienced an unplanned readmission for CHF, PN, or AMI to an acute care hospital within 30 days of discharge. A CHF, PN, and AMI readmission was consistent with a set of technical reports prepared by CMS (see Appendix 3 for list of ICD-9 codes; CMS 2011). To calculate the readmission rate for each condition, the numerator was the number of individuals with 30-day readmissions for that condition (based on ICD-9 codes), while the denominator was the total number of admissions for the same condition.

Outcome: All-Cause Readmissions

As HRRP expanded to include more conditions, more readmission outcome measures were incorporated into the penalty. These readmissions range from surgical readmissions for elective hip/knee replacements to COPD and coronary artery bypass graft surgery. Proactively, hospitals may have attempted to reduce HRRP readmissions and nontargeted readmissions in a one-size-fits-all type of practice, anticipating that CMS might add multiple measures in the future. Moreover, hospitals may have attempted to reduce all-cause readmissions simply because it improved their overall processes and quality of care. We calculated the 30-day all-cause readmissions rate based on the CMS technical report (CMS 2014). There were five outcome variables. The first three measured the all-cause readmission rate for Medicare FFS, Medicare Advantage, and private payers separately. The other two outcomes were the difference between Medicare FFS and Medicare Advantage; and Medicare FFS and private payers.

Independent Variable

HRRP is the year fixed effect. A binary variable signified as HRRP marked the years after 2012–2013 as a value of 1 (reference), indicating the time of implementation.[3] The value 0 was for all other years prior to 2012. As Bertrand, Duflo, and Mullainathan (2004) recommended, years were collapsed into pre and post periods to produce consistent standard errors.

Controls: Client and Hospital Characteristics

We included Herfindahl-Hirschman Index (HHI) for hospital market concentration as a control. The HHI is a measure of how evenly hospital share is distributed across hospitals in the market. Herfindahl-Hirschman Index values range from 0 to 10,000; an HHI closer to zero indicates a more competitive market, and an HHI closer to 10,000 indicates a less competitive market. An HHI index below 1,000 generally indicates a highly competitive market; an HHI between 1,000 and 1,500 indicates an unconcentrated market; a score between 1,500 and 2,500 indicates moderate concentration; and a value above 2,500 indicates a highly concentrated (uncompetitive) market. We categorized this variable as a dummy variable for hospitals above or below median HHI.

We also controlled for commercial managed care penetration. We relied on data from Interstudy to determine county-level private managed care organization penetration. Commercial managed care organization penetration was defined as the number of commercial enrollees (Medicare Advantage and private) in a given county divided by the county's total population. We then categorized commercial managed care organization penetration into quartiles (high, above-average, average, and low penetration).

We also controlled for hospital structural components, such as the type of health system governing a hospital (Bazzoli et al. 1999). We categorized health systems as centralized, moderately centralized, decentralized, and independent hospitals. We also included a hospital's nurse-to-bed ratio, size of the hospital, primary care and specialty physician supply, number of full-time nurses, and ownership. Moreover, we controlled for several patient characteristics that included county-level median household income, percent insured, and percent insured in Medicare.

Analytic Strategy

We used ordinary least squares (OLS) to model the predicted average of being readmitted within thirty days of discharge from an index admission for Medicare FFS, Medicare Advantage, and the privately insured. We also used a modified difference-in-difference regression model to test whether the effect of the HRRP was the same between Medicare, Medicare Advantage, and private readmissions. Our unit of analysis was hospitals. We first estimated the average change in readmissions after the HRRP using the baseline specification given in equations (1, 2). We estimated the baseline model separately for condition-specific and all-cause cohorts in Medicare and privately insured populations.

(1, 2, 3) $Readmit^{k}_{it} = \beta_0 + \beta_1 HRRP_{it} + \beta_2^{k} X_{it} + \Upsilon^{k}_{i} + \varepsilon^{k}_{it}$

Within the regression equation, $Readmit^k_{it}$ signified the rate of preventable readmissions for Medicare FFS (1), Medicare Advantage (2), or privately (3) insured patients for readmission *k* at hospital *i* in time period *t*. Models 1, 2, and 3 determined the effects of HRRP on the payers individually. $HRRP_{it}$ is a dummy variable for pre- and post-HRRP policy. X_{it} represents a vector of control variables. Υ_i is a time-invariant unobserved hospital-specific effect, and ε_{it} represents a random error.

(3, 4) $\Delta Q^k_{it} = \beta_0 + \beta_1 HRRP_{it} + \beta_2^k X_{it} + \Upsilon^k_i + \varepsilon^k_{it}$

In order to assess whether the HRRP has the same effect on hospital readmission rates for Medicare and Medicare Advantage (3) or private payer (4) hospital readmissions, Models (3, 4) is the modified DD model, where ΔQ^k_{it} is the difference in preventable readmission rate between Medicare and Medicare Advantage, or private insurance patients at hospital *i* in time period *t*.

Results

Sample Characteristics

Table 1 displays descriptive statistics for the study sample. The Medicare CHF preventable readmission rate across all years was 21.3%; for private payers, it was 16.0%. The Medicare PN and AMI preventable readmission rates was 17.5% and 14.0%; for private payers 10.6% and 6.4%, respectively.

Overall, after the HRRP, hospitals experienced a modest decrease in Medicare FFS, Medicare Advantage, and private CHF preventable readmissions by 1.8%, 1.2%, and 1%, respectively (Table 2). Furthermore, this trend continued for other targeted conditions. Hospitals experienced a modest decrease in PN and AMI readmission rates for all payers after the HRRP. Medicare FFS and Medicare Advantage saw a 1.1% decrease in all-cause readmissions, while private saw a slight increase of 0.5% after the HRRP.

Effects of HRRP on Targeted Readmissions

Table 3 presents the main regression results for all models. The first results (models 1, 2, and 3) examined the effects of HRRP on CHF, PN, and AMI preventable readmissions on each payer individually, and models 4 and 5 tested whether the HRRP had the same effect on Medicare FFS, Medicare Advantage, private payers, respectively. In model 1, hospitals exhibited a significant decrease in Medicare CHF preventable readmissions post-HRRP implementation (-0.97%, $P<0.05$), and models 2 and 3 indicated that there was no effect of HRRP on Medicare Advantage and private payer CHF preventable readmissions. Model 3 showed that there was no difference in CHF readmissions for Medicare FFS and Medicare Advantage. Jointly, as model 4 showed, the HRRP had a much larger effect on Medicare than on private readmissions. Medicare had a significant decrease in CHF readmissions relative to private (-1.73%, $P<0.05$).

The next results found that post-HRRP, hospitals exhibited a decrease in Medicare PN preventable readmissions (-2.75%, $P<0.05$); and, there was no significant change for Medicare Advantage and private PN preventable readmissions, indicating no spillover. Jointly, the HRRP had a much larger effect on Medicare FFS than on private readmissions. Medicare had a significant decrease in PN readmissions relative to private (-3.11%, $P<0.05$). There was no difference in Medicare FFS and Medicare Advantage PN readmissions. The third results found that the HRRP had no effect on hospital Medicare FFS, Medicare Advantage, and private AMI readmissions.

Effects of HRRP on All-Cause Readmissions

Table 4 presents the results that show that hospital Medicare FFS and Medicare Advantage all-cause readmissions displayed about a 1% decrease after the HRRP ($P<0.05$) and there appeared to be no spillover into private payers. Testing sought to determine whether the difference between Medicare and Medicare Advantage all-cause readmissions showed no statistical difference between the two payers. This meant that the rate change between the payers was statistically equivalent to each other. In other words, both payers saw significant differences in all-cause readmissions; however, the effect of the HRRP was the same for each payer. This suggests that Medicare Advantage may have had a positive spillover due to the HRRP. Testing whether the HRRP had the same effect on Medicare and private readmissions found that hospitals had a 2.22% decrease in Medicare all-cause readmissions relative to private payers ($P<0.05$).

Discussion

The results from our analyses confirmed and expanded on previous literature. First, consistent with prior literature, we found that hospitals, on average, displayed decreased rates in Medicare FFS targeted readmissions after the implementation of HRRP (Carey and Lin 2015; Zuckerman et al. 2016; Demiralp, He, and Koenig 2017; Desai et al. 2016). We observed decreases in two of the three targeted readmission outcomes. Furthermore, much like other studies that found reductions in nontargeted readmissions (Carey and Lin 2015; Desai et al. 2016; Demiralp, He, and Koenig 2017), we found decreases in all-cause readmissions after HRRP implementation.

Our results expanded on other findings, and we found a positive spillover of the HRRP on Medicare Advantage. We found, on average, that the HRRP significantly affected Medicare FFS and Medicare Advantage all-cause readmission outcomes. We did not find any indication of a spillover into the private market. This was consistent with several other studies that found no changes in non-Medicare targeted readmissions (Carey and Lin 2015; Demiralp, He, and Koenig 2017). Taken together, our findings, based on the insurance population in five states provided evidence on HRRP’s spillover effects. This supported the view that financial implications played at least some role in the way hospitals managed care related to readmissions, and hospital providers might not be able to discern similar patient populations such as Medicare FFS and Medicare Advantage. Furthermore, hospital providers could provide private payer quality of care related to readmissions without having any negative consequences due to the HRRP. Hospitals must improve patient experiences and quality of care with fixed budgets and constraints, which may lead them to identify the optimal allocation of resources to reduce readmissions for certain populations.

Our findings suggest, on average, that hospitals may not be targeting condition specific readmissions penalized under the HRRP. However, hospitals may be implementing readmission reduction initiatives that extend to a wider variation of conditions and populations that go beyond those targeted by HRRP. Additionally, the results found that Medicare Advantage could have benefitted in quality improvements and the privately insured was not negatively impacted due to the HRRP. This can be interpreted that hospitals are most likely not allocating resources away from nontargeted outcomes and different populations treated in the hospital, similar to the conclusions by Demirlap and colleagues (2017). Our results suggest a decrease in Medicare FFS and Medicare Advantage all-cause readmissions, which may be interpreted as hospitals finding it easier to implement a “one-size fits all” readmission reduction initiative rather than targeting specific conditions and populations that fall under the HRRP penalty. This all-inclusive approach to readmission reductions may be due to the hospitals having difficulty identifying certain conditions and populations that are counted in the HRRP penalty calculation.

The study had several limitations. First, we did not see large effects of the HRRP on hospital Medicare readmissions and spillovers. The little to no effect could possibly be from hospitals not making significant changes to their processes and care because the incentive factor of the HRRP was too small. In other words, the HRRP may not put substantial revenue at risk and thus may not be worth the hospital's cost and time to lower the readmissions, so the hospital decides to pay the penalty. An informal term for this is "budget dust." The HRRP could be considered budget dust because the penalty did not create enough incentive for hospitals to make major institutional reforms to reduce preventable readmissions. Second, although our sample was much larger than previous studies, the sample was limited to five states; therefore, results might not be generalizable. Third, there might be unobserved patient and hospital level effects that were not perfectly controlled for in models related to risk differences between Medicare and private insurance patients. Fourth, lag time and other policies around the implementation of the ACA and the HRRP might confound the results. Fifth, prior research suggested that targeted readmissions might be an unreliable estimator of hospital performance and all-cause readmissions could be a better metric to assess overall hospital quality of care (Thompson et al. 2016). Therefore, our results related to targeted conditions should be interpreted with caution. Sixth, although we controlled for managed care penetration, we could not be sure that decreases in Medicare Advantage all-cause readmissions were due to the HRRP. Medicare Advantage plans may be congruently working with hospitals (i.e., via value-based contracts) to improve their beneficiaries' quality of care related to readmissions, thus the results of HRRP may be overstated. Lastly, we cannot be certain that the decreases in readmission rates were due to genuine improvements in quality.

