Profit Pressures in Nonprofit Care:
Executive Responses to Financial Incentives in Hospitals*

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Abstract

This paper examines how executive backgrounds shape organizational responses to financial incentives in mission-driven settings. Using U.S. nonprofit hospitals, I study whether clinically trained executives influence behavior under pay-for-performance policies. Hospitals led by non-clinical executives respond more strongly to quality-based financial incentives than those led by clinically trained leaders. This difference reflects active management rather than organizational objectives and operates through two mechanisms: clinically trained leaders prioritize patient-centered care and possess expertise that lowers the cost of quality improvements. These findings highlight the role of leadership in firm objectives and suggest incentive design should account for managerial heterogeneity.

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1 Introduction

Financial incentives are a fundamental tool for shaping organizational behavior, yet firms rarely respond uniformly to them (Cala et al. 2022). Executives could play a central role in shaping these responses, influencing strategy, resource allocation, and performance. Prior research links executive heterogeneity such as gender, age, and professional background, to firm outcomes, including financial performance and behaviors like wage setting and mergers.[1] While early evidence comes from large, publicly traded corporations, emerging work has pointed to the importance of leadership in public sectors, including public schools and hospitals.[2] Still, we know little about how leadership traits, particularly those of entire executive teams, interact with shifting organizational objectives.

This paper examines how specialized executive training shapes organizational behavior when external shocks alter incentives, specifically in the context of private nonprofit hospitals in the U.S. Health care in the U.S. makes up almost 20% of spending (Medicare & Medicaid Services 2024), and operates under evolving incentives, reflecting policymakers' initiatives to enhance quality without increasing costs, even as the U.S. continues to trail other high-income countries on these measures. Additionally, private nonprofit hospitals dominate U.S. health care[3] and operate under dual pressures: financial constraints and mission-driven obligations to deliver community benefit. While existing research consistently finds that leadership influences firm outcomes, it remains unclear whether these effects would extend to private nonprofit hospitals, organizations that are not directly governed publicly or owned by shareholders, yet operate in a policy-intensive environment with shifting incentives.

A key executive characteristic in this context is clinical training. Physicians combine clinical and administrative expertise, offering insights that may benefit staff and improve care quality (Stajduhar 2023, Ahmed 2022). However, hiring physician executives is controversial because many lack formal business training, which can result in inefficient management and reduced quality (Harvard Business Review 2018; Muñoz and Otero 2025). Thus, I estimate how the presence of clinically trained executives on a hospital C-suite team influences decision making. I scrape executive names and titles of nonprofit hospitals in the U.S. from publicly available Tax Form 990s. Combining

[1] Bertrand and Schoar 2003; Matsa and Miller 2011; Renee B Adams and D. Ferreira 2009; Ahern and Dittmar 2012; Flabbi et al. 2019; Benmelech and Frydman 2015; Custódio, M. A. Ferreira, and Matos 2013; Frydman 2019

[2] Best, Hjort, and Szakonyi 2023; Bertrand, Burgess, et al. 2020; Choudhury, Khanna, and Makridis 2020; Fenizia 2022; Lavy, Rachkovski, and Boiko 2023

[3] Private nonprofit hospitals account for 50% of all U.S. hospitals and average 207 beds, compared to for-profit hospitals, which comprise 36% and average 107 beds, and government hospitals, which make up 14% and average 175 beds.(ASPE 2023).

this with other hospital data, I construct a novel data set of nonprofit hospitals from 2010-2014 containing information on both executive team characteristics and quality metrics.

The non-random selection of leaders complicates causal interpretation of direct comparisons between executive teams. Therefore, I leverage pay-for-performance policies enacted in the U.S. as an exogenous shock to hospital incentives on quality and compare changes in readmission and mortality rates between hospitals with and without clinically trained executives using a synthetic difference-in-differences estimation strategy. Assuming the two types of teams would have followed similar trends absent the policy change, I find that hospitals without clinically trained executives respond more strongly to financial incentives than those with clinical executives. In other words, both types of leadership teams reduce readmission rates after the policy change, but hospitals without clinical executives do so at a faster rate. The gap widens in hospitals with a higher share of clinically trained executives but disappears when limiting only to CEOs rather than the entire C-suite, highlighting the importance of expertise on the entire leadership team rather than only the top manager.

I investigate several mechanisms to explain the observed difference. First, I leverage the timing of clinically trained executives to show that clinicians actively manage hospitals differently, rather than acting as a signal of underlying preferences. Next, I show theoretically that hospitals that prioritize profit over patient welfare respond more strongly to policies that incorporate quality into the profit function. I test this empirically by comparing responses of hospitals with and without clinically trained executives to those of for-profit hospitals, which are known to be more profit-driven by ownership structure. I find that nonprofit hospitals without clinically trained executives respond to quality incentives similarly to for-profits, whereas those with clinically trained executives respond differently. Similarly, I show theoretically that expertise may drive the observed difference, and investigate this empirically by comparing different physician specialties which are more or less knowledgeable about the conditions targeted by the policies. This analysis suggests that expertise is a likely underlying mechanism. Finally, I find that changes in aggregate patient populations and investment decisions do not explain the observed difference in response.

Outside of health care, many researchers have documented a correlation between executive characteristics and firm actions, beginning with Bertrand and Schoar (2003), who show that manager fixed effects are an important factor in many firm behaviors and decisions. Greater female representation among executives correlates with higher female employee wages and shifts in corporate strategy (Flabbi et al. 2019; Matsa and Miller 2013). Young male CEOs tend to be more aggressive in mergers and acquisitions, whereas those with military experience are less aggressive (Levi, Li, and Zhang 2010; Benmelech and Frydman 2015). CEOs with general managerial ability receive higher pay and achieve better performance (Kaplan, Klebanov, and Sorensen 2012; Custódio, M. A. Ferreira, and Matos 2013; Renée B Adams, Akyol, and Verwijmeren 2018; Frydman 2019). Older CEOs are associated with differences in corporate culture (Graham et al. 2022). Finally, Chief Diversity Officers have not been found to influence diversity in university hiring (Bradley et al. 2022). Additionally, there is a rich emerging literature on CEOs in the public sector. Choudhury, Khanna, and Makridis (2020) provide evidence that better incentive alignment between CEOs and middle managers positively affects productivity in public R&D labs in India; Fenizia (2022) finds that higher quality managers in the public sector improves productivity in Italy; Lavy, Rachkovski, and Boiko (2023) shows that higher quality CEOs in public schools improve student outcomes (Choudhury, Khanna, and Makridis 2020; Fenizia 2022; Lavy, Rachkovski, and Boiko 2023).

To my knowledge, Brickley, Van Horn, and Wedig (2010) provide the only study in the U.S. setting using the Tax Form 990 executive/board of directors data. Using exogenous variation in expected Medicare profits, the authors find that internal boards increase CEO compensation, while physician board members reduce public donations (Brickley, Van Horn, and Wedig 2010). Two additional studies examine hospital leadership and performance in other countries. Janke, Propper, and Sadun (2019) use data from England to study whether CEOs affect hospital production, and find no association (Janke, Propper, and Sadun 2019). However, Muñoz and Otero (2025) investigate the role of CEOs in public hospitals in Chile, and find an 8% decrease in mortality rates for hospitals with top managers. Further, a major contributor of this quality improvement is the exodus of older physicians as CEOs (Muñoz and Otero 2025). Finally, although not in a hospital context, La Forgia (2023) find that OB-GYNs acquired by financially driven Physician Practice Management Companies (PPMCs) perform more C-sections than those acquired by clinically driven PPMCs (La Forgia 2023). Thus, the motivations of the management of health care facilities matter for provider behavior. This paper contributes to understanding how executive team characteristics affect firm behavior by (1) examining the critical setting of private nonprofit hospitals, which serve the majority of health care consumers in the U.S., (2) extending a relevant leadership characteristic to the entire executive team as opposed to CEOs only, and (3) observing behavior under an exogenous incentive change.

Additionally, this paper contributes to understanding how providers respond to pay-for-performance incentives in health care. The most in-depth study of hospital responses to the Hospital Readmissions Reduction Program (HRRP), one of the two major pay-for-performance initiatives, is by Gupta (2021). This study finds that hospitals decreased readmissions by 5% and mortality rates by 2% on average as a result of the program, confirming prior studies (Mellor, Daly, and Smith 2017; Ziedan 2018; Ody et al. 2019; Gupta 2021). Around 40% of the decrease in readmissions is due to selective patient practices. Further, market concentration and hospital systems play a large role in how hospitals respond to the program (Kunz et al. 2024). Research on the other large pay-for-performance initiative, the Hospital Value Based Purchasing Program, generally concludes that the program had no effect on underlying hospital quality (Office 2015; Norton et al. 2018; Friedson, Horrace, and Marier 2019). This paper extends this literature by examining how hospital leadership characteristics shape responses to pay-for-performance incentives.

2 Setting and Data

I compile novel data on individual hospital executives by scraping publicly available tax forms, and merge this with publicly available data sets containing other hospital characteristics: the American Hospital Association Survey (AHA), the Centers for Medicare and Medicaid Services (CMS) Hospital Compare data and Case Mix Index files, and Healthcare Cost Report Information System (HCRIS) data. Ultimately, I employ hospital-level data spanning 2010-2014 containing executive team characteristics and mortality and readmission rates as measures of quality. In this section, I describe the institutional setting and data collection process. I include more details on the data construction in Appendix A.

2.1 Nonprofit Hospital Executives

Nonprofit hospitals, as with most nonprofits, are typically governed by a board of directors, whose role is complex but generally involves setting broad goals and providing oversight (National Council of Nonprofits 2025). The board selects executives, the highest level of management, to carry out day-to-day operations. An executive team usually consists of at least a Chief Executive Officer (CEO) and Chief Financial Officer (CFO), but there is variation in how firms organize these teams. Some hospital executives specialize in health care administration by earning a degree in health care management, or an MBA specific to health care. There are executive positions that are often filled by someone with clinical training (ex. Chief Medical Officer), but medical doctors can also fill other executive positions. While some doctors earn additional degrees before stepping into an executive role, this is not a necessary condition for becoming a physician executive.

Hospital executive teams are understudied in part because of the inaccessibility of granular data. I compile a novel data set of nonprofit hospitals in the U.S. which contains names, titles, and positions of all board members and executives associated with each hospital in 2009-2015. I gather this data from publicly available Tax Form 990s. To my knowledge, this is the first largescale gathering of executive names from these forms.[4] All tax-exempt organizations in the U.S. are required to file a Form 990 with Internal Revenue Services (IRS) each year. There are different types of forms, but any organization grossing over $200,000 must file the most extensive Form 990. Sections of this form include a statement of revenue, functional expenses, a balance sheet, and, as used in this project, a list of key employees, executives, and board members.

For each hospital in the tax forms, I merge with hospital records in the AHA data that match based on name and location.[5] For matched hospitals, I use optical character recognition (OCR) methods to extract the names, titles, and positions of each individual listed in the tax form. While board members are an important aspect of hospital organization, I do not include them in this analysis as they are beyond the scope of this paper. I extract text spanning 2009-2015, but I retain a much larger sample of hospitals by restricting the sample to hospitals with text information in 2010-2014. This yields 847 nonprofit hospitals that are matched to the AHA survey and contain complete leadership information in each year from 2010-2014. For clarity, I include a table outlining the number of observations in each sample restriction in Table 1.

Table 1: Observations in Sample Restrictions

Sample	Observations
Hospital EINs	5,588
Hospital EINs Matched to AHA Hospital or System	1,340
Hospital EINs Matched to AHA Hospital Only	1,152
Hospitals with Leadership Info, 2010-2014	847

Clinical training need not be limited to physicians. However, physicians are the most common and verifiable clinicians in the data. I verify clinical training for individuals identified as doctors, and obtain additional information about clinically trained executives by matching names to the National Plan and Provider Enumeration System (NPPES) database of all registered physicians. I present a table of means for various characteristics of doctor executives in Table 2. In total, there are 954 clinically trained executives. On average, they are 52 years old, and 11% of clinically trained executives are female. While it is more likely they are a Chief Medical Officer than a Chief Executive Officer, less than one-third hold CMO positions. The most common specialty is internal medicine. While I cannot perfectly verify nurse experience in the data, in Appendix C.1, I include

[4] Brickley, Van Horn, and Wedig (2010) collect compensation data for a select number of hospitals.

[5] I assess the observable differences between matched and non-matched hospitals in Appendix **??**, and conclude that the samples are overall similar apart from an under-sampling of hospitals that belong to systems.

executives who are labeled as registered nurses in the tax forms. The results are similar to those of the main analysis, which is unsurprising given that only 0.5% of executives have a nursing title.

Table 2: Clinical Executive Summary Statistics

Variable	Mean
Age	52.61
Female	0.12
CEO	0.14
CMO	0.39
Specialty	
Internal Medicine	0.32
Surgery	0.08
Anesthesiologist	0.04
Family Medicine	0.18
Emergency Medicine	0.11
Other	0.27
N	954.00

As the organization of specific C-suite positions can vary drastically across hospitals, I focus on executive teams as a whole rather than individual positions. It is not uncommon for two hospitals to have the same position but the tasks performed to be drastically different, or to have two distinct positions that essentially perform the same tasks. I use various hospital-level characterizations based on their executive team, such as the existence of a clinically trained executive, the number of clinically trained executives, the number of total executives, and whether the hospital has a Chief Medical Officer.

2.2 Policies Targeting Readmission and Mortality Rates

The purpose of this paper is to investigate hospital behavior under financial incentives that change how hospital quality affects payment. Two programs under the Affordable Care Act that focused on pay-for-performance incentives for hospitals: the Hospital Readmissions Reduction Program (HRRP) and the Hospital Value-Based Purchasing Program (HVBP). HRRP focused on penalizing hospitals with poor quality, and HVBP focused on rewarding hospitals with higher quality.

In October 2011, the Centers for Medicare & Medicaid Services (CMS) released a set of rules under HRRP mandating penalties for hospitals with above-average readmission rates. The goal of HRRP is to lower readmissions through better care coordination, less initial stay complications, and better post-care instructions. Beginning in October 2012, hospitals with higher readmission rates than the national average in pneumonia, heart failure, or acute myocardial infarction (AMI) received a fixed lower reimbursement rate for all Medicare patients seen in their hospital. Penalties are given in the form of a fixed-rate reduction of 1-3% for every Medicare patient regardless of the condition. Excess readmission rates are calculated using a rolling, 3 year look-back period to determine whether the hospital is penalized. Therefore, hospitals had an incentive to react immediately once details of the program were announced in October of 2011.

