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Operational Drivers of Hospital and Physician Adaptation to Industry Change

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OPERATIONAL DRIVERS OF HOSPITAL AND PHYSICIAN ADAPTATION TO INDUSTRY CHANGE

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ABSTRACT

Hospitals and physicians are often required to adapt their operations in response to macro changes in their industry environment. This dissertation examines the operational factors which influence and incentivize changes in hospital and physician operating performance. The first essay in this dissertation investigates how legislative political support and competition in the area in which a hospital operates influences hospitals' investments and commitment to complying with performance mandates implemented by the Patient Protection and Affordable Care Act (ACA) legislation in the United States. Leveraging United States hospital performance data from 2007 to 2014, results indicate a differential impact of government ideology on recently introduced patient experience metrics versus traditional clinical metrics. These findings contribute to the research regarding the impact of firms' operating environments on the effectiveness of industry policy adoption, particularly in situations where future uncertainty of existing legislative mandates is high.

The second essay in this dissertation focuses on the unintended impacts to physician opioid prescribing behavior created by the passage of the ACA. This study aims to enhance our understanding of the factors associated with opioid prescription behavior and provide prescriptive insights to reduce opioid prescribing, which serves as the principal gateway to opioid addiction. Specifically, this study examines how prescriber workload, introduction of the Value Based Purchasing (VBP) program, and market competition influence opioid prescribing. Results demonstrate an increase in opioid prescription rates following the introduction of the VBP program, along with a moderating impact of prescriber workload and market competition on opioid prescription rates. These findings inform the discussion on the health and societal impacts of the opioid epidemic in the United States, while providing prescriptive implications to hospital managers, prescribers and policymakers about the influence of operational and competitive factors on opioid prescription rates. Together, these studies provide empirical support for the influence of operational factors on hospital and physician responses to environmental changes in the US healthcare industry.

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LIST OF ABBREVIATIONS

ACA	Patient Protection and Affordable Care Act
CDC	Centers for Disease Control and Prevention
CMS	Centers for Medicare and Medicaid Services
CQ	Conformance Quality
EHR	Electronic Health Records
EQ	Experiential Quality
HCAHPS	Hospital Consumer Assessment of Healthcare Providers and Systems
HSA	Hospital Service Area
MME	Morphine Milligram Equivalent
PDMP	Prescription Drug Monitoring Program
VBP	Value Based Purchasing

CHAPTER 1

INTRODUCTION

The Patient Protection and Affordable Care Act (ACA) of 2010 drastically altered the United States healthcare industry, ushering in sweeping changes aimed at transforming the US healthcare industry from a fee-for-service to a pay-for-performance environment (Werner et al. 2011). Among the many policy changes included within the ACA were reimbursement programs designed to financially incentivize hospitals and physicians to modify their operating behavior towards a focus on improving clinical and experiential quality. Shifting towards a new payment model required hospitals to invest a significant amount of nonrecoverable financial and human resources to maintain compliance with new regulations, particularly with regard to non-traditional performance measures (Merlino and Raman 2013, Levinson et al. 2010).

The ACA was, and continues to be, a highly contested piece of legislation, enduring routine attempts at repeal and amendment (Rovner 2018, Collins et al. 2017). Such ongoing debate induces considerable uncertainty about the future viability of the ACA, rendering hospitals and physicians to carefully consider the most appropriate manner with which to alter their operating behavior. Evidence exists to support the belief that organizations will uniformly adapt to new industry regulation imposed by policymakers (Shaffer 1995), yet the presence of environmental uncertainty raises the possibility that organizations may differ in how they implement policy changes which are unlikely to remain in effect (Li et al. 2017).

With this in mind, this dissertation seeks to examine first, how hospitals weigh the decision to invest in complying with industry policy which may not be applicable in the future. More specifically, which factors in hospitals' operating environments influence the degree to which hospitals invest in complying with the ACA's operational performance mandates. To investigate this research question, a longitudinal study is conducted which analyzes US hospital performance data across an eight year period. Reliant upon existing research that informs the factors influencing adoption of public policy, the empirical analysis tests the impact of both external institutional forces (Guler et al. 2002, Joglekar et al. 2016), and forces internal to the firm (Berry and Berry 1992).

Relevant to the dichotomous operational performance domains imposed by the passage of the ACA, prior healthcare operations research has demonstrated tradeoffs between clinical and experiential quality (Senot et al. 2016, Chandrasekaran et al. 2012), such that a focus on one performance domain may be disadvantageous to the other. Following such evidence, this dissertation extends the analysis of the impact of hospitals operating environments on investments to comply with legislative mandates to examine differential impacts to each distinct performance domain.

Although the ACA and its associated programs primarily focused on establishing a link between hospital operational performance and hospital reimbursement, examinations of physician contracting structures indicates alignment between physician and hospital reimbursement structures (SullivanCotter 2018, American Medical Group Association 2017). That is, hospitals have restructured the contracts of the physicians in their employ to mirror the reimbursement mechanisms provided to hospitals by the ACA. While hospitals and physicians have traditionally been aligned in focusing their efforts on continuously improving clinical quality (Levinson et al. 2010), the addition of financial incentives and public monitoring, both of which are proven to be effective methods for altering individual behavior (Song et al. 2018, Tosi et al. 1997), has jointly induced pressure on physicians to place an emphasis on patient satisfaction.

Although existing research is limited in its examination of the relationship between incentivizing patient satisfaction and prescribing practices, some evidence exists to suggest an association between patient satisfaction and the denial of patient requests for prescriptions (Jerant et al. 2018, Calcaterra et al. 2017, Kelly et al. 2016). A more thorough analysis of this relationship is particularly relevant given that patient pain management is one of the domains incentivized within the focus on experiential quality. With this in mind, and against the backdrop of the opioid epidemic underway in the US (Scholl et al. 2019, Frazier et al. 2017), this dissertation next seeks to investigate the impact of the ACA's reimbursement program, the Value Based Purchasing (VBP) program, on opioid prescribing rates in US hospitals. To investigate this research question, a longitudinal study is conducted which analyzes the trends in opioid prescribing rates amongst hospital based physicians before and after the implementation of the VBP program.

Taken together, this dissertation examines the operational impacts to the US hospital industry following the implementation of legislation which incentives hospitals and physicians to improve clinical and experiential quality performance. Findings inform the discussion on the effectiveness of industry policy implementation in the US healthcare industry as well as its impacts to the operating behavior of hospitals and physicians.

CHAPTER 2

GOVERNMENT IDEOLOGY AND RESPONSES FROM HOSPITALS TO THE AFFORDABLE CARE ACT LEGISLATION

The Patient Protection and Affordable Care Act (ACA) of 2010 ushered in sweeping changes to the United States healthcare industry. Grounded in the goal of transforming the US healthcare industry from a fee-for-service to a pay-for-performance environment (Werner et al. 2011), the ACA introduced a reimbursement program which financially incentivized hospitals to improve both clinical and experiential quality. Although hospitals have traditionally focused on continuously improving clinical quality (Levinson et al. 2010), experiential quality was a newly introduced performance measure (Groopman 2008) which required hospitals to undertake significant investments of financial and human resources (Lynn et al. 2015, Merlino and Raman 2013).

Following passage of the ACA, the legislation has endured constant opposition and multiple Congressional votes aimed at repealing or substantially amending the foundational components of the law, including a Supreme Court review of the constitutionality of the law along with a successful 2017 repeal of the ACA’s individual insurance mandate (Rovner 2018, Collins et al. 2017). Given the considerable uncertainty associated with the future viability of the ACA and recognizing that investments to comply with industry policy are often nonrecoverable (Parkhe 1993), hospitals may be concerned with investing significant levels of resources to comply with its operational performance mandates. Such concerns are likely exacerbated by an ACA mechanism which imposes financial penalties to hospitals for noncompliance with its operational performance mandates.

Prior research examining the adoption of public policy establishes that adoption rates are strongly influenced by both external institutional forces, such as federal legislative pressure (Guler et al. 2002, Joglekar et al. 2016), and internal determinants, such as regional political and social factors (Berry and Berry 1992). Evidence also exists that organizations may differ in the degree to which they feel the need to implement industry changes that are perceived as unlikely to remain in effect (Li et al. 2007). Given these competing beliefs regarding which factors are most relevant to industry policy adoption, particularly under environmental uncertainty, we set out to answer the following research question: *What are the characteristics of hospitals' operating environments that influence their likelihood to invest in complying with industry mandates which may not remain in effect in the future?*

In addition, prior healthcare operations research has found evidence of tradeoffs between clinical and experiential quality (Senot et al. 2016, Chandrasekaran et al. 2012), such that a focus on one may be detrimental to the other. Building upon evidence of this tension between the two types of performance quality incentivized by the ACA, we also seek to answer the following research question: *Do the characteristics of hospitals' operating environments differentially impact the likelihood to invest in complying with the various types of performance mandated by industry policy?*

To explore these questions, we analyzed performance data from 3,078 short stay and critical access hospitals for the eight year period from 2007 – 2014. Our results reveal that political support for the ACA in the area where a hospital operates influences the degree to which hospitals invest in complying with the ACA's operational performance mandates, but only for newly introduced performance metrics. Specifically, hospitals operating in areas that support the ACA are more likely to invest in improving their experiential quality scores than their peers operating in areas that do not support the ACA. However, we find no impact of political support for the ACA on investments in more traditional clinical quality performance metrics. We also find evidence of the influence of hospitals' competitive environments on both types of operational performance. Post hoc testing further indicates the influence of ACA political support on experiential quality performance rates of change over time, providing support for the notion that hospitals are altering their rate of investments in compliance over time.

In examining these relationships, we contribute to the literature by establishing the impact of firms' operating environments on compliance with industry legislation. In doing so, we provide evidence of firms seeking information from their political environment for signals about how to respond to industry legislation. These findings have implications for the effectiveness of legislative policy implemented without bipartisan support, which may impact economic growth and quality improvement within industries. Our findings also have implications for industry leaders such that limiting investment in legislative mandates which are liable to change may free up resources to be invested in alternative operational areas.

2.1 BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1.1 Affordable Care Act Legislation and Hospital Performance

Since the ACA was signed into law in 2010, the healthcare industry has endured a continuous period of flux and uncertainty (Becker's Hospital Review 2013, Deloitte

Center for Health Solutions 2017). The ACA was a non-bipartisan legislation, supported and passed by the Democratic Party and strongly opposed by the Republican Party in the United States (111th United States Congress 2009-2010). The strong opposition and multiple calls to repeal the ACA introduced considerable uncertainty regarding the future viability of the Act, especially in the event of a change in the political administration in power. Since the passage of the ACA, opposition has included a 2012 Supreme Court ruling to uphold its constitutionality, numerous Congressional votes aimed at repealing the foundational tenets of the Act, and a successful repeal of the individual insurance mandate in 2017.

The ACA included a directive to the Centers for Medicare and Medicaid Services (CMS) to establish a Hospital Value-Based Purchasing (VBP) Program under which value-based incentive payments are made in a fiscal year to hospitals that meet specified performance standards for both clinical quality of care and patient experience (111th US Congress - H.R.3590, Section 3001). Failure to meet specified performance targets is to result in the withholding of Medicare reimbursement, effectively creating financial penalties for underperforming hospitals.

The VBP program operationalized clinical quality through a metric known as conformance quality (CQ), which measures a hospital's adherence to evidence-based best practices for patient care (Garvin 1987, Senot et al. 2016, Senot et al. 2016, Sharma et al. 2016). Research indicates that implementing these practices leads to improvements in patient outcomes (Chassin et al. 2010). While hospitals have traditionally focused on conformance quality (Levinson et al. 2010), patient experience is a relatively new performance domain that has struggled to receive broad support from clinicians

(Groopman 2008). Patient experience encompasses the quality of communication between the patient and caregivers regarding care delivery, as well as the quality of the ambiance and amenities provided during their hospital stay (Bechel et al. 2000). To capture patient experience, also known as experiential quality (EQ), CMS relies on results from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey.

Improving EQ is a challenging task for hospitals for several reasons. First, improving EQ primarily depends on the commitment of front line service workers (i.e. nurses and physicians) to patient communication and responsiveness (Levinson et al. 2010). Quantifying and identifying EQ improvement opportunities can also be difficult, requiring extensive investment of financial and human resources by hospitals (Lynn et al. 2015, Merlino and Raman 2013). As an example, to improve EQ performance, the Cleveland Clinic invested approximately $11 million to implement a mandatory training program for all employees and instituted mandatory hourly nursing rounds to check on patient needs (Merlino and Raman 2013).

Given the expenses and substantial cultural shift associated with improving EQ performance, hospitals would likely prefer not to commit resources towards complying with the EQ performance mandate until necessary. In the following sections, we consider how various components of hospitals' operating environments influence the decision to invest in complying with operational performance mandates incentivized by the ACA.

2.1.2 Real Options and Legislative Uncertainty

Real options theory provides a framework for understanding how organizations make commitments to strategic actions and allocate scarce resources (McGrath et al.

2004). The value of real options is tied to information related to uncertainty in an investment's value. One option that can benefit organizations is the opportunity to delay, or limit, investment, since deferring commitment of resources offers the strategic flexibility of waiting until additional information can be incorporated into investment decisions (Li et al. 2007). The decision to withhold investment is most valuable when investment decisions are nonrecoverable and greatly reduce the value for alternative use (Parkhe 1993).

In our context, we focus on uncertainty related to the ACA legislation, or legislative uncertainty. We define legislative uncertainty as the lack of clarity that exists regarding the future of legislation requiring compliance by hospitals. Legislative uncertainty is important to hospitals' real options value for three reasons. First, ACA mandates impose costs of compliance on hospitals without corresponding direct positive changes in cash flow. At the same time, ACA directives include penalties for noncompliance. When costs of compliance outweigh penalties for noncompliance, it is rational for hospitals to seek to delay complying with ACA mandates. Second, the degree to which the future of ACA mandates is uncertain influences the expected cash outflows for noncompliance. That is, when hospitals believe the ACA will be repealed, the expected value of potential costs for noncompliance are reduced and the option to limit compliance increases in value. Finally, investments in compliance represent an opportunity cost, where scarce financial resources allocated to compliance trade off with other investment options. If the ACA were to be repealed, hospitals could not revisit prior compliance investment decisions to reallocate those resources to more productive uses, rendering the costs of investing in compliance as nonrecoverable (Parkhe 1993).

Building on the literature which investigates options under future uncertainty, we suggest that hospitals operating in environments that support repeal of the ACA should have a discounted value of noncompliance costs relative to compliance costs. As such, we expect these hospitals to delay investments in compliance. In contrast, hospitals operating in environments that support maintaining the ACA will not delay investments in compliance. In the following section, we consider various factors in hospitals' operating environments which influence investments in compliance with, and ultimately performance on, ACA performance domains.

2.1.3 Political Support for Legislation

Due to a lack of bipartisan support for the ACA, and the divisive nature of political sentiment in the US, the level of political support for the ACA in the area in which a given hospital is located is likely to influence a hospital's perception of the legislation's future and, relatedly, the degree to which the hospital invests in its compliance with its performance directives. Consistent with this argument, researchers studying adoptions of public policy argue that adoption rates are strongly influenced by two factors: external institutional forces such as federal legislative pressures, and internal determinants such as lower level political affiliation. Scholars further argue that there could be potential adoption synergies or tensions between these factors depending on whether there is alignment between these forces (Berry and Berry 1992). From an external standpoint, financial penalties for noncompliance lead to institutional pressures (DiMaggio and Powell 1983, Guler et al. 2002, Joglekar et al. 2016) which can influence investments in initiatives to federal legislative directives. For example, healthcare studies demonstrate that hospitals implement quality improvement initiatives, following legislation mandating public reporting on such metrics, even when they are not ready to do so (Hibbard et al. 2003, Tu and Cameron 2003).

However, internal determinants of adoption based on more regional political and social factors can also overpower external determinants (Berry and Berry 1992). For instance, in a study of greenhouse gas reduction across 900 US cities, Krause (2011) found that regional political characteristics had a strong association with local leaders' decisions to sign a climate protection agreement. Such evidence suggests that regional political characteristics may influence hospital decisions regarding compliance with a federal policy. That is, when the political environment in the area where the hospital operates supports the ACA, the hospital may suffer consequences if it fails to comply with the ACA's performance directives, decreasing the value of the option to limit investment. Alternatively, when the political environment does not support the ACA, the option to delay, or limit, investment in compliance is more valuable. Concisely, when a hospital's political environment suggests the ACA will remain in place, hospitals are more likely to invest in complying with its performance mandates; however, when a hospital's political environment suggests the ACA will be repealed, hospitals are less likely to invest in complying with its performance mandates.

As noted previously, the ACA mandated two distinct domains to measure hospital operational quality performance (Young 2017). EQ is a recently introduced performance domain in the hospital setting which mandates a focus on the interaction between caregivers and patients, as viewed from the patient's perspective (Chandrasekaran et al. 2012). Due to the considerable investment of financial and human resources required by hospitals to shift their focus toward improvements in EQ (Lynn et al. 2015, Merlino and

Raman 2013), hospitals may favor limiting their investments in EQ if their political environment suggests that the legislation is likely to be repealed. Conversely, when a hospital's political environment suggests that the legislation will remain, hospitals have no incentive to delay investments in EQ compliance.

