

Balancing Workforce Fissuring and Service Quality: Evidence from Dialysis Operations

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The increasing use of fissured workforces in core operational roles challenges conventional assumptions about workforce design and service quality. Using panel data from 3,914 U.S. dialysis facilities between 2016 and 2020, we examine how the proportion of contract registered nurses (RNs) affects care quality. Drawing on relational coordination and organizational information-processing theories, we hypothesize an inverted U-shaped relationship in which quality initially improves through the infusion of external knowledge but is eventually offset by rising coordination and information-processing needs. To address endogeneity, we employ a control-function design that combines an external peer-market instrument with a heteroskedasticity-based restriction. Results from our analyses support this nonlinear relationship. We also show that high support intensity from patient care technicians mitigates coordination frictions, elevating the quality peak and shifting the quality-maximizing turning point to the right. Conversely, high patient severity increases information load and relational strain, shifting the turning point to the left, although we do not find a significant change in the quality peak, indicating that the value of fissured staffing is bounded rather than uniformly beneficial or harmful. Our results demonstrate that fissured workforces can be strategically deployed in high-skill core operations, provided there is sufficient relational capacity to manage compounding coordination costs.

KEYWORDS

dialysis, fissured workforce, healthcare operations, service quality, relational coordination

1 | INTRODUCTION

Over the past decade, healthcare organizations have increasingly relied on fissured employment to cope with workforce shortages by offloading non-essential activities to external providers. Fissured employment refers to positions that are outsourced or delegated to independent providers, temporary agencies, or third parties. Under these arrangements, individuals are contracted

to work outside the traditional boundaries of the firm while leading organizations exert strict control over work standards and brand reputation through detailed requirements (Handley, 2012; Weil, 2014). For example, the proportion of healthcare facilities employing contract nurses through staffing agencies doubled from 23% in 2018 to nearly 50% in 2022 (Bowblis et al., 2024). Fissured employment provides organizations with staffing flexibility and access to specialized expertise, enabling them to respond quickly to fluctuations in demand and skill requirements, particularly in industries with seasonal or volatile workloads such as healthcare and hospitality. However, this model also introduces significant challenges, including coordination difficulties, loss of organizational knowledge, and potential declines in service quality. These risks are particularly pronounced in healthcare, where care delivery relies heavily on specialized skills and team-based collaboration. As the healthcare industry increasingly embraces a fissured workforce, healthcare organizations face challenges such as coordination and fragmented employment relationships, which can weaken team cohesion and impede the sharing of critical knowledge about organizational processes and individual patients. Hence, understanding how a fissured workforce affects service quality is essential in contexts that require specialized expertise and complex coordination (Handley and Benton Jr, 2009).

In addition to peripheral low-skill functions such as administrative support, catering, and logistics, workers under fissured arrangements can also undertake high-skill core activities and actively participate in an organization's internal processes and team collaborations. Here, we define low-skill peripheral jobs as those that require only short training or certifications (i.e., no need for formal education) and are not authorized for high-stakes decisions at work. In contrast, high-skill core jobs require extensive formal education at colleges and graduate schools, along with significant supervised training, and are authorized to design and execute plans and hold accountability for high-stakes decisions. Studies in Operations Management (OM) literature have focused primarily on fissured workforces in low-skill peripheral jobs, and research on how the fissuring of high-skill core jobs affects service quality remains limited (Weil, 2014). This gap is particularly salient in healthcare operations, where care delivery depends on continuous coordination between specialized professionals, real-time adaptation to patient conditions, and the preservation of facility-specific knowledge (Mishra et al., 2020; Tucker et al., 2007).

We chose to study outpatient hemodialysis operations because they provide an ideal setting to examine the operational consequences of a fissured workforce. Outpatient hemodialysis facilities frequently employ contract registered nurses (RNs) specialized in nephrology (hereafter, contract RNs), a highly skilled segment of the fissured workforce, as integral members of the clinical team alongside nephrologists (specialist physicians) and patient care technicians (PCTs). According to our panel data on U.S. dialysis facilities from 2016 to 2020, these facilities exhibit substantial variation in their use of contract RNs, providing a solid foundation for robust statistical analysis. Furthermore, dialysis treatment requires repeated visits over an extended period and is typically delivered through RNs working closely with PCTs, with RNs providing clinical oversight and PCTs performing routine support tasks. The structural design of dialysis care creates a unique setting in which coordination between RNs and PCTs is essential for delivering safe and effective care (Havens et al., 2018). While the Centers for Medicare & Medicaid Services (CMS) regulatory frameworks mandate that a designated, accountable governing body maintains ultimate clinical accountability, the operational reality is that nephrologists typically act as intermittent consultants, dividing their time across a geographically dispersed network of clinics and hospitals (Centers for Medicare & Medicaid Services, 2008; Slinin et al., 2014). Consequently, the high-velocity, day-to-day execution of treatments, as well as the immediate response to clinical contingencies, depends on the unit's staffing configuration and relational coordination between RNs and PCTs. Our study focuses on facility-level use of contract RNs and clinical quality, examining how variation in staffing configuration shapes relational coordination and unit-level quality outcomes.

This paper addresses the following research questions: How does the share of contract RNs among all RNs (contract RN ratio, or CRR hereafter) affect clinical quality? How is this relationship further moderated by contextual factors in dialysis facilities, including support intensity (i.e., PCT full-time equivalents (FTEs) per patient served) and patient severity (i.e., the share of patients with hemoglobin (Hgb) outside the recommended range)? Our results suggest that CRR and clinical quality exhibit an inverted U-shaped relationship, with the optimal quality occurring at a fissuring level of around 6.9%. Drawing on

relevant healthcare literature about team-based care, adding new members to a team can introduce complementary skills and fresh perspectives while also challenging established routines, thereby increasing cognitive diversity and stimulating knowledge sharing (March, 1991; Tjosvold et al., 2004). When strong integration processes are in place, contract RNs can refresh the collective knowledge base, promote innovation, and improve performance (O'Connor et al., 1993; Li and van Knippenberg, 2021). On the other hand, relational coordination theory suggests that effective service delivery in interdependent settings requires shared goals, mutual knowledge, timely communication, and capacities that develop through sustained collaboration (Hoffer Gittel, 2002; Havens et al., 2018). Excessive use of contract RNs undermines these mechanisms, depleting the knowledge base and coordination, thereby compromising the quality of dialysis treatments. The observed inverted U-shaped relationship between CRR and service quality reflects the interplay of these dynamics.

Our empirical analysis reveals that the relationship between workforce fissuring and service quality is subject to the unit's structural and clinical context. Specifically, we find that higher support intensity, as measured by PCT coverage, increases the unit's potential to maximize clinical quality. The results suggest that PCTs act as a knowledge and coordination buffer, providing operational continuity and facility-specific knowledge, thereby mitigating the potential adverse effects of contract RNs and enabling facilities to achieve better quality even with higher CRRs. In contrast, patient severity acts as a performance constraint, limiting the unit's potential to maximize clinical quality. This pattern reflects the increased information load and tighter interdependencies inherent in managing unstable patients. In high-severity environments, the unit lacks the cognitive slack required to absorb the coordination friction introduced by contract RNs. Consequently, the relational and facility-specific knowledge gaps associated with contract RN use become consequential sooner, leading to performance decline at lower levels of fissuring (Huckman and Pisano, 2006; KC and Terwiesch, 2011). These findings collectively demonstrate that the value of fissuring in healthcare operations is not uniform but contingent on the intensity of organizational support structures and the complexity of the service context.

This study makes several contributions to the literature. First, it demonstrates that clinical quality follows an inverted U-shaped pattern as CRR increases, challenging linear assumptions about the effects of fissuring and highlighting the operational trade-offs inherent in fissured workforce design (Weil, 2014). Second, it identifies organizational conditions that enable the effective use of a fissured workforce in high-skill core roles, suggesting that support staff act as critical safeguards against knowledge loss and coordination breakdown. Third, it reveals that higher patient severity limits the effective use of contract RNs by increasing information load and coordination costs. The findings advance our understanding of how firms can design resilient operations despite the fragmentation of the workforce and address recent calls for research on managing capability erosion in fissuring settings (Handley, 2012; Mishra et al., 2020; Peng et al., 2023).

2 | LITERATURE REVIEW

This section develops the theoretical basis for understanding how fissuring in high-skill core roles affects performance in team-based care. We draw on the relational coordination theory to identify mechanisms that shape knowledge retention and team coordination. These mechanisms form the foundation of our conceptual framework, which we use to develop hypotheses for the dialysis context.

2.1 | High-Skill Core vs. Low-Skill Peripheral Roles in Dialysis Facilities

The healthcare industry is highly specialized and hierarchically structured. Physicians and RNs are considered high-skill jobs due to extensive formal education, significant supervised training, and accountability for clinical decisions. Physicians, including surgeons, upon completing medical training as MD/DOs, continue with residency and fellowships before establishing

their specialties. RNs complete accredited nursing programs, pass the national exam, and hold state licenses, with many subsequently pursuing specialty certifications or graduate training. In the dialysis setting, kidney physicians (nephrologists) direct patient treatment with advanced training in kidney diseases. Patients typically begin dialysis under treatment plans prescribed by nephrologists, who are not continuously present during routine dialysis treatments. Nephrology nurses are licensed RNs specialized in the care of patients with kidney failure. They are responsible for working with nephrologists to ensure that prescribed medications and treatment are administered correctly. As suggested by clinical guidelines from CMS (Centers for Medicare & Medicaid Services, 2004), nephrology nurses are required to present at dialysis centers to oversee dialysis processes on a daily basis. Specifically, they are responsible for monitoring labs and assessing patients, assuring that patients' medications and treatment are administered correctly, implementing protocol-based erythropoiesis-stimulating agent (ESA)/iron dose changes, checking for bleeding or infection, and coordinating with nephrologists. Nephrology nurses also supervise daily dialysis processes, including PCTs' execution of the treatment plan. This structure positions nephrology nurses as the primary high-skill core clinical decision-makers at dialysis facilities, bridging physicians' medical prescriptions with frontline operational execution. They also educate patients on adherence, side effects, and follow-up testing. Nephrologists and nephrology nurses, regulated by distinct accreditation bodies, specialize in kidney disease management and bear primary responsibility for clinical (i.e., core) decision-making, including treatment eligibility and medication protocols. Given nephrologists' limited presence at dialysis centers, we focus on nephrology nurses as the primary high-skill core providers in our study context.

By contrast, low-skill peripheral roles perform technical and support functions under the clinical supervision of high-skill core roles. Such roles require shorter certification programs (e.g., 18 months post-high school for technicians (Centers for Medicare & Medicaid Services, 2009)) rather than extended formal medical education and clinical training. In general healthcare settings, technicians and nursing assistants execute delegated orders under RNs and physicians' supervision without authority to modify treatment plans or exercise independent clinical judgment (Cahill et al., 2021). The separation of high-skill core and low-skill peripheral roles is consistent with established labor hierarchies in the medical literature, based on training duration, license requirements, and decision-making autonomy (Yu and Wijesekera, 2013; Plantinga et al., 2024). In the dialysis setting, PCTs serve a low-skilled peripheral role by preparing dialysis machines between treatments, starting and ending dialysis sessions, recording patients' vital signs, and reporting acute changes such as hypertension and bleeding to RNs, but are not authorized to adjust doses or treatments. While outpatient centers utilize various support roles (e.g., nursing assistants, dietitians, and social workers), these positions focus on non-clinical tasks and are not considered part of the core clinical team in dialysis operations (Centers for Medicare & Medicaid Services, 2008; Cahill et al., 2021). Consequently, outpatient hemodialysis services are typically delivered with RNs and PCTs as the primary frontline clinical workforce (Webb and Wish, 2024).

2.2 | Team-based Care

Since the publication of *To Err is Human* (Institute of Medicine, 1999), the healthcare industry has increasingly recognized the value of the team-based care approach. A decade later, the Institute of Medicine (IOM) affirmed this trend, stating, "Team-based care is one of the guiding principles of a learning health system" (McGinnis et al., 2011). According to the Agency for Healthcare Research and Quality (AHRQ), "the primary goal of medical teamwork is to optimize the timely and effective use of information, skills, and resources by teams of health care professionals for the purpose of enhancing the quality and safety of patient care" (Agency for Healthcare Research and Quality, 2014). The medical literature has shown that team-based care reduces medical errors, improves patient outcomes, and manages chronic diseases at lower costs (Meyers et al., 2019). For example, team-based care for type 2 diabetes delivers better care with improved glucose, blood pressure, and lipid levels (Levensgood et al., 2019). After comparing primary care delivered through integrated team-based practices and traditional practice at Intermountain Healthcare, Reiss-Brennan et al. (2016) claimed that the former care model led to better quality of care, lower acute care utilization, and reduced payments. Based on a systematic review of published studies between 2000 and 2015, Welp and Manser (2016) conclude

that teamwork in hospitals improves patient outcomes and clinical occupational well-being.

Team-based care usually consists of a team of members with complementary skills who divide work among themselves, collaborate, and coordinate to co-deliver shared goals (Institute of Medicine, 2007; Edmondson, 2012). In a typical surgery, the attending surgeon performs incisions and grafts, with instruments passed by the scrub technician, while the anesthesiologist monitors medications/vital functions and the surgical assistant sutures and controls bleeding. Although each member performs distinct jobs, their work is orchestrated to ensure a successful surgical operation. Divided work, however, forces organizations to tackle the coordination challenges that come with operating under uncertainty (Galbraith, 1973), which is naturally embedded in healthcare operations. To address coordination issues, organizations typically resort to hierarchy by empowering managers to allocate work to subordinates and hold them accountable through supervision, thereby improving information processing capacity (Lawrence and Poliquin, 2023). In the healthcare setting, such hierarchical relationships include physician-nurse, attending physician-resident, nurse-technician, etc., in which members are ranked by disciplines and authorities. In the above surgery example, the attending surgeon dictates task assignments and the surgical team defers to the surgeon's directives. More broadly, in any tightly coupled clinical team, these same coordination demands make fissuring in high-skill core roles especially consequential, a point we develop next.

2.3 | Team-based Care with Fissured High-Skill Core Roles

Originally confined to low-skill peripheral roles, such as cleaning, maintenance, and food service (Kalleberg, 2000; Weil, 2014), the fissured workforce has spread to high-skill core roles in professional services, R&D, IT, and clinical services (Weil, 2014; Boston-Leary et al., 2024). This shift brings strategic and operational benefits: flexible scaling, reduced labor costs, and access to external expertise without internal development (Holcomb and Hitt, 2007). Related OM evidence on part-time service work likewise shows that workforce composition is an operational design choice with measurable performance consequences (Sharma et al., 2024). Managers, under pressure to prioritize core competencies, are increasingly fissuring even complex tasks to focus on what the firm does best (Weil, 2014; Abraham and Taylor, 1996). In a recent survey study by KPMG, healthcare executives also cited cost, care quality, and relevant experience as the top three factors for employing contracted RNs, with 17% planning to increase the share of contract RNs by 5% in the next 12 months (KPMG, 2026).

2.3.1 | Relational Coordination

We ground our theoretical development in Relational Coordination (RC) Theory, which posits that in work systems characterized by high interdependence, uncertainty, or time sensitivity, success depends not only on formal processes and individual skills, but also on the quality of relationships among team members (Hoffer Gittell, 2002; Gittell et al., 2010). High levels of RC are characterized by common goals, shared knowledge, and mutual respect, reinforced by frequent, timely, and solution-oriented communication. These relational conditions build trust and shared understanding, allowing team members to synchronize their actions and adapt rapidly to changing environments. Through this RC lens, fissuring in high-skill core roles, despite its benefits, can affect team performance by altering the relational structures through which the team-based care is coordinated and delivered.

Effective coordination requires a level of relational investment that is often precluded by the structural constraints of fissured work. A fissured workforce, such as contract RNs, exhibits two key characteristics that undermine RC's core mechanisms. First, they are employed by third-party staffing agencies rather than the clinics/hospitals where they work (i.e., their compensation and benefits are handled by staffing agencies). This separation between the employment relationship and the site of care delivery can complicate the alignment of facility-specific training, accountability, work expectations, and communication practices across organizational boundaries (Wilkin et al., 2018; Health Services Safety Investigations Body, 2024). This separation is definitional rather than incidental: Medicare cost reports classify staffing by who issues the IRS Form W-2, separating the facility's payroll

employees from contracted staff supplied under external agreements (Centers for Medicare & Medicaid Services, 2011). Agency-supplied nurses, including travel nurses, therefore enter our setting as contract labor, and such agency arrangements fall within fissured employment as work delegated to temporary agencies while the facility retains control over operating standards (Weil, 2014). Second, contract staffing can involve short or fixed-term assignments intended to address staffing gaps, although HCRIS does not identify contract type or duration. Agency and travel-nursing arrangements often follow fixed cycles (CoreMedical Group, 2025), and the lack of assignment continuity forces facilities to repeat orientation and integration for new contractors.

Such cross-boundary arrangements lead to transactional and corrective communication (i.e., focused on immediate task remediation) at the expense of proactive and anticipatory communication that high-performance teams require (Health Services Safety Investigations Body, 2024; Wilkin et al., 2018). RC relies heavily on the interpersonal accumulation of “tacit knowledge” of local micro-routines, unit-specific technologies, and idiosyncratic patient histories. Low assignment continuity may cause limited relational knowledge of the unit’s specific nuances. This familiarity gap increases coordination friction within the unit, as the lack of a shared mental model necessitates frequent clarifications and raises coordination costs (Teekens et al., 2023; Lazar et al., 2022).

