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# Impact of the Hospital Readmission Reduction Program on hospital readmission and mortality: An economic analysis

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**Abstract**

Reduction in hospital readmissions has long been identified as a target area for healthcare public policy reform by the US government. In October 2012, the Affordable Care Act (ACA) established the Hospital Readmissions Reduction Program (HRRP) program, which requires the Centers for Medicare and Medicaid Services to reduce payments to hospitals with excess readmissions. Even with recent changes in ACA, the HRRP program is still in place. In this study, we empirically examine the effectiveness of the introduction of the HRRP on hospital readmission and mortality rates. We observe that, in general, the introduction of the HRRP has significantly reduced readmission rates. However, the introduction of the HRRP does not necessarily decrease the mortality rates, which highlights the unintended consequences of public policy. What is more interesting is that the impact of the HRRP is heterogeneous in hospital size and racial groups. First, after the HRRP introduction, large hospitals have experienced a greater reduction in readmission rates than small hospitals. Second, after the introduction of the HRRP, the zip code regions with a higher percentage of Hispanic and African-American populations have experienced a larger reduction in readmission rates. These results contribute to both theory and practice in public policy and provide important and nuanced policy implications for evaluating the effectiveness of the HRRP. Policy-makers also need to pay close attention to these results for future implementations of policies similar to the HRRP.

**KEYWORDS**

acute care hospitals, econometric model, empirical study, HRRP, mortality rate, readmission rate

## 1 | INTRODUCTION

The US national healthcare expenditure as a percentage of gross domestic product (GDP) has been growing since 1960. In 1960, it was 5% of the GDP, while in 2000, it was 13.3%, and in 2020, it reached 18% (Statista, 2020). According to the American Medical Association, healthcare spending in the United States is projected to grow 4.8% in 2019, reflecting rising prices of medical goods and services and higher Medicaid costs. This increase represents a sharp uptick from 2017 spending. The Centers for Medicare and Medicaid Services (CMS) projects that healthcare spending will, on average, rise 5.4% annually from 2019 to 2028. By 2028, healthcare spending is projected to reach nearly $6.2 trillion (CMS, 2020).

The steady rise of healthcare costs has worried policymakers for a long time. In October 2012, the Affordable Care Act (ACA) established the Hospital Readmissions Reduction Program (HRRP). Even with recent changes in ACA, the HRRP program is still in place. The HRRP is a pay-for-performance policy that lowers payments to inpatient prospective payment system (IPPS) hospitals with too many readmissions (Desai et al., 2016). Within the context of Medicare, readmission includes all-cause unplanned readmissions that happen within 30 days of discharge from the initial admission. Patients can be readmitted to the same hospital or another applicable acute care hospital for any reason. Reduction in hospital readmissions has long been identified as a target area for health reform by the US government. The HRRP requires CMS to reduce payments to hospitals with

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[Correction added on 10th June, after first online publication: The last author name has been updated.]

  

excess readmissions. Currently, CMS uses five readmission measures (for patients admitted for heart failure (HF), acute myocardial infarction (AMI), pneumonia, chronic obstructive pulmonary disease (COPD), and total hip/knee arthroplasty) for adjusting payments to a hospital based on its readmission rate.

Hospital readmission has been publicized as a quality measure to help bend the healthcare cost curve. Different types of readmission studies have been conducted, including the predictive performance of readmission models, the impact of specific health insurance types on readmission, the influence of patient-level predictors on readmission, the association between health information exchange (HIE) usage and readmission, the relationship between quality of healthcare environment and readmission, the influence of diagnoses/procedures on readmission, the relationship between postdischarge conditions/strategies and readmission, and the effect of sociodemographic variables (e.g., Amarasingham et al., 2010; Senot, 2019; Senot & Chandrasekaran, 2015; Senot et al., 2016; Vest et al., 2014). In this study, we empirically examine the effectiveness of the HRRP with respect to readmission rates and mortality rates by analyzing Medicare data. The dataset captures the pre- and postlaunch of the HRRP on hospital readmissions.

Despite its importance, the impact of the HRRP on the reduction in hospital readmission rate has not been studied rigorously. Many prior studies have mainly focused on the simple correlation between the introduction of the HRRP and the reduction in hospital readmission rates. For example, Desai et al. (2016) simply compare readmission rates before and after the intervention without controlling for other factors. However, without considering individual or common time trends in the sample period, it is difficult to estimate the true effect of the HRRP. In our study, we fill this gap by using (i) the correlated random trend model and (ii) the fixed effects model combined with interrupted time series to evaluate more precisely the intervention effects of the HRRP.

## 1.1 | Motivation

Because of the HRRP, it has become critical for hospital administrations to analyze the factors influencing readmissions. Based on a survey of leadership across several hundred acute care hospitals subject to the HRRP, Joynt et al. (2016) find that the program had a major impact on hospital leaders' efforts to reduce readmission rates, but some hospital leaders have concerns about "the size of the penalties, lack of adjustment for socioeconomic and clinical factors, and hospitals' inability to impact patient adherence and post-acute care."

In the last 5 years, Medicare has fined a large number of hospitals for excessive readmissions. The total Medicare readmissions penalty incurred by hospitals in the fiscal year (FY) 2017 was over $500 million. The number of hospitals penalized has remained flat at approximately 78% in FYs 2015, 2016, and 2017 (Boccuti & Casillas, 2017). During those 3 years, the number of hospitals paying the maximum penalty (3% of a hospital's base Medicare inpatient payments) has risen from 1.2% to 1.8%. The 3-year moving average of readmission rates fell across all diagnosis categories during the last 5 years, indicating the introduction of new intervention policies by hospitals since 2012. However, average hospital penalties have not declined. During the 2013 to 2017 period, it reached a maximum in FY 2017 (Boccuti & Casillas, 2017).

Hansen et al. (2011) review past studies on 43 interventions (to reduce the 30-day hospital readmission rate) and find that the quality of those studies, in general, has been low, with only 16 being randomized controlled trials. Further studies on readmission and mortality rates have examined patient-level data in an effort to understand the underlying causes, such as diagnosis and procedure codes (Black, 2014; Shadmi et al., 2015; Xenos et al., 2014); type of health insurance (Shah et al., 2015); premature discharge (Berenson et al., 2012); and failure to coordinate and reconcile medications (Berenson et al., 2012). These studies analyze hospital readmission at the patient level.

Several recent rigorous studies have begun to notice the unintended consequences or spillover effect of the HRRP. Batt et al. (2018) find that the HRRP has an unintended spillover effect: a significant improvement in readmission rate for nontargeted patients (patients who are not targeted by the policy). In a closely related study, Wadhera et al. (2018) find that HRRP implementation was associated with a significant increase in 30-day mortality rates for HF and pneumonia, but not for AMI, based on patient-level discharge data. In addition, Wadhera et al. (2018) demonstrate an unintended consequence of HRRP: It may increase the mortality rates. Note that Wadhera et al. (2018) conduct a patient-level analysis, while the unit of analysis in our study is a hospital. Our focus on the hospital-level data is based on gaining more insights across all hospitals in the United States and not on a specific panel of patients in a few hospitals. A hospital-level analysis is important because the incentives of HRRP would be felt at the hospital level and inadvertently create trade-offs between mortality and readmissions, which can be captured better in the hospital-level data. We study the impact of the HRRP on readmission and mortality rates at the hospital level and find an increase in mortality rates for some medical conditions, which is similar to the findings in Wadhera et al. (2018) and complement them using hospital-level data. Different from Wadhera et al. (2018), a hospital-level analysis allows us to examine how hospital characteristics (i.e., hospital size) and racial characteristics moderate the impact of the HRRP. We demonstrate that the impact of the HRRP is heterogeneous in hospital size and racial groups, which provides guidelines for CMS managers to dig deeper into the underlying economic and operational reasons rather than just looking at the overall result.

## 1.2 | Research questions and contributions

Prior literature on the effectiveness of the HRRP has mainly focused on the correlation (e.g., Desai et al., 2016). However, as discussed earlier, common time trends and hospital-specific time trends may lead to spurious relationships and confound identification. To the best of our knowledge, little is known about the true impact of the HRRP on readmission and mortality rates, as well as the moderating effects of hospital characteristics and region-wide demographics.

In order to systematically bridge this research gap, we begin by asking our first research question (1) *What is the impact of the HRRP on readmission and mortality rates?* Even though some past studies have examined the factors that influence readmission and mortality rates using patient-level data (e.g., Batt et al., 2018; Wadhera et al., 2018), there is a dearth of research on the influence of hospital-level factors on readmission and mortality rates. Among various disease conditions considered by the CMS for the HRRP, our focus in this research is on understanding how hospital readmissions and mortality rates depend on the following three disease conditions: HF, AMI, and pneumonia.

As mentioned earlier, an empirical challenge lies in establishing the true effect of the HRRP. Randomized field experiments are considered the ideal approach for assessing the casual effectiveness of interventions (Bapna et al., 2017; Kumar & Qiu, 2022; Qiu & Kumar, 2017). However, not all interventions can be assessed with a randomized field experiment, in particular for health policies and programs targeted at the hospital level. In our context, it is difficult to imagine a nationwide experiment regarding the implementation of the HRRP at the hospital level. Due to the lack of control over confounding variables, such as time trends, the conclusions from prior studies using observational approaches are considered to be weaker in terms of establishing causation and policy evaluation. Without addressing the issue of time trends, the estimation of the effect of the HRRP would be biased. Using a correlated random trend model and a fixed effects model combined with interrupted time series, we provide an empirically driven comprehensive understanding of the effectiveness of the HRRP. In particular, the correlated random trend model allows us to consider hospital-specific linear trends, and the interrupted time series design allows trend change after the intervention. Note that the approach of interrupted time series has been increasingly used for the evaluation of public health interventions (Bernal et al., 2017; Kontopantelis et al., 2015). In our context, a fixed effect model with an interrupted time series analysis is a useful quasi-experimental design to help us be a step closer to the true effects of the HRRP.