In conclusion, the findings contributed to the general understanding of how policies motivated medical providers to improve performance and whether there were unintended positive or negative spillovers. Overall, the main results found evidence of a positive spillover into Medicare Advantage and no effect on the privately insured. This novel study lent support to the notion that the HRRP decreased condition specific for Medicare FFS readmissions and all-cause Medicare FFS and Medicare Advantage readmissions. While further work was needed to better delineate why these relationships exist, the findings suggested that the incentive factor of the HRRP did make improvements in preventable readmissions for Medicare FFS and Medicare Advantage patients; in some cases, and did not affect care for private payers. The study extended beyond the normal pre and post study related to the HRRP and provided a new avenue of interpretation to explore ways to improve the quality of care and outcomes of patients in an often forgotten interconnected complex of delivery systems.

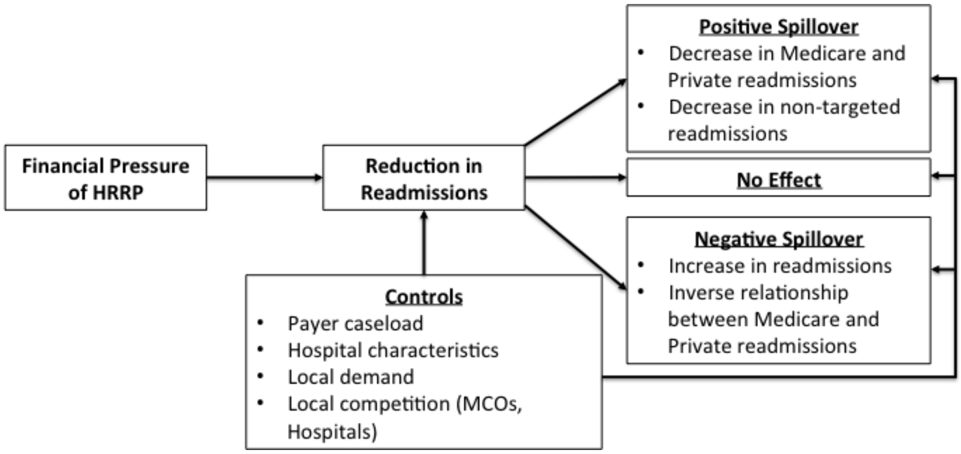

Figure 1. Conceptual Framework.

Table 1. Sample Characteristics.

30-Day Preventable Readmissions	
Congestive Heart Failure (CHF)	
Medicare	20.4%
Private	15.5%
Medicare Advantage	19.9%
Pneumonia (PN)	
Medicare	16.7%
Private	10.3%
Medicare Advantage	16.0%
Acute Myocardial Infraction (AMI)	
Medicare	13.3%
Private	6.1%
Medicare Advantage	12.7%
All-cause	
Medicare	15.31%
Private	7.58%
Medicare Advantage	13.38%

Table 2. Changes in Preventable Readmissions, Pre- and Post-HRRP.

Readmission Type	Pre-HRRP (2009-2010)	Post-HRRP (2012-2013)
30-Day Preventable Readmissions		
Congestive Heart Failure (CHF)		
Medicare	21.2%	19.4%
Medicare Advantage	20.4%	19.2%
Private	15.8%	14.9%
Pneumonia (PN)		
Medicare	17.2%	15.8%
Medicare Advantage	16.5%	15.3%
Private	10.5%	10.1%
Acute Myocardial Infarction (AMI)		
Medicare	13.7%	12.7%
Medicare Advantage	13.3%	12.3%
Private	6.4%	6.2%
All-Cause		
Medicare	15.4%	14.4%
Medicare Advantage	13.9%	12.8%
Private	8.3%	8.8%

Table 3. Main regression results.

	Model 1 Medicare	Model 2 Private (Spillover)	Model 3 MA (Spillover)	Model 4 Private (DD)	Model 5 MA (DD)
CHF					
HRRP	-0.97%***	0.85%	-1.88%	-1.73%**	1.14%
	(0.12)	(0.68)	(1.55)	(0.57)	(1.63)
Controls	Yes	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	0.24	0.55	-0.07	-0.28	0.38
	(0.13)	(0.32)	(0.11)	(0.22)	(0.28)
Observations	1,618	1,591	1,562	1,591	1,562
R-squared	0.03	0.02	0.03	0.02	0.0215
Number of panel_id	481	476	576	476	476
PN					
HRRP	-2.75%***	0.47%	0.32%	-3.11%**	-2.61%
	(0.75)	(0.82)	(0.92)	(1.21)	(1.24)
Controls	Yes	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	0.30	0.21	-0.02	0.12	0.48
	(0.21)	(0.30)	(0.13)	(0.37)	(0.26)
Observations	1,618	1,604	1,561	1,604	1,561
R-squared	0.0	0.0	0.02	0.0	0.02
Number of panel_id	481	480	476	480	476
AMI					
HRRP	-0.47%	-0.14%	-0.69%	-0.44%	-0.19%
	(1.34)	(0.78)	(0.87)	(0.40)	(0.80)
Controls	Yes	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	-0.0020	-0.1380	0.02	0.1974	0.10
	(0.2770)	(0.1824)	(0.46)	(0.1381)	(0.70)
Observations	1,601	1,512	1,509	1,508	1,505
R-squared	0.03	0.02	0.02	0.03	0.02
Number of panel_id	480	463	466	463	466

Reported regressions control for hospital, client, and market forces characteristics.
Coefficients are presented in percentage.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Effect of HRRP on all-cause readmissions.

All-cause readmissions	Medicare	Private (Spillover)	Medicare Advantage (Spillover)	Difference between Medicare and Private	Difference between Medicare and Medicare Advantage
	Difference	**Difference**	**Difference**	**(DD)**	**(DD)**
HRRP	−1.11%***	1.11%	-1.00%**	−2.22%**	-0.11%
	(0.17)	(0.89)	(0.43)	(0.80)	(0.46)

Reported regressions control for hospital, client, and market forces characteristics.
Coefficients are presented in percentage.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3: Spillover Effects Of Medicare Advantage: Does The Market Penetration of MA Plans Affect Hospital Care Quality?

Abstract

Objective: To investigate the spillover effects of the Medicare Advantage program on Medicare FFS hospital quality of care.

Data Source: Health Care Utilization Project's (HCUP) State Inpatient Database (SID) administrative claims data to calculate condition-specific thirty-day preventable readmissions. American Hospital Association (AHA) data, Interstudy Commercial Managed Care, and Area Health Resource File (AHRF) were used to determine hospital, managed care, and county-level characteristics. Medicare Advantage county-level payment schedules originate from CMS.

Study Design: Ordinary least squares (OLS) and instrumental variable models were used to isolate exogenous increases in Medicare Advantage enrollment and to trace out the effects of greater managed care penetration on hospital quality of care.

Principal Findings: We found that Medicare Advantage penetration had no effect on Medicare FFS readmissions as well as Medicare Advantage readmissions. There appeared to be no spillover from Medicare Advantage on Medicare FFS.

Conclusions: As found in other studies, Medicare Advantage penetration was unlikely to influence Medicare FFS hospital quality of care, such as preventable readmissions. In contrast with earlier studies, there was no evidence that greater Medicare Advantage penetration was likely to reduce Medicare Advantage readmissions.

Introduction

Since the mid 2000s, Medicare Advantage has seen a dramatic increase in enrollees. In 2016, 17.6 million beneficiaries—31% of the Medicare population—were enrolled in a Medicare Advantage plan (Jacobson et al. 2016). This growth reflects the ongoing expansion the position of Medicare Advantage plays in the Medicare program. While the rise of a meaningful Medicare managed care sector could affect both the financial health of the program and the physical health of Medicare enrollees, we focused on the former. In particular, we asked the question: Does Medicare Advantage penetration affect utilization sustained by fee-for-service beneficiaries?

Spillover effects refer to changes in the care delivered to fee-for-service beneficiaries that arise due to changes in Medicare Advantage enrollment among Medicare beneficiaries, holding the health status of fee-for-service beneficiaries constant. Moreover, Medicare fee-for-service policies have shown spillover into Medicare Advantage and vice versa. There are several reasons to expect spillovers. For instance, if providers tend to practice similarly for all patients, a larger share of Medicare Advantage may alter practice patterns for Medicare fee-for-service patients. While the cost effectiveness of Medicare Advantage is up to debate, several studies concluded that increased Medicare Advantage enrollment affected the treatment costs and utilization of Medicare fee-for-service patients.

We expanded the typical spillover analysis with an examination of the impact of Medicare Advantage penetration on Medicare FFS beneficiaries that had preventable readmissions for acute myocardial infraction (AMI), health failure (HF), and pneumonia (PN) for Medicare FFS enrollees.[1] We also analyzed the spillover effects on FFS members for all-cause preventable readmissions. We examined these outcomes due to prevalence, costs, and

[1]Limiting the sample to AMI, HF, and PN enabled us to examine the impact of increased MA penetration on disease-specific readmissions and diagnostic procedures.

importance to CMS as measures of hospital performance and quality of care. Furthermore, this study expanded on prior spillover research by examining spillovers in two different periods: 2008 to 2010 and 2011 to 2013 in order to capture the effectiveness of MA penetration coexisting with and without a Medicare policy (Hospital Readmissions Reduction Program [HRRP]) intended for FFS preventable readmissions, and to assess whether highly concentrated market areas of Medicare Advantage influenced Medicare FFS readmissions prior to HRRP. Leveraging methods from Chernew et al. (2008) and Callison (2016), we investigated county-level MA penetration using payment rates to MA plans in order to address the likely endogeneity issues inherent in changes in the MA market share (Baicker, Chernew, and Robbins 2013; Callison 2016). The fundamental contribution of this study was in the potential to identify various causal pathways through which Medicare Advantage penetration affected Medicare FFS preventable readmissions.

Conceptual Framework

Increased enrollment in MA could impact care for the traditionally insured Medicare beneficiaries through effects on intensive or extensive margins of patient care. The "norms hypothesis" developed by Newhouse and Marquis (1978) suggested that when treating patients with various types of health insurance, medical providers would balance payment rates so that practice styles were uniform, regardless of payer status (Newhouse and Marquis 1978). For instance, as MA enrollment rose and MA plans incentivized providers to reduce utilization, providers uniformly altered their care for traditional FFS patients. This resulted in a positive spillover via an improvement in Medicare FFS quality of care. Fee-for-service beneficiaries may gain from this due to MA plans being paid on a capitated basis, which makes plans more likely to invest in coordinated care efforts with the expectation of reduced future outlays (Baicker, Chernew, and Robbins 2013). As a result, processes of care, such as post-acute care would be the same or improved for Medicare FFS patients. In contrast, McGuire and Pauly (1991) suggested providers were able to distinguish profitable and unprofitable patients and provided different levels of utilization of services given their patients' payer status; this was known as the "Utility Maximizing Theory"(McGuire and Pauly 1991); which may result in a negative spillover.

Several studies discussed the potential of increased MA enrollment to induce structural changes in health care markets primarily through capacity and utilization reductions. Yet, when a policy targeting FFS patients was introduced into a spillover analysis, little was known on whether MA enrollment amplified or condensed spillover effects in combination with a Medicare policy. To arrive at whether the private sector works in concert with the public sector to affect FFS utilization and costs, the period in which Medicare's HRRP was implemented was used in the second analysis. The HRRP designates the reduction of avoidable FFS readmissions as a target for health care cost savings and authorizes the Center for Medicare and Medicaid Services (CMS) to lower payments to hospitals with high risk-standardized rates of 30-day readmissions. This policy was put into place as a response to control the cost associated with FFS Medicare readmissions. In the first year of the policy, hospitals were penalized up to 2%, second year up to 3%, and in all other years it maintained a 3% penalty by CMS withholding Medicare inpatient payments.