In contrast, since hospitals have traditionally focused on CQ (Levinson et al. 2010) and evidence indicates that such practices lead to improvements in patient outcomes (Chassin et al. 2010), hospitals should universally invest in improvements to CQ. As such, the political environment within which a hospital operates should have no impact on compliance with CQ performance mandates. Accordingly, we introduce the following hypotheses:

Hypothesis 1a: Hospitals operating in states that support the ACA will have higher experiential quality (EQ) performance.

Hypothesis 1b: State political support for the ACA will have no impact on hospital conformance quality (CQ) performance.

2.1.4 Competition

A second important consideration in determining the value of limiting investment in response to ACA mandates are the decisions of competitors to invest in compliance (Li et al. 2007). In the healthcare setting, distance is an important consideration for patients seeking medical care (Tay 2003). Thus, competition among hospitals is geographically constrained. Competition is generally thought to promote investments in activities aimed at achieving differentiation (Ocasio 1997). At the same time, it also creates a bandwagon effect (Abrahamson and Rosenkopf 1993), where firms imitate the actions of their competitors. Failing to invest in legislative mandates may leave one hospital behind its competition, decreasing the value of the option to limit investment (Kester 1984). These mechanisms in combination could influence investments to support legislative directives within a competitive market.

Although research indicates that investments in quality that is easily observed and understood by customers are likely to have a higher impact than improvements in difficult to observe clinical metrics (Goldman and Romley 2008, Propper et al. 2007), the ACA linked financial incentives (penalties) to both experiential and clinical quality performance. Hence hospitals may financially suffer by limiting investment to comply with legislative mandates on both types of quality metrics if their competition chooses to do so. Further, the ACA commissioned public reporting of hospital performance scores, providing hospitals with access to the performance of their local competitors. Given the localized nature of competition in the healthcare sector and the availability of competitor performance information, it is likely that hospitals will attempt to imitate competitor actions related to both EQ and CQ performance. Thus, hospitals that face higher levels of market competition will be more likely to invest in both performance domains mandated by the ACA, leading to the following hypotheses:

Hypothesis 2a: Hospitals operating in highly competitive environments will have higher experiential quality (EQ) performance.

Hypothesis 2b: Hospitals operating in highly competitive environments will have higher conformance quality (CQ) performance.

2.1.5 Impact of Competition on the Relationship between Political Support for Legislation and Hospital Performance

Perceptions of the future of the ACA are likely to bound the value of the option hospitals can exercise in the face of competitor actions. Research notes that uncertainty has a discouraging effect on investments under less competitive pressure (Guiso and Parigi 1999). As such, we suggest that high levels of competitor actions will overpower the relationship between government ideology and hospital performance. The localized nature of competition in healthcare creates the potential for significant financial losses if patients migrate to hospitals with better performance. Therefore, competitive forces are likely to lead hospitals to imitate competitor actions related to performance, regardless of the political environment within which the hospital is operating. Hence, when competitors invest in improving operational performance, the option to limit investment decreases in value regardless of the prevailing political environment in which the hospital operates.

Further, based on our prior arguments for H1b that the political environment in which a hospital is operating will have no impact on compliance with CQ performance mandates, we believe that competition will only influence the relationship between a hospital's political environment and its compliance with EQ performance mandates. Accordingly, we introduce our final hypotheses:

Hypothesis 3a: Competition attenuates the relationship between state political support for the ACA and experiential quality (EQ), such that EQ will be greater at higher levels of competition, regardless of state political support for the ACA.

Hypothesis 3b: Competition will not impact the relationship between state political support for the ACA and conformance quality (CQ).

2.2 METHODS

2.2.1 Sample

We test our hypotheses by leveraging a unique, longitudinal dataset combining state government ideology scores, Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores, CMS Cost Reports, and US Census data. The unit of analysis in our study is the firm, more specifically, a hospital. We collected data on short stay acute care and critical access hospitals for the eight year period from 2007 – 2014. To avoid biasing results with data from specialty hospitals with excessive average length of stays and uniquely complex patient conditions, such as long term acute care or rehabilitation hospitals, our sample population does not include these types of hospitals. These hospitals also have significantly different operations compared to acute care hospitals and are often not required to report or incur penalties based on EQ performance. The hospitals included in our dataset are derived from all short term acute care hospitals registered with Medicare, as reported by the Centers for Medicare and Medicaid Services. Our final dataset contains up to 19,982 hospital–year observations for our dependent variables.

2.2.2 Measures

The financial and human resources committed by a hospital to comply with ACA performance mandates should be reflected in the relative improvement in a hospital's performance over time. Therefore, consistent with prior literature, we measure hospitals' resource commitment and investments in complying with ACA performance mandates, which are difficult to capture, in terms of the actual achievement on this performance outcome (Hitt et al. 1991).

Experiential quality: In this study, we measure experiential quality (EQ) based on scores of an industrywide consumer assessment tool, the HCAHPS survey, which captures patient beliefs about their interaction with providers during their inpatient hospital stay. The measures selected to represent a hospital's EQ reflect a consensus between healthcare reporting agencies CMS and the Agency for Healthcare Research and Quality and include six questions related to provider communication and responsiveness to patient needs. Specifically, the HCAHPS survey items that are averaged include, (1) How often did doctors communicate well with patients? (2) How often did nurses communicate well with patients? (3) How often did patients receive help quickly from hospital staff? (4) How often did staff explain about medicines before giving them to patients? (5) How often was the patient pain controlled? (6) Were patients given information about what to do during their recovery at home? Consistent with prior literature, we invoke a logit transformation of a hospital's percentage score (Chandrasekaran et al. 2012, Sharma et al. 2016). Following guidelines from CMS, a minimum of 300 completed HCAHPS surveys from each hospital for a 12-month period was required to compute a hospital's EQ, such that EQ for a hospital i with a percentage score Q_i is calculated by,

$$EQ_i = Ln\left[\frac{Q_i}{1 - Q_i}\right]$$

Conformance Quality: Following prior literature, we measure conformance quality (CQ) through a logit transformation (Collett 2003, Sharma et al. 2016) of the weighted average P_i of the percentage compliance along four dimensions: Heart Attack (AMI), Heart Failure (HF), Pneumonia (PN) and Surgical Care Improvement Project (SCIP). Following guidelines from CMS, a sample of at least 25 eligible patients was required to compute a hospital's CQ, such that CQ for a hospital i with a compliance percentage P_i is calculated by,

$$CQ_i = Ln\left[\frac{P_i}{1 - P_i}\right]$$

Government Ideology: Political support for the ACA is operationalized using a scale adapted from political science (Berry et al. 2010), government ideology. The measure is reflective of the ideological orientation of five key groups within each state government: the governor and both major party delegations in the state's Senate and House of Representatives. The ideological position of each group is estimated using coordinates derived from a comprehensive set of roll-call voting records of state legislators elected to the United States Congress (Poole 1998). The ideological orientation of each group is then weighted by the power each of these actors has over state policy decisions (Berry et al. 1998). Unique to this measure is its ability to capture varying degrees of ideology within a given political party (i.e. the ideology of one Republican-dominated state legislature is not equal to the ideology of another Republican-dominated state legislature).

Since the policy orientation of each group in state government changes slightly from year to year, as does the performance of an organization, our study requires a time variant measure of government ideology to accurately assess its longitudinal impact on hospital performance. As such, the government ideology measure employed in this study reflects changes in the policy orientation of elected officials between election cycles, absorbing ideological nuances which would not be revealed through the utilization of a static measure that only captures ideological beliefs at the onset of each elected official's term. The state government ideology scores employed in our study have been extensively validated against alternative measures of government ideology in prior literature. For a complete description of measure validation, we refer readers to Berry et al. (2010).

Competition: The competition construct in our study is operationalized using a market-based classification developed by the Dartmouth Atlas of Healthcare[1], which establishes that hospitals should be grouped not by traditional population metrics, such as the metro statistical area defined by the United States Census, but instead by a collection of zip codes whose Medicare residents receive the majority of their hospitalizations from the hospitals in that area. This geographic area is defined as the Hospital Service Area (HSA) in which a hospital conducts business. Although the numbers of hospitals included in a specific HSA have changed over time (due to hospital consolidation and closures), the zip code linkages composing each HSA have remained constant, enabling accurate comparison of changes within each HSA over time.

After establishing the service area to which each hospital belongs, we operationalize each hospital's competition within its service area as the average EQ (CQ) performance in that HSA. Since our dependent variable of interest is a hospital's EQ (CQ) performance, and because we are interested in the impact of a hospital's direct competitors' performance on this outcome variable, we exclude each hospital's own EQ (CQ) performance score from our calculation of competition.

Covariates: Common in this research, we control for several hospital-specific factors previously identified to influence hospital performance. Following the belief that larger

[1] The data set forth at "Data by Region" of publication was obtained from The Dartmouth Atlas, which is funded by the Robert Wood Johnson Foundation and the Dartmouth Clinical and Translational Science Institute, under award number UL1TR001086 from the National Center for Advancing Translational Sciences (NCATS) of the National Institutes of Health (NIH).

hospitals may affect resource utilization (Brown et al. 2003), we control for hospital size by including the number of staffed beds as reported by CMS. The complexity of a hospital's patient mix may influence its operational performance; therefore, we incorporate each hospital's case mix index (CMI) to enable unbiased comparisons of hospital performance among hospitals treating variable levels of patient complexity. We also control for the average patient length of stay in each hospital in our dataset as reported by CMS. Medical residents are at the onset of their medical careers and often require more resources to facilitate their training and development as clinicians (Grosskopf et al. 2001), which may compromise a hospital's operational performance (Sharma et al. 2016). As such, we control for the ratio of medical residents per licensed hospital bed. We also include a continuous measure of a hospital's Medicare payer mix to control for the impact that this subset of patients may have on hospital performance.

To account for differences in hospital performance before and after the introduction of the VBP program, which operationalized the performance mandates from the ACA, we include a binary variable equal to 1 beginning in the year that VBP took effect (2011). Since ideological and cultural beliefs vary by regions within the United States, we control for regional differences in our model by including a dummy variable for each of the four main region classifications in the United States: South, Northeast, Midwest, and West. Lastly, we included a dummy variable for each year in our dataset to account for time effects.

We present summary statistics for the key variables in our analysis in Table 2.1 below, followed by Pearson correlations (using pairwise deletion) in Table 2.2. These statistics provide an initial assessment of our data's validity, showing a significant correlation between government ideology and EQ performance ($r = -0.146$, $p<0.05$). We also see a positive and significant correlation between competition and hospital EQ ($r = 0.892$, $p<0.05$) and CQ ($r = 0.882$, $p<0.05$) performance, indicating that increased competition leads hospitals to invest more heavily in improving both types of performance. Each of the continuous independent variables in our models were centered prior to analysis.

Table 2.1 Descriptive statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Experiential quality (EQ)	0.938	0.255	− 0.936	3.664
Conformance quality (CQ)	3.309	1.153	− 1.740	8.874
Government ideology	46.582	28.671	0.000	92.451
Competition (EQ)	0.940	0.228	− 0.936	3.664
Competition (CQ)	3.271	1.017	− 1.740	8.722
Percent Medicare	0.466	0.144	0.000	0.971
Case mix index (CMI)	1.429	0.281	0.660	4.810
Length of stay (LOS)	4.343	0.885	0.643	11.798
Bed count	235.366	196.164	4.000	1928.000
Resident to bed	0.062	0.155	0.000	1.996

Table 2.2 Pairwise Correlation Table

	1	2	3	4	5	6	7	8	9	10
1. EQ	1.000									
2. CQ	0.1790*	1.000								
3. Government Ideology	− 0.1459*	− 0.0841*	1.000							
4. Competition (EQ)	0.8916*	0.1675*	− 0.1595*	1.000						
5. Competition (CQ)	0.1519*	0.8815*	− 0.0841*	0.1680*	1.000					
6. Medicare pct	0.1380*	− 0.2775*	0.0031	0.1537*	− 0.2821*	1.000				
7. Case mix index (CMI)	− 0.0779*	0.3987*	− 0.0262*	− 0.1307*	0.3542*	− 0.3545*	1.000			
8. Length of stay (LOS)	− 0.2831*	0.0059	0.0812*	− 0.2294*	0.0162*	− 0.1126*	0.2824*	1.000		
9. Bed count	− 0.2786*	0.1583*	0.0571*	− 0.2592*	0.1469*	− 0.3072*	0.5709*	0.4863*	1.000	
10. Resident to bed	− 0.1792*	0.0634*	0.1378*	− 0.1776*	0.0780*	− 0.3454*	0.3544*	0.3435*	0.5025*	1.000

* $p < 0.05$

2.2.3 Model Specification

We conduct our analysis using ordinary least squares panel regression with clustering by hospital. When analyzing panel data in which observations are repeated for the same hospital over time, adhering to the traditional linear regression assumption that all standard errors are independently and identically distributed may lead to biased results. To avoid such bias, we cluster standard errors by hospital to allow for correlation of model errors for the same hospital in different time periods.

Prior to analysis, we examined our proposed set of control variables by employing the Least Absolute Shrinkage and Selection Operator (LASSO) method (Tibshirani 1996) to avoid introducing unnecessary control variables into our model, which may lead to model overfitting. LASSO involves a penalized regression, with each additional control variable incurring a penalty based on the data structure. Regressor–specific penalty loadings for the heteroskedastic and clustered cases are derived following the methods described in Belloni et al. (2012). The LASSO procedure results provide statistical validation of the control variables that we selected for inclusion in our model. Although the LASSO procedure did not select hospital bed count and resident to bed ratio as relevant controls, we continue to include them in our models to maintain consistency with prior healthcare operations literature (Sharma et al. 2016, Brown et al. 2003).[2]

We test our hypotheses using the regression equation below in which the dependent variable $Y_{i,t}$ represents the EQ (CQ) performance for hospital i in year t, $X_{i,t}$ is the covariate vector for the variables of interest – government ideology and competition,

[2] Empirical results remain consistent with (or without) the inclusion of hospital bed count and resident to bed ratio as additional control variables

$Z_{i,t}$ is a vector of control variables and $\varepsilon_{i,t}$ is the error term, with standard errors clustered by N hospitals in our sample, where N equals up to 3,078 hospitals.

$$Y_{i,t} = X_{i,t}\beta + Z_{i,t}\gamma + \varepsilon_{i,t}$$

$$\text{where } E\left[\varepsilon_{ig}\varepsilon_{jg'}\right] = \begin{cases} \sigma_{(ij)g} \; if \; g = g' \\ 0 \; if \; g \neq g' \end{cases} ; g = 1 \ldots \mathrm{N}$$

The results for the main effects of government ideology on EQ (H1a) and CQ (H1b) performance, along with the results for the main effects of competition on EQ (H2a) and CQ (H2b) performance are presented in Table 2.3.

We further test the hypothesized interaction between government ideology and competition on EQ (H3a) and CQ (H3b) performance by modifying the regression equation to include the addition of an interaction term between these variables and report these results in Table 2.4. Following hypothesis testing, we conduct several robustness and post hoc tests to validate our findings.

2.3 RESULTS

Prior to reporting findings from tests for each of our hypotheses, we tested a model with only control variables to establish a baseline of the variance explained by control variables alone. These results are reported in Table 2.3 (Models 1 and 3). Table 2.3 (Models 2 and 4) also reports results for the hypothesized main effects of government ideology on EQ (H1a) and CQ (H1b) performance. The results indicate that government ideology has a positive impact (coefficient = 0.001; p-value = 0.017) on hospital EQ performance, lending support for H1a. This finding means that hospitals operating in states that support the ACA (government ideology one standard deviation above the mean) are associated with 12.3% higher EQ performance scores, on average, than hospitals operating in states which do not support the ACA (government ideology one standard deviation below the mean). In contrast, results from Model 4 indicate that government ideology has no significant impact (coefficient = − 0.001; p-value = 0.206) on hospital CQ performance, supporting H1b.

Table 2.3 (Models 2 and 4) shows results for the hypothesized main effects of competition on EQ (H2a) and CQ (H2b) performance. The results indicate that competition has a positive impact (coefficient = 0.915; p-value = 0.000) on hospital EQ performance, supporting H2a. This finding means that hospitals operating in highly competitive areas (one standard deviation above the mean) are associated with 44% higher EQ performance scores, on average, than hospitals operating in areas with low competition (one standard deviation below the mean). Further, results from Model 4 indicate that competition has a positive impact (coefficient = 0.886; p-value = 0.000) on hospital CQ performance, lending support for H2b. This finding means that hospitals operating in highly competitive areas (one standard deviation above the mean) are associated with 55% higher CQ performance scores, on average, than hospitals operating in areas with low competition (one standard deviation below the mean). We also note that integrating our variables of interest has substantially increased the variance explained in our models, relative to baseline models with only control variables included.