When the government imposes new public policies, it may create outcomes that differ from the original intent (Friedson, 2012; Hall, 2014). Understanding the exact effects of a given policy is a complicated task, given the unintended consequences of public policy. Batt et al. (2018) find that the HRRP has an unintended spillover effect: a significant improvement in readmission rate for nontargeted patients (patients who are not targeted by the policy).

Our study illustrates another unintended effect on nontargeted metrics (i.e., mortality rate) instead of nontargeted patients. In our context, we find that the introduction of the HRRP has significantly reduced the hospital readmission rates in all three diseases (HF, AMI, and pneumonia). However, the introduction of the HRRP does not necessarily decrease the mortality rate. In fact, the mortality rates of HF and pneumonia increased significantly post HRRP. Some prior studies focus only on reductions in readmissions and declare that the HRRP might be a success (e.g., Desai et al., 2016). Our study raises the concern that HRRP may also have unintended consequences that adversely affect patient care, potentially leading to increased mortality. One possible reason is that hospitals may have shifted their focus toward the readmission rate metric (penalized under the HRRP) from the quality of care metrics (not penalized under the HRRP), which include the reduction of mortality rate. This effect is exacerbated by the Hawthorne effect in the healthcare domain (Leonard & Masatu, 2010): Doctors change their behaviors when hospital managers closely observe their practices and encourage behaviors that could lead to reductions in readmissions. Individuals' internal motives are associated with organizational recognition (Grant, 2012). Paying too much attention to reductions in readmissions may trigger employees (doctors) to think that the value of other objectives/tasks is no longer appreciated or recognized in organizations (hospitals), which crowds out their internal motivation. In other words, "some hospitals may have focused more resources and efforts on reducing or avoiding readmissions than on prioritizing survival" (Wadhera et al., 2018, p. 2550). This tends to be further supported by the fact that, post-HRRP, while inpatient readmissions went down, emergency department (ED) and observation visits among patients returning within 30 days for the target conditions went up (Hsuan et al., 2020; Noel-Miller & Lind, 2015). For example, because of HRRP penalties, hospitals may be increasingly treating patients in EDs or observation settings to avoid readmissions (Wadhera et al., 2019). The possibility of unintended consequences on mortality rates makes careful and thorough cost-benefit analysis a must in public policymaking. Our research highlights that the impact of unforeseen consequences should be factored into future policy planning.

The effectiveness of the HRRP may critically depend on hospital characteristics, such as hospital size and region-wide demographics. However, the direction of the moderating effect is not clear. Larger hospitals may have a greater incentive to reduce the readmission rate after the introduction of the HRRP. The reputation cost associated with the HRRP penalty might be nonlinear in hospital size, and the reputation cost can be much higher for larger hospitals (M. Chen & Grabowski, 2019; Winborn et al., 2014): Journalists and reporters typically focus only on large hospitals rather than small hospitals. There is a significant amount of news media coverage of the HRRP penalties for large hospitals but much less for small hospitals. Only when a hospital is sufficiently large, journalists and reporters start to pay attention to it, and a high reputation cost occurs. Therefore, large hospitals typically have a higher reputation cost as a percentage of the revenue than small hospitals, and they are more incentivized to avoid negative reputation effects associated with being penalized under the HRRP than small hospitals. Furthermore, Winborn et al. (2014) have shown that the reputation cost is not trivial for large hospitals, compared to the monetary value of the penalty. The HRRP penalties and excess readmissions of large hospitals have been widely disseminated in the news media and scrutinized by the general public. This type of media exposure can impose significant reputational effects that go far beyond the size of the HRRP penalty. In addition, because large hospitals are more likely to experience payment cuts under the HRRP (Joynt & Jha, 2013), they have a greater incentive to focus on the reduction of readmission rates.

On the other hand, larger hospitals are more likely to be involved in multiple evaluation programs with different performance measures.[1] They may have priorities other than reducing the readmission rate in the sample period, and hence, the HRRP could be less effective for larger hospitals. Both directions are theoretically plausible, presenting a viable opportunity for empirical testing.

In terms of region-wide demographics, according to prior studies (Dotson et al., 2015; Jiang et al., 2005; Li et al., 2017; McHugh et al., 2010), readmission is significantly lower for Whites than for Hispanics and African Americans for many diagnoses, including the target conditions (HF, AMI, pneumonia). One potential reason is that minority patients (Hispanics and African Americans) tend to have a lower level of education and have insufficient knowledge about self-care, such as diet and symptom management (M. Chen & Grabowski, 2019; Dickson et al., 2013). Prior literature has shown that using patient-centered education to improve self-care can lead to substantial reductions in readmission rates (Nair et al., 2020; Shull et al., 2018).[2] For example, since minority patients tend to have a lower education level and lower health literacy, they may have difficulty understanding their discharge instructions (Dickson et al., 2013). Some hospitals prioritize ensuring that patients understand their discharge instructions, which may benefit minority patients with a low level of health literacy more: They make sure that the discharge instructions are written at a fifth-grade reading level and ask hospital staff to ensure that patients can "teach back" the instructions they have been given (Loria, 2018).

In addition, a pharmacist-driven intervention program may help these minority patients more because pharmacists can work directly with patients to provide education and promote engagement through counseling and medication management strategies (Shull et al., 2018). Some hospitals also implement healthy literacy programs, which provide nurse visit services to patient homes if patients have limited health literacy (Loria, 2018). Therefore, the zip code regions with higher percentages of Hispanic and African-American populations (historically disadvantaged racial groups) have greater potential in reducing readmission rates, and the HRRP can be more effective in these regions.

Prior research has not directly addressed the moderating effects of hospital characteristics and region-wide demographics on the effectiveness of the HRRP, which leads to our research questions (2) and (3):

(2) How does the hospital size moderate the impact of the HRRP on readmission rates and mortality rates?

(3) After the introduction of the HRRP, did regions with higher percentages of Hispanic and African-American populations experience a larger or smaller reduction in readmission and mortality rates?

We find that the impact of the HRRP is heterogeneous in terms of hospital size and racial groups: (i) Post HRRP, large hospitals have experienced a larger reduction in readmission rates than small hospitals, and (ii) post HRRP, zip code regions with higher percentages of Hispanic and African-American populations experienced a larger reduction in readmission rates. The impact of HRRP on mortality is also moderated by hospital size and racial groups. These results provide important and nuanced policy implications for evaluating the effectiveness of the HRRP. Public policymakers may need to design policies to account for the heterogeneity within the healthcare industry (Joglekar et al., 2016).

## 1.3 | Literature review

In this section, we review the literature from two different perspectives. Each of these perspectives depends on the type of data used in the analysis: (i) using retrospective patient-level data and (ii) using national hospital-level data. Here, we also highlight our contributions with respect to past studies.

### 1.3.1 | Using retrospective patient-level data

Research on readmission based on retrospective data includes variables that are not available early during hospitalization. For example, a model that uses length-of-stay or discharge information for the index hospitalization would be classified as using retrospective patient-level data. Prior studies in readmissions research have examined a wide range of issues, including the predictive performance of readmission models (He et al., 2014; Shadmi et al., 2015; Walsh & Hripcsak, 2014), the impact of specific health insurance types on readmission (Shah et al., 2015), the influence of patient-level predictors on readmission (Black, 2014), the association between HIE usage and readmission (Vest et al., 2014), the relationship between the quality of the healthcare environment and readmission (Ma et al., 2015), the influence of diagnoses/procedures on readmission (Black, 2014; Shadmi et al., 2015; Xenos et al., 2014), the relationship between postdischarge conditions/strategies and readmission (Glance et al., 2014), and the effects of sociodemographic variables (Black, 2014; Helm et al., 2016), and so forth.

Martsolf et al. (2016) examine how adding socioeconomic status and race/ethnicity to the CMS risk-adjusted algorithm affects excess readmission ratios and penalties. They find that the risk adjustment for socioeconomic status and race/ethnicity has an impact on HRRP penalties, affecting more than 83% of hospitals. In particular, including these two factors in the calculation has a disproportionately favorable effect on safety net and rural hospitals. Batt et al. (2018) find that the implementation of HRRP can significantly improve the readmission rate for nontargeted patients (patients who are not targeted by the policy). Desai et al. (2016) compare trends in readmission rates for target and nontarget conditions among patients admitted to hospitals that were subject to HRRP penalties and those that were not. The target conditions in the study were AMI, congestive HF, and pneumonia. They find that prior to the HRRP announcement, readmission rates remained stable for target and nontarget conditions, irrespective of penalty status, except for AMI. After the announcement, readmission rates declined significantly for all the target conditions at hospitals subject to penalties. On the other hand, at hospitals not subject to penalties, there was no significant decrease in readmission rates for any of the three target conditions. Medicare fee-for-service patients at hospitals subject to penalties witnessed greater reductions in readmission rates, compared to those at hospitals not subject to penalties. Andritsos and Tang (2018) examine the "joint effect" of the hospital and patient financial incentives on readmission. Liu et al. (2018) develop effective checkup plans to monitor patients following hospital discharge. They use a delay-time analysis model to identify the optimal type and timing of checkups to implement postdischarge monitoring plans.

Our study is closely related to Wadhera et al. (2018). The main finding of Wadhera et al. (2018) is that HRRP implementation was associated with a significant increase in 30-day mortality rates for HF and pneumonia based on the patient-level discharge data. On the one hand, our research using hospital-level data further confirms the mortality results in Wadhera et al. (2018). On the other hand, using hospital-level data, we are able to examine how the impact of HRRP is moderated by hospital size, which cannot be studied using patient-level data in a few hospitals. In particular, we find that the beneficial effect of HRRP is not observed in a consistent manner across all hospitals: After the HRRP introduction, larger hospitals have experienced a greater reduction in readmission rates than smaller hospitals. In addition, after the introduction of the HRRP, the zip code regions with a higher percentage of Hispanic and African-American populations have experienced a larger reduction in readmission rates.

