Impact of the value-based purchasing program on hospital operations outcomes: An econometric analysis

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Abstract
The Hospital Value-Based Purchasing (VBP) Program, one of several federal regulations mandated by the Patient Protection and Affordable Care Act, uses Medicare provider payment penalties and bonuses to encourage hospital administrators to improve performance in four domains: clinical processes, patient outcomes, patient experiences, and efficiency. Before VBP's launch, some practitioners claimed VBP would have little impact, while others feared well-off hospitals would be unfairly rewarded at the expense of previously poor-performing hospitals. We examine whether and how the VBP penalties affect aggregate operating outcomes of healthcare providers in hospitals. Using secondary data, we find empirical evidence that hospitals with prior-year VBP penalties exhibit positive associations between the penalty magnitude and certain current-year care process improvements. Over the prior year, penalized hospitals also tend to exhibit increased patient case mix metrics, which should enhance revenue as a spillover effect. In a post hoc analysis, we observe that bonus-receiving hospitals are less apt to exhibit subsequent performance improvements for these same metrics. Our contributions result from theoretically framing differences in hospital operating activities when facing the VBP Program's penalties as well as empirically demonstrating consequences of the penalty's magnitude.

KEYWORDS
empirical, healthcare policy, hospital, service operations, value-based purchasing program

“...the notion of ‘value-based’ healthcare. It's a form of reimbursement to healthcare providers that's tied to the quality of care and patient outcomes. In other words, it rewards providers for efficiency and effectiveness... Of course, the mere desire to adopt a new approach to care doesn't ensure success.”

Bowman (2018)

1 | INTRODUCTION

Health policy makers and regulators in the United States are experimenting with many new ways to improve health system performance and enhance patient value (Naveh, Katz-Navon, & Stern, 2005; Green, 2012: Averill, Fuller, McCullough, & Hughes, 2016; Makary & Daniel, 2016). This drive to improve performance has spawned innovative regulatory policies seeking to encourage internal efficiency, better outcomes, and positive patient experiences. For example, the Centers for Medicare and Medicaid Services (CMS) developed several value-based, pay-for-performance programs requiring physicians and hospitals to evaluate and demonstrate service delivery effectiveness (CMS, 2018a). Unique among the programs is the Hospital Value-Based Purchasing Program (hereafter VBP), designed to motivate better care and service provision for Medicare beneficiaries...
by financially penalizing poorly performing hospitals while providing bonuses to their higher performing counterparts (Averill et al., 2016; Werner & Dudley, 2012). Yet, little is known about how the “magnitude” of these penalties influences performance. Thus, we raise the following research questions: Will VBP financial penalties result in a better-managed hospital—one that creates more patient value with respect to clinical processes, patient outcomes and experiences, and overall efficiency? Or, are hospitals likely to adopt alternate tactics to mitigate VBP penalty costs, such as through work process standardization or diagnostic coding that has potential spillover effects on the case mix index (CMI)?

To address these questions, we develop theory-based hypotheses and draw upon several hospital-level data sets that provide information about the VBP performance metrics associated with process quality, patient experience, and overall performance, along with related hospital information and competitive environment data. The VBP Program is revenue neutral and mandatory for all hospitals, public and private, in the United States. Each year since 2013, CMS has withheld a percentage of Medicare reimbursement dollars to create an incentive funding pool for the bonuses. In 2018, the VBP funding pool held an estimated $1.9 billion (CMS, 2018b). While hospital successes with value-based healthcare are mounting, and the operational transformations needed to achieve value-based aims are salient, some practitioners claim only 10–20% of mandated hospitals have responded with process changes that support VBP aims (Bowman, 2018). Thus, our study investigates the consequences of hospital VBP penalties based on their magnitude. Understanding the magnitude of the penalties is essential for three strategic reasons. First, due to the annual increases of the VBP penalty and low hospital margins, VBP’s financial risk may creep up across time, and may become non-negligible for U.S. hospital administrators. Were the policy effective, hospital administrators would respond by (a) improving operational and clinical quality and by (b) reducing costs through lowering care process variation, reducing medical errors, and increasing Medicare beneficiary value. Such a strategy follows directly from classical quality management theory (Batalden & Buchanan, 1989; Berwick, Godfrey, & Roessner, 1991; Roth, 1993).

Second, conversely, unintended consequences of the VBP penalty may reveal that some hospitals may avoid future penalties by adjusting their administrative and/or reimbursement systems (e.g., via upcoding or case mix [Dafny, 2005; Silverman & Skinner, 2004]). Third, alternatively, VBP may not incentivize hospitals to act. Administrators may do little or nothing to meet the VBP goals, owing to insufficient internal pressures, non-optimal decision-making, or a culture of inertia (Figueroa, Tsugawa, Zheng, Orav, & Jha, 2016; Muhlestein, Tu, de Lisle, & Merrill, 2016). A do-little strategy may be attributed to institutional frictions (e.g., the rewards are not sufficient from taking any actions). See Sacarny (2018) for examples of agency problems associated with the reporting of cardiac care procedures to Medicare.

Healthcare professionals’ skepticism about VBP’s effects on hospital performance (e.g., Rau, 2013) creates a need for careful scrutiny of VBP’s longitudinal operational impacts. In response to previous government policies, healthcare researchers have documented institutional and operational actions (Carter, Newhouse, & Relles, 1990; Lloyd & Rissing, 1985; McMahon & Smits, 1986; Rosenberg & Browne, 2001). Ironically, doctors can respond to financial uncertainty in ways that may worsen healthcare outcomes (Smyth, 2016). Surgeons have modified treatment processes in response to financial incentives (Schwartz & Tartter, 1998). Hospitals may react to penalties by tactically focusing on complex patient cases and new patient sectors that provide better CMS remuneration (Baugh & Schuur, 2013). Given this body of evidence, it is important to study whether administrators address hospital VBP penalty magnitudes through appropriate operational changes or through alternate tactics. Healthcare policy makers, hospital administrators, and taxpayers deserve to know how much of an effect the VBP incentives have had on healthcare provider operations and relevant stakeholders.

We subject to rigorous empirical scrutiny the extent to which the magnitude of the VBP incentive influences hospital operations. Prior studies demonstrate that when healthcare organizations are concerned with unavoidable external pressures, they protect the clinical domain from the uncertainties and contingencies of the regulatory and policy environment (Ata, Killaly, Olsen, & Parker, 2013; Cook, Shortell, Conrad, & Morrissey, 1983; Lee & Zenios, 2012; Scott, Ruef, Mendel, & Caronna, 2000). Specific to VBP, empirical studies find that hospital participation in VBP (a) had no effect during VBP’s initial implementation period (Ryan, Burgess Jr, Pesko, Borden, & Dimick, 2015); (b) did not improve patient mortality from 2008 to 2013 (Figueroa et al., 2016); and (c) may decrease hospital cost efficiency (Izón & Pardini, 2018). However, in review papers about mandated pay-for-performance programs such as VBP, the papers find econometric problems and inconsistent or weak results (Mendelson et al., 2017).

Using longitudinal panel data analyses, we observe that VBP financial penalty magnitudes are associated with subsequent hospital operations improvements. Yet, unexpectedly, penalized hospitals also tend to exhibit subsequent increases in the CMI metric, compared to non-penalized hospitals. It is likely that a higher VBP penalty motivates hospitals to tackle improving the accuracy of their coding, which
We quantify VBP impacts on hospitals, capturing intended improvements, and potentially unintended consequences. Third, since VBP is a touchstone procurement-related program, among several similar CMS programs, we identify salient findings that generalize to other industries, in contrast to clinical service delivery. While not investigated here specifically, it is also reasonable to posit that increases in the magnitude of the penalty will coincide with spillover effects, such as putting pressure on administrators to focus on error proofing the coding practices of their physicians and staff. By coding VBP procedures more precisely, hospitals can more fully capture Medicare revenues. Thus, we also find that the magnitude of the penalty coincides with hospitals being more apt to exhibit an increase in their patient case mix metric, which could potentially negate some of the penalty. In post-hoc analyses, we observe bonus-receiving hospitals tend not to exhibit subsequent performance improvements, which is likely associated with their typically high levels of extant performance.

In response to our findings, government policy makers should consider adopting additional regulatory metrics and/or policies that foster more effective hospital incentives. They might empirically identify specific hospitals that exhibit hedging behaviors, and in turn, gather pertinent facts to inform their policies. To protect their own hospitals, administrators may need to carefully evaluate internal stakeholder actions to counteract unintended operational processes, such as focused efforts targeting patients with more complex healthcare needs, or driving up DRG coding to produce a more complex case mix, without regard to cost or risk (HCPro, 2015).

In Section 2, we review VBP details, discuss relevant management theory, and develop hypotheses. Section 3 describes methods. Section 4 presents results. Section 5 discusses implications and concludes.

### 2 | BACKGROUND AND HYPOTHESES

In this section, we first review the quality management origins of the VBP regulations. Next, we explore institutional and quality management theoretical perspectives underlying administrator actions in response to VBP. We then pose hypotheses about hospital reactions to VBP.

#### 2.1 | Quality management origins of the value-based purchasing program

Over the past two decades, government-initiated healthcare regulatory programs have made great efforts to motivate improved medical service quality. Such programs require healthcare providers to comply with certain rules, standards, and expectations. U.S. healthcare government policy, regulatory bodies, and reimbursement bodies (e.g., Medicare, Department of Health & Human Services) developed sets of best practice management protocols aimed at improving patient care (Benner & Tushman, 2003; Chandrasekaran, Senot, & Boyer, 2012). Long inspired by the evolution of total quality and lean practice adoption in health care, these process management practices support providers in the quest to deliver consistent operations and objective, evidence-based clinical services and procedures (Batalden & Buchanan, 1989; Berwick et al., 1991; Graban, 2011; Westphal, Gulati, & Shortell, 1997). However, not all quality transformations of operational processes are easy to accomplish. Roth, Johnson, and Short (1996) go beyond clinical quality. Using a service operations strategy lens to describe patient perceived quality outcomes, they empirically reveal the large gaps hospitals had in developing operational quality capabilities, in contrast to clinical service delivery.
Corresponding to recommendations from the Institute of Medicine to tackle healthcare service quality, CMS in 2003 developed quality measurement programs to reduce process variation and promote quality improvements (Boyer, Gardner, & Schweikhart, 2012; Kohn, Corrigan, & Donaldson, 2000). Notably, CMS provided best-practice process measures for hospitals to assess general and severe health issues, from the timing of antibiotic treatments for general surgery patients to quick response to stroke and heart attack patients. Healthcare providers participating in Medicare or Medicaid programs must provide related data to CMS to verify the extent to which their operations conform to such practices.