The HVBP Program instead rewards hospitals with high quality or significant improvement in quality. Specifically, CMS reduces Medicare payments by 2% for all eligible hospitals, collects this sum, and redistributes it among the rewarded hospitals. Several quality and cost measures surrounding safety, efficiency, cost reductions, clinical outcomes, and community engagement are combined to create a single metric for each hospital. Hospitals are then compared to the average and are rewarded for being above average quality or showing improvement (CMS 2023b).

I focus on outcomes of readmission and mortality, which are publicly available at the hospital-condition-level in CMS Hospital Compare. I combine rates for pneumonia, AMI, and heart failure (the relevant HRRP conditions), weighted by the number of patients in each condition.

2.3 Summary Statistics

In Table 3, I present mean values of relevant variables for several hospital samples used throughout the paper. First, in column (1), are means for hospitals that have a clinical executive at any point in time. Column (2) contains means for hospitals that have a clinical executive for the entire sample period, and column (3) shows means for hospitals that never had a clinical executive in the sample period. The main analysis compares hospitals in columns (2) and (3), and supplemental analyses draw on hospitals in column (1).

Comparing columns (2) and (3), hospitals that never had a clinical executive are smaller, less likely to be an academic medical center, and less likely to be affiliated with a system. Further, they have smaller executive teams by an average of 1-2 people, and are less likely to have a designated CMO. Finally, with regard to exposure to pay-for-performance programs, hospitals that never had clinical executives are less likely to receive benefits from the HVBP Program, but seem more similar to hospitals with clinical leadership in terms of penalties from HRRP.

Next, I plot weighted average readmission rates, mortality rates, and patient case mix index across time for different hospital types in Figure 1. The effective start year of pay-for-performance incentives is indicated as a dotted line in 2012. Average readmission rates follow similar trends

Table 3: Summary Statistics by Leadership Team Type

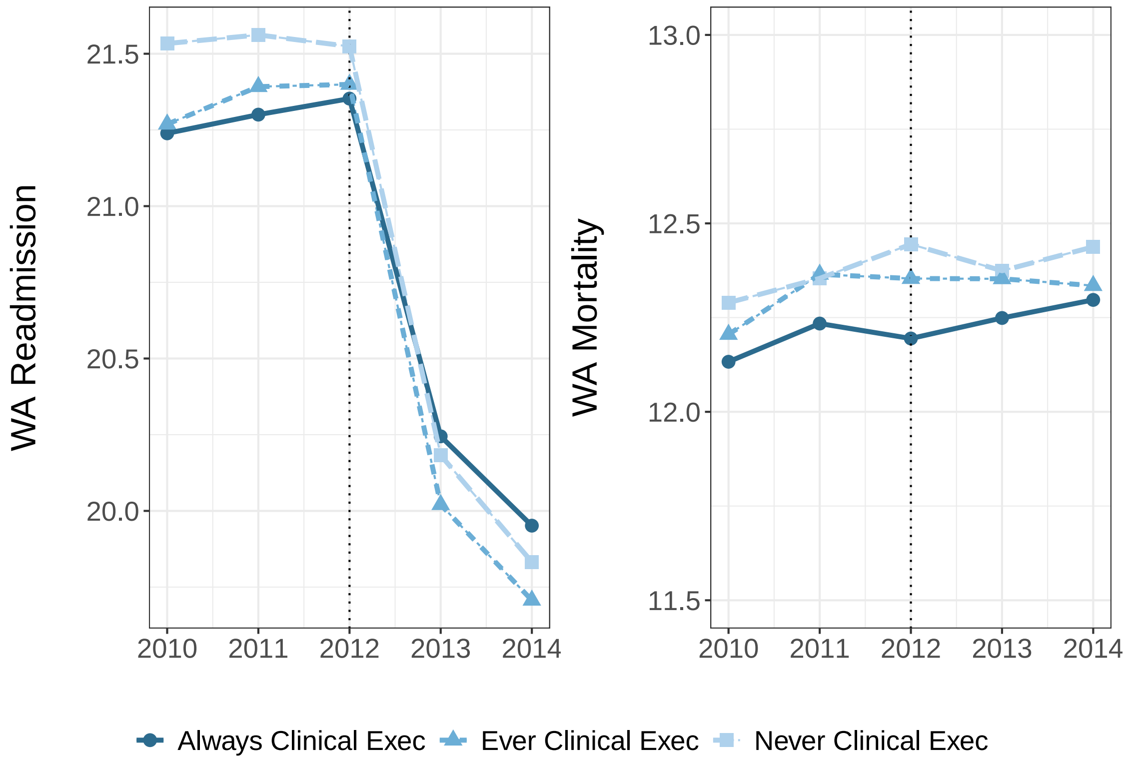
	(1)	(2)	(3)
Variable	Ever Clinical Exec	Always Clinical Exec	Never Clinical Exec
Hospital Characteristics			
Academic Med. Center	0.41	0.51	0.20
Number Beds	226.21	218.15	101.37
Physician Owned	0.01	0.02	0.02
System Affiliated	0.69	0.66	0.54
Executive Team Characteristics			
Number Executives	4.82	5.19	2.86
Fraction Clinical Execs	0.20	0.26	0.00
Fraction Int. Medicine Execs	0.06	0.08	0.00
Has a CMO	0.55	0.52	0.07
Has Clinical CEO	0.25	0.10	0.00
Penalty/Payment Variables			
Ever Received HVBP Incentive	0.80	0.77	0.58
Penalized for AMI	0.04	0.05	0.03
Penalized for HF	0.05	0.10	0.05
Penalized for Pneumonia	0.08	0.10	0.05
Penalized for AMI + HF	0.07	0.05	0.03
Penalized for AMI + Pneumonia	0.02	0.02	0.02
Penalized for HF + Pneumonia	0.41	0.40	0.33
Penalized for All Conditions	0.30	0.31	0.19
Num. Hospitals	452.00	62.00	389.00

prior to 2012, and all hospital types exhibit a decrease in raw readmission rates after 2012. However, there is a faster rate of decrease for hospitals that have a clinically trained executive at some point. When considering mortality, there is not a drastic change in 2012 for any hospital type, but hospitals that always have a clinical executive continue on an increasing trend in mortality while the other hospitals types remain relatively flat.

3 Effect of Clinical Leadership on Quality Incentive Response

I test empirically whether having clinically trained executives affects how hospitals respond to the pay-for-performance policies effective in 2012. The quality metrics targeted by the programs are readmission and mortality rates, and therefore I focus on these measures as outcomes. To establish a

Figure 1: Main Outcomes Over Time



clear control and treatment group, I limit the sample to hospitals that always have clinical executives or never have clinical executives. That is, the hospitals in this analysis do not change their propensity to hire a clinical executive during the sample period.[6] I employ a two-way fixed effects strategy as follows:

$$y_{ht} = \beta \text{ (clinical training x post 2012)}_{ht} + \gamma_h + \delta_t + \epsilon_{ht}, \quad (1)$$

where the variable y_{ht} denotes outcome variables (readmission or mortality rates) discussed in Section 2.2, and γ_h and δ_t are hospital and time fixed effects, respectively. The coefficient of interest is β, capturing the effect of having a clinician on changes in quality after 2012, following the implementation of pay-for-performance policies. All hospitals had an incentive to improve quality in response to the policy change, as penalties and payments are determined by comparing quality among hospitals. Thus, I exploit the timing of the policy change rather than variation in policy

[6] An important assumption underlying this analysis is that sample selection is not correlated with the program enactment. I investigate this assumption in Section 4.1.1, and find no evidence that hospitals are more or less likely to change their propensity to hire a clinical executive because of the pay-for-performance programs.

design.

One may be concerned about potential differences in quality trends between clinical and non-clinical executive team hospitals leading to a violation in the parallel trends assumption. To account for this, I ultimately implement a synthetic difference-in-differences strategy (Arkhangelsky et al. 2021), which assigns greater weight to non-clinical team hospitals with pre-trends similar to clinical team hospitals in the outcome being considered, effectively ensuring no differential pre-trends between always and never clinical teams. Using this strategy, the never-clinical group consists of approximately 240 hospitals, and I show the relatively uniform distribution of their weights in Appendix A.4. As a robustness check, I also pre-select the sample of always and never clinical hospitals using the Coarsened Exact Matching (CEM) procedure as described by Azoulay, Graff Zivin, and Wang (2010). I match based on observable characteristics such as hospital size, number of patients in each condition, and eventual penalty status. For brevity, I only present the synthetic difference-in-differences results here. In Appendix C.4, I show that the results are robust to using standard two-way fixed effects, matching, and synthetic control.

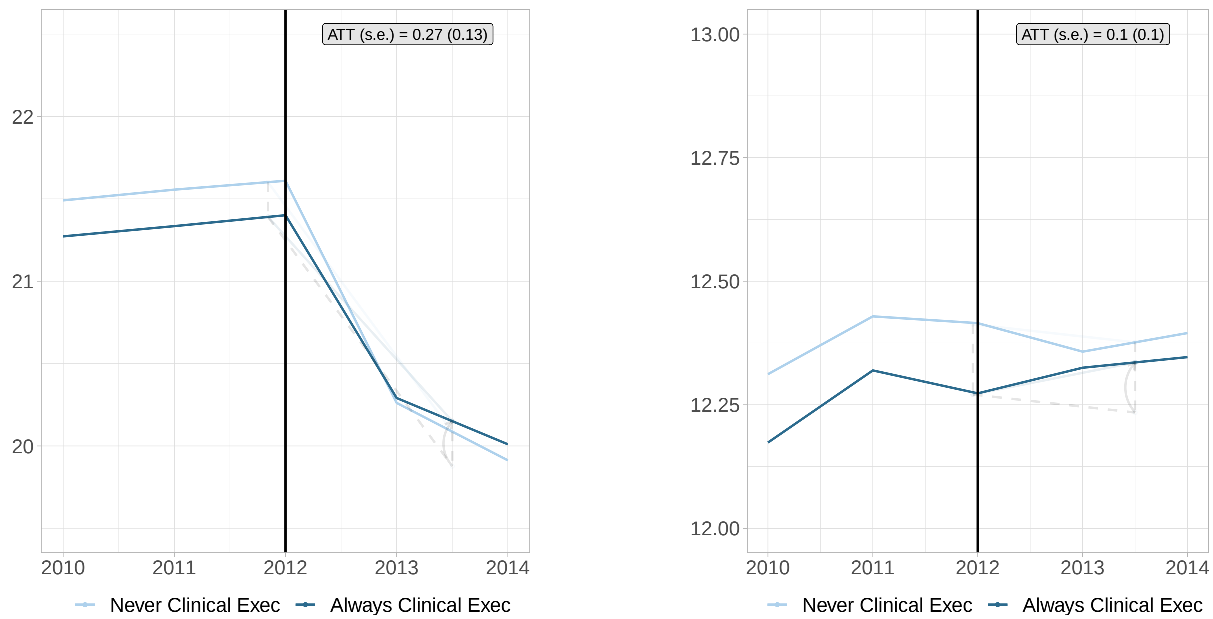
For identification, I assume that given the weighted clinical and non-clinical hospital composition, trends would have continued in a parallel manner in the absence of the incentive change in 2012. This includes an implicit assumption that no other event occurred in 2012 correlated with both the outcomes and composition of the leadership team. Finally, I assume that there is no anticipation of the policy change prior to 2012. The rules of the policies were announced in October 2011, so 2012 was the first full year that hospitals could meaningfully respond to the policies.

The estimated difference in readmission and mortality rates between hospitals with and without clinical executives is shown in Figure 2. Estimate β is represented by the difference in slope after pay-for-performance incentives began. Panel 2a shows the estimated difference in readmission rates, and reveals that non-clinical teams decrease readmissions by 0.3 (standard error 0.13) more than clinical teams. This is a relatively small magnitude given an average readmission rate of 21%. However, Gupta (2021) finds that hospitals overall decrease readmissions by around 3 percentage points due to the program, so this reveals a meaningful difference in behavior relative to the overall behavior change. Using estimates from Gupta (2021), a 1 percentage point reduction in readmissions across three penalized conditions corresponds to approximately \$110 million in avoided Medicare reimbursements annually. Our results indicate that hospitals led by non-clinical executive teams achieve an additional 0.3 percentage point reduction in readmissions compared to those led by clinical teams. Under the same assumptions, this differential accounts for approximately \$33 million in annual avoided spending—equivalent to 30% of the savings associated with a 1 percentage point reduction for these conditions. This back-of-the-envelope calculation reflects the incremental contribution of leadership composition to payer-side savings.

In Figure 2b, I show the estimated difference in mortality for always-clinical and never-clinical leadership teams after 2012. While the magnitude of the difference is similar to that of readmission rates (relative to the mean), mortality is a noisy measure, and I cannot rule out the possibility of a null effect.