We investigated the impact of Medicare Advantage penetration on medical care utilization incurred by Medicare FFS enrollees, pre (years 2009-2010) and post (years 2012-2013) HRRP. If the norms hypothesis held true, we would expect readmissions and its expenditures to have a positive spillover in that higher Medicare Advantage penetration led to lower preventable readmissions for FFS beneficiaries. Furthermore, there should be no significant differences in preventable readmissions between Medicare FFS and Medicare Advantage. However, if the utility maximizing theory held true, we would expect readmissions to have a negative spillover—meaning that there would be significant readmission differences between Medicare and Medicare Advantage beneficiaries. We also examined the differences in spillover effects before and after HRRP in order to understand how the Medicare policy affected these events.

Mechanisms of Spillover Effects

Prior evidence suggests that the expansion of managed care plans may negatively impact the care of traditional Medicare FFS beneficiaries through several mechanisms. Greater managed care market share may make it more difficult to access hospital care due to high demand and providers not being able to expand output and increase the use of factors of production (Qianwei Shen 2015). Underperformance on process-of-care measures, which recorded the percentage of patients who received appropriate care for specific conditions, was often considered an indicator of low hospital quality of care. According to one study, individuals living in areas with higher levels of managed care were more likely to report problems obtaining care than areas with lower levels of managed care (Litaker and Cebul 2003).

Spillover effects may also occur through a negative impact on infrastructure investments, such as the volume of beds, the adoption of advanced medical technology, or allocation of services over time. Managed care providers are assumed to have highly elastic demand so higher levels of managed care penetration will force managed care providers to compete with each other, and as a result, managed care plans may be more successful at negotiating lower prices with medical providers (Baker and Phibbs 2002). Additionally, lower managed care payments; the encouragement of practicing conservative practice patterns (Baker 2001; Heidenreich et al.

2002); and slowing the timing of adopting more advanced but costly technologies (Cutler and Sheiner 1998), requires providers to reduce cost, thereby reducing the number of specialty providers and the number of services provided (Baker 2001; Heidenreich et al. 2002). Because, all patients share hospital resources, fewer advanced technologies affect the quality of care of managed care and Medicare FFS beneficiaries. Prior evidence suggests that as managed care penetration increased, there was an inverse relationship with the number hospital beds per capita (Chernew 1995). Furthermore, higher levels of managed care penetration associated with lower levels of MRI access (Baker and Wheeler 1998) and hospital acquisition of certain medical technologies (Mas and Seinfeld 2008).

To the contrary, evidence suggested that higher levels of managed care penetration were likely to have a positive spillover on quality of care received by Medicare FFS patients. According to several studies, managed care could influence physicians' practice patterns due to the incentive structures of managed care payments. Given the economic assertion that, *ceteris paribus*, effort level to managed care patients was lower than that for FFS patients, as managed care penetration increases, patterns of care for managed care and FFS would converge (Glied and Zivin 2002). In other words, providers who treat mostly managed care patients appear to adopt an equivalent practice style for all patients, regardless of payer. Evidence also suggests that hospital investment in technology infrastructure can have a positive spillover. Managed care plans must have the ability to collect and transfer administrative data within an internal market (Culyer and Newhouse 2000; Qianwei Shen 2015). The information collection capacity gives hospitals the incentive to increase quality of care in order to attract customers. Thus, patients will benefit from advanced medical technology because they do not have the choice but to use more expensive and effective technology.

Spillover Effect on Traditional Medicare FFS

Evidence suggests that managed care penetration has an effect on Medicare FFS expenditures and quality of care. Baicker et al. (2013) analyzed county- and MSA- level data, and found that Medicare FFS expenditures had a concave relationship with managed care penetration (Baker 2003). Baker (2003) found that as managed care penetration increased, Medicare FFS expenditures decreased. Chernew et al. (2008) leveraged county-level Medicare Advantage benchmark payment data as an instrument for Medicare Advantage penetration and found that every one percent increase in county-level penetration associated with a one percent reduction in annual spending for Medicare FFS beneficiaries.

Research found that higher levels of managed care penetration could lead to lower Medicare FFS expenditures. Despite these lower expenditures, this may result in reduced quality of care. Medicare FFS' payments are set administratively; therefore, reductions in expenditures must result from reduced utilization. If reduced services are necessary, quality of care will decline. However, quality of care may improve in low expenditure areas if reduced expenditures result in reductions of unnecessary or inappropriate services. Therefore, it is essential to determine the spillover effect for measuring quality.

Unlike measuring expenditures, measuring quality of health care is difficult due to several confounding dimensions. No single variable can capture all the factors associated with hospital quality of care. As a result, researchers have found several ways to measure quality of care: outcome quality as measured by effectiveness of care, readmission rates, and mortality rates (Baicker, Chernew, and Robbins 2013; Callison 2016; Chernew, DeCicca, and Town 2008); process quality as measured by access to care, preventable admissions, length of stays, and number of test performed (Decker 2012); and input quality as measured by the adoption of advanced technologies, and staffing levels (i.e., nurses, primary care, and specialist) (Kaestner and Guardado 2008).

Evidence of system-wide spillover on quality of care is mixed. However, due to limited data, only a few studies provided evidence that managed care could influence the quality of care provided to Medicare FFS beneficiaries. One study found that managed care penetration was negatively associated with Medicare FFS 30-day post-admission mortality (Mukamel, Zwanziger, and Tomaszewski 2001). Another study found that areas with higher levels of managed care penetration received better quality of care for AMI admissions than areas with lower levels of managed care (Heidenreich et al. 2002). To the opposite effect, another study found managed care penetration negatively associated with Medicare FFS AMI admission treatment (Meara et al. 2004). Another study found that higher levels of Medicare Advantage penetration reduced Medicare FFS beneficiaries' rates of hospitalization and mortality (Callison 2016). Baicker et al. (2013) used changes in MA payment as a natural experiment and found Medicare Advantage penetration was not associated with fewer hospitalization, but was associated with lower expenditures and shorter hospital lengths of stay (Baicker, Chernew, and Robbins 2013). Using the same methods as Chernew et al. (2008), Callison (2015) found that MA penetration associated with reduced treatment intensity of Medicare FFS AMI admissions.

Medicare Advantage Penetration Effects Medicare Advantage Quality of Care

Medicare Advantage enrollment has seen steady increases over the past couple decades, resulting in greater influence over the U.S. health delivery system. Even with rising MA penetration and the slow changes to Medicare FFS delivery that result from the shifting federal policy conditions, MA beneficiaries continue to have fewer avoidable hospitalizations—compared to those in Medicare FFS. Furthermore, areas with high levels of MA penetration tend to have lower avoidable hospitalization and readmission rates compared to Medicare FFS, even after controlling for selection effects and the health status of enrollees (Lemieux et al. 2012; Center 2016). This disparity may be due to a network effect, where managed care plans leverage pragmatic interventions and selectively contract with higher performing providers and refer patients to such providers in order to reduce avoidable hospitalizations and readmissions (Lemieux et al. 2012). As a result, we would expect that areas with higher Medicare Advantage penetration to have lower Medicare Advantage readmissions, and as a consequence, we would expect this to be the same for Medicare FFS, because of managed care's influence over provider practice behaviors.

Based on prior theoretical frameworks and evidence of MA spillover into Medicare FFS, we hypothesized that greater concentration of Medicare Advantage penetration:

H1: will have a positive spillover into Medicare FFS quality of care. More specifically, the higher the MA concentration, the lower Medicare FFS readmissions will be.

H2: will have a positive spillover into Medicare Advantage quality of care

We also examined these spillovers before and after the HRRP, because it was important to control for any influences that the policy could have had on quality of care outcomes.

Methods

Data and Study Population Overview

The primary data used in the analyses came from the Health Care Utilization Project's State Inpatient Databases (SIDs). The SID contains detailed information on the diagnoses and conditions associated with readmissions and the treatments received for the universe of patients in a given state along with the primary source of payment, as well as basic demographic information such as age, gender, and race/ethnicity. Not all states differentiate specific information between Medicare managed care and traditional Medicare. Therefore, these analyses were limited to the following states that reported specific information on Medicare plan type for the years 2009-2013: California, Iowa, Florida, Massachusetts, and New York. The full sample used in the subsequent analyses consisted of all Medicare beneficiaries from the aforementioned states over the age of 65 years readmitted with a primary diagnosis of AMI, HF, PN, or all-cause. This data was then aggregated to the hospital level. We then excluded hospitals in rural areas, dual-eligible individuals, individuals with planned readmissions, and hospitals with less than 30 admissions. Data on MA and FFS enrollment originated from the Interstudy Managed Care Survey. Center for Medicare and Medicaid Service also provided data on county-level payment rates to MA plans. The Area Health Resource File provided county-level data on the supply of health services. More specifically, the total number of hospital beds and general practitioners and specialists was used as a measure of capacity and availability of medical and hospital resources.

Outcome: Condition Specific Readmissions

Dependent variables are presented in rates. There are six outcome variables CHF, PN, and AMI Medicare FFS readmission rates; and CHF, PN, and AMI Medicare Advantage readmission rates. A preventable readmission was considered a 30-day preventable readmission for individuals hospitalized at a short-stay acute care hospital and who experienced an unplanned readmission for CHF, PN, or AMI to an acute care hospital within 30 days of discharge. A CHF, PN, and AMI readmission was consistent with a set of technical reports prepared by CMS (see Appendix 3 for list of ICD-9 codes; CMS 2011). To calculate the readmission rate for each condition, the numerator was the number of individuals with 30-day readmissions for that condition (based on ICD-9 codes), while the denominator was the total number of admissions for the same condition.

Outcome: All-Cause Readmissions

Hospitals may attempt to reduce all-cause readmissions simply because it improves their overall processes and quality of care. Furthermore, managed care plans may establish value-based benchmarks that hospitals must meet in order to receive optimal payments. Additionally, reducing all-cause readmissions may be more practical for hospitals to implement, and has been a more reliable estimate of quality of care (Thompson et al. 2016). We calculated the 30-day all-cause readmissions rate based on the CMS technical report (CMS 2014). There were two outcome variables: all-cause readmission rate for (1) Medicare FFS and (2) Medicare Advantage.

Medicare Advantage Penetration of Plans

We relied on data from Interstudy to determine county-level Medicare managed care organization penetration. Medicare managed care organization penetration was defined as the number of commercial enrollees in a given county divided by the county's Medicare population. This was considered our endogenous variable in our IV estimation.

Hospital-level Characteristics

We included Herfindahl-Hirschman Index (HHI) for hospital market concentration as a control. The HHI is a measure of how evenly hospital share is distributed across hospitals in the market. The HHI values range from 0 to 10,000; an HHI closer to zero indicates a more competitive market, and an HHI closer to 10,000 indicates a less competitive market. An HHI index below 1,000 generally indicates a highly competitive market; an HHI between 1,000 and 1,500 indicates an unconcentrated market; a score between 1,500 and 2,500 indicates moderate concentration; and a value above 2,500 indicates a highly concentrated (uncompetitive) market. We categorized this as a dummy variable for hospitals above or below median HHI.

We also controlled for hospital structural components, such as the type of health system governing a hospital (Bazzoli et al. 1999). We categorized health systems as centralized, moderately centralized, decentralized, and independent hospitals. We also included a hospital's nurse-to-bed ratio, size of the hospital, primary care and specialty physician supply, number of full-time nurses, and ownership.