In 2010, CMS introduced the VBP Program, which connects the Medicare payment system directly to patient care delivery and perceived quality metrics. The program's purpose is to reduce cost and improve healthcare quality (Dalzell, 2017; Rau, 2012). To do so, Medicare imposes reimbursement penalties or provides reimbursement bonuses based on a hospital's annual quality measures and actual healthcare outcomes across several prior years (CMS, 2018d). With VBP, Medicare withhold a percentage of its reimbursements (i.e., 1% in 2013; 1.25% in 2014; 1.5% in 2015; 1.75% in 2016; and 2% after 2017) from hospitals that do not perform well along a set of pre-specified healthcare quality metrics (CMS, 2018d). Hospitals that do perform well can receive reimbursement bonuses. Among the 3,000+ hospitals required to participate in VBP, penalties were levied on a generally decreasing number of hospitals: 1,401 in 2013, 1,451 in 2014, 1,361 in 2015, and 1,235 in 2016 (CMS, 2018d). The program awarded bonuses to 1,529 hospitals in 2013, 1,231 in 2014, 1,700 in 2015, and 1,806 in 2016 (CMS, 2018d). The average penalty for a low-performing hospital was $1.2 million, while the average bonus for a high performer was $203,000. Controlling for patient case mix, the effect on most hospitals in 2016 was ±0.5% of CMS-generated hospital revenue. However, individual hospitals have historically experienced bonuses as large as 4% and penalties up to 2% (Dalzell, 2017).

Since its launch, VBP Program objectives have stayed consistent. Yet, Medicare annually updates the VBP metrics used to evaluate hospitals. Medicare evaluated hospital performance for 2013 using two weighted dimensions: (a) clinical process of care (70%) and (b) patient care experiences (30%). By 2016, Medicare used four weighted dimensions that combine into a single composite metric: (a) clinical process of care (10%), (b) clinical outcomes (40%), (c) patient care experiences (25%), and (d) efficiency (25%).

Table 1 lists VBP Program metrics by year. Regarding quality measures, the underlying rationale for VBP is to consider two types of multidimensional metrics: (a) medical performance quality, and (b) patient "perceived" care quality outcomes. The first type of metric captures the process of adherence to clinical procedures, whereby a healthcare provider follows CMS' recommended guidelines when treating patients. For instance, for each of the four conditions measured (e.g., heart failure), one of the VBP clinical measures is the percentage of hospital patients receiving an appropriate antibiotic selection. The second type of metric relates to perceived patient experience, a quality measure that considers how patients feel about aspects of care given during their hospital stay. For example, the degree of nurse/doctor communication with patients is one measure. In addition to these service delivery processes and patient care quality metrics, VBP also evaluates providers via a third set of objective outcome-of-care measures based on mortality rates for three conditions: heart failure, acute myocardial infarction, and pneumonia. Each of these conditions is a critical disease that results in high rates of death and hospitalization, and accordingly, large costs accrue to all

<table>
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<th>Table 1</th>
<th>Key metrics for the VBP Program</th>
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| **Process of care measures** | - Acute myocardial infarction (AMI)  
- Heart failure (HF)  
- Pneumonia (PN)  
- Surgical care improvement project (SCIP)  
CMS measures each metric's performance and improvement rates |
| **Patient experiences** | - Communication  
- Responsiveness  
- Pain management  
- Hospital environment conditions  
- After discharge satisfaction  
Hospital Consumer Assessment of Healthcare Providers and Systems Survey (HCAHPS) measures patient satisfaction using patient survey data |
| **Outcome of care measures** | - Heart failure  
- Heart attack (AMI)  
- Pneumonia  
Mortality rate of patients who died within 30 days after being treated for these conditions |
| **Efficiency** | - Medical spending per beneficiary |

Note: A checkmark (✓) indicates the use of this metric to determine hospital bonuses and incentives in that calendar year.
stakeholders (e.g., patients, care providers, third party payers, and taxpayers).

### 2.2 Organizational theories

Organizational theorists argue that external pressures such as government regulations, as well as political, financial, and time pressures, influence the motivation of organizational actions (Cook et al., 1983; DiMaggio & Powell, 1983; Scott et al., 2000). Institutionalization refers to mechanisms by which external policies obtain legitimacy for an organization (Meyer & Rowan, 1977; Westphal et al., 1997). Organizational literature proposes legitimacy as “a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions” (Suchman, 1995, p. 574). For example, to improve technical performance, organizations are more likely to operate using similar strategies or decision-making systems, a situation called an isomorphism (DiMaggio & Powell, 1983; Heugens & Lander, 2009). Organizational theory perspectives are reasonable for our study because the hospital is our organizational unit of analysis; hospitals reimbursed by Medicare have the potential to be pressured by VBP penalties.

From the institutional perspective, three types of isomorphic processes exist: coercive, mimetic, and normative (DiMaggio & Powell, 1983). Coercive isomorphism comes from formal or informal pressures exerted on organizations by governments or other dominant agencies upon which they depend. Prior literature relates to coercive isomorphism exerted by government regulators (Barratt & Choi, 2007), customers (Choi & Eboch, 1998), and headquarters (Kostova & Roth, 2002). Mimetic isomorphism refers to a cognitive isomorphic process in which organizations recognize taken-for-granted beliefs (DiMaggio & Powell, 1983; Scott et al., 2000). Organizations often face unexpected environments that entail risks. Via a mimetic isomorphic process, an organization follows best practices within an industry to tackle economic peril and acquire legitimacy (Heugens & Lander, 2009). Finally, the normative isomorphic process refers to a pursued value among peers of a professional network, such as professional organizations, trade associations, and public opinion (DiMaggio & Powell, 1983; Scott et al., 2000). These groups impose pressure on organizations to conform to specific standards (Peng, 2003). In response to the isomorphic processes, organizations may enact different strategic responses (Markóczy, Li Sun, Peng, Shi, & Ren, 2013; Oliver, 1991).

Prior management literature suggests health care administrators translate external pressures such as government regulations into internal healthcare executive actions (Elsbach, Sutton, & Principe, 1998; Oliver, 1991; Pfeffer, 1981; Ruef & Scott, 1998). Goodrick and Salancik (1996) argue that, depending on administrator characteristics and capabilities, the degree of compliance with a regulation will differ, and the constraints under which top management makes strategic choices will matter. There is scant empirical OM research, however, that tackles healthcare providers’ operational actions or outcomes when they must address salient pressures such as VBP.

Overall, organizational theory literature offers plausible explanations for the various ways that institutionalization occurs and for types of institutional pressures. Yet, related studies often use a qualitative approach to examine such issues in healthcare. Little research empirically quantifies the impact of such pressures upon hospital administrators’ outcomes. Moreover, there is no guarantee that all hospitals will react in the ways intended by the VBP incentive policy. Internal institutional frictions may exist where some administrators find meeting VBP performance goals too costly to achieve, or they may lack the operational competence to better manage the process complexity to do so, therefore precluding them from taking sufficient actions. Sacarny (2018) describes such agency problems regarding Medicare reimbursement for cardiac care. He observed that between 2008 and 2010, hospitals only captured 52% of the potential revenue they might have captured. Furthermore, he attributed this observation to an agency problem, namely, administrators' difficulty in aligning physicians' and hospital interests. Some hospitals have been more successful aligning physician actions with the financial exigencies of the hospital. We contribute by investigating outcomes of this tension between institutional phenomena and agency phenomena longitudinally in the context of hospital VBP reimbursement incentives. In addition, we next theorize and examine complementary process improvement associations.

### 2.3 Quality improvements and complementary spillovers

Quality management theory emphasizes the need to make systemic process changes to improve service quality (Waldman, 1994). In healthcare, hospital administrators deploy various practices pertaining to quality improvements for healthcare services (Batalden & Buchanan, 1989; Berwick et al., 1991; Roth, 1993; Shortell et al., 1995). For example, the total quality management (TQM) perspective, introduced from the manufacturing domain, focuses on improving operational process quality within an organization (Roth et al., 1996; Westphal et al., 1997; Young, Charns, & Shortell, 2001). TQM initiatives entail cross-functional collaboration for quality improvements (Young et al., 2001; Zinn, Weech, & Brannon, 1998).

In response to VBP incentives, hospitals administrators are likely to undertake quality management practices to enhance both clinical healthcare outcomes and service delivery process quality. Consider for example, hospitals facing a large penalty
are motivated to focus on designing new medical care and service delivery strategies that will improve overall clinical and patient experience outcomes, and/or developing error-proofing of the coding processes and clinical documentation in order to be reimbursed fully for the actual treatment costs they have incurred. Notably, both approaches can lead to improved hospital process standardization. There is some evidence that these various process improvement practices may benefit from each other (Charland, 2017), creating mutually reinforcing spillover effects for the entire system of diagnosis coding, as operationalized by Clark and Huckman (2012). Quality management processes that drive standardized clinical care practices, which in turn reduce clinical uncertainties (e.g., better and faster diagnoses) and drive better care processes, may act to lower process variation in errors associated with documentation, coding, and billing. Consider that if a cardiac patient was coded Heart Failure (HF) “unspecified,” but the patient was actually HF “systolic acute,” the hospital would lose $2,143 in billing fees (Sacarny, 2018).1 Thus, as VBP-mandated hospitals focus on heart failure, pneumonia, and acute myocardial infarction (AMI), administrators will learn there is much to be gained by accurate coding. Conversely, quality management practices aimed at more precise documentation and coding accuracy should, in turn, drive process improvements that achieve practitioner adherence to evidence-based best care practices, as non-standard clinical approaches are identified and reduced, conforming practitioners to standardized best practices. Moreover, as hospitals improve coding and documentation, they create a spillover effect on the overall CMI. In both directions above, it is likely that efforts made to improve one of above process types will spillover, making it easier to obtain returns for the other.

2.4 | Research hypotheses

We next develop theory-based hypotheses regarding expected outcomes for hospitals arising from the magnitude of VBP penalties.

1Consider the following: One of the process-of-care measures under VBP is heart failure (HF). There are 14 diagnostic codes for HF depending on the cardiac cycle affected (e.g., systolic and/or diastolic) and whether the condition was chronic or acute. Before 2008, the Medicare payments for all 14 HF diagnoses were similar; there was no financial incentive to add more details about the anatomical part of the cardiac cycle affected. Consequently, the most commonly used diagnostic code for 85% of HF patients was a vague code labeled “congestive heart failure unspecified” requiring less documentation (Sacarny, 2018). Notably, in 2008, a change in Medicare reimbursement policy paid hospitals less for the unspecified HF code and as much as 2% more for patients with higher severity HF codes (Sacarny, 2018). This example suggests that in order to earn more revenue, hospitals can provide more accurate clinical documentation on the type of heart failure.

2.4.1 | Hospital performance and government regulations

Hospital administrators must endeavor to conform to the particular government-mandated performance criteria (Oliver, 1991; Pfeffer, 1981; Scott et al., 2000). For example, administrators at penalized hospitals may work to improve patient experiential quality or clinical performance. Specifically, with respect to VBP, to convincingly demonstrate efforts to follow the VBP mandate, the administrators in penalized hospitals should show empirical evidence of actual improvements to their patients and corresponding communities in a subsequent period.