Figure 2: Effect of Clinical Training on Readmission and Mortality Rates

(a) Readmission Rate (b) Mortality Rate



3.1 Intensive Margin

Additionally, I estimate the intensive margin of clinical leadership: whether the fraction of clinically trained executives affects the response to financial incentive changes. I categorize hospitals into two bins: above the median and below the median fraction of clinically trained executives. Again, I present the unweighted version of the synthetic difference-in-differences that I ultimately employ:

$$y_{ht} = \beta \left(\mathbb{1}\{\rho \leq \eta\} \text{ x post 2012}\right)_{ht} + \gamma_h + \delta_t + \epsilon_{ht}, \text{ and} \tag{2}$$

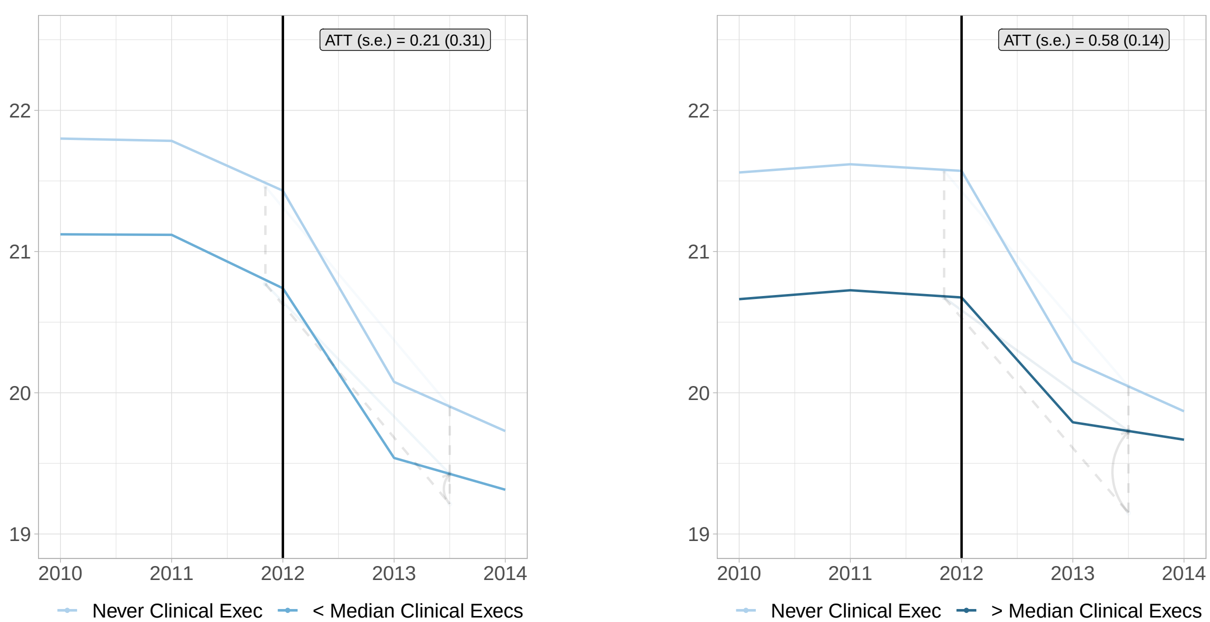
$$y_{ht} = \beta \left(\mathbb{1}\{\rho > \eta\} \text{ x post 2012}\right)_{ht} + \gamma_h + \delta_t + \epsilon_{ht}, \tag{3}$$

where ρ is the fraction of clinical executives on hospital h's executive team, η is the median fraction of clinically trained executives, which is 0.2 in this sample, and γ and δ are hospital and time fixed effects.

I present the estimation results for readmission rates as the outcome in Figure 3. In Figure 3a, I compare executive teams with no clinical training to those with a fraction of clinically trained executives up to the median value (20%). With an average treatment effect of 0.21 (standard error 0.31), hospitals having this range of clinically trained executives do not appear to drive the main finding. However, in panel 3b, I compare hospitals with no clinically trained executives to hospitals with a fraction of clinically trained executives over the median of 20%. I find that hospitals without clinically trained executives decrease readmissions by 0.6 (standard error 0.14) more than hospitals with clinically trained executives. Thus, while the entire readmission rate response is not driven by teams with a higher proportion of clinically trained executives, the effect is exacerbated for hospitals that have a higher proportion of clinicians.[7]

Figure 3: Effect of Clinical Training on Readmission Rates, Binned Treatment

(a) $\rho \leq \eta$ (b) $\rho > \eta$

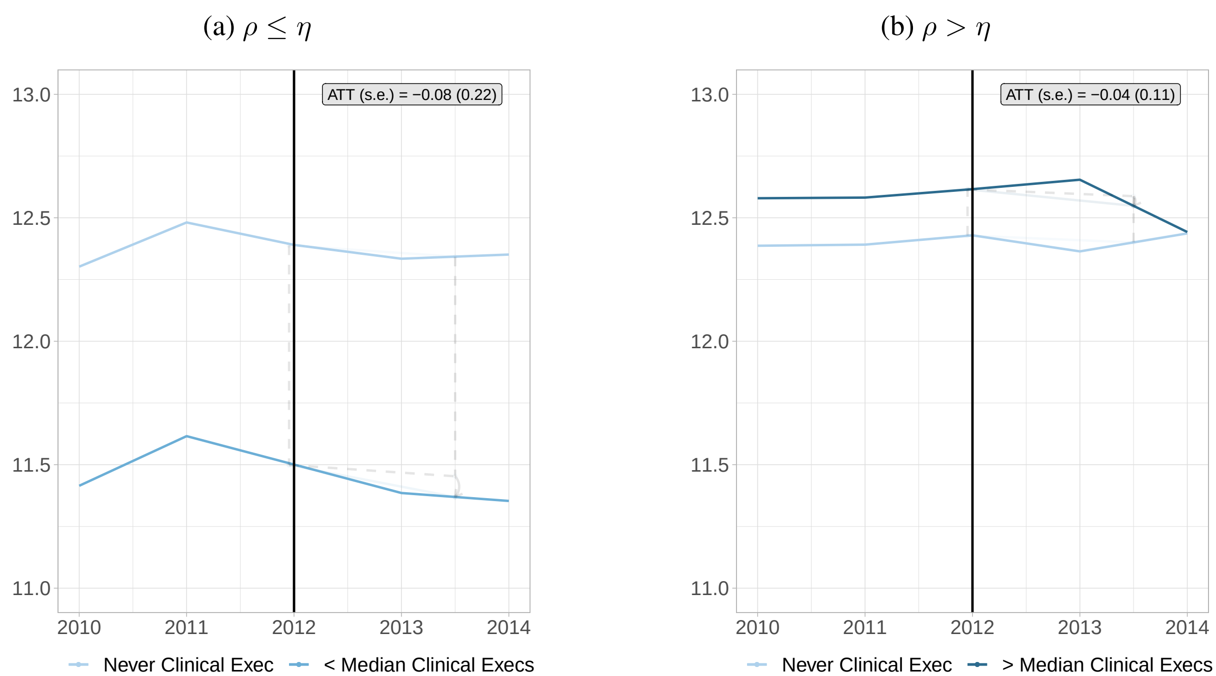


I present the estimation results for mortality in Figure 4. Unsurprisingly given the noisiness in the main findings for mortality, it is unclear whether there is any intensive margin effect. Both average treatment effect estimates are smaller than those in the primary analysis and are associated

[7]This result holds even when limiting the sample to hospitals with a similar total executive team size (Appendix C.2)

with large standard errors. Thus, the intensive margin appears less influential for mortality than for reducing readmission rates.

Figure 4: Effect of Clinical Training on Mortality Rates, Binned Treatment



3.2 Clinical CEO

Additionally, I consider the same comparison of clinical and non-clinical leaders, restricted to CEOs. Specifically, I examine whether the results hold when focusing exclusively on the CEO rather than the entire executive team. This analysis is motivated by the literature, which often emphasizes the CEO as the central figure in organizational leadership. Therefore, this analysis serves to assess whether team-level analysis offers different insights compared to CEO-focused analysis.

I compare hospitals led by a clinically trained CEO to those led by a non-clinical CEO by applying the same synthetic difference-in-differences strategy described in Section 3. I present the average treatment effect and standard errors in Table 4. For both readmission and mortality rates, the estimated effect of having a clinical CEO after 2012 is statistically insignificant. Point estimates suggest clinical CEOs may improve quality slightly more than non-clinical CEOs, though the results lack statistical precision. This highlights the importance of considering executive teams as a whole rather than just upper managers.

Table 4: Effect of Clinically Trained CEO on Readmission and Mortality Rates

	Readmission Rate	Mortality Rate
Clinical CEO x Post 2012	-0.75	-0.4
	(0.45)	(0.43)
Observations	1,630	1,630

Note:
Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

4 Potential Mechanisms

While identifying foundational differences between clinical and non-clinical hospital leaders is important in its own right, understanding why these differences arise is especially relevant. In this section, I present several theoretical predictions consistent with the observed differences in quality following pay-for-performance incentives and test these predictions empirically. First, I investigate whether clinicians actively manage hospitals differently or simply signal underlying hospital preferences. I do this by by leveraging the timing of clinical leaders relative to the incentives in Section 4.1. Second, the difference could be driven by altruism, or patient-centered focus of clinicians. I investigate this in Section 4.2by comparing nonprofit hospitals with varying leadership teams to for-profit hospitals. Third, I consider whether differences reflect altruism or expertise through a heterogeneity analysis of physician specialties in Section 4.3. In Section 4.4, I consider whether different types of executives may differ in their propensity to engage in 'gaming' through selective patient practices. Finally, I analyze whether whether executives alter aggregate investment behavior in response to incentives in Section 4.5.

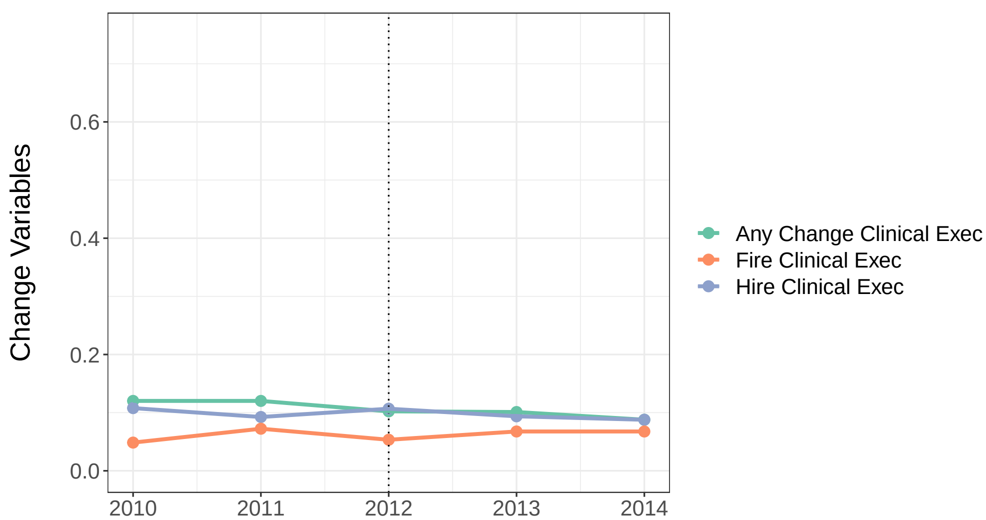
4.1 Signaling versus Managing

Given that having clinically trained executives affects hospitals' response to financial incentives on quality, an important distinction is whether the existing clinical leaders *reveal* the underlying objectives of the hospital or *manage* the hospital differently. In the main analysis, I limited the sample of nonprofit hospitals to those that do not alter their propensity to hire a clinically trained executive over the sample period, which combines signaling and managing effects. However, under the assumption that hiring or firing these types of executives is not correlated with the pay-for-performance policy changes, such changes can be leveraged to decompose the effect into signaling versus managing. If the difference is driven by underlying preferences of the hospital, the observed difference in quality will still hold whether the hospital ever had a clinical executive, even if they were not in leadership in 2012 when the policies took effect. Alternatively, if the observed difference is driven by managing, then the difference should only appear when a clinician is in leadership during policy enactment. Because this decomposition relies heavily on the assumption that clinical executive hiring is exogenous, I first examine leadership changes in response to the policy. I provide details of the decomposition estimation in Section 4.1.2.

4.1.1 Analysis of Executive Team Changes

Decomposing the observed difference in response based on timing is dependent on executive team changes not being correlated with the financial incentive. First, I present raw means over time showing the fraction of hospitals that hire a clinical executive, fire a clinical executive, or change their propensity to have a clinical executive in Figure 5. The proportion of hospitals that make changes to their leadership team is small, around 15% on average. Additionally, the data show no drastic changes in 2011 or 2012 when the policies became relevant to hospitals, especially when aggregating any change.

Figure 5: Leadership Change Means Over Time

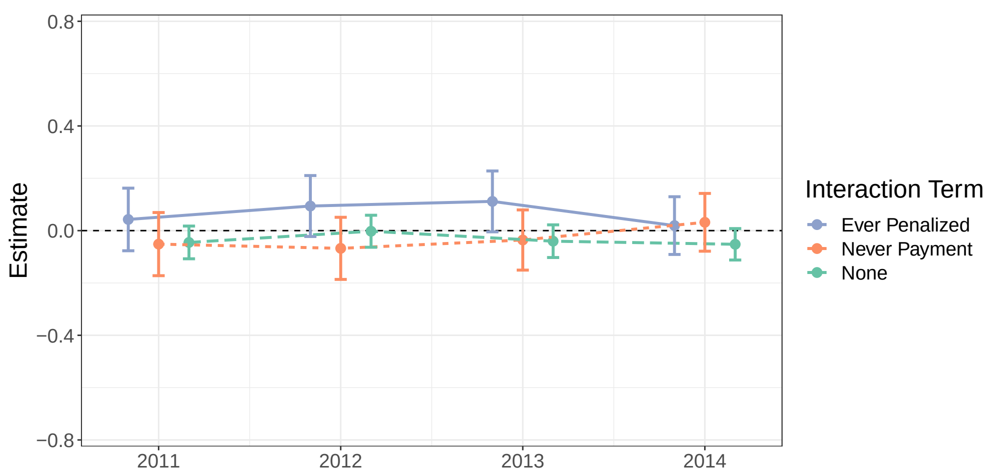


Next, I assess whether this assumption holds by analyzing executive team changes over time for specific hospital groups. I estimate the following two-way fixed effects specification:

$$\text{change}_{ht} = \sum_{j=2011}^{2014} \beta_j(\mathbf{1}\{t=j\} \times \text{Program Exposed})_{ht} + \alpha_h + \epsilon_{ht}, \tag{4}$$

where the variable Program Exposed$_h$ takes three forms. First, I define it as an indicator for whether the hospital ever faced penalties under HRRP. Second, I define it as an indicator for whether the hospital ever received payments under HVBP. Finally, I omit the Program Exposed variable to examine how changes correlate with calendar years for all hospitals. The outcome variable change$_{ht}$ indicates whether the hospital changes the number of clinical executives in a given year. Figure 6 shows the estimates from this analysis. All estimates remain statistically indistinguishable from zero, indicating that expectations of program exposure do not drive changes in the propensity to hire a clinical executive. These results suggest that endogenous team changes are unlikely to bias the estimates.