County-level Characteristics

We controlled for several county-level characteristics. These included county-level median household income, percent insured, and percent insured in Medicare.

Chronic Conditions

Spillover may be affected by selection bias. According to Chernew et al. (2008), relatively healthier beneficiaries may be more likely to be enrolled in Medicare Advantage plans, and those in worse health may be left or more likely to choose Medicare FFS. As a result, this may create selection bias and confound the spillover results. Therefore, we introduced the Elixhauser Comorbidity Index to control for chronic conditions that could influence readmission outcomes in a hospital. This was obtained based on a patient's index admission.

Analytic Strategy

The analyses goals were: (1) to estimate the effect of Medicare Advantage penetration on various measures of utilization for FFS Medicare patients with preventable readmissions; and (2) to estimate the effect of Medicare Advantage penetration effects on various measures of utilization prior to the year 2011 and after 2011.

An initial model to describe association between Medicare Advantage penetration and utilization is as follows:

(1) $Y_{ict} = \delta_c + \Upsilon_t + \beta MA_{ct} + \alpha X_{ict} + \lambda Z_{ct} + \Phi PAYER_{ct} + \varepsilon_{ict}$,

where Y is a measure of Medicare FFS preventable readmission utilization for hospital i in county c in year t; MA is the county-level share of Medicare Advantage enrollment in year t; X is a vector of county-level characteristics; Z is a vector of hospital-level characteristics that vary over time including the total number of hospital beds and the total number of general practitioners and specialists; $PAYER$ is the percentage of Medicare insured in a given county; δ and Υ are county and year fixed effects, respectively. When we restricted the sample to traditional Medicare patients, the coefficient βMA_{ct} in equation (1) returned estimates of the spillover effect associated with Medicare Advantage penetration.

In equation (1), ordinary least squares (OLS) estimation would likely result in biased estimates of the effect of Medicare managed care penetration on traditional Medicare utilization. This is because changes in Medicare managed care enrollment may be related to county-level utilization (Baker 1997; Chernew, DeCicca, Town 2008). Evidence suggests that managed care organizations are more likely to enter markets where costs are higher (McGuire, Newhouse, Sinaiko 2011; Mukamel, Zwanziger, Tomaszewski 2001). If Medicare managed care plans expand into areas where costs and utilization are higher, they may exploit potential cost-saving applications, then OLS estimates of the association between Medicare managed care and utilization will be biased towards zero (Chernew, DeCicca, Town 2008; Gowrisankaran and Town 2004).

For this reason, the models implemented in several other studies were used to minimize endogeneity issues related to MA plan behavior and enrollment (Baicker, Chernew, Robbins 2013; Callison 2015; Chernew, DeCicca, Town 2008; Gowrisankaran and Town 2004). Medicare Advantage payment rates from CMS were used as an instrument for Medicare managed care penetration. The following two-stage model is produced:

$MA_{ct} = \delta'_c + \Upsilon'_t + \pi RATE_{ct} + \alpha' X_{ict} + \lambda' Z_{ct} + \varepsilon'_{ict}$,

(2) $Y_{ict} = \delta_c + \Upsilon_t + \beta MA_{ct} + \alpha X_{ict} + \lambda Z_{ct} + \varepsilon_{ict}$,

where *RATE* is the benchmark Medicare Advantage plan payment rate in county *c* in year *t* and the remaining variables are all as previously defined. The instrumental variable approach relied on the relationship between Medicare Advantage payment rates and Medicare Advantage enrollment (i.e., higher payment rates will attract Medicare Advantage plans that will, in turn, increase enrollment). These rates have been shown to be unrelated to contemporaneous changes in Medicare managed care enrollment (Chernew, DeCicca, Town 2008). We leveraged the two-stage least squares methodology in two mutually exclusive ways. We first did this for the years 2009-2010 (pre-HRRP), 2011-2013 (post-HRRP), and across all years. This was to examine how Medicare Advantage spillover affected Medicare FFS prior to HRRP and to what extent HRRP contributed to the utilization of preventable readmissions in combination with MA penetration. Moreover, this allowed us to examine whether HRRP was improving or worsening preventable readmissions and/or to what extent Medicare Advantage penetration influenced quality of care with and without HRRP.

Results

Sample Characteristics

To demonstrate that Medicare Advantage payments have not drastically changed over the course of the study, Figure 1 shows the distribution of CMS Medicare Advantage payment benchmarks from years 2009 to 2013. The average payment remained similar across all years. The average Medicare Advantage monthly payment for 2010 was about \$785 and then had a small decline in 2013 to \$765. Figure 2 demonstrates the rapid enrollment growth in Medicare Advantage plans for our sample of states. Medicare Advantage plans grew steadily in enrollment from 2009, with an estimated additional 2 million enrollees in 2013, totaling 5.7 million. The average Medicare Advantage penetration rate was 30%.

Table 1 shows the unadjusted average readmission rate for the sample. The average readmission rate for CHF was 21% and 20%; PN was 17% and 15%; AMI was 13% and 11%; and all-cause was 15% and 13% for Medicare FFS and Medicare Advantage, respectively. Table 2 shows the unadjusted average readmission rate across years of the sample. Unadjusted condition-specific readmissions for Medicare FFS saw relatively small decreases in condition-specific and all-cause readmissions from 2009 to 2013. The largest decreases happened after HRRP implementation. This trend was similar for Medicare Advantage condition-specific and all-cause readmissions as well.

Endogeneity Tests

Prior research found county-level Medicare Advantage plan penetration was endogenous due to time-variant county-level variables correlated with Medicare Advantage plans and quality of care in Medicare FFS. Due to these concerns, we tested the endogeneity assumption prior to running the full model to conclude whether our predictors were unbiased and efficient. We tested the non-zero average causal effect assumption for the CMS Medicare Advantage payment benchmark instrument. In order to evaluate the strength of instrument, we conducted a partial F-test after the first stage regression results (first-stage results and partial F-test located in Appendix A). The F-test results indicated the instrument was highly significant ($P<0.01$) and had an F-statistic higher than 10. This test suggested the instrument had a non-zero causal effect and was robust.

Years 2009-2013

Table 3 shows our main results. The IV estimates suggest that Medicare Advantage penetration has no effect on hospital Medicare FFS CHF readmissions. This result is the same for PN and AMI readmissions as well. Furthermore, the IV estimates suggest that Medicare Advantage penetration has no effect on Medicare Advantage condition-specific readmissions. The IV results also suggest that MA penetration has a negative effect on Medicare FFS and MA all-cause readmissions—with each additional 1 percentage point increase in penetration, all-cause readmissions decrease. However, this is not significant at the alpha-level of 0.05.

Pre-HRRP (2009-2011)

Table 4 shows our pre- and post-HRRP results. Similar results were found prior to the HRRP. There appears to be no association between Medicare Advantage penetration and any condition-specific type of readmission for Medicare FFS and Medicare Advantage prior to the HRRP. Moreover, these results were the same for all-cause readmissions, regardless of payer.

Post-HRRP (2012-2013)

Results from the post-HRRP analysis were similar to the pre-HRRP results. The IV estimates suggest that there was no association between penetration and condition-specific and all-cause readmissions for Medicare FFS and Medicare Advantage. Taken together when pooling across separate periods, the results remain the same: our IV estimation did not find an association between any type of readmission and Medicare Advantage penetration.

Discussion

Medicare Advantage plan penetration has long been associated with changes in treatment costs among the traditional FFS Medicare population. The instruments underlying these cost and utilization spillovers have remained unclear. This research worked to address this discrepancy by estimating the changes in utilization for FFS Medicare beneficiaries readmitted with AMI, HF, or PN, pre and post the HRRP. The overarching goal of this study was to better understand how Medicare Advantage penetration rates "spill over" into Medicare FFS, considering its vast enrollment growth in recent years. More specifically, we conducted IV estimation used from several other studies to examine how Medicare Advantage affected Medicare FFS quality of care. We conducted several analyses stratified by years while controlling for selection effects.

Using Medicare Advantage payment rates from CMS as an instrumental variable, our results found no associations between Medicare Advantage penetration and Medicare FFS condition-specific and all-cause readmissions. Likewise, there was no association found for Medicare Advantage readmissions. This non-significant relationship remained the same when stratified pre and post HRRP implementation. Since there was no primary effect on MA readmissions, a spillover into Medicare FFS was even more unlikely. Our results were similar to those of Baicker et al. who found no MA spillover of Medicare FFS quality of care outcomes (hospitalizations).

Overall, our results suggest that Medicare Advantage penetration does not affect provider practice patterns or the sharing of resources, such as advanced medical technology. No spillover may be indicative of many things. First, care related to readmissions between the two payers, such as post-acute care may be roughly the same. Second, Medicare Advantage may simply not influence provider care of beneficiary Medicare FFS readmissions. Third, the constraining of medical resources directly related to Medicare FFS quality of care may not be influenced by Medicare Advantage utilization review requirements. Although, this study found no evidence of a spillover, Medicare Advantage penetration may influence Medicare FFS readmissions. The average penetration rate within our sample was almost 30%. As of 2017, California and Florida had penetration rates above 40% and several of the other states in our sample experienced increases of more than 10% (Jacobson et al. 2016). As Medicare Advantage enrollment growth continues to grow, and plans become increasingly dominant throughout the United States, influence over provider practice patterns and utilization control processes may create more pronounced spillover into Medicare FFS. An analysis with newer years of data and examining the association of MA penetration and readmission costs may result in different results.

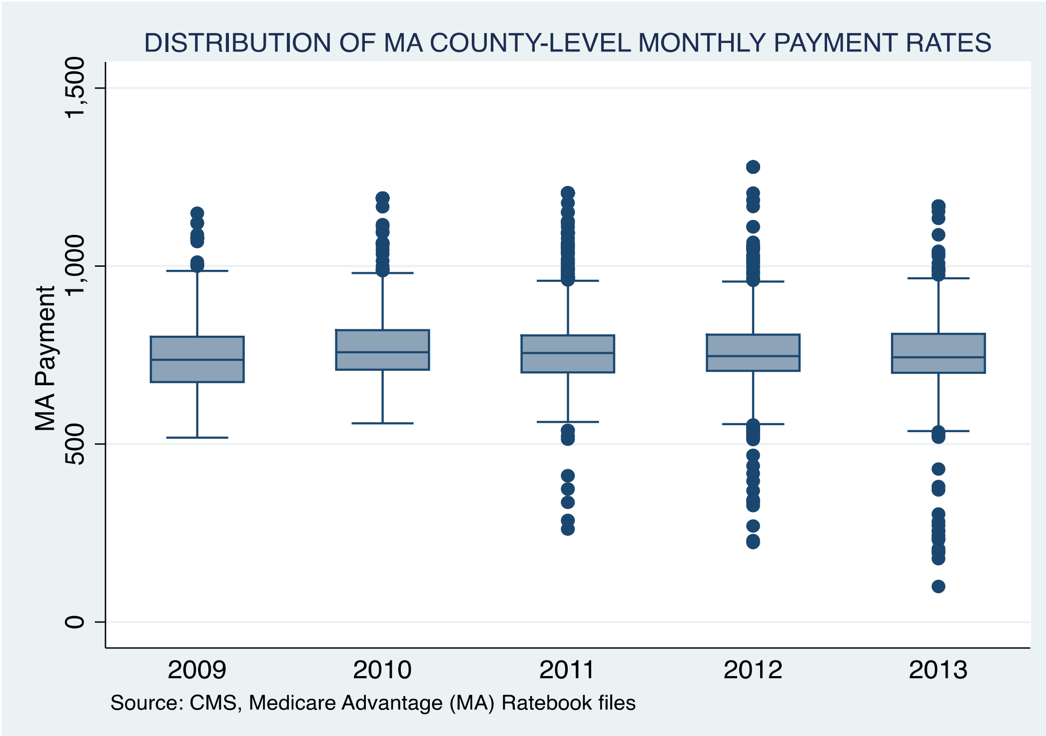

Figure 1. Distribution of Medicare Advantage County-Level Monthly Payment Rates.