As RC weakens, the likelihood of misaligned actions, delayed responses, and safety lapses increases, especially in settings where patient conditions can change during treatment and errors carry serious consequences, such as in outpatient dialysis facilities (Mishra et al., 2020). Research shows that when tasks are complex or tightly coupled, teams with strong relational coordination are more resilient to disruptions, as members proactively fill gaps for one another, communicate emergent issues promptly, and coordinate responses smoothly through shared understanding (Faraj and Xiao, 2006; Huckman et al., 2009).

Ultimately, the sustainability of these relational processes depends on the continuity of the social interfaces that facilitate coordinated action, and in turn, on the team’s coordination capacity. In our setting, this continuity takes the form of recurring coordination between the RN and PCT roles. The collaboration allows for the accumulation of shared knowledge and the refinement of intuitive, trust-based coordination routines, hence enhancing coordination capacity. Fissuring can place pressure on these interfaces by increasing the need to integrate externally employed RNs into established facility workflows (Hoffer Gittel, 2002; Bolton et al., 2021). When the integration demands exceed the facility’s coordination capacity, interpersonal exchanges become delayed and reactive, undermining the team’s ability to maintain safety and efficiency (Starmer et al., 2023, 2014). Building on this RC perspective, we examine how contextual knowledge is created and anchored within the dialysis unit, focusing on the roles of support staff and patient severity in sustaining the dialysis unit’s relational integrity and coordination capacity.

2.3.2 | Contextual Knowledge

In hierarchical relationships, where high-skill core roles supervise low-skill peripheral roles in performing routine tasks, fissuring of high-skill roles introduces an asymmetry between formal authority and situational expertise. Contract RNs who are newly assigned to a facility initially possess less facility-specific knowledge of operational routines, specialized equipment, or idiosyncratic cultural norms. Although newcomer entry can initially prompt staff to articulate and codify tacit knowledge and improve unit-specific routines, these benefits may erode over time as the use of fissured roles increases (Zollo and Winter, 2002). This “learning-by-teaching” phase often represents a costly disruption in high-reliability healthcare settings. These dynamics reflect three conceptually distinct channels through which contract staffing operates: the general clinical expertise that contract RNs bring, the cross-facility learning transferred through exposure to other sites, and the facility-specific contextual familiarity that develops only through repeated local practice. The first two channels travel with the individual RN, but the third does not: a permanently employed RN accumulates and retains facility-specific familiarity, whereas a newly assigned contract RN must rebuild it during each engagement and largely forgoes it once the contract ends. The adaptation burden is therefore prolonged by the cross-boundary employment arrangement, which repeatedly resets this facility-specific channel. For instance, the use of agency nurses has been associated with a 6.4% increase in pressure ulcers, a critical nurse-sensitive safety indicator (Pittman

et al., 2025). Such evidence shows how gaps in unit-specific knowledge can translate directly into adverse patient outcomes.

In comparison, low-skilled peripheral roles such as PCTs usually work on the frontline, interacting with patients, operating equipment, and communicating with other staff on a daily basis. Over time, they accumulate first-hand tacit knowledge, such as patient preferences (e.g., pain tolerance, chair positions), equipment configurations, handoff procedures, and other nuances that can be difficult to document. Given the repetitive nature of dialysis (i.e., 2–3 weekly treatments over months to years), this context and patient-specific knowledge are critical to ensuring smooth and individualized treatment. When continuity in the supervisory RN role is lower, critical unit-specific knowledge is disproportionately held by PCTs. As a result, PCTs must provide extensive local guidance to the supervisor. The additional upward clarification cycles create process frictions in a workflow designed primarily for downward delegation, which can increase the likelihood of execution errors (Parmigiani, 2007).

As a complement to the RC theory, Organizational Information Processing Theory (OIPT) provides a structural lens on why process frictions are problematic in high-severity patient cases. OIPT posits that task complexity dictates the volume and variety of information that must be processed during execution (Galbraith, 1974, pp. 28). In clinical settings, this complexity encompasses not only information volume and individual tasks but also their interconnections and communication demands (Ding and Peng, 2022). As a patient's severity increases, the "information load" on the focal care team rises significantly, requiring a corresponding increase in processing capacity (Gardner et al., 2015). When fissured core RN roles are accompanied by gaps in facility-specific contextual knowledge, part of the unit's information-processing capacity must be devoted to bridging those gaps, leaving less bandwidth available for patient-care demands. While PCTs might attempt to fill gaps with tacit and unit-specific knowledge, it is unclear whether expanding peripheral roles can systematically offset the information overload induced by the fissuring of high-skill roles.

In this paper, we argue that organizations can design structural safeguards to preserve tacit knowledge and protect coordination capacity even when high-skill core roles are fissured (Handley, 2012; Parmigiani, 2007). In healthcare settings, one such safeguard is maintaining a relatively stable peripheral base that serves as a repository and buffer for institutional know-how (Handley, 2012). Within dialysis units, PCTs serve the peripheral roles and are directly employed by providers, performing daily operational tasks. The relatively stable group of PCTs retains the majority of tacit knowledge, allowing incoming contract RNs to draw upon for guidance on routines and handoff processes. This arrangement may reduce the recurring facility-specific familiarization burden and facilitate more consistent information exchange, allowing dialysis units to unlock the benefits of a fissured workforce without compromising care quality. As fissuring has shifted from a peripheral cost-saving tactic to a central operational strategy, balancing contractor flexibility with the preservation of institutional knowledge and relational coordination has become a key challenge in managing quality-critical, interdependent work systems.

3 | HYPOTHESES DEVELOPMENT

Building on the theoretical mechanisms outlined in Section 2, we now theorize how fissuring of high-skill core roles shapes clinical quality in outpatient hemodialysis facilities and how two contextual conditions, support intensity and patient severity, affect this relationship.

3.1 | Empirical Context: Workflow in Outpatient Hemodialysis Centers

Outpatient hemodialysis centers provide life-sustaining treatment to patients with end-stage renal disease through a standardized process that requires intensive coordination among care team members. Building on the role definitions and the RN–PCT structure established in Section 2.1, the daily operations of outpatient hemodialysis depend primarily on the coordinated efforts of RNs and PCTs. Their typical workflow is illustrated in Figure 1. At the start of a treatment session, the RN assesses the patient's

pretreatment condition and carries out the dialysis prescription, such as ultrafiltration parameters and medication administration, according to the physician’s orders. Meanwhile, the PCT prepares the dialysis machine and supplies. Under the RN’s supervision, the PCT cannulates vascular access and initiates treatment (Plantinga et al., 2024). During dialysis, the PCT monitors vital signs and machine settings, makes routine adjustments, and documents care, while the RN oversees progress and intervenes if complications arise (Cahill et al., 2021). After treatment, the PCT disconnects the patient and secures the access site, followed by the RN’s post-treatment evaluation. The shaded area in Figure 1 highlights urgent situations in which complications, such as sudden hypotension, vascular access issues, or machine alarms, require immediate RN intervention.

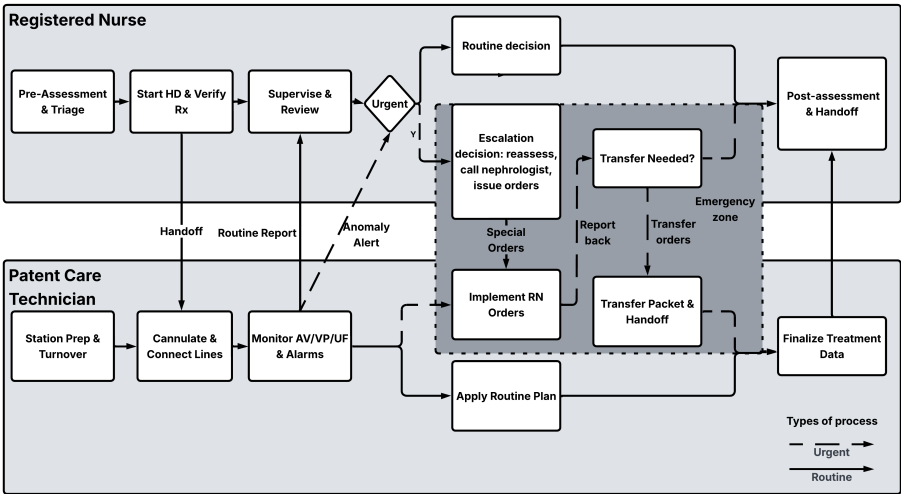


FIGURE 1 Typical Workflow of an Outpatient Hemodialysis Session

Patient-care assignments are typically organized at the shift level, with PCTs monitoring several assigned patients and RNs overseeing the broader treatment process across patients and frontline staff. This division of labor results in a tightly coupled workflow, with RNs assuming responsibility for clinical oversight and medication administration, and PCTs handling technical tasks such as machine setup and cleanup, vascular access cannulation, and patient monitoring (Cahill et al., 2021). Because PCTs monitor an average of about ten patients per shift while RNs coordinate clinical oversight across the shift, the workflow requires frequent handoffs and information exchange between the two roles (Plantinga et al., 2024). In cases where patients develop acute conditions, including toxic imbalances and volume overload, the demand for rapid coordination is even more pronounced (Yu and Wijesekera, 2013). By working with the same patients three times a week (National Kidney Foundation, 2025), the repeated RN–PCT encounters allow team members to become familiar with each other’s communication patterns and preferences, building trust and a strong base of shared knowledge (Hayes et al., 2015). Over time, these repeated working relationships support consistent treatment adherence and improve overall compliance (Gittell et al., 2008).

Driven by rising operating expenses and staffing shortages, dialysis centers increasingly rely on contract RNs (Plantinga et al., 2024). Although contract RNs can bring external expertise from other facilities, lower assignment continuity under contract-staffing arrangements can increase the need for facility-specific onboarding and relational integration. Here, onboarding refers to the process by which a newly assigned RN becomes familiar with local treatment protocols, equipment and documentation routines, patient histories, shift-level work allocation, escalation channels, and RN–PCT handoff practices. Until such familiarity is established, the care team relies more heavily on explicit clarification and information exchange. It also becomes more difficult to engage in anticipatory coordination, which in this setting refers to communicating emerging patient- or equipment-related

cues, such as downward blood-pressure trends or abnormal machine readings, before they develop into alarms or complications requiring immediate RN intervention. Prior work suggests that deficits in relational coordination and tacit knowledge contribute to delayed responses in urgent situations, communication breakdowns, and increased risk of medical errors (Thomas-Hawkins et al., 2008). Therefore, the combination of technical complexity, frequent high-stakes team interaction, and stringent safety requirements in dialysis care makes it a suitable context to study how workforce composition and varying degrees of fissuring affect service quality (Pisano et al., 2001; Tucker et al., 2007).

3.2 | Impact of CRR on Clinical Quality

As we discussed earlier, the introduction of contract RNs at a low-level fissuring setting serves as a catalyst for knowledge codification, which arises not only from assignment discontinuity but also from the cross-organizational nature of contract staffing. The verbalization and explication of unit-specific routines, such as equipment workarounds and handoff nuances, reduce ambiguity and support consistent practices of clinical processes (Zollo and Winter, 2002). As the facility codifies and institutionalizes the clarified routines, this deliberate explication of routines and know-how leads to an initial increase in service quality. In addition, contract RNs can introduce effective practices and innovations drawn from other facilities (March, 1991; Li and van Knippenberg, 2021). Under these conditions, low levels of fissuring on RNs can boost the relational foundations of teamwork while maintaining the stability and cohesion of established workflows, thereby improving care quality. However, this benefit exhibits diminishing marginal returns: once the unit's core tacit routines have been surfaced and subsequently standardized, the incremental gains from additional contract RNs wear off, resulting in a concave benefit curve (see Figure 2(a)).

While low levels of contract labor can be managed through a facility's stable support staff and codified routines, higher levels pose increasing challenges to the RC channels of common goals, shared knowledge, and mutual respect that underpin high-performance teamwork. As CRR increases, the growing share of cross-boundary shifts communication away from a proactive, anticipatory mode toward reactive, transactional exchanges. The dilution of unit-specific know-how destabilizes the transactive memory system (Wegner, 1987; Lewis, 2003), the collective understanding of who knows what, thereby increasing clarification cycles, making handoffs more error-prone, and slowing the team's response to complications (Wilkin et al., 2018; Tucker et al., 2007). These coordination frictions compound at high CRR, causing performance deterioration at an increasing rate and resulting a concave-down cost curve (see Figure 2(b)). The mechanism is consistent with empirical studies showing that facilities overly relying on contract RNs experience higher rates of intradialytic hypotension, treatment interruptions, blood pressure instability, and other complications, as well as higher levels of patient complaints (Thomas-Hawkins et al., 2008; Jeong, 2023). In acute care hospitals, when contract RNs account for more than 15% of total unit hours, patient falls increase, and staff face greater fatigue and burnout (Bae et al., 2010).

Ultimately, the net effect of CRR on clinical quality reflects the balance of the above two countervailing processes. At a low level of CRR, gains from knowledge explication and operational flexibility outweigh the initial relational costs. As the level of fissuring increases, however, growing coordination challenges and related costs offset and eventually outweigh the benefits of knowledge injection. As a result, gains diminish and then reverse, leading to declining quality at higher CRR. Hence, we propose an inverted U-shaped relationship between CRR and clinical quality in the outpatient hemodialysis setting (see Figure 2(c)).

H1: There is an inverted U-shaped relationship between CRR and outpatient hemodialysis clinical quality; that is, quality initially increases and subsequently decreases as CRR rises.

3.3 | Support Intensity as a Knowledge–Coordination Buffer

Building on H1, we examine how contextual factors moderate the CRR–quality relationship within the unit. First, we theorize how support intensity, defined as the number of PCT FTEs per patient, acts as a knowledge–coordination buffer that shapes how

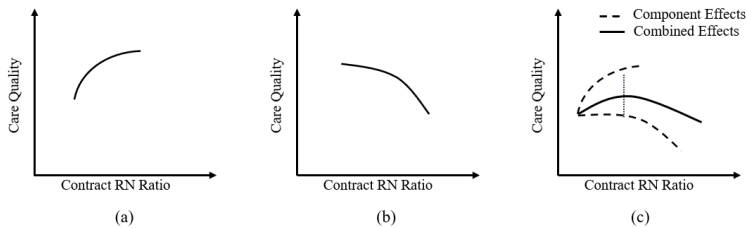


FIGURE 2 Inverted U-shaped Relationship between CRR and Care Quality

CRR affects clinical quality.

In the dialysis setting, PCTs are “the heart of the center” and spend the most chairside time with patients. In addition to performing routine direct care tasks, they also serve as liaisons between patients and other dialysis staff and are heavily relied on by the team (Urbanski et al., 2025). Through repeated interactions with patients and the performance of routine procedures, PCTs accumulate a rich base of tacit knowledge about patient preferences, equipment nuances, handoff rhythms, and other operational details that are difficult to codify or document. The tacit knowledge becomes particularly salient as the RN workforce becomes more fissured. From an OIPT perspective, PCTs function as the primary stable nodes in a dialysis unit’s information architecture, expanding its capacity to retain and diffuse practice-embedded tacit knowledge (Hoffer Gittell, 2002; Argote and Miron-Spektor, 2011; Parmigiani, 2007). A stronger PCT base increases monitoring capacity and communication bandwidth, serving as a structural buffer that mitigates the uncertainty introduced by the fissuring of high-skill core roles.

In this context, a higher support intensity, reflected by higher PCT capacity per patient served, can strengthen the absorptive capacity within the unit. While employed RNs remain central for clinical supervision and for transferring unit-specific protocols to incoming contract RNs, PCTs provide a complementary and continuous pathway for surfacing and reinforcing local operational knowledge and other nuances. Because PCTs and RNs are fundamentally interdependent, PCTs’ tacit insights can supplement contract RNs’ clinical oversight by providing the immediate situational context needed for smooth execution (e.g., patient-specific cues, equipment workarounds, and shift-to-shift routines). When the PCT base is high, the unit has more “informational interfaces” that can capture the specialized expertise of contract RNs while simultaneously providing localized context when facility-specific familiarity is limited. This ensures that the influx of external perspectives from contract RNs is effectively synthesized into improved practice rather than being lost to coordination friction. Thus, at low levels of fissuring, the unit captures greater value from external expertise when it possesses a stronger internal knowledge base through PCTs. This implies that the attainable peak of the CRR–quality relationship (i.e., the maximum CRR-attributable quality gain) is higher with stronger support intensity.

In addition, greater PCT coverage increases the unit’s information redundancy, which is critical to absorbing coordination friction within the dialysis unit. Based on OIPT, an increase in CRR leads to greater demand for communication among PCTs, as they must spend more bandwidth to back-feed contract RNs with operational nuances and tacit knowledge. Higher support intensity provides the extra bandwidth to detect emerging complications and transmit patient and unit-specific context before relational gaps manifest as execution errors (Handley, 2012). This buffering effect also protects the care process from the coordination friction typically associated with a fissured workforce (Argote and Miron-Spektor, 2011). As a result, facilities with higher support intensity can accommodate higher levels of fissuring before the detrimental effects of relational decay take over. Accordingly, higher support intensity could shift the quality-maximizing level of fissuring (i.e., the turning point of the inverted-U) to the right.

Taken together, support intensity functions as a knowledge-coordination buffer: it both elevates the clinical quality performance frontier and extends the range of beneficial fissuring (see Figure 3(a)).

H2a: Higher support intensity increases the maximum level of clinical quality associated with CRR, such that the peak of the inverted-U relationship between CRR and quality is higher when support intensity is greater.

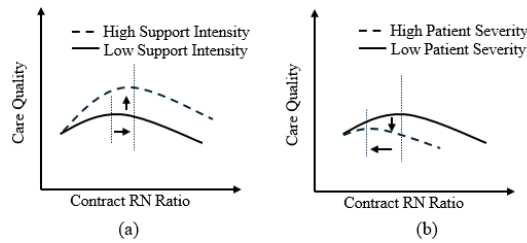


FIGURE 3 Moderation Effects by Support Intensity and Patient Severity

H2b: Higher support intensity raises the CRR level at which clinical quality is maximized, such that the turning point of the inverted-U relationship occurs at a higher CRR when support intensity is greater.