Figure 6: Leadership Analysis Results



4.1.2 Estimation

To disentangle clinical executives as signals of underlying hospital preferences or a different type of hospital manager, I carefully define the treatment and comparison group of hospitals in the following estimating equation. For clarity, I also present the specification details in Figure 7.

$$y_{ht} = \beta\ (\text{treat x post 2012})_{ht} + \gamma_h + \delta_t + \epsilon_{ht}, \tag{5}$$

If clinically trained leaders only signal underlying objectives, the timing of hiring a clinical

Figure 7: Decomposition Model Specification Details

Signaling:		Managing:	
Treat Group:	Never MD	Treat Group:	MD in 2012
Comparison Group:	Ever MD	Comparison Group:	Ever MD (not in 2012)

executive should not matter. For example, consider two hospitals: Hospital A employs a clinically trained executive from 2010 to 2011, while Hospital B employs one from 2010 to 2013. If clinically trained executives signal underlying objectives, both hospitals should respond similarly to pay-for-performance policies, even though only one has a clinical executive in 2012. However, if clinically trained leaders manage hospitals differently, the hospitals should respond differently because only one has clinical leadership in 2012 when the policy changes occurred.

Thus, in one specification I compare hospitals that ever have a clinically trained executive to hospitals that never have one. This specification captures the signaling effect. In another specification, I exclude hospitals that never had a clinically trained executive and compare hospitals with a clinical executive in 2012 to those with a clinical executive in any other year, capturing the managing effect. As in the previous analyses, I apply the synthetic difference-in-differences approach to each specification. That is, I assign greater weight to control units with pre-trends similar to treated units and to time periods that balance pre- and post-policy trends for the control group. I discuss the assumptions of parallel trends, no anticipation, and no confounding events in Sections 3 and 4.2, and these assumptions also apply here. I also assume executive team changes are exogenous to policy changes, an assumption I examine in Section 4.1.1.

Table 5 reports the estimates for each decomposition specification. Columns (1) and (2) report readmission rate estimates, and columns (3) and (4) report mortality rate estimates. The first row compares hospitals that ever had a clinical executive to those that never had one (signaling), and the second row compares hospitals with a clinical executive in 2012 to those with a clinical executive in any other year (managing). Although none of the estimates are statistically significant, the managing effect coefficients closely match the full effect reported in Section 3. Signaling effect coefficients are statistically insignificant and near zero. These results rule out the possibility that clinical executives merely signal underlying hospital objectives and provide evidence that it is likely a difference in management.

Table 5: Decomposition of Readmissions and Mortality Synthetic DiD Results

	Weighted Avg. Readmission Rate		Weighted Avg. Mortality Rate	
	(1)	(2)	(3)	(4)
Signaling Effect	-0.01		0.03	
	(0.07)		(0.06)	
Managing Effect		0.17		0.12
		(0.1)		(0.09)
Observations	3,005	1,595	3,005	1,595

Results from Equation with readmission and mortality rates as outcome variables.
Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

4.2 Financially Driven versus Patient Driven

4.2.1 Theoretical Model

I now examine a potential mechanism based on financial and altruistic motivations. Consider a simplified model of hospital objectives, in which hospitals choose an optimal level of quality of care that maximizes an objective function capturing the trade-off between profit and patient welfare. Formally,

$$\max_{\theta} \quad \alpha\pi(\theta) + (1-\alpha)u(\theta),$$

where $\pi(\theta)$ is a profit function depending on quality θ, $u(.)$ represents additional utility from patient welfare, which increases with quality θ and is concave, and $\alpha \in [0,1]$ captures the relative weight on profit versus patient welfare. The model assumes an implicit stay-open condition.

Under traditional fee-for-service settings, where performance is not financially incentivized, hospitals maximize profit π by maximizing patient volume. However, pay-for-performance incentives incorporate quality into the profit function (Dranove 2011). Hospitals that prioritize financial profit consider quality only when it enters the profit function, and thus respond more strongly to pay-for-performance than hospitals that value quality for patient welfare before incentives.

I now formalize this intuition mathematically. For simplicity, I abstract away from quality having a direct impact on quantity of patients or price.[8] Taking the first order condition yields:

[8] As long as the relationship between quality and quantity/price is not correlated with α, this does not change the conclusion of the model.

$$(1-\alpha)u'(\theta) = -\alpha\pi'(\theta),$$

where marginal benefit equals marginal cost of increasing quality. Solving for $u'(\theta)$ and differentiating with respect to α,

$$\frac{du'(\theta)}{d\alpha} = \frac{-1}{(1-\alpha)^2}\pi'(\theta).$$

Now, consider incentives when the hospital is in a strictly fee-for-service environment. That is, quality benefits patients, but hospitals do not directly derive profit from having a high quality. Assuming a positive cost to increasing quality, $\pi(\theta)$ is decreasing in θ. Then $\frac{du'(\theta)}{d\alpha} > 0$. Using the Implicit Function Theorem, I can write $\frac{d\theta}{d\alpha}$ as $\frac{du'(\theta)/d\alpha}{du'(\theta)/d\theta} < 0$, revealing that in a fee-for-service setting, the more weight the hospital places on profit, the lower quality of care chosen at baseline.

Alternatively, assume the hospital is in a pay-for-performance setting, where quality benefits patients and directly increases profit. If the marginal financial benefit of increasing quality is greater than the marginal financial cost, $\pi(\theta)$ is increasing in θ. Then $\frac{du'(\theta)}{d\alpha} < 0$, revealing that in a pay-for-performance setting, the more weight placed on profit, the higher quality of care chosen. I combine both scenarios into a single response function that depends on α, where θ_{p4p} denotes quality under pay-for-performance and θ_{ffs} denotes quality under fee-for-service:

$$\begin{aligned}\frac{d\Delta\theta}{d\alpha} &= \frac{d(\theta_{p4p} - \theta_{ffs})}{d\alpha} \\ &= \frac{d\theta_{p4p}}{d\alpha} - \frac{d\theta_{ffs}}{d\alpha} \\ &> 0.\end{aligned}$$

Therefore, the response to pay-for-performance incentives depends on α. Hospitals that prioritize profit respond more strongly to financial incentives, while hospitals that prioritize patient welfare respond less to financial incentives on quality.

4.2.2 Empirical Estimation

The first prediction of the model is that, in a fee-for-service setting with all else held equal, hospitals that value profit have a lower quality than those who value patient welfare. Second, the change in quality after pay-for-performance depends on how much weight the hospital places on profit versus patient welfare. Particularly, hospitals that place greater weight on profit respond more strongly than those that emphasize patient welfare. To investigate this hypothesis empirically, I merge general for-profit hospitals from the AHA survey to my sample of nonprofit hospitals. I then compare readmission and mortality rates of always clinical executives and never clinical executives to for-profit hospitals after the incentive change.

Although I lack data on leadership teams of for-profit hospitals, their ownership status indicates they prioritize profit and likely have an α close to 1. This is not inconsistent with previous work suggesting that nonprofits and for-profits act similarly on average (Duggan 2002). In fact, my data is consistent with this idea when nonprofits are not disaggregated by leadership teams. However, comparing different executive team behavior to for-profit behavior helps reveal how profit driven certain leadership teams are, which could reveal why there are similarities between nonprofits and for-profits on average. I estimate the weighted synthetic difference-in-differences version of

$$y_{ht} = \beta\ (\text{for-profit x post 2012})_{ht} + \gamma_h + \delta_t + \epsilon_{ht} \tag{6}$$

where y_{ht} is readmission or mortality rate, discussed in Section 2.2, for-profit$_{ht}$ is an indicator for having for-profit ownership status, and γ and δ are hospital and time fixed effects. In my estimation, nonprofits in the comparison group are more heavily weighted if their pre-trends are more similar to for-profits, and time periods are weighted to balance pre- and post-trends of for-profit hospitals. These weights follow the synthetic difference-in-differences approach, which is more robust to violations in the parallel trends assumption.

I create two data subsets to compare for-profit responses with nonprofit responses by executive team type. First, I include for-profits and nonprofits that always have clinically trained executives. Second, I include for-profits and nonprofits that never have clinically trained executives.[9] Appendix A.4 reports summary statistics for relevant variables for for-profit hospitals. I again use a synthetic difference-in-differences strategy to reduce reliance on a strong parallel trends assumption across hospital types.

The identification assumptions here mirror those in Section 3, but now include for-profit hospitals. First, I assume that without the incentive change, the weighted composition of for-profits and the comparison group would follow parallel outcome trends. Second, I assume no anticipation of policy changes before 2012, which is reasonable because the rules were announced in October 2011. Finally, I assume no other changes correlated with hospital type (for-profit, nonprofit with or without clinically trained executives) and quality occurred alongside the 2012 pay-for-performance policies.

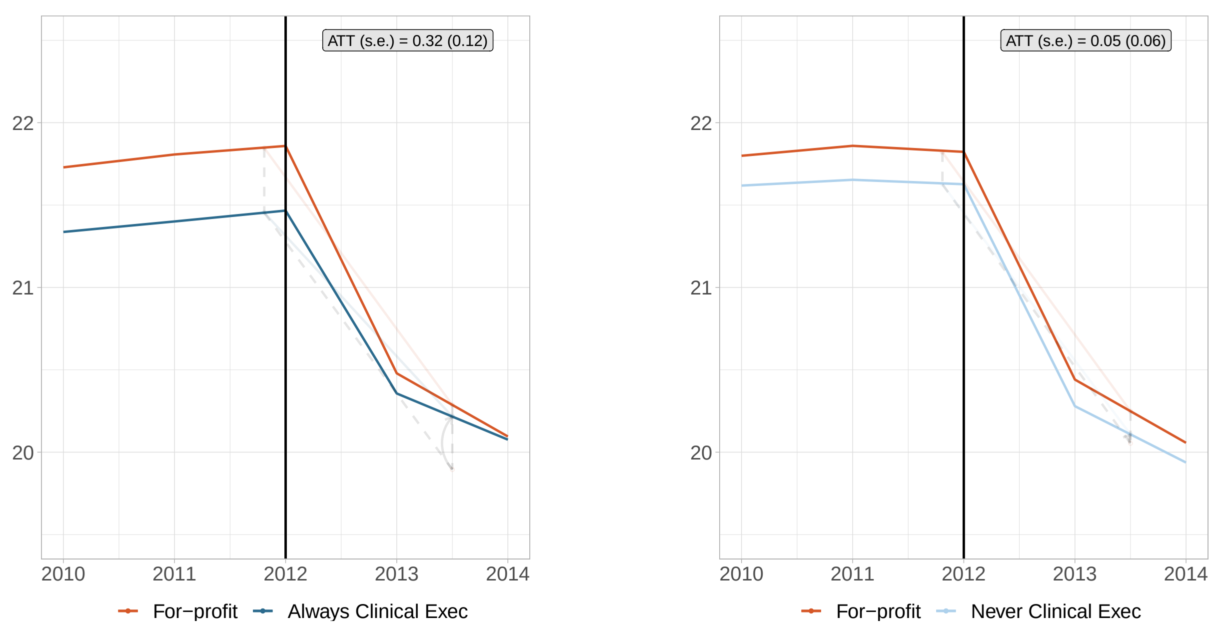
[9] I assume sample selection of stable leadership teams does not correlate with policy changes. See Section 4.1 for analysis and discussion of this assumption.

The estimates and graphical representation of the effect of being for-profit are shown in Figure 8. In Figure 8a, I present the effect of being for-profit compared to nonprofit with clinical executives on readmission rates after pay-for-performance changes. I find that for-profits decrease readmission rates by 0.3 (standard error 0.12) more than nonprofits with clinically trained executives. That is, for-profits respond more aggressively to the incentive change than nonprofits with clinical leadership. This difference is nearly identical to the difference between clinical and non-clinical teams shown in Section 3. Figure 8b shows no such difference when comparing for-profits to nonprofits without clinically trained executives. Not only is the estimate not statistically significant, but the magnitude indicates a precise zero. That is, a lack of clinically trained executives leads nonprofits to act like for-profits in terms of readmission rates when responding to this incentive change.

Figure 8: Comparison to For-Profit: Readmission

(a) For-Profit and Always Clinical Exec

(b) For-Profit and Never Clinical Exec

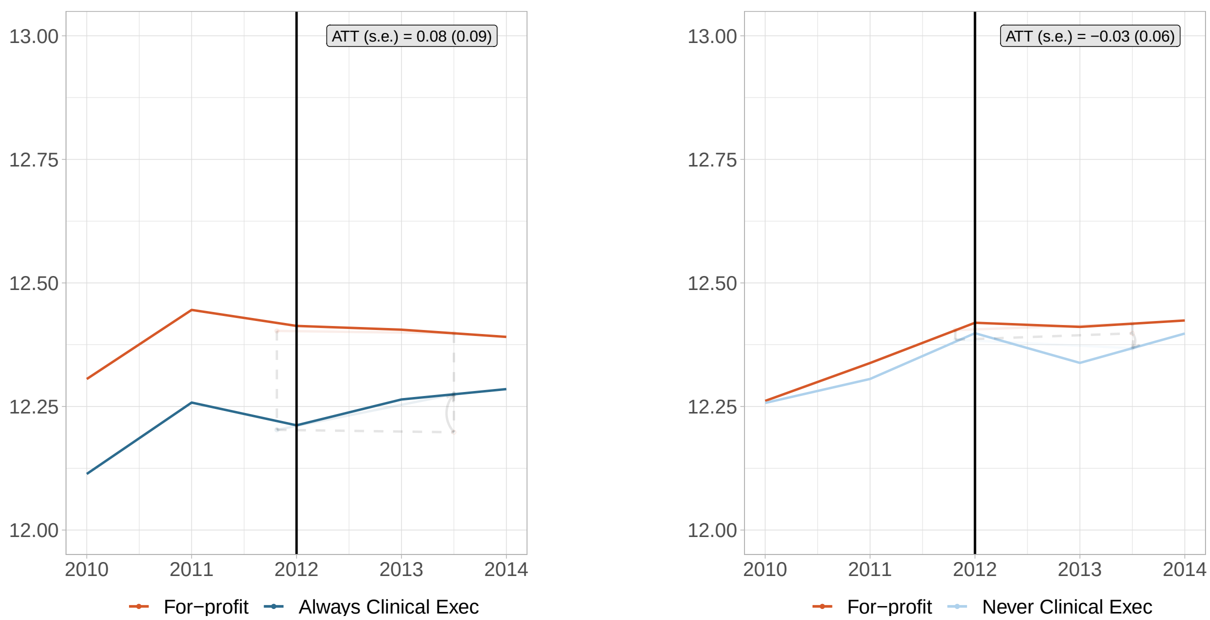


Next, I present estimated differences in mortality rates across hospital types in Figure 9. Figure 9a compares for-profits to nonprofits with clinically trained executives. The difference in mortality rates is 0.08: clinical team hospitals continue an upward trend, while for-profits remain stable. Although I cannot rule out no differential response, the documented noisiness of mortality measures (Mackenzie et al. 2016) suggests the true effect may differ from zero. However, the estimated difference in mortality between for-profits and nonprofits without clinically trained executives is certainly zero with a magnitude of 0.03, shown in Figure 9b.