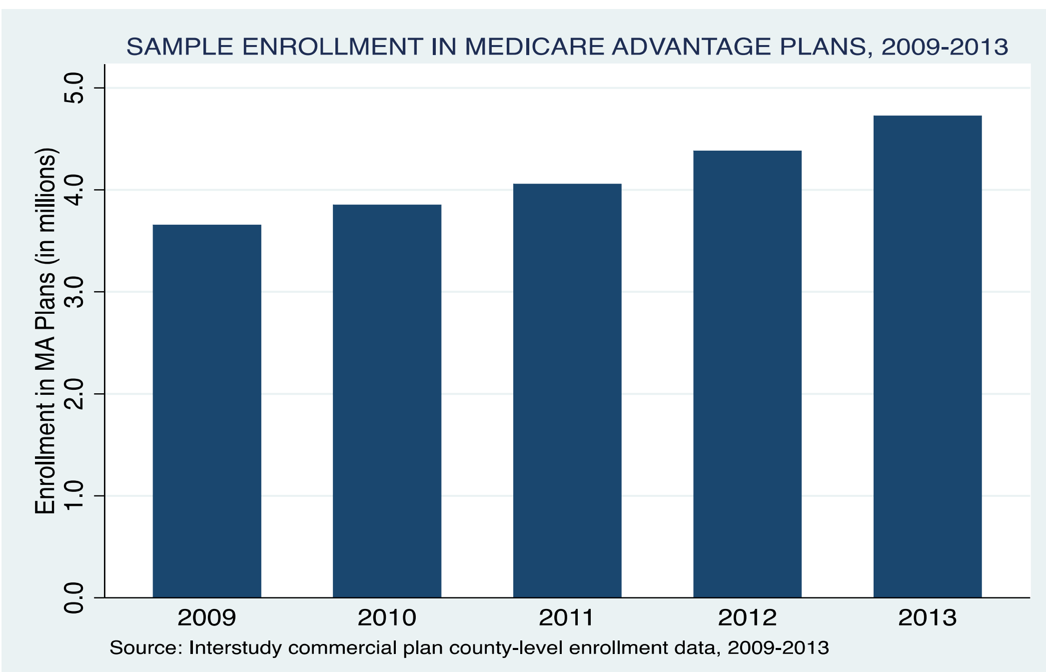

Figure 2. Sample Enrollment in Medicare Plans, 2009-2013.

Table 1. Sample Characteristics.

30-Day Preventable Readmissions	
Congestive Heart Failure (CHF)	
Medicare	20.4%
Medicare Advantage	19.9%
Pneumonia (PN)	
Medicare	16.7%
Medicare Advantage	16.0%
Acute Myocardial Infraction (AMI)	
Medicare	13.3%
Medicare Advantage	12.7%
All-cause	
Medicare	15.31%
Medicare Advantage	13.38%

Table 2. Changes in Preventable Readmissions, Pre- and Post-HRRP.

Readmission Type	**Pre-HRRP (2009-2010)**	**Post-HRRP (2011-2013)**
30-Day Preventable Readmissions		
Congestive Heart Failure (CHF)		
Medicare	21.2%	19.4%
Medicare Advantage	20.4%	19.2%
Pneumonia (PN)		
Medicare	17.2%	15.8%
Medicare Advantage	16.5%	15.3%
Acute Myocardial Infraction (AMI)		
Medicare	13.7%	12.7%
Medicare Advantage	13.3%	12.3%
All-Cause		
Medicare	15.4%	14.4%
Medicare Advantage	13.9%	12.8%

Table 3. Effects of Medicare Advantage penetration on condition specific 30-day preventable readmissions.

	Traditional Medicare FFS		**Medicare Advantage**	
	OLS	IV	OLS	IV
Dependent Variable	(1)	(1)	(2)	(2)
CHF Readmission	0.02%	-0.84%	0.02%	-1.75%
	(0.02)	(0.71)	(0.14)	(1.44)
PN Readmission	-0.03%	0.07%	0.04%	-0.53%
	(0.02)	(0.89)	(0.18)	(1.65)
AMI Readmission	0.00%	-1.25%	-0.13%	-1.73%
	(0.02)	(1.70)	(0.22)	(2.58)
All-cause	0.01%	-0.94%	0.02%	-0.63%
	(0.02)	(0.49)	(0.05)	(0.58)
Controls	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

FFS, fee-for-service; OLS, ordinary least squares; IV, instrumental variable.

Controls include indicators for age, race, gender, emergency admission, a set of 30 comorbidities associated with increased hospital utilization, and county-level counts of the number of hospital beds, general practitioners, medical specialists, median household income, uninsured, and Medicare insurance rate.

The IV regressions instrument for Medicare Advantage penetration rates using Centers for Medicare and Medicaid Services benchmark payment rates to Medicare Advantage plans.

Robust standard errors are used.

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

Table 4. Effects of Medicare Advantage penetration on 30-day preventable readmissions pre- and post-HRRP.

	Traditional Medicare FFS				Medicare Advantage			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Dependent Variable	Pre-HRRP	Pre-HRRP	Post-HRRP	Post-HRRP	Pre-HRRP	Pre-HRRP	Post-HRRP	Post-HRRP
CHF Readmission	0.39%	-3.12%	-0.10%	0.06%	-0.17%	-1.05%	0.02%	-0.94%
	(0.25)	(5.57)	(0.08)	(0.35)	(0.39)	(9.47)	(0.03)	(0.87)
PN Readmission	0.09%	-9.57%	-0.15%	0.13%	0.11%	4.71%	0.02%	0.24%
	(0.30)	(10.28)	(0.11)	(0.42)	(0.57)	(13.64)	(0.03)	(0.96)
AMI Readmission	-0.43%	5.68%	-0.33%	0.31%	0.12%	4.73%	0.05%	-2.02%
	(0.73)	(9.77)	(0.24)	(0.83)	(0.68)	(18.76)	(0.04)	(1.42)
All-cause	0.20%	1.11%	-0.04%	-0.02%	0.06%	2.38%	-0.06%	-0.02%
	(0.14)	(2.53)	(0.05)	(0.02)	(0.19)	(4.92)	(0.07)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

FFS, fee-for-service; OLS, ordinary least squares; IV, instrumental variable.

Controls include indicators for age, race, gender, emergency admission, a set of 30 comorbidities associated with increased hospital utilization, and county-level counts of the number of hospital beds, general practitioners, medical specialists, median household income, uninsured, and Medicare insurance rate.

The IV regressions instrument for Medicare Advantage penetration rates using Centers for Medicare and Medicaid Services benchmark payment rates to Medicare Advantage plans.

Robust standard errors are used.

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

Appendix 1. Test for Endogeneity and Strength of Instrument.

```
                                                      Number of obs =     2174
                                                      F( 13,  1681) =   191.64
                                                      Prob > F      =   0.0000
Total (centered) SS     =   .807981601                Centered R2   =   0.5895
Total (uncentered) SS   =   .807981601                Uncentered R2 =   0.5895
Residual SS             =   .331673173                Root MSE      =   .01405

------------------------------------------------------------------------------
             |               Robust
   MApenrate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       year1 |   .0098332    .000602    16.34   0.000     .0086526    .0110139
      hhidum |    .005961   .0064285     0.93   0.354    -.0066478    .0185697
 integration |  -.0013749   .0005969    -2.30   0.021    -.0025456   -.0002042
   ownership |  -.0023933    .002532    -0.95   0.345    -.0073595    .0025729
    nursebed |  -.0032888    .001739    -1.89   0.059    -.0066997     .000122
     pcp_md1 |   .0073998   .0146429     0.51   0.613    -.0213203      .03612
    spec_md2 |  -.0208477   .0051729    -4.03   0.000    -.0309938   -.0107017
       ftern |   9.14e-06   7.53e-06     1.21   0.225    -5.63e-06    .0000239
       bdtot |   -.000021   .0000141    -1.49   0.136    -.0000487    6.65e-06
   income_mh |  -1.49e-06   2.48e-07    -6.00   0.000    -1.97e-06   -1.00e-06
 ins_percent |   .5690869   .0746685     7.62   0.000      .422634    .7155399
    mde_rate |   .0853359   .0644709     1.32   0.186    -.0411158    .2117876
      ab_pay |  -.0000291   6.78e-06    -4.29   0.000    -.0000423   -.0000158
------------------------------------------------------------------------------
Included instruments: year1 hhidum integration ownership nursebed pcp_md1
                      spec_md2 ftern bdtot income_mh ins_percent mde_rate ab_pay
------------------------------------------------------------------------------
F test of excluded instruments:
  F(  1,  1681) =    18.39
  Prob > F      =   0.0000
```

The result from the first stage regression where we performed a regression on our instrument and all exogenous variables against Medicare Advantage penetration rate. Then, we used a partial F-test to test for endogeneity. The p-value was less that 0.00; therefore, we could reject the null hypothesis and concluded that endogeneity existed. Moreover, we obtained an F-statistic larger than 10, indicating that our instrument was not weak.

Chapter 4: Spillovers: Does Community Uninsurance Rates Affect Access to Behavioral Health Services for the Privately Insured?

Abstract

Objective: To investigate the effect of local uninsurance rates on access to behavioral health services for individuals with continuous employer-sponsored insurance that had mental health problems.

Data Sources: Individual-level data from the 2011-2015 Medical Expenditure Panel Survey (MEPS), the Area Health Resource File (AHRF), and the Small Area Health Insurance Estimator (SAHIE).

Study Design: County-level and year fixed effects models estimated the effect of changes in uninsurance rates within communities on behavioral health access to care, measured by whether an individual had a reported a emergency room or inpatient visit, outpatient visit, or had a prescription related to mental health problems.

Principal Findings: Higher community uninsurance rates were associated with fewer mental health related outpatient and prescription utilization among those who had continuous insurance coverage and had mental-health related problems. There was no association between community uninsured rates and emergency department and inpatient behavioral health related visits.

Conclusions: High levels of community uninsurance were likely to affect behavioral health access for individuals with continuous insurance who had mental health related issues. Results suggest that long-term levels of high uninsurance in communities may lack community resources to expand behavioral health provider capacity.

Introduction

The recent expansions of Medicaid and private insurance through the Affordable Care Act (ACA) in conjunction with the Mental Health Parity and Addiction Equity Act allowed more individuals to gain access to behavioral health services. As more individuals with behavioral health conditions obtain a form of insurance through one of these mechanisms, a change in demand for behavioral health services is expected.

However, previous studies did not show how coverage expansions affected access to mental health care for individuals with behavioral health conditions who already had employer sponsored insurance. The recent uptake of the number of insured individuals could have created “positive or negative spillovers” that either improved or reduced the ability of people who were already insured to access care. As insurance expansions and behavioral health needs increase, positive or negative spillovers may be more pronounced for individuals with behavioral health conditions who already have insurance. Negative spillovers may be due to the shortages in the mental health and addiction workforce not being able to meet the new demand for behavioral health services (Anderson 2014). Moreover, these negative spillovers could be greatest where there were the largest gains in the insured as a percentage of the local population (Abdus and Hill 2017).