3.4 | Patient Severity as a Performance Constraint

While a higher support intensity enhances the unit's capacity to absorb and integrate knowledge from contract RNs, greater patient severity increases the information load and tightens operational constraints, thereby amplifying the disruptive effects of fissuring on RN-PCT coordination. From an OIPT perspective, greater severity increases the volume and velocity of information that must be processed during both routine care and contingency response. In the context of hemodialysis, we operationalize patient severity as the proportion of patients with hemoglobin levels outside the clinically recommended range of 10–12 g/dl (KDIGO, 2012), which signals greater clinical complexity and coordination demand on the care team.

As patient severity increases, the care team must rule out underlying factors and adjust medications or administer blood transfusions. Key decisions have to be made within a compressed time window to prevent further hypoxia-related kidney damage (Palaka et al., 2020). The compressed decision windows highlight the need for rapid, reliable communication and shared situational awareness (Hoffer Gittell, 2002). Under these high-acuity conditions, RNs and PCTs must synchronize actions under intense time pressure, leaving little cognitive slack to orient new contract RNs, share unit-specific tacit knowledge, or adapt external practices from other facilities (Manser, 2009). In this context, the extra information that contract RNs bring adds little value and can even compete with attention to time-sensitive events such as episodes of intradialytic hypotension or access infections. As a result, the potential quality gains from fissuring are limited in these conditions, and the maximum achievable quality at higher CRR is lower.

High-severity environments also magnify the demand for anticipatory coordination, the proactive communication of emerging patient and equipment cues before an alarm requires RN intervention (Faraj and Xiao, 2006; Starmer et al., 2014). Even marginal delays in communication can lead to “failure-to-rescue” events when patients are clinically unstable. Although contract RNs bring strong general competencies, their limited local familiarity, relational intimacy, and tacit knowledge can make it difficult to interpret subtle cues from PCTs during fast-moving situations (Thomas-Hawkins et al., 2020). As patient severity increases, the coordination friction associated with less-familiar teams becomes unaffordable at lower levels of CRR, reducing the unit's capacity to accommodate fissuring. Evidence from nursing research links strained RN staffing to failure-to-rescue events and other adverse outcomes (Needleman et al., 2002), and studies of temporary and agency staffing report quality risks as such use deepens (Bae et al., 2010). These patterns are most consequential under high-acuity conditions where rapid team response is essential. The increased information load reduces the unit's absorptive capacity, causing the detrimental effects of relational decay to dominate at lower levels of fissuring. Thus, higher severity shifts the quality-maximizing turning point of the inverted-U to the left.

Taken together, patient severity operates as a performance constraint that both dampens the potential benefits of fissuring and accelerates the onset of coordination failure (see Figure 3(b)).

H3a: Higher patient severity reduces the maximum level of clinical quality associated with CRR, such that the peak of the inverted-U relationship between CRR and quality is lower when patient severity is higher.

H3b: Higher patient severity lowers the CRR level at which clinical quality is maximized, such that the turning point of the inverted-U relationship occurs at a lower CRR when patient severity is higher.

4 | DATA SOURCES AND RESEARCH DESIGN

This section outlines the data sources, sample construction, and variables used to test the proposed hypotheses in the outpatient hemodialysis setting.

4.1 | Data Sources and Sample Construction

The End-Stage Renal Disease Quality Incentive Program (ESRD QIP) was established by the Medicare Improvements for Patients and Providers Act (MIPPA) in 2008. It is considered the first mandatory federal pay-for-performance initiative that tied renal dialysis facility payments directly to quality measures (Weiner and Watnick, 2017). The program requires dialysis facilities to submit comprehensive performance data to CMS as a condition of participation in the Medicare program (Centers for Medicare & Medicaid Services, 2008). CMS uses the collected data to calculate and publish performance scores and to allocate a portion of Medicare reimbursement based on compliance with these quality standards (Centers for Medicare & Medicaid Services, 2023a).

Our empirical analysis draws on a comprehensive panel dataset of U.S. outpatient dialysis facilities, constructed by integrating multiple CMS-administered data sources. These sources provide standardized, facility-level information on operations, staffing, and quality performance, enabling longitudinal analysis of workforce composition and service outcomes.

- *Quarterly Dialysis Facility Care Compare (QDFCC)* provides facility-level characteristics, including facility ownership (independent vs. chain-affiliated), treatment modality (in-center vs. home), capacity (number of dialysis stations), and patient volumes, which we use as operational covariates.
- *End-Stage Renal Disease Quality Incentive Program (ESRD QIP)* publishes standardized quality performance scores for selected clinical and reporting measures based on data submitted by facilities. The total performance score for each facility is then calculated as the weighted sum of the measure compositions. These scores are updated annually for all participating facilities and serve as our primary outcome metrics.
- *Healthcare Cost Report Information System (HCRIS) Dataset* contains the annual ESRD cost reports for all Medicare-certified dialysis facilities. These reports detail financial expenditures and labor information, including full-time equivalent (FTE) counts for both employed (salaried) and contracted personnel across clinical and administrative roles. We use these data to construct facility-level staffing measures, including the contract RN ratio.

The analysis uses the facility-year as the unit of observation, with each dialysis facility uniquely identified by its CMS Certification Number. Although we downloaded and aggregated data from the three sources described above for 2015–2023, our final analysis focuses on 2016–2020. We excluded 2021 and 2022 because the COVID-19 pandemic led to measurement suppression in ESRD QIP, resulting in missing values for key QIP quality scores (Centers for Medicare & Medicaid Services, 2020). We also excluded 2023, the single post-pandemic year in our data, to avoid potential structural or operational shifts caused by the pandemic. Finally, we excluded 2015 because one of the two QIP measures used to construct our dependent variable, the NHSN Bloodstream Infection (BSI) metric, was first introduced in 2016. Thus, the study period is defined by the availability and consistency of the relevant QIP measures.

We then screened the 2016–2020 sample to ensure data completeness and alignment with CMS reporting requirements. The initial panel contains 37,781 facility-year records from 8,428 facilities. We first retained only records with complete values for the

clinical measures, RN and PCT staffing, and patient severity; CRR values within the unit interval; measure scores within the CMS 0–10 scale; and nonnegative FTE and expense entries. This validity screen left 26,162 observations from 6,011 facilities. We then applied CMS public reporting criteria. CMS publicizes quality data only for facilities that meet three conditions: more than 30 adult hemodialysis patients, at least one year of operation since certification, and the publication of all three CMS facility-level assessments for that year (the Five-Star quality rating, the ICH CAHPS score, and the QIP total performance score) (University of Michigan Kidney Epidemiology and Cost Center, 2023; Centers for Medicare & Medicaid Services, 2023*b*, 2017). Requiring all three assessments restricts the sample to facility-years that CMS evaluates in full, so clinical quality is measured on the same basis for every facility. Applying the first two conditions (census and tenure requirements) left 24,610 observations from 5,750 facilities. Applying the third condition (ratings-completeness requirement) yielded 16,270 facility-year observations from 4,910 facilities, following prior facility-level research that retains only facilities with complete data on all three programs (Kshirsagar et al., 2019). Finally, we require complete values for the thirteen staffing, structural, and moderator covariates that enter every specification, and retain the facility-years with full covariate records, yielding the final analysis sample of 14,749 facility-year observations from 3,914 facilities. Table 1 summarizes the sample construction process.

TABLE 1 Sample Construction Steps

Selection Criteria	Observations	Facilities
Initial facility-year observations, 2016–2020	37,781	8,428
(1) Validity screen: complete model variables; CRR within the unit interval; measure scores within the CMS 0–10 scale; nonnegative FTE and expense entries	26,162	6,011
(2) CMS rating coverage: more than 30 adult hemodialysis patients and at least one year since certification	24,610	5,750
(3) CMS rating completeness: Five-Star rating, ICH CAHPS score, and QIP total performance score all published	16,270	4,910
(4) Record completeness: complete records on the thirteen staffing, structural, and moderator covariates entering the estimations	14,749	3,914

As a robustness check reported in Section 7.2, we test the main effect on the larger panel obtained in step (2) of Table 1 with 24,610 observations from 5,750 facilities, and the results are consistent. We also mention that, although our theoretical mechanisms focus on workflow and RN–PCT chairside coordination in in-center hemodialysis, we do not classify facilities by treatment modality (in-center, home, or peritoneal). Dialysis providers frequently deliver multiple modalities and cannot be cleanly partitioned into a single modality type. We retain all qualifying facility-year observations and capture cross-facility variation in in-center focus through the *Hemodialysis Share* control variable defined in Section 4.2.4.

4.2 | Variable Construction

This section details the operationalization of key variables used in our models.

4.2.1 | Dependent Variable: Clinical Quality

The dependent variable of Clinical Quality (CQ) is calculated as a weighted average of two ESRD QIP clinical measures:

$$CQ_{it} = \frac{N_{it}^{KtV} S_{it}^{KtV} + N_{it}^{BSI} S_{it}^{BSI}}{N_{it}^{KtV} + N_{it}^{BSI}}, \tag{1}$$

where S_{it}^{KtV} and S_{it}^{BSI} are the facility's QIP scores for the Kt/V dialysis adequacy measure and the NHSN bloodstream infection measure, respectively. N_{it}^{KtV} and N_{it}^{BSI} are the numbers of patients whom CMS includes in computing the corresponding measure for that facility-year.

- **Kt/V Dialysis Adequacy Measure (Kt/V Adequacy).** This measure quantifies the percentage of patients whose delivered dose of dialysis meets the specified threshold and serves as a key indicator of adequate care (Centers for Medicare & Medicaid Services, 2017). While adequacy is also influenced by physician prescriptions and facility infrastructure (e.g., machine performance, access to equipment), the actual delivered dose depends heavily on treatment execution (AlSahow et al., 2021). Key tasks include ensuring full prescribed treatment time, maintaining appropriate blood and dialysate flow rates, minimizing access recirculation, and following correct timing and procedures for blood sampling (National Kidney Foundation, 2006). These responsibilities fall primarily on dialysis nurses and technicians, making this measure sensitive to chairside practice.
- **National Healthcare Safety Network (NHSN) Bloodstream Infection (BSI).** This measure reports the standardized infection ratio of bloodstream infections among patients and is a critical patient-safety indicator (Centers for Medicare & Medicaid Services, 2017). Although BSI risk is also shaped by physician decisions (e.g., reducing catheter use) and facility-level infection prevention and control systems, infection prevention in routine dialysis care is fundamentally driven by frontline aseptic technique carried out at the chairside. Core nursing/technician responsibilities include rigorous hand hygiene, catheter hub disinfection, dressing changes, connection/disconnection technique, active surveillance, timely reporting of dialysis events, and adherence to routine competency evaluations for access care and aseptic practice (Centers for Disease Control and Prevention, 2024; Centers for Medicare & Medicaid Services, 2021).

The construction of CQ captures quality components relevant to frontline dialysis care. First, both Kt/V adequacy and BSI reflect dimensions of care directly associated with treatment and medication administration, aseptic technique, and monitoring; both are conformance-type clinical execution measures, kept separate from experiential quality following the distinction drawn in the OM-healthcare literature (Senot et al., 2016). Section 7.1 reports robustness checks using alternative dependent-variable constructions, including different weighting schemes and transformations of the clinical-quality outcome, and shows that the results remain consistent.

4.2.2 | Independent Variable: Contract RN Ratio

Our primary independent variable is the Contract RN Ratio (CRR), defined as the proportion of RN FTEs staffed through contracts out of the total RN FTEs in a facility:

$$CRR = \frac{\text{Contract RN FTEs}}{\text{Total RN FTEs}}.$$

The HCRIS dataset records facility staffing as annual FTEs counts separately for both employed (salaried) and contracted personnel, so both the contract RN FTEs in the numerator and the total RN FTEs in the denominator are observed directly from the same source. The employed and contracted categories are distinguished in the cost reports by the employment relationship itself: payroll counts cover staff for whom the facility issues an IRS Form W-2, whereas contract counts cover staff supplied under external agreements, including nurses placed by staffing agencies (Centers for Medicare & Medicaid Services, 2011). RNs represent core, high-skilled personnel in dialysis care, responsible for clinical oversight, medication administration, and emergency response, as explained in detail in Section 3.1. CRR is commonly used as an indicator of the degree of fissuring, reflecting the extent to which a dialysis facility relies on fissured RNs for core clinical operations (Weil, 2014; Senek et al., 2020; Ajmal, 2017). Because HCRIS does not report the terms or duration of individual contracts, we use CRR as a facility-level measure of contract RN use and leave heterogeneity in contract arrangements to future research in Section 8.4.

4.2.3 | Moderators

We incorporate two contextual factors as moderators, Support Intensity (SI) and Patient Severity (PS), to capture the organizational and clinical conditions that shape the relationship between the CRR and quality performance.

Support Intensity (SI)

Support intensity (SI) is defined as total PCT FTEs per patient:

$$SI = \frac{\text{Total PCT FTEs}}{\text{Number of Patients}}. \quad (2)$$

The numerator counts the support personnel (PCTs) available to RNs, and the denominator counts the number of patients whose treatments generate coordination demands. Note that contract PCT staffing accounts for a very small share of PCT staffing in our data and is included separately as a control. A per-patient measure aligns the unit's buffering capacity with the patient load it must absorb. In hemodialysis, coordination work accrues per patient treated, and two facilities with the same physical capacity can face different patient loads. SI captures the intensity of support each care episode actually commands. Higher SI signals greater buffering capacity, enabling facilities to absorb the variability introduced by contract RNs. To limit the influence of extreme cost-report entries, SI is winsorized at its 0.5th and 99.5th percentiles. Results are robust to alternative winsorization thresholds at the 1st and 99th percentiles.

Patient Severity (PS)

Patient severity is defined as the percentage of patients whose hemoglobin levels fall outside the clinically recommended range of 10–12 g/dL:

$$PS = \frac{\text{Patients with Hgb } < 10 \text{ or } > 12 \text{ g/dL}}{\text{Total Patients}}$$

We use the degree of deviation of patient hemoglobin from the recommended clinical range (10–12 g/dL) as a proxy for patient severity, reflecting the complexity of care and coordination demands for out-of-range patients (KDIGO, 2012). Patients with low Hgb (< 10 g/dL) require intensified care, including frequent laboratory monitoring, ESA administration, intravenous iron adjustments, and potentially red blood cell transfusions. These interventions increase coordination demands across clinical, pharmacy, and laboratory teams (KDIGO, 2012). Patients with elevated Hgb (> 12 g/dL) also require clinical attention, as elevated Hgb may signal ESA overuse and is associated with increased risks of vascular access clots and stroke in patients with chronic kidney disease (Besarab et al., 1998; Pfeffer et al., 2009). In this context, ESA overuse refers to the clinical interpretation of the elevated-Hgb tail rather than to a separately constructed variable. The elevated-Hgb component captures cases for which guidelines call for holding or reducing ESA dosing (KDIGO, 2012), requiring timely coordination with clinical, imaging, and interventional services (Besarab et al., 1998; Pfeffer et al., 2009). Table A.1 in Appendix A.1 summarizes these scenarios and associated tasks for RN and PCT roles, illustrating how deviations from the target range trigger additional interventions that require precise, real-time coordination among clinical team members. As a result, higher PS signals greater operational interdependence and urgency, intensifying the risks associated with workforce fissuring. This PS measure is consistent with prior healthcare OM studies that use it to capture facility-level patient severity (Dreyfus et al., 2020).

While our analysis centers on frontline clinical work in the dialysis unit, we recognize that clinical quality also depends on the broader operational infrastructure of the facility. A facility's staffing depth across clinical and support roles, its treatment and resource intensity, and its operating scale all shape the conditions under which frontline care is delivered.