Furthermore, hospital-level data allow us to conduct a "dose–response" analysis. Under the HRRP, hospitals were charged a maximum penalty of 1% for FY 2013 (performance period: June 2008–July 2011), 2% for FY 2014 (performance period: June 2009–July 2012), and 3% for FY 2015 (performance period: June 2010–July 2013) and beyond. We find that hospitals might be more incentivized to reduce readmission under the full penalty (3% penalty period). We also find a larger unintended effect of HRRP, which adversely affects mortality, under the full penalty (3% penalty period).

In terms of methodology, the main identification method in Wadhera et al. (2018) is propensity score matching (PSM): They match each treated patient with a more comparable control patient based on patient-level characteristics and generate a more balanced new data sample. Note that PSM takes care of only observable characteristics and may be biased in the case of selection-on-unobservables. Our research addresses the issue of selection-on-unobservables using a correlated random trend model, which considers unobserved hospital-specific time trends.

### 1.3.2 | Using retrospective hospital-level data

Research on readmission based on hospital-level data collected nationally (usually from CMS) includes variables related to hospital demographics, utilization, ratings, how the hospital compares with others nationally, and so forth. The objective of this type of research is to study and analyze the readmission decisions at the hospital level to understand the effectiveness of the HRRP policy. The benefit of this type of analysis is to focus on all hospitals across the nation.

The problem of readmission is intimately related to the HRRP policies that have been implemented by CMS. Our review of the literature shows that many researchers have studied this problem. However, most of them have just reviewed the problem by describing the penalties levied on hospitals, the transitions of care and care coordination, and the outcomes of the program like readmissions reduction, along with the discussed pros and cons of the HRRP policies. Others like N. Lu et al. (2015) evaluate the HRRP penalties on readmissions for HF, AMI, and pneumonia at nonfederal, short-term acute care hospitals for FYs 2013, 2014, and 2015. They find that there was a significant decrease in excess readmissions for the three conditions between FY 2013 and FY 2015. However, they do not find any evidence that the effect of HRRP is associated with the proportion of Medicare/Medicaid patients admitted to a hospital for any of the three conditions under investigation. Carey and Lin (2016) emphasize that even though the rate of hospital readmission has fallen, concerns are being raised about the impact of the HRRP program on safety-net hospitals, which typically have a high proportion of low-income patients. They observe that the risk-adjusted readmission rates for heart attack, HF, and pneumonia conditions are higher in safety-net hospitals than in other hospitals.

Zuckerman et al. (2016) find that the readmission rates for AMI, HF, and pneumonia declined from 21.5% to 17.8%, while the rates for nontargeted conditions declined from 15.3% to 13.1%. Similar results are observed by Ibrahim et al. (2018): They find that from 2008 to 2014, rates of readmission declined for both targeted conditions (6.8% to 4.8%) and nontarget conditions (17.1% to 13.4%). The rate of reduction was most prominent after the announcement of the HRRP for both targeted and nontargeted conditions.

Wasfy et al. (2017) find that lower-performing hospitals have experienced the greatest improvement after the HRRP. They conjecture two reasons: (a) lower-performing hospitals have more room for improvement ("regression to the mean"), and (b) lower-performing hospitals are more likely to serve socially and economically disadvantaged patients. However, Wasfy et al. (2017) do not provide empirical evidence on the moderating effect of the percentage of Hispanic and African-American patients.

Most of the previous studies have mainly focused on the time series trend of readmission rates before and after the implementation of HRRP. In our study, we use a correlated random trend model and a fixed effects model combined with interrupted time series to further address confounding factors, such as unobserved hospital heterogeneity, hospital-specific time trends, and trend change after the intervention.

## 2 | THEORETICAL FRAMEWORK AND RESEARCH BACKGROUND

In this section, we discuss our underlying theoretical framework of multitasking incentives and provide a description of the research background.

### 2.1 | Theoretical framework

The seminal work of Holmstrom and Milgrom (1991) builds a theory of multitasking incentives based on game-theoretic principal-agent analyses. They show that

a. if a job is involved with multiple tasks and one task is incentivized with a task-specific performance contract, agents will tend to shift their focus toward this incentivized task from other tasks.
b. Furthermore, if the incentive from the focal task-specific performance contract is stronger, agents will tend to shift their focus more toward the incentivized task from other tasks.

In our context, evaluating hospital performance is a job that consists of multiple tasks, and two important tasks are (i) reducing readmission and (ii) reducing mortality (Wadhera et al., 2018). Applying the theory of multitasking incentives (Holmstrom & Milgrom, 1991), the HRRP is a task-specific performance contract that provides incentives for reducing readmission rather than for reducing mortality. In fact, in the current practice (after the implementation of the HRRP), the penalties for excess mortality rates under the hospital Value-Based Purchasing (VBP) Program (VBP) are far outweighed by the HRRP penalties for excess readmissions (Abdul-Aziz et al., 2017): Financial penalties are 10 times greater for excess readmission than for excess mortality. Therefore, according to part (a) of the theory of multitasking incentives, hospitals will tend to shift their focus toward reducing readmission from reducing mortality (focusing on reducing readmissions rather than on prioritizing survival), and they may experience a decrease in the readmission rate and an increase in the mortality rate.

As we mentioned earlier, larger hospitals would have greater incentives to reduce readmission rates because of the larger potential HRRP penalty and higher reputation cost (M. Chen & Grabowski, 2019; Joynt & Jha, 2013; Winborn et al., 2014). This means that the incentives of larger hospitals from the task-specific performance contract (i.e., HRRP) are stronger than those of small hospitals. According to part (b) of the theory of multitasking incentives, larger hospitals will tend to shift their focus more toward reducing readmission from reducing mortality (focusing more on reducing readmissions than on prioritizing survival).

A prediction from the theory of multitasking incentives (Holmstrom & Milgrom, 1991) is that if the objectives of the multiple tasks conflict with each other to a large degree, agents will tend to shift their focus toward the objective with the one task being incentivized with a task-specific performance contract. However, as the degree of conflict between those objectives decreases, the issue of shifting focus becomes less severe. In other words, when those objectives are less inconsistent, the incentive tension between these tasks is less severe. The reason is that when the objectives of the multiple tasks are less inconsistent, working on one task may benefit another task.

In our context, the objectives of reducing readmission and mortality in the zip code regions with a high percentage of Hispanic and African-American populations are less inconsistent because minority patients (Hispanics and African Americans) tend to have a lower level of education and insufficient knowledge about self-care, such as diet and symptom management (M. Chen & Grabowski, 2019; Dickson et al., 2013). The main purpose of hospitals' effort of providing patient-centered education is to improve self-care and reduce readmission rates, but at the same time, it may also reduce mortality rates. In other words, a well-documented fact in the literature is that the zip code regions with a higher percentage of Hispanic and African-American populations started with a much worse situation before the introduction of the HRRP: Both the readmission rates and mortality rates were significantly higher for Hispanics and African-Americans (Baumgartner et al., 2020; Dotson et al., 2015; Jiang et al., 2005; Li et al., 2017; McHugh et al., 2010). Therefore, the zip code regions with higher percentages of Hispanic and African-American populations (historically disadvantaged racial groups) have much greater potential in reducing readmission and mortality rates, and hospitals can focus on strategies that may both reduce readmission and mortality (such as providing patient-centered education).

In contrast, in the zip code regions with low percentages of Hispanic and African-American populations, the room to reduce readmission without increasing mortality is small. In those regions, many patients may have sufficient knowledge about self-care (and more general healthcare literacy), and the strategies that can both reduce readmission and mortality are limited (the tension between reducing readmission and mortality is more severe). Hence, according to the prediction from the theory of multitasking incentives, we should observe a less severe tension after the introduction of the HRRP for zip code regions with a higher percentage of Hispanic and African-American populations.

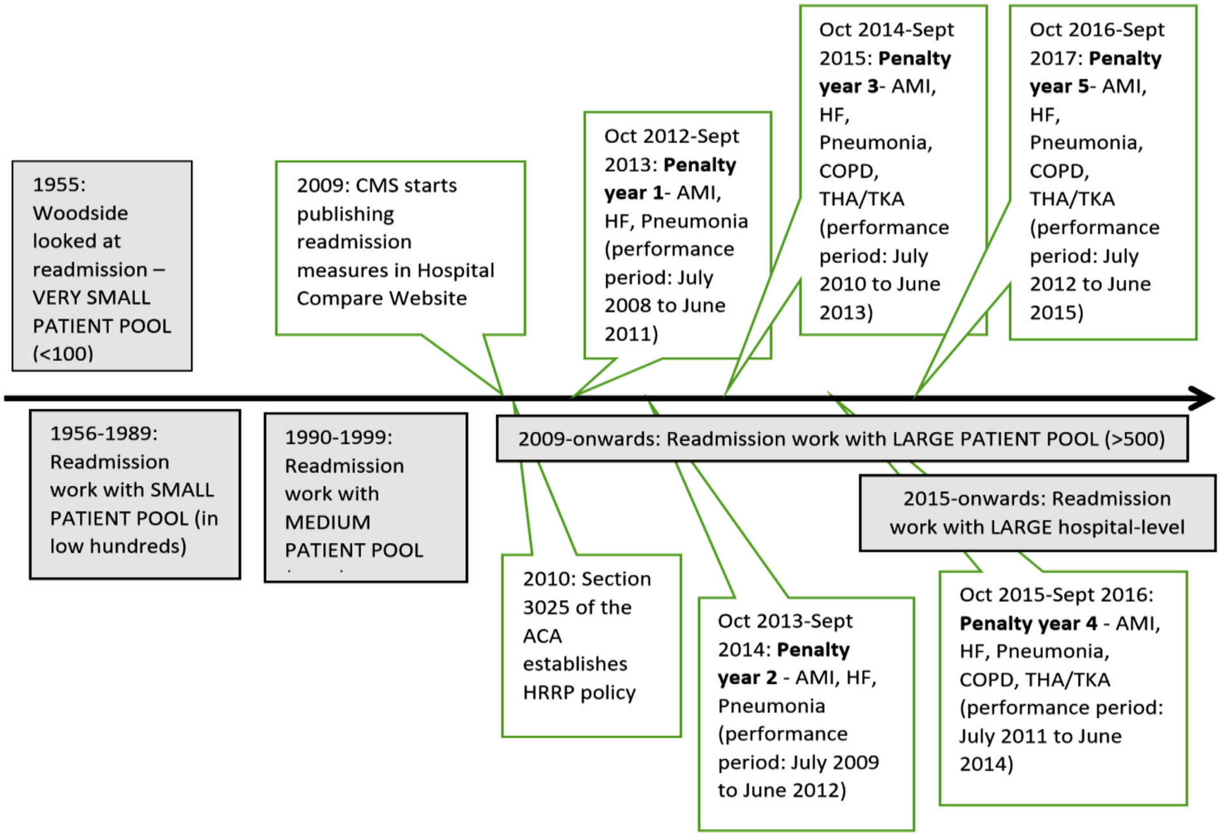


**FIGURE 1** Timeline for readmission research with respect to the Hospital Readmissions Reduction Program (HRRP) policy [Color figure can be viewed at wileyonlinelibrary.com]