We conjecture that hospital administrators, after being penalized by the VBP Program, will focus on improved operational performance, and as stated earlier, patient experience and/or clinical performance quality. The general message being sent from CMS via a VBP penalty is this: when a hospital’s delivery processes are out of control, they are likely operating in ways that are inconsistent with the best practice protocols recommended by CMS; therefore, moving forward, corrective actions should be taken to improve them. In part, losing Medicare revenues creates coercive isomorphism pressures, which should drive a hospital to fall in line with CMS’s directives, yet not every hospital is under the same magnitude of pressure. Mimetic isomorphic pressures arising from public knowledge of a hospital’s VBP penalty would move a hospital to adopt CMS best practices. Thus, a normative response to a VBP penalty is that hospital administrators would seek out and undertake quality management initiatives and process variability reductions that are in a hospital’s interest. In short, the magnitude of a VBP penalty should incentivize administrators to improve operational performance in the following year. Taken together, we propose:

Hypothesis 1a (H1a): The higher the magnitude of a hospital’s VBP penalty, based on its prior year’s operating metrics, the more likely it will act to increase its overall operational performance by the end of the current year.

Hypothesis 1b (H1b): The higher the magnitude of a hospital’s VBP penalty, based on its prior year’s operating metrics, the more likely it will act to increase its patient experiential quality by the end of the current year.

Hypothesis 1c (H1c): The higher the magnitude of a hospital’s VBP penalty, based on its prior year’s operating metrics, the more likely it will act to increase its clinical performance by the end of the current year.

2.4.2 | Performance and patient case mix

Penalized hospitals may achieve patient care and operational performance improvements. Coincident to such efforts,
hospital administrators may also achieve improved coding accuracy as a part of quality improvement initiatives. If administrators can improve the accuracy of admission, diagnosis, and treatment procedure coding processes, those managerial efforts can translate immediately and directly into better care and higher future revenues. Historically, some diagnoses are harder to code, and better documentation and small coding changes can result in large revenue differences (Lindenauger, Lagu, Shieh, Pekow, & Rothberg, 2012). While difficult to observe such phenomena via hospital revenue statistics, due to the uncertain number of revenue cycles it takes until a hospital gets reimbursed, we do expect to observe such changes via a hospital’s annually updated patient CMI.

CMI, a hospital’s level of clinical complexity for inpatient services (CMS, 2018c), is built upon the system of DRGs. The U.S. Congress adopted this system in 1983, making it the first patient classification system used to pay hospitals a flat amount per diagnosis (Chilingerian, 2008). A team of operations researchers at Yale University designed the system to segment patients into similar groups by their resource requirements. Each DRG is assigned a relative weight that represents the expected resource consumption for a typical patient at an average hospital. For example, a DRG relative weight of “2” indicates that a patient’s diagnosis requires twice as many clinical resources to treat as an average admission. Each year, every hospital’s records of patient diagnoses are aggregated and summarized into an overall CMI score that refers to a hospital’s level of clinical complexity for inpatient services (Chilingerian, 2008; CMS, 2018c). CMI calculation depends on several partitioning variables, such as principal and secondary diagnoses, age, procedures performed, the presence of co-morbidities and/or complications, discharge status, and gender. CMI reflects the inpatient mix appropriately because the index is weighted by government analytics (i.e., Medicare) adjusted for complexity of treatment and admitted patient conditions (Frick, Martin, & Shwartz, 1985; Martin, Frick, & Shwartz, 1984). Thus, an increasing CMI indicates an increase in weighted resource consumption by a typical patient, and therefore, indicates an increase in CMS-generated revenue for a hospital.

Local patient acuity population distributions should not be expected, a priori, to shift substantially across short periods. However, in a context of quality management and process improvement efforts, if physicians consistently document CMI-relevant partitioning variables correctly, if patient classes are properly admitted as inpatients, or if hospital reimbursement coders translate patient treatment records correctly, then a hospital’s CMI measure will be standardized and improved. Extant literature empirically shows that a change in CMI can result from organizational responses, such as a coding practice change (Carter et al., 1990; Simborg, 1981), or a change in patient distribution (Goldfarb & Coffey, 1992; Rosenberg & Browne, 2001). Therefore, we conjecture that hospitals can observe some positive spillover affecting their CMI measure simply by improving quality standards and processes.

Prior research reveals that increases in metrics that measure hospital patient acuity can result from changes in inpatient coding practices (Lindenauger et al., 2012). To do so, hospitals might use quality improvement methods to improve physicians’ documentation of patient conditions and treatments, ensure higher-complexity patients’ conditions are coded into higher-weighted diagnosis-related groups (DRGs), undertake clinical documentation improvements, or refine inpatient admissions protocols. The CMI metric is known to be sensitive to the extent of physician documentation as well as to the expertise of coders who translate medical documentation into ICD-9-CM codes for reimbursement (Mendez, Harrington, Christenson, & Spellberg, 2014). Consequently, responding to VBP, administrators may focus on process and service quality improvements, and as a side effect, will benefit from more accurate coding of patients, coding process improvement initiatives, or tactical targeting of more complicated tertiary-care inpatient admissions, whose attributes will increase CMI and bring in more revenue (HCPro, 2010; Jha, Orav, & Epstein, 2010). In essence, more process quality management efforts should enhance payback from performing better administrative tasks, resulting in positive spillover effects (Clark & Huckman, 2012).

Thus, hospitals penalized by VBP would be able to focus subsequent business process improvement efforts on improving the specificity of admission and reimbursement procedures. Underlying VBP are CMS’ objectives to standardize processes and remove unnecessary process variability. Yet, these desirable business process improvements remain to be evaluated. Overall, penalized hospitals will tend to enhance process quality, thereby acting in ways that tend to exhibit a spillover effect on the CMI measure, as a by-product of standardizing their documentation and coding. As a bonus for penalized hospitals, such efforts also should somewhat mitigate the financial consequences of a VBP penalty. Therefore:

Hypothesis 2 (H2): The higher the magnitude of a hospital’s VBP penalty, based on its prior year’s operating metrics, the more likely that hospital will exhibit an increase in its CMI over the current year.

3 | RESEARCH METHODOLOGY

We next describe our data sources. Then, we describe the construction of our variables. We conclude the section with a description of our econometric model and estimation strategy.
3.1 | Data sources

Data for this study represent hospital-level information related
to hospital VBP performance and hospital operations. Table 2
lists specific data sources from which each variable was
obtained. The data come from several sources, including Medi-
care Hospital Compare, CMS Cost Report, CMS Impact Files,
Dartmouth Atlas, and the Healthcare Information and Manage-
ment Systems Society (HIMSS). The data used in our econo-
metric models pertain to fiscal years 2013 through 2016, with
some variables calculated using lagged data from 2012 or fol-
lowing year data from 2017.

As shown in Table 2a, data from Medicare Hospital
Compare pertain to three hospital performance variables.
From the CMS Acute Inpatient PPS Case Mix Index file, we
obtain annual data for CMI, which provides information
about the extent to which hospitals admit patients requiring
complex treatment procedures. From the CMS Acute Inpa-
tient PPS Impact File, we obtain data for our focal dependent
variable regarding the hospital-level annual VBP penalty
percentage for each hospital. For instrumental variables, we
obtain data for a hospital’s actual VBP score from Medicare
Hospital Care and data on hospital readmission levels from
the CMS Acute Inpatient PPS Impact File.

Table 2b presents information about control variables
and variables used in robustness tests and post-hoc analyses.
For example, data from the CMS Cost Report provides the
number of ancillary services offered by a hospital, which
can reflect the service scope of each hospital. We also collect
several other hospital-level control variables from those
same data sources, including hospital size (i.e., number of
beds), a proxy for teaching intensity (i.e., the resident-to-bed
ratio), and other control variables.

3.1.1 | Dependent variables

To examine hospital operational performance, we use three
variables: overall performance score, patient experiential
quality, and clinical performance metrics. The overall performance
score (\( OPerformance \)) is a hospital’s weighted composite per-
f ormance index for a fiscal year, as reported by Medicare Hos-
pital Compare results 2 years after that year (e.g., the 2018
Medicare reports contain operating metrics for the 2016 year).
By collecting Medicare reports released in 2015 through 2018,
specifically for the Total Performance Score (TPS) as calcu-
lated by CMS and issued annually to hospitals, we can observe
the differently weighted and measured \( OPerformance \) for the
fiscal years FY2013 through FY2016. For example, the
\( OPerformance \) variable for year 2013 comprises 20% of cli-
c ical process, 30% of patient experience, 30% of outcome, and
20% of efficiency performance. The variable in 2014 consists
of 10% of clinical process, 25% of patient experience, 40% of
outcome, and 25% of efficiency. The variable in 2015 involves
5% of clinical process, 25% of patient experience, 25% of out-
come, 20% of safety, and 25% of efficiency performance.

Finally, the variable in 2016 includes 25% of clinical process,
25% of patient experience, 25% of safety, and 20% of efficiency
performance.

Since annual changes to the composite weightings for this
overall performance metric may affect how administrators react
to VBP penalties, we also examine operational performance
variables that do not change on an annual basis, to alleviate any
concerns. Patient experiential quality (\( PatientExp \)) and the
clinical performance measure (\( ClinicalPer \)) are unweighted mea-
sures that enter into the \( OPerformance \) calculation. They are
inputs that are involved in deciding which hospitals receive a
VBP financial penalty; thus, penalized hospitals have an incen-
tive to improve these metrics in subsequent periods. Therefore,
we include these two unweighted operational performance
measures as dependent variables. \( PatientExp \) is measured using
Hospital Consumer Assessment of Healthcare Providers and
Systems (HCAHPS) survey information. The scores were
obtained directly from Medicare. We use \( PatientExp \) to reflect
the unweighted hospital-level patient experience. Finally, the
clinical performance measure (\( ClinicalPer \)) represents a simple
sum of the two different aggregated annual Medicare Hospital
Compare scores for clinical process and outcome. The two
input scores were taken directly from Medicare Hospital Com-
pare and were neither modified nor weighted. By constructing
this measure, we can examine the impact of the VBP penalty
on subsequent improvements to clinical operations.

To measure hospital case mix changes, we use the change
in CMI (i.e., \( \Delta CMI \)) as a dependent variable. CMI is measured
by summing the weighted treatment cases related to inpatient
services in a hospital and dividing by the number of cases
(CMS, 2018c). Because the VBP penalty is announced toward
the beginning of each fiscal year, we estimate the CMI change
in each hospital \( i \) from the fiscal year when the penalty is
announced to the next fiscal year, using the following formula:

\[
\Delta CMI_{i,t+1} = CMI_{i,t+1} - CMI_{i,t}
\]

where \( t \) is the time period. Although researchers have hypothe-
sized the possibility of utilizing DRGs in response to external
policies (Simborg, 1981; Stern & Epstein, 1985), other studies
have found that two-thirds of a CMI increase fairly reflect more
complex admissions, while the remainder can result from more
accurate and effective coding (Lindemauer et al., 2012).