4.2.4 | Controls

To isolate the effects of CRR and moderators on clinical quality, we control for operational-level facility conditions known to influence dialysis performance: staffing composition, treatment and resource intensity, operating scale and scheduling, and facility and year fixed effects. All staffing-count controls are measured as annual FTE counts reported in HCRIS. The controls are:

- *Nurse Aides*: Additional support staff who assist with basic patient care tasks. These personnel help maintain continuity in routine care (Webb and Wish, 2024; O’Keefe, 2014).
- *Social Workers*: Staff who handle psychosocial support, care coordination, and discharge planning. Their presence reflects the facility’s investment in non-clinical support services that may compensate for or complement variations in the contract RNs ratio (Pun et al., 2022; Friedman and Bernell, 2006).
- *Physicians*: Physician staffing captures medical director involvement and physician oversight intensity. Greater physician presence may influence how effectively facilities integrate contract RNs into clinical workflows and maintain quality standards (Weiner and Watnick, 2017; Mishra et al., 2020).
- *Management Staffing*: Management personnel are recorded in the cost reports as their own staffing category, separate from the administrative and clinical categories (Centers for Medicare & Medicaid Services, 2011). We include this variable to hold constant the facility’s governance capacity, which is determined largely by chain affiliation and ownership structure (Schiller, 2015).
- *Drugs Expense*: Annual pharmaceutical spending, measured in U.S. dollars (reported in thousands of U.S. dollars in Table 2 for readability), representing medication management demands and clinical complexity. This variable captures the treatment intensity that affects nursing workload and coordination requirements, particularly relevant when contract RNs must navigate facility-specific drug protocols (KDIGO, 2012; Pfeffer et al., 2009).
- *Laboratory Expense*: Annual spending on laboratory services, measured in U.S. dollars (reported in thousands of dollars in Table 2), and employed as a proxy for resource intensity and diagnostic capacity (Piri, 2024; Reaves and Weiner, 2021).
- *Week Shift*: The total count of hemodialysis treatment shifts scheduled in a typical week, reflecting operational intensity and scheduling complexity. While standard operations typically range from 12 to 18 shifts, facilities offering nocturnal programs may reach 24 shifts (four shifts daily over six days), with a theoretical maximum of 28 shifts representing a continuous seven-day operation. Facilities with extended weekly schedules face different staffing pressures and may rely differently on contract RNs to maintain coverage across additional shifts (Plantinga et al., 2024; Thomas-Hawkins et al., 2020).
- *Years Since Certification*: Continuous measure of facility age, measured in years since Medicare certification, reflecting organizational experience and process maturity (Ajmal, 2017; Pisano et al., 2001).
- *Dialysis Stations*: The number of dialysis stations, controlling for the facility’s fixed concurrent treatment capacity. Because support intensity is normalized by patients, stations enter separately so that capacity and realized support intensity are distinguished rather than conflated (Plantinga et al., 2024).
- *Hemodialysis Share*: The share of the facility’s dialysis patients receiving in-center hemodialysis, capturing variation in the extent of in-center focus among facilities that offer additional modalities, which can affect staffing practices and the patient mix underlying the quality measures (Plantinga et al., 2024; Yoder et al., 2013).
- *Contract PCTs*: Contract PCT staffing is included to distinguish the stable PCT support capacity captured by Support Intensity from temporary contract PCT staffing.
- *Facility Fixed Effects*: Facility-specific intercepts that absorb all time-invariant heterogeneity at the individual dialysis center level. Because each facility is located in a single state throughout the panel, these intercepts also subsume state-level time-invariant factors, including geographic variation in regulatory environments, labor market conditions, and Medicaid reimbursement policies (Ajmal, 2017; Weiner and Watnick, 2017), as well as baseline care practices, organizational culture, and other unobserved structural characteristics that may influence quality and outcomes independently of patient mix or market

conditions.

- *Year Fixed Effects*: Temporal intercepts that control for industry-wide shocks common to all facilities in a given year, such as CMS policy changes, reimbursement adjustments, or secular trends in dialysis care delivery (Centers for Medicare & Medicaid Services, 2023a; Reaves and Weiner, 2021).

These controls align with prior research and ensure that estimated effects of workforce fissuring are not confounded by structural, staffing, or resource-related differences across facilities (Weiner and Watnick, 2017; Ajmal, 2017; Reaves and Weiner, 2021; Plantinga et al., 2024). Table 2 reports descriptive statistics and pairwise correlations for all variables.

5 | MODELS & METHODOLOGY

This section outlines the framework and estimation approaches used to test the hypothesized nonlinear and moderation effects, addressing model specification, endogeneity, and instrument validity.

5.1 | Panel Models

To test the proposed hypotheses, we estimate a series of panel models linking workforce fissuring to in-center hemodialysis facility quality performance. In all models, i indexes facilities and t indexes years, and $\widetilde{CQ}$ denotes the log-transformed weighted clinical-quality composite, $\widetilde{CQ} = \ln(CQ)$. We log transform the contract RN ratio as $\widetilde{CRR} = \ln(CRR + 1)$, adding 1 to accommodate facilities with zero contract RNs. This transformation reduces skewness and limits the influence of extreme values (Rönkkö et al., 2022). The moderator variables, support intensity (SI) and patient severity (PS), also enter in log-transformed form, denoted by $\widetilde{SI} = \ln(SI)$ and $\widetilde{PS} = \ln(PS)$. To capture nonlinear and moderated effects, we include $\widetilde{CRR}$, its quadratic term, and their interactions with $\widetilde{SI}$ and $\widetilde{PS}$. Note that $\widetilde{CRR}$, $\widetilde{SI}$, and $\widetilde{PS}$ are mean-centered at their estimation-sample means before the quadratic and interaction terms are constructed, so lower-order coefficients are interpreted at sample-mean levels of the centered predictors. The quadratic terms, the quadratic interactions, the turning-point-shift statistics, and the turning point on the original CRR scale are numerically invariant to this centering. Because the hypotheses concern nonlinear moderation, we evaluate the moderation tests using the quadratic interaction terms, the turning-point-shift statistic, and conditional curvature at observed moderator values.

Model Specification

The baseline model evaluates the inverted U-shaped relationship between the contract RN ratio and quality outcome (H1):

$$\widetilde{CQ}_{it} = \beta_{10} + \beta_{11} \widetilde{CRR}_{it} + \beta_{12} \widetilde{CRR}_{it}^2 + \beta_{13} \widetilde{SI}_{it} + \beta_{14} \widetilde{PS}_{it} + \mathbf{X}_{it}^T \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{it} \quad (3)$$

where $\mathbf{X}_{it}$ denotes the vector of control variables, α_i and δ_t represent facility and year fixed effects, respectively, and ε_{it} captures the idiosyncratic error term. Support for H1 requires a statistically significant positive coefficient on the linear term ($\beta_{11} > 0$) and a significant negative coefficient for the quadratic term ($\beta_{12} < 0$), which jointly describe an inverted U-shaped relationship between $\widetilde{CQ}$ and $\widetilde{CRR}$.

To test moderation hypotheses (H2 and H3), we estimate two separate models, each focuses on one moderator's interactions while controlling for the other moderator:

TABLE 2 Statistic Summary and Pairwise Correlations

	Mean	SD	Min	Max	Correlations														
					(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) CQ	6.212	1.840	0.306	10.000	1.000														
(2) CRR	0.026	0.068	0.000	0.953	−0.058***	1.000													
(3) SI	0.087	0.049	0.000	1.353	0.055***	−0.028**	1.000												
(4) PS	0.163	0.098	0.000	0.890	−0.131***	0.025***	−0.055***	1.000											
(5) Contract PCTs	0.172	0.674	0.000	10.630	−0.038**	0.374***	0.010	0.037***	1.000										
(6) Nurse Aides	1.395	3.308	0.00	33.660	0.047***	−0.021**	−0.619***	−0.101***	−0.011	1.000									
(7) Social Workers	0.950	0.678	0.010	40.000	−0.028**	−0.006	−0.043**	0.040***	0.020**	0.247***	1.000								
(8) Management Staffing	1.843	1.352	0.000	15.280	0.121***	−0.080***	0.196***	−0.108***	−0.014	−0.015	0.198***	1.000							
(9) Physicians	0.831	8.597	0.000	200.000	−0.119**	0.085***	−0.128**	0.133***	0.055***	0.078***	0.100***	−0.367**	1.000						
(10) Dialysis Stations	22.239	8.001	1.000	80.000	−0.063***	0.006	0.054***	0.080***	0.011	0.066***	0.549***	0.224***	0.002	1.000					
(11) Drugs Expense	549.993	299.749	5.529	3707.294	−0.019**	0.012	0.033***	0.042***	0.035***	0.170***	0.642***	0.257***	0.036***	0.576***	1.000				
(12) Laboratory Expense	127.601	73.719	0.228	761.605	−0.059***	0.019**	0.145***	0.034***	0.017*	−0.123***	0.505***	−0.145***	0.146***	0.400***	0.473***	1.000			
(13) Week Shift	11.216	8.746	1.000	28.000	0.115***	−0.048**	−0.102**	−0.039**	0.002	0.326***	0.250***	0.338***	−0.138**	0.063***	0.173***	−0.114**	1.000		
(14) Years Since Certification	20.252	10.251	3.000	49.000	−0.029***	−0.030***	0.031***	−0.012	−0.023**	−0.024**	0.117***	0.115***	−0.049***	0.296***	0.137***	0.104***	0.006	1.000	
(15) Hemodialysis Share	0.859	0.102	0.319	1.000	0.036***	−0.014	0.166***	−0.136**	0.003	−0.015	−0.272**	−0.023**	−0.022**	−0.080**	−0.189**	−0.295**	0.033***	−0.040**	1.000

Notes: The table reports descriptive statistics and correlations based on within-facility variation in the analysis sample.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$\begin{aligned}\widetilde{CQ}_{it} = & \beta_{20} + \beta_{21} \widetilde{CRR}_{it} + \beta_{22} \widetilde{CRR}_{it}^2 + \beta_{23} \widetilde{SI}_{it} + \beta_{24} \widetilde{PS}_{it} \\ & + \beta_{25} \widetilde{CRR}_{it} \widetilde{SI}_{it} + \beta_{26} \widetilde{CRR}_{it}^2 \widetilde{SI}_{it} + \mathbf{X}_{it}^T \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{it}\end{aligned}\quad (4)$$

$$\begin{aligned}\widetilde{CQ}_{it} = & \beta_{30} + \beta_{31} \widetilde{CRR}_{it} + \beta_{32} \widetilde{CRR}_{it}^2 + \beta_{33} \widetilde{SI}_{it} + \beta_{34} \widetilde{PS}_{it} \\ & + \beta_{35} \widetilde{CRR}_{it} \widetilde{PS}_{it} + \beta_{36} \widetilde{CRR}_{it}^2 \widetilde{PS}_{it} + \mathbf{X}_{it}^T \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{it}\end{aligned}\quad (5)$$

Eqs. (4) and (5) correspond to the tests of H2 and H3, respectively, maintaining the same control variables, facility and year fixed effects as in Eq. (3). In Eq. (4), β_{25} and β_{26} capture how support intensity moderates the slope and curvature of the CRR–quality relationship; in Eq. (5), β_{35} and β_{36} capture moderation effects associated with patient severity.

Estimation Approach

To justify our panel specification and avoid unnecessary first differencing, we assess whether the dependent variable is stationary using a Fisher-type panel unit-root test based on Augmented Dickey-Fuller statistics. The test results reject non-stationarity ($p < 0.01$), indicating that the dependent variable is suitable for panel regression without additional differencing (see Table 3).

We then evaluate model specification and estimator choice. Multicollinearity does not appear to be a major concern with all variance-inflation factors (VIFs) below 5 and the condition index (CI) below 30. Comparing the pooled ordinary least squares (OLS), random effects (RE), and fixed effects (FE) models, the Breusch-Pagan LM test shows significant unobserved heterogeneity ($p < 0.10$), which favors RE over pooled OLS. The Hausman test ($p < 0.10$) further points to FE as the preferred estimator, as it addresses bias arising from correlation with regressors (see Table 4).

TABLE 3 Fisher-Type Panel Unit-Root Test (Augmented Dickey-Fuller)

Statistic	p-value
Inverse χ^2 (P)	< 0.01
Inverse Normal (Z)	< 0.01
Inverse Logit t (L^*)	< 0.01
Modified Inverse χ^2 (P_m)	< 0.01

Notes: H_0 : all panels contain unit roots; H_a : at least one panel is stationary.

TABLE 4 Model-Selection and Specification Diagnostics

Test	Decision Rule / Purpose	Result
<i>Collinearity Diagnostics</i>		
Variance Inflation Factors (VIF)	Multicollinearity a concern if VIF > 10	< 5
Condition Index (CI)	Multicollinearity a concern if CI > 30	< 30
<i>Model Diagnostics</i>		
Breusch-Pagan LM	Prefer RE to pooled OLS if $p < 0.10$	$p < 0.10$
Hausman	Prefer FE to RE if $p < 0.10$	$p < 0.10$

5.2 | Addressing Endogeneity

A fundamental challenge in estimating the causal effect of staffing configurations on healthcare quality is endogeneity (Lu, Rui and Seidmann, 2018; Peng et al., 2023; Lu, Ding, Peng and Chuang, 2018). Two concerns motivate our identification strategy. First, *reverse causality* may bias estimates if facilities experiencing quality declines increase contract staffing in response to perceived deficiencies, or if high-performing facilities attract full-time staff and reduce their use of contract workers (Ketokivi and McIntosh, 2017). Second, *omitted-variable bias* and *simultaneity* may arise from unobserved time-varying conditions, such as changes in management quality, local labor-market tightness, or patient demand shocks, that jointly shape staffing composition and quality outcomes (Lu, Rui and Seidmann, 2018; Peng et al., 2023). While facility fixed effects absorb time-invariant confounders, they cannot eliminate bias from either channel (Wooldridge, 2010).

We first assess reverse causality directly, following the Granger-causality tradition (Granger, 1969; Modi and Mishra, 2011; Catena et al., 2020; Barker et al., 2026). Within facilities, we regress $\widehat{CRR}_{it}$ and $\widehat{CRR}_{it}^2$ on their own one-year lags and lagged quality performance, with facility and year fixed effects and facility-clustered standard errors. We find no evidence that lagged quality Granger-causes $\widehat{CRR}_{it}$ (0.001, $p = 0.27$) or $\widehat{CRR}_{it}^2$ (−0.000, $p = 0.86$), so reverse causality is unlikely to be the primary endogeneity concern in our setting. The identification strategy is accordingly designed to prevent omitted-variable bias and simultaneity by supplementing the fixed-effect specification with an instrumental-variable control-function approach.

To do so, we use a fixed-effects control-function design with two excluded instruments that shift contract RN use for reasons unrelated to a facility's own quality. We first use the leave-one-out peer CRR measure that provides design-based variation from contract RN use among other facilities in the same chain-state-year. We then add a heteroskedasticity-based internal instrument constructed from management staffing following Lewbel (2012). The maintained specification is therefore an over-identified instrument set: the peer measure supplies the external staffing-shock source, while the HBIV instrument supplies an additional excluded restriction that makes the Hansen over-identification check possible. This external-instrument-plus-control-function architecture follows recent OM practice (see, e.g., Barker et al. (2026)). Identification therefore rests primarily on the external peer instrument, whose exclusion can be defended on institutional grounds, with the heteroskedasticity-based moment entering as the over-identifying supplement.

5.2.1 | Instrument Development

We first use a leave-one-out design, instrumenting the endogenous variable with peer facilities' staffing practices. Peer facilities in the same chain and state face common agency availability, licensure conditions, procurement environments, and chain-level staffing benchmarks. Because administrators routinely benchmark staffing patterns across sister facilities, the average contract RN staffing ratio among peers in the same chain and state is a strong predictor of the focal facility's practice (Tan and Netessine, 2014). Excluding facility i from the average ensures that the instrument does not mechanically embed i 's own staffing choice or realized quality.

Formally, we construct

$$\overline{CRR}_{-i,t} = \frac{1}{N_{cst} - 1} \sum_{j \in (c,s), j \neq i} \widehat{CRR}_{jt}, \quad (6)$$

where (c, s) indexes the chain-by-state cell and N_{cst} is the number of chain c 's facilities operating in state s and year t . Thus, $\overline{CRR}_{-i,t}$ calculates the leave-one-out mean of $\widehat{CRR}_{jt}$ from other facilities within the same chain and in the same state and year.

The leave-one-out approach has been widely used in econometrics to identify demand using related variation in other markets (Nevo, 2001), to generate exogenous variation from peer behavior such as judge leniency (Kling, 2006; Aizer and Doyle, 2015; Borusyak et al., 2021), and in healthcare operations to predict a focal unit's staffing or practice patterns from its peers' (Peng et al.,

2023; Bavafa and Terwiesch, 2019; Ko et al., 2019). Beyond relevance, the exclusion condition requires that $\overline{CRR}_{-it}$ affects the focal facility's quality only through its own $\widetilde{CRR}_{it}$. The institutional structure of contract nursing supports this condition. Specifically, contract RNs are engaged by the local facility and work under the focal unit's own supervision rather than under a chain-level deployment plan (U.S. Government Accountability Office, 2024). Each facility draws on its own local agency pool, so the nurses staffed at peer facilities within the same chain are different individuals from those working at the focal facility, and a contract RN at a peer facility does not provide care at the focal facility. What peer facilities' contract RN use shares with the focal facility is the chain-state staffing market itself: agency access, licensure, and procurement conditions that make the peer average a strong predictor of the focal facility's own contract RN use. The remaining pathways are absorbed by the design. Facility fixed effects, which nest chain and state, remove persistent chain-level conditions, consistent with within-facility design used in studies of chain behavior (Grieco and McDevitt, 2017; Eliason et al., 2020); year fixed effects and the maintained controls absorb common shocks; and locally staffed agency assignments leave no direct personnel or care-delivery route from peer facilities into focal clinical quality other than the focal facility's own staffing choice.

Specifically, we supplement the peer instrument by creating a heteroskedasticity-based instrument (HBIV) (Lewbel, 2012). HBIV generates internal instruments for an endogenous variable by exploiting heteroskedasticity in the data. Prior studies use HBIV either in the absence of external instruments or, as in our setting, alongside an external instrument to over-identify the instrument set (e.g., Dong et al., 2020; Lagzi et al., 2023; Pal et al., 2024; Wowak et al., 2025). Recent OM applications especially relevant to our design include nonlinear team-dynamics models (Pal et al., 2024), hospital efficiency (Bonnett and Heim, 2024), medical-product safety with fixed effects (Wowak et al., 2025), part-time workforce effectiveness with a control function (Sharma et al., 2024), hospital capacity pooling combining HBIV with selection correction (Lim et al., 2024), and a healthcare model that uses HBIV to strengthen an existing external instrument (Bok et al., 2025). In the first step of HBIV, we regress the endogenous variable (i.e., $\widetilde{CRR}$) on the control variables, the two moderators, one lag of clinical quality, and facility and year fixed effects to extract the residual $\hat{e}_{it}$ (Appendix Table A.5 reports this auxiliary regression). Next, we create the instrumental variable using equation 7, where Z_{it} denotes management staffing, and $\bar{Z}$ is its sample mean in the estimation sample. Management staffing is an exogenous control in our model specification - it generates heteroskedasticity rather than serving as an instrument itself. Management Staffing comprises the employed and contracted FTEs in the cost reports' management category, distinct from the administrative and physician categories Centers for Medicare & Medicaid Services, 2011. As management staffing tightens, its capacity to absorb contract-staffing volatility declines, and contract RN reliance fluctuates more widely around its conditional mean. However, management staffing itself reflects organizational structure, such as chain affiliation and corporate ownership, rather than facility-year quality conditions, while the facility's clinical staffing and operational variables are included as separate controls. Hence, we expect a strong association between management staffing and the dispersion of contract RN reliance.