## 2.2 | Research background

The idea to study hospital readmissions first appeared in the medical literature by Woodside (1955) examining outcomes in psychiatric patients in London. Increasingly, health services research has examined hospital readmissions, in part, as a response to rising healthcare costs and the recognition that certain groups of patients were high consumers of healthcare resources. Since 1980, readmission study has been done to understand the effect of the *intervention* (like home health teaching, transitional care, geriatric consultation, home visitation, pharmacological counseling, and others), *payment guidelines* for (inpatient) PPSs intended for containing cost for certain diagnosis-related groups, and many others.[3] According to a 2009 study, nearly 20% of Medicare beneficiaries are rehospitalized within 30 days after discharge, at an annual cost of $17 billion. The causes of avoidable readmissions include hospital-acquired infections and other complications; premature discharge; failure to coordinate and reconcile medications; inadequate communication among hospital personnel, patients, caregivers, and community-based clinicians; and poor planning for care transitions. Starting in July 2009, CMS began publishing three readmission measures (30-day readmission rates for patients admitted for HF, AMI, and pneumonia) to its Hospital Compare website. Figure 1 describes the evolution of readmission research starting from Woodside (1955) with a very small patient pool to the current work using a large pool of patients. The readmission analysis using hospital-level data is relatively new.

The ACA of 2010 contains a number of provisions intended to improve quality and reduce spending in the Medicare program. One of the provisions requires the HRRP to provide a financial incentive for hospitals to reduce preventable readmissions. The HRRP defines readmission as a Medicare patient who is readmitted to the same or another acute care hospital within 30 days of discharge. For the first 2 years (FYs 2013 and 2014), the HRRP applied to readmissions of Medicare patients with diagnoses of acute AMI, HF, or pneumonia.

CMS began applying the excess readmissions penalties using a complex formula to hospital payments on October 1, 2012 (FY 2013) based on Medicare hospital data from 2008 to 2011. More than 2200 hospitals were penalized for an aggregate of approximately $280 million in Medicare payments because of their excess readmissions. This amounts to 0.3% of total Medicare base payments to hospitals. About 9% of hospitals received the maximum 1% penalty, and approximately 30% paid no penalty. Hospitals serving the poorest patients were not only more likely to incur a penalty but also more likely to incur the maximum penalty. At this time, CMS concentrated on core measures based on three diseases—HF,

**TABLE 1** The first 5 years of Hospital Readmissions Reduction Program (HRRP)

| Years penalties applied | Fiscal year (FY) 2013 | FY 2014 | FY 2015 | FY 2016 | FY 2017 |
|---|---|---|---|---|---|
| Performance measurement period | June 2008–July 2011 | June 2009–July 2012 | June 2010–July 2013 | June 2011–July 2014 | June 2012–July 2015 |
| Diagnoses of initial hospitalization | Heart attack | Heart attack | Heart attack | Heart attack | Heart attack |
| | Heart failure (HF) | HF | HF | HF | HF |
| | Pneumonia | Pneumonia | Pneumonia | Pneumonia | Pneumonia |
| | | | Chronic obstructive pulmonary disease (COPD) | COPD | COPD |
| | | | Hip or knee replacement | Hip or knee replacement | Hip or knee replacement |
| Maximum rate of penalty | 1% | 2% | 3% | 3% | 3% |
| Average hospital payment adjustment (among all hospitals) | −0.27% | −0.25% | −0.49% | −0.48% | −0.58% |
| Average hospital penalty (among penalized hospitals only) | −0.42% | −0.38% | −0.63% | −0.61% | −0.74% |
| Percent of hospitals penalized | 64% | 66% | 79% | 78% | 79% |
| Percent of hospitals at max penalty | 8% | 0.6% | 1.2% | 1.1% | 1.8% |

*Source*: Boccuti and Cassillas (2017).

AMI, and pneumonia. Over time, they started to include other diseases. In order to get maximum dataset for multiyear analysis, we choose the three diseases that are consistently in play over all the years of HRRP existence.

In the second year, 1371 hospitals received lower penalties, whereas 1074 hospitals received greater penalties; the average penalty decreased from 0.42% to 0.38%. Table 1 provides a summary of the first 5 years of the HRRP (Boccuti & Casillas, 2017). The conditions initially included in the HRRP were AMI, HF, and pneumonia. The list was expanded in 2015 to include patients with acute exacerbation of COPD and patients admitted for elective total hip arthroplasty and total knee arthroplasty.

One thing researchers generally agree upon is that the HRRP has achieved its key objective of reducing readmissions. Most of the studies use patient-level data. However, "skeptics say those results belie a darker truth—that hospitals are taking shortcuts, and in some cases compromising patient care, to avoid financial pain and public embarrassment."[4] Two recent research studies (Gupta et al., 2018; Ibrahim et al., 2018) using patient-level data observe that a large percentage of the reduction in readmissions could be attributed to changes in the way hospitals were describing their patients in claims data. Ibrahim et al. (2018) raise "concern that a substantial portion of estimated reductions in readmissions after implementation of the HRRP are the result of hospital documentation rather than underlying improvements in the delivery of care." By describing them as sicker, hospitals could increase their risk adjustments, thus reducing financial penalties.

## 3 | DATA

In this study, we first use Medicare's Hospital Compare database hosted at DataMedicare.gov.[5] This is a consumer-oriented website that provides information on the quality of care that the hospitals deliver to their patients. Hospital Compare allows us to directly compare multiple hospitals for their performance measures related to heart attack, ED care, preventive care, stroke care, and other conditions. CMS created this website to better inform consumers about a hospital's quality of care. Hospital Compare provides data on over 4000 Medicare-certified hospitals. We downloaded the data from FY 2010 to FY 2018. Even though the HRRP started in 2012 (see Section 2), we decided to download the data from FY 2010 in line with Congress's work on the ACA in 2009.

Hospital Compare data are typically uploaded and refreshed in April, May, October, and December. As the refresh cycle is subject to change in a year and not all measures are updated in each release, we have only downloaded the December data for each year starting 2009. The data include, among many things, hospital general information, hospital readmissions, and deaths (30-day rates of readmissions and 30-day mortality rates), both at the hospital level and at the national level, and readmission reduction metrics. Note that readmission and mortality rates were provided as 3-year averages. Our focus in this paper is on HF, AMI, and pneumonia. We also excluded hospitals that were not eligible for the HRRP (psychiatric, rehabilitation, long-term care, children's, cancer, and critical access hospitals, as well as all

**TABLE 2** The average readmission and mortality rates in FYs 2010–2018

| Year | FY 2010 | FY 2011 | FY 2012 | FY 2013 | FY 2014 | FY 2015 | FY 2016 | FY 2017 | FY 2018 |
|---|---|---|---|---|---|---|---|---|---|
| Average HF readmission | 24.54 | 24.73 | 24.86 | 24.78 | 23.095 | 22.77 | 22.04 | 21.95 | 21.70 |
| Average acute myocardial infarction (AMI) readmission | 19.94 | 19.97 | 19.88 | 19.72 | 18.35 | 17.894 | 17.03 | 16.89 | 16.31 |
| Average pneumonia readmission | 18.20 | N/A | 18.45 | 18.53 | 17.64 | 17.38 | 16.97 | 17.11 | 17.05 |
| Average HF mortality | 11.17 | 11.28 | 11.39 | 11.65 | 11.78 | 11.93 | 11.69 | 12.16 | 11.96 |
| Average AMI mortality | 16.50 | 16.17 | 15.79 | 15.45 | 15.13 | 14.80 | 14.16 | 14.06 | 13.56 |
| Average pneumonia mortality | 11.64 | 11.68 | 11.97 | 12.11 | 12.03 | 11.99 | 11.62 | 16.40 | 16.03 |

hospitals in Maryland). Table 2 shows the average readmission and mortality rates for the hospitals in our sample.

In the abovementioned dataset, we have added some pertinent hospital demographics data from other sources. For example, in order to create a proxy for the hospital size, we have collected number-of-beds data for each hospital in the United States from the American Hospital Association.[6] Our dataset includes 4795 hospitals[7] in the United States, where large hospitals (> = 400 beds) account for 4.4%, medium hospitals (200–399 beds) account for 10.2%, and the rest are small hospitals (< 200 beds). In our dataset, 25.3% of the hospitals are public hospitals, 57.5% of them are not-for-profit hospitals, and the rest of the hospitals are for-profit hospitals. A total of 12.8% of the hospitals are in the Northeast region, 29.2% are in the Midwest region, 37.5% are in the South region, and 20.5% are in the West region. Finally, 92.6% of the hospitals provide emergency services.

We also complement the hospital-level data with the zip code-level demographic data collected from the US Census Bureau. By collecting the demographic data, we focus on the percent of Hispanic and African-American populations in the zip code region of a hospital.

## 4 | EMPIRICAL ANALYSIS AND RESULTS

In this section, we first examine the impact of HRRP on hospital readmission and mortality rates in general. Then, we further investigate factors that can moderate the impact of HRRP, such as hospital size and racial groups.