Table 2.3 Main Effects of Government Ideology and Competition on Hospital Performance

	DV = Experiential Quality (EQ)		DV = Conformance Quality (CQ)	
	Controls only (1)	Main model (2)	Controls only (3)	Main model (4)
Government ideology		0.001** (0.000)		− 0.001 (0.000)
Competition		0.915*** (0.010)		0.886*** (0.008)
Value Based Purchasing	0.234*** (0.007)	0.011*** (0.004)	2.228*** (0.030)	0.322*** (0.025)
Percent Medicare	0.063* (0.035)	− 0.018 (0.019)	− 0.113 (0.176)	0.117 (0.109)
Case mix index (CMI)	0.081*** (0.019)	0.035** (0.014)	0.464*** (0.103)	0.115** (0.055)
Length of stay (LOS)	– 0.014*** (0.004)	– 0.009*** (0.002)	– 0.065*** (0.016)	– 0.017 (0.004)
Bed count	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)
Resident to bed	0.024 (0.062)	0.009 (0.050)	0.034 (0.201)	0.066 (0.151)
Observations	19,982	19,982	19,571	19,571
R^2	0.136	0.797	0.323	0.746

Models include year and region fixed effects; robust standard errors (in parentheses) clustered by hospital; *** Significant at 1%; ** significant at 5%; * significant at 10%

The interaction results in Table 2.4 (Model 5) provide support for the moderating impact (coefficient = 0.001; p-value = 0.000) of competition on the relationship between government ideology and hospital EQ performance, supporting H3a. In contrast, the interaction results in Table 2.4 (Model 6) indicate no moderating impact (coefficient = − 0.001; p-value = 0.886) of competition on the relationship between government ideology and hospital CQ performance, lending support for H3b. As shown by the interaction plot in Figure 2.1, plotted over the range of one standard deviation above and below the mean, when hospitals are embedded within highly competitive service areas, there is a minimal difference (about 1.4%) in the EQ scores of hospitals operating in states with low government ideology (do not support the ACA) versus those hospitals operating in states with high government ideology (supported the ACA). When hospitals are embedded in service areas with low competition, there is also a minimal difference (about 1.1%) in the EQ scores of hospitals operating in states with low government ideology (do not support the ACA) versus those hospitals operating in states with high government ideology (supported the ACA). Perhaps more importantly, hospitals operating in service areas with high competition are always associated with superior EQ performance, regardless of the level of support for the ACA, indicating that competitor responses to the legislation dominate the effect of government ideology on hospital EQ.

Table 2.4 Interaction of Government Ideology and Competition on Hospital Performance

	DV = Experiential Quality (EQ) (5)	DV = Conformance Quality (CQ) (6)
Government ideology	0.001 (0.000)	− 0.001 (0.000)
Competition	0.919*** (0.010)	0.886*** (0.008)
Govt Ideology x competition	0.001*** (0.000)	− 0.001 (0.000)
Value Based Purchasing	0.012*** (0.004)	0.323*** (0.025)
Percent Medicare	− 0.022 (0.019)	0.118 (0.110)
Case mix index (CMI)	0.036*** (0.014)	0.115** (0.055)
Length of stay (LOS)	– 0.008*** (0.002)	– 0.017 (0.011)
Bed count	0.000 (0.000)	0.000 (0.000)
Resident to bed	0.009 (0.050)	0.066 (0.151)
Observations	19,982	19,571
R^2	0.798	0.746

Models include year and region fixed effects; robust standard errors (in parentheses) clustered by hospital; *** Significant at 1%; ** significant at 5%; * significant at 10%

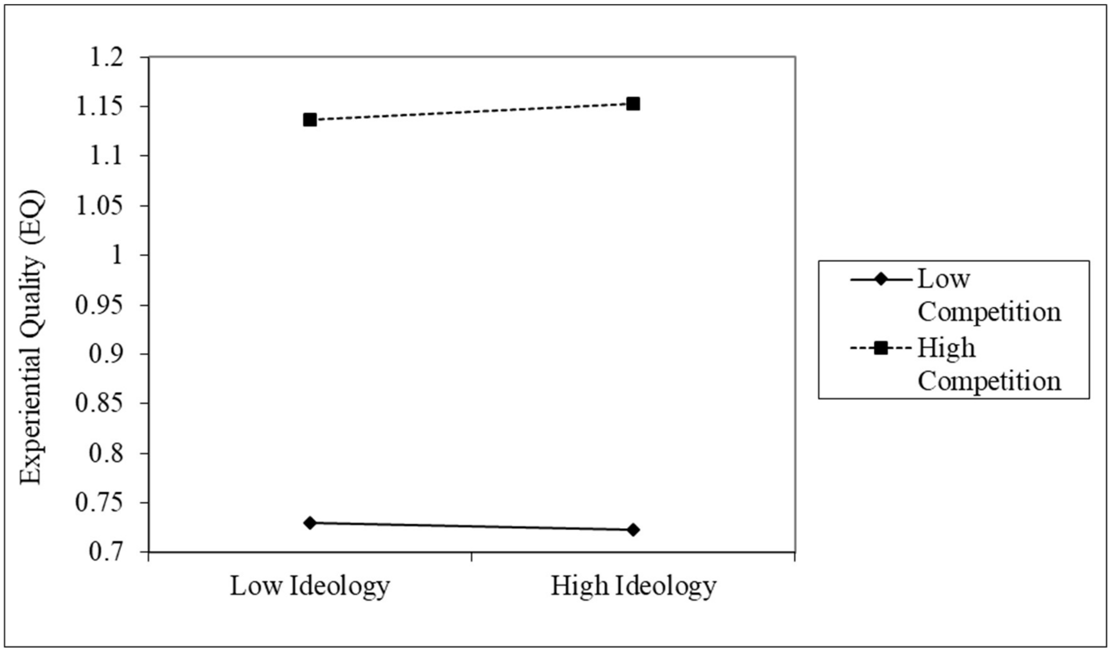

Figure 2.1 Interaction of Government Ideology and Competition on Experiential Quality

2.3.1 Post Hoc Testing

The VBP program, which operationalized the performance mandates implemented by the ACA, went into effect in July 2011. Since the introduction of this program marked the beginning of the penalty period for hospitals, we set out to investigate whether the relationship between government ideology and hospital performance differed before and after the start of this program. To empirically test this hypothesis, we interacted government ideology and the binary VBP variable in our regression equation and examined the impact on EQ (CQ) hospital performance. The results of the post hoc test for EQ performance are reported in Table 2.5 (Model 7) and provide support for the moderating impact (coefficient = 0.001; p-value = 0.014) of the VBP program on the relationship between government ideology and hospital EQ performance. In contrast, the interaction results in Table 2.5 (Model 8) indicate no moderating impact (coefficient = − 0.001; p-value = 0.683) of the VBP program on the relationship between government ideology and hospital CQ performance. As shown by the interaction plot in Figure 2.2, plotted over the range of one standard deviation above and below the mean, prior to the start of the VBP program, there is no significant difference in the EQ scores of hospitals operating in states with low government ideology (do not support the ACA) versus those hospitals operating in states with high government ideology (supported the ACA). However, after the start of the VBP program, hospitals operating in states with high government ideology (supported the ACA) have higher EQ scores than their peers operating in states with low government ideology (do not support the ACA). This finding lends support to our main findings in that hospitals operating in areas that support the ACA are more likely to invest in complying with the legislation's EQ performance mandates. The insignificant interaction term for the impact of the VBP program on the relationship between government ideology and CQ performance further validates our main findings in that hospitals appear to be investing equally in improving CQ performance before and after the start of the VBP program, regardless of the level of support for the ACA in their operating area.

Table 2.5 Interaction of Government Ideology and Value Based Purchasing on Hospital Performance

	DV = Experiential Quality (EQ) (7)	DV = Conformance Quality (CQ) (8)
Government ideology	0.001 (0.000)	− 0.001 (0.000)
Competition	0.916*** (0.010)	0.886*** (0.008)
Value Based Purchasing	0.011*** (0.004)	0.323*** (0.025)
Govt Ideology x VBP	0.001** (0.000)	− 0.001 (0.000)
Percent Medicare	− 0.022 (0.019)	0.120 (0.111)
Case mix index (CMI)	0.035*** (0.014)	0.115** (0.055)
Length of stay (LOS)	– 0.008*** (0.002)	– 0.017 (0.011)
Bed count	0.000 (0.000)	0.000 (0.000)
Resident to bed	0.008 (0.050)	0.066 (0.151)
Observations	19,982	19,571
R^2	0.797	0.746

Models include year and region fixed effects; robust standard errors (in parentheses) clustered by hospital; *** Significant at 1%; ** significant at 5%; * significant at 10%

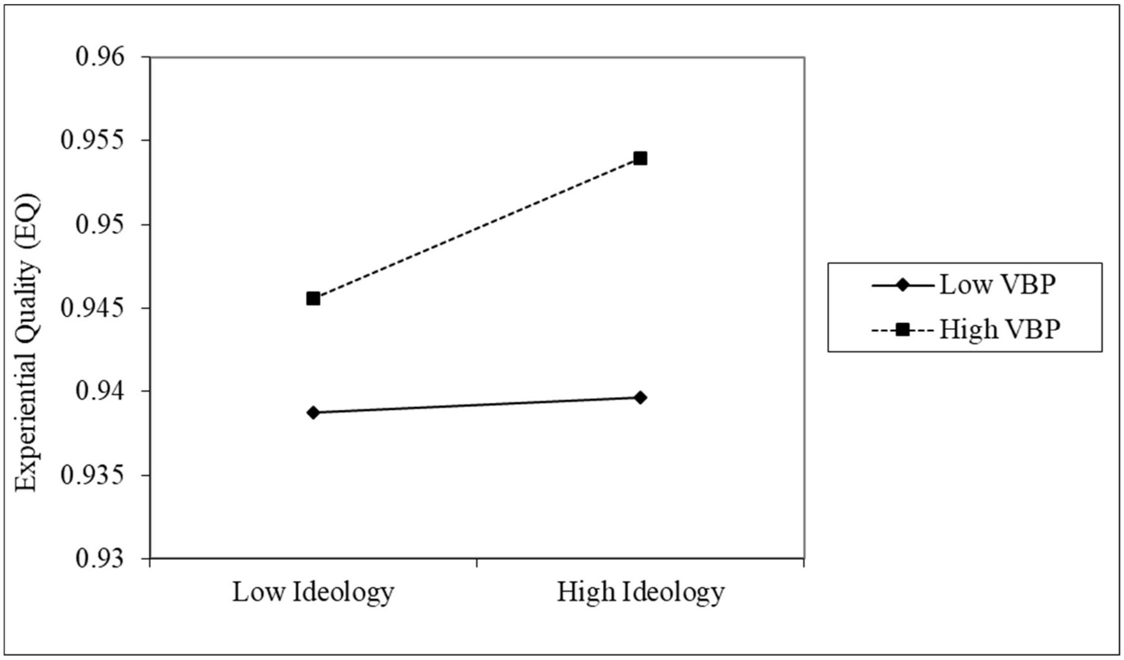

Figure 2.2 Interaction of Government Ideology and Value Based Purchasing on Experiential Quality

To further investigate how hospital EQ performance was changing after the start of the VBP program, we conduct a post hoc test in which we re-operationalize our dependent variable as the rate of change in EQ as compared to each hospital's baseline EQ (from 2007). In doing so, we are testing whether hospital EQ performance was changing at a greater rate after (as opposed to before) the start of the VBP program. The results of this post hoc test are reported in Table 2.6 (Model 9) and provide support for the moderating impact (coefficient = 0.001; p-value = 0.014) of the VBP program on the relationship between government ideology and hospital EQ performance rate change. As shown by the interaction plot in Figure 2.3, plotted over the range of one standard deviation above and below the mean, prior to the start of the VBP program, there is a small difference in the EQ rate change of hospitals operating in states with low government ideology (do not support the ACA) versus those hospitals operating in states with high government ideology (supported the ACA). That is, hospitals operating in states that support the ACA have 4.3% higher EQ rate growth than their peers operating in states that do not support the ACA. However, after the start of the VBP program, hospitals operating in states that supported the ACA have even higher EQ rate growth (about 9.5%) than their peers operating in states that do not support the ACA. This finding lends support to our prior post hoc finding that hospitals operating in areas that support the ACA are more likely to invest in complying with the legislation's EQ performance mandates, and appear to do so at a faster rate than their peers operating in areas that do not support the ACA.

Table 2.6 Experiential Quality (EQ) Rate Change

	DV = Experiential Quality (EQ) Rate Change
	(9)
Government ideology	0.000 (0.000)
Competition	0.906*** (0.013)
Value Based Purchasing	0.015*** (0.005)
Govt Ideology x VBP	0.001** (0.000)
Percent Medicare	0.001 (0.000)
Case mix index (CMI)	0.030* (0.018)
Length of stay (LOS)	– 0.009*** (0.002)
Bed count	0.000*** (0.000)
Resident to bed	0.027 (0.075)
Observations	13,282
R^2	0.041

Model includes year and region fixed effects; robust standard errors (in parentheses) clustered by hospital;
*** Significant at 1%; ** significant at 5%;
* significant at 10%

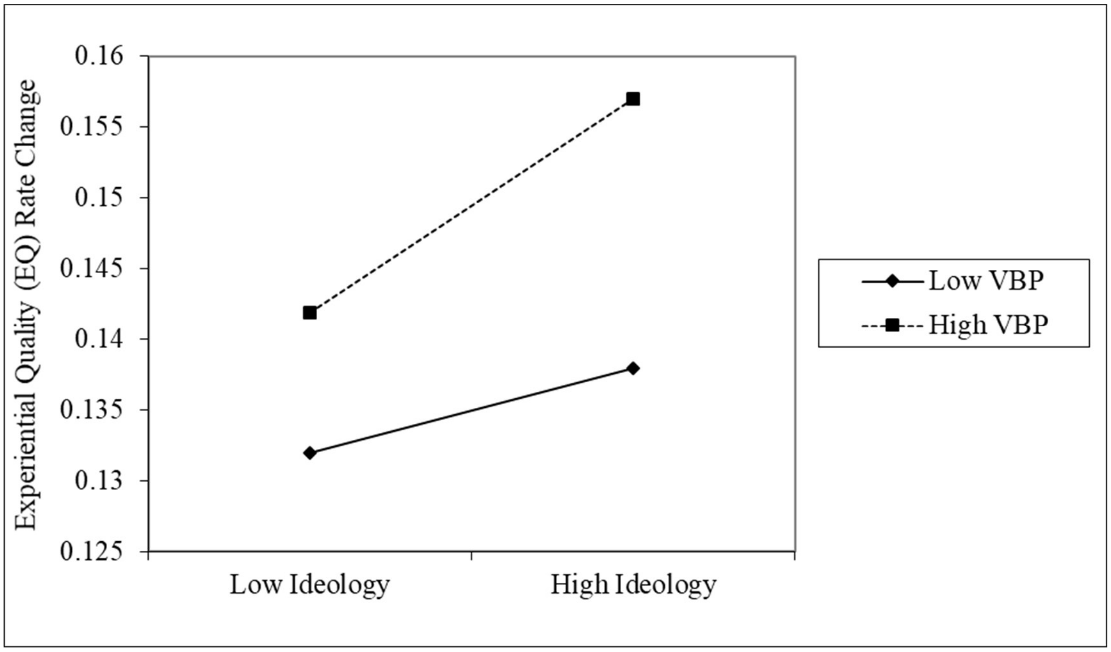

Figure 2.3 Interaction of Government Ideology and Value Based Purchasing on Experiential Quality Rate of Change

Although elected state level legislators are the policymakers most involved with drafting and voting on ACA legislation, we believe it prudent to investigate the potential impact of political ideology at more granular levels. In other words, do political beliefs at the county level in which hospitals operate induce a similar influence on hospital operating performance. To empirically test this assumption, we replace the state-level government ideology measure from our main analysis with a binary indicator of political affiliation in the county in which a hospital resides. Since county level ideology is time invariant, we run this post-hoc test as a panel regression with random effects. The results in Table 2.7 (Model 10) provide no support (coefficient = 0.004; p-value = 0.298) for the impact of local political ideology on hospital EQ performance. Further, the results reported in Table 2.7 (Model 11) provide no support (coefficient = − 0.009; p-value = 0.602) for the impact of local ideology on CQ performance, validating our finding from the test for H1b. Taken together, these findings indicate that hospitals are investing in

ACA compliance related to EQ based on the political support for the legislation at the state level, as opposed to the local level.