Specifically, we construct

$$HBIV_{it} = (Z_{it} - \bar{Z}) \hat{e}_{it}, \quad (7)$$

$HBIV_{it}$ is the instrumental variable generated for $\widetilde{CRR}$; it joins the external peer instrument $\overline{CRR}_{-it}$ in the excluded-instrument set. Two assumptions underpin the validity of the HBIV approach (Lewbel, 2012). First, Z_{it} should be uncorrelated with the product of the structural and auxiliary disturbances ($\text{cov}[Z_{it}, \epsilon_{it} \mu_{it}] = 0$, where μ_{it} denotes the disturbance of the auxiliary regression underlying $\hat{e}_{it}$). Following Baum and Lewbel (2019), the Pagan-Hall test (Pagan and Hall, 1983) failed to reject a lack of correlation between ϵ_{it}^2 and Z_{it} ($p > .1$). Re-estimating with an alternative driver, the cost reports' other employees outside the clinical, administrative, and management categories (Dreyfus et al., 2020), returns consistent results (Appendix Table A.8). Second, the created instrument should be relevant, which requires $\text{cov}[Z_{it}, \mu_{it}^2] \neq 0$ (Lewbel, 2012). The Breusch-Pagan test (Breusch and Pagan, 1979) rejected homoskedasticity of the auxiliary residuals with respect to management staffing ($\chi^2(1) = 17.2$, $p < 0.01$; Table A.5). Hence, we find evidence that the instrument is relevant. To provide additional evidence of the relevance

of the instrumental variables, we report the first-stage coefficients and F statistics. The first-stage coefficients on the excluded instruments are 0.136 for the peer instrument and -0.845 for the HBIV, both significant with a joint F statistic of 223.1 (Table 5). The F statistic exceeds the critical threshold of 19.93 proposed by Stock and Yogo (2005), suggesting the two-stage least-squares estimates suffer no more than a 10% maximal size distortion. The Hansen J p -value exceeds 0.10, showing no evidence against the overidentifying restriction. Together, above diagnostics confirm the relevance and internal consistency of the instrument set.

5.2.2 | Estimation: Control Function

As $\widetilde{CRR}_{it}$ appears in the structural models in three ways (i.e., level, square, and interactions with moderators), any endogeneity in the variable carries into all terms in which it appears. We therefore follow the parsimonious control-function implementation for one endogenous source: the contract RN ratio is projected on the excluded instruments, and a single first-stage residual accompanies the level, square, and interaction terms in the structural equation (Wooldridge, 2015; Akkus et al., 2021; Janakiraman et al., 2023). This approach is recommended for nonlinear functions of a single endogenous regressor because the square and moderator interactions are deterministic functions of the same endogenous staffing choice, not separately chosen treatments. Our implementation follows recent OM applications that use the same control-function structure for nonlinear and interaction models (Pal et al., 2024; Barker et al., 2026; Goradia and Chandrasekaran, 2025). A closely related workforce application separately first-stages two potentially endogenous part-time staffing measures before entering their corrections jointly in a probit control function (Sharma et al., 2024).

The first stage is

$$\widetilde{CRR}_{it} = \pi_1 \overline{CRR}_{-i,t} + \pi_2 \text{HBIV}_{it} + \theta^\top \mathbf{W}_{it} + a_i + d_t + v_{it}, \quad (8)$$

and the single reduced-form residual enters each structural model in Section 5.1,

$$\widetilde{CQ}_{it} = \beta_1 \widetilde{CRR}_{it} + \beta_2 \widetilde{CRR}_{it}^2 + \cdots + \rho \hat{v}_{it} + \theta^\top \mathbf{W}_{it} + \alpha_i + \delta_t + e_{it}, \quad (9)$$

The ellipsis ($\cdots$) in Eq. (9) stands for the moderator main effects, and in the moderation models, the $\widetilde{CRR} \times M$ and $\widetilde{CRR}^2 \times M$ terms for one moderator at a time, as shown in Eqs. (3)–(5). The coefficient on $\hat{v}_{it}$ is the regression-based endogeneity test. Appendix A.4 reports residual-structure checks: adding a squared residual is insignificant, and the residual-by-moderator additions are insignificant in the support-intensity and patient-severity models, so no higher-order or interacted correction is warranted in the reported single-residual specification.

Two alternative implementations were considered and set aside for the maintained specification. A lag-based instrument for $\widetilde{CRR}$ has limited power when facility and time effects are partialled out, and lagging an endogenous regressor relocates rather than resolves the problem when the omitted condition persists over time (Reed, 2015; Bellemare et al., 2017), which is exactly the case a persistent facility condition would present. We therefore reserve lags for the moderator corrections in Section 7.5 and for the lagged-outcome control included in every specification. Two-stage least squares, in turn, must treat each nonlinear function of the endogenous variable as a separate endogenous regressor; substituting fitted values into the nonlinear terms is the forbidden regression that Wooldridge (2010) cautions against. In our data the separate projections spread the same instrument variation across the collinear level and squared terms, leaving the quadratic first stage below the Stock-Yogo threshold (Appendix A.9), whereas the control function handles the same nonlinearity with the identical instrument set. We retain 2SLS as a benchmark in Appendix A.9, augmenting the excluded instruments with the squared external peer instrument $\overline{CRR}_{-i,t}^2$ so that the over-identification test remains available in that framework as well.

5.3 | Diagnostic Tests

We assess the identification strategy against three key conditions for instrumental-variable design: relevance, validity, and endogeneity correction.

Relevance and exclusion diagnostics. Beyond the first-stage estimates and the over-identification check reported above, Table 5 reports the single first-stage equation with each equation excluded instrument shown separately. A state-by-year fixed-effects specification absorbs additive shocks common to facilities in the same state and year; results are largely similar (Appendix Table A.6). Replacing the peer instrument with the shift-share supply instrument leaves the main curvature conclusion unchanged (see Section 7 and Appendix A.2). Appendix A.2 reports the auxiliary regression generating the heteroskedasticity instrument, the instrument-set strength and curvature diagnostics, and the full control-function coefficient table.

Endogeneity. The control-function residual is significant in the lead specification ($p < 0.01$), rejecting the exogeneity of $\widehat{CRR}_{it}$ conditional on the controls and supporting use of the correction. The sign of the correction is consistent with the selection mechanism described above: facilities may rely more heavily on contract staffing under unobserved operational strain, which would bias uncorrected estimates of the early benefit phase downward. In addition to these instrument-based diagnostics, Section 7.4 and Appendix A.8 report negative-control and outcome-proxy omitted-variable-bias checks that ask whether a remaining unobserved facility condition could still generate the curvature after the control function has residualized the modeled endogenous staffing component of CRR.

Moderator exogeneity. Beyond the three IV conditions above, identification of the moderation terms requires the moderators not be driven by the same annual quality shock that motivates contract staffing. In this setting, support intensity and patient severity characterize the operating context in which contract RN use affects quality, rather than the short-run contracting response itself. Although both may evolve over time, their annual movements are conceptually distinct from the unobserved quality realization that induces facilities to adjust contract RN use. Interaction terms involving an endogenous regressor can also inherit the endogeneity concern. Thus, our empirical treatment first corrects the endogenous CRR terms through the control-function structure. The remaining interaction-specific condition is the one formalized by Nizalova and Murtazashvili (2014) and extended to nonlinear interaction settings by Bun and Harrison (2018): once the endogenous component of $\widehat{CRR}_{it}$ is residualized, omitted-variable bias in the interaction coefficient vanishes when the moderator is independent of the remaining unobserved determinants of the endogenous variable across the moderation contrast. In this sense, the relevant residual threat is not generic facility heterogeneity, which fixed effects and controls already absorb, but a moderator-linked omitted factor that both shifts the moderator and reproduces the CRR selection component.

Two further checks support this treatment. First, Section 7.5 instruments support intensity and patient severity with their respective one-year lags and adds the corresponding control-function residuals to probe moderator-specific endogeneity. Second, Appendix A.8 examines the residual omitted-variable-bias channel that remains after the control-function corrections. Negative-control outcomes are flat, and an outcome-proxy sensitivity adjustment preserves the negative curvature. Together, these analyses address the modeled endogenous CRR component and probe moderator feedback and selected shared-confounding channels; they do not eliminate every possible time-varying confounder.

6 | RESULTS

This section presents empirical results from our panel models. We first examine the main nonlinear effect of the $\widehat{CRR}_{it}$ (Section 6.1), then assess moderation by support intensity and patient severity (Sections 6.2 and 6.3), and conclude with an extended cost-quality efficiency analysis (Section 6.4).

Table 5 reports three specifications. Model (1) is a quadratic baseline specification corresponding to Eq. (3), which tests the inverted U-shaped relationship between the contract RN ratio and the quality outcome (H1). Model (2), based on Eq. (4),

examines moderation by support intensity by interacting support intensity with both the linear and quadratic terms of $\widetilde{\text{CRR}}$ (H2). Model (3), based on Eq. (5), examines moderation by patient severity through its interactions with $\widetilde{\text{CRR}}$ and $\widetilde{\text{CRR}}^2$ (H3). For the moderation hypotheses, we focus on two comparative statistics implied by the estimated quadratic functions: changes in the predicted peak quality and shifts in the model-implied turning point (quality-maximizing $\widetilde{\text{CRR}}$).

TABLE 5 First-Stage and Control-Function Estimates with Bootstrap Inference

Variable	First stage	(1) Main		(2) SI moderation		(3) PS moderation	
		SE	Bootstrap	SE	Bootstrap	SE	Bootstrap
Panel A. Excluded instruments (first stage)							
Peer instrument L	0.136*** (0.052)						
HBIV instrument H	−0.845*** (0.084)						
Panel B. Structural estimates							
CRR		0.689* (0.380)	0.699* (0.462)	0.893** (0.385)	0.904* (0.513)	0.589 (0.421)	0.605 (0.457)
$\widetilde{\text{CRR}}^2$		−5.440*** (1.591)	−5.442*** (2.012)	−7.531*** (1.729)	−7.531*** (2.878)	−5.064*** (1.853)	−5.092** (1.908)
$\widetilde{\text{SI}}$	−0.002** (0.0008)	0.091*** (0.013)	0.091*** (0.015)	0.095*** (0.013)	0.095*** (0.015)	0.094*** (0.013)	0.094*** (0.015)
$\widetilde{\text{PS}}$	−0.000 (0.0002)	−0.026*** (0.008)	−0.026*** (0.008)	−0.026*** (0.008)	−0.026*** (0.008)	−0.027*** (0.008)	−0.027*** (0.008)
$\widetilde{\text{CRR}} \times \widetilde{\text{SI}}$				2.311*** (0.697)	2.331*** (0.900)		
$\widetilde{\text{CRR}}^2 \times \widetilde{\text{SI}}$				−11.117*** (3.150)	−11.151** (4.684)		
$\widetilde{\text{CRR}} \times \widetilde{\text{PS}}$						−1.426*** (0.543)	−1.450* (0.784)
$\widetilde{\text{CRR}}^2 \times \widetilde{\text{PS}}$						2.068 (2.050)	2.160 (2.717)
Control-function residual (ρ)		2.466*** (0.438)	2.478*** (0.676)	2.803*** (0.449)	2.816*** (0.625)	2.519*** (0.440)	2.523*** (0.612)
Panel C. Diagnostics and sample							
Controls	✓	✓	✓	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Single control-function residual		✓	✓	✓	✓	✓	✓
Excluded-instrument joint F	223.11						
Regression observations				14, 749			
Regression facilities				3, 914			
Chi-square	1603.66***	3423.89***		3439.40***		3461.64***	

Notes: Standard errors are clustered at the facility level. Facility-clustered bootstrap standard errors are based on 1,000 replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.1 | Inverted U-Shaped Relationship Between $\widetilde{\text{CRR}}$ and $\widetilde{\text{CQ}}$

Model (1) in Table 5 shows that the coefficient of $\widetilde{\text{CRR}}$ is positive ($\beta_{11} = 0.689$), while the coefficient of the squared term is negative and significant ($\beta_{12} = -5.440$, $p < 0.01$), suggesting an inverted U-shaped relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{CQ}}$.

To further validate the inverted-U relationship, Lind and Mehlum (2010) proposed a three-step validation test, which has been applied in prior OM research (Pal et al., 2024): (1) test whether the quadratic term is significant and has the expected sign; (2) ensure the turning point estimate lies within the observed range; (3) verify that the slope is significantly positive at the lower bound and significantly negative at the upper bound. Haans et al. (2016) extended this approach by adding an additional step: (4)

a local slope robustness test to confirm that the marginal effect changes sign in a neighborhood around the turning point. The purpose of this localized slope test is to detect rare but consequential violations of U-shaped patterns, such as flattening near the extremum or misleading curvature driven by sparse data. We adopt the extended four-step approach and implement it using the IV-FE quadratic specification of Model (1). The results pass all these steps and jointly support the inverted U-shaped relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{CQ}}$ (H1).

To estimate the optimal CRR implied by the quadratic specification, we compute the turning point from the estimates in Model (1). The turning point on the estimation scale is 0.063; undoing the mean-centering and the logarithmic transformation places the model-implied quality-maximizing CRR at approximately 6.9% on the original scale. This value provides a descriptive benchmark for where the fitted relationship reaches its maximum within the observed support.

6.2 | The Moderation Effect of Support Intensity

Next, we evaluate whether Support Intensity (SI) moderates the relationship between contract RN ratio and quality performance, as predicted in H2a and H2b. Model (2) in Table 5 shows that the linear interaction term $\widetilde{\text{CRR}} \times \widetilde{\text{SI}}$ has a significant positive coefficient ($\beta_{25} = 2.311$, $p = 0.01$), while the quadratic interaction term $\widetilde{\text{CRR}}^2 \times \widetilde{\text{SI}}$ is negative and significant ($\beta_{26} = -11.117$, $p = 0.02$). This coefficient pattern is consistent with support intensity reshaping the inverted-U relationship (Haans et al., 2016; Pal et al., 2024). To formally test H2a and H2b, we move beyond the individual coefficients to two model-implied comparative statics: (i) the change in the attainable peak of quality (a vertical shift) and (ii) the movement of the quality-maximizing turning point (a horizontal shift).

First, to test H2a, we compute the model-implied maximum contribution of $\widetilde{\text{CRR}}$ to quality at a given level of support intensity. For Eq. (4), the $\widetilde{\text{CRR}}$ -related component is a concave quadratic function, $g(\widetilde{\text{CRR}}|\widetilde{\text{SI}}) = (\beta_{21} + \beta_{25} \cdot \widetilde{\text{SI}}) \cdot \widetilde{\text{CRR}} + (\beta_{22} + \beta_{26} \cdot \widetilde{\text{SI}}) \cdot \widetilde{\text{CRR}}^2$, whose maximum equals

$$\Delta_{\text{peak}}(\widetilde{\text{SI}}) = \widetilde{\text{CQ}}^* - \widetilde{\text{CQ}}|_{\widetilde{\text{CRR}}=0} = -\frac{(\beta_{21} + \beta_{25} \cdot \widetilde{\text{SI}})^2}{4 \cdot (\beta_{22} + \beta_{26} \cdot \widetilde{\text{SI}})}, \quad (10)$$

provided that $\beta_{22} + \beta_{26} \widetilde{\text{SI}} < 0$. Following derivative-based inference for nonlinear moderation (Wirsich et al., 2016) and range-wide evaluation of nonlinear marginal effects using delta-method standard errors (Caner et al., 2017), we differentiate Eq. (10) with respect to $\widetilde{\text{SI}}$:

$$\frac{\partial \Delta_{\text{peak}}(\widetilde{\text{SI}})}{\partial \widetilde{\text{SI}}} = \frac{(\beta_{21} + \beta_{25} \widetilde{\text{SI}}) \left[(\beta_{21} + \beta_{25} \widetilde{\text{SI}}) \beta_{26} - 2\beta_{25}(\beta_{22} + \beta_{26} \widetilde{\text{SI}}) \right]}{4(\beta_{22} + \beta_{26} \widetilde{\text{SI}})^2}. \quad (11)$$

We compute pointwise delta-method standard errors for the right-hand side of Eq. (11) from the cluster-robust variance–covariance matrix of the model estimates (Mize, 2019) and evaluate the derivative throughout the observed domain using the `predictnl` command in Stata 19-MP (StataCorp, 2025), which applies the same delta method as `nlcom` at every observed value of $\widetilde{\text{SI}}$ and produces pointwise 90% confidence intervals. Within the portion of the domain for which the conditional curve remains concave, the derivative is significantly positive over the upper range of support.

We then evaluate $\Delta_{\text{peak}}(\widetilde{\text{SI}})$ at representative levels of $\widetilde{\text{SI}}$ (the 25th and 75th percentiles of $\widetilde{\text{SI}}$, denoted as $\widetilde{\text{SI}}_{25}$ and $\widetilde{\text{SI}}_{75}$) and test whether $\Delta_{\text{peak}}(\widetilde{\text{SI}}_{75}) - \Delta_{\text{peak}}(\widetilde{\text{SI}}_{25}) > 0$ using the delta method (Mize, 2019). A positive and significant difference ($\Delta_{\text{peak}}(\widetilde{\text{SI}}_{75}) - \Delta_{\text{peak}}(\widetilde{\text{SI}}_{25}) = 0.063$, $p = 0.02$) provides evidence for H2a.