The HRRP is implemented at the national level (Desai et al., 2016); hence, it is challenging to find an appropriate control group. A control group in our study should be the subset of hospitals that are not subjected to the HRRP policies and are still using the standard IPPS. It is easy to think that hospitals from the state of Maryland must fall into this category and therefore can be used as a control group. However, a detailed analysis of the payment system used for Maryland hospitals reveals that they have been using a unique model called the Maryland All-Payer Model for its payments. The requirements for this model are many. Restrictions imposed by the model on Maryland hospitals include requiring Maryland to limit its annual all-payer per capita total hospital cost growth to 3.58%; generating $330 million in Medicare savings over a 5-year performance period; shifting all of its hospital revenue over the 5-year performance period to global payment models,[8] and many others.[9] Hence, it may not be a good idea to use Maryland hospitals as a control group.

Moreover, other nontargeted clinical conditions are not appropriate controls. Prior studies suggest a spillover effect of the HRRP: The implementation of the HRRP can reduce readmissions for nontargeted clinical conditions (Batt et al., 2018; M. S. Lee et al., 2019). Because of this spillover effect, using other nontargeted clinical conditions as controls does not satisfy the stable unit treatment value assumption in causal inference: A subject's potential outcome is not affected by other subjects' exposure to the treatment (Imbens & Rubin, 2015).

Therefore, in this section, we mainly use the time variation (before the launch of the HRRP versus after the launch of the HRRP) to identify the impact of the HRRP. In Section 5, we conduct various robustness checks to strengthen our casual identification and alleviate the concern regarding the lack of appropriate control groups.

### 4.1 | Impact of the HRRP on hospital readmission and mortality rates

Following Zhang and Zhu (2011), we study the changes in hospital readmission and mortality rates after the introduction of HRRP in the following benchmark fixed effects model:

$$Outcome_{it} = c_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 t + \varepsilon_{it}, \qquad (1)$$

where our dependent variable, $Outcome_{it}$, is the readmission/mortality rate of hospital $i$ at time $t$ for a given medical condition, including HF, AMI, and pneumonia, and $t$ is the time period index ($t$ = 1, 2, 3, …). $PostLaunch_t$ is a dummy variable indicating whether the HRRP is launched (1 indicates the postlaunch period; 0 indicates the prelaunch period). Hospitals were aware of the forthcoming changes since March 2010 (CMS, 2011; Wasfy et al., 2017). Therefore, we decided to drop the FY 2013, FY 2014, FY 2015, and FY 2016 readmission data from our analysis. In our empirical analysis, "before the HRRP implementation" periods are FY 2010 (performance period: July 2005–June 2008), FY 2011

**TABLE 3** The Impact of HRRP on readmission and mortality: Fixed effects model

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −1.954*** | 1.723*** | −2.216*** | −0.643*** | −1.026*** | 2.351*** |
| | [−62.17] | [61.36] | [−78.26] | [−32.15] | [−38.32] | [67.41] |
| *Constant* | 26.31*** | 12.74*** | 19.88*** | 16.42*** | 17.29*** | 11.71*** |
| | [2562] | [1743] | [1467] | [1094] | [2014] | [1352] |

*Note*: Robust $t$-statistics are in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

(performance period: July 2006–June 2009), and FY 2012 (performance period: July 2007–June 2010). The "after the HRRP implementation" periods are FY 2017 (performance period: July 2012–June 2015) and FY 2018 (performance period: June 2013–July 2016). We control for the time trends in all of our analyses.

In addition, under the HRRP, hospitals started getting penalized for excess readmissions only since FY 2013. They were charged a maximum penalty of 1% for FY 2013, 2% for FY 2014, and 3% for FY 2015 and beyond. Given that the full penalty of 3% was imposed only since FY 2015, our selection of the postlaunch periods ensures that we can evaluate the effectiveness of the HRRP under the full penalty. In our main analysis, our sample does not include Veterans (VA) hospitals because the HRRP does not apply to VA hospitals (VA hospitals are not subject to the HRRP since they are not reimbursed by CMS). In Section 5.3, we use VA hospitals as a placebo test.

The time-invariant variable, $c_i$, is the unobserved hospital fixed effect. In this fixed effect model, we have controlled for all time-invariant hospital characteristics.

The estimation results are presented in Table 3. In Columns 1, 3, and 5, the dependent variables are readmission rates for different medical conditions, and in Columns 2, 4, and 6, the dependent variables are mortality rates for different medical conditions. When the dependent variables are readmission rates, we find that the coefficients of *PostLaunch* are negative and statistically significant. This implies that the introduction of the HRRP significantly reduces the readmission rate in all three diseases (HF, AMI, and pneumonia). These results suggest that the introduction of the HRRP may have incentivized hospitals to adopt interventions, such as timely follow-up telephone calls, patient hotlines, and home visits, to reduce hospital readmission (Kripalani et al., 2014).

However, the introduction of the HRRP does not necessarily decrease the mortality rate: We find that the mortality rates of HF and pneumonia increase significantly, which is consistent with our theoretical framework of multitasking incentives. As mentioned earlier, one possible explanation is that the HRRP measure does not incorporate death as a competing risk. As Wadhera et al. (2019) point out, "A patient who dies can no longer be readmitted. But because deaths aren't factored into readmission rates, hospitals that keep more patients alive and therefore discharge a sicker group of people may be penalized for having higher readmission rates rather than rewarded for having good outcomes."

The problem is compounded by the fact that the HRRP penalties for high readmission rates are 10 to 15 times higher than the incentives for lowering mortality rates under the VBP (Wadhera et al., 2018, 2019). Therefore, the HRRP announcement may have sent a signal to hospitals to start focusing on readmissions (Jha, 2018) and lead hospitals—especially the larger ones—to focus more on reducing readmissions than on prioritizing survival (Joynt et al., 2016; Wadhera et al., 2018). As Wadhera et al. (2019) note, this "also creates strong incentives to treat patients in EDs or observation units to avoid readmissions, even if inpatient hospitalization would improve their access to appropriate care." Patients who would have benefited from inpatient care are being increasingly pushed by physicians and hospitals to EDs and observation units, thus affecting the quality of care (Wadhera et al., 2018; Wang & Gupta, 2014).

In addition, the unintended consequences of the HRRP may vary based on clinical conditions. Although the mortality rates of HF and pneumonia increased significantly, the mortality rate of AMI decreased. One potential reason is that the financial penalties imposed by the HRRP may have also inadvertently pushed some physicians to avoid readmitting patients who needed hospital care. Especially, some recent medical studies (i.e., Wadhera et al., 2018) show an association between an increase in postdischarge mortality for patients with pneumonia and an increase in patients who were not readmitted and died within 30 days of discharge after the implementation of the HRRP but no association for AMI. In other words, the changes varied based on clinical conditions: Postdischarge mortality for patients with pneumonia increased significantly after the implementation of the HRRP, largely driven by an increase in patients who were not readmitted and died within 30 days of discharge. However, this is not observed for AMI.

Note that AMI is very different from the other two diseases because AMI patients usually require immediate treatment and surgical operations, such as coronary artery bypass graft (Sun et al., 2020). Therefore, AMI patients are typically placed with the highest priority (L. X. Lu & Lu, 2018). As mentioned earlier, under the incentives created by the HRRP, patients who would have benefited from inpatient care are being increasingly diverted by physicians and hospitals to

EDs and observation units, thus affecting the quality of care (Wadhera et al., 2018). This mechanism applies to the other two diseases but not AMI because AMI typically requires immediate treatment and surgical operations. Therefore, we observe that when the mechanism applies (HF and pneumonia), the mortality rates increase. When the mechanism does not apply (AMI), the mortality rate decreases.

In our main analysis, we also consider the following correlated random trend model (Angrist & Pischke, 2008, p. 238; Wooldridge, 2002, p. 315):

$$Outcome_{it} = c_i + \beta_0 + g_i t + \beta_1\ PostLaunch_t + \beta_2\ Controls + \varepsilon_{it}, \tag{2}$$

where $g_i t$ is the hospital-specific time trend for hospital $i$. The specification $g_i$ (unobserved factor) allows different hospitals to follow different linear time trends, and $t$ is the time period index ($t = 1, 2, 3, \ldots$), which captures the linear time trends. From an estimation point of view, $g_i$ is an unobserved factor, which is similar to the unobserved fixed effects $c_i$ but can capture different linear time trends for different hospitals. Note that the correlated random trend model is widely used in the prior literature and is arguably a better model than a specification simply including time trends (e.g., Angrist & Pischke, 2008; Besley & Burgess, 2004; Khurana et al., 2019; Kumar et al., 2022; Rivera et al., 2021; Wooldridge, 2002). The reason is that in a typical econometric model with time trends, all units are assumed to have the same time trends. In our context, this means that all hospitals need to have the same time trends, which may not be true. The advantage of the correlated random trend model is that it allows hospitals to follow different linear time trends, which is more realistic in our setting. The specification of hospital-specific time trends allows different hospitals to follow different trends in a limited but potentially revealing way. A possible reason for the observed increased mortality rate is that the severity of patients has increased. However, the term $g_i t$ can potentially capture the severity trends of patients (the trends may vary across hospitals), and we can account for the severity trends in regression (2).

Control variables include the number of patients for each medical condition in hospital $i$ at time $t$ (*NumberOfPatients*) and a dummy variable indicating whether the readmission/mortality rate is greater than the US national average rate (*NationalAverageDummies*). The estimation results are presented in Table 4. We find that the directions and statistical significance of the coefficients of *PostLaunch* remain the same.

A potential concern in our estimation is that 1 year after the launch of the HRRP, CMS started the VBP program. Our estimated coefficients may pick up some effects from the VBP. Note that the VBP (Section 3001 of the ACA) and the HRRP (Section 3025 of the ACA) are two different value-based payment reform programs of Medicare.[10] While the HRRP focuses on reducing the 30-day readmission rate in acute care hospitals, the VBP rewards acute care hospitals with incentive payments for the quality of care they deliver in an inpatient hospital setting. The quality of care measures is grouped into four domains: (i) safety, (ii) clinical care, (iii) efficiency and cost reduction, and (iv) patient- and caregiver-centered experience of care/care coordination. Each domain has a weight of 25%. The mortality rate measures for the three diagnoses—AMI, HF, and pneumonia—belong to the clinical care domain and, taken together, contribute only 25% toward the total performance score. Therefore, readmissions, as assessed in the HRRP, have a much stronger weight than mortality rates in the VBP.