Table 2.7 Impact of Local Ideology on Hospital Performance

	DV = Experiential Quality (EQ) (10)	DV = Conformance Quality (CQ) (11)
Local ideology	0.004 (0.004)	− 0.009 (0.017)
Competition	0.931*** (0.009)	0.889*** (0.008)
Value Based Purchasing	0.003 (0.004)	0.270*** (0.022)
Percent Medicare	− 0.012 (0.014)	− 0.080 (0.066)
Case mix index (CMI)	0.065*** (0.010)	0.402*** (0.045)
Length of stay (LOS)	– 0.017*** (0.002)	– 0.025*** (0.009)
Bed count	0.000*** (0.000)	0.000 (0.000)
Resident to bed	– 0.027 (0.020)	– 0.265*** (0.060)
Observations	19,170	18,797
R^2	0.809	0.746

Models include year and region fixed effects; robust standard errors (in parentheses) clustered by hospital; *** Significant at 1%; ** significant at 5%; * significant at 10%

2.3.2 Robustness Checks

The formula invoked for our operationalization of government ideology relies on an estimate of the ideological position of each of the five key groups in state legislature, which is itself derived from a comprehensive set of roll-call voting records of state legislators elected to the United States Congress (Poole 1998). To further validate the use of this operationalization, we replace our measure of government ideology with an alternative measure which substitutes roll-call voting records with interest-group ratings calculated by the Americans for Democratic Action and the AFL-CIO Committee on Political Education (Berry et al. 1998). The results presented for the hypothesized main effects in Table 2.3 and interaction terms in Table 2.4 remain robust to this alternative operationalization, validating our initial findings.

We also examine the impact of competition on hospital performance through an alternative operationalization which replaces the average EQ (CQ) performance of competitors in a hospital's service area (HSA) with the average EQ (CQ) performance of competitors in a larger geographic area, the hospital's referral region (HRR). The main effects of this alternative competition measure remain robust to those findings reported in Table 2.3 (Models 2 and 4).

2.4 DISCUSSION AND CONCLUSION

Legislative directives often require organizations to invest a substantial amount of financial and human resources to comply with their mandates. Despite the prevalence of such directives, and the degree to which they can reshape entire industries, little research focuses on the factors within firms' operating environments which influence their compliance with legislative mandates. Leveraging real options theory and empirical data from the US hospital industry, we examine how political support for the ACA legislation in the area in which a hospital operates impacts its compliance with legislative mandates.

We find that, when a hospital's political environment suggests the ACA will remain in place, it decreases the value for hospitals to limit their investments to comply with its operational performance directives. In contrast, when a hospital's political environment suggests the ACA will be repealed, hospitals are more likely to limit their investments to comply, with the expectation that the legislation will be amended or repealed. This result is particularly true for newer performance metrics, namely experiential quality, which require a significant investment of human and financial resources. Our findings also indicate that competitor actions incentivize firms to comply with legislative directives, for both new and traditional performance metrics.

Through examining these relationships, we contribute to the literature by enhancing our understanding of the impact of firms' operating environments on compliance with industry legislation. More specifically, we illustrate that government ideology in the area where a firm operates alters how the organization values the costs of noncompliance, such that when the political environment suggests a certain future of repeal or substantial amendment, firms find greater value in not complying with the directives of the legislation. Instead, firms limit their investments in compliance for fear of allocating finite resources to those areas of their business which may not be mandated by legislation in the future.

In addition, we extend the literature on real options surrounding exogenous shocks by identifying the concept of legislative uncertainty in influencing how organizations responds to legislative directives. In doing so, we provide support for the notion that firms look to their political environment for signals about how to respond to macro-policy decisions. Finally, our study setting illustrates that options can contribute value not only through generating future cash inflows, but also through avoiding cash outflows to respond to compliance changes which may be altered in the future. Such perceptions may lead firms to carefully consider investments to comply with tenuous legislative directives, particularly when resources are finite, scarce and unable to be recouped in the future. Firms may instead prefer to invest their finite resources in areas of their business with a historically demonstrated and more stable return on investment, while concurrently hoping for an amendment or repeal of the legislation. Doing so may lead firms to realize a future competitive advantage if the legislation is repealed and other competitors have exhausted resources toward complying with mandates which no longer exist.

2.4.1 Practice and Policy Implications

First, our results indicate that support for legislation in a firm's political environment has varying degrees of impact, dependent upon the type of performance. Specifically, in the case of the ACA we find that government ideology had a significant impact on EQ, a recently introduced performance metric, as compared to CQ, a more traditional performance metric. This finding has implications on the design and rollout of legislative policy. Given the increasing non-bipartisan nature of legislative actions, compliance for legislative directives can be increased by building consensus amongst industry stakeholders before rollout.

Second, our findings introduce questions about the impact that non-bipartisan legislation may have on firms' decisions and the relative degree of compliance with legislative directives. Such concerns regarding the likelihood of firms to comply not only apply in the short term, but also span across political administrations if governing power shifts after the next popular election. Such swings in regulatory policy may lead to poor economic investment decisions by firms, dampening economic growth and quality improvement across entire industries. Finally, our findings have practical implications for health system managers such that limiting investment in government policies which are liable to change (or may not exist) in the future may free up nonrecoverable resources to be invested in other areas of firm operations.

2.4.2 Limitations and Conclusion

Our study has some limitations that should be considered in future research. While we have taken steps to follow guidance from prior literature, the EQ measure employed in our study is one of many ways to operationalize patient experience. Although not the aim of this study, future research should examine multiple aspects of experiential quality to validate consistency across measures. Additionally, the government ideology construct available to us was measured at the state level. Although broad scale legislative policy, such as the ACA, is most often created and implemented by state and national legislators, future work may explore the nuances of more granular levels of ideology, such as Congressional districts or census tract data, to determine if the relationships between the constructs in our study hold at more concentrated levels of geography. Finally, we are unable to directly measure the level of resources that hospitals allocated toward improving both EQ and CQ in response to the ACA, and instead must utilize the actual performance on these domains as a proxy for hospital investments. Although performance has been used as a proxy for difficult to measure constructs in other streams of literature (for example, Hitt et al. 1991), future work might explore alternative operationalizations of the resource investment construct through survey data or analysis of firm accounting statements.

In conclusion, our study provides empirical evidence of the impact of firms' political environments on firm organizational performance following the introduction of an exogenous legislative shock. Through an examination of the political and competitive environment within which a firm operates, we contribute to a more nuanced understanding of how firms comply with legislative directives. Specifically, we leverage real options theory and data from the U.S. hospital industry to illustrate that hospitals differ in the degree to which they comply with ACA mandates based on the degree of political support for the legislation in the area in which they operate.

CHAPTER 3

THE UNINTENDED CONSEQUENCES OF HEALTH POLICY: AN EMPIRICAL ANALYSIS OF OPIOID PRESCRIBING BEHAVIOR

"As a result of the consequences of the opioid crisis affecting our Nation, on this date and after consultation with public health officials as necessary, I, Eric. D. Hargan, Acting Secretary of Health and Human Services, pursuant to the authority vested in me under Section 319 of the Public Health Service Act, do hereby determine that a public health emergency exists nationwide."

With this signed statement on October 26, 2017, the United States Department of Health and Human Services officially declared the country's opioid epidemic to be a national health emergency. This policy declaration follows statistics which indicate that opioids were responsible for greater than 42,000 overdose deaths in the United States in 2016 (Scholl et al. 2019), while the latest projections from the United States Council of Economic Advisers (2017) estimated the economic impact of the opioid epidemic in 2015 to be over $500 billion, equivalent to approximately 2.8% of U.S. GDP. Statistics such as these quantify the negative health and economic outcomes of the opioid crisis, leading researchers to investigate possible factors contributing to the societal consequences of the opioid epidemic.

Underlying the overall death rate attributed to the general group of controlled substances classified as opioids, recent research shows that over 40% of all opioid-related deaths are attributable to prescription opioids, equating to upwards of 46 deaths per day

(Scholl et al. 2019). Evidence also indicates that for each daily death attributable to an opioid overdose, 30 non-fatal overdoses also occur (Frazier et al. 2017). Supporting these statistical claims linking opioid overdose deaths to prescription opioids, researchers at the Centers for Disease Control and Prevention (CDC) have indicated that the increase in opioid prescribing is among the principal factors contributing to the growing epidemic of opioid addiction and abuse in the U.S. (Rudd et al. 2016). Opioid dependence often begins when patients become addicted to opioids following receipt of a legal opioid prescription from a licensed prescriber for a legitimate medical reason. Recent evidence indicates that while supply-side interventions over the last decade have reduced the rate at which legal prescriptions lead to opioid addiction, prescribed drugs, such as oxycodone and hydrocodone, still constitute greater than 60% of opioid initiators (Cicero, Ellis and Kasper 2017). That is, opioid prescriptions continue to serve as the principal gateway to the growing epidemic of opioid addiction and abuse in the U.S. Recognizing the role of opioid prescription rates in this crisis, and following direction from the President in April 2017, the U.S. Department of Health and Human Services included reducing opioid prescribing for pain management as one of the five priorities of its Opioid Strategy (U.S. Department of Health and Human Services 2018).

Prior research has examined the prevalence of controlled substance abuse and, in particular, the role that prescribers play in this epidemic. Much of this research has focused on the field of pain management and post-surgical care. As one example, a 2011 study of patients who received prescription narcotics for pain management following urologic surgery concluded that 67% of patients had a surplus of medication in their initial prescriptions (Bates et al. 2011). More recent studies have alluded to the role played by medical groups and policymakers in enabling, perhaps even encouraging, an increase in opioid prescribing to manage patient pain. Clarke, Skoufalos, and Scranton (2016), for example, identify the following events, which are widely believed to have contributed to an increase in opioid prescribing. Beginning in 1995, the American Pain Society advocated for clinicians to assess patient pain at every clinical assessment, regardless of a patient's chief complaint; a campaign titled ``Pain: The Fifth Vital Sign'' (Campbell 1996). After further assessment and following recommendations from the American Pain Society, in 1999, the Joint Commission on Accreditation of Healthcare Organizations officially established pain as ``The Fifth Vital Sign'', elevating the importance of patient pain assessment and management on par with the traditional vital signs of heart rate, respiratory rate, blood pressure and body temperature (Walid et al. 2008). Finally, further establishing the importance of pain management among the primary responsibilities of clinicians to their patients, in 2000, the largest integrated health system in the United States, the Veterans Health Administration, also added pain as ``The Fifth Vital Sign'' (Department of Veterans Affairs 2000). Despite the consensus that pain is a critical health factor, unlike the four other vital signs, pain assessment is predicated upon a complex and subjective process which requires substantial investment of time and effort for diagnosis (Carr and Jacox 1997). Thus, including pain as a default on a physician's patient checklist could significantly increase the time a physician needs to spend with each patient.

Given that prior research has demonstrated a link between physicians, as prescribers, and the opioid epidemic, we set out to investigate how a key operational factor, namely prescribers' workload, influences opioid prescribing behavior. In the operations management literature, workload has been shown to influence worker behavior, leading to changes in service quality and speed (Tan and Nettesine 2014). More specifically, in the healthcare operations literature, increasing physician workload is shown to result in temporary improvements to patient throughput, yet prolonged periods of high workload often lead to reductions in operational efficiency and adverse patient health outcomes (Kc and Terwiesch 2009, 2012). Further, Powell et al. (2012) demonstrate evidence that higher workloads not only compromise the speed and quality at which physicians care for patients but may also have a detrimental impact on tasks which require attention to detail. Building on this body of work and extending the investigation of workload into an area of study with severe societal consequences, we set out to examine how physician workload impacts opioid prescribing behavior.

The U.S. healthcare system has been plagued with capacity shortfalls (Kirch and Petelle 2017), and new policies implemented under the Patient Protection and Affordable Care Act (ACA) have only exacerbated the supply imbalance. Access expansion, along with rising clerical burdens and the introduction of stringent regulatory requirements have increased the workload on physicians (Shanafelt et al. 2017), who were already facing high burnout rates (Shanafelt et al. 2015). Higher physician utilization has been linked to an increase in the cognitive load on physicians (Laxmisan et al. 2007). Prior work in the field of psychology has shown evidence that increases to an individual's cognitive burden are attributed to time pressures which may induce individuals to alter their typical work routines (Miller 1960, Zur and Breznitz 1981), through avoidance or filtration of certain tasks. With higher workloads, physicians have less time to gather and incorporate additional patient information into their clinical decision making. Tasks particularly susceptible to avoidance and filtration are those viewed by the decision maker as subjective in nature. Patient pain assessment, because of the complex and subjective nature of the task, is an onerous process necessitating a "social transaction between caregiver and patient" (Carr and Jacox 1997). The subjective nature of the task may motivate physicians with higher workloads to engage in avoidance or filtering, rather than spending the time to complete a thorough assessment of patient pain. In fact, prior studies have found some evidence of prescription rate increases for physicians with a greater number of daily patient interactions (Davidson et al. 1994) and physicians with shorter length patient visits (Tamblyn et al. 1997). These studies, however, focused on a narrow range of patient populations with similar characteristics and did not examine those drugs classified as opioids. In an effort to fill this gap in the literature, we explore how physician workload impacts the prescribing rate of opioids across a medically and geographically diverse population of prescribers and patients.

To examine the impact of prescriber workload on opioid prescribing rates, we analyze 43 months of prescription data in the hospital setting from a state-governed Prescription Drug Monitoring Program (PDMP). PDMPs are electronic databases, managed by each state, to track the prescribing and dispensing of controlled substances to patients (Centers for Disease Control and Prevention 2017). Figure 3.1, which shows opioid prescribing trends from our sample of hospital-based prescribers, indicates that prescriber workload has a substantial impact on opioid prescribing behavior, such that prescribers operating at high levels of workload (75th percentile) prescribe a significantly higher level of opioids, on average, per prescription, than their peers with low levels of workload (25th percentile).

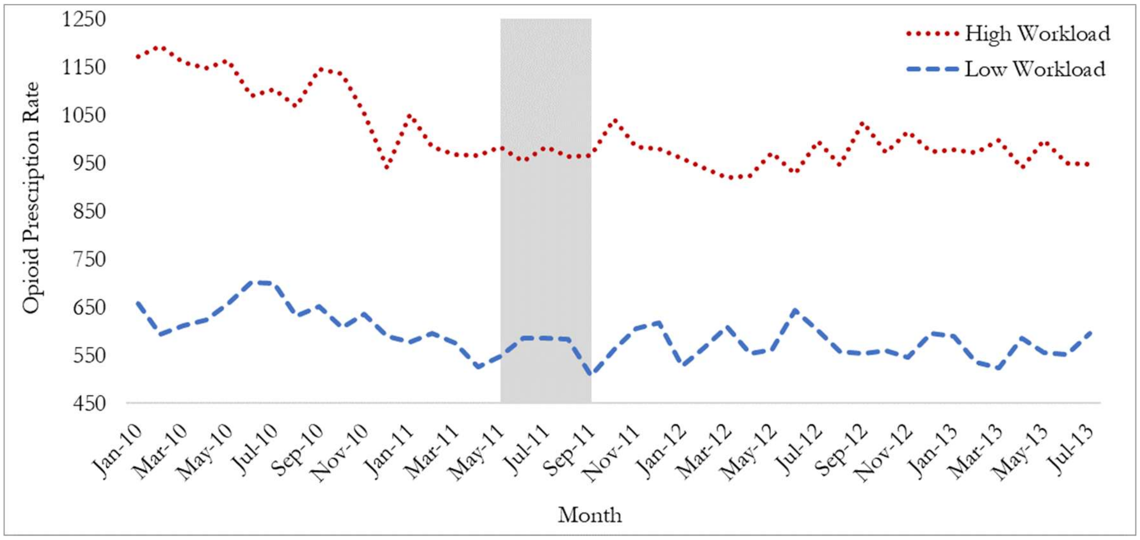

Figure 3.1 Opioid Prescription Rates by Prescriber Workload

Upon more detailed examination of the opioid prescribing trends resulting from differential levels of prescriber workload, we noticed a decreasing trend in opioid prescription rates (beginning with the start of our study period) which appears to level off during the middle of 2011. In fact, the decreasing trend appears to not only terminate, but even turn slightly positive around this time. This inflection point becomes even more evident when plotting the mean opioid prescription rate over time, reflected in Figure 3.2.