Second, we examine whether SI shifts the turning point. Setting the first derivative of Eq. (4) with respect to $\widetilde{\text{CRR}}$ to zero

yields the conditional optimum (Haans et al., 2016):

$$\widetilde{\text{CRR}}^* = -\frac{\beta_{21} + \beta_{25} \cdot \widetilde{\text{SI}}}{2 \cdot (\beta_{22} + \beta_{26} \cdot \widetilde{\text{SI}})} \quad (12)$$

To test whether the turning point changes significantly with SI, we calculate the derivative of Eq. (12) with respect to $\widetilde{\text{SI}}$ (Haans et al., 2016):

$$\frac{\partial \widetilde{\text{CRR}}^*}{\partial \widetilde{\text{SI}}} = \frac{\beta_{21} \cdot \beta_{26} - \beta_{22} \cdot \beta_{25}}{2 \cdot (\beta_{22} + \beta_{26} \cdot \widetilde{\text{SI}})^2} \quad (13)$$

Because the denominator in Eq. (13) is always positive, the direction of the turning-point shift is determined by the numerator, $\beta_{21} \cdot \beta_{26} - \beta_{22} \cdot \beta_{25}$, and a rightward shift requires this term to be positive. Based on our estimation, the numerator is positive and statistically significant (coefficient = 7.476, 90% bootstrap interval [0.92, 17.53]). Table 6 reports the conditional curvature and conditional turning points at the 25th, mean, and 75th percentiles of SI. As seen, the conditional quadratic coefficients are negative and significant for these SI values, confirming that these turning points are maxima rather than minima. Thus, these test results support H2b.

TABLE 6 Conditional Curvature and Conditional Turning Points at Moderator Quartiles

Moderator level	Conditional curvature	(SE)	<i>p</i>	Conditional turning point
<i>Panel A. Support intensity (Model 2)</i>				
SI, 25th percentile	−5.165	(2.488)	0.04	4.3%
SI, mean	−7.531	(2.921)	0.01	6.5%
SI, 75th percentile	−12.162	(4.343)	0.01	8.3%
<i>Panel B. Patient severity (Model 3)</i>				
PS, 25th percentile	−5.825	(2.436)	0.02	10.4%
PS, mean	−5.064	(1.927)	0.01	6.4%
PS, 75th percentile	−4.290	(1.884)	0.02	1.0%

Notes: Delta-method standard errors use the facility-cluster-robust covariance matrix; conditional turning points are reported on the original CRR scale. The conditional quadratic coefficient remains negative at the 10th and 90th percentiles and at other conventional evaluation values of each moderator (see Table A.7 in the Appendix).

Taken together, these estimates indicate that greater support intensity systematically shifts and elevates the fitted $\widetilde{\text{CRR}}\text{--}\widetilde{\text{CQ}}$ relationship. In particular, higher $\widetilde{\text{SI}}$ increases the maximum quality gain attainable along the curve (H2a) and shifts the model-implied quality-maximizing $\widetilde{\text{CRR}}$ to the right (H2b). Support intensity therefore strengthens the quality benefits of fissuring and allows facilities to accommodate higher levels of fissuring before quality begins to deteriorate, consistent with H2. Figure 4(a) plots the fitted CRR–quality profiles at the 25th percentile, the mean, and the 75th percentile of SI, visually showing the increase of the quality peak and the rightward shift of the turning point.

6.3 | The Moderation Effect of Patient Severity

We now evaluate whether Patient Severity (PS) moderates the relationship between the contract RN ratio and quality performance, as predicted in H3a and H3b. Model (3) in Table 5 shows that the linear interaction term ($\widetilde{\text{CRR}} \times \widetilde{\text{PS}}$) is negative and statistically significant ($\beta_{35} = -1.426$, $p = 0.08$), while the quadratic interaction term ($\widetilde{\text{CRR}}^2 \times \widetilde{\text{PS}}$) is positive but not statistically significant ($\beta_{36} = 2.068$, $p = 0.45$). Because the individual coefficients cannot by themselves establish how patient severity reshapes the inverted-U relationship, we again follow the comparative-statics logic in Haans et al. (2016) and base the formal tests of H3a and

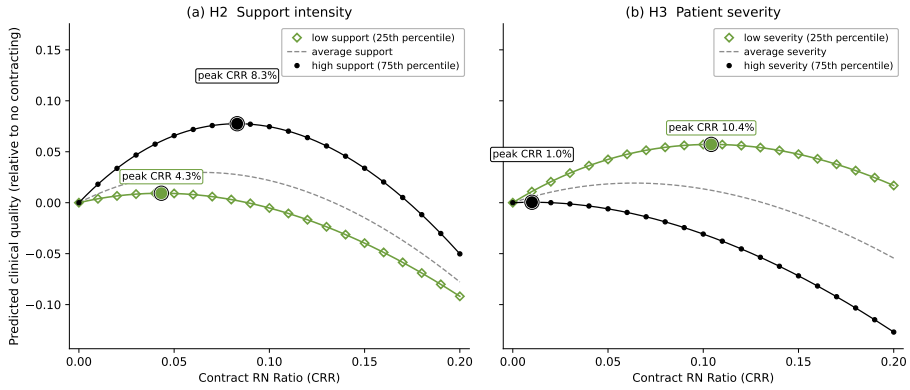


FIGURE 4 Moderation of the CRR–Quality Relationship by Support Intensity and Patient Severity. Fitted relationships are shown at the 25th percentile, the mean, and the 75th percentile of each moderator.

H3b on (i) the change in the attainable peak of quality and (ii) the shift of the quality-maximizing turning point.

First, to test H3a, we compute the model-implied maximum contribution of $\widetilde{CRR}$ to quality at a given level of patient severity. For Eq. (5), the $\widetilde{CRR}$ -related component is a concave quadratic function, $g(\widetilde{CRR} \mid \widetilde{PS}) = (\beta_{31} + \beta_{35} \cdot \widetilde{PS}) \cdot \widetilde{CRR} + (\beta_{32} + \beta_{36} \cdot \widetilde{PS}) \cdot \widetilde{CRR}^2$, whose maximum equals

$$\Delta_{\text{peak}}(\widetilde{PS}) = \widetilde{CQ}^* - \widetilde{CQ}|_{\widetilde{CRR}=0} = -\frac{(\beta_{31} + \beta_{35} \cdot \widetilde{PS})^2}{4 \cdot (\beta_{32} + \beta_{36} \cdot \widetilde{PS})}, \quad (14)$$

provided that $\beta_{32} + \beta_{36} \widetilde{PS} < 0$. Following the same derivative-based procedure (Wirsich et al., 2016; Caner et al., 2017), we differentiate Eq. (14) with respect to $\widetilde{PS}$ and evaluate the resulting derivative over the observed domain using `predictnl`, with pointwise 90% delta-method confidence intervals computed from the cluster-robust variance–covariance matrix. The derivative is significantly negative only over the lower range of the observed patient-severity domain and is not statistically distinguishable from zero over the remainder.

We then evaluate $\Delta_{\text{peak}}(\widetilde{PS})$ at representative levels of $\widetilde{PS}$ (the 25th and 75th percentiles of $\widetilde{PS}$, denoted as $\widetilde{PS}_{25}$ and $\widetilde{PS}_{75}$) and test whether $\Delta_{\text{peak}}(\widetilde{PS}_{75}) - \Delta_{\text{peak}}(\widetilde{PS}_{25}) < 0$ using delta-method inference (Mize, 2019). A negative but statistically insignificant difference ($\Delta_{\text{peak}}(\widetilde{PS}_{75}) - \Delta_{\text{peak}}(\widetilde{PS}_{25}) = -0.053$, $p = 0.16$) nonetheless indicates directional consistency within H3a.

Second, we examine whether $\widetilde{PS}$ shifts the turning point. Setting the first derivative of Eq. (5) with respect to $\widetilde{CRR}$ to zero yields the conditional optimum (Haans et al., 2016):

$$\widetilde{CRR}^* = -\frac{\beta_{31} + \beta_{35} \cdot \widetilde{PS}}{2 \cdot (\beta_{32} + \beta_{36} \cdot \widetilde{PS})} \quad (15)$$

To test whether the turning point changes significantly with $\widetilde{PS}$, we calculate the derivative of Eq. (15) with respect to $\widetilde{PS}$ (Haans et al., 2016):

$$\frac{\partial \widetilde{CRR}^*}{\partial \widetilde{PS}} = \frac{\beta_{31} \cdot \beta_{36} - \beta_{32} \cdot \beta_{35}}{2 \cdot (\beta_{32} + \beta_{36} \cdot \widetilde{PS})^2} \quad (16)$$

Because the denominator in Eq. (16) is always positive, the direction of the turning-point shift is determined by the numerator,

$\beta_{31}\beta_{36} - \beta_{32}\beta_{35}$, and a leftward shift requires this term to be negative. Based on our estimation, the numerator is negative and statistically significant (coefficient = -6.001 , 90% bootstrap interval $[-13.57, -0.81]$), providing evidence that the turning point of $\widehat{\text{CRR}}$ shifts leftward as patient severity increases. Table 6 reports the conditional curvature and conditional turning points at the 25th, mean, and 75th percentiles of PS. As seen, the conditional quadratic coefficients are negative and significant for these PS values, confirming that these turning points are maxima rather than minima. Thus, these results support H3b.

Overall, higher patient severity shifts the quality-maximizing level of fissuring to a lower $\widehat{\text{CRR}}$ (H3b), while the estimated reduction in peak quality is not statistically significant, and H3a is not supported. Figure 4(b) plots the fitted CRR–quality profiles at the 25th percentile, the mean, and the 75th percentile of PS, supporting the above findings visually.

6.4 | Extended Study: Cost–Quality Analysis

To complement our quality-focused analysis, we conduct an illustrative cost–quality exercise that combines the estimated moderation pattern with a representative facility profile. Using the coefficients from Model (2) in Table 5, we compute predicted quality over a feasible range of CRR and SI and overlay these predictions with relative labor-cost differences implied by alternative staffing mixes (Figure 5). The detailed procedure and inputs are provided in Appendix A.5.

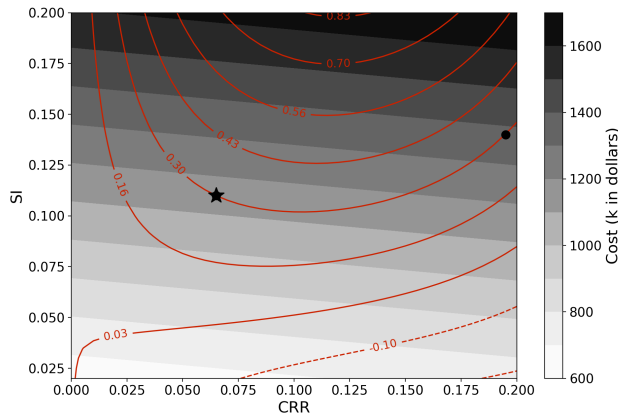


FIGURE 5 Cost–Quality Efficiency Analysis

Figure 5 shows that multiple CRR–SI combinations can achieve the same quality target but with substantially different cost implications. In particular, quality-equivalent configurations at the extremes can differ markedly in cost, and the most cost-efficient region for a given quality goal tends to lie in an interior zone that balances introducing fissuring with relatively lean support staffing.

7 | ROBUSTNESS CHECKS

The validity of the results depends on six distinct dimensions, and this section examines each one, following the logic of the identification chain (Ketokivi and McIntosh, 2017). Specifically, we examine whether our conclusions depend on the construction of the dependent variable, the sample, the instruments, omitted variables, moderator endogeneity, or the estimation method. Each subsection explains the assumption being tested, the empirical design used to test it, and the result.

7.1 | Dependent Variable Construction

The main dependent variable (CQ) weights the two clinical scores by the patient counts they cover, a weighting with an established record in composite quality measurement (Senot et al., 2016; Dimick et al., 2012), and it enters the model in logs, so the estimates are interpreted as relative quality relationships. Hence, we assess the robustness of this construction with respect to weighting and scaling. An alternative construction that addresses this concern is using the standardized composite $z(\text{Kt/V}) + z(\text{BSI})$ as the dependent variable. Table A.9 in Appendix A.6 reports the full estimates of this specification, where the hypothesis patterns are reproduced in full: the inverted-U, the SI quality peak moderation, and both directional turning-point shifts, with only the PS quality peak component again unsupported. Table 7 presents five primary outcome constructions; estimates for the remaining rescalings among the eight constructions examined are available upon request. The Kt/V-only and BSI-only specifications each yield a concave quadratic profile with an interior turning point. These results show that the inverted-U does not depend on weighting, scaling, or either component alone.

TABLE 7 Robustness of the Inverted-U Across Dependent Variable Constructions

Outcome construction	β_1 (p)	β_2 (p)	Turning Point (%)
Log of patient-weighted sum (main)	0.689 (0.07)	−5.440 (< 0.01)	6.9
Standardized composite (z -sum)	3.086 (0.03)	−23.823 (< 0.01)	7.1
Log of unweighted sum	0.718 (0.03)	−5.607 (< 0.01)	7.0
Kt/V component, standardized	2.053 (0.03)	−15.858 (< 0.01)	7.1
BSI component, standardized	1.015 (0.36)	−7.904 (0.09)	7.0

7.2 | Sample Construction

We test the robustness of the findings to three choices used to construct the estimation sample: the treatment-modality composition, the availability of CMS quality-reporting measures, and the selected panel window.

A facility’s treatment-modality mix shapes both its staffing practices and the patient mix underlying the CMS quality measures (Plantinga et al., 2024; Yoder et al., 2013). Because dialysis providers frequently operate several modalities within a single facility and cannot be cleanly partitioned by modality type, our main analysis retains facilities of all modality mixes and controls for Hemodialysis Share in every model. To confirm that this pooling does not drive the results, we re-estimate the full model on the subsample of facilities for which in-center hemodialysis is the predominant modality (Hemodialysis Share ≥ 0.5), i.e., the facilities that a modality-based exclusion would have retained. In this subsample, the quadratic term remains negative and significant (-5.36 , $p < 0.01$), the turning point remains within the data range, the control-function residual remains significant, and the moderation components match the maintained model: the support-intensity curvature interaction and both moderation effects on turning-point shifts remain significant (-11.23 , $p < 0.01$; $\theta_{SI} = 7.51$, $p = 0.07$; $\theta_{PS} = -5.87$, $p = 0.04$), while the patient-severity curvature interaction remains insignificant, as in the main model. The same pattern holds among facilities that provide hemodialysis only (Hemodialysis Share = 1, without peritoneal dialysis patients): the quadratic term remains negative and significant (-4.34 , $p = 0.04$), and the fitted turning point remains within the data range. The findings are therefore not driven by the modality composition of the retained sample.

We next assess whether the inverted-U relationship is sensitive to requiring the relevant CMS public quality-reporting measures to be observed when constructing the primary estimation sample. This requirement ensures a common measurement basis across facilities, because CMS publicly reports dialysis-facility quality information through the ESRD QIP and QDFCC (Centers for Medicare & Medicaid Services, 2026*b,a*). On the other hand, restricting the sample based on data availability may condition the analysis on a nonrandom subset of providers, raising external validity concerns (Heckman, 1979; Shadish

et al., 2002; Findley et al., 2021). To examine this issue, we re-estimate the relationship between contract RN reliance and clinical quality using a larger panel obtained after step (2) of Table 1, before imposing the requirement that all three CMS public quality-reporting measures be available. In this larger panel with 24,610 facility-year observations from 5,750 facilities, the inverted-U relationship remains supported. The quadratic term remains negative and statistically significant ($\beta_2 = -1.96$, $p < 0.1$), the excluded-instrument first stage remains strong ($F = 28.7$), the control-function residual remains significant ($p = 0.07$), and the estimated turning point lies within the observed data range. These results indicate that the nonlinear pattern, instrument relevance, endogenous-treatment correction, and turning-point support are not attributable to the public quality-reporting availability screen. We retain the screened sample in the main analysis because it provides a consistent CMS public-reporting measurement basis across accredited facilities and is supported by relevant clinical management literature (Kshirsagar et al., 2019).

Finally, the panel spans 2016 through 2020, with both boundary years set by the availability and stability of the CMS measures, as explained in Section 4.1. Every specification carries the prior year outcome together with an indicator for whether a prior year is observed, so the estimates do not lean on any single year's records. We conduct three checks by holding the peer-plus-HBIV control function and all other design choices fixed while varying one feature at a time. First, excluding each boundary year in turn, the quadratic term remains negative and significant (-6.40 and -5.59 , both $p < 0.01$), the first stage remains strong (F -statistic = 140.5 and 226.7), the control-function residual remains significant ($p < 0.01$ in both), the turning point remains interior, and the supported moderation components are preserved (support-intensity curvature interactions -13.95 and -10.74 , both $p < 0.01$; turning-point shifts $\theta_{SI} = 12.42$, $p = 0.04$, and 7.29 , $p = 0.07$; severity shift without the initial year $\theta_{PS} = -6.19$, $p = 0.03$). Second, changing the lagged-outcome base from 2015 to 2016 data leaves the estimates unchanged ($\beta_2 = -5.44$, $p < 0.01$, turning point interior). Third, shifting the baseline a year earlier reproduces every supported pattern, including both turning-point shifts ($\beta_2 = -4.30$, $p < 0.01$; support-intensity interactions 1.94 and -8.76 , both $p < 0.01$; severity interaction -1.28 , $p < 0.01$; $\theta_{SI} = 4.46$, $p < 0.1$; $\theta_{PS} = -4.03$, $p = 0.07$). Neither the window, nor the lag base, nor the boundary years carry the results.