In a study using complete FY 2014 data from 1963 hospitals, Abdul-Aziz et al. (2017) find that readmission penalties closely track excess readmissions but are minimally and inversely related to excess mortality. Although the two programs were run in parallel for the first time in FY 2014, the results of Abdul-Aziz et al. (2017) indicate that the impact of the VBP penalties for excess mortality rates was far outweighed by that of the HRRP penalties for excess readmissions. They attribute the findings to the fact that the two types of penalties are totally unbalanced: Financial penalties are 10 times greater for excess readmission than for excess mortality. Therefore, the effect observed in our analysis is more likely to be driven by HRRP.

Moreover, since the VBP provides financial incentives for hospitals to reduce mortality rates, if the effect captured in our data comes from the VBP rather than HRRP, we should observe that the mortality rates decrease. However, in the data, we observe that the mortality rate increases for HF and pneumonia, which is more likely to be driven by the unintended effect of the HRRP rather than the effect of the VBP. As a suggestive test, we further conduct an analysis using only the FY 2013 data as the postpolicy change period (when the HRRP was in vogue, but the VBP was not in existence). The results are robust and are presented in Table A.1 in Online Appendix A. Although this test does not provide a definite answer, it suggests that VBP is less likely to be a significant confounding factor.

## 4.2 | Moderating factors

First, we study the moderating role of hospital size. We use the number of beds to measure hospital size (Allon et al., 2013). We estimate the following model:

$$Outcome_{it} = c_i + \beta_0 + g_i t + \beta_1 PostLaunch_t + \beta_2\ (PostLaunch_t * Size_i) + \beta_3\ Controls + \varepsilon_{it}, \tag{3}$$

where $Size_i$ is the size of a hospital measured by the number of beds. It is worth noting that the control variables *NumberOfPatients* and $Size_i$ are two different measures capturing different aspects of health care. *NumberOfPatients* is the number of patients for each medical condition in hospital $i$ at

**TABLE 4** The impact of HRRP on readmission and mortality: Correlated random trend model

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −2.362*** | 2.415*** | −2.816*** | −0.413*** | −0.862*** | 2.264*** |
| | [−52.37] | [62.74] | [−72.45] | [−20.36] | [−37.81] | [63.22] |
| *Constant* | 22.48*** | 10.62*** | 20.47*** | 17.54*** | 19.42*** | 13.24*** |
| | [202.3] | [137.4] | [106.7] | [106.2] | [211.8] | [151.4] |

*Note*: Robust *t*-statistics in brackets
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE 5** The moderating impact of hospital size

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −0.743*** | 0.463*** | −0.824*** | −0.511*** | −0.212*** | 0.271*** |
| | [−24.32] | [18.72] | [−31.32] | [−18.12] | [−9.028] | [9.350] |
| *PostLaunch*Size* | −9.32e-07 | 0.000351*** | −0.000772** | 0.000167*** | −0.000445*** | 0.00117*** |
| | [0.0134] | [3.613] | [−2.352] | [7.523] | [−2.619] | [2.713] |
| *NumberOfPatients* | 0.00105*** | −0.00118*** | 0.000932 | −0.00189** | 0.000175 | −0.000856*** |
| | [3.325] | [−3.543] | [1.253] | [−2.124] | [0.512] | [−2.924] |
| *NationalAverageDummies* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 24.38*** | 12.76*** | 22.14*** | 18.54*** | 21.07*** | 14.26*** |
| | [204.7] | [131.5] | [73.24] | [89.75] | [163.2] | [143.4] |

*Note*: Robust *t*-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

time $t$, which captures the served demand for each medical condition in a hospital. $Size_i$ is the number of beds in each hospital, which captures the capacity of a hospital (hospital size).

The estimation results are presented in Table 5. We find that for readmission rate regressions (Columns 1, 3, and 5 in Table 5), the coefficients of the interaction term ($PostLaunch_t * Size_i$) are negative (statistically significant for AMI and pneumonia), which implies that after the HRRP introduction, larger hospitals have experienced a higher reduction in readmission rates than smaller hospitals. We also find that for mortality rate regressions (Columns 2, 4, and 6 in Table 5), the coefficients of the interaction term ($PostLaunch_t * Size_i$) are significantly positive, which implies that after the HRRP introduction, larger hospitals have experienced a higher increase in mortality rates than that in smaller hospitals.

In summary, through this moderating analysis, we find that other things being equal (e.g., hospitals are in the zip code regions with similar percentages of Hispanic and African-American populations), larger hospitals have experienced (i) a higher increase in mortality rates and (ii) a greater reduction in readmission rates than those in smaller hospitals after the HRRP introduction. In fact, larger hospitals have a greater incentive to focus more on the reduction of readmission rate due to the larger potential HRRP penalty and higher reputation cost. Because large hospitals are more likely to experience payment cuts under the HRRP (Joynt & Jha, 2013), they have a greater incentive to focus on the reduction of readmission rates. In addition, a larger hospital is more incentivized to avoid any negative reputation effects associated with being penalized under the HRRP (Winborn et al., 2014). Further, according to the HRRP policy, the maximum penalty for a hospital with excess readmissions was 1%–3% of its total Medicare base payment (CMS, 2016). Therefore, a larger hospital faces larger potential penalties. Note that this explanation is a plausible mechanism. Conceptually, there might be other explanations for our results on this moderating analysis. For example, large hospitals are also more likely to have dedicated staff to allocate resources and focus on reducing admissions.

We also examine the moderating impact of racial groups. We estimate the following model:

$$\begin{aligned} Outcome_{it} = c_i + \beta_0 + g_i t + \beta_1 PostLaunch_t \\ + \beta_2 \left(PostLaunch_t * HispanicAfrican_i\right) \\ + \beta_3 Controls + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $HispanicAfrican_i$ is the percent of Hispanic and African-American populations in zip code region $i$. Note that $HispanicAfrican_i$ is conceptually different from our previous

**TABLE 6** The moderating impact of racial groups

| Variables | (1) HF readmission | (2) HFmortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −0.758*** | 0.471*** | −0.768*** | −0.462*** | −0.231*** | 0.311*** |
| | [−26.42] | [18.92] | [−27.42] | [−14.12] | [−9.427] | [11.24] |
| *PostLaunch*HispanicAfrican* | −0.463*** | −0.237** | −0.387*** | 0.0733 | −0.298** | −0.232* |
| | [−3.425] | [−2.142] | [−3.721] | [0.587] | [−2.475] | [−1.753] |
| *NumberOfPatients* | 0.000862*** | −0.00114*** | 0.00173*** | −0.00151** | −0.000112 | −0.000668*** |
| | [3.523] | [−4.257] | [3.012] | [−2.189] | [−0.465] | [−2.732] |
| *NationalAverageDummies* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 24.53*** | 12.54*** | 21.86*** | 17.21*** | 20.76*** | 14.53*** |
| | [271.5] | [161.2] | [102.1] | [103.7] | [223.2] | [179.3] |

*Note*: Robust *t*-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

moderator hospital size, $Size_i$. Conceptually, larger hospitals may not be more likely to be located in zip code regions with a higher percentage of Hispanic and African-American populations. The estimation results are presented in Table 6. From Columns 1, 2, and 3 in Table 6, we find that the coefficient of the interaction term $PostLaunch_t * HispanicAfrican_i$ is negative and statistically significant, which indicates that after the introduction of the HRRP, other things being equal (e.g., hospitals with similar sizes), the zip code regions with a higher percentage of Hispanic and African-American populations experience a significantly larger reduction in readmission rates. Note that a confounding explanation for a negative coefficient of the interaction terms is the general improvement in lower-performing hospitals ("regression to the mean"). Our correlated random trend model can alleviate this concern because lower-performing hospitals' "regression to the mean" trends are captured by $g_i t$. The coefficient of $PostLaunch_t * HispanicAfrican_i$ is more likely to capture the improvement in the care of the Hispanic and African-American patient groups.

In the moderating analysis on the Hispanic and African-American group, the results are very consistent with the main analysis: (a) For all three medical conditions, the readmission rates in zip code regions with a very high percentage of Hispanic and African-American populations (e.g., 50%) decrease after the introduction of the HRRP; and (b) for HF and pneumonia, the mortality rates in zip code regions with a very high percentage of Hispanic and African-American populations (e.g., 50%) increase after the introduction of the HRRP. Note that the impact of the HRRP on mortality rates is captured by the coefficient of *PostLaunch* plus the coefficient of *PostLaunch*HispanicAfrican* (rather than the coefficient of *PostLaunch*HispanicAfrican* alone). In other words, after the introduction of the HRRP, the HF mortality rate in zip code regions with a very high percentage of Hispanic and African-American populations (e.g., 50%) increases (Table 6, Column 2, 0.471 – 0.237 * 0.5 = 0.3525), and similarly, the pneumonia mortality rate increases (Table 6, Column 6, 0.311 – 0.232 * 0.5 = 0.195).

The moderating results of Hispanic and African-American populations are consistent with our main theoretical framework of multitasking incentives. For example, from Columns 1 and 2 of Table 6, we know that there is tension between the reduction in the HF readmission rate and the increase in the HF mortality rate after the introduction of the HRRP. In a zip code region with a low percentage of Hispanic and African-American populations (e.g., 5%), a percent decrease in the HF readmission rate is associated with a 0.581% ([0.471 – 0.237 * 0.05]/[0.758 + 0.643 * 0.05] = 0.581) increase in the HF mortality rate. Our moderating results show that this tension is less severe for zip code regions with a higher percentage of Hispanic and African-American populations. In a zip code region with a high percentage of Hispanic and African-American populations (e.g., 50%), a percent decrease in the HF readmission rate is associated with a 0.327% ([0.471 – 0.237 * 0.5]/[0.758 + 0.643 * 0.5] = 0.327) increase in the HF mortality rate. In other words, we observe less severe tension after the introduction of HRRP for zip code regions with a higher percentage of Hispanic and African-American populations. As mentioned earlier, these results are consistent with our theoretical framework of multitasking incentives: When the objectives of the multiple tasks are less inconsistent, the incentive tension between these tasks is less severe. In our context, the objectives of reducing readmission and mortality are less inconsistent for the zip code regions with higher percentages of Hispanic and African-American populations because there is a larger room to reduce the readmission rate without increasing the mortality rate.