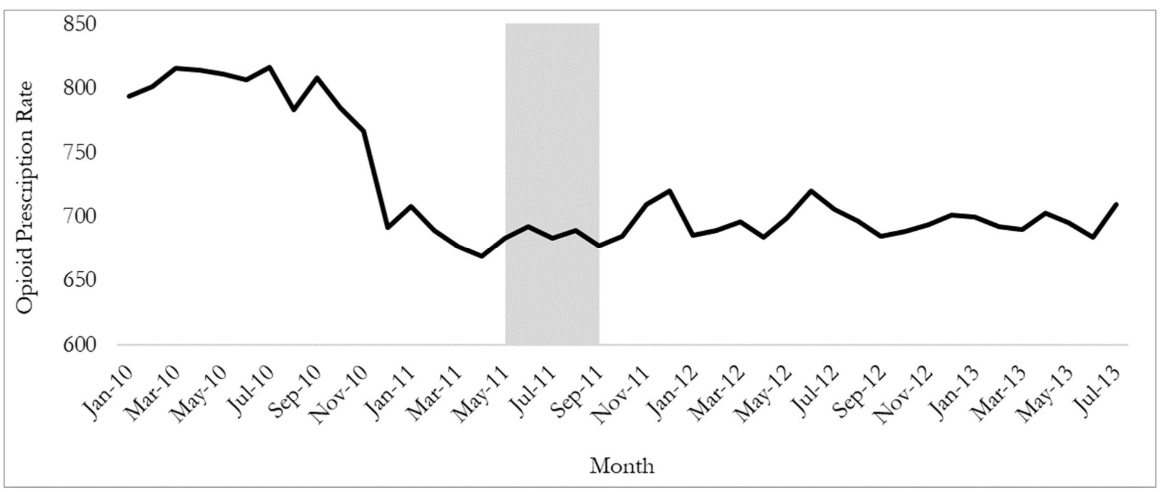

Figure 3.2 Mean Opioid Prescription Rate by Month

Having observed this trend change in opioid prescriptions rates in the middle of 2011, we turn our attention to macro-level environmental factors that may be associated with such a shift. Following careful consideration and empirical testing of related macro-level policy changes which may impact hospital operations[3], the event associated with changes to hospital-based opioid prescribing was a policy change that took effect in July 2011, the implementation of the Value Based Purchasing (VBP) program. The VBP program was among the foundational components of the ACA, passed by Congress and signed into law by the President on March 23, 2010, with the goal of shifting healthcare services from a fee-for-service structure to a pay-for-performance model (Werner et al. 2011). The VBP program operationalized this pay-for-performance environment in the hospital setting by introducing publicly reported performance metrics focused on the short-term health outcomes of patients, including a survey to assess how patients viewed their hospital experience. Among the patient experience metrics are specific components related to patients' assessment of how well their pain was managed by hospital providers. The VBP program directly linked reimbursement payments of hospitals and physicians to their performance on these metrics.[4]

Prior literature has demonstrated that individual behavior can be altered through incentive alignment and monitoring (Tosi, Katz and Gomez-Mejia 1997), and this

[3] The authors conducted numerous empirical tests examining the potential impact of alternative environmental and policy changes on hospital-based opioid prescribing. These results, which indicate no significant impact of alternative events on opioid prescribing, are reported in the Empirical Supplement.
[4] Surveys of health systems and physician groups indicate that physician pay is increasingly tied to organization level patient satisfaction and other value-based metrics (American Medical Group Association 2017, SullivanCotter 2018), leading to alignment between the reimbursement of hospitals and physicians in their employ.

phenomenon has been validated in clinical settings (Staats et al. 2017, Song et al. 2019). Jointly, these mechanisms of monitoring (e.g. public reporting) and incentive alignment create pressure on hospitals and physicians to satisfy the short-term quality outcomes (e.g. patients' subjective assessment of their care experience and pain management) incentivized by VBP. Such pressure may induce higher levels of opioid prescribing by physicians (to improve the likelihood that patients perceive a more positive experience and better pain management), since denial of patient requests for pain medicine is associated with lower patient satisfaction (Jerant et al. 2018). In fact, responding to physician concerns, and despite a lack of empirical evidence with respect to the association between VBP incentives and opioid prescribing, the Centers for Medicare and Medicaid Services (CMS) has proposed future elimination of pain management questions on patient surveys (Minemyer 2018). Our empirical findings indicate a positive and statistically significant increase in opioid prescription rates immediately following the onset of the initial VBP performance period in July 2011, followed by a significant positive trend in opioid prescription rates in subsequent time periods, indicating that the introduction of policy incentives focused on short-term quality outcomes are associated with an increase in hospital-based opioid prescription rates.

If the shift in opioid prescribing trends is truly attributable to VBP, we would anticipate that this effect is stronger in areas with more competition. Competition is widely believed to encourage businesses to either differentiate themselves from other competitors (Ocasio 1997) or engage in imitation (Abrahamson and Rosenkopf 1993) to reduce the degree of differentiation that a competitor currently possesses. It is also known that medical outcomes that are easily observed and understood by patients are likely to have a higher impact on patient choice of medical provider. For example, Goldman and Romley (2008) find that in highly competitive markets, patients are more likely to favorably respond to improvements in observable metrics than improvements in difficult to observe clinical metrics. Along similar lines, we argue that patients can easily discern whether (or not) they received a prescription to manage their pain as well as the relative volume (e.g. quantity of pills, days' supply) of the prescription received. If patients are unhappy with the perceived manner in which a provider managed their pain, they may not only be dissatisfied with the current care episode but may also migrate to other providers who they perceive as being more responsive to their needs. In areas of high competition, such migration is easier and may result in negative economic ramifications for providers with departing patients, exerting added pressure on hospitals and physicians to satisfy patient expectations for pain management. Thus, one indicator that should lend support to our hypothesis that the implementation of VBP led to an increase in the rate of opioid prescriptions is if the effect was stronger under conditions of higher competition, since patient satisfaction results are publicly reported and may have a larger influence on customer defections in areas where more choices are available.[5] We find that opioid prescribing is amplified in areas of intense competition, such that in the pre-VBP period areas of high competition experienced a slower decrease in opioid prescription rates, while experiencing higher increases in opioid prescription rates following the introduction of VBP.

[5] Since public reporting of patient satisfaction scores is limited to hospitals, the study sample is restricted to hospital-based physicians.

Our findings contribute to literature and practice in several ways. Although prior work has focused on the investigation of opioid specific policies on opioid prescribing rates, to the best of our knowledge, no study has examined the impact of physician workload or macro health policy changes on opioid prescription rates. Further, the current body of literature provides only a partial understanding of the factors associated with opioid prescribing while also lacking prescriptive operational insights which can contribute to its reduction. Our study fills this gap by focusing on the role of recent legislation aimed at improving the quality of healthcare services provided, while also considering the operational and competitive environment where care is administered. In doing so, we expand our understanding of the factors associated with opioid prescription practices and offer insights on reducing opioid prescription rates, leading to actionable solutions which can reduce the societal impact of the opioid epidemic underway in the U.S.

3.1 METHODOLOGY

To study the impact of prescriber workload, the introduction of the VBP program, and market competition on opioid prescribing rates, we compiled a data set of 43 months of prescription data from a state-governed PDMP. The state selected for analysis in this study is among the most populous in the United States and displays an opioid prescription rate trend that is similar to other highly populous states.[6] Since our study is focused only on the impact of opioid prescribing practices, we limit the data set to only those

[6] Student t-tests between the opioid prescribing rate trend in our state versus the remaining ten most populous states found no statistically significant difference for eight of nine states. The ninth state is Florida, which has a significantly different age demographic than the other eight states.

controlled substance prescriptions that were written for substances classified as opioids by the CDC, encompassing 13,269 distinct National Drug Code numbers (Centers for Disease Control and Prevention 2016). Further, because patient satisfaction surveys (which inform the reimbursement incentives and penalties under the VBP program) are only completed by patients following a qualified, overnight inpatient hospital stay (Centers for Medicare and Medicaid Services), we further restrict our empirical analysis of opioid prescribing to only those prescriptions which were written by physicians that provide care to patients in inpatient hospital settings (for example, hospitalists, critical care medicine, surgeons[7], etc.). Following data inclusion restrictions for opioid prescriptions written by hospital-based prescribers, the final data set consisted of more than 68,000 unique prescriber-month observations across our study period.

We begin our analysis by examining the underlying policy change (VBP), which we believe is associated with the trend change seen in the middle of 2011 (Figure 3.2). To do so, we divide our 43 month study period into two parts, in accordance with the timeline shown in Figure 3.3. The pre-VBP period encompasses opioid prescriptions written during the 18-month period from January 2010 through June 2011, the month prior to the start of the initial VBP performance period. The initial VBP performance period began in July 2011(Centers for Medicare and Medicaid Services 2017), in which hospital performance at the start of this month was incorporated into hospitals' reimbursement calculations. We delineate July 2013 as the final month for inclusion in our analysis to avoid biasing our results with potential confounding effects from a second

[7] To rule out any possibility that outpatient surgeries may be confounding our results, we also ran our models by further restricting the data set to exclude surgeons. Empirical findings remain consistent and are reported in Table 3.6 of the Empirical Supplement.

policy change, Open Payments Reporting, which went into effect in August 2013 and may also impact opioid prescribing rates. As such, we established the 25-month period from July 2011 - July 2013 as the VBP performance period, where we analyze the impact of VBP program implementation on opioid prescription rates, as compared to prescription rates from the pre-VBP period.

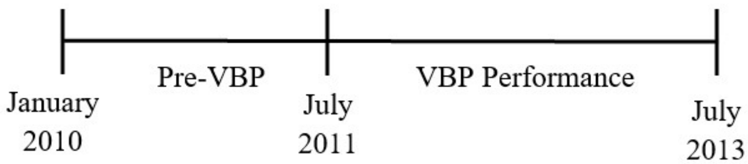

Figure 3.3 Study Timeline

Since our research questions are related to how the VBP program, prescriber workload, and the competitive environment are associated with changes in opioid prescribing behavior, we are concerned with the average opioid prescription rates by month across the prescribers in our data set. Complicating our ability to systematically examine average opioid prescription rates across time are two issues: the unobservable differences in prescribers (such as their medical training or clinical beliefs about the role of opioids in managing patient pain) and the observable differences across the 13,269 unique drugs classified as opioids by the CDC (such as the relative strength of each drug versus other opioids).

To account for the differences in individual prescribers, which are observed in repeated observations over time within our data set (i.e. opioid prescriptions nested within prescribers over time), we employ a fixed effects longitudinal model with maximum likelihood estimation. The fixed effect longitudinal model (Hausman 1978, Mundlak 1978) has many similarities to the piecewise hierarchical linear model

(Raudenbush and Bryk 2002) and the discontinuous growth model (Bliese and Lang 2016, Lang and Bliese 2009) in that it enables the researcher to test for the impact of an event when data is available across a collection of individuals, both before and after an event, and the outcome variable is thought to change at different rates before and after the event in question. This modeling approach also has the benefit of controlling, through prescriber fixed effects, for endogeneity due to pooling (i.e. multiple observations on prescribers over time), and endogeneity due to time, through the introduction of multiple time covariates to capture the change before, at, and after the event, which occurs independent of the higher level entity (i.e. prescribers). Leveraging this empirical strategy, we introduce three time related covariates as independent variables of interest in our model: *Time*, which represents the pre-VBP slope trend; *Transition*, which reflects the transition point at which the VBP program took effect; and *Recovery*, which captures the post-VBP slope trend.

To account for the relative differences across the 13,269 drugs classified as opioids, we employ a technique recommended by the CDC to convert prescriptions to their respective morphine milligram equivalents (MME) (Centers for Disease Control and Prevention 2016). The conversion to an MME value incorporates the quantity of pills prescribed (including refills), the strength of each pill, and an MME conversion factor determined by the CDC. Operationalizing our outcome variable in this manner enables us to capture the various ways in which a prescriber may increase the level of opioids prescribed to a patient -- volume, strength, drug choice, drug form -- and accurately accounts for each on a common scale.[8] Finally, we normalize our outcome variable by dividing the total MME value prescribed (by a given prescriber in a given month) by the number of opioid prescriptions written by the prescriber per month to arrive at the average MME per prescription for each prescriber in each month of our data set.

To examine the moderating impact of prescriber workload and competition present in the prescriber's geographic area, we introduce the following time variant measures into our fixed effects longitudinal analysis. Workload is a normalized continuous measure which captures the number of all controlled substance prescriptions (not just opioids) written by a prescriber divided by the total days available in a given month. This variable measures the relative patient demand and cognitive burden placed on each prescriber in each month of the study period. Competition is a normalized continuous variable which captures the relative level of access that patients have to prescribers and is operationalized as the number of primary care and specialty physicians per 100,000 census population in the service area.[9]

Finally, we include several additional variables in our analysis to control for market and prescriber-level characteristics. We include the number of Medicare beneficiaries per 100,000 census population in the geographic service area to account for the potential that older populations may receive more prescriptions than younger

[8] The operationalization of our dependent variable builds on volume-based measures utilized in prior literature (Levy, Paulozzi, Mack and Jones 2015, North, Crane, Ebbert, and Tulledge-Scheitel 2018) while also incorporating research conducted by the CDC that links small increases in MME values to heightened risks of opioid addiction and overdose.

[9] Value Based Purchasing legislation and competition are exogenous variables that occur independent of the prescriber. Prescriber workload is susceptible to endogeneity so we report results from an instrumental variable regression in Table 3.10 of the Empirical Supplement, substantiating the validity of our main findings.

populations. Further, because public interest in opioid addiction in the United States was beginning to build during our study period, we included an interest trend in our model which captures the relative public interest in opioids, operationalized as the Google analytics trend for opioids in each month within our study period. Lastly, because the type of patients treated by prescribers may influence the rate at which opioids are prescribed, we control for all available patient-level characteristics in each prescribers' patient population, including the average age of patients, the percentage of males and females, and the percentage of various types of patient insurance treated by each prescriber in each month.

3.2 RESULTS AND IMPLICATIONS

The results of our analysis indicate that, although opioid prescription rates exhibited a consistent decline in the 18-month period leading up to the onset of the initial VBP performance period, they exhibited a significant increase immediately following the introduction of VBP legislation. This result is displayed by the plot of points from our fixed effects longitudinal model in Figure 3.4, which normalizes the unexplainable randomness of the actual values. More specifically, the average opioid prescription was declining by approximately 9.5 MME's per month from January 2010 through June 2011, prior to the onset of the initial VBP performance period.[10] That is, patients were receiving less prescription opioids, on average, in each month during this 18-month pre-VBP period. In the first month of the VBP performance period (July 2011), opioid prescriptions immediately increased by approximately 39.5 MME's per prescription,

[10] Coefficients, standard errors and p-values for this analysis are reported in Model (2) in Table 3.4 of the Empirical Supplement.

negating more than four months of MME reductions seen in the pre-VBP period. Throughout the remainder of the 25-month post-VBP implementation period, the average opioid prescription grew slightly, by approximately 0.1 MME's per month. In other words, not only did opioid prescription rates experience a one-time increase immediately following the start of the VBP performance period, but VBP is associated with reversing the negative trend in opioid prescription rates experienced prior to the onset of VBP.[11]

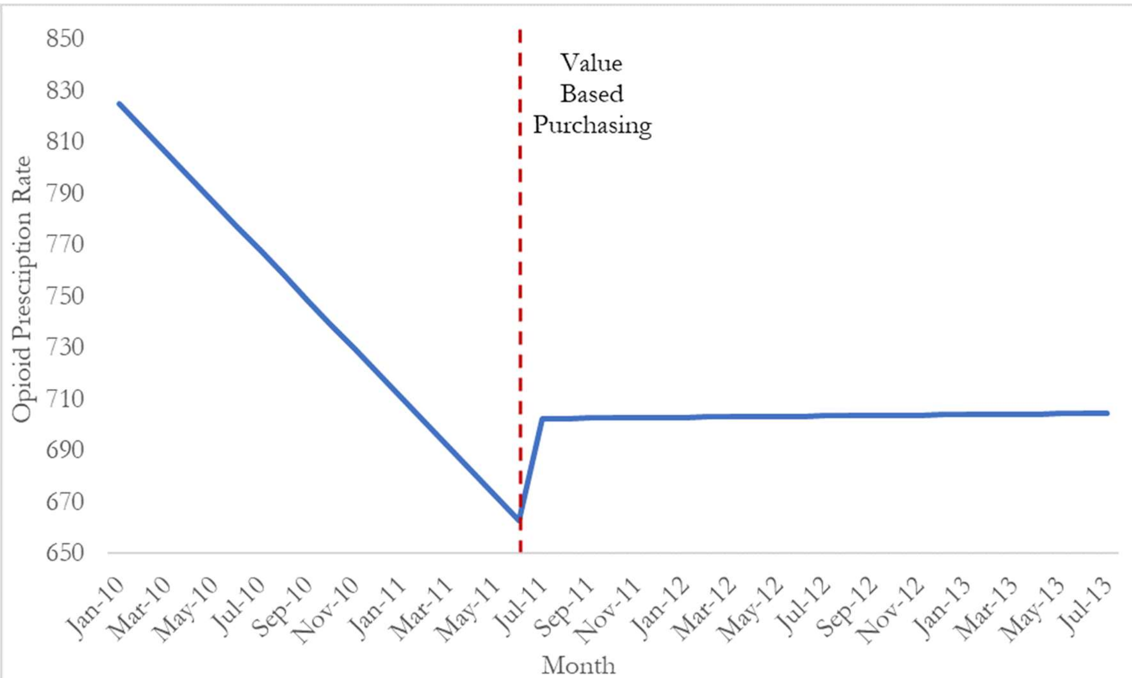

Figure 3.4 Impact of Value Based Purchasing Legislation on Opioid Prescription Rates

This finding supports our belief that VBP, with its focus on enhancing patients' experiential quality of care, is associated with an increase in opioid prescription rates, a phenomenon with long-term consequences to patient and societal health, which is at odds with the fundamental aim of the ACA. The implication of this finding is that, while well

[11] Fit statistics (i.e. R^2, Log Likelihood, AIC and BIC) reported in Table 3.4 of the Empirical Supplement indicate that the introduction of our time covariates, prescriber workload and competition improve model fit over a base model with controls only.

intentioned, the financial incentives of VBP created an agency problem which encouraged prescribers to prioritize short-term outcomes, potentially at the expense of long-term patient health. To remedy this hazard, future policy should incorporate a more balanced approach in which providers are incentivized to achieve a more equitable allocation of short and long-term health goals.