7.3 | Instrument Set

The baseline specification identifies the model using the chain-state leave-one-out peer instrument, together with the HBIV. As an alternative over-identified instrument set, we replace the peer instrument with a shift-share (Bartik) measure of national contract-labor supply propagated through predetermined state exposure (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2021), while retaining the HBIV instrument and all other elements of the design. This check retains the same two-instrument identification strategy, replacing only the peer instrument rather than evaluating either instrument in isolation. The shift-share construction stays in the robustness check rather than the main results because it draws on the same market-level structural variation as the peer measure, so the two do not constitute independent instrument sources. The alternative set has a strong first stage (F -statistic = 56.5) and reproduces the negative, statistically significant main curvature ($\beta_2 = -5.60$, $p < 0.01$), with the turning point inside the observed domain. Appendix A.2 reports the corresponding instrument-set strength and curvature diagnostics.

A related concern is that peer facilities may share unobserved conditions with the focal facility. We address this common-shock concern through a state-by-year fixed-effects specification, which absorbs shocks common to facilities in the same state and year, and through five complementary peer constructions that map distinct remaining pathways (Kling, 2006; Aizer and Doyle, 2015; Nevo, 2001): excluding the focal CBSA targets local-market shocks; excluding the focal state targets state-year shocks; using prior-year chain-state peers targets contemporaneous simultaneity; combining the outside-state and prior-year filters jointly targets spatial and temporal overlap; and pooling all other same-chain facilities nationally tests dependence on the chain-state aggregation cell (Appendix Figure A.1). The figure illustrates the peer-construction family, while Appendix Table A.6 reports the maintained specification, the state-by-year absorption check, and the CBSA-excluded specification in one comparison. As a

separate falsification, we replace the same-chain peer mean with an out-of-chain, same-state-year peer mean. This out-of-chain mean does not materially predict the focal facility's CRR, consistent with relevance arising from same-chain ties; it does not itself validate exclusion for the same-chain instrument.

Because heteroskedasticity-based identification can be sensitive to the choice of the variable that generates the first-stage heteroskedasticity (Baum and Lewbel, 2019; Quiroga, 2025), we also re-estimate using an alternative support-staffing driver while retaining management staffing as a control; the reported curvature and turning-point shifts are qualitatively similar (Appendix Table A.8).

7.4 | Omitted-Variable Bias

The identification strategy in Section 5.2 relies on exclusion restrictions for the instrumental variables. This subsection checks whether an unobserved facility condition, such as operational distress, generates the inverted-U relationship and the supported moderation pattern. We do not claim that every residual facility condition is eliminated. Instead, we check whether such a condition could be sufficiently strong and well aligned with the model to reproduce the evidence, once the CRR control function is in place. Three diagnostics address this channel, each targeting a piece of the design.

Coefficient stability. Following Oster (2017), we assess whether omitted variables could plausibly eliminate the estimated effects. The test compares the influence of unobserved factors with the influence of the observed controls already included in the model. For both the main CRR curvature and the support-intensity curvature interaction, unobserved factors would need to be substantially stronger than the observed controls to reduce the estimates to zero. Moreover, adding the observed controls moves the supported interaction estimates farther from zero, not closer to it.

Negative-control outcomes. We test whether the inverted-U relationship also appears in outcomes that could reflect general facility problems but are not part of the proposed team-coordination mechanism. If an unobserved facility condition were driving the result, a similar curved pattern should appear in these other quality-related outcomes as well (Lipsitch et al., 2010). We examine two outcomes: the ICH CAHPS caring-and-communication achievement score and the standardized readmission ratio. Caring and communication may worsen when a facility deteriorates overall, but they rely mainly on transferable interpersonal skills rather than facility-specific coordination. Readmission is a downstream utilization outcome rather than a direct measure of conformance quality. Neither outcome shows a similar curvature ($\beta_2 = 0.10$, $p = 0.78$; readmission $p = 0.91$), which rejects the facility-specific confounding condition and is consistent with the proposed coordination mechanism.

Outcome-proxy adjustment. We next apply the proximal adjustment proposed by Tchetgen Tchetgen et al. (2024) to address possible remaining omitted-variable bias in the outcome equation. The method adds a negative-control outcome as a proxy for an unobserved facility characteristic, such as overall management quality or organizational deterioration, to absorb outcome-side confounding that the instruments alone may not eliminate. The test complements the instrument-validity checks in Section 7.3 but modifies only the outcome equation, leaving the first-stage model unchanged. After applying the adjustment, the quadratic CRR term remains negative and statistically significant ($\beta_2 = -4.34$, $p = 0.02$), and the estimated turning point remains within the observed range at 5.4%.

Together, these three tests provide no evidence that an omitted facility characteristic is strong enough to explain away the main results. Appendix A.8 provides the design details, equations, and full estimates.

7.5 | Moderator Measurement and Exogeneity

The remaining concern is the endogeneity in the moderators themselves: because support intensity and patient severity are facility-level variables, bias in the moderation terms could arise if either responds to quality or shares unobserved drivers with it. Nizalova and Murtazashvili (2014) separate this concern into two sources with different consequences. For omitted variables, the

condition stated in Section 5.3 applies: once the control function has residualized $\widetilde{CRR}$ and the diagnostics of Section 7.4 have addressed the residual omitted-variable concern, endogeneity in a moderator is absorbed by the moderator's main effect rather than contaminating the interaction coefficient, provided the moderator is not aligned with the remaining unobserved determinants of contract staffing (Bun and Harrison, 2018). Consistent with this requirement, the moderators are close to orthogonal to both the endogenous regressor and its first-stage residual within facility and year, with correlations of 0.01 and -0.03 with $\widetilde{CRR}$ for patient severity and support intensity, respectively, and 0.00 with $\hat{v}_{it}$ for both. The result does not rule out reverse causality because a moderator might respond to the outcome itself.

To address reverse causality directly, we follow the same source-specific control-function logic used for $\widetilde{CRR}$: each potentially endogenous source contributes its own first-stage residual, and the residuals enter the moderation equation jointly. This implementation follows Pal et al. (2024), whose nonlinear moderation models jointly include one residual for each endogenous source, and Sharma et al. (2024), who separately first-stage two endogenous workforce measures before entering their corrections jointly in a control-function model. Instrumenting patient severity with its one-year lag and adding the corresponding first-stage residual alongside the $\widetilde{CRR}$ residual in Model (3) leaves the supported severity moderation, and with it the leftward shift of the turning point, essentially unchanged: the $\widetilde{CRR} \times \widetilde{PS}$ interaction is -1.47 ($p < 0.01$), against -1.43 ($p < 0.1$) in the maintained model, with a strong lagged-severity first stage (F-statistic = 71.08) (Wooldridge, 2015). The same correction applied to support intensity (lagged-SI first-stage F-statistic = 17.8) likewise leaves both supported components stable: $\widetilde{CRR} \times \widetilde{SI} = 2.52$ ($p < 0.01$) and $\widetilde{CRR}^2 \times \widetilde{SI} = -10.95$ ($p < 0.01$), against 2.31 and -11.12 in the maintained model (Rivers and Vuong, 1988).

Hence, the two remaining threats are addressed directly: residual omitted-variable bias via the moderators' orthogonality to the residualized staffing variation, and reverse causality via the lagged control-function checks. The supported moderation pattern, the steepening and rightward shift under support intensity and the leftward shift under severity, is therefore not an artifact of moderator endogeneity.

7.6 | Estimation Framework

The estimation-framework question is whether the within-facility fixed-effects control function is the estimator matched to the identifying variation, rather than a specification choice that manufactures the pattern. One feature of the panel matters for what the estimator identifies: some fully rated dialysis facilities operated with a permanent RN roster within the observed time window. The average contract RN share among ever-contracting facilities in our sample is around 3.0%, in line with the national average (U.S. Government Accountability Office, 2024; Aiken et al., 2007). Because the fixed-effect control function estimator leverages within-facility changes in CRR, the estimates are based on the subset of facilities that actually contract (Griliches and Hausman, 1986). As the inverted-U, support-intensity curvature, and patient-severity left-shift patterns remain significant under the within-facility design, and the endogeneity correction further sharpens these effects. The relationship, therefore, appears to be a stable feature of how contracting facilities operate.

The choice of estimator was settled in the diagnostics of Section 5 (Table 4), and the two-stage benchmarks of Appendix A.9 show why the control function, rather than direct projection, carries the quadratic term. What remains is whether the maintained estimator's conventions, the log outcome scale, and the single residual are doing the work. To test it, the fixed-effects Poisson pseudo-maximum-likelihood control function (PPMLFE-CF) re-estimates the maintained equation on the level-scale outcome (Silva and Tenreiro, 2006), keeping $\ln(1 + CRR)$, the full control set and the first-stage residual in a two-stage residual-inclusion design (Terza et al., 2008; Wooldridge, 2015); the inverted-U reproduces on the exponential conditional mean ($\beta_2 = -4.09$, $p = 0.01$; facility-clustered bootstrap $p = 0.01$), together with the support-intensity moderation (1.59 , $p = 0.02$; -7.36 , $p = 0.03$) and the severity interaction (-1.02 , $p = 0.10$). A flexible control function in the Garen (1984) tradition, which adds the residual-by- $\widetilde{CRR}$ interaction to every model, likewise leaves the estimates intact ($\beta_2 = -4.43$, $p = 0.07$; support-intensity interactions 2.23 , $p = 0.01$, and -11.04 , $p = 0.02$; severity interaction -1.40 , $p = 0.07$), and the added flexibility contributes nothing that

the single residual does not already capture ($p > 0.10$). The pattern is therefore not an artifact of the estimator, the outcome scale, or the residual specification.

8 | DISCUSSION

Our results reveal that workforce fissuring does not operate in a vacuum. Instead, its impact depends on the unit’s underlying coordination capacity and clinical setup. In the baseline estimates, the relationship between CRR and quality follows an inverted-U shape, with performance peaking at around 6.9% of CRR (H1).

The magnitude can be interpreted in light of how exposure is measured. We constructed CRR from annual FTE counts in Medicare cost reports, whereas many agency assignments, particularly travel and local contract assignments, follow fixed cycles of about thirteen weeks (CoreMedical Group, 2025; Aiken et al., 2007). In dialysis, staffing needs can be especially demanding during the winter season, when patient acuity and mortality peak (Usvyat et al., 2012). For example, an RN engaged for one thirteen-week assignment would contribute about one quarter of an annual FTE. The annual CRR can therefore understate the contractor share during the period in which the assignment occurs. The inverted-U, accordingly, characterizes annual reliance on contract RNs while allowing for shorter agency assignments within the year.

The rightward shift of the quality peak under high support-staff intensity (H2) suggests that PCTs serve as an informational buffer. While contract RNs bring clinical skills, they lack site-specific tacit knowledge. Our results indicate that support staff help bridge this gap by guiding contract workers through local routines and patient histories. This redundancy in communication channels expands the unit’s coordination capacity, allowing the facility to successfully absorb higher levels of fissured labor without degrading quality. By contrast, the leftward shift under high patient severity (H3) is consistent with information-load saturation. Complex cases require tighter interdependencies and leave little room for relational frictions, such as communication delays and handoff breakdowns associated with contract labor. In these high-stakes settings, the unit lacks the relational slack to accommodate temporary workers and manage complex patients simultaneously. As task complexity rises, the feasible range for fissuring shrinks, and quality deteriorates more rapidly once the unit moves beyond it. The estimated reduction in the attainable peak as patient severity increases is directionally consistent with H3a in the primary analysis, although this contrast does not reach statistical significance. Table 8 summarizes the hypothesis tests and findings.

TABLE 8 Summary of Hypothesized Relationships and Key Findings

Hyp.	Predicted Relationship	Statistical Test	Significance	Finding
Panel A. Main Effect				
H1	Inverted-U relationship between $\widetilde{CRR}$ and $\widetilde{CQ}$	Four-step validation following Lind and Mehlum (2010) and Haans et al. (2016)	$p < 0.01$	Supported
Panel B. Support Intensity Moderation				
H2a	Higher support intensity raises the attainable peak	$\Delta_{\text{peak}}(\widetilde{SI}_{75}) - \Delta_{\text{peak}}(\widetilde{SI}_{25}) > 0$	$p = 0.02$	Supported
H2b	Higher support intensity shifts the turning point rightward	$\beta_{21}\beta_{26} - \beta_{22}\beta_{25} > 0$	$p = 0.03$	Supported
Panel C. Patient Severity Moderation				
H3a	Higher patient severity lowers the attainable peak	$\Delta_{\text{peak}}(\widetilde{PS}_{75}) - \Delta_{\text{peak}}(\widetilde{PS}_{25}) < 0$	$p = 0.16$	Not supported
H3b	Higher patient severity shifts the turning point leftward	$\beta_{31}\beta_{36} - \beta_{32}\beta_{35} < 0$	$p = 0.05$	Supported

8.1 | Theoretical Contributions

This study advances operations management theory by examining the mechanics of fissured workforces in high-skill, quality-critical settings. Our findings offer three primary contributions to the literature on workforce design, relational coordination, and the information-processing view of service operations.

First, we challenge the traditional core/non-core dichotomy that has long guided outsourcing and employment-boundary decisions (Weil, 2014; Abraham and Taylor, 1996). By focusing on the percentage of contract RNs in the outpatient hemodialysis setting, we demonstrate that even the workforce central to service delivery can be strategically fissured without necessarily degrading performance. These findings cast new light on “core” roles in workforce design, which should be defined more by the relational density and informational stability of such roles in the work system, rather than by formal employment status. In doing so, we extend research on the complementarities between governance and capability (Parmigiani, 2007; Holcomb and Hitt, 2007) and position fissured workforce not as an ancillary add-on, but as a configurable component of the operational architecture (Benjaafar and Hu, 2020; Altman et al., 2023).

Second, we establish a robust inverted U-shaped relationship between workforce fissuring and quality outcomes, providing a mechanistic explanation for the “performance frontier” of contract RNs. We find that quality reaches its peak at a specific turning point where the benefits of resolving task uncertainty through external expertise are maximized before being overtaken by coordination friction, which erodes the shared goals and knowledge central to relational coordination. This curvilinear pattern refines capability-erosion arguments in the literature by clarifying when fissuring can be performance-enhancing and why quality deteriorates beyond that range (Handley, 2012). It echoes evidence that safety/quality can remain stable up to agency use initially but deteriorate past a certain threshold (see, e.g., Bae et al. 2010). More broadly, the results align with OM research showing that hybrid workforce configurations generate value only when the relational core is preserved to sustain the mobilization of tacit knowledge (Lu et al., 2023).

Third, we identify organizational and clinical contingencies that shift the properties of this performance frontier. We demonstrate how the unit’s internal capacity and external load shape the quality-maximizing turning point. Consistent with OIPT, a robust PCT base expands the unit’s information-processing capacity. By functioning as a buffer, high support intensity elevates the peak of the quality curve and shifts the turning point to the right. This allows the facility to successfully integrate a higher proportion of fissured workforce in high-skill core roles while preserving the local tacit knowledge within permanent peripheral low-skill roles. Conversely, higher patient severity acts as an information load that exhausts the unit’s cognitive and relational slack, compressing decision windows and heightening coordination demands. This constraint shifts the turning point to the left. The estimated reduction in the attainable peak as patient severity increases is directionally consistent with H3a in the primary analysis, although this contrast does not reach statistical significance. The supported shift finding indicates that coordination friction manifests more rapidly in high-acuity environments, causing quality performance to deteriorate at lower levels of fissuring than in less acute clinical contexts.

Collectively, our findings extend relational coordination theory into the domain of workforce design by demonstrating how coordination capacity and task complexity jointly affect an organization’s ability to integrate fissured roles into its own workforce design. We emphasize that when interdependence is high, organizational support structures govern performance, determining whether the organization can successfully capitalize on external expertise or suffer from coordination breakdown (Weil, 2014; Massimino and Lawrence, 2019; Mishra et al., 2020; Benjaafar and Hu, 2020). This mechanism connects to a broader operations literature on governing externalized work at the contracting interface, where the effectiveness of buyer oversight in limiting effort-withholding depends on relational and cultural context (Skowronski et al., 2022), and where the structure of the sourcing arrangement itself shapes coordination outcomes (Handley et al., 2022).

8.2 | Managerial Insights

Our findings speak directly to ongoing workforce decisions in healthcare settings, where managers increasingly rely on contracted RNs to address persistent labor shortages. A recent survey study conducted by KPMG reports that healthcare executives cite cost, care quality, and relevant experience as the three most important considerations when employing contracted RNs, with 17% of respondents planning to increase the share of contract RNs by at least 5% in the next 12 months (KPMG, 2026). This evidence suggests that fissuring in core clinical roles is not a temporary response to crisis conditions, but an increasingly deliberate and forward-looking workforce strategy.

Our results indicate that such strategies can be viable, and even performance-enhancing, when implemented within an appropriate organizational context. In outpatient hemodialysis centers, contracted RNs are embedded in the core of clinical care delivery, making quality outcomes sensitive not only to the extent of fissuring, but also to how staffing arrangements are supported and coordinated. Rather than viewing contract staffing as a binary choice, managers should treat fissuring as a continuous design variable whose performance implications evolve as the use of external labor increases, consistent with calls to bring an explicitly operational lens to the management of externalized and franchised service delivery (Lawrence and Zhang, 2022). Specifically, as the contract RN ratio moves towards a turning point, managers must be vigilant about the rising coordination friction that can eventually offset the benefits of fissuring. Effective use of contract RNs therefore requires ongoing monitoring of quality outcomes and iterative adjustment of staffing practices, rather than adherence to fixed targets or one-time staffing decisions.

A key managerial implication concerns the role of peripheral support as a knowledge-coordination buffer. In tightly coupled service environments such as dialysis care, RNs and PCTs work with high interdependence, despite occupying different clinical roles. Facilities that maintained high PCT support were better able to preserve local tacit knowledge, stabilize coordination routines, and absorb new knowledge/practices introduced by contract RNs. In this sense, PCTs function as a source of operational continuity that allows contracted RNs to contribute flexibility and external expertise without disrupting care processes. For managers facing sustained RN shortages, investing in stable peripheral roles offers a practical mechanism for retaining institutional know-how and coordination capacity while accommodating workforce variability.