## 5 | ROBUSTNESS CHECKS

In this section, we conduct various robustness checks to further strengthen our results. In our main analysis, we adopt a correlated random trend model, which considers hospital-specific time trends. However, the time trends might be different after the intervention (i.e., the introduction of HRRP). Therefore, in Section 5.1, we use the fixed effects model combined with interrupted time series to further address this time-varying confounder. In Section 5.2, we conduct a regression discontinuity in time (RDiT) approach to include flexible high-order polynomial controls in time, which addresses possible confounders from different functional forms of time trends. Further, in Section 5.3, using hospitals that are not subject to the HRRP, we conduct a placebo analysis, which suggests that the effect of the HRRP is likely to be true.

## 5.1 | Fixed effects model combined with interrupted time series

The golden standard of establishing convincing causality is to run randomized experiments (Bapna et al., 2017; Qiu & Kumar, 2017). However, randomized trials are not always available because of cost or political reasons. With a quasi-experimental design, researchers are able to estimate causal effects using observational data. Interrupted time series analysis is a useful quasi-experimental design for evaluating the effectiveness of health interventions that have been implemented at a clearly defined point in time (Kontopantelis et al., 2015; Bernal et al., 2017). It is a method to retrospectively evaluate interventions that have already been implemented without relying on randomization or any control groups. Interrupted time series has been widely used for the evaluation of public health interventions, including new vaccines (Dennis et al., 2013), cycle helmet legislation (Lau et al., 2015), and traffic speed zones (Grundy et al., 2009).

The main idea of the interrupted time series is to use preintervention trends to establish a counterfactual trend, which is the hypothetical scenario under which the intervention had not taken place, and the trend continues unchanged. This counterfactual trend provides a comparison for the evaluation of the impact of the treatment by examining any change occurring in the posttreatment period (Bernal et al., 2017; Kontopantelis et al., 2015). The classical interrupted time series model relies on only time-series data, which cannot rule out individual fixed effects as a confounding factor. In our study, we adopt a fixed effects model combined with interrupted time series addressing hospital fixed effects as well as common time trends. In particular, we estimate the following regression model:

$$Outcome_{it} = c_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 t + \beta_3 (t \cdot PostLaunch_t) + \beta_4 Controls + \varepsilon_{it}, \quad (5)$$

where $\beta_1$ captures the level change following the intervention, $\beta_2$ is interpreted as the change in outcome associated with a time unit increase (representing the underlying preintervention trend), and $\beta_3$ indicates the trend (slope) change after the intervention.

In our data, consecutive observations might be autocorrelated. This autocorrelation issue can be addressed by regression models designed to adjust (adjusted standard errors) for autocorrelation (Linden, 2015). In our context, we use robust standard errors. In addition, as Bernal et al. (2017) points out, “autocorrelation is largely explained by other variables, in particular, seasonality; therefore, after controlling for these factors, residual autocorrelation is rarely a problem.” In the analysis, we have controlled for time trends, which alleviates the concern of autocorrelation. The results of the interrupted time series (Table 7) are consistent with our main results in terms of directions and statistical significance.

## 5.2 | RDiT

Recently, RDiT has been widely used as an identification method without a control group (Anderson, 2014; Hausman & Rapson, 2018; S. Y. Lee et al., 2018). RDiT has adapted the regression discontinuity framework to applications where time is the running variable, and treatment begins at a particular threshold in time. The advantage of RDiT is the ability to include flexible high-order polynomial controls in time (Hausman & Rapson, 2018). In our context, the regression model is as follows:

$$Outcome_{it} = c_i + \beta_0 + \beta_1 PostLaunch_t + \beta_2 Duration_t + \beta_3 Duration_t^2 + \varepsilon_{it}, \quad (6)$$

where $Duration_t$ is the number of years after the HRRP introduction, where a positive value means that year $t$ is after the HRRP introduction, and vice versa. In this analysis, we use the full sample of our data.

Our empirical results are shown in Table 8 and are robust when we use RDiT.

## 5.3 | Placebo test

To strengthen the identification, we conduct an additional placebo analysis, which suggests that the effect of the HRRP is likely to be true. In a placebo analysis, researchers examine a pseudo-outcome that is known not to be affected by the treatment (Athey & Imbens, 2017). In our context, we look at the readmission and mortality rates of VA hospitals because the HRRP does not apply to VA hospitals (VA hospitals are not subject to the HRRP since they are not reimbursed by CMS). The main idea of our placebo test is that if the effect of the HRRP observed earlier is not driven by other policy changes, we should observe that VA hospitals are significantly less influenced under the HRRP implementation period than other hospitals, which are subject to the HRRP.

In Table 9, VA is a time-invariant binary variable indicating whether a hospital is a veteran hospital (1: veteran hospital, 0: no). The coefficient of the interaction term, *PostLaunch*VA*, captures the differential impact (the impact of HRRP on VA hospitals minus the impact of HRRP on non-VA hospitals). We estimate the regression using the correlated random trend model. Our results show that the sign of the coefficient of *PostLaunch*VA* is always different from the coefficient of

**TABLE 7** The impact of HRRP on readmission and mortality: Interrupted time series

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −0.843*** | 0.287*** | −0.927*** | −0.621*** | −0.392*** | 0.354*** |
| | [−30.15] | [3.436] | [−27.39] | [−28.74] | [−12.63] | [11.75] |
| *t* | 0.148*** | 0.121*** | −1.921*** | −0.272*** | 0.141*** | 0.182*** |
| | [11.65] | [12.26] | [−60.45] | [−9.714] | [11.86] | [15.12] |
| *t* PostLaunch* | −1.807*** | −0.0182 | 0.583*** | −0.0173 | −1.015*** | −0.273*** |
| | [−76.34] | [−0.894] | [40.37] | [−1.326] | [−49.33] | [−11.28] |
| *NumberOfPatients* | 0.000621*** | −0.000527** | 0.000667 | −0.00211*** | 0.000756*** | 0.000464* |
| | [2.764] | [−2.194] | [1.478] | [−3.475] | [3.229] | [1.883] |
| *NationalAverageDummies* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 24.32*** | 14.17*** | 27.34*** | 17.79*** | 21.12*** | 14.53*** |
| | [256.7] | [163.2] | [156.1] | [101.2] | [209.4] | [164.6] |

*Note*: Robust *t*-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE 8** Robustness check: Regression discontinuity in time analysis

| Variables | (1) HF | (2) HF | (3) AMI | (4) AMI | (5) Pneumonia | (6) Pneumonia |
|---|---|---|---|---|---|---|
| *PostLaunch* | −1.585*** | −1.430*** | −1.771*** | −1.239*** | −0.799*** | −2.091*** |
| | [−42.99] | [−13.57] | [−6.99] | [−35.81] | [−26.35] | [−38.47] |
| *Duration* | 0.153*** | −0.115 | −0.689*** | −0.993*** | 0.112*** | 0.971*** |
| | [11.76] | [−1.53] | [−78.82] | [−71.26] | [10.20] | [35.79] |
| *Duration^2* | | −0.0448*** | | 0.154*** | | 0.143*** |
| | | [−3.63] | | [34.70] | | [38.51] |

*Note*: Robust *t*-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE 9** Placebo test (interaction term with VA hospital)

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −1.708*** | 0.557*** | −1.878*** | −1.127*** | −0.758*** | 1.571*** |
| | [−71.60] | [29.61] | [−80.38] | [−44.96] | [−41.20] | [65.93] |
| *PostLaunch*VA* | 0.482*** | −0.489*** | 0.479*** | 0.484*** | 0.602*** | −2.009*** |
| | [3.45] | [−4.38] | [4.65] | [4.16] | [4.81] | [−14.26] |
| *Constant* | 24.69*** | 11.28*** | 19.81*** | 15.73*** | 18.31*** | 11.79*** |
| | [2133] | [1,41] | [1,73] | [875.2] | [1669] | [997.2] |

*Note*: Robust *t*-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Note that we estimate the model in Table 9 using the correlated random trend model mentioned earlier. One concern is that VA hospitals and HRRP hospitals may follow different time trends even prior to the intervention. As mentioned earlier, our correlated random trend model allows hospitals to follow different linear time trends. In this context, this means that in the correlated random trend model, we have controlled for the possible different time trends for VA hospitals and HRRP hospitals. Therefore, different pretreatment trends for VA hospitals and HRRP hospitals are unlikely to be a significant confounder after controlling for hospital-specific time trends.

*PostLaunch*, which indicates that VA hospitals are significantly less influenced than other hospitals under the HRRP implementation period. Note that we observe a large negative coefficient of *PostLaunch*VA* in Column 6 of Table 9 (−2.009). This large negative coefficient does not mean a large drop in post-HRRP pneumonia mortality for VA hospitals. The reason is that in the regression of Table 9, we have the independent variables *PostLaunch* and *PostLaunch*VA*.

**TABLE 10** The impact of HRRP on readmission and mortality: Full penalty effect

| Variables | (1) HF readmission | (2) HF mortality | (3) AMI readmission | (4) AMI mortality | (5) Pneumonia readmission | (6) Pneumonia mortality |
|---|---|---|---|---|---|---|
| *PostLaunch* | −0.783*** | 0.449*** | −0.833*** | −0.466*** | −0.256*** | 0.308*** |
| | [−34.28] | [23.24] | [−41.95] | [−21.54] | [−13.99] | [13.52] |
| *PostLaunch*FPenalty* | −1.657*** | 0.216*** | −1.730*** | −0.899*** | −0.914*** | 1.218*** |
| | [−73.38] | [11.55] | [−74.01] | [−38.37] | [−51.45] | [54.36] |
| *Constant* | 24.71*** | 11.27*** | 19.86*** | 15.75*** | 18.32*** | 11.77*** |
| | [1693] | [956.6] | [1050] | [760.0] | [1382] | [793.9] |

*Note*: Robust $t$-statistics in brackets.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The drop in post-HRRP pneumonia mortality for VA hospitals should be captured by the coefficient of *PostLaunch* plus the coefficient of *PostLaunch*VA*, which is $1.571 - 2.009 = -0.438$. In other words, the drop in post-HRRP pneumonia mortality for VA hospitals is 0.438, which is reasonable and not very large.