To explore the impact of prescriber workload (Figure 3.1), we modify the longitudinal fixed effects model to incorporate the moderating impact of prescriber workload. Results indicate that prescribers with higher workloads are, on average, associated with higher opioid prescription rates across our entire study period, as displayed in Figure 3.5. Specifically, during the pre-VBP period, prescribers with higher workloads (75th percentile) are prescribing opioids that are approximately 20 MME's per prescription higher, on average, than their lower workload (25th percentile) peers.[12] Consistent with the finding in the main model (Figure 3.4), we find that opioid prescriptions, on average, increased approximately 40 MME's per prescription in the month immediately following introduction of the VBP program (July 2011), regardless of prescriber workload level. Finally, in the post-VBP period, prescribers with higher workloads (75th percentile) are prescribing opioids that are approximately 16 MME's per prescription higher, on average, than their lower workload (25th percentile) peers.

[12] Coefficients, standard errors and p-values for this analysis are reported in Model (3) in Table 3.4 of the Empirical Supplement.

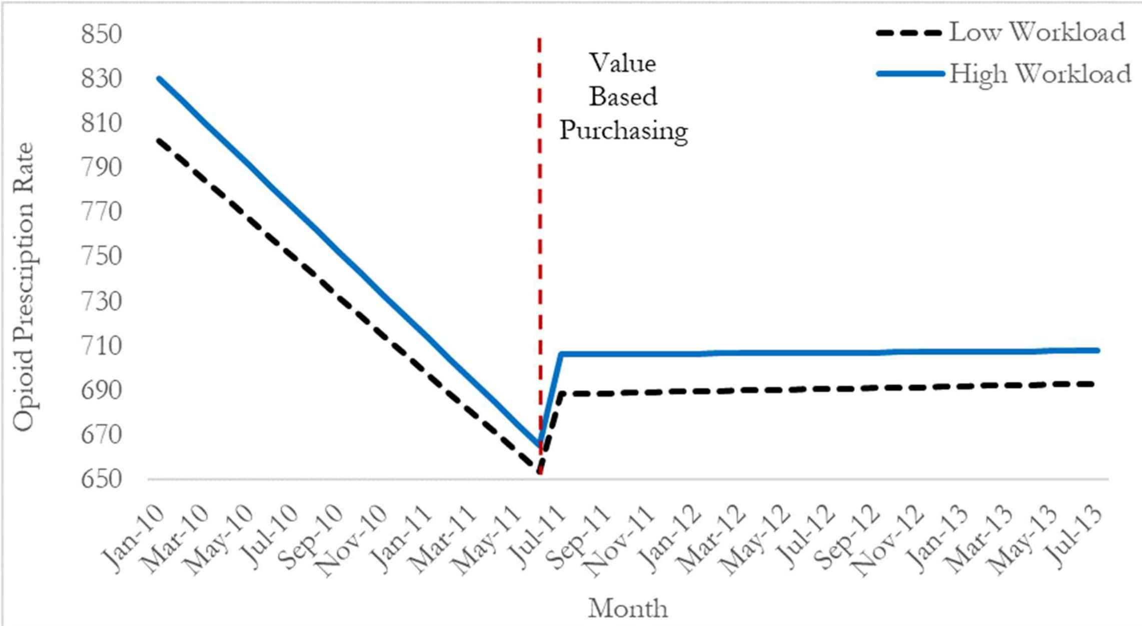

Figure 3.5 Impact of Prescriber Workload on Opioid Prescription Rates

This result supports our belief that increased workloads are associated with time pressures which compromise clinical information processing and increase reliance on prior heuristics, leading to cognitive shortcuts and altered work routines which do not incorporate all available clinical information into the pain management clinical decision making process. The implication of this finding is that future health policy should consider prescriber operational routines during large scale policy implementation. Going forward, policymakers may consider prolonged program launch periods which enable healthcare providers more time to adequately alter their work routines to adjust to new performance expectations. Alternatively, new performance metrics could be simultaneously introduced with the dissemination of “best practice” information so that physicians are not forced to develop their own work routines to balance new expectations with existing high workloads. Further, hospital managers can take steps to mitigate the impact of high workloads through flexible staffing and increased supplementary staff support, such as medical technicians, medical assistants and contract staff.

Lastly, our findings show that prescribers practicing in geographic areas with high levels of competition begin the study period with lower opioid prescription rates, on average, but over time experience higher opioid prescription rates than their peers practicing in less competitive areas, as shown in Figure 3.6. Specifically, during the pre-VBP period, prescribers practicing in areas with higher competition (75th percentile) are prescribing opioid prescriptions that are initially 20 MME's per prescription lower, on average, than their peers practicing in areas with lower competition (25th percentile), yet they surpass the opioid prescription rates of their peers in less competitive areas as the VBP performance implementation period nears.[13] Further supporting our finding from the main model (Figure 3.4), opioid prescriptions, on average, immediately increased by approximately 40 MME's per prescription in the first month of the VBP performance period (July 2011), regardless of the level of competition in the area where prescribers practice. Lastly, in the post-VBP period, prescribers practicing in more competitive areas (75th percentile) prescribed opioids that are approximately 3 MME's per prescription higher, on average, than their peers practicing in less competitive areas (25th percentile), with this rate differential gradually increasing over time.

[13] Coefficients, standard errors and p-values for this analysis are reported in Model (4) in Table 3.4 of the Empirical Supplement.

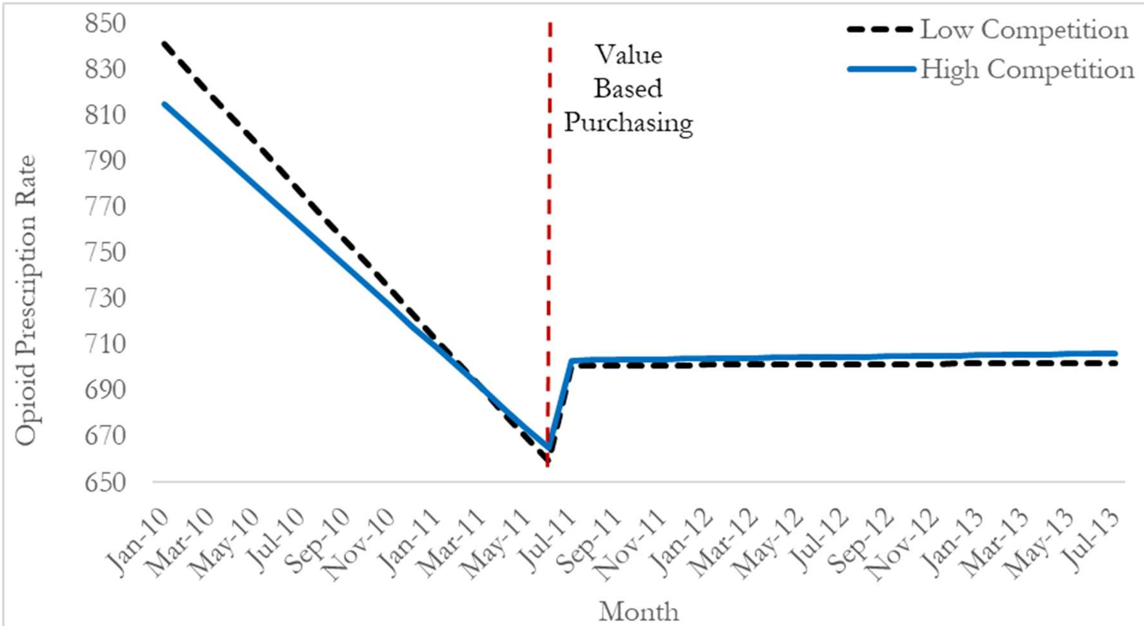

Figure 3.6 Impact of Competition on Opioid Prescription Rates

This finding supports our assertion that, following VBP, higher levels of competition may lead to increased pressure on prescribers to satisfy patient expectations, potentially to avoid migration of patients to alternative care providers which may be perceived as more willing to yield to patient expectations. Interestingly, prescribers in highly competitive areas appear to begin adjusting for the impact of VBP prior to the actual transition, as evidenced by higher opioid prescription rates (than their peers in less competitive areas) in the months leading up to the transition. The theoretical implication of this finding is that the diffusion of practices, specifically through the imitation of competitors, is strongest in regions with high levels of competition. Practically speaking, while often believed to drive improvements in health outcomes (e.g. reduced cost, improved clinical outcomes), competition can also induce negative ramifications to long-term patient outcomes. As such, policymakers should consider the potential consequences of publicly reporting customer satisfaction surveys which focus solely on short-term metrics. One alternative may be to incorporate metrics which also account for patients' satisfaction with longer term outcomes, appropriately balancing public reporting to capture the short and long-term health interests of patients.

Taken together, our results inform the discussion on the connections among workload, policy incentives, competition and opioid prescribing behavior within the U.S. healthcare system. Our findings also provide prescriptive implications to hospital managers, prescribers and policymakers about the relationship between operational, legislative and competitive factors and opioid prescription rates, and their contributing role to the opioid epidemic, in the U.S.

3.3 EMPIRICAL SUPPLEMENT

3.3.1 Variable Operationalization

The dependent variable in our study is an index composed of the average morphine milligram equivalent (MME) per prescription prescribed by prescriber i in month t. Because each distinct National Drug Code number assigned to each prescription opioid varies in the drug type (e.g. buprenorphine, hydrocodone, oxycodone, etc.), physical form (e.g. tablet, capsule, solution) and strength per unit (e.g. number of milligrams), we followed guidelines established by the Centers for Disease Control and Prevention (CDC 2016) to convert each opioid prescription in our data set to its corresponding MME. This conversion allows for accurate comparison of all opioid prescriptions (regardless of type, strength, or quantity of pills) on a standardized scale, resulting in a continuous variable indicating the average relative strength and volume of opioid prescriptions executed by each prescriber in each month of our data set, as outlined in Equation 3.1.

$$Opioid\ Prescription\ rate_{it} = \frac{\sum[Strength\ per\ Unit\ \times \#of\ Units \times \#\ of\ Refills \times MME\ Conversion\ Factor]_{it}}{[\#\ of\ Opioid\ Prescriptions]_{it}}$$

Equation 3.1 Opioid Prescription Rate Dependent Variable

Since our analysis is concerned with how the VBP legislative policy affects the growth rate of opioid prescriptions, the independent variables of interest in our study are three time related covariates: *Time*, *Transition*, and *Recovery*. The *Time* covariate represents the initial time trend before the introduction of the VBP legislative policy (January 2010 - June 2011). The *Transition* covariate represents the transition point at which the VBP policy change occurred (July 2011). The *Recovery* covariate captures the post-transition slope, in effect, the new time trend after the policy change (August 2011 - July 2013). Through introducing all three time covariates simultaneously into our model, we are able to accurately model the average opioid prescription rate for the prescribers in our data set leading up to the implementation of VBP legislation (*Time*) and compare the immediate change in opioid prescription rates following the introduction of VBP (*Transition*), along with the trend in opioid prescription rates post-implementation (*Recovery*), relative to the pre-policy trend.

Additional independent variables of interest in our analysis are prescriber workload and the level of competition present in the prescriber's geographic area. Since a prescriber's workload can be influenced by all patients that are seen (not just those patients receiving an opioid prescription), we operationalize prescriber workload as the total number of prescriptions available to us in our data set. Therefore, workload is a normalized continuous measure representing the number of all controlled substance prescriptions written by prescriber *i* in month *t*, divided by the total days available in month *t* (Equation 3.2).

$$Workload_{it} = \frac{\sum[Controlled\ Substance\ Prescriptions]_{it}}{Days\ in\ Month_{it}}$$

Equation 3.2 Workload Variable

Competition is a normalized continuous variable representing the relative level of access that patients have to prescribers, which we operationalize as the number of primary care and specialty physicians per 100,000 census population in the geographic service area where prescriber *i* is practicing in month *t* (Equation 3.3).

$$Competition_{it} = \frac{\sum[Primary\ Care\ Physicians + Specialty\ Physicians]_{it}}{Population_{it}}$$

Equation 3.3 Competition Variable

Finally, as noted in Chapter 3.1 of the manuscript, we also include several control variables in our analysis to account for market and prescriber-level characteristics which may influence our dependent variable. A summary description of key model variables is displayed in Table 3.1.

Table 3.1 Description of Key Variables

Variable	Description	Type	Level of Analysis
Opioid prescription rate	Monthly index (by prescriber) of average MME per opioid prescription	Dependent (Continuous)	Prescriber
Time	Time trend prior VBP	Independent (Continuous)	Macro
Transition	Transition point; equal to 0 prior to VBP, equal to 1 after VBP	Independent (Categorical)	Macro
Recovery	Time trend after the introduction of VBP	Independent (Continuous)	Macro
Workload	Volume of all controlled substance prescriptions written by a prescriber divided by total days in month	Independent (Continuous)	Prescriber
Competition	Primary care and specialty physicians per 100,000 population in service area	Independent (Continuous)	Market
Medicare population	Medicare beneficiaries per 100,000 population in service area	Independent (Continuous)	Market
Public interest	Relative level of public interest in opioids (in month)	Independent (Continuous)	Macro
Average age	Average birth year of patients, among all patients receiving any controlled substance prescription from prescriber (in month)	Independent (Continuous)	Prescriber
Percent female	Percentage of female patients, among all patients receiving any controlled substance prescription from prescriber (in month)	Independent (Continuous)	Prescriber
Percent Medicare	Percentage of patients with Medicare insurance, among all patients receiving any controlled substance prescription from prescriber (in month)	Independent (Continuous)	Prescriber
Percent Medicaid	Percentage of patients with Medicaid insurance, among all patients receiving any controlled substance prescription from prescriber (in month)	Independent (Continuous)	Prescriber
Percent commercial	Percentage of patients with commercial insurance, among all patients receiving any controlled substance prescription from prescriber (in month)	Independent (Continuous)	Prescriber

3.3.2 Summary Statistics

We report summary statistics and correlation coefficients (with pairwise deletion) for the data sample employed to test the impact of Value Based Purchasing legislation, prescriber workload and competition on opioid prescribing rates in Tables 3.2 and 3.3, respectively.

Table 3.2 Summary statistics

	Mean	Std. Dev.	Min	Max
Opioid prescription rate	719.595	778.585	5	5297.667
Time	21.334	12.413	0	42
Transition	0.591	0.492	0	1
Recovery	7.184	8.146	0	24
Workload	1.227	1.938	0.032	57.032
Competition	310.796	210.990	0	1432.847
Medicare population	18854.740	12462.130	58	62373
Public interest	31.141	5.200	21	42
Average age	1955.717	41.309	0	2012
Percent female	0.548	0.281	0	1
Percent Medicare	0.065	0.146	0	1
Percent Medicaid	0.037	0.109	0	1
Percent Commercial	0.505	0.363	0	1

Observations = 68,150 physician-month observations

Table 3.3 Pairwise Correlation Matrix

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. Opioid prescription rate	1.000									
2. Workload	0.258*	1.000								
3. Competition	− 0.023*	− 0.078*	1.000							
4. Medicare population	0.011*	− 0.014*	0.108*	1.000						
5. Public Interest	− 0.005	− 0.002	− 0.003	0.000	1.000					
6. Average age	− 0.044*	0.016*	0.007	0.002	0.052*	1.000				
7. Percent female	− 0.031*	0.014*	− 0.004	0.013*	0.000	0.032*	1.000			
8. Percent Medicare	0.095*	− 0.010*	− 0.028*	− 0.004	0.125*	− 0.077*	− 0.012*	1.000		
9. Percent Medicaid	− 0.008*	− 0.025*	− 0.030*	− 0.023*	0.059*	0.010*	0.000	− 0.004	1.000	
10. Percent Commercial	0.023*	0.023*	0.000	0.018*	0.296*	− 0.018*	0.030*	− 0.072	− 0.063*	1.000

* $p < 0.05$

3.3.3 Results

Examining the impact of the Value Based Purchasing policy on opioid prescription rates, we employ the following fixed effects model, reflected by Equation 3.4, in which γ_{it} represents the control variables listed in Table A.1 and α_{it} represents prescriber fixed effects.

$$\begin{aligned} Opioid\ Prescription\ Rate_{it} \\ &= Time_{it} + Recovery_{it} + Workload_{it} + Competition_{it} + \gamma_{it} + \alpha_{it} \\ &+ \varepsilon_{it} \end{aligned}$$

Equation 3.4 Fixed Effects Empirical Model

In Table 3.4 we list the parameter coefficients for the fixed effects analysis of the introduction of VBP legislation (2), the moderating impact of prescriber workload (3), and the moderating impact of competition (4). We also list coefficients for a base model (1) without our coefficients of interest included. The results of the fixed effects analysis for the introduction of VBP (2) show a significant negative slope for the time trend prior to the introduction of VBP legislation (coefficient = − 9.519, p-value = 0.000), indicating that opioid prescription rates were consistently decreasing prior to the start of the initial VBP performance period (July 2011). Further, the significant positive coefficient on the transition point at the introduction of VBP legislation (coefficient = 49.089, p-value = 0.000) indicates an immediate increase in opioid prescription rates (i.e. increase in the intercept) at the onset of the VBP performance period (July 2011). Lastly, the positive and statistically significant recovery slope for the time trend after the introduction of VBP legislation (coefficient = 9.606, p-value = 0.000) indicates a slight growth trend in opioid prescription growth rates following the onset of the initial VBP performance period. Taken together, the results of the fixed effects analysis (2) indicate that the introduction of VBP legislation is associated with an immediate increase in opioid prescription rates, followed by a slight, but stable, growth trend. Further, our results show that the VBP legislation is associated with reversing the prior decline in opioid prescription rates seen before VBP legislation took effect.