Figure 9: Comparison to For-Profit: Mortality

(a) For-Profit and Always Clinical Exec

(b) For-Profit and Never Clinical Exec



4.3 Driven by Expertise

4.3.1 Theoretical Model

The observed difference in quality after pay-for-performance may be correlated with the expertise of leadership teams. While most doctors take a Hippocratic Oath to deliver care with integrity and compassion, doctors with training in certain specialties could be more equipped to improve care for specific patients. Because the pay-for-performance incentive programs directly target three conditions, physicians with knowledge of these conditions may be especially suited to respond to these policies. Specifically, a pulmonologist typically treats pneumonia, and a cardiologist typically treats heart failure and patients with heart attacks, the three conditions included in HRRP penalties. Both of these specialties are under the umbrella of internal medicine, which is the most granular specialty type in the data.

I extend the model discussed in Section 4.2 by introducing a measure of expertise, λ. To capture the role of hospital leadership expertise in shaping quality decisions, we introduce a binary variable $\lambda \in \{0, 1\}$, where $\lambda = 1$ indicates high expertise and $\lambda = 0$ indicates low expertise.

Expertise affects the marginal cost of quality improvements: hospitals with high expertise can implement quality enhancements more efficiently, reducing the effective cost of quality. The hospital's objective function becomes:

$$\max_{\theta} \alpha\big[R(\theta) - \frac{c(\theta)}{1+\lambda}\big] + (1-\alpha)u(\theta), \tag{7}$$

where $R(\theta)$ is revenue, which depends on quality, $c(\theta)(1+\lambda)$ is the cost of quality, increasing and convex in θ, and scaled by expertise, $u(\theta)$ is patient welfare, increasing and concave in θ, $\alpha \in [0,1]$ is the weight on profit relative to patient welfare. The hospital's first-order conditions under fee-for-service and pay-for-performance are then:

$$F_{ffs}(\theta,\alpha,\lambda) = (1-\alpha)u'(\theta) - \alpha\frac{c'(\theta)}{1+\lambda} = 0,$$

$$F_{p4p}(\theta,\alpha,\lambda) = (1-\alpha)u'(\theta) - \alpha\left[\frac{c'(\theta)}{1+\lambda} - R'(\theta)\right] = 0.$$

I make the following assumptions on patient welfare, cost, and revenue: $u'(\theta) > 0,\ u''(\theta) < 0,\ c'(\theta) > 0,\ c''(\theta) > 0,\ R'(\theta) > 0,\ R''(\theta) \approx 0$. By the Implicit Function Theorem,

$$\begin{aligned}\frac{d\theta}{d\lambda} &= -\frac{\partial F/\partial\lambda}{\partial F/\partial\theta} &(8)\\ &= -\frac{\alpha c'(\theta)/(1+\lambda)^2}{(1-\alpha)u''(\theta) - \alpha\big[c''(\theta)/(1+\lambda) - R''(\theta)\big]} &(9)\\ &> 0. &(10)\end{aligned}$$

I now want to compare the change in θ when going from fee-for-service to pay-for-performance depending on different levels of λ. The partial derivative of quality response with respect to expertise is defined as

$$\begin{aligned}\frac{\partial\Delta\theta}{\partial\lambda} &= \frac{\partial\theta_{p4p}}{\partial\lambda} - \frac{\partial\theta_{ffs}}{\partial\lambda} &(11)\\ &= \frac{-\alpha c'(\theta)/(1+\lambda)^2}{(1-\alpha)u''(\theta) - \alpha\big[c''(\theta)/(1+\lambda) - R''(\theta)\big]} - \frac{-\alpha c'(\theta)/(1+\lambda)^2}{(1-\alpha)u''(\theta) - \alpha\big[c''(\theta)/(1+\lambda)\big]}. &(12)\end{aligned}$$

Since $\theta_{p4p} > \theta_{ffs}$, $u(\theta_{p4p}) > u(\theta_{ffs})$, which means $u(\theta_{p4p})$ is less negative than $u(\theta_{ffs})$. Therefore, the denominator under pay-for-performance is less negative than under fee-for-service. Hence, $\frac{\partial\theta_{p4p}}{\partial\lambda} > \frac{\partial\theta_{ffs}}{\partial\lambda}$. This implies that as expertise increases, the response to pay-for-performance policies becomes stronger.

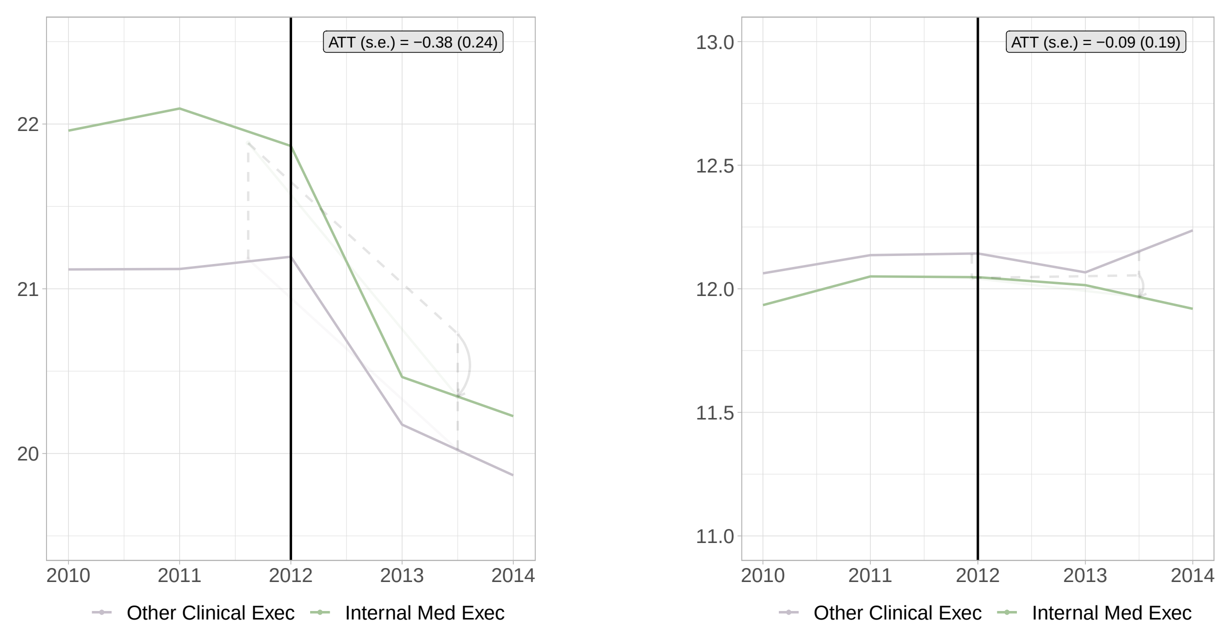
4.3.2 Estimation

To test this empirically, I limit the sample to hospitals that consistently have a clinical executive throughout the sample period. Then, I estimate the difference in readmission and mortality rates after pay-for-performance among hospitals that do and do not have an internal medicine clinical executive. This restriction reduces the sample size substantially: 60 hospitals consistently have either an internal medicine executive or an executive from a different specialty. The summary statistics for these samples are in Appendix A.4. I present the results from this comparison in Figure 10.

Figure 10: Effect of Internal Medicine Training on Quality

(a) Readmission Rates

(b) Mortality Rates



Although statistical power is limited due to the small sample size, I provide evidence that hospitals with internal medicine executives may change readmission rates differently compared to teams led by executives from other specialties. The estimated effect of having an internal medicine executive is -0.38 (standard error 0.24), indicating that hospitals with internal medicine executives reduce readmissions at a faster rate than those with executives from other specialties. Results for mortality rates are similar, though still not statistically significant, but smaller in magnitude and relative to the main findings. This likely reflects the greater relevance of specialty-specific conditions to readmission penalties compared to quality rewards. Although the small sample size limits statistical power, the results point to a potential role for leadership expertise in shaping hospital responses to policy incentives. Future research with larger samples could clarify whether these patterns hold more broadly.

4.4 Patient Selection

Gupta (2021) finds that a large portion of hospital readmission reductions result from hospitals being less willing to readmit their own patients, while continuing to readmit patients from other hospitals. Given the differential response to HRRP by clinical and non-clinical leaders, a natural question is whether these groups differ in their propensity to game the system, as explored in prior work (Gupta 2021). Although patient-level data are unobserved, I can test whether the overall hospital patient population changes differentially under clinician versus non-clinician leadership.

I examine three outcomes to test this hypothesis. First, I use the CMS Case Mix Index, which provides an aggregate measure of patient complexity for each hospital and year. A higher index indicates that the hospital's patient population requires more complex treatment. Additionally, I examine the share of patients discharged from the hospital who have public insurance, either Medicare or Medicaid. These outcomes help assess whether certain leadership types attempt to shift costs relative to others after penalties or rewards take effect.

I estimate the same synthetic difference-in-differences specification described in Section 3. The results are presented in Table 6. For Case Mix Index, clinically the estimate of -0.03 is statistically significant, but this is such a small magnitude (relative to a mean of 1.5) that this is a precise null effect. The estimated treatment effects for both Medicare and Medicaid populations are statistically insignificant and near zero, indicating no evidence that overall hospital patient populations change differentially by leadership type. This does not rule out changes in specific readmission behavior, as documented by Gupta (2021). However, a limitation of this dataset is that it only permits analysis of aggregate patient populations rather than individual readmissions.

4.5 Changes in Investment

Lastly, I examine whether clinician and non-clinician leaders differ in their investment strategies after the policies took effect. Ideally, more granular hospital-level data would allow observation of management differences, which is a limitation of the publicly available hospital-level data used in this analysis. I apply the same synthetic difference-in-differences estimation strategy to compare

Table 6: Effect of Clinically Trained Executive on Patient Population

	CMI	Frac. Medicare	Frac. Medicaid
Clinical Exec x Post 2012	-0.03***	0	0
	(0.01)	(0)	(0.01)
Observations	1,645	2,490	2,390

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

clinical leaders with non-clinical leaders before and after 2012. The variables I use as outcomes are the number of full-time nurses hired (AHA), movable equipment purchases, fixed equipment purchases, labor costs, building purchases, and total operating expenses (HCRIS). Because over 90% of observations for several HCRIS variables are missing in 2010, I exclude this year from the analysis. Table 7 presents the results, which show no evidence that hospitals with different leadership teams changed their investment strategies in response to the policies.

Table 7: Effect of Clinically Trained Executive on Hospital-Level Expenses

	Nurses	Moveable Equip	Fixed Equip	Labor	Building	Total
Clinical Exec x Post 2012	9.08	-1	6.95	-1.37	0.56	1.83
	(8.1)	(1.83)	(6.78)	(2.38)	(7.42)	(8.18)
Observations	2,485	1,532	660	1,670	1,435	2,485

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

5 Conclusion

This paper examines how executive backgrounds shape organizational responses to financial incentives in mission-driven settings. Using U.S. nonprofit hospitals, I study whether clinically trained executives influence hospital behavior when a policy shock alters incentives for quality. I construct a unique dataset of nonprofit hospitals that includes executive characteristics, hospital traits, and quality outcomes.

In 2012, two pay-for-performance policies went into effect: one penalized hospitals with high readmission rates, and the other rewarded hospitals with low readmission or mortality rates. These policies significantly affected hospital finances and created strong incentives to improve quality. I leverage this exogenous policy change to estimate how clinically trained executives influence readmission and mortality rates using a synthetic difference-in-differences approach. I find that hospitals without clinically trained executives improve quality more than hospitals with clinically trained executives after the incentive change.

I explore several hypotheses to explain this differential response. First, I leverage the timing of clinically trained executive appointments to decompose the effect into signaling versus management. This decomposition shows that having a clinically trained executive in a leadership role during policy implementation is crucial, suggesting the difference reflects management practices rather than underlying hospital preferences. Next, I compare the two types of nonprofits to for-profit hospitals on average, revealing that non-clinical executive teams behave similarly to for-profits. I also examine whether the observed difference reflects the expertise of specific physician specialties by comparing internal medicine executives to others, and find evidence that this may be a contributing mechanism. Finally, I show that the difference is not explained by changes in aggregate patient populations or investment strategies.

These findings have two key implications. First, leadership composition, not just ownership structure, matters for organizational behavior. While the nonprofit versus for-profit distinction remains important, executive backgrounds is a critical determinant of how hospitals respond to policy incentives. Second, incentive design should account for managerial heterogeneity. Policymakers aiming to improve quality without raising costs must consider how leadership expertise interacts with financial pressures and mission-driven obligations. Understanding these dynamics can inform strategies that better align incentives with quality goals across sectors.

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A Data

A.1 Gathering Hospital Leadership Names

I use the API of ProPublica's Nonprofit Explorer to access the archive of nonprofit Tax Form 990s.[10] I extract the Employee Identification Number (EIN) for all nonprofits categorized under a National Taxonomy of Exempt Entities (NTEE) code of E20 (hospital), E21 (community health system), and E22 (general hospital). There are 5,588 EINs in total in this list.