Recent studies examining the spillover effects of community-level uninsured rates on access to care are mixed. Studies examining health reform in Massachusetts suggested that insurance expansions resulted in access problems, longer waiting times, increased use of the emergency department for nonemergency conditions, and individuals that had difficulty finding providers that accepted their insurance (Long and Stockley 2010; Skopec et al. 2015). After expansion of Medicaid in Michigan, previously insured adults experienced longer waiting times to see their primary care doctor, while the newly insured had shorter waiting times (Tipirneni et al. 2015). Other studies found positive spillovers. Communities with lower levels of uninsurance were associated with timely access, and improved quality of care for insured and the uninsured (Cunningham 1999; Cunningham and Ginsburg 2001; Cunningham and Kemper 1998; Pagán and Pauly 2006), and no negative spillovers with insurance expansions (Joynt et al. 2013). Other studies found that growing insurance coverage or community uninsured rates had no effect on primary care access for those enrolled prior to initiation of policies aimed at increasing the uptake of insurance (Abdus and Hill 2017; Sabik 2012).

The purpose of this study was to analyze the relationship between community uninsured rates and access to behavioral health services for individuals who were continuously enrolled throughout the year in employer-sponsored insurance. Data from the 2011 to 2015 Medical Expenditure Panel Survey (MEPS), Area Health Resource File (AHRF), and the Small Area Health Insurance Estimation (SAHIE), allowed this study to estimate county-level fixed-effect logistic models to assess whether community uninsured rates were related to behavioral health service access for individuals with behavioral health conditions. We hypothesized that among continuously insured adults with mental health problems; those living in communities with high-uninsured rates used fewer behavioral health services compared to those in communities with low uninsured rates.

Conceptual Framework

The ways in which population-level increases in insurance coverage affected people who were already insured during the recent insurance expansions depended on several assumptions (Abdus and Hill 2017; Pagán and Pauly 2006; Kellermann and Snyder 2004). The first was provider capacity and willingness to offer more visits and supply additional services (Abdus and

Hill 2017; Pagán and Pauly 2006; Kellermann and Snyder 2004). If providers had excess capacity, then increased demand could easily be met, but many professionals expressed concern that providers could not supply enough additional services—especially behavioral health and primary care services (Abdus and Hill 2017; Pagán and Pauly 2006; Kellermann and Snyder 2004; Hoge et al. 2013). A Substance Abuse and Mental Health Services Administration (SAMHSA) report concluded that there was major shortfall in professionals who were adequately trained and actively engaged in meeting the behavioral health needs of adults due to the workforce's insufficient size, frequent turnover, and relatively low compensation (Hyde 2013; Hoge et al. 2009; Substance Abuse and Mental Health Services Administration 2014). The lack of adequate compensation, behavioral health provider capacity, and continuity between the patient-provider relationship has been shown to be associated with lower quality of care, less timely access to care and a range of services, and reduced availability of specialty care when needed, especially for vulnerable populations (Hyde 2013; Alegria et al. 2012; Kellermann and Snyder 2004). To exacerbate this capacity issue even further, psychiatrists were least likely of all specialists to accept insurance of all kinds (Bishop et al. 2014).

The second factor was the extent to which the provider market was segmented by the types of insurances patients carried, if any (Abdus and Hill 2017; Pagán and Pauly 2006; Kellermann and Snyder 2004). The third factor was the effects of ACA provisions intended to increase health care capacity (Abdus and Hill 2017; Pagán and Pauly 2006; Kellermann and Snyder 2004). The ACA set its capacity-building activities in motion before the largest insurance expansions occurred by providing funding to expand the safety-net; training more physicians, mid-level practitioners, and nurses; and encouraging more providers to work in primary care and in underserved areas (Decker 2012; Heisler 2013). Moreover, the ACA temporarily increased

Medicaid payments for some services provided by primary care providers (Zuckerman, Skopec, and Epstein 2017; Tipirneni et al. 2015). Overwhelmingly, the largest portion of funds directed at increasing capacity went towards primary care capacity, while fewer resources were available to expand behavioral health care capacity. A recent report from the Department of Health and Human Services projected that the ACA expanded benefits for 62 million Americans (Beronio et al. 2014), while SAMHSA concluded that every 10% increase in demand for behavioral health related treatment would result in the need for 6,800 additional mental health providers (Substance Abuse and Mental Health Services Administration 2014). Meeting such demands could be difficult because about 5% of the adult population reported having unmet medical needs in the past year (Broderick 2013). The ACA developed provisions designed to address behavioral health capacity through mechanisms such as grants for education, training, and loan repayment, with specific focus on social workers and psychologist. However, physicians and nurses are not eligible for these grants (Hoge et al. 2013, 2009; Eden et al. 2012). Despite the attempt to improve the capacity of the behavioral health delivery system funds have not been authorized for many of these provisions and funding appropriated to such initiatives remains small relative to the resources devoted to primary care capacity (Hoge et al. 2013). Moreover, as suggested by some reports, recent health reforms that expand coverage and benefits for behavioral health to improve access to mental health care do not adequately incentivize or mandate behavioral health provider participation (Beronio, Glied, and Frank 2014; Hoge et al. 2013).

The spillover effects associated with community insured rates has been a major concern since the early 2000's. At the time, high and mounting uninsured rates in numerous U.S. communities generated concern for the potential of negative spillovers. The major concern was that high-uninsured rates would negatively affect access to care for both the insured and uninsured. In a 2003 report, the Institute of Medicine (IOM) hypothesized that high community uninsured rates could affect access to or quality of care for the insured and uninsured (Kellermann and Snyder 2004). More recently, a 2009 IOM report summary suggested evidence of a negative spillover effect on the insured, and stated that high community-level rates of uninsurance was associated with the insured having more difficulty obtaining needed health care (IOM 2009). Other evidence examining community uninsured rates and access to care found that adults with private insurance residing in high uninsurance communities were associated with being less likely to have a usual source of care, seeing a specialist, and being satisfied with their treatment and care from doctors (Pagán and Pauly 2006). Other evidence suggested uninsured adults reported forgoing, postponing, or having difficulty obtaining needed medical care as a function of the community uninsured rate (Cunningham and Kemper 1998). The main implications from the aforementioned evidence was that reductions in community uninsured rates through expansions of insurance could generated positive spillover effects on access to care for those that were insured.

To the contrary, there was a second line of research posits that coverage expansions—such as the through the ACA—could generate negative spillover effects on access to care for the privately and continuously insured. Abdus and Hill (2017) hypothesized that the recent and immediate uptake of insurance via the ACA's coverage expansions could negatively affect those that were already insured because the newly insured adults would stress provider capacity and decrease their access to medical care. They concluded there was little to no association between the recent uptake of insurance in communities and access to care (Abdus and Hill 2017). Other evidence found negative spillovers of the immediate uptake of insurance. The Massachusetts insurance expansions resulted in access problems, longer waiting times, increased use of the emergency department for nonemergency conditions, and individuals with difficulty finding providers that accepted their insurance, but this dissipated over the course of time (Long and Stockley 2010; Skopec et al. 2015). Medicaid expansion in Michigan led to previously insured adults temporarily seeing longer waiting times to visit their primary care doctor, while the newly insured saw shorter waiting times (Tipirneni et al. 2015).

The difference between these two perspectives could reflect short-term and long-term spillover effects of coverage expansions in the community. Short-term expansions could generate negative spillovers, while long-term effects might lead to positive spillovers. These short-term increases in community uninsured rates could lead to provisional decreases in access to care for those already insured, as the health care system has had insufficient time to adjust to the increase in demand for care. Any negative spillover effects on access to care associated with an increase in community insurance rates may be temporary and eventually diminish over the long term, as higher coverage rates of insurance increase community resources and assist in the expansion of provider capacity.

Furthermore, different study designs assessing spillovers may reflect differences between short-term and long-term effects. Studies showed positive spillovers associated with low uninsured rates that generally employed a community and year fixed effects study design (Pagán and Pauly 2006; Sabik 2012; Daysal 2012; McMorrow 2013). By contrast, studies that found negative or no spillovers associated with coverage expansions employed study designs that examined a 1- or 2-year change in community uninsured rates (Abdus and Hill 2017). For the purposes of this study, we focused on understanding the spillover effects on behavioral health care access that reflected more cumulative and long-term patterns of health insurance coverage across communities, rather than spillover effects that could be associated with short-term changes in coverage rates associated with the ACA. If communities with a large uninsured presence exist, the capacity of providers, the predictability and stability of the insurance market, and the willingness of providers to see patients may suffer. The presence of high uninsured rates in communities could lead to lower revenue streams for providers due to lower demand for care or a greater proportion of uncompensated care, which could affect the insured (Kellermann and Snyder 2004; Sabik 2012; Pagán and Pauly 2006). As a result, communities with higher uninsured rates may put greater stress on public hospitals, community health centers, and other safety net providers (Kellermann and Snyder 2004; Sabik 2012). For providers who treat both insured and uninsured patients, financial constraints due to uncompensated care burden may reduce the number of service lines offered to patients. Therefore, communities with high-uninsured rates may be less attractive to medical providers, thus reducing health system capacity and access for the insured as well as uninsured.

We examined the cumulative long-term association between community uninsured rates and behavioral health access for the privately insured. We justified this approach for several reasons. Examining immediate short-term spillovers from a policy, such as the ACA, could result in little to no spillover effects. Results indicating little to no spillovers may be related to dedicated (or lack thereof) resources invested into provider capacity building that has not had adequate time to operationalize and deliver care effectively for individuals and communities. Thus, examining spillovers from a cumulative perspective rather than from a short-term policy-driven analysis perspective may be better suited at capturing delayed full spillover effects of community uninsured rates and access to care. To our knowledge, this is the first study to investigate the association between community uninsured rates and access to behavioral health care services for adults who already had and continued to have employer-sponsored insurance.

High community uninsured rates are associated with poorer access to care, because there is an insufficient supply of behavioral health providers across the United States. Therefore, we hypothesized that adults living in communities with higher uninsured rates—as compared to lower uninsured rates:

H1: will have less behavioral health related prescription utilization.

H2: will have less ambulatory utilization related to behavioral health issues.

H3: and higher utilization of emergency department and inpatient utilization related to behavioral health problems.

We expected that communities with higher uninsured rates would have higher emergency department and inpatient visits for behavioral health problems under the assumption that having adequate access to primary care services, such as behavioral health ambulatory care services and appropriate prescriptions would assist in the deterrence of preventable and unintended emergency department and inpatient visits.

Methods

Data and Sample Population Overview

We used data from the 2011-2015 Medical Expenditures Panel Survey-Household Component (MEPS-HC). The MEPS is the most comprehensive source of nationally representative data on health care utilization, expenditures, and insurance coverage of the U.S. noninstitutionalized population. The MEPS-HC sample is drawn from a nationally representative subsample of households that participated in the prior year's National Health Interview Survey (NHIS), which is based on a multi-stage area probability design that includes oversampling of African-Americans, Hispanics, and Asians (Agency for Healthcare Research and Quality 2017a).

We used the MEPS-HC, which included three rounds per year, and we combined years 2011-2015 as repeated cross-sections to increase the sample size and the statistical precision of results. During each round of in-person interviews, information on health insurance coverage, health care utilization, health care conditions, and health care expenditures for each person in the household were collected. A Medical Provider Component (MPC) collected data from a sample of providers identified by survey respondents to both validate and supplement missing information on health care utilization (Agency for Healthcare Research and Quality 2017b). Respondents were also asked to complete self-administered questionnaires that included more detail on health status, access to care, and perceived quality of care.