The results of the fixed effects analysis in the prescriber workload moderated model (3) follow a similar trend to that seen in the main model (2), albeit with differential impacts of prescriber workload on the pre-VBP and post-VBP slope trends. For the prescriber workload moderated model, high prescriber workload reflects a prescriber operating at the 75th percentile of workload amongst all prescribers in our sample, whereas low prescriber workload represents a prescriber operating at the 25th percentile of workload. The results of the prescriber workload moderated model (3) suggest that, although they begin the study period at higher opioid prescription rates, prescribers with a higher workload experience a more negative slope for the time trend prior to the introduction of VBP legislation (coefficient = − 0.759, p-value = 0.007) than their peers with low workload, indicating some convergence in prescription rates between the two levels of workload leading up to the start of the initial VBP performance period (although rates for high workload prescribers always remain higher). The insignificant interaction between prescriber workload and the transition point at the introduction of VBP legislation (coefficient = 5.488, p-value = 0.151) indicates that there is no statistically significant difference in the increase seen between the two levels of workload (i.e. no differential change in intercept), at the onset of the VBP performance period. Lastly, the statistically significant positive coefficient for the interaction between prescriber workload and the recovery time trend after the introduction of VBP legislation (coefficient = 0.661, p-value = 0.043) indicates a significantly higher slope trend in opioid prescription rates for prescribers with a high workload, as opposed to their peers with a low workload, following the onset of the initial VBP performance period. Taken together, the results of the prescriber workload moderated model (3) indicate that, on average, higher levels of prescriber workload are associated with higher opioid prescription rates. Further, our results confirm the impact of the VBP legislation seen in the main model (2), regardless of the level of prescriber workload, in which the VBP legislation is associated with reversing the prior decline in opioid prescription rates seen before VBP legislation took effect.

The results of the fixed effects analysis in the competition moderated model (4) also follow a similar trend to that seen in the main model (2), albeit with differential impacts of competition on the pre-VBP and post-VBP slope trends. For the competition moderated model, high competition reflects geographic areas in which the volume of total prescribers was at the 75th percentile amongst all geographic areas in our sample, whereas low competition represents geographic areas in which the volume of total prescribers was at the 25th percentile amongst all geographic areas in our sample. The results of the competition moderated model suggest that, although they begin the study period at lower opioid prescription rates, prescribers practicing in geographic areas with high competition experience a less negative slope for the time trend prior to the introduction of VBP legislation (coefficient = 0.008, p-value = 0.001) than their peers practicing in geographic areas with low competition, ultimately leading to higher average opioid prescription rates for prescribers operating in highly competitive areas, even before the introduction of VBP legislation. The insignificant interaction between competition and the transition point at the introduction of VBP legislation (coefficient = − 0.024, p-value = 0.474) indicates that there is no statistically significant difference in the increase seen in opioid prescription rates between the two levels of competition (i.e. no differential change in intercept), at the onset of the VBP performance period. Lastly, the statistically significant negative coefficient for the interaction between competition and the recovery time trend after the introduction of VBP legislation (coefficient = − 0.008, p-value = 0.005) indicates a significantly higher slope trend in opioid prescription rates for prescribers practicing in areas with high levels of competition, as opposed to their peers practicing in areas with low levels of competition, following the onset of the initial VBP performance period. Taken together, the results of the competition moderated model (4) indicate that, on average, higher levels of competition are associated with higher opioid prescription rates. Further, our results confirm the impact of the VBP legislation seen in the main model (2), regardless of the level of competition, in which the VBP legislation is associated with reversing the prior decline in opioid prescription rates seen before VBP legislation took effect.

Table 3.4 Fixed Effects Model Coefficients

	Base Model	Introduction of VBP	Moderating Impact of Prescriber Workload	Moderating Impact of Competition
	(1)	(2)	(3)	(4)
Time		− 9.519***	− 8.565***	− 12.073***
		(0.512)	(0.622)	(0.906)
Transition		49.089***	42.130***	56.329***
		(8.688)	(9.872)	(13.419)
Recovery		9.606***	8.783***	12.062***
		(0.681)	(0.791)	(1.111)
Workload		13.436***	22.619***	13.432***
		(2.489)	(3.856)	(2.488)
Time x Workload			− 0.759***	
			(0.283)	
Transition x Workload			5.488	
			(3.825)	
Recovery x Workload			0.661**	
			(0.327)	
Competition		− 0.009	− 0.009	− 0.114***
		(0.020)	(0.020)	(0.031)
Time x Competition				0.008***
				(0.002)
Transition x Competition				− 0.024
				(0.033)
Recovery x Competition				− 0.008***
				(0.003)
Medicare population	− 0.001*	− 0.001**	− 0.001**	− 0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Public interest	− 2.232***	− 1.130***	− 1.130***	− 1.123***
	(0.351)	(0.382)	(0.382)	(0.382)
Average age	− 0.020	0.018	0.017	0.019
	(0.043)	(0.043)	(0.043)	(0.043)
Percent female	− 42.466***	− 43.137***	− 43.196***	− 43.026***
	(7.443)	(7.418)	(7.417)	(7.417)
Percent Medicare	110.980***	83.386***	83.432***	83.021***
	(13.121)	(14.048)	(14.047)	(14.048)
Percent Medicaid	16.484	− 29.415	− 29.694*	− 30.252*
	(17.325)	(18.013)	(18.013)	(18.013)
Percent Commercial	71.325***	36.227***	35.907***	35.844***
	(5.582)	(7.247)	(7.248)	(7.246)

Observations	68,150	68,150	68,150	68,150
R^2	0.6973	0.6994	0.6994	0.6995
Log Likelihood	− 509689.2	− 509451.5	− 509446.5	− 509439.3
AIC	1019394	1018929	1018925	1018911
BIC	1019467	1019048	1019071	1019057

Models include fixed effects for 2,242 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

3.3.4 Robustness Checks

Due to multiple changes occurring in the U.S. healthcare environment during our study period, it is possible that the significant association between the implementation of VBP and change in the rate of opioid prescribing could be due to alternative environmental factors. To help rule out the possibility that other events are confounding our findings, we conduct multiple "placebo" tests, or falsification tests (Nicolae et al. 2016), in which we select other time points in our study and statistically test whether opioid prescription rates increased at these pseudo-transition points. In doing so, we are attempting to rule out the argument that the VBP transition point was incorrectly specified in our main model, thus leading to conclusions that are attributable to a false positive. In our first placebo test, we selected a pseudo-transition point to test whether other VBP related programs introduced in 2011 had a significant impact on opioid prescribing rates. When choosing an appropriate 2011 pseudo-transition point to test, we wanted to select a month which occurred prior to the transition point hypothesized in our main analysis (July 2011), but also occurred far enough into the year such that it could reasonably pick up the effects of environmental changes introduced in 2011, without mistakenly capturing residual effects from 2010. The placebo test results for the selected pseudo-transition point in April 2011 were not statistically significant (coefficient = 0.248, p-value = 0.976), lending support that other changes occurring in the U.S.

healthcare environment in 2011 are not likely confounding the effects found in our main analysis. Taking a different approach of selecting a pseudo-transition point, in which we are not motivated by specific environmental changes, we chose to test the midpoint of the post-VBP implementation period in our main analysis. The placebo test results for the July 2012 pseudo-transition point were not statistically significant (coefficient = − 2.764; p-value = 0.735), lending further support that our model is not incorrectly specified. As another approach of selecting a pseudo-transition point, we wanted to isolate a feature of the ACA which could practically lead to changes in hospital-based opioid prescribing rates, particularly one related to the recent (at the time of our study period) emphasis placed on electronic health records (EHR). As such, we test a time point that revolves around the introduction of regulations surrounding EHR adoption and information exchange, the first of which took effect in October 2012 (National Academy of Sciences 2014). Since EHRs were designed with the intention of reducing administrative burdens, reducing medical errors and improving the quality of care, it is plausible that more accurate and reliable storage and exchange of patient health information could lead to changes in hospital-based opioid prescribing patterns. The placebo test results for this October 2012 pseudo-transition point were not statistically significant (coefficient = 7.244, p-value = 0.371), indicating that the implementation of the EHR requirement did not result in sudden changes to hospital-based opioid prescribing rates. We also considered the impact that the expansion of insurance access, via insurance marketplaces, may have induced on opioid prescribing. Open enrollment via Health Insurance Marketplaces, however, did not begin until October 1, 2013, which was two months after the end of our study period (National Academy of Sciences 2014). Therefore, although we were unable to conduct a placebo test for this ACA initiative, any impact from this initiative should not confound our findings since it occurred chronologically after our study period. Taken together, these results provide support that our main analysis findings are not attributable to incorrect model specification.

As noted in Chapter 3.1, there are several ways in which a physician could increase the level of opioids prescribed to a patient in response to VBP legislation (e.g. change in the type of opioid prescribed, increase in strength per pill, increase in quantity of pills). The dependent variable in our main analysis, MME per prescription, accounts not only for the differences across disparate types of opioids, but also incorporates the strength of each pill prescribed and the total quantity of pills prescribed in each prescription. To further explore the nuances of how prescribers are altering opioid prescribing behavior in response to VBP legislation, we selected alternative dependent variables which would provide insight into whether prescribers are increasing the strength or quantity of opioids prescribed. To test whether strength increased following the introduction of VBP legislation, we replaced our primary dependent variable, MME per prescription, with an alternative operationalization, MME per day, which is equivalent to the MME per prescription divided by the number of days of supply intended for the prescription. Through normalizing the MME calculation by the prescriber's intended length (i.e. days' supply) of the prescription, we can analyze whether the strength of opioid prescriptions is increasing following the introduction of VBP. The results of this test (reported in Table 3.5) are largely consistent with our main analysis and confirm that the strength of opioid per day within a prescription was decreasing prior to the introduction of VBP and increased immediately at the onset of VBP.[14] To test whether the number of pills increased following the introduction of VBP legislation, we replaced our primary dependent variable, MME per prescription, with the quantity of pills prescribed per opioid prescription. Once again, the results of this test confirm the impact of VBP found in our main analysis. Specifically, the quantity of pills per prescription was decreasing in the time leading up to VBP and increased immediately at the onset of VBP. Taken together, this robustness check confirms our main findings while also providing statistical support that both the intended strength per day and overall quantity of pills per prescription contributed to the increase in opioid prescription rates following VBP.

[14] We note that the scale of the coefficients for each time covariate is smaller due to the nature of the dependent variable, however, the directionality and significance remain consistent with those reported for the main analysis.

Table 3.5 Alternative Dependent Variables

	Strength per Day (5)	Quantity of Pills (6)
Time	− 0.518***	− 0.062**
	(0.031)	(0.025)
Transition	1.117**	1.674***
	(0.529)	(0.424)
Recovery	0.492***	0.009
	(0.042)	(0.033)
Workload	1.033***	0.154
	(0.151)	(0.121)
Competition	0.001	0.001
	(0.001)	(0.001)
Medicare population	− 0.000	− 0.000
	(0.000)	(0.000)
Public interest	0.002	− 0.017
	(0.023)	(0.019)
Average age	− 0.000	0.001
	(0.003)	(0.002)
Percent female	− 2.697***	− 1.432***
	(0.452)	(0.362)
Percent Medicare	− 2.384***	4.660***
	(0.855)	(0.685)
Percent Medicaid	− 4.503***	0.436
	(1.096)	(0.879)
Percent Commercial	− 0.110	0.752**
	(0.441)	(0.353)
Observations	68,040	68,150
R^2	0.3946	0.5730
Log Likelihood	− 318131.4	− 303594.7
AIC	636288.9	607215.5
BIC	636407.5	607334.2

Models include fixed effects for 2,242 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

Due to the growing proportion of surgeries that are conducted in an outpatient setting (Steiner et al. 2017), it is plausible that the surgeons included in our data set are executing some of their prescriptions in an ambulatory setting. If this were the case, the patients receiving these prescriptions would not be eligible to complete a patient satisfaction survey (because they did not qualify as a hospital inpatient), potentially biasing our results. To rule out any possibility that prescriptions received by ambulatory surgery patients are confounding our findings, we excluded all surgeons from our data set and repeated our analysis. Results from this restricted data sample are presented in Table 3.6 and remain largely consistent with the findings in our main model. Although the scale of coefficients and in some cases, level of statistical significance, vary slightly from the main results in Table 3.4, the directionality and relative scale (when plotted) remain consistent, thus confirming that our findings are not confounded by the possible presence of ambulatory surgery patients in our data.

Table 3.6 Fixed Effects Model Coefficients - Excluding Surgeons

	Introduction of VBP (7)	Moderating Impact of Prescriber Workload (8)	Moderating Impact of Competition (9)
Time	– 12.636***	– 11.650***	– 15.904***
	(1.214)	(1.451)	(2.166)
Transition	66.255***	57.805**	76.154**
	(20.006)	(22.717)	(31.837)
Recovery	12.727***	11.654***	16.148***
	(1.601)	(1.844)	(2.663)
Workload	25.332***	32.884***	25.595***
	(8.972)	(11.923)	(8.973)
Time x Workload		– 0.900	
		(0.724)	
Transition x Workload		7.556	
		(9.891)	
Recovery x Workload		0.985	
		(0.843)	
Competition	– 0.029	– 0.030	– 0.158**
	(0.052)	(0.052)	(0.077)
Time x Competition			0.011*
			(0.006)
Transition x Competition			– 0.032
			(0.080)

Recovery x Competition			− 0.011 (0.007)
Medicare population	− 0.004*** (0.001)	− 0.004*** (0.001)	− 0.004*** (0.001)
Public interest	− 1.718* (0.909)	− 1.721* (0.909)	− 1.708* (0.909)
Average age	0.042 (0.094)	0.041 (0.094)	0.041 (0.094)
Percent female	− 54.095*** (14.101)	− 54.131*** (14.101)	− 53.656*** (14.104)
Percent Medicare	99.936*** (25.326)	100.076*** (25.330)	99.708*** (25.329)
Percent Medicaid	– 23.271 (34.875)	– 23.441 (34.880)	– 23.870 (34.875)
Percent Commercial	44.875*** (15.431)	44.562*** (15.442)	44.246*** (15.433)
Observations	24,739	24,739	24,739
R^2	0.5775	0.5775	0.5776
Log Likelihood	− 193782.9	− 193782.1	− 193780.1
AIC	387591.8	387596.2	387592.2
BIC	387697.3	387726.1	387722

Models include fixed effects for 965 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

Additionally, to further validate our findings, we tested for the impact of VBP legislation in a group of prescribers which are not hospital based and thus do not have their patient satisfaction scores publicly reported or tied to reimbursement. Therefore, this population of prescribers should not have experienced changes in opioid prescribing behavior associated with VBP legislation. To do so, we executed our main model on a population of office-based prescribers from our study state which often conduct clinical procedures in the office setting and may prescribe pain medication post-procedure -- dermatologists. As displayed in model (10) of Table 3.7, all three time covariates for dermatologists are not statistically significant, indicating that this group of prescribers did not experience changes in opioid prescribing behavior associated with VBP. In model

(11) of Table 3.7, we display results from another sample of office-based prescribers, pediatricians. Although this group of office-based prescribers exhibits a statistically significant negative opioid prescribing trend prior to the introduction of VBP, the VBP transition point is not statistically significant (i.e. no intercept change), indicating that this group of prescribers did not experience immediate changes in opioid prescribing associated with VBP. We also apply our fixed effects longitudinal model to general dentists, who also conduct procedures in an office-based setting and may prescribe pain medication post-procedure. These results are displayed in model (12) in Table 3.7 and confirm that VBP is not associated with an immediate significant impact on opioid prescription rates. Although the initial *Time* trend and *Recovery* covariate for dentists indicate significance, the magnitude of the coefficients relative to those in our main analysis (Model (2) in Table 3.4) is extremely low, indicating very little change in the opioid prescription rate month over month. We also conducted this analysis on an expanded population of dentists (not reported in Table 3.7) to include dental specialties (for example, endodontics and periodontics), resulting in similar findings of no immediate impact of VBP on opioid prescription rates.