3.1.2 | Independent variable

The key independent variable pertaining to our research
hypotheses represents the magnitude of the financial VBP Pro-
gram penalty. The variable \( ValPenalty_{i,t} \) reflects the percentage
of VBP penalty assigned to hospital \( i \) in time \( t \). For example, if
<table>
<thead>
<tr>
<th>(a) Key dependent and independent variables</th>
<th>Variable name</th>
<th>Variable measure</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variables</td>
<td><strong>OPerformance</strong></td>
<td>Sum of the fiscal year's total performance score, as determined from the current year's operating metrics including patient experience, clinical measures, efficiency, and safety (2015, 2016 only)</td>
<td>Medicare Hospital Compare: HVBP TPS</td>
</tr>
<tr>
<td>PatientExp</td>
<td>Normalized and unweighted patient experiential quality score as determined by HCAHPS survey results</td>
<td>Medicare Hospital Compare: HVBP TPS</td>
<td></td>
</tr>
<tr>
<td>ClinicalPer</td>
<td>Normalized and unweighted clinical performance (i.e., process + outcome) quality score as determined by Medicare</td>
<td>Medicare Hospital Compare: HVBP TPS</td>
<td></td>
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<tr>
<td>ΔCMI</td>
<td>Case mix index differences from the current year to the following year</td>
<td>CMS Acute Inpatient PPS: Case mix index file</td>
<td></td>
</tr>
<tr>
<td>Independent variable</td>
<td><strong>ValPenalty</strong></td>
<td>Percentages of each fiscal year VBP penalty, as determined from previous year's operating metrics collected by CMS and announced in the prior year, for 2013–2016</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
</tr>
<tr>
<td>Instrument variables</td>
<td><strong>VBP</strong></td>
<td>Actual VBP score</td>
<td>Medicare Hospital Compare</td>
</tr>
<tr>
<td>ReadmissionFactor</td>
<td>Payment adjustment factor for the CMS readmission penalty program</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>(b) Control variables</th>
<th>Variable name</th>
<th>Variable measure</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control variables</td>
<td><strong>N_ASC</strong></td>
<td>Count of the number of ancillary services provided by a hospital</td>
<td>CMS Cost Report</td>
</tr>
<tr>
<td>MedicareDay</td>
<td>Percentage of total inpatient Medicare days to total inpatient days</td>
<td>Medicare Hospital Compare: Hospital general information</td>
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<tr>
<td>ResidentBedRatio</td>
<td>Resident to bed ratio in a hospital</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
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<tr>
<td>LnBeds</td>
<td>Natural logarithm transformed number of beds</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
<tr>
<td>Dshpct</td>
<td>Disproportionate share hospital (DSH) percentage. If the percentage exceeds 15%, hospitals are eligible for a DSH payment adjustment</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
<tr>
<td>OpCost</td>
<td>Medicare operating costs ratio to Medicare covered charges</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
<tr>
<td>CapCost</td>
<td>Medicare capital costs ratio to Medicare covered charges</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
<tr>
<td>OpOutlier</td>
<td>Percentage of operating outlier payment to operating payments</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
<tr>
<td>CapOutlier</td>
<td>Percentage of capital outlier payments to capital payments</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
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<tr>
<td>CMI</td>
<td>A hospital's case mix index during the fiscal year</td>
<td>CMS Acute Inpatient PPS: Case mix index file</td>
<td></td>
</tr>
<tr>
<td>Robustness test and post hoc variables</td>
<td><strong>MeaningfulUse</strong></td>
<td>Indicator variable: 1 = a hospital has attested to meeting the stage 1 meaningful use requirements; 0 = otherwise</td>
<td>HIMSS Analytics</td>
</tr>
<tr>
<td>%HRRPenalty</td>
<td>% of penalized hospitals within an HRR region</td>
<td>Dartmouth Atlas and Medicare Hospital Compare</td>
<td></td>
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<tr>
<td>ValBonus</td>
<td>Percentages of each fiscal year VBP bonus.</td>
<td>CMS Acute Inpatient PPS: Impact file</td>
<td></td>
</tr>
</tbody>
</table>
a hospital is penalized 1% of its annual CMS reimbursement, $ValPenalty_{it}$ is 0.01. If a hospital is not penalized, or received a bonus, $ValPenalty_{it}$ is 0. Table 2a presents definitions of the above dependent and independent variables.

### 3.1.3 Control variables

For the main analyses, we construct several control variables that may influence our dependent variables. We use a count of the number of ancillary services ($N_{ASCit}$), which serves as a proxy for hospital service scope. $N_{ASCit}$ controls for the scope of services, which may affect the operations performance metrics and the $\Delta CMI$. Since the types of payment accepted by a hospital may also affect a hospital's operations, we use the percentage of Medicare share ($MedicareDay_{it}$) as a general proxy for payment mix. We also control for hospital-level factors that potentially may affect the dependent variables. The number of beds ($LnBeds_{it}$) accounts for the size of each hospital. Due to the skewness of the bed size distribution, we employ the log of the number of hospital beds as a control variable. The variable $ResidentBedRatio_{it}$ measures the ratio of the number of medical residents to the number of hospital beds, and controls for the hospital's teaching intensity. Prior healthcare operations articles studying clinical and experiential quality outcomes have used similar controls (e.g., Roth, Tucker, Venkataraman, & Chilingerian, 2019; Senot, Chandrasekaran, Ward, Tucker, & Moffatt-Bruce, 2015; Sharma, Chandrasekaran, Boyer, & McDermott, 2016; Wani, Malhotra, & Venkataraman, 2018). We also control for Medicare operating/capital costs ($OpCost_{it}$, $CapCost_{it}$) and outlier payments ($OpOutlier_{it}$, $CapOutlier_{it}$) because hospitals treating a higher volume of patients accounting for outlier payments could potentially have lower operational performance outcomes. We include the current year's $CMI_{it}$ as a control variable, providing each hospital with a baseline anchoring point for measuring impacts on the contemporary operations performance as well as the subsequent year-to-year change in $CMI$. Finally, we include year dummies to account for trends across time. Table 2b presents definitions of the above control variables.

Table 3 shows descriptive statistics for our data. Table 4 shows a correlation matrix of the variables. We checked for multicollinearity in the data using variance inflation factor (VIF). Because the maximum VIF score does not exceed 3.15 and the average VIF is 1.99, we find no evidence of multicollinearity.

### 3.1.4 Sample sizes for models

For the period 2013–2016, we collect data for 2,861 VBP-participating hospitals for which consistent longitudinal data were available. The sampling frame for these hospitals consists of all acute care hospitals in the United States that admit Medicare inpatients and that qualify annually to receive a TPS, making them eligible to participate in the mandatory VBP Program.
(CMS, 2018e). Thus, hospitals excluded from our data set include ineligible hospital types (e.g., psychiatric, rehabilitation, long-term care, children’s, exempt cancer hospitals, and critical access hospitals), as well as hospitals that were excluded from VBP eligibility for various reasons (e.g., payment reductions, prior dangerous operating deficiencies, disaster or extraordinary circumstance exceptions, not having a sufficient number of domains to calculate a TPS for a fiscal year, and short-term acute care hospitals from Maryland). For certain regressions, a limited number of hospitals have variables exhibiting missing data, as shown in Table 3. Individual observations are missing at random; they were automatically dropped by the regression procedure. As such, combining the different data sets from various sources resulted in an unbalanced sample having a total sample size ranging from 10,010 (Model 3 for H1c) to 10,820 (Model 4 for H2) hospital-year observations.

3.2 | Econometric models

To examine whether the magnitude of the VBP penalty may improve operational performance or may lead to a CMI increase, we use a longitudinal data analysis from 2013 to 2016. We believe that ValPenaltyit could be correlated with time-varying unobserved factors that can potentially lead to inconsistent within Fixed Effects (FE) model estimators. Thus, we also consider instruments for the key variable of interest ValPenaltyit. We use a two-stage least squares (2SLS) estimator to study our hypotheses, implemented in Stata 14.0, via the Stata procedure xtivreg2 (xtivreg was also used to generate certain model fit statistics).

3.2.1 | Fixed effects model

We employ a FE model to account for unobserved hospital-specific effects (i.e., time-invariant component of the error). The Hausman test further indicated the FE model is more appropriate (p < .001) for consistent estimates. The general regression model is the following:

\[
DV = \beta_0 + \beta_1 ValPenaltyit + \beta_2 N_{ASCit} + \beta_3 MedicareDayit + \beta_4 LnBedsit + \beta_5 ResidentBedRatioit + \beta_6 OpCostit + \beta_7 CapCostit + \beta_8 OpOutlierit + \beta_9 CapOutlierit + \beta_{10} CMIit + YearDummiesit + E_i + \nu_i \tag{1}
\]

where ValPenaltyit is the key independent variable (β1), which represents the hospitals’ VBP penalty percentage applied to Medicare’s inpatient payments in a fiscal year. To assess H1a, H1b, and H1c, we used OPerformanceit, PatientExpit, and ClinicalPerit as dependent variables (i.e., DV) in Equation (1). To assess H2, we used ΔCMIit+1 as the dependent variable in Equation (1). N_{ASC}, MedicareDay, Beds, ResidentBedRatio, OpCost, CapCost, OpOutlier, CapOutlier, CMI, and Year dummies are control variables. Finally, E and \nu represent time-invariant and idiosyncratic errors, respectively.

3.2.2 | Instrumental variables

Following Greene (2008), we employ instrumental variables to account for endogeneity because ValPenaltyit could be correlated with \nuit. ValPenaltyit may be associated with top management decisions, an unobserved variable. Also, hospital administrators may actively decide to incur a VBP penalty, especially during the uncertain early years of the VBP Program.

We thus use instrumental variables for consistent estimation. The actual VBP score should affect the value of a penalty, but not directly affect the dependent variables. Thus, we include the hospital’s raw VBP score from Medicare Hospital Compare, which is measured as a function of a hospital’s previous performance, as an instrumental variable. We also include the Hospital Readmission Factor (ReadadminFactorit) as another instrument because it does not directly determine the dependent variables and is correlated with the value of the VBP penalty. Instrumental variable definitions and the corresponding summary statistics are in Tables 2 and 3. When we conduct an overidentification test (i.e., Sargan statistic) and the underidentification test (i.e., Anderson-Rubin Wald test), we confirm no evidence exists pertaining to an overidentifying restriction or a weak instruments problem (p < .05). Thus, our instrumenting strategy employs the following equation:

\[
ValPenaltyit = \alpha_0 + \alpha_1 VBPit + \alpha_2 ReadmissionFactorit + \Pi Other \text{ Independent Variables}_it + \xi_i \tag{2}
\]

We use robust standard error estimates to control for arbitrary heteroskedasticity in our data.