Survey response rates for the five years averaged 53%. We restricted the analysis to individuals continuously enrolled in employer-sponsored insurance. We also restricted the sample to people ages 18-64, and stratified the sample based on whether they were experiencing psychological distress (defined below). We identified continuously insured individuals with employer-sponsored insurance by monthly measures that indicated whether a person had insurance or not. Each individual was asked during each round whether he/she had insurance, and the type of insurance he/she had, for all three rounds. All years were pooled together to make a pooled-cross section of data.

We combined data for the period of 2011-2015 from the MEPS-HC, the Area Health Resource File (AHRF), and the Small Area Health Insurance Estimation (SAHIE) dataset. The data from the five years of MEPS-HC conducted during this period allowed us to observe how behavioral health services for privately insured adults changed over the course of time after implementation of the ACA. Moreover, because spillover effects might have been largest in communities with the highest uninsured rate, we augmented MEPS-HC data with year and county specific measures of the percent uninsured, observed from the SAHIE. We then examined a subgroup with a behavioral health condition that was particularly vulnerable to potential spillovers: adults with severe psychological distress residing in communities with varying levels of uninsured rates. We examined three outcomes: emergency department and inpatient, prescription, and ambulatory behavioral health related utilization.

Identification of Behavioral Health Problems

To examine and identify people with psychological distress, we used the six item Kessler Psychological Distress Scale, a validated measure previously used to screen for prevalence and severity of mental illness (diagnosed and undiagnosed; Kessler et al. 2010). We identified people who had a score of nine or higher, which included people at the 75^{th} percentile or higher of the sample, and considered these adults to have severe psychological distress.

Outcomes: Identification of Behavioral Health Utilization

The MEPS respondents were asked to report on all health care utilization, including inpatient care, outpatient physician and nonphysician visits, and prescription drugs. For each medical encounter, respondents were asked a series of questions, including the specific health conditions associated with the visits. Our measures of behavioral health care utilization reflect medical encounters and prescription drugs associated with behavioral health conditions.

Behavioral health conditions were based on self-reports by survey respondents, who were asked to identify up to five health conditions associated with each medical encounter or visit (including inpatient, emergency department, ambulatory, prescription drugs; Agency for Healthcare Research and Quality 2017a). These conditions were recorded by interviewers as verbatim text and were subsequently coded into ICD-9 and Clinical Classification Codes by professional coders following specific guidelines. Behavioral health conditions were based on those with Clinical Classification Codes of 650-652, 656-663, and 670. Anxiety, depression, and other mood disorders were by far the most prevalent self-reported conditions, but our definition also included psychoses, personality disorders, and substance use disorders.

We included three utilization measures in our analysis: (1) outpatient visits related to behavioral health conditions (both hospital-based and office-based); (2) hospital emergency department and inpatient utilization related to behavioral health conditions; and (3) prescription drugs related to behavioral health problems. All visits associated with medical encounters and prescription drug utilization that had Clinical Classification Codes associated with behavioral health conditions (see above) were considered a visit for behavioral health. One exception was for outpatient provider visits, which were defined as behavioral health-related if the survey respondent reported that the primary reason for the visit was psychotherapy, or the provider seen was a psychiatrist, psychologist, social worker, or other type of mental health counselor.

Independent Variable: Community Uninsured Rates

We extracted the county-level uninsured rate from the AHRF. The AHRF pulls county-level measures from a variety of federal data sources and obtains the county-level uninsured rates from the SAHIE. The SAHIE estimates are conducted by the Census Bureau, which provides local-area estimates of the proportions of population that are uninsured (Bureau 2017). We used the SAHIE uninsured rates pulled from the AHRF versus the American Community Survey (ACS), because it allowed us to make estimates for counties with less than 60,000 people. We computed the annual proportion of uninsured by including adults ages 18 to 64 without insurance and categorized them into low, average, and high uninsured areas. County areas were defined as communities, if the communities were large enough to support estimates for all of the period

2011-2015. Community area uninsured rates from the AHRF were then merged with MEPS-HC data by county.

Controls: Other sociodemographic, health status, provider capacity, and health behavior variables

Both the descriptive and multivariate analysis described below included key sociodemographic characteristics, including age, gender, race/ethnicity (white, African-American, Hispanic, Asian, other), and education (high school graduate or less than high school). Low income was defined as having a family income less than 200% of the federal poverty level; moderate income was defined as having family income between 200 and 400% of the federal poverty level; high income was defined as having family income greater than 400% of poverty. Self-reported general health status was reported as a person having excellent or very good, average, and fair or poor health. We controlled for county-level employment and provider capacity variables. We also controlled for the supply of county-level primary care by using the simple counts of physicians, psychiatric care, and office-based psychiatric care within a given community.

Analytic Strategy

We followed a similar analytical approach as Pauly and Pagán (2006), Sabik (2012), Daysal (2012), and McMorrow (2013) where we used county-level and year fixed-effects logistic regression models to control for community-area and year factors to examine the effects of living in high or low uninsured communities and its association with behavioral health services over the course of time. For each access to care behavioral health utilization measure, we regressed on community-area adult uninsured rate. Each logistic regression was stratified by the little to no distress sample and whether a person had severe psychological distress (Kessler score of nine or above). We then converted our regression results to predicted average probabilities for ease of interpretation.

$$(1)\ E(Y_{i,c,t} = 1) = f\,(\alpha + \beta_1 Uninsured_{c,t} + \beta_2 Year_1 + \beta_3 X_1 + \beta_4 County\ Supply_1 + \beta_4 County_1 + \varepsilon_{i,c,t})$$

The dependent variables in the equation (Y_{ict}) are binary measures of health care utilization individual i, residing in community c, and in year t. The variable (Uninsured_{ct}) is a categorical variable, categorized into terciles, which takes the value 0 if individual i resided in a low uninsured rate community area, the value 1 if individual i resided in an average community uninsured rate area, and 2 if individual i resided in the highest community uninsured rate area. Year_1 is the year fixed-effect. X is the vector of individual characteristics (age, sex, race/ethnicity, employment status, education, and health status). County Supply is a vector of the number of physicians practicing in a given community (primary care physicians, psychiatrists, and office-based psychiatrists). County is the county fixed effect. Including these measures allowed us to estimate a spillover of whether the association between behavioral health utilization varied by the community-level uninsured rate.

Survey weights were used to produce nationally representative estimates, to correct for the unequal probabilities of selection in the MEPS sample, and to correct for survey non-response. The MEPS public use files included variables to obtain weighted estimates and corrected standard errors that took into account the complex survey design, using the Taylor-series linearization approach. Because MEPS public use files use a common variance structure beginning in 2002, the weight variables for the years 2011-2015 are combined in order to produce weighted estimates with the pooled data, as recommended in the MEPS survey documentation (Agency for Healthcare Research and Quality 2017a). All reported standard errors and tests of statistical significance accounted for the complex survey design. We conducted all analyses using STATA 14.2.

Results

Prevalence of Severe Psychological Distress

Of adults in the sample with continuous employer-sponsored insurance identified in Table 1, those with little to no psychological distress comprised about 33% and those with severe psychological distress comprised about 5% of the total sample. Overall, unadjusted estimates in Table 2 indicated that adults with psychological distress had higher prevalence of emergency department and inpatient, ambulatory, and prescription behavioral related utilization than those with little to no distress. Those who had severe distress had about six percentage points more ambulatory care visits, 10 percentage points more prescriptions, and about one percentage point more emergency department and inpatient visits. There was little to no difference between samples in community uninsured rates. Adults with severe distress lived in areas with higher supply of primary care physicians (*Mean*: 847.91) psychiatric physicians (*Mean:* 161.34), and office-based psychiatric physicians (*Mean:* 114.25) compared to those with little to no distress. Both samples had slightly more females than males. The majority of both samples were also White. On average, those with severe distress were less educated with approximately 7% that had less than a high school education; however, 5% of those with little to no distress had less than a high school education. Furthermore, 36% of adults with severe distress graduated from college, whereas those with little to no distress amounted to about 42%. Both samples were relatively similar in age. Income as a percent of the federal poverty line was also similar between both samples; however, the prevalence of adults that were less than 200% of the federal poverty line who had severe distress was slightly higher. People who had little to no distress were more likely to be employed and to report being in excellent or very good health.

Characteristics of Community Uninsured Rate and Behavioral Health Services

Table 3 displays the characteristics of adults that live in communities with low, average, or high-uninsured rates that use behavioral health services. Focusing on the last column of the table, adults with severe distress in communities with the highest uninsured rates as compared to those in the lowest, had less ambulatory visits (9.99%), about the same amount of prescriptions (21.44%), and more emergency department and inpatient visits (1.40%). In general, the prevalence of emergency department and inpatient visits, ambulatory care, and prescriptions was much higher for those with severe distress across all communities than those with little to no distress.

Community Uninsured Rate and Behavioral Health Access

Full logistic regression results are presented in Appendix I. We converted these results to probabilities for ease of interpretation. Table 4 presents the predicted average probabilities of our full logistic regression results. Overall, adults with severe psychological distress in communities with the highest uninsured rates reported a lower probability of prescriptions and ambulatory visits than those in communities with the lowest uninsured rate. Results indicated that adults with severe psychological distress that resided in communities with average and the highest uninsured rates were prescribed behavioral health related medications 7 percentage points ($p<0.05$) and 8.28 percentage points ($p<0.1$) less than those who lived in the lowest uninsured communities, respectively. This trend continues with ambulatory care as well. Adults that live in communities with an average uninsured rate reported utilizing outpatient or office-based care 8.57 percentage points (p<0.01) less than those in the lowest uninsured communities. Adults living in counties with the highest uninsured rate saw even a larger disparity—they reported 10.58 percentage points (p<0.01) less outpatient or office-based visits. Adults living in the highest uninsured areas saw about 5% higher probability of emergency department and inpatient visits relative to communities with the lowest uninsured rate; however, this was not significant. For individuals with little or no psychological distress, there were no statistically significant differences between community uninsured rate and behavioral health care utilization.

Discussion

Our results found that high levels of community uninsurance and access to behavioral health services did not only affect the uninsured, but the insured as well. There appeared to be a negative spillover in communities with the highest uninsured rates. The privately insured reported lower probabilities of prescription utilization and ambulatory care for behavioral health related issues. We found similar results by Pauly and Pagán (2006), but different than Abdus and Hill (2017) and other studies that examined the spillover effects of the ACA coverage expansions. Like Pauly and Pagán (2006), Sabik (2012), Daysal (2012), and McMorrow (2013), our year and county fixed-effects study design might reflect the long-term cumulative effects of living in high and low uninsured communities; whereas, Abdus and Hill and other studies assessed the short-term changes in utilization that occurred when a community experienced a change in coverage over a 1- or 2-year period. A short-term increase in the community insurance rate could lead to a short-term decrease in access for those who already insured, as the health care system had insufficient time to adjust to the increased demand for care. However, any negative spillover effects on access associated with an increase in community insurance rates could be temporary and eventually reversed over the long term, as higher coverage rates were associated with increases in community resources. As demonstrated by our results, communities with high uninsured rates affected privately insured individuals' access to behavioral health services negatively, which could be a symptom of insufficient provider capacity and inadequate community resources. The implication is that over the long term, coverage expansions have positive spillover effects on the continuously insured as higher coverage rates increase community resources and lead to an expansion in system capacity.

In greater detail, the negative spillover effects in high-uninsured communities may have occurred for several reasons. First, the thin profit margins per service that accompany a large uninsured presence (Pagán and Pauly 2006; Sabik 2012; Chen, Lo Sasso, and Richards 2018). Second, in communities with high-uninsured rates the uncertain mix of privately uninsured and insured adults could add unpredictability and instability to the respective markets (Chen, Lo Sasso, and Richards 2018; Pagán and Pauly 2006). Third, the return on investment for primary care specialties such as psychiatry may be negative and a far more risky discipline to enter than other specialties (Chen, Lo Sasso, and Richards 2018). These reasons create a scenario that may be detrimental to behavioral health provider capacity, reduce the demand and access for behavioral health services, and disincentivize behavioral health providers from seeing patients and offering more services.