Lastly, in model (13) of Table 3.7, we examine a group of prescribers practicing in the hospital setting but which are not financially incentivized to place an emphasis on patient satisfaction as a result of the VBP program. Recall that we excluded emergency medicine physicians from our main analysis because patient satisfaction surveys (tied to reimbursement) are not administered to patients discharged directly from the emergency room. Notice that this sample of prescribers also experiences a statistically significant negative opioid prescribing trend in the study period leading up to the introduction of the

VBP program, however it is at a rate which is (approximately 95%) less than that experienced by inpatient hospital-based prescribers in our main analysis (Model (2) in Table 3.4). Further, although emergency medicine physicians experience a slight increase in opioid prescribing behavior at the onset of the VBP program, it is markedly (greater than 80%) less than that experienced by inpatient hospital-based prescribers in our main analysis (Model (2) in Table 3.4). It is important to note, however, that emergency medicine physicians do not experience a prolonged increase in opioid prescribing after the introduction of VBP, as the post-VBP recovery period is not statistically significant. A possible explanation for this finding may be the influence of social and spatial proximity on diffusion of prescribing practices between physicians in the same physical setting (Angst et al. 2010). Combined, these findings provide support for our conclusion that substantial changes in opioid prescribing associated with the introduction of the VBP program are limited to prescribers practicing in inpatient hospital settings.

Table 3.7 Alternative Specialty Prescribers

	Dermatology (10)	Pediatrics (11)	General Dentists (12)	Emergency Medicine (13)
Time	− 1.822	− 4.667***	− 0.549***	− 0.498**
	(1.815)	(1.674)	(0.188)	(0.233)
Transition	− 27.185	6.231	− 0.905	8.489**
	(29.472)	(27.854)	(2.990)	(3.941)
Recovery	1.924	7.665***	0.872***	0.066
	(2.317)	(2.208)	(0.236)	(0.307)
Workload	142.948**	71.482**	0.913	14.153***
	(61.509)	(18.370)	(3.846)	(1.726)
Competition	0.016	− 0.185**	− 0.001	− 0.006
	(0.085)	(0.073)	(0.009)	(0.010)
Medicare population	− 0.001	− 0.002	0.000	0.000**
	(0.003)	(0.001)	(0.000)	(0.000)
Public interest	− 0.034	0.623	− 0.006	0.079
	(1.378)	(1.305)	(0.140)	(0.172)
Average age	− 0.123	− 0.146**	− 0.004	− 0.012
	(0.088)	(0.067)	(0.009)	(0.017)
Percent female	− 35.631**	38.301***	1.264	− 23.237***
	(16.418)	(14.094)	(1.859)	(1.780)
Percent Medicare	− 82.320**	264.565**	18.584***	22.212*
	(38.782)	(55.030)	(5.986)	(11.432)
Percent Medicaid	42.415	− 92.745***	− 6.168	− 33.781***
	(53.739)	(30.184)	(5.863)	(9.683)
Percent Commercial	− 4.264***	− 22.731	0.135	14.224***
	(19.304)	(18.683)	(2.019)	(3.852)
Observations	3,273	8,201	24,871	28,490
R^2	0.5665	0.5132	0.3369	0.4442
Log Likelihood	− 23627.5	− 62116	− 148450.3	− 177892.2
AIC	47280.9	124258	296926.6	355810.5
BIC	47630.2	124349.2	297032.2	355917.8

Model (10) includes fixed effects for 167 prescribers; Model (11) includes fixed effects for 672 prescribers; Model (12) includes fixed effects for 944 prescribers; Model (13) includes fixed effects for 814 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

We also ran our models with an alternative operationalization of competition and report these results in Table 3.8. We replaced our existing measure of competition, the total number of physicians per 100,000 census population in the service area, with the total number of hospitals in the hospital service area (Dartmouth Atlas 2019).[15] Although the scale of coefficients and in some cases, level of statistical significance, vary slightly from the moderated coefficients in Table 3.4, results for this alternative operationalization remain largely consistent with our main findings.

Table 3.8 Alternative Operationalization of Competition

	Introduction of VBP (14)	Moderating Impact of Prescriber Workload (15)	Moderating Impact of Competition (16)
Time	− 9.192*** (0.811)	− 8.184*** (1.038)	− 10.367*** (1.033)
Transition	51.274*** (12.834)	44.451*** (14.750)	51.191** (15.098)
Recovery	9.093*** (1.064)	8.352*** (1.266)	10.913*** (1.287)
Workload	25.806** (11.651)	37.227*** (14.257)	25.853*** (11.659)
Time x Workload		− 0.796* (0.476)	
Transition x Workload		5.426 (3.939)	
Recovery x Workload		0.585 (0.472)	
Competition	1.986 (3.355)	2.000 (3.353)	− 1.306 (0.077)
Time x Competition			0.329* (0.173)
Transition x Competition			0.025 (2.303)
Recovery x Competition			− 0.509** (0.206)

[15] The data set forth at time of publication was obtained from Dartmouth Atlas Data website, which is funded by the National Institutes of Health (NIH) Health Economics Common Fund Program through an award [U-01 Supplement Award, National Institutes of Health Common Fund (3U01AG046830-03S1)].

Medicare population	− 0.001*	− 0.001*	− 0.001***
	(0.001)	(0.001)	(0.001)
Public interest	− 1.139***	− 1.137***	− 1.138***
	(0.367)	(0.367)	(0.367)
Average age	0.007	0.005	0.007
	(0.041)	(0.041)	(0.041)
Percent female	− 41.770***	− 41.905***	− 42.010***
	(15.200)	(15.204)	(15.212)
Percent Medicare	101.898***	102.250***	101.928***
	(30.878)	(30.864)	(30.873)
Percent Medicaid	– 36.033	– 36.412	– 35.786
	(28.757)	(28.777)	(28.794)
Percent Commercial	40.417***	40.087***	40.475***
	(12.286)	(12.296)	(12.276)
Observations	66,181	66,181	66,181

Alternative operationalization of competition is time invariant, therefore models in this table include random effects; clustered standard errors for 2,178 prescribers in parentheses;
*** Significant at 1%; ** significant at 5%; * significant at 10%

Disparate proportions of primary care versus specialty physicians in an area may induce differential influence on the relationship between the competition present in an area and opioid prescription rates. That is, it is possible that the effects of competition on opioid prescription rates are driven more by the presence of primary care physicians as opposed to specialty physicians, or vice versa. To investigate this possibility further, we conduct a supplementary analysis to analyze whether the moderating impact of competition on opioid prescription rates is driven by a specific type of competition (primary care versus specialists) and present these results in Table 3.9. To do so, we disaggregate the competition variable in the primary analysis such that competition is no longer represented by one variable (representing all prescribers in a geographic area), but instead is represented by two variables, one reflecting the volume of primary care prescribers in a geographic area and the other representing the volume of specialty physicians in a geographic area. The results in the main model with disaggregated competition (17) produce coefficients comparable to those in the main model (2) previously reported in Table 3.4, indicating that splitting competition into two types has no significant impact on the main findings for the introduction of VBP.

We then interact the level of primary care competition in a geographic area with each of the time covariates in our model (18) to determine whether the moderating impact of primary care competition is driving the results seen when we previously investigated the moderating impact of total competition (Model (4) in Table 3.4) on opioid prescribing rates. Results for the moderating impact of primary care competition in a geographic area (18) are comparable to those produced when operationalizing competition as the total competition in a geographic area (Model (4) in Table 3.4). Similarly, we also interact the level of specialist competition in a geographic area with each of the time covariates in our model (19) to determine whether the moderating impact of specialist competition is driving the results seen when we previously investigated the moderating impact of total competition (Model (4) in Table 3.4) on opioid prescribing rates. Results for the moderating impact of specialist competition in a geographic area (19) are also comparable to those produced when operationalizing competition as the total competition in a geographic area (Model (4) in Table 3.4). Taken together, this finding indicates that primary care and specialist competition in a geographic area are both contributing to the overall moderating impact of competition on opioid prescription rates.

Table 3.9 Disaggregated Competition Models

	VBP Introduction with Disaggregated Competition (17)	Moderating Impact of Primary Care Competition (18)	Moderating Impact of Specialist Competition (19)
Time	− 9.521***	− 12.629***	− 11.724***
	(0.512)	(1.088)	(0.830)
Transition	49.159***	46.602***	58.541***
	(8.688)	(15.688)	(12.469)
Recovery	9.604***	12.791***	11.649***
	(0.681)	(1.313)	(1.026)
Workload	13.444***	13.440***	13.437***
	(2.489)	(2.488)	(2.489)
Primary Physician Competition	0.148	− 0.299**	0.147
	(0.102)	(0.136)	(0.102)
Time x Primary Competition		0.031***	
		(0.009)	
Transition x Primary Competition		0.022	
		(0.128)	
Recovery x Primary Competition		− 0.031***	
		(0.011)	
Specialist Physician Competition	− 0.066	− 0.066	− 0.194***
	(0.042)	(0.042)	(0.051)
Time x Specialist Competition			0.010***
			(0.003)
Transition x Specialist Competition			− 0.045
			(0.043)
Recovery x Specialist Competition			− 0.010***
			(0.004)
Medicare population	− 0.001*	− 0.001*	− 0.001*
	(0.001)	(0.001)	(0.001)
Public interest	− 1.123***	− 1.114***	− 1.117***
	(0.382)	(0.382)	(0.382)
Average age	0.018	0.019	0.018
	(0.043)	(0.043)	(0.043)
Percent female	− 43.130***	− 42.994***	− 43.031***
	(7.418)	(7.416)	(7.417)
Percent Medicare	83.400***	82.873***	83.116***
	(14.048)	(14.047)	(14.048)
Percent Medicaid	− 29.296	− 31.021*	− 29.837*
	(18.013)	(18.014)	(18.013)
Percent Commercial	36.319***	35.617***	36.023***
	(7.247)	(7.247)	(7.247)

Observations	68,150	68,150	68,150
R^2	0.6994	0.6995	0.6995
Log Likelihood	− 509450.3	− 509433.8	− 509439.9
AIC	1018929	1018902	1018914
BIC	1019056	1019057	1019069

Models include fixed effects for 2,242 prescribers; standard errors in parentheses;
*** Significant at 1%; ** significant at 5%; * significant at 10%

Although VBP legislation and competition are exogenous variables that occur independent of the prescriber, we recognize that prescriber workload is susceptible to endogeneity concerns. Therefore, we conduct a series of instrumental variable regressions (results reported in Table 3.10) in which we instrument prescriber workload using both external and generated instruments. In Model (20), we use a lagged measure of prescriber workload as our external instrument, resulting in findings that are consistent in directionality, statistical significance, and magnitude with the findings reported in our main analysis (Model (2) in Table 3.4). We also conduct post-estimation statistical tests for overidentification, underidentification, and weak identification, with each test validating that we have selected an appropriate instrumental variable. As added robustness, we also ran an instrumental variable regression combining the use of our selected external instrument with instruments generated following Lewbel's method (Baum and Schaffer 2012), with results reported in Model (21) of Table 3.10. These findings are consistent in directionality and statistical significance with the findings reported in our main analysis (Model (2) in Table 3.4) albeit with some differences in magnitude of the coefficients. Once again, we conducted post-estimation statistical tests for overidentification, underidentification, and weak identification, with each test validating that we have selected appropriate instrumental variables. We note that slight discrepancies in sample size exist between these models and our main model (Model (2) in Table 3.4) due to differences in estimation techniques and the incorporation of a lagged variable (which is not available for all prescribers in our dataset). As further assurance that the presence of the workload variable is not inappropriately biasing our findings related to the impact of the VBP program, we have also run our main model without the inclusion of the workload variable; empirical results for the three time covariates remain consistent in statistical significance, directionality, and magnitude with those previously reported. Taken together, these findings lend support that our main findings are robust to potential endogeneity related to prescriber workload.

Table 3.10 Instrumental Variable Regression Models

	External Instruments (20)	Generated and External Instruments (21)
Time	− 10.579***	− 9.208***
	(0.539)	(0.959)
Transition	55.650***	120.375***
	(8.612)	(14.594)
Recovery	10.664***	4.332***
	(0.708)	(1.213)
Workload	19.003***	104.709***
	(3.138)	(1.530)
Competition	− 0.011	− 0.004
	(0.020)	(0.014)
Medicare population	− 0.001	0.001***
	(0.001)	(0.000)
Public interest	− 1.022***	− 0.811
	(0.372)	(0.667)
Average age	− 0.029	− 0.876***
	(0.047)	(0.081)
Percent female	− 43.887***	− 112.314***
	(8.076)	(11.231)
Percent Medicare	61.109***	622.327***
	(15.042)	(23.141)
Percent Medicaid	− 51.645***	21.746
	(19.289)	(30.241)
Percent Commercial	38.464***	71.935***
	(7.433)	(10.724)
Observations	61,145	61,211
R^2	0.0117	0.5188

Models include fixed effects for 2,242 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

Lastly, in an effort to examine whether the VBP program had a similar effect on opioid prescribing rates in other geographic areas (beyond the state selected for our main analysis) we acquired and analyzed data from an additional state PDMP, from a substantially different region of the U.S. than our primary sample. We note that state PDMPs have disparate laws and regulations with respect to data sharing for researchers.

As a result, data acquired from this additional state did not enable for direct matching of variables with the data source used in the main analysis and also required that we examine a broader population of prescribers (aggregate samples of hospital-based and office-based prescribers). However, we were able to recreate the three time covariates of interest to match the new sample with our primary sample. Results for the time covariate comparison between these two samples are presented in Table 3.11 and indicate that the introduction of the VBP program is associated with similar changes in opioid prescribing across both samples.[16]

Table 3.11 Fixed Effects Model Coefficients – State Comparison

	Main Analysis (22)	Additional Analysis (21)
Time	– 5.689***	– 10.032***
	(0.073)	(0.184)
Transition	12.965***	31.249***
	(1.010)	(2.476)
Recovery	6.997***	11.385***
	(0.086)	(0.219)
Average age	− 0.039***	3.064**
	(0.004)	(0.069)
Observations	3,351,440	636,372
R^2	0.7758	0.7418

Model (22) include fixed effects for 154,717 prescribers; Model (23) include fixed effects for 69,390 prescribers; standard errors in parentheses; *** Significant at 1%; ** significant at 5%; * significant at 10%

[16] When combined with the analysis referenced in Footnote 4, the authors empirically validated statistically similar opioid prescribing trends for approximately 20% of states in the U.S.

CHAPTER 4

CONCLUSION

This dissertation investigates the impact of operational performance incentive programs, implemented under the Patient Protection and Affordable Care Act (ACA) of 2010, on the operating responses of hospitals and physicians. The ACA launched a significant transformation in the US healthcare industry through the shift from a fee-for-service to a pay-for-performance environment (Werner et al. 2011). This reformed service and reimbursement model encouraged hospitals to invest a significant amount of financial and human resources to meet new standards related to clinical and experiential quality (Merlino and Raman 2013).

Leveraging a longitudinal investigation of hospitals' operating environments, this dissertation reveals specific factors which influence the degree to which hospitals invest in compliance with the new operational performance standards mandated by the ACA. Findings indicate that political support for the ACA in the area where a hospital operates renders a hospital more likely to invest in complying with performance measures related to experiential quality, and that this investment appears to occur at a faster rate than hospitals operating in areas that do not express political support for the ACA. Interestingly, the role of political support for the ACA is only relevant for the non-traditional measure of experiential quality, as political support for the ACA is not relevant hospital investments to comply with the traditional measure of clinical quality. Findings also provide evidence of the substantial influence of competitor actions on hospitals' likelihood to invest in complying with both experiential and clinical quality measures. Further, the relationship between political support for the ACA and experiential quality is dominated by high levels of competitor action, supporting the notion that hospitals view competitor actions as more salient than the level of political support for the ACA in their operating environments.

Motivated by the ACA's focus on experiential quality and the severity of the opioid epidemic in progress in the US, this dissertation also examines the impact of financially incentivizing hospitals and physicians to improve experiential quality, and the unintended impact on opioid prescribing rates. Findings indicate that hospital-based opioid prescribing rates significantly increased following the introduction of the Value Based Purchasing (VBP) program, which was the operational mechanism linking hospital and physician reimbursement to experiential quality performance. Empirical findings further reveal that the increase in opioid prescribing rates associated with VBP are exacerbated by high levels of market competition and prescriber workload.

Taken together, the findings from this dissertation provide considerable support for the significant influence of several factors within hospital and physician operating environments, and their joint impact on the operational responses of hospitals and physicians to the ACA. This dissertation informs the discussion on the relative effectiveness of ACA implementation in the US healthcare industry as well as its intersection with the ongoing operations of hospitals and physicians.

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