## 5.4 | "Dose–response" analysis

The main idea of a "dose–response" analysis is that if A causes B, then usually a larger dose of A causes a stronger response B, and this type of analysis provides further empirical evidence for causal relationships (Pearl & Mackenzie, 2018). In this section, we conduct a "dose–response" analysis using the maximum HRRP penalty.

In our context, under the HRRP, hospitals were charged a maximum penalty of 1% for FY 2013 (performance period: June 2008–July 2011), 2% for FY 2014 (performance period: June 2009–July 2012), and 3% for FY 2015 (performance period: June 2010–July 2013) and beyond. Given that the full penalty of 3% was imposed only since FY 2015, hospitals should be more incentivized to reduce readmission when the full penalty of 3% was imposed (a larger "dose"). If this is true, then it provides additional empirical evidence for the effect of the HRRP on readmission rates. On the other hand, our previous analysis shows the unintended effect of the HRRP: The mortality rates of HF and pneumonia increase significantly. If, indeed, this is the case, we should observe a larger unintended effect under the full penalty of 3%. In this analysis, we use the full sample of our data.

We estimate the following equation:

$$Outcome_{it} = c_i + \beta_0 + g_i t + \beta_1 PostLaunch_t + \beta_2 \left(PostLaunch_t * FPenalty_t\right) + \varepsilon_{it}, \quad (7)$$

where $FPenalty_t$ is a dummy variable indicating when the full penalty of 3% was imposed. The coefficient of $PostLaunch_t$, $\beta_1$, captures the effect of the HRRP when the full penalty was not imposed, and $\beta_1 + \beta_2$ captures the effect of the HRRP when the full penalty was imposed. Therefore, $\beta_2$ captures whether the effect of the HRRP under the full penalty is larger than that when the full penalty was not imposed. From Columns 1, 3, and 5 of Table 10, we find that the coefficient of $PostLaunch_t * FPenalty_t$ is negative and statistically significant, suggesting that a larger dose causes a stronger response: Hospitals are more incentivized to reduce readmission under the full penalty. From Columns 2 and 6 of Table 10, we find that the coefficient of $PostLaunch_t * FPenalty_t$ is positive and statistically significant, indicating a larger unintended effect on mortality rates under the full penalty. These results provide additional empirical evidence for the effect of the HRRP on readmission and mortality.

# 6 | DISCUSSION AND CONCLUSION

In this section, we begin by presenting the public policy implications and managerial insights. Then, we provide concluding remarks and directions for future research.

## 6.1 | Public policy implications and managerial insights

Evaluating the effect of HRRP is critical for CMS managers and hospital administrators to understand the effectiveness of HRRP. First, the bottom line is that the HRRP is effective for its main purpose: reducing the readmission rate. We show that the introduction of the HRRP has significantly reduced readmission rates using hospital-level data. The results are robust and highly consistent across different model specifications, such as a fixed effects model, correlated random trend model, and fixed effects model combined with interrupted time series.

Second, CMS managers and hospital administrators should pay close attention to the possible side effects of the HRRP. In the theoretical framework of multitasking incentives, our results show a tension between the reduction in the readmission rate and the increase in the mortality rate after the introduction of the HRRP using hospital-level data: A decrease in readmission rate is associated with an increase in the mortality rate. It should remind CMS managers and hospital administrators that the implementation of the HRRP might have focused their attention disproportionately on the reduction of readmission rate at the cost of quality of care (at least in certain cases). Hence, they need to be cautious in measuring the impact of the HRRP in terms of only the readmission rate. This result also has important implications for policy-makers. Although the readmission rate is an important metric for measuring the quality of healthcare delivery, too much focus on readmission rate may negatively impact the mortality rate, which is another (and arguably the more important) metric of healthcare delivery. One way to address this concern is to employ a composite measure that incorporates both the readmission and mortality-related penalties.

Third, we find that the tension between the reduction in the readmission rate and the increase in the mortality rate is heterogeneous in terms of hospital size and racial groups. Consistent with the predictions from the theory of multitasking incentives, our moderating analysis shows that this tension is more severe for larger hospitals (because of stronger incentives of reducing the readmission rate) and for hospitals in zip code regions with lower percentages of Hispanic and African-American populations (because of less consistent objectives of the tasks). In other words, our results inform policy-makers where the monetary incentives of the HRRP may backfire the most. As mentioned earlier, one way to address the tension is to employ a composite measure incorporating both the readmission and mortality-related penalties, and our moderating results highlight that it might be more urgent for larger hospitals and hospitals in zip code regions with lower percentages of Hispanic and African-American populations to build this composite measure because the potential incentive distortion is larger in these hospitals. These results provide guidelines for CMS managers to dig deeper into the underlying economic and operational reasons rather than just look at the overall result. Policy-makers also need to pay close attention to these results for future implementations of policies similar to the HRRP.

Fourth, the possible underlying mechanisms behind the results for our moderating analysis suggest that policy-makers should evaluate reductions in readmission more comprehensively, depending on different scenarios: Reductions in readmission could be caused by different mechanisms. In the zip code regions with high percentages of Hispanic and African-American populations, the room to reduce readmission without increasing mortality is large. The reductions in readmission are more likely to be caused by strategies that may both reduce readmission and mortality, such as providing patient-centered education to improve self-care (M. Chen & Grabowski, 2019; Dickson et al., 2013). In contrast, in the zip code regions with low percentages of Hispanic and African-American populations, the room to reduce readmission without increasing mortality is small, and the strategies that can both reduce readmission and mortality are limited. The reductions in readmission are more likely to be caused by the fact that hospitals shift their focus toward reducing readmission from reducing mortality. Therefore, it might be helpful for policy-makers to take racial metrics into consideration when implementing and evaluating future policies similar to the HRRP.

## 6.2 | Concluding remarks and future research directions

In this study, we investigate the impact of the HRRP on hospital readmission and mortality rates. We find that although the HRRP is effective in reducing hospital readmission rates, the hospital mortality rates have increased for two of the conditions, post HRRP. This could be because hospitals are increasingly treating patients in EDs and observation units to avoid inpatient readmissions. This could also be because of a shift in focus toward the readmission rate metric from the quality of care metrics such as mortality rate. Our study also fills an important gap in the literature by providing a deeper understanding of the heterogeneous effects of the introduction of HRRP in terms of hospital size and racial groups.

Our research is not without limitations. First, as stated earlier, a possible explanation for our racial moderator is about discharge and pharmaceutical intervention: Minority patients (Hispanics and African Americans) tend to have a lower level of education and have insufficient knowledge about self-care, such as diet and symptom management. However, we would like to point out that it is one of the possible explanations. As a future research direction, researchers can dig deeper into the empirical evidence of these underlying mechanisms. Under the incentives of the HRRP, hospitals have adopted different programs, including discharge and pharmaceutical intervention (Loria, 2018; Shull et al., 2018). It would be interesting to examine the differential impact of these programs on readmission, mortality, and other care quality measures for minority patients and nonminority patients.

Second, one limitation of our hospital-level data is that we are only able to obtain 3-year averages for the admission and mortality rates, and there are overlaps in performance periods. Using 3-year average data is a common approach for hospital-level studies (e.g., Ryan et al., 2017; Upadhyay et al., 2019; Wasfy et al., 2017), and in many of these studies, there are similar overlaps in performance periods. Therefore, we believe this data limitation is not likely to change our results and insights significantly. Future research can use patient-level data to examine readmission and mortality pattern in a high level of granularity.

Third, when we analyze the moderating effect of the percentage of Hispanic and African-American patients, it is difficult to distinguish between general improvement in lower-performing hospitals (regression to the mean) and improvement in the care of Hispanic and African-American patients. Future studies can use patient-level data to further disentangle those two effects.

Fourth, since the HRRP is introduced nationwide, we lack a control group to clearly identify the causal impact of the HRRP. A potential future research direction is to focus more on causal identification strategies. Finally, prior literature has shown the important impact of health information technology (Ayabakan et al., 2017; Bardhan & Thouin, 2013; W. Chen et al., 2021; Green et al., 2013; Yan & Tan, 2014). In the future, we would like to examine how health information technology moderates the effect of the HRRP.

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## ENDNOTES

[1] In addition to the HRRP, CMS also started the hospital VBP program.

[2] Joynt et al. (2016) find that some hospital leaders feel that hospitals may not be able to impact patient adherence and postacute care. However, it does not imply that patient-centered education is not effective. Actually, prior empirical literature shows that using patient-centered education to improve self-care can lead to substantial reductions in readmission rates (Shull et al., 2018, Nair et al., 2020). One possible reason is that hospital leaders' feelings may suffer from attribution bias (Mezulis et al., 2004): They may attribute the behavior of patients to something personal (that cannot be changed) rather than to something about patients' situations.

[3] See https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/ProspMedicareFeeSvcPmtGen/index.html?redirect=/prospmedicarefeesvcpmtgen/.

[4] See https://www.statnews.com/2017/12/11/hospital-readmissions-debate.

[5] See https://data.medicare.gov/data/hospital.

[6] See https://www.ahd.com/search.php.

[7] Although the HRRP does not apply to veteran (VA) hospitals, we include them in the sample to conduct a placebo test.

[8] https://innovation.cms.gov/initiatives/md-tccm/.

[9] https://www.cms.gov/newsroom/fact-sheets/maryland-all-payer-model-deliver-better-care-and-lower-costs.

[10] Compilation of Patient Protection and ACA, Office of the Legislative Council for the use of the US House of Representative, May 2010.

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