Policymakers and medical professionals should be cognizant that the lack of behavioral health supply- and demand-side incentives may have unintended consequences that may also affect individuals with insurance, especially those with behavioral health needs. This study demonstrates that high levels of community uninsured rates can have negative effects on privately insured individuals' behavioral health service access. Supply-side policies that influence demand should be developed to bolster behavioral health provider capacity. Evidence of supply-side financial incentives such as provider bonuses, benefit expansions, and payment increases for specific services have been documented as having positive effect on providers entering less-desired specialties, improving provider capacity in high need areas, and increasing access to medical care (Chen, Lo Sasso, and Richards 2018). As a result, resources should be targeted to communities with the highest uninsured rates so that individual access to behavioral health services is improved.

This study had several limitations. First, we used the Kessler scale as a proxy to identify whether an individual had a behavioral health condition. We used this scale because of the endogeneity issues between identifying our sample by using behavioral health conditions at a provider visit and measuring behavioral health utilization. Second, there could be under-reporting of diagnoses for behavioral health problems and over-estimates of treated cases. Third, a larger sample would yield more precise estimates to detect differences across community uninsured rates and behavioral health access. Fourth, there could be measurement error of the community uninsured rate in the SAHIE. Fifth, community uninsured rates continued to decline past 2015; therefore, spillovers on the continuously insured may have changed. Lastly, we could not be completely sure that disparities in behavioral health access in communities with higher uninsured rates were due to lower provider capacity and payments.

Adults with psychological distress and that have continuous employer-sponsored coverage, in communities with higher levels of the uninsured, was associated with a negative spillover. On average, people were less likely to use prescriptions, and to use ambulatory services to receive services related to their behavioral health. There appears to be no statistically significant differences in county-level uninsured rates and emergency department and inpatient utilization. Although, these individuals have insurance, their access to behavioral health related medication and ambulatory services were less likely if they lived in a highly uninsured area.

Table 1. Sample Summary.

Continuously enrolled in employer-sponsored insurance	(n=181,529)
Little no psychological distress	33.04%
Severe Psychological Distress	5.43%

Table 2. Summary Statistics.

	Little to no distress	Severe Distress
	%	%
	Mean	Mean
Behavioral Health Utilization		
Emergency Department/Inpatient	0.27%	1.12%
Prescription	11.48%	21.09%
Ambulatory	4.19%	10.66%
Community Uninsured Rate[1]		
Low	37.37%	38.07%
Average	34.28%	34.97%
High	28.35%	26.96%
County Supply-Side Variables		
Primary Care Physicians	778.27	847.91
Psychiatric Physicians	144.82	161.34
Office-based Psychiatric Physicians	102.90	114.25
Controls		
Sex		
Male	49.18%	48.13%
Female	50.82%	51.87%
Education		
LT High school	3.56%	6.75%
High School or GED equivalent	23.45%	25.57%
Some College/Associates or Vocational	30.53%	31.51%
College graduate	42.45%	36.17%
Race/Ethnicity		
White	57.89%	55.20%
Hispanic	11.04%	12.08%
Black	9.01%	8.95%
Asian	20.00%	21.58%
Other	2.06%	2.20%
Age		

Table 2. Summary Statistics.

	Little to no distress	Severe Distress
	%	%
	Mean	Mean
18-34	29.62%	31.68%
35-49	33.89%	32.76%
50-64	36.50%	35.57%
Income (percent of federal poverty line)		
LT than 200%	9.38%	12.17%
200%-400%	30.95%	32.99%
GT than 400%	59.67%	54.84%
Employment	86.01%	78.25%
General Health Status		
Excellent or Very Good	70.20%	58.63%
Good	23.54%	27.62%
Fair or Poor	6.26%	13.75%
Year		
2011	20.20%	20.77%
2012	20.53%	17.41%
2013	19.82%	18.25%
2014	19.66%	21.56%
2015	19.79%	22.01%

[1]Community Uninsured Categories are defined as follows:
Low: LT 14.44%
Average: 14.44%-21.06%
High: GT 21.06%

Table 3. Behavioral Health Services by Community Uninsured Area.

	Little to no distress	Severe Distress
Community Uninsured Rate		
Emergency Department/Inpatient		
Low	0.24%	0.88%
Average	0.35%	1.17%
High	0.21%	1.40%
Prescription		
Low	12.27%	21.25%
Average	11.94%	20.65%
High	9.89%	21.44%
Ambulatory		
Low	4.94%	11.62%
Average	4.28%	10.13%
High	3.10%	9.99%

Table 4. Adjusted Probabilities: Stratified by Psychological Distress.

Variable	**Little to no distress**	**Severe distress**
Utilization Measures	**Predicted Average**	**Predicted Average**
Emergency Department/Inpatient		
Low community-level uninsured rate (reference)	0.68%	3.40%
	(0.21)	(1.56)
Average community-level uninsured rate	1.40%	2.27%
	(0.32)	(0.60)
High community-level uninsured rate	1.10%	8.34%
	(0.61)	(3.59)
RX Use		
Low community-level uninsured rate (reference)	11.77%	28.12%
	(0.07)	(2.23)
Average community-level uninsured rate	12.79%	21.12%**
	(0.53)	(1.11)
High community-level uninsured rate	11.92%	19.84%*
	(0.97)	(2.36)
Outpatient/Office Based		
Low community-level uninsured rate (reference)	4.76%	20.25%
	(0.41)	(2.77)
Average community-level uninsured rate	5.59%	11.67%***
	(0.41)	(1.08)
High community-level uninsured rate	5.59%	9.62%***
	(0.89)	(1.51)

[1]Community Uninsured Categories are defined as follows:
Low: LT 14.44%
Average: 14.44%-21.06%
High: GT 21.06%
*p<0.1, **p<0.05, ***p<0.01 significantly different from reference group

Appendix 2. Regression Results: Association Between Community Uninsurance and Behavioral Health Services.

	Emergency Department/Inpatient		Ambulatory		Prescription	
	Little to no distress	Severe Distress	Little to no distress	Severe Distress	Little to no distress	Severe Distress
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
Community Uninsured Rate[1]						
Low (Reference)						
Average	2.17	0.61	1.20	0.44***	1.11	0.60***
	(1.11)	(0.51)	(0.19)	(0.12)	(0.12)	(0.11)
High	1.66	3.36	1.28	0.34***	1.02	0.54*
	(1.45)	(3.99)	(0.32)	(0.14)	(0.17)	(0.18)
County Supply-Side Variables						
Primary Care Physicians	1.00	1.03**	1.00	0.99**	1.00	1.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Psychiatric Physicians	1.03	1.00	1.00	1.02	1.00	1.01
	(0.02)	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)
Office-based Psychiatric Physicians	0.93**	0.86**	1.00	1.02	0.99	0.99
	(0.03)	(0.06)	(0.01)	(0.02)	(0.01)	(0.02)
Controls						
Sex						
Male (Reference)						
Female	1.98**	1.57	1.55***	1.94***	2.12***	2.01***
	(0.59)	(0.60)	(0.15)	(0.26)	(0.13)	(0.24)
Education						
LT High school (reference)						
High School or GED equivalent	1.09	5.19***	1.06	1.66	1.19	2.00***
	(0.74)	(3.68)	(0.37)	(0.63)	(0.21)	(0.56)
Some College/Associates or Vocational	0.68	4.52***	1.51	1.88*	1.37**	2.45***
	(0.45)	(3.57)	(0.53)	(0.67)	(0.21)	(0.67)
College graduate	0.74	3.19	1.98	3.29***	1.36*	3.03***

Appendix 2. Regression Results: Association Between Community Uninsurance and Behavioral Health Services.

	Emergency Department/Inpatient		Ambulatory		Prescription	
	Little to no distress	Severe Distress	Little to no distress	Severe Distress	Little to no distress	Severe Distress
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
	(0.52)	(2.78)	(0.69)	(1.19)	(0.21)	(0.88)
Race/Ethnicity						
Hispanic (Reference)						
White	1.62	3.17**	2.08***	2.012***	2.18***	2.56***
	(0.75)	(1.71)	(0.31)	(0.43)	(0.23)	(0.54)
Black	0.76	0.86	0.82	0.59**	0.51***	0.45***
	(0.44)	(0.64)	(0.16)	(0.16)	(0.07)	(0.12)
Asian	1.49	0.57	1.36**	0.74	1.30*	1.22
	(0.78)	(0.39)	(0.21)	(0.19)	(0.15)	(0.28)
Other	2.14	2.13	1.59	1.00	1.30	2.21**
	(2.32)	(1.81)	(0.50)	(0.39)	(0.37)	(0.76)
Age						
18-34 (Reference)						
35-49	0.69	0.31***	1.04	0.97*	1.17*	1.19
	(0.24)	(0.14)	(0.13)	(0.18)	(0.10)	(0.18)
50-64	0.67	0.14***	0.98	0.71**	1.55***	1.27*
	(0.20)	(0.06)	(0.11)	(0.11)	(0.12)	(0.16)
Income (percent of federal poverty line)						
LT than 200% (Reference)	-	-				
200%-400%	1.00	1.05	1.21	0.99	0.97	0.83
	(0.46)	(0.57)	(0.21)	(0.19)	(0.10)	(0.14)
GT than 400%	0.64	1.07	1.13	1.07	1.00	0.77
	(0.34)	(0.60)	(0.20)	(0.22)	(0.11)	(0.14)
Employment	1.91	0.68	0.64***	0.40***	0.73***	0.52***
	(0.80)	(0.27)	(0.07)	(0.08)	(0.05)	(0.07)
General Health Status						
Excellent or Very Good (Reference)						
Good	2.61***	7.38***	1.74***	3.05***	1.73***	2.95***
	(0.76)	(3.31)	(0.17)	(0.48)	(0.10)	(0.37)

Appendix 2. Regression Results: Association Between Community Uninsurance and Behavioral Health Services.

	Emergency Department/Inpatient		Ambulatory		Prescription	
	Little to no distress	Severe Distress	Little to no distress	Severe Distress	Little to no distress	Severe Distress
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
Fair or Poor	4.77***	15.38***	2.73***	3.97***	3.20***	5.03***
	(1.65)	(6.82)	(0.44)	(0.68)	(0.31)	(0.73)
Year						
2011 (Reference)						
2012	1.23	1.95	0.71***	0.84	0.73***	0.66***
	(0.51)	(1.06)	(0.07)	(0.17)	(0.06)	(0.11)
2013	0.86	2.27	0.66***	0.72	0.72***	0.67**
	(0.46)	(1.39)	(0.08)	(0.18)	(0.07)	(0.12)
2014	1.36	1.08	0.86	0.58**	0.81**	0.60***
	(0.80)	(0.76)	(0.13)	(0.14)	(0.09)	(0.12)
2015	1.13	1.13	0.75*	0.39***	0.72***	0.43***
	(0.76)	(0.88)	(0.12)	(0.12)	(0.09)	(0.10)
Constant	0.04	0.00***	0.74***	0.23	0.02***	0.01***
	(0.28)	(0.00)	(0.02)	(1.57)	(0.00)	(0.00)

[1]Community Uninsured Categories are defined as follows:
Low: LT 14.44%
Average: 14.44%-21.06%
High: GT 21.06%
*p<0.1, **p<0.05, ***p<0.01

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