I query more detailed information from the API on each hospital EIN. I save the name, secondary name, state, and zip code, none of which vary by year. I also record URL links to the Tax Form 990 PDFs, which are unique in each year. For the sake of a comprehensive data set, I keep years 2006-2020 (I later limit to 2010-2014 when focusing on pay-for-performance initiatives in 2012). Thus, I finish this step with a panel data set of EIN characteristics and PDF locations. Importantly, there are multiple types of Tax Form 990s depending on the size of the nonprofit. In many cases, one nonprofit has at least two different forms filed in a given year. I filter out any EIN-years for which there are no PDFs available. There are numerous foundations or auxiliary firms with the purpose of raising funds for the hospital, but do not provide services to patients. I filter out any not-for-profit with "foundation" or "auxiliary" in the name. I also filter out various specialty centers such as hospice or cancer centers.

For my analysis, I need to link these nonprofits with other sources of data to recover penalties from HRRP, payments from HVBP, bed size, and outcomes of interest. I match to the American Hospital Association (AHA) Survey, which contains hospital characteristics and Medicare ID number, and will easily merge to other data sets used for hospital information. An EIN to AHA ID crosswalk does not exist. Therefore, I take a conservative approach to matching EINs to AHA ID based on hospital name and location.

In the AHA data, I keep general acute care hospitals in the contiguous US, Alaska, and Hawaii (excluding places like Puerto Rico) that are classified as nonprofit or state/community. I remove hospitals who weren't present in the data or change system ID in 2009-2015, meaning they either closed or were acquired. Due to the survey nature of this data, a hospital name may look slightly different from one year to the next. For example, "Waldo County General Hospital" is also "Waldo County General Hospital Maine Health". Further, zip codes often change by one or two digits, making them unreliable to match based on. To deal with this, I first keep only unique AHA ID, name, zip, state, and system name combinations. Then, I convert the data from long to wide so

[10] At the time of writing this, information on using version 2 of the API can be found at https://projects.propublica.org/not-for-profits/api.

that each AHA ID occurs only once, but may have multiple names, zip codes, or system names associated with it.

I proceed matching based on names in several steps. I focus on exact string matches, so I remove all spaces and common characters that could cause mismatches such as &, ', -, and "inc". I loop through each AHA ID, limit to nonprofits in the same state, and extract any exact name matches. When an exact match is found, I record the link between AHA ID and EIN. In this first layer of matching, 860 hospitals in the AHA data are linked to an EIN, equivalent to 31% of nonprofit hospitals in the sample. In the next layer of matching, I remove common words such as "healthcare", "regional", "hospital", etc. That way if there are subtle differences in names, removing common words may allow for an exact match. Again, I take each AHA hospital name and look for exact matches in the nonprofits in the same state. This adds an additional 90 hospital matches, accounting for a total of 34.5% of AHA hospitals. Finally, I manually search through unmatched EINs to identify any matches. From Google searches, I identify an additional 300 EIN-AHA ID matches. yielding a total of 1,200 EINs.

Although analyzing all nonprofit hospitals would be ideal, a sample size of 852 firms is considered relatively large in the executive literature. I present a comparison of in-sample and out-of-sample nonprofits. I present means and standard deviations of these measures in Table **??**. The in-sample nonprofits are slightly larger in terms of beds and patients seen. They are also slightly more likely to be penalized or receive payments under the pay-for-performance incentives. However, average readmission and mortality rates are very similar, as well as case mix index. The largest difference in the two samples is that I under-represent nonprofit hospitals in systems. This is due to the nature of the tax form 990s, where systems often file one tax form for the entire system, making it difficult to discern the true managers of a specific hospital. Because of this, I drop hospitals from the sample who only have leadership information from a system tax form.

I then extract the names of board members and executives from the Tax Form 990 PDFs for matched hospitals. In the data set of hospital PDF URLs that I collected earlier, I limit to the hospitals with solid matches described above. I then loop through each EIN, downloading PDFs locally and using the tesseract package in R to extract text from the relevant pages of the PDF using OCR text extraction methods. In particular, I loop through each page of the PDF, look for the title associated with leadership names: "Officers, Directors, Trustees, Key Employees, and Highest Compensated Employees", and save all the text from any pages where this title is found. I save the text to a list of all EIN, years present.

One aspect of the NonProfit Explorer API is that in some cases, if two forms are present for an EIN-year, only the first one is pulled. Therefore, for some hospitals, a couple years will have

Table A.1: NFP Sample Comparison

	In-sample NFP		Out-of-sample NFP	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Hospital Characteristics				
Academic Med. Center	0.31	0.46	0.25	0.43
Number Beds	169.09	203.57	143.11	186.70
Physician Owned	0.01	0.12	0.01	0.07
System Affiliated	0.50	0.50	0.63	0.48
Executive Team Characteristics				
Number Executives	3.92	2.75		
Fraction Clinical Execs	0.09	0.17		
Fraction Int. Medicine Execs	0.03	0.09		
Has a CMO	0.33	0.47		
Has Clinical CEO	0.12	0.33		
Penalty/Payment Variables				
Ever Received HVBP Incentive	0.70	0.46	0.61	0.49
Penalized for AMI	0.04	0.19	0.03	0.17
Penalized for HF	0.05	0.21	0.06	0.24
Penalized for Pneumonia	0.07	0.25	0.04	0.20
Penalized for AMI + HF	0.05	0.22	0.03	0.18
Penalized for AMI + Pneumonia	0.02	0.14	0.01	0.11
Penalized for HF + Pneumonia	0.37	0.48	0.33	0.47
Penalized for All Conditions	0.26	0.44	0.20	0.40
Num. Hospitals	843		2,222	

gaps in text extraction data. I locate EIN-years where this problem is occurring, and a team of RAs locates and downloads the correct forms manually. I extract text from these manually downloaded forms in the same manner as above.

The form of the extracted text data is a data frame with one column, where each line of text is saved in a different row. Typically on the same page as the names and positions is a list of the highest compensated employees and their compensation. In order to not record extra names, I filter out any rows after the start of this section. I then remove any digits, parentheses and brackets, other punctuation, letters that occur by themselves, two letter "words" that have no meaning, and excess space between words. I then split up the phrase into individual words, so one phrase with 5 words is broken up into 5 variables. I write a text cleaning function that locates names, positions, titles, and indications of resigning. I flag name rows using the Census name list data for the year 2000.

The columns with the most flags are then identified as name columns. I then extract any text that indicates a doctor title and link it to the name located the closest to it. Similarly, I extract text of all potential positions such as CEO, CFO, CMO, president, board member, etc., and link it to the name most closely located to it.

I then create a name-level data set that only includes executives. That is, I remove all board members from the data. I now seek to match people in this data set to existing physicians in the National Plan and Provider Enumeration System (NPPES) data, where all physician National Provider Identifiers (NPI) are recorded. For each executive (not just those identified as doctors), I record the number of name matches found in the NPPES data. There are several steps to identifying physicians with a true match. First, if an executive self-identifies as a doctor and has a unique match in NPPES, I record the unique NPI number for that executive. Second, if an executive self-identifies as a doctor and has multiple name matches in NPPES, I manually search online for information on the executive, and find the unique NPI most likely associated with the executive. Finally, for any executives who do not self-identify as a physician, but have name matches in the NPPES data, I manually research them and record the unique NPI number if they are a physician.

The data is now an executive-year-level data set with information on clinical training and specialty when relevant. I then create hospital-level indicators based on the names, titles and positions associated with the hospital: the number of clinically trained executives, the number of executives with particular specialties, the number of total executives, and whether the hospital employs a CMO.

A.2 Executive Team Changes

For the main analysis, I limit to hospitals who either always have a clinically trained executive or never have a clinically trained executive. In a supplemental analyses, I leverage changes to hospital propensity to hire a clinically trained executive. I explore the exogeneity of such changes in Section 4.1.1. Additionally, I present the frequency of hospitals who change their propensity to hire a clinically trained executive at different times in Table **??**. I break the timing up into pre-2012, 2012, and post-2012. I show the number of hospitals who have clinically trained executives in different time combinations. The number of hospitals that only have an MD executive in 2012, but at no other time, is only 6. The majority of hospitals (197) who ever have a clinical executive have one in every time period.

Table A.2: Timing of MD Exec Changes

Has MD Pre-2012	Has MD 2012	Has MD Post 2012	Num. Hospitals
0	1	1	35
1	1	0	24
0	1	0	8
1	1	1	197
0	0	1	60
1	0	0	43
0	0	0	452
1	0	1	24

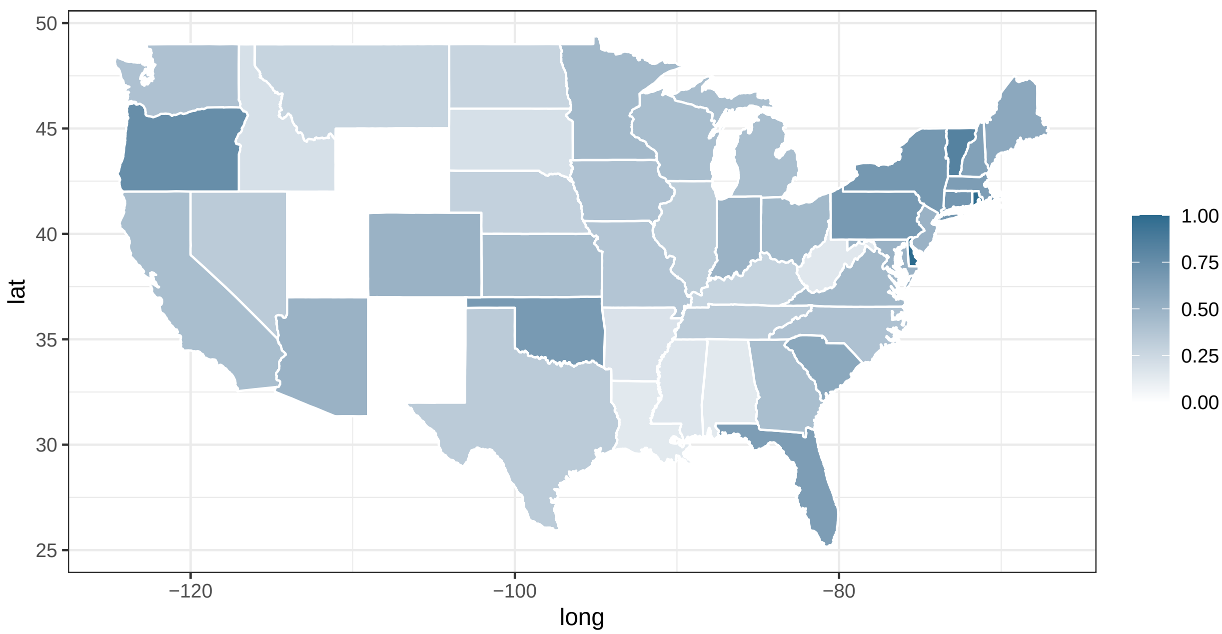
A.3 Merging to Other Hospital Data

Using the hospital Medicare ID number found in the AHA survey, I merge the executive information to various publicly available hospital data sets. For information on penalties or payments given by the pay-for-performance policies, I use the Hospital Cost Report Information System (HCRIS) data. For 30-day readmission rates, 30-day mortality rates, and the number of patients in the relevant conditions, I merge in the CMS Hospital Compare data. Finally, to investigate the role of selective patient practices I use a case mix index variable, which comes from the CMS Case Mix Index files.

A.4 Additional Summary Statistics

In this section, I present several additional figures and tables providing more information on the data. In Figure A.11, I show that clinical executives are not concentrated in one region geographically. In Table A.3, I provide means of all relevant variables for for-profit hospitals. In Table A.4, I show means of all relevant variables for hospital with and without internal medicine executives. In Figures A.12 and A.13, I provide the time and control weights from the synthetic difference-in-differences estimation with readmission rate as the outcome. In Figures A.14 and A.15, I provide the time and control weights from the synthetic difference-in-differences estimation with mortality rate as the outcome.

Figure A.11: Percent of Hospitals with Clinical Executives by State



Notes: This graph shows the percent of hospitals with a clinically trained executive in each state.

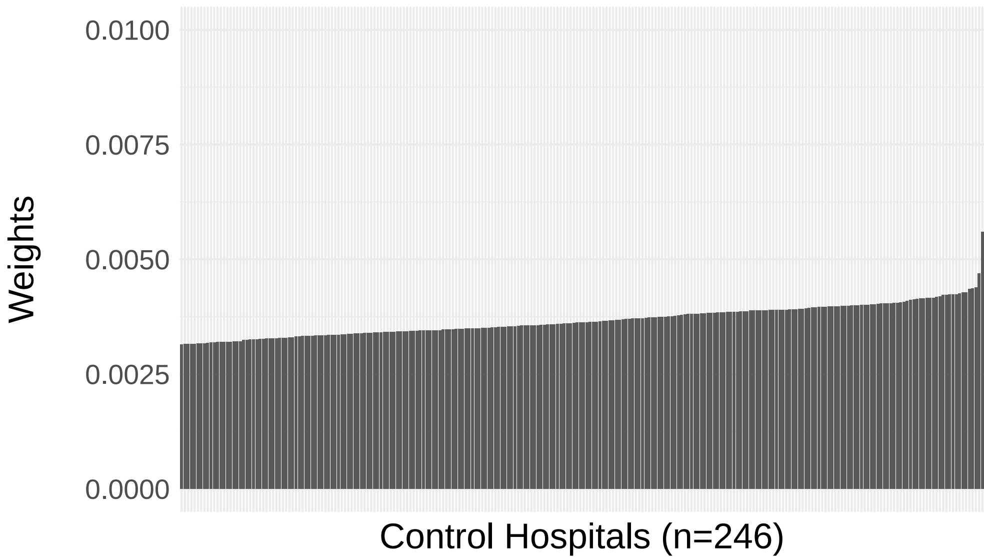
Table A.3: Summary Statistics by Hospital Type