4 | EMPIRICAL FINDINGS

We estimate four models. Table 5 provides estimation results for each hypothesis. We note that the VBP penalty is given at the beginning of each year, and the hospital outcomes, except for in Model 4, are reported at the end of the year. Model 1 regresses hospital operational performance on the value of the VBP penalty (H1a). Model 2 regresses patient experience on the value of the VBP penalty (H1b). Model 3 examines associations of the VBP penalty with the clinical performance (H1c). Finally, Model 4 presents the regression results for subsequent hospital CMI changes (H2).
**TABLE 4**  Correlation matrix

<table>
<thead>
<tr>
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<th>1</th>
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<th>16</th>
<th>17</th>
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<tbody>
<tr>
<td>1. OPerformance</td>
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<tr>
<td>2. PatientExp</td>
<td></td>
<td>0.64*</td>
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<tr>
<td>3. ClinicalPer</td>
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<td>0.08*</td>
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<td>4. ΔCMI</td>
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<td>−0.01</td>
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<td>5. ValPenalty</td>
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<td>−0.30*</td>
<td>−0.13*</td>
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<tr>
<td>6. N_ASC</td>
<td>−0.30*</td>
<td>−0.34*</td>
<td>0.07*</td>
<td>0.02</td>
<td>0.07*</td>
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<tr>
<td>7. MedicareDay</td>
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<td>0.13*</td>
<td>0.07*</td>
<td>−0.04*</td>
<td>−0.06*</td>
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<tr>
<td>8. LnBeds</td>
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<td>−0.43*</td>
<td>0.09*</td>
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<td>0.13*</td>
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<tr>
<td>9. ResidentBedRatio</td>
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<tr>
<td>10. OpCost</td>
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<td>−0.07*</td>
<td>−0.03</td>
<td>−0.06*</td>
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<tr>
<td>11. CapCost</td>
<td>0.21*</td>
<td>0.28*</td>
<td>−0.05*</td>
<td>−0.02</td>
<td>−0.09*</td>
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<tr>
<td>12. OpOutlier</td>
<td>−0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
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<td>13. CapOutlier</td>
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<td>14. CMI</td>
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<td>15. VBP</td>
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<td>−0.72*</td>
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<td>18. ReadmissionFactor</td>
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<td>−0.02</td>
<td>0.07*</td>
<td>0.06*</td>
<td>0.05*</td>
<td>0.02</td>
<td>0.15*</td>
<td>0.03</td>
<td>−0.01</td>
<td>−0.09*</td>
</tr>
</tbody>
</table>

*p < .001, bold numbers = p < .01, italicized numbers = p < .05. Due to rounding, some similarly rounded numbers above exhibit different p-values.
The coefficient of ValPenalty ($\beta_1 = 11.51, p < .001$) with Operational performance is positive and statistically significant, providing support for H1a, namely that operational improvements are associated with the magnitude of the penalty. We also observe a statistically significant association between ValPenalty and PatientExp ($\beta_1 = 5.60, p < .001$), indicating more heavily penalized hospitals focus on perceived patient satisfaction (H1b). In the case of the clinical performance (ClinicalPer), the ValPenalty coefficient ($\beta_1 = 37.61, p < .001$) suggests that penalized hospitals tend to improve both clinical processes and outcomes (H1c). Finally, for H2, ValPenalty is also positively associated with $\Delta CMI$ ($\beta_1 = 1.75, p < .05$), making the case that VBP penalties are positively associated with patient CMIs that are higher on average compared to the prior year.

Regarding the effect of the magnitude of the financial VBP penalty on operational performance, the estimation results (i.e., Models 1, 2, and 3) offer support for the different aspects of performance specified in Hypotheses 1a–1c. All other things held equal, a 1% VBP penalty increase tends to be associated with an improvement of 11.51% (i.e., 11.51 higher out of the 100 total score) in the overall performance score; 5.60% (i.e., 5.60 higher out of the 100 total score), in the patient experiential quality; and 18.8% (i.e., 37.61 higher

<table>
<thead>
<tr>
<th>Regression model</th>
<th>Model 1 OPerformance(t)</th>
<th>Model 2 PatientExp(t)</th>
<th>Model 3 ClinicalPer(t)</th>
<th>Model 4 $\Delta CMI(t + 1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ValPenalty</td>
<td>11.506*** (0.717)</td>
<td>5.596*** (0.882)</td>
<td>37.606*** (2.256)</td>
<td>1.752* (0.760)</td>
</tr>
<tr>
<td>$N_{ASC}$</td>
<td>-0.111 (0.143)</td>
<td>-0.320** (0.177)</td>
<td>-0.168 (0.439)</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>MedicareDay</td>
<td>0.237 (0.652)</td>
<td>-0.856 (0.909)</td>
<td>9.414* (3.925)</td>
<td>-0.07 (0.007)</td>
</tr>
<tr>
<td>LnBeds</td>
<td>-0.446 (0.913)</td>
<td>0.319 (1.233)</td>
<td>2.649 (3.125)</td>
<td>0.011 (0.008)</td>
</tr>
<tr>
<td>ResidentBedRatio</td>
<td>-11.241** (4.361)</td>
<td>4.496* (5.033)</td>
<td>-32.472† (16.691)</td>
<td>0.100* (0.044)</td>
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<tr>
<td>OpCost</td>
<td>1.368 (3.698)</td>
<td>-0.127 (4.694)</td>
<td>21.172† (11.702)</td>
<td>-0.039 (0.031)</td>
</tr>
<tr>
<td>CapCost</td>
<td>7.199 (13.873)</td>
<td>-8.567 (15.188)</td>
<td>46.857 (46.089)</td>
<td>0.293 (0.160)</td>
</tr>
<tr>
<td>OpOutlier</td>
<td>6.181* (3.134)</td>
<td>6.759 (4.743)</td>
<td>-27.871† (17.038)</td>
<td>-0.140 (0.156)</td>
</tr>
<tr>
<td>CapOutlier</td>
<td>-1.416† (0.798)</td>
<td>-0.911 (0.959)</td>
<td>3.790 (5.462)</td>
<td>0.061 (0.062)</td>
</tr>
<tr>
<td>CMI(t)</td>
<td>1.687 (1.434)</td>
<td>-0.505 (1.859)</td>
<td>11.856*** (4.958)</td>
<td>-0.756*** (0.018)</td>
</tr>
<tr>
<td>Year2013</td>
<td>3.869*** (0.255)</td>
<td>6.495*** (0.333)</td>
<td>58.188*** (0.826)</td>
<td>-0.038*** (0.002)</td>
</tr>
<tr>
<td>Year2014</td>
<td>2.119*** (0.202)</td>
<td>2.346*** (0.270)</td>
<td>65.008*** (0.671)</td>
<td>-0.040*** (0.002)</td>
</tr>
<tr>
<td>Year2015</td>
<td>-2.616*** (0.191)</td>
<td>-0.157 (0.257)</td>
<td>53.649*** (0.720)</td>
<td>0.002 (0.002)</td>
</tr>
<tr>
<td>Year2016</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
</tr>
</tbody>
</table>

Instrumental variables Included Included Included Included
Prob. > $\chi^2$ 0.00 (a) 0.00 0.00 0.00
Prob. > $F$ 0.00 (b) 0.00 0.00 0.00
N 10,652 10,635 10,010 10,820

*p < .1, *p < .05, **p < .01, ***p < .001. (a) $p$-Value for the Wald $\chi^2$ statistic for model fit. (b) $p$-Value for the test of model fit for the first stage model using instrumental variables.
out of the 200 total score), in clinical care performance. Finally, the estimated effect for Hypothesis 2 suggests, ceteris paribus, a 1% VBP penalty increase is associated with a subsequent mean CMI change of 0.018. In essence, the penalized hospitals tend to increase CMI, which coincidentally should tend to yield higher net revenues that can somewhat compensate for a VBP penalty (HCPro, 2010).

Overall, these estimation results provide empirical evidence regarding our main research question, namely that financially penalized hospitals appear likely to improve performance in three areas: total operations performance, and its composite elements—patient experience, and clinical care performance. In addition, we observe empirical evidence that penalized hospitals also exhibit an increased CMI, a potentially unintended spillover consequence.

5 | ROBUSTNESS TESTS

To examine the consistency of our empirical results, we perform four additional analyses. First, we control for the potential effect of information technology (IT) adoption on hospital operations outcomes (Section 5.1). Second, we control for potential effects of penalized hospitals in the same hospital referral region (Section 5.2). Finally, we explore the impact of alternate model specifications for the ΔCMI model (Section 5.3). As a post-hoc test (Section 5.4), we also examine the consequences for hospitals that are receiving a VBP bonus, based on the annual VBP evaluation.

5.1 | Effects of IT adoption

Hospital IT investments conforming to government mandates reflect an attempt to achieve institutionalization (DiMaggio & Powell, 1983). Prior information systems studies have explored IT adoption and corresponding impacts on hospital operational performance (e.g., Agarwal, Gao, DesRoches, & Jha, 2010). Modern hospitals incorporate advanced IT to handle service processes smoothly (Angst & Agarwal, 2009). IT usage can enable process improvements, and in turn, improve objective hospital performance, such as financial and quality performance (Devaraj, Ow, & Kohli, 2013), and enhanced process transparency (Kohli & Kettinger, 2004). Thus, we expect possible effects of IT adoption on hospital operational performance. Even for hospitals that have low VBP performance, successfully adopting new government-mandated IT systems should enable hospital administrators to improve actual process performance and the accuracy of their diagnostic coding, which may create a spillover effect on the overall patient case mix as well on operational improvements.

We use a dichotomous variable (MeaningfulUse) as an indicator to describe whether a hospital has achieved Meaningful Use Stage 1 (HealthIT, 2015) during a year. If a hospital has adopted an IT system compliant with government mandates pertaining to IT adoption (i.e., Meaningful Use), we capture the hospital as 1, and 0 otherwise. We use the following equation to control for this possible confounder:

\[
DV = \tau_0 + \tau_1 ValPenalty_{it} + \tau_2 MeaningfulUse_{it} + \tau_3 ValPenalty \times MeaningfulUse_{it} + \tau_4 N_{ASC_{it}} + \tau_5 MedicareDay_{it} + \tau_6 LnBeds_{it} + \tau_7 ResidentBedRatio_{it} + \tau_8 OpCost_{it} + \tau_9 CapCost_{it} + \tau_{10}OpOutlier_{it} + \tau_{11}CapOutlier_{it} + \tau_{12}CMI_{it} + YearDummies_t + \varepsilon_{it},
\]

where ValPenalty * MeaningfulUse is the key variable to estimate this association. Table 6 provides results for the VBP penalty association with hospital outcomes, after controlling for Meaningful Use of IT.

Overall, the results in Table 6 are consistent with those from Table 5. Similar to the main effect in Section 4, the VBP penalty increase is associated with hospital operational performance metrics. Thus, the results for receiving a VBP penalty on hospital operational outcomes provide further support for H1a (14.71, p < .001), H1b (7.14, p < .001), and H1c (50.38, p < .001). Also, the VBP penalty is positively associated with the hospital CMI change, which more moderately supports H2 (2.44, p < .1). Interestingly, the moderating effects of IT Meaningful Use attenuate the influence of the VBP penalty on the outcomes. The value of each penalty parameter decreases for H1a (14.71–6.30 = 8.41), H1b (7.137–3.047 = 4.09), and H1c (50.38–25.43 = 24.95). We do not observe a significant effect for H2. The estimates provide further evidence that the penalized hospitals are more likely to improve their operational performance, and as illustrated by the ValPenalty * MeaningfulUse interactions, the VBP penalties are more effective in hospitals that have not yet adopted government initiated IT requirements. This finding is consistent with IT adoption literature, especially when associated with system-wide complexities like hospitals. IT adoption often takes years to improve performance, often with setbacks. Yet, this phenomenon can cause hospitals to push back from adoption when VBP penalties are low. Also, the results indicate that for penalized hospitals, the MeaningfulUse IT adoption does not mitigate such actions.