Patient severity further acts as a performance constraint that conditions these decisions. Facilities serving patients with higher clinical complexity operate under narrower margins for error, limiting the degree to which fissuring can be expanded without undermining quality. In such settings, even slight increases in contract RN use place greater strain on coordination unless accompanied by strong support structures. By contrast, facilities with less severe case mixes have greater latitude to capitalize on external expertise without compromising outcomes. These findings indicate that fissuring decisions cannot be based on cost considerations alone; they must reflect the interaction between workforce design, support intensity, and patient complexity.

Our results caution against evaluating fissuring strategies solely in terms of short-term labor cost savings. When support to frontline staff is under-resourced, apparent efficiencies are offset by reliability losses, rework, and diminished quality, consistent with capability-erosion mechanisms documented in prior operations research (Handley, 2012). When organizations deliberately invest in coordination capacity and support roles, however, fissuring becomes a lever for expanding capacity and accessing external expertise without suffering from coordination breakdown. The managerial challenge is therefore not to identify a single optimal staffing mix, but to continuously recalibrate the balance between fissuring and support as labor markets, patient populations, and care technologies evolve.

While our study is set in dialysis clinics, the empirical patterns we identify, specifically the inverted-U relationship and its moderated shifts, travel effectively to other high-skill service sectors. In IT Services, patient severity maps to incident criticality; a high-severity system failure requires deep contextual knowledge of the legacy code, leaving little relational slack for external consultants to operate effectively (a leftward shift of the quality peak). Conversely, in manufacturing, support-staff intensity mirrors the presence of cell leads or project coordinators. These permanent staff members act as the operational glue, allowing for a higher ratio of temporary technicians by back-filling the necessary tacit knowledge of standardized work processes. By framing

workforce fissuring as a manageable trade-off between general expertise and contextual intimacy, managers in diverse sectors can use these patterns as a decision tool to calculate the ROI of onboarding investments versus the risk of coordination failure.

8.3 | Policy and Societal Implications

Our findings offer a new perspective for policymakers and healthcare regulators tasked with balancing workforce shortages against patient safety. Traditionally, regulatory bodies have relied on one-size-fits-all limits for contract staffing to ensure quality. However, our evidence suggests that such rigid thresholds may be counterproductive, particularly in regions facing chronic labor shortages where some degree of fissuring is necessary to maintain service access. This implies some headroom to use contract labor, but only within a finite operating envelope; beyond that, fissuring shifts from flexibility to performance constraints.

We further propose that regulators move toward conditioned guidance, a framework where staffing flexibility is tied to a facility's specific operational context. For example, state health departments could set severity-adjusted staffing bands. Under this model, a dialysis center might be permitted a higher share of contract RNs only if they document a minimum threshold of support-staff intensity (PCTs) and maintain stable hospitalization or infection benchmarks. Conversely, for facilities treating highly acute patients, the allowable band of fissured labor would be tighter.

The societal value of this approach is twofold. First, it provides a practical lever for policymakers to maintain healthcare access in rural or underserved areas during workforce shortages without compromising care quality. Second, it shifts the regulatory focus from a simple headcount of permanent employees to a more sophisticated assessment of systemic coordination capacity. By recognizing that support staff and patient complexity condition the success of workforce fissuring, regulators can create more resilient, data-driven guidelines that reflect the realities of modern service operations.

8.4 | Limitations and Future Research

Similar to other empirical studies, our study is subject to limitations. In the following, we discuss several key limitations that warrant attention and open avenues for future research.

First, our empirical context centers on the coordination interface between the RN and PCT roles in outpatient dialysis centers. While this setting provides a particularly clean environment for examining fissured workforces in high-skill, team-based operations, the coordination mechanisms and knowledge-transfer processes observed here may not generalize directly to other healthcare domains or to industries with different task interdependencies. Future work could examine whether similar patterns emerge in settings such as physician-nurse collaboration in acute care, engineer-technician teams in manufacturing, or project-based professional services where contractual labor is also embedded in core workflows.

Second, a specific limitation concerns the configuration of labor fissuring within our study context. In the outpatient hemodialysis setting, contract labor is almost exclusively concentrated in the high-skill RN role, whereas less than 1% of low-skill Patient Care Technicians (PCTs) are contracted, meaning the 'support core' remained largely permanent. While this allowed us to isolate the effects of fissuring in a high-skill core role, these dynamics may not necessarily generalize to environments with a higher percentage of fissured workers in low-skill peripheral roles. In many service and manufacturing contexts, the support functions are often the first to be outsourced or fissured. Future research should investigate the compounding fissuring effect, where both the high-skill core and the low-skill peripheral roles are contracted, to determine if the coordination buffers identified in this study (such as Support Intensity) still hold when the relational core of the team is itself transient.

Third, our quality outcome is constructed from QIP components that most closely reflect nursing and frontline operational performance. Although these measures capture clinically meaningful dimensions of care, they do not incorporate other outcomes that may be affected by fissuring, such as clinician well-being or workforce morale. Future research that integrates multiple stakeholder perspectives could provide a more comprehensive assessment of the trade-offs associated with fissured workforce

arrangements.

Fourth, our measurement of the fissured RN ratio relies on FTE-based data from Medicare cost reports. We assume that the employment structure of fissured RNs is relatively consistent across dialysis facilities in the U.S. The ratio does not capture nuances such as contract duration, experience level, agency affiliation, or pay rate. These factors could likely influence how quickly fissured RNs integrate into local routines and how much tacit knowledge is lost or retained. Future studies should draw on richer data sources or mixed-method approaches to capture these dynamics.

Finally, our analysis focuses on dialysis operations from 2016 to 2020, immediately prior to the COVID-19 pandemic. This period captures staffing and coordination practices under relatively stable operating conditions, before the widespread disruptions to labor markets, care delivery, and clinical protocols that followed. The pandemic fundamentally altered the use of contract labor and the operational environment in healthcare, introducing emergency staffing arrangements and crisis-driven coordination challenges that differ from the mechanisms examined in this study. Future research should therefore examine how fissuring dynamics evolve under extreme shocks and prolonged uncertainty, as well as whether investments in training, knowledge retention systems, and integration practices play a similar role in sustaining performance during and after such disruptions.

Overall, these limitations delineate a broader research agenda around fissured workforces as a central feature of modern operations. Our findings provide evidence that fissuring in high-skill roles can enhance performance when matched with sufficient coordination capacity, while also highlighting the conditions under which these benefits break down. Understanding how organizations design, govern, and adapt such workforce arrangements remains a critical direction for future operations management research.

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A | APPENDIX

APPENDIX SECTION A.1 | Increased RN–PCT Coordination for Out-of-Range Hemoglobin

Table A.1 summarizes clinical scenarios and coordination tasks for out-of-range Hemoglobin, illustrating the increased RN–PCT coordination and justifying the definition of PS moderator.

TABLE A.1 Clinical Scenarios and Coordination Tasks for Out-of-Range Hemoglobin for RNs and PCTs

Scenario (Hgb)	Operational Response	Coordination Requirements	Local Execution Factors
Low (<10 g/dL)	RNs: Trigger re-test and increase monitoring; adjust medicines (ESA/Intravenous iron); escalate for transfusion if criteria are met.	RNs: Ensure lab results flow into the monitoring system; confirm supply and scheduling of blood products; track and log any adverse events.	Lab turnaround times; transfusion process steps; patient compliance and attendance patterns.
	PCTs: Start and end each dialysis treatment, record vital signs	PCTs: Report acute changes (e.g., hypotension, signs of bleeding) to RNs	
High (>12 g/dL)	RNs: Hold or reduce ESA order; monitor blood pressure and vascular access; escalate for imaging or procedure if thrombosis is suspected; adjust dialysis timing around the procedure.	RNs: Maintain a fast communication loop between orders, labs, and scheduling; secure imaging or procedure slots; align treatment sessions with interventions.	Availability of imaging or procedure slots; transport and caregiver logistics; dialysis sequencing rules; local access-protection protocols.
	PCTs: Start and end each dialysis treatment, record vital signs	PCTs: Report acute changes (e.g., hypotension, signs of bleeding) to RNs	

APPENDIX SECTION A.2 | Instrument Diagnostics and First Stages

Table A.2 reports the instrument-combination diagnostics: the first-stage strength statistic and the significance of the main quadratic curvature term. Each row uses the fixed-effects control-function specification with the indicated excluded-instrument set, the same controls, facility and year fixed effects, lagged-outcome terms, and one control-function residual. Both instrument sets show strong first-stage relevance and a negative, statistically significant quadratic term.

TABLE A.2 Instrument-Set Strength and Curvature Diagnostics

Instrument set	Excluded-instrument F	$\widetilde{CRR}^2$ coefficient	Curvature p -value
Peer + HBIV (maintained)	223.1	−5.440	< 0.01
Shift-share + HBIV	56.5	−5.599	< 0.01

Notes: Each row uses the fixed-effects control-function specification with the indicated excluded-instrument set and the same controls and fixed effects.

Table A.3 summarizes the methodological precedents for our instrument set and single-residual control-function design, clarifying how each component relates to prior empirical applications. Table A.4 then reports the full coefficient estimates for the maintained control-function specifications, including the control variables, fixed effects, and first-stage residual that are omitted from the more compact presentation in the main text.

Table A.5 reports the fixed-effects regression of $\widetilde{CRR}$ on the exogenous controls whose residual $\hat{e}_{it}$ enters the heteroskedasticity instrument $HBIV_{it} = (Z_{it} - \bar{Z})\hat{e}_{it}$ in Eq. (7). It is estimated on all analytic facility-years with the required covariates, excluding facility-years in singleton fixed-effect groups. A Breusch-Pagan test of the residuals’ homoskedasticity with respect to management staffing rejects ($\chi^2(1) = 17.2$, $p < 0.01$), establishing the heteroskedasticity that identifies the instrument.

TABLE A.3 Prior Applications of the Instrument and Control-Function Design

Study	Setting	Construction
<i>Panel A. Leave-one-out peer instrument (our L)</i>		
Nevo (2001), Econometrica	Cereal demand	brand price $\leftarrow$ same brand's price in other markets
Kling (2006), AER	Incarceration and earnings	sentence $\leftarrow$ assigned judge's leave-out mean severity
Peng et al. (2023), JOM	Hospital nursing units	unit staffing, turnover $\leftarrow$ leave-one-out mean among other same-type units
Barker et al. (2026), JOM	Supply-base change	focal supply-base configuration $\leftarrow$ peer firms' industry-segment patterns
This paper	Dialysis facilities	contract RN use $\leftarrow$ leave-one-out mean of the chain's other facilities, same state-year
<i>Panel B. Heteroskedasticity-based instrument (our H)</i>		
Lewbel (2012), JBES	Engel curves (origin)	$(Z - \bar{Z})\hat{\epsilon}$, identified by first-stage heteroskedasticity
Dong et al. (2020), JOM	Supply base innovation	supply base innovation $\leftarrow$ HBIV instruments
Wowak et al. (2025), Mgmt. Science	Medical-product recalls	TMT political ideology $\leftarrow$ HBIV robustness instruments
Lim et al. (2024), Mgmt. Science	Hospital capacity pooling	off-service placement $\leftarrow$ HBIV with Heckman selection correction
Bok et al. (2025), MSOM	Family engagement in healthcare	illness severity $\leftarrow$ external IV plus LASSO-selected HBIV instruments
Lagzi et al. (2023), JOM	Radiology platform	workload spillovers $\leftarrow$ HBIV instruments
Pal et al. (2024), JOM	Open-source software teams	team interaction $\leftarrow$ HBIV instruments
Bonnett and Heim (2024), JOM	Hospital mid-level providers	mid-level-provider use $\leftarrow$ HBIV robustness instruments
Chen et al. (2024), JOM	E-commerce warehouse coordination	turnover level $\leftarrow$ HBIV robustness instruments
Li et al. (2023), JOM	Operational resilience	multiple endogenous regressors $\leftarrow$ HBIV instruments
This paper	Dialysis facilities	$(Z - \bar{Z})\hat{\epsilon}$, Z = management staffing; supplies the over-identifying moment
<i>Panel C. Parsimonious control function: one residual per endogenous source</i>		
Wooldridge (2015), JHR	Applied econometrics	single reduced-form residual for nonlinear functions of one endogenous regressor
Akkus et al. (2021), Mgmt. Science; Janakiraman et al. (2023), Mgmt. Science	Finance and healthcare	reviewer-specified applied precedents for control-function correction
Pal et al. (2024), JOM	Open-source software teams	one first-stage residual per endogenous source, entered jointly with nonlinear and interacted terms
Barker et al. (2026), JOM	Supply-base change	peer-based instruments, first-stage residual, and Hansen over-identification diagnostics
Sharma et al. (2024), JOM	Food-bank SNAP outreach	two endogenous workforce sources, separately first-staged and entered jointly in a probit control function
This paper	Dialysis facilities	one first-stage residual accompanies CRR, CRR ² , and CRR-moderator interactions

Notes: AER = American Economic Review; JBES = Journal of Business & Economic Statistics; JHR = Journal of Human Resources; JOM = Journal of Operations Management; MSOM = Manufacturing & Service Operations Management.

TABLE A.4 Fixed Effects Control-Function Estimates (Full Coefficient Table)

Variables	First stage	Structural models		
	CRR	(1) Main	(2) Support-Intensity Moderation	(3) PS Moderation
Peer instrument L	0.1360*** (0.0521)			
HBIV instrument H	-0.8447*** (0.0839)			
$\widehat{CRR}$		0.689* (0.380)	0.893** (0.385)	0.589 (0.421)
$\widehat{CRR}^2$		-5.440*** (1.591)	-7.531*** (1.729)	-5.064*** (1.853)
$\widehat{CRR} \times \widehat{SI}$			2.311*** (0.697)	
$\widehat{CRR}^2 \times \widehat{SI}$			-11.117*** (3.150)	
$\widehat{CRR} \times \widehat{PS}$				-1.426*** (0.543)
$\widehat{CRR}^2 \times \widehat{PS}$				2.068 (2.050)
$\widehat{SI}$	-0.0019** (0.0008)	0.091*** (0.013)	0.095*** (0.013)	0.094*** (0.013)
$\widehat{PS}$	-0.0002 (0.0002)	-0.026*** (0.008)	-0.026*** (0.008)	-0.027*** (0.008)
$\hat{\theta}$		2.466*** (0.438)	2.803*** (0.449)	2.519*** (0.440)
Social Workers	-0.0003 (0.0009)	-0.025* (0.013)	-0.025* (0.014)	-0.024* (0.013)
Management Staffing	-0.0015*** (0.0006)	0.012* (0.007)	0.013* (0.007)	0.013* (0.007)
Contract PCTs	0.0252 (0.0184)	-0.026 (0.036)	-0.021 (0.037)	-0.024 (0.036)
Dialysis Stations	-0.0002 (0.0001)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
Drugs Expense ($\times 10^6$)	-0.0014 (0.0038)	0.101*** (0.026)	0.102*** (0.026)	0.099*** (0.026)
Laboratory Expenses ($\times 10^6$)	0.0536* (0.0312)	-0.149 (0.186)	-0.127 (0.186)	-0.157 (0.185)
Years Since Certification	-0.0000 (0.0006)	0.429 (0.316)	0.426 (0.316)	0.433 (0.316)
Hemodialysis Share	-0.0006 (0.0052)	-0.205* (0.113)	-0.209* (0.113)	-0.200* (0.113)
Lagged Clinical Quality	0.0014** (0.0007)	-0.084*** (0.011)	-0.084*** (0.011)	-0.084*** (0.011)
Lagged Clinical Quality Missing	0.0039** (0.0017)	-0.129*** (0.022)	-0.129*** (0.022)	-0.129*** (0.022)
Constant	0.0007 (0.0150)	-6.817 (6.612)	-6.743 (6.608)	-6.898 (6.608)
<i>Fixed effects and sample statistics</i>				
Facility FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Chi-square	1603.66***	3423.89***	3439.40***	3461.64***
Facilities			3,914	
Observations			14,749	

Notes: Coefficient estimates for Table 5; clustered standard errors are in parentheses. Results are consistent whether or not the FTE counts of registered and licensed practical nurses are included as controls.

$\hat{\theta}$ is the first-stage residual; dollar coefficients and standard errors are scaled by 10^6 .

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.5 Auxiliary Regression Generating the Heteroskedasticity Instrument

Dependent variable	$\widehat{CRR}$
Support Intensity	−0.0140*** (0.0052)
Patient Severity	−0.0000 (0.0029)
Nurse Aides	−0.0005 (0.0006)
Social Workers	0.0012* (0.0006)
Management Staffing	0.0017** (0.0008)
Dialysis Stations	−0.0008*** (0.0003)
Drugs Expense (×10 ⁶)	0.0044 (0.0027)
Week Shift	0.0000 (0.0001)
Laboratory Expenses (×10 ⁶)	0.0355 (0.0217)
Physicians	0.0000 (0.0001)
Years Since Certification	−0.0001 (0.0001)
Hemodialysis Share	−0.0024 (0.0074)
Constant	0.0013 (0.0089)
Facility FE, Year FE	✓

Notes: Cluster-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

APPENDIX SECTION A.3 | Additional Instrument-Robustness Checks

Figure A.1 illustrates the five peer-LOO robustness constructions summarized in Section 7.3. In the notation of the figure, c , s , and b denote chain, state, and CBSA. Table A.6 reports the state-by-year absorption and CBSA-isolation checks together, and Table A.8 reports the alternative heteroskedasticity driver.