Variable	Ever Clinical Exec	Always Clinical Exec	Never Clinical Exec	For-Profit
Hospital Characteristics				
Academic Med. Center	0.41	0.52	0.24	0.17
Number Beds	231	222	116	157
Physician Owned	0.01	0.02	0.02	0.19
System Affiliated	0.58	0.52	0.44	0.89
Executive Team				
Number Executives	4.85	5.25	3.11	
Fraction Clinical Execs	0.20	0.26	0.00	
Fraction Int. Medicine Execs	0.06	0.10	0.00	
Has a CMO	0.53	0.45	0.15	
Has Clinical CEO	0.25	0.11	0.00	
Penalty/Payment Variables				
Ever HVBP Incentive	0.79	0.75	0.62	0.87
Penalized for AMI	0.05	0.04	0.03	0.03
Penalized for HF	0.05	0.07	0.05	0.06
Penalized for Pneum.	0.08	0.09	0.05	0.06
Penalized for AMI + HF	0.06	0.05	0.04	0.06
Penalized for AMI + Pneum.	0.03	0.04	0.02	0.01
Penalized for HF + Pneum.	0.41	0.39	0.34	0.55
Penalized for All Conditions	0.30	0.27	0.22	0.36
Num. Hospitals	391	56	445	680

Table A.4: Summary Statistics by Specialty

Variable	Always Int Med Exec	Always Other Exec
Hospital Characteristics		
Academic Med. Center	0.61	0.49
Number Beds	343.84	181.61
Physician Owned	0.00	0.02
System Affiliated	0.57	0.58
Executive Team Characteristics		
Number Executives	5.89	5.13
Fraction Clinical Execs	0.27	0.27
Fraction Int. Medicine Execs	0.24	0.00
Has a CMO	0.60	0.39
Has Clinical CEO	0.20	0.10
Penalty/Payment Variables		
Ever Received HVBP Incentive	0.83	0.75
Penalized for AMI	0.07	0.06
Penalized for HF	0.07	0.06
Penalized for Pneumonia	0.03	0.12
Penalized for AMI + HF	0.07	0.06
Penalized for AMI + Pneumonia	0.07	0.02
Penalized for HF + Pneumonia	0.57	0.35
Penalized for All Conditions	0.43	0.20
Num. Hospitals	30	35

Figure A.12: Control Group Weights, Readmission and Baseline Case Mix



B HRRP and HVBP Programs

In October 2011, the Center for Medicare and Medicaid Services (CMS) released a set of rules under HRRP mandating penalties for hospitals with above average readmission rates. The goal of HRRP is to lower readmissions through better care coordination, less initial stay complications, and better post-care instructions. Beginning in October 2012, hospitals with higher readmission rates than the national average in pneumonia, heart failure, or AMI (after adjusting for demographic characteristics) receive a fixed lower reimbursement rate for all Medicare patients seen in their hospital. In 2015, CMS also included chronic obstructive pulmonary disease, coronary artery bypass graft surgery, and elective primary total hip arthroplasty and/or total knee arthroplasty as conditions which go into the penalty calculation (CMS 2023a).

Penalties are given in the form of a fixed rate reduction of 1-3% for every Medicare patient regardless of the condition. Further, CMS does not distinguish a necessary readmission from an avoidable readmission; any repeat hospital visit is included in the penalty calculation. Excess readmission rates are calculated using a rolling look-back period of 3 years to determine whether the hospital is penalized. Therefore, hospitals had incentive to react immediately once details of the program were announced in October of 2011.

The HVBP Program instead rewards hospitals with high quality or significant improvement in quality. Specifically, CMS deducts Medicare payments by 2% from all eligible hospitals, collects this sum, and divides it among the rewarded hospitals. Several quality and cost measures surround-

Figure A.13: Time Weights, Readmission and Baseline Case Mix

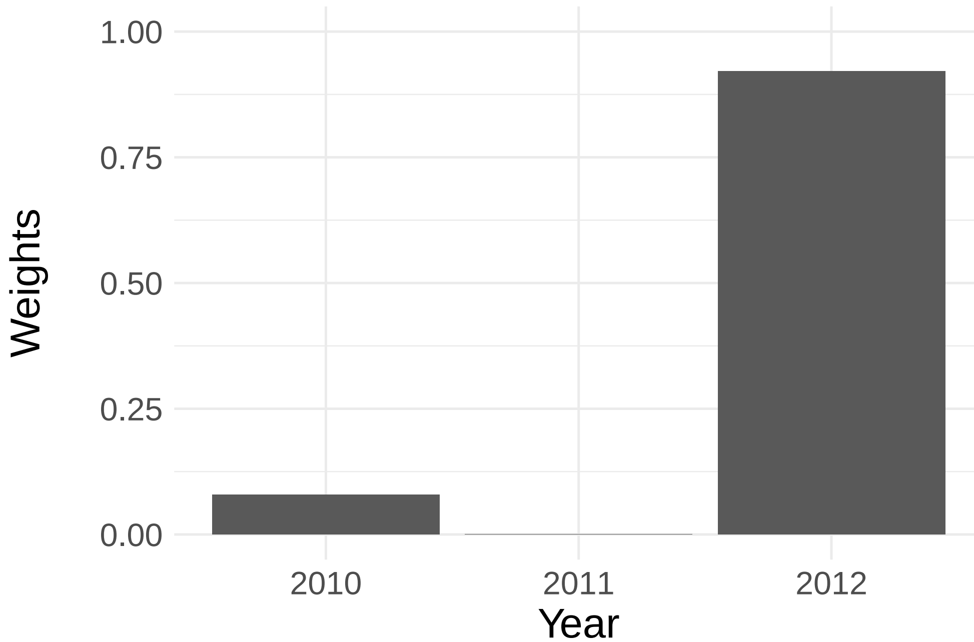


Figure A.14: Control Group Weights, Mortality and Baseline Case Mix

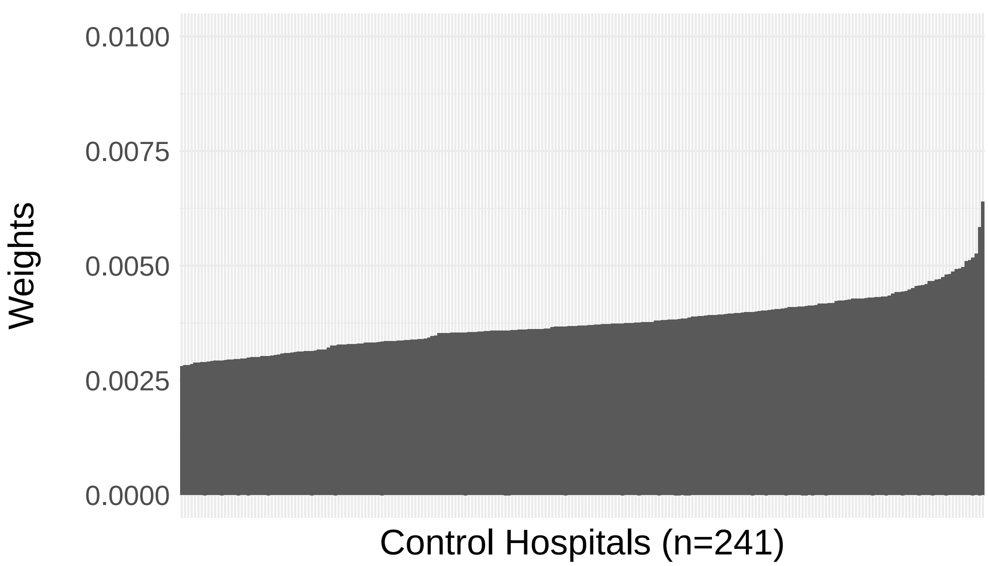
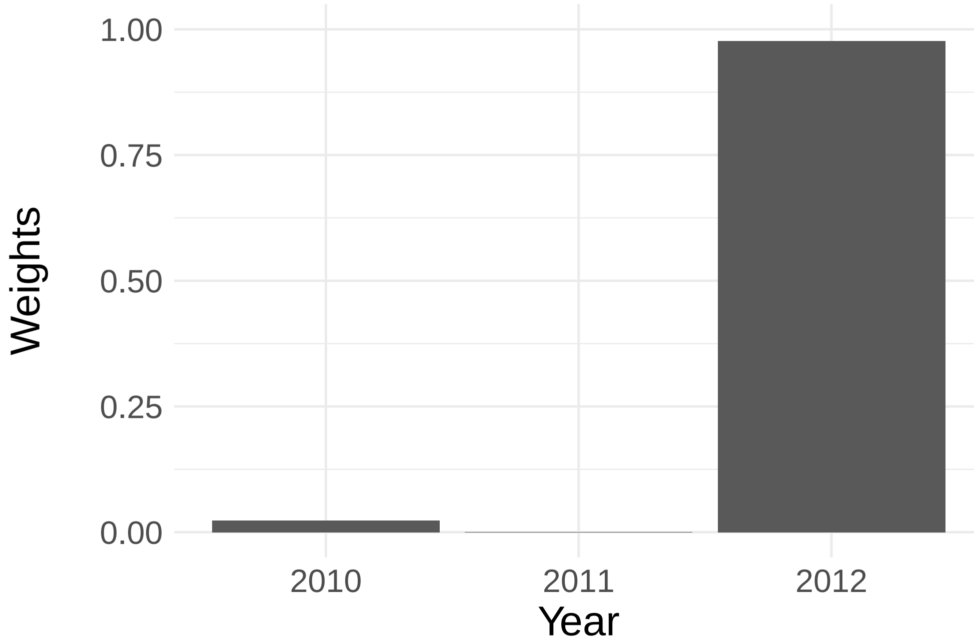


Figure A.15: Time Weights, Mortality and Baseline Case Mix



ing safety, efficiency, cost reductions, clinical outcomes, and community engagement are combined to create a single score metric for each hospital. Hospitals are then compared to the average and are rewarded for being above average quality or for showing improvement (CMS 2023b).

C Supplemental Analyses

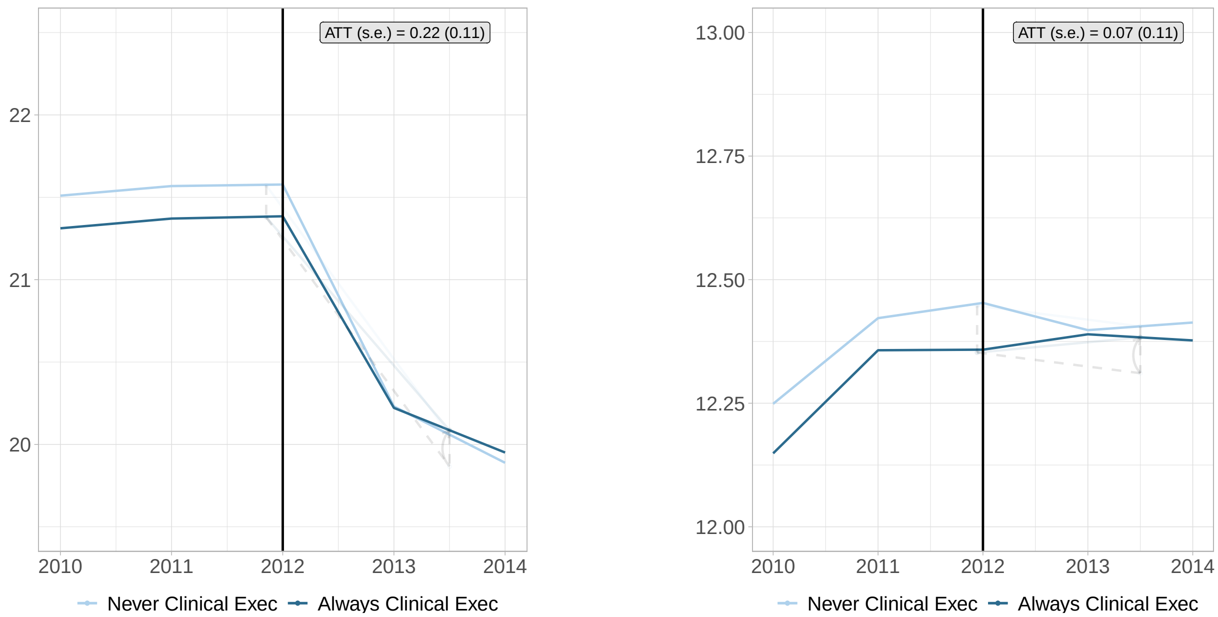
C.1 Including Nurses as Clinical Executives

Everything in this section is identical to the main analysis, apart from the definition of clinical executive. Here, I include executives labeled as a registered nurse in the tax forms as a clinical executives. These are relatively rare, as only of executives say they are a registered nurse. Unlike doctors, there is no publicly available database of all nurses, so the cost of verifying this type of clinical training is much higher. Therefore, in the main body of the paper I only consider doctor executives. However, the results when including nurses are identical, as I show in Figure A.16.

Figure A.16: Effect of Clinical Training on Readmission/Mortality Rates, Including Nurses

(a) Readmission Rates

(b) Mortality Rates



C.2 Intensive Margin, Controlling for Num. Executives

In Section 3, I present intensive margin results by binning hospitals according to the fraction of their executive team with clinical experience. There, when comparing hospitals with greater than the median (20%) to less than the median fraction of clinical executives, I find that the difference in response is driven by hospitals with a fraction greater than the median. One concern could be that this result is driven by a difference in the total size of hospital executive teams, the denominator of that fraction. In this section, I use the same estimating equation, but I limit to only nonprofit hospitals with 7 or less executives in total, removing outliers of executive team size. The results are shown in Figure **??**, and show that the response is still driven by hospitals with a fraction of clinical executives above the median.

I also present results with mortality as the dependent variable, shown in Figure **??**. These results do not differ from the main finding in that there is no statistical difference in response for hospitals with different types of leadership teams with above or below the median clinically trained executives.