5.2 | Effects of regional peer hospital penalties

Institutionalization entails adaptive responses logically connected by organizational regulative, mimetic, and cognitive characteristics (DiMaggio & Powell, 1983) and may to some extent explain the diffusion of outcomes due to the VBP
Program penalty into peer hospitals in the same region. Different yet socially similar hospitals may take part in the policy and develop similar normative beliefs (Festinger, 1954) that may precede similar practice adoption. Extant literature has empirically found that organizations may respond variously to institutional pressures depending on location (Doshi, Dowell, & Toffel, 2013; Lounsbury, 2001, 2007; Marquis, 2003; Marquis, Glynn, & Davis, 2007). Thus, we examine whether the extent of nearby peer hospital penalties affect a hospital's performance. To control for these potential confounding effects, we include a variable representing the percentage of penalized hospitals within each hospital's Hospital Referral Region (i.e., %HRRPenalty) in our main model.

### TABLE 6 Controlling for effects of IT adoption

<table>
<thead>
<tr>
<th>Regression model</th>
<th>Model 5 H1a</th>
<th>Model 6 H1b</th>
<th>Model 7 H1c</th>
<th>Model 8 H2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OPerformance</td>
<td>PatientExp</td>
<td>ClinicalPer</td>
<td>ΔCMI t+1</td>
</tr>
<tr>
<td>ValPenalty</td>
<td>14.711***</td>
<td>7.137***</td>
<td>50.378****</td>
<td>2.439†</td>
</tr>
<tr>
<td>(1.241)</td>
<td>(1.496)</td>
<td>(0.867)</td>
<td>(1.374)</td>
<td></td>
</tr>
<tr>
<td>MeaningfulUse</td>
<td>0.742</td>
<td>1.657*</td>
<td>0.780</td>
<td>0.009†</td>
</tr>
<tr>
<td>(0.579)</td>
<td>(0.738)</td>
<td>(2.110)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>ValPenalty * MeaningfulUse</td>
<td>-6.300***</td>
<td>-3.047†</td>
<td>-25.430***</td>
<td>-1.408 (1.349)</td>
</tr>
<tr>
<td>(1.667)</td>
<td>(4.446)</td>
<td>(2.438)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N_ASC</td>
<td>-0.122</td>
<td>-0.327†</td>
<td>-0.197</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.144)</td>
<td>(0.442)</td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MedicareDay</td>
<td>0.214</td>
<td>-0.889</td>
<td>9.346*</td>
<td>-0.007</td>
</tr>
<tr>
<td>(0.653)</td>
<td>(0.908)</td>
<td>(3.947)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>LnBeds</td>
<td>-0.424</td>
<td>-0.325</td>
<td>2.861</td>
<td>0.011</td>
</tr>
<tr>
<td>(0.913)</td>
<td>(1.232)</td>
<td>(3.117)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>ResidentBedRatio</td>
<td>-10.712**</td>
<td>5.365</td>
<td>-28.988†</td>
<td>0.102*</td>
</tr>
<tr>
<td>(4.315)</td>
<td>(4.999)</td>
<td>(16.821)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>OpCost</td>
<td>1.329</td>
<td>0.081</td>
<td>19.491†</td>
<td>-0.039</td>
</tr>
<tr>
<td>(3.752)</td>
<td>(4.969)</td>
<td>(11.753)</td>
<td>(0.031)</td>
<td></td>
</tr>
<tr>
<td>CapCost</td>
<td>7.416</td>
<td>-8.518</td>
<td>49.618</td>
<td>-0.136</td>
</tr>
<tr>
<td>(14.002)</td>
<td>(15.198)</td>
<td>(48.234)</td>
<td>(0.156)</td>
<td></td>
</tr>
<tr>
<td>OpOutlier</td>
<td>6.146†</td>
<td>6.560</td>
<td>-26.812</td>
<td>0.062</td>
</tr>
<tr>
<td>(3.167)</td>
<td>(4.778)</td>
<td>(17.211)</td>
<td>(0.062)</td>
<td></td>
</tr>
<tr>
<td>CapOutlier</td>
<td>-1.413†</td>
<td>-0.854</td>
<td>3.570</td>
<td>-0.016</td>
</tr>
<tr>
<td>(0.819)</td>
<td>(0.978)</td>
<td>(5.610)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>CMI(t)</td>
<td>1.937</td>
<td>-0.440</td>
<td>12.931**</td>
<td>-0.756***</td>
</tr>
<tr>
<td>(1.442)</td>
<td>(1.857)</td>
<td>(4.986)</td>
<td>(0.018)</td>
<td></td>
</tr>
<tr>
<td>Year2013</td>
<td>3.900***</td>
<td>6.518***</td>
<td>58.299***</td>
<td>-0.039***</td>
</tr>
<tr>
<td>(0.257)</td>
<td>(0.333)</td>
<td>(0.831)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Year2014</td>
<td>2.135***</td>
<td>2.349***</td>
<td>65.071***</td>
<td>0.040***</td>
</tr>
<tr>
<td>(0.204)</td>
<td>(0.271)</td>
<td>(0.675)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Year2015</td>
<td>-2.591***</td>
<td>-0.150</td>
<td>53.751***</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.191)</td>
<td>(0.257)</td>
<td>(0.724)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Year2016</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
</tr>
<tr>
<td>Instrumental variables</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Prob. &gt; χ²</td>
<td>0.00 (a)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Prob. &gt; F</td>
<td>0.00 (b)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>N</td>
<td>10,652</td>
<td>10,635</td>
<td>10,010</td>
<td>10,820</td>
</tr>
</tbody>
</table>

*p < .1, *p < .05, **p < .01, ***p < .001. (a) p-Value for the Wald χ² statistic for model fit. (b) p-Value for the test of model fit for the first stage model using instrumental variables.
$DV = v_0 + v_1 ValPenalty_{it} + v_2 %HRRPenalty_{it} + v_3 N_{ASCit} + v_4 MedicareDay_{it} + v_5 LnBeds_{it} + v_6 ResidentBedRatio_{it} + v_7 OpCost_{it} + v_8 CapCost_{it} + v_9 OpOutlier_{it} + v_{10} CapOutlier_{it} + v_{11} CMI_{it} + YearDummies_{it} + E_i + \nu_{it}, \quad (4)$

where $%HRRPenalty$ is the key variable to estimate the effects of nearby peer hospital penalties. Table 7 provides results for the VBP penalty association with hospital outcomes, controlling for the peer hospitals.

Again, we observe consistent empirical evidence that the magnitude of the VBP penalty is positively associated with hospital performance and a positive CMI change. The results provide consistent support for H1a (11.50, $p < .001$), H1b (5.58, $p < .01$), and H1c (37.61, $p < .001$). However, we observe no evidence related to a significant impact of penalized, peer hospitals in the same referral region on any of the operational performance metrics. Next, we observe the VBP penalty is again associated with a positive CMI change, which supports H2 (1.76, $p < .05$). Also, a significant peer

<table>
<thead>
<tr>
<th>Regression model</th>
<th>Model 9</th>
<th>Model 10</th>
<th>Model 11</th>
<th>Model 12</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H1a</td>
<td>H1b</td>
<td>H1c</td>
<td>H2</td>
</tr>
<tr>
<td></td>
<td>OPerformance(t)</td>
<td>PatientExp(t)</td>
<td>ClinicalPer(t)</td>
<td>ΔCMI(t+1)</td>
</tr>
<tr>
<td>ValPenalty</td>
<td>11.499*** (0.717)</td>
<td>5.575*** (0.881)</td>
<td>37.608*** (2.256)</td>
<td>1.762* (0.761)</td>
</tr>
<tr>
<td>%HRRPenalty</td>
<td>0.240 (0.510)</td>
<td>0.705 (0.511)</td>
<td>0.417 (4.147)</td>
<td>0.019* (0.009)</td>
</tr>
<tr>
<td>N_ASC</td>
<td>$-0.115$ (0.143)</td>
<td>$-0.332^\dagger$ (0.176)</td>
<td>$-0.171$ (0.439)</td>
<td>$0.001$ (0.001)</td>
</tr>
<tr>
<td>MedicareDay</td>
<td>0.242 (0.654)</td>
<td>$-0.841$ (0.912)</td>
<td>9.414$^\dagger$ (3.926)</td>
<td>$-0.007$ (0.006)</td>
</tr>
<tr>
<td>LnBeds</td>
<td>$-0.439$ (0.913)</td>
<td>0.298 (1.232)</td>
<td>2.654 (3.126)</td>
<td>0.012 (0.008)</td>
</tr>
<tr>
<td>ResidentBedRatio</td>
<td>$-11.250^*$ (4.363)</td>
<td>4.938 (5.029)</td>
<td>$-32.475^\dagger$ (16.692)</td>
<td>0.100* (0.044)</td>
</tr>
<tr>
<td>OpCost</td>
<td>1.415 (3.701)</td>
<td>0.017 (4.700)</td>
<td>21.221$^\dagger$ (11.709)</td>
<td>$-0.038$ (0.031)</td>
</tr>
<tr>
<td>CapCost</td>
<td>7.228 (13.874)</td>
<td>$-8.477$ (15.183)</td>
<td>46.880 (48.091)</td>
<td>$-0.139$ (0.156)</td>
</tr>
<tr>
<td>OpOutlier</td>
<td>6.170$^*$ (3.135)</td>
<td>6.726 (4.745)</td>
<td>$-27.880$ (17.038)</td>
<td>0.061 (0.062)</td>
</tr>
<tr>
<td>CapOutlier</td>
<td>$-1.414^\dagger$ (0.798)</td>
<td>$-0.904$ (0.959)</td>
<td>3.796 (5.464)</td>
<td>$-0.015$ (0.030)</td>
</tr>
<tr>
<td>CMI(t)</td>
<td>1.684 (1.435)</td>
<td>$-0.513$ (1.858)</td>
<td>11.874* (4.958)</td>
<td>$-0.756^{***}$ (0.018)</td>
</tr>
<tr>
<td>Year2013</td>
<td>3.846*** (0.260)</td>
<td>6.426*** (0.339)</td>
<td>58.157*** (0.878)</td>
<td>$-0.040^{***}$ (0.003)</td>
</tr>
<tr>
<td>Year2014</td>
<td>2.129*** (0.203)</td>
<td>2.375*** (0.271)</td>
<td>65.028*** (0.701)</td>
<td>0.039*** (0.002)</td>
</tr>
<tr>
<td>Year2015</td>
<td>$-2.620^{***}$ (0.191)</td>
<td>$-0.167$ (0.257)</td>
<td>53.643*** (0.723)</td>
<td>0.002 (0.002)</td>
</tr>
<tr>
<td>Year2016</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
</tr>
<tr>
<td>Instrumental variables</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Prob. &gt; $\chi^2$</td>
<td>0.00 (a)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Prob. &gt; $F$</td>
<td>0.00 (b)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>N</td>
<td>10,652</td>
<td>10,635</td>
<td>10,010</td>
<td>10,820</td>
</tr>
</tbody>
</table>

* $p < .1$, $^* p < .05$, $^{**} p < .01$, $^{***} p < .001$. (a) $p$-Value for the Wald $\chi^2$ statistic for model fit. (b) $p$-Value for the test of model fit for the first stage model using instrumental variable.
hospital effect on CMI (0.019, \( p < .05 \)) is found. This result suggests that, under VBP, hospitals in a referral region are impacted by local penalized hospitals, effectively increasing the average CMI across the hospital referral region. Overall, these empirical results again support our main findings.

### 5.3 Alternate model specifications for CMI

Finally, we also explored the impact on the empirical results for the \( \Delta CMI \) model (i.e., for H2) via different variable lag specifications, and inclusion/omission of the CMI control. In our models presented above, we use \( \Delta CMI_{t+1} = f(X, CMI_t) \).

When our model specification instead used \( \Delta CMI_t = f(X, CMI_{t-1}) \), the results were largely unchanged. When we dropped the CMI control variable, we observe similar results, but worse model fit statistics. Overall, model specification changes do not affect the key findings for the estimated parameters for \( ValPenalty \).

### 5.4 Impact of VBP bonus on hospital performance

As a post-hoc analysis, we also examine subsequent effects for hospitals that received a VBP bonus. We expect hospitals

---

**TABLE 8** Models with the value of bonus

<table>
<thead>
<tr>
<th>Regression model</th>
<th>Model 13</th>
<th>Model 14</th>
<th>Model 15</th>
<th>Model 16</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bonus</td>
<td>Bonus</td>
<td>Bonus</td>
<td>Bonus</td>
</tr>
<tr>
<td></td>
<td>OPerformance(t)</td>
<td>PatientExp(t)</td>
<td>ClinicalPer(t)</td>
<td>( \Delta CMI(t + 1) )</td>
</tr>
<tr>
<td>ValBonus</td>
<td>−7.242*** (0.456)</td>
<td>−3.521*** (0.554)</td>
<td>−26.366*** (1.581)</td>
<td>−1.101* (0.477)</td>
</tr>
<tr>
<td>( N_{ASC} )</td>
<td>−0.104 (0.143)</td>
<td>−0.315** (0.177)</td>
<td>−0.152 (0.451)</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>MedicareDay</td>
<td>0.415 (0.639)</td>
<td>−0.768 (0.898)</td>
<td>9.725** (3.628)</td>
<td>−0.007 (0.006)</td>
</tr>
<tr>
<td>LnBeds</td>
<td>−0.435 (0.922)</td>
<td>−0.311 (1.237)</td>
<td>2.570 (3.090)</td>
<td>0.011 (0.008)</td>
</tr>
<tr>
<td>ResidentBedRatio</td>
<td>−10.635* (4.444)</td>
<td>5.261 (5.106)</td>
<td>−32.451† (16.649)</td>
<td>0.100* (0.044)</td>
</tr>
<tr>
<td>OpCost</td>
<td>3.477 (3.774)</td>
<td>0.724 (4.706)</td>
<td>23.167* (11.512)</td>
<td>−0.038 (0.031)</td>
</tr>
<tr>
<td>CapCost</td>
<td>4.945 (13.867)</td>
<td>−9.716 (15.359)</td>
<td>53.374 (48.644)</td>
<td>−0.142 (0.157)</td>
</tr>
<tr>
<td>OpOutlier</td>
<td>5.451† (2.897)</td>
<td>6.441 (4.692)</td>
<td>−17.474 (16.520)</td>
<td>0.062 (0.061)</td>
</tr>
<tr>
<td>CapOutlier</td>
<td>−1.637* (0.681)</td>
<td>−1.017 (0.946)</td>
<td>−1.201 (5.328)</td>
<td>−0.016 (0.027)</td>
</tr>
<tr>
<td>CMI(t)</td>
<td>2.381† (1.148)</td>
<td>−0.171 (1.856)</td>
<td>12.266* (4.961)</td>
<td>−0.756*** (0.018)</td>
</tr>
<tr>
<td>Year2013</td>
<td>2.040*** (0.261)</td>
<td>5.610*** (0.344)</td>
<td>52.167*** (0.864)</td>
<td>−0.041*** (0.002)</td>
</tr>
<tr>
<td>Year2014</td>
<td>0.779*** (0.207)</td>
<td>1.696*** (0.278)</td>
<td>60.232*** (0.718)</td>
<td>−0.040*** (0.002)</td>
</tr>
<tr>
<td>Year2015</td>
<td>−3.248*** (0.193)</td>
<td>−0.465 (0.260)</td>
<td>51.181*** (0.734)</td>
<td>0.001 (0.002)</td>
</tr>
<tr>
<td>Year2016</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
<td>Omitted</td>
</tr>
<tr>
<td>Instrumental variables</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Prob. &gt; ( \chi^2 )</td>
<td>0.00 (a)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Prob. &gt; ( F )</td>
<td>0.00 (b)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>( N )</td>
<td>10,652</td>
<td>10,635</td>
<td>10,101</td>
<td>10,820</td>
</tr>
</tbody>
</table>

\( p < .1, * p < .05, ** p < .01, *** p < .001. \) (a) \( p \)-Value for the Wald \( \chi^2 \) statistic for model fit. (b) \( p \)-Value for the test of model fit for the first stage model using instrumental variable.
that receive a VBP reimbursement bonus for current year operations would be less motivated to further improve their current operational processes because such hospitals may be already fully utilizing their operational resource, or are good enough not to seek further investments. In a sense, high-performing hospitals may be located very close to a performance frontier, meaning they have nowhere to go but down (i.e., they will regress toward the mean). We estimate a fixed-effects model, again, as described in Section 3, replacing ValPenalty with ValBonus. Table 8 provides estimated impacts of the VBP bonus. ValBonus represents the hospitals’ VBP bonus percentage applied to Medicare’s inpatient reimbursement payments in a fiscal year. As expected, we observe significant negative main effects for Operformance \( (\beta = -7.24, \ p < .001) \), PatientExp \( (\beta = -3.52, \ p < .001) \), and ClinicalPer \( (\beta = -26.37, \ p < .001) \). The coefficients of ValBonus indicate that hospitals rewarded at the beginning of a year, based on prior performance, perform less well during the current year. We also observe a significant negative association \( (\beta = -1.10, \ p < .05) \) of the VBP bonus with \( \Delta \text{CMI} \), indicating that highly rewarded hospitals tend to exhibit a decrease in CMI. This decrease in CMI may yield lower revenue for hospitals that receive a VBP bonus as compared to their penalized counterparts. Overall, the empirical implication of this bonus further illuminates the academic importance to study the observable impacts of the VBP policy on operational performance.

6 | DISCUSSION, LIMITATIONS, AND CONCLUSIONS

This study highlights impacts on aggregate hospital operating patterns resulting from their responses to VBP penalty magnitude. The empirical estimation tends to support our hypotheses, which healthcare OM researchers have yet to quantitatively explore. When examined longitudinally, penalized hospitals appear to have changed their operations in ways that have led to operational performance improvements. Next, we also observe fairly consistent evidence that the VBP Program’s penalized hospitals subsequently tend to exhibit an increased CMI metric for their patient populations, typically moving those hospitals’ CMI metrics toward patient groups requiring more (and more complex) care procedures. Such CMI movements are known to lead to higher hospital revenues (HCPro, 2010). Overall, however, our empirical findings reveal that VBP, on average, drives penalized hospitals to act operationally in manners consistent with the program’s underlying objectives. Previously penalized hospitals are likely to improve processes in ways that enhance hospital operational outcomes and financial revenues.

6.1 | Theoretical and empirical contributions

This study contributes by exploring hospital administrative responses to VBP on hospital performance dimensions and patient populations as reflected by CMI. Little empirical research in healthcare OM examines the impact of VBP penalty magnitude on hospital operations. Moreover, by quantifying longitudinal operational consequences of the VBP penalty, the study analyzes administrative effects of an incentive-driven shift from service delivery volume to realized service delivery value on the CMI, which is derived from corresponding patient admission, diagnosis, and treatment coding processes. Since the VBP performance targets have changed annually, whereas prior studies typically just looked at the program’s impact in the first year of VBP outcomes, the previous studies are not equivalent to our study, another contribution of our research. Because VBP seeks to encourage improvements in patient-centered service delivery and hospital operating strategies, it is an important strategic topic in healthcare OM (Green, 2012). This section explains the results and discusses implications for hospital administrators and operations managers, health policy makers, and researchers.

Our findings offer a plausible explanation of administrative patterns in response to VBP, which may not surprise practitioners involved in hospital payment and reimbursement. When facing or experiencing financial penalties, hospital administrators are likely to evaluate the risks and the relative paybacks from two possible approaches: (a) focusing on designing new operating strategies that will improve overall clinical performance, and (b) improving coding accuracy and clinical documentation. Both approaches can lead to clinical and financial gains. However, each approach occurs over different time spans and with varying degrees of uncertainty and operational variance reduction.

From a quality management perspective, an operations strategy aimed at excellent patient care and waste-free medical care often requires deep cultural changes. Hospital administrators must focus on continuous process improvements that result in better relational coordination and that encourage more collaborative teamwork. While the quality management approach takes much administrative diligence and steadfastness, it also exposes the hospital to the chance of short-term losses in exchange for long-term gains. It is well known that a major process change often will make an organization worse off, before things eventually get better (Heim & Ketzenberg, 2011). Consider pneumonia, which is also a high-cost, high-mortality diagnosis. It is a perfect candidate for a care process improvement project under VBP, if staff can focus on reducing waste and medical errors from diagnosis to treatment. Process improvement for stroke care is another example, where time is of the essence to clinical
outcomes. A team of nurses, pharmacists, administrators and physicians, using operations tools and techniques such as lean principles (Batalden & Buchanan, 1989; Kovach & Fredendall, 2015; Lawal et al., 2014) can work to redesign the inpatient care processes that also include improving the patient experience. Multidisciplinary teams could observe and record all of the process steps from admission, to lab investigations, from medical therapies to discharge, and create value stream maps. While quality improvement projects can remove waste, they depend on clinician engagement, require much longer periods of time to obtain results, and exhibit varying degrees of success.

Importantly, as discussed, improving process quality and patient care quality also may lead to spillover effect outcomes (Clark & Huckman, 2012), such as in the form of enhanced documentation and coding accuracy, which can result in hospitals and practitioners getting paid for the clinical work they are already doing. Financially, documentation and coding improvements can be a relatively fast fix with low residual uncertainty. Historically, some diagnoses are harder to code, and better documentation and small coding changes can result in large revenue differences (Lindemauer et al., 2012). If administrators can improve the accuracy of diagnosis and treatment procedure coding processes and admissions processes, those managerial efforts can translate immediately and directly into more revenues. If an administrator reviews a patient's medical records and asks the attending physician if he or she agrees with an updated diagnosis, and the physician agrees, with 100% certainty more accurate coding processes would restore potentially lost revenues. In a sense, tackling pre-existing administrative coding deficiencies enables hospitals to immediately gain back these “low-hanging fruits.” In this case, however, the administrators will likely need to allocate sufficient physician capacity to their coding tasks so as not to infringe upon the requisite clinical care for their patients.

In summary, this study empirically analyzed and explained how hospitals have responded in aggregate to the VBP regulation and interpreted how an average hospital might behave. Under VBP pressures, if a hospital has been penalized and thereby lost reimbursement money, they face major financial uncertainties and have critical managerial problems to solve. Administrators have an immediate incentive to determine how much of their problem was a direct or indirect result of process of care, efficiency, patient experiences, and/or patient outcomes. They also have an immediate incentive to restore the “lost” revenues, perhaps through quality improvement and process standardization initiatives. Both problems are important. Under continuous improvement, physicians and hospital administrators can work together to identify diagnoses that have converged around clear clinical practice guidelines and processes, and then can continue to reduce uncertainty about coding accuracy and the related revenue losses arising from agency problems that often affect coding accuracy (Sacarny, 2018). Which effort should begin first is still open for further study. Roth (1993) proposes using competitive progression theory in healthcare, whereby process quality is the first step forward. Drawing upon Roth et al. (2019), hospitals may wish to reduce bed utilization, wherein traditional queuing theory improves system flows and frees up capacity, at least for a short term, to work on such improvements.

Although this study was not designed to understand the detailed causes of the CMI changes and the changes to overall performance, these findings have important implications for the practice of health care management. Healthcare organizations are often so complex that clinicians and administrators are not sure what they can do to optimize performance. Moreover, many physicians and administrators historically may have assumed that the documentation-to-coding-to-billing-to-payment processes and handoffs had always been accurate (Letourneau, 2015), but that assumption has been challenged by the available data and our findings. Recent coding studies illustrate that compared to the 95% coding accuracy goal set by industry, average coding accuracy can end up far below this standard, in some hospital departments below 35% accuracy (Charland, 2017). Pushing only for coding productivity may further reduce coding accuracy. Notably, there has long been a wide gap between hospital operational processes and hospital clinical processes (Roth et al., 1996); our data suggest administrators facing high VBP penalties are much more apt to invest in clinical quality processes, compared to improving patient experiences.

Programs like VBP require a managerial shift in focus to the various ways that patients and materials flow through clinical care programs and processes together. Hospital administrators using this approach improve performance by employing value stream maps, electronic health records, telemedicine, E-prescribing technology, and re-designed care processes. This new pay-for-performance focus requires new and strengthened partnerships among clinicians and administrators (Letourneau, 2015). However, our findings also suggest that the partnership between physicians and administrators must extend beyond enabling technologies, to collaboration required to enhance overall operational effectiveness and benefit from potential positive spillovers.

We also found changes in CMI to be significant. Among the possible root causes of a subsequent increase in CMI is the underlying lack of common data literacy across hospitals about reimbursement processes. In an environment where physicians will talk in the language of Current Procedural Terminology (CPT) codes for patient treatments (e.g., CPT code 70551—MRI Brain w/o Contrast), whereas administrators and
reimbursement coders talk in the language of Diagnosis Related Group (DRG) codes (e.g., DRG code 065—Intracranial hemorrhage or cerebral infarction w CC), the two groups have commonly been talking at each other, rather than collaborating with each other. Nevertheless, reimbursement process adaptations appear to have begun, based on the observed empirical impacts of the VBP magnitude penalties upon ΔCMI. Thus, a key implication of our findings is that healthcare institutions need to take managerial cost accounting for healthcare operations more seriously. Getting the healthcare operations data to be accurate requires serious understanding and buy-in between both sets of parties (i.e., administrators and clinicians) of what the other party does to transform diagnoses and treatment procedures into enough revenues that compensate appropriately and support the healthcare institution (Letourneau, 2015).

In the future, clinicians, with the help of hospital administrators, must evaluate and manage clinical decision-making (Letourneau, 2015). The performance improvement tools include updated protocols, better clinical decision support systems, and management control aimed at holding clinicians accountable not only for diagnosing and coding more accurately, but also learning systems for the new targets of performance: patient experience, efficiency, and technical outcomes. To manage clinical decision-making, administrators must create platforms and methodologies that give wide access to timely and accurate clinical data, which will allow clinicians to query and benchmark their individual and departmental performance against the VBP measures. To accomplish this, administrators must partner with and empower physicians to take the lead responsibility for clinical data literacy—so every physician can offer their clinical insights to educate and improve performance in their hospitals in ways that will benefit (and create value) for patients, physicians, and the hospital. At the same time, administrators must allocate scarce physician capacity wisely, and ensure these processes are not so overwhelming as to reduce their ability to deliver high quality clinical care.

The empirical findings here also have significant implications for health policy makers. As government policy makers review the VBP Program, including diagnostic metrics, ultimate aims, and the organizational behavior of hospitals under financial pressure, they can make their assumptions more explicit and begin to turn these assumptions into testable hypotheses. For example, one assumption is that the shift from volume to value will make hospitals more accountable and result in lower costs, better patient experience, and better patient outcomes. We have shown one way that policy makers can study such assumptions.

Finally, we found several implications for future research questions, with many new questions to investigate. In this study, empirical evidence about increasing annual levels of CMI at penalized hospitals potentially provides evidence that some hospitals may also be reducing uncertainty about coding accuracy by improving processes for physicians’ documentation of patient maladies and reimbursement coders’ patient diagnosis/treatment coding practices. Improvements to these administrative and reimbursement practices will reduce coding uncertainty. Does better coding increase overall reimbursement process consistency and reliability, as well as shorten the lifecycle until final payment? Will better documentation and coding create a more stable, less volatile reimbursement system that allows hospital administrators to focus on and invest in needed operational improvements?

While we motivate our ΔCMI analyses based on spillovers (Clark & Huckman, 2012), uncovered issues remain to be resolved in future research. This study raises the possibility that some hospital administrators may be reducing the level of uncertainty as to why certain patients were admitted. Thus, they may be tactically increasing CMI by conforming to more stringent criteria for inpatient admissions. As a side effect of using a case management protocol for inpatient admissions, newly standardized admission protocols coincidentally can remove unnecessary inpatients from entering the system and thereby, de facto allow only those patients truly requiring more sophisticated treatments (i.e., owing to complications and comorbidities) into this system. This basic admission process improvement will arithmetically increase a hospital’s CMI index measurement, which can bring in incentive-based financial bonuses. At the same time, since only a small body of prior research studies the actual extent to which admissions changes versus more accurate coding will drive a CMI increase (Lindenauer et al., 2012), more research clearly is needed to untangle generalizable findings for these two antecedent causes (i.e., spillovers vs. tactical management) of CMI.

### 6.2 Limitations and future research directions

While our study provides meaningful findings for academic scholars and practitioners, several possible limitations are worth mentioning. First, although the findings provide empirical evidence on recent hospital operational outcomes, our methods cannot address how administrators may change specific tactics or processes in response to the annual VBP penalties and changing targets. Future research should examine transactional data to analyze VBP consequences in more fine-grained detail. Researchers might study whether some (or all) hospitals eventually will conform to VBP objectives or whether penalized and non-penalized hospitals will engage in an ongoing exchange of penalization outcomes across multiple time periods. Future research also might
investigate whether penalized hospitals that have not yet implemented mandated IT levels in response to government Meaningful Use criteria, but may be in the process of doing so, are being hindered by VBP.

Second, our methods cannot elucidate the actions of individual administrators. Thus, researchers might address whether hospital administrators may act in unintended ways to accommodate external pressures. Although it is not easy to directly observe unintended actions in response to a government healthcare policy, policy makers and other third party payers need to figure out which practices can be used to reliably identify and drive actual hospital performance improvements.

Finally, our study is based on an analysis of data representing four fiscal years. Future research might examine impacts of the magnitudes of VBP penalties and bonuses using panel data for many more time periods, as such data become available. Given the salient financial consequences of VBP penalties and bonuses, future academic focus on their longitudinal impacts is clearly critical. Future research also might expand data sets to include hospital department-level or patient-level data. Future research also could incorporate granular reimbursement data, after adjusting such metrics for the uncertain effects of revenue reimbursement cycles. The lack of such granular financial data is a limitation of all studies at the hospital level of analysis. In performing such analyses, researchers could gain generalizability and triangulate findings.

Moving beyond potential study limitations, research sponsored by policy makers should study drivers of the efficacy of these possible hospital administration practices and should consider whether to encourage such practices more broadly. Researchers should perform careful empirical studies of the new protocols and initiatives to determine their true organizational impacts at a more granular level of data. For example, while coercive isomorphism, in the form of a government penalty program, clearly provides the foundation for hospital administrative responses, what supplemental roles do mimetic isomorphism (e.g., beliefs about best practices in a medical domain) and normative isomorphism (i.e., local peer pressures) play to further push hospital administrators to comply with other CMS penalties and incentives?

While we have shown the improvement phenomena at a hospital level, hospitals operationally are comprised of many ephemeral teams, forming around an individual patient’s care needs, and subsequently dissolving after a care delivery task is complete (Chilingerian & Sherman, 1990). Attending physicians steer patients through the steps in the care process, performing complicated tasks in limited time spans, and drawing on the talents of a hidden network of care teams during transient relationships. Physicians and temporary teams are the principal decision makers, admitting, diagnosing, ordering investigations and therapies, and deciding to discharge patients (Chilingerian & Glavin, 1994). As such, emerging hospital administration practices will be difficult to discover using hospital-level data. Thus, understanding the behavior and performance of decision-making units requires study at a lower and more granular level of the organization. This type of study would connect institutional theory incentive mechanisms toward agency perspectives in the shaping of clinical staff behaviors.

Finally, these sorts of granular physician and administrator responses to government incentives and penalty programs should be evaluated more broadly, as the VBP Program is only one among many such programs. For example, a recent descriptive study by Burns and Pauly (2018) found that efforts to create financial incentives and efforts to create new provider organizations (such as alternative payment models, accountable care organizations, and patient-centered medical homes) have had a weak impact on quality and cost. Healthcare OM scholars can extend this study’s findings to examine financial pay-for-performance penalties and bonuses across the healthcare industry.

Indeed, there are numerous CMS reimbursement, incentive, and penalty programs rolled out to date as well as planned for upcoming rollouts. For example, scholars interested in recent operational transformation programs, such as the Bundled Payments for Care Improvement (BPCI) program (CMS, 2018f), might similarly examine the process changes taking place in hospitals after a hospital administration opts in to BCPI. We also wonder about the extent to which VBP penalty magnitudes and Meaningful Use incentives, among other programs, interact with other emerging value-based incentives and initiatives (e.g., Hospital Readmissions Reduction Program (HRRP), Hospital Acquired Condition Reduction Program (HACRP), and others [CMS, 2018a]). Will such programs and penalties end up complementary to each other, or will they force managerial tradeoffs? Is there an optimal longitudinal order through which to address this portfolio of programs? Analyzing such questions may enable hospital administrators to avoid potentially costly implementation mistakes. As in related organizational literature (Elsbach et al., 1998; Fiss & Zajac, 2006; Rogers, Purdy, Safayeni, & Duimering, 2007; Westphal & Graebner, 2010), researchers might explore other OM-related measures in healthcare organizations. Future research might seek to develop various measurement scales and approaches suited to this task.

In closing, this study is one of the few empirical OM research studies that subjects healthcare reimbursement processes to rigorous empirical scrutiny. Thus, our research is a
stepping-stone for future OM scholars to enhance theoretical and practical knowledge by expanding their research interests into healthcare reimbursement processes, many of which have yet to be examined in detail relative to operational outcomes. We sincerely hope that this study encourages substantially more research along this path that will enhance insights into healthcare practice and policy.

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