Figure A.17: Effect of Clinical Training on Readmission Rates, Binned Treatment

(a) $\rho \leq \eta$ (b) $\rho > \eta$

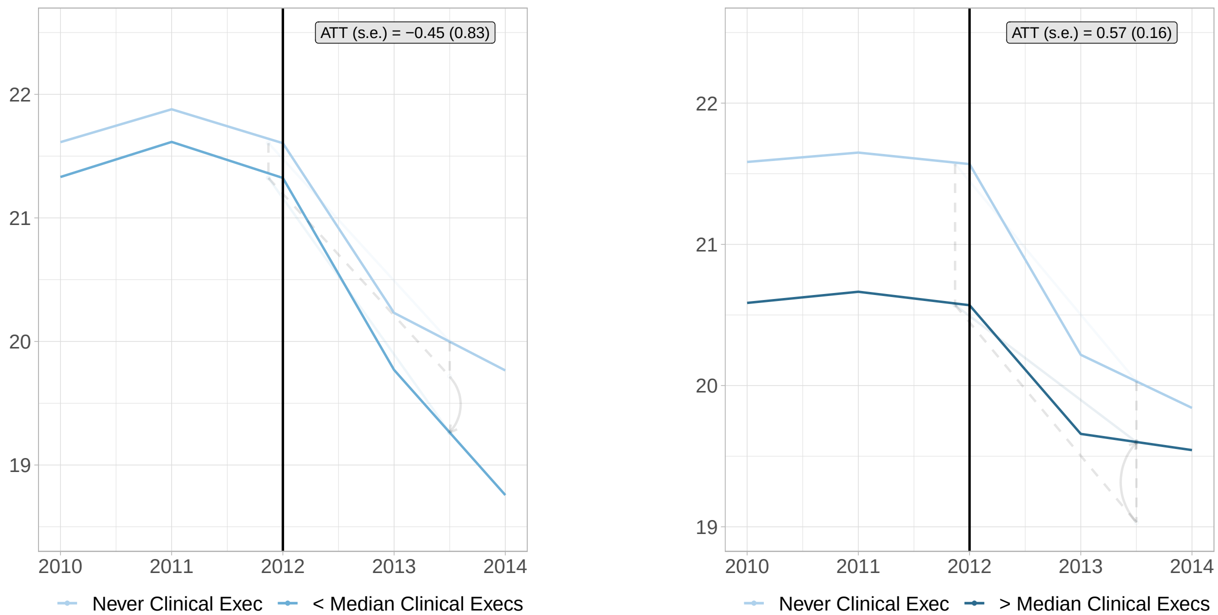
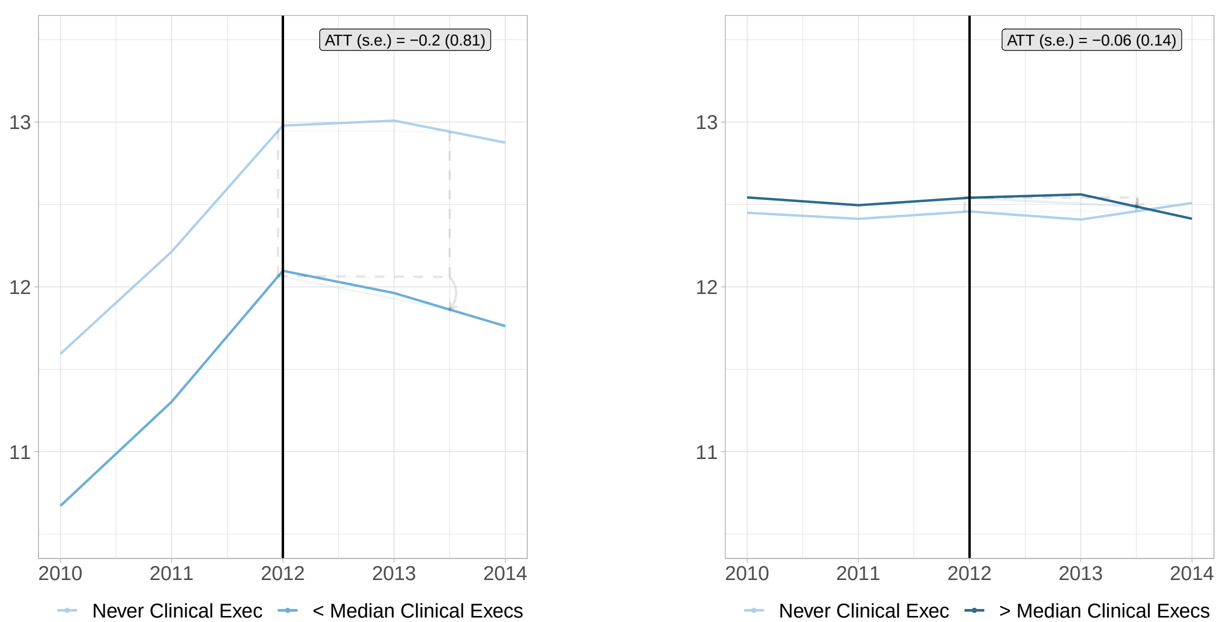


Figure A.18: Effect of Clinical Training on Mortality Rates, Binned Treatment

(a) $\rho \leq \eta$ (b) $\rho > \eta$



C.3 Results By Condition

In the main body of the paper, the main dependent variables I consider are weighted averages of readmission and mortality rates for several conditions relevant to the policy changes, weighted by the number of patients seen with each condition. Here, I investigate whether the findings are driven by any particular condition. The conditions I consider are heart attack (AMI), heart failure, and pneumonia, which are the conditions that go into the calculation for HRRP penalties. Thus, I consider the effect of clinically trained executives on readmission and mortality rates for each condition individually. I estimate equation 1 with these outcome variables.

I present the resulting estimates and standard errors in Table A.5. Columns (1)-(3) show results for readmission rate outcomes in each condition. The main finding, that clinically trained executives lead hospitals to have higher readmission rates after pay-for-performance policies, is primarily driven by patients with pneumonia. While magnitudes are positive for all conditions, pneumonia has the largest magnitude and is the only statistically significant estimate. Columns (4)-(6) present results for mortality rates of each condition. Similarly to the results for weighted average mortality, there are no statistically significant results here. However, pneumonia has the largest positive magnitude, just like pneumonia readmissions.

Table A.5: Effect of Clinically Trained Executive on Condition-Specific Readmission and Mortality Rates

	Readmission Rates			Mortality Rates		
	AMI	HF	Pneum.	AMI	HF	Pneum.
	(1)	(2)	(3)	(4)	(5)	(6)
Always Clinical Exec x Post Program	0.25	0.14	0.46**	-0.13	0.03	0.3
	(0.18)	(0.18)	(0.14)	(0.19)	(0.13)	(0.19)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1,135	1,640	1,635	1,300	1,640	1,635

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

C.4 Robustness to Other Estimations

In analyses presented in the main body of the paper, I use a synthetic difference-in-differences approach to identify the effect of clinically trained executives. I choose this as the main estimation strategy due to potential unobserved differences correlated with executive choice, where synthetic DiD assures parallel trends by choosing the optimal composition of control and treatment hospitals. As a robustness check, I now present results under three different estimation techniques for robustness: classic two way fixed effects, two-way fixed effects with manual weights that balance case mix index and penalties of hospitals with different leadership teams, and synthetic control.

For the manual weighting strategy, I apply the Coarsened Exact Matching (CEM) procedure as described by Azoulay, Graff Zivin, and Wang (2010). This approach involves grouping hospitals based on observable characteristics such as bed size, the number of patients in each relevant condition, and eventual HRRP penalty status in each relevant condition. Hospitals are then placed into bins according to these characteristics, and matches are made exactly between hospitals within the same bin. Hospitals that do not find an exact match in this process are excluded from the sample.

C.4.1 Effect of Clinically Trained Executives on Response to Financial Incentive on Quality

In Section 3, I first establish the effect of clinically trained executives on response to change in incentives on quality using a synthetic difference-in-differences approach. Now, I present results using various estimation techniques in Table A.6 in order to assess to robustness of this finding. Columns (1)-(3) present estimates and standard errors for the three estimations: TWFE, TWFE with matched sample, and synthetic control, respectively. For both TWFE and TWFE with matching, the magnitude is larger than that for synthetic DiD (0.27) and statistically significant. The estimate and standard error for synthetic control are very similar to those for synthetic DiD. In columns (4)-(6), I present the results for mortality rates, which confirm no differential response. This exercise supports the finding that clinically trained executives affect the readmission rate response of hospitals to change in incentives on quality.

Additionally, I estimate an event study version of the two way fixed effects specifications. The estimates and 95% confidence intervals are shown in Figure A.19. These confirm the main findings with slightly noisier estimates, and show that the difference in response in readmission rates occurs in 2013 and 2014, one and two years after the policy changes. The mortality results confirm the main findings, that there is no difference in response in mortality rates.

Table A.6: Effect of Clinically Trained Executive, Various Estimations

	Readmission Rate			Mortality Rate		
	TWFE	Matched	SC	TWFE	Matched	SC
	(1)	(2)	(3)	(4)	(5)	(6)
Ever Clinical Exec x Post Program	0.42**	0.65*	0.25	0.11	0.03	0.06
	(0.15)	(0.3)	(0.14)	(0.15)	(0.4)	(0.12)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	2,387	1,025	1,640	2,381	1,023	1,640

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

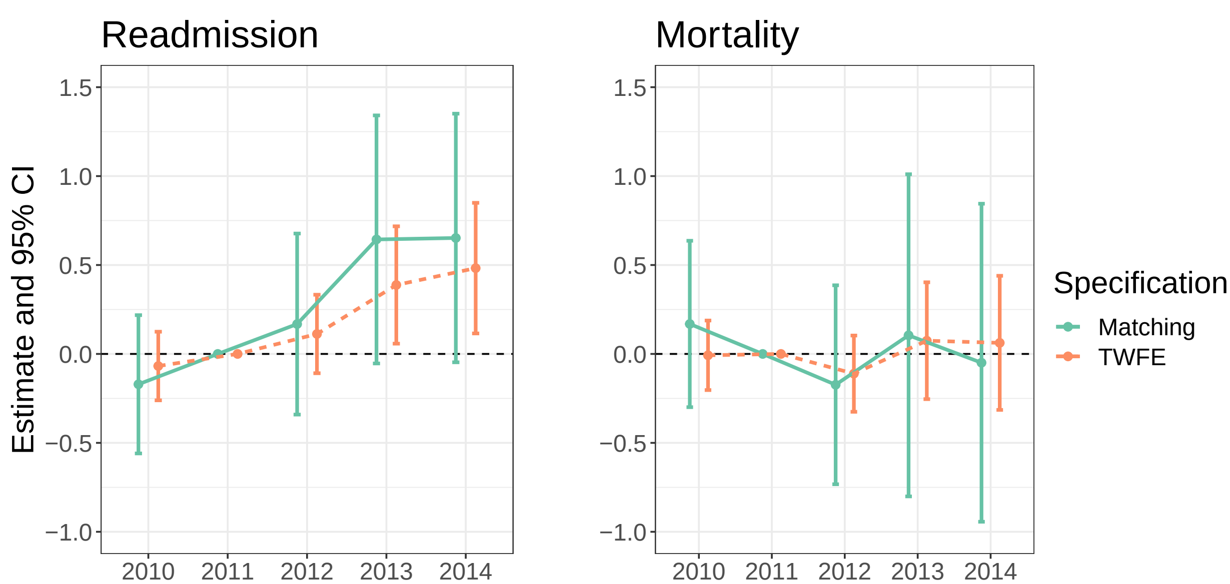


Figure A.19: Effect of Clinical Executives; Event Study Results

C.4.2 Are Clinical Executives Less Profit Driven?

In Section 4.2, I test empirically whether nonprofits with different leadership teams respond differently to the incentive change than for-profit hospitals using a synthetic difference-in-differences methodology. Here, I present results from various other estimation strategies. In Table A.7, I present estimates and standard errors with weighted average readmission rate as the outcome. These results confirm what is shown in the main body of the paper, that nonprofits without clinically trained executives act similarly to for-profits, but nonprofits with clinically trained executives do not.

Table A.7: Compare For-Profit to Types of Leadership (Readmission Rates), Various Estimations

	Compare to Always Clinical Exec			Compare to Never Clinical Exec		
	TWFE	Matched	SC	TWFE	Matched	SC
	(1)	(2)	(3)	(4)	(5)	(6)
For-Profit x Post Program	-0.37*	-0.28	-0.43*	-0.03	-0.08	0.09
	(0.15)	(0.44)	(0.19)	(0.07)	(0.12)	(0.1)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	2,660	660	2,660	3,820	1,790	3,820

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

While the results in the main body of the paper for mortality rates as the dependent variable do not indicate differences in response, I still present the estimates from other estimations in Table A.8. These results do not contradict what I show in the main body of the paper, as I still see small and statistically insiginificant estimates.

Table A.8: Compare For-Profit to Types of Leadership (Mortality Rates), Various Estimations

	Compare to Always Clinical Exec			Compare to Never Clinical Exec		
	TWFE	Matched	SC	TWFE	Matched	SC
	(1)	(2)	(3)	(4)	(5)	(6)
For-Profit x Post Program	0.03	0.09	-0.16	0.06	0.05	0.03
	(0.14)	(0.45)	(0.2)	(0.07)	(0.11)	(0.1)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	2,660	660	2,660	3,820	1,790	3,820

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

C.4.3 Signaling vs. Managing Decomposition

In Section 4.1, I test empirically whether clinical executives make a difference because of a signaling or managing effect. That is, I leverage the timing of hiring clinically trained executives. Here, I present results from the same specification, but various estimation strategies. In Table A.9, I present estimates and standard errors with weighted average readmission rate as the outcome. These results confirm what is shown in the main body of the paper, that the managing effect is driving the findings.

Table A.9: Signaling vs. Managing Decomp. (Readmission Rates), Various Estimations

	Signaling Effect			Managing Effect		
	TWFE	Matched	SC	TWFE	Matched	SC
	(1)	(2)	(3)	(4)	(5)	(6)
Estimate	0.03	0.18	-0.04	0.25*	0.26	0.18
	(0.08)	(0.16)	(0.08)	(0.11)	(0.22)	(0.11)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	3,005	670	3,005	1,595	320	2,040

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

While the results in the main body of the paper for mortality rates as the dependent variable do not indicate differences in response, I still present the estimates from other estimation strategies in Table A.10. These results do not contradict what I show in the main body of the paper, as I still see small and statistically insiginificant estimates. Therefore, there is no opposing signaling vs. managing effect.

Table A.10: Signaling vs. Managing Decomp. (Readmission Rates), Various Estimations

	Signaling Effect			Managing Effect		
	TWFE	Matched	SC	TWFE	Matched	SC
	(1)	(2)	(3)	(4)	(5)	(6)
Estimate	-0.01	-0.23	0.02	0.14	-0.05	0.11
	(0.08)	(0.18)	(0.06)	(0.11)	(0.28)	(0.08)
Hospital FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	3,005	670	3,005	1,595	320	2,040

Standard errors are clustered at the hospital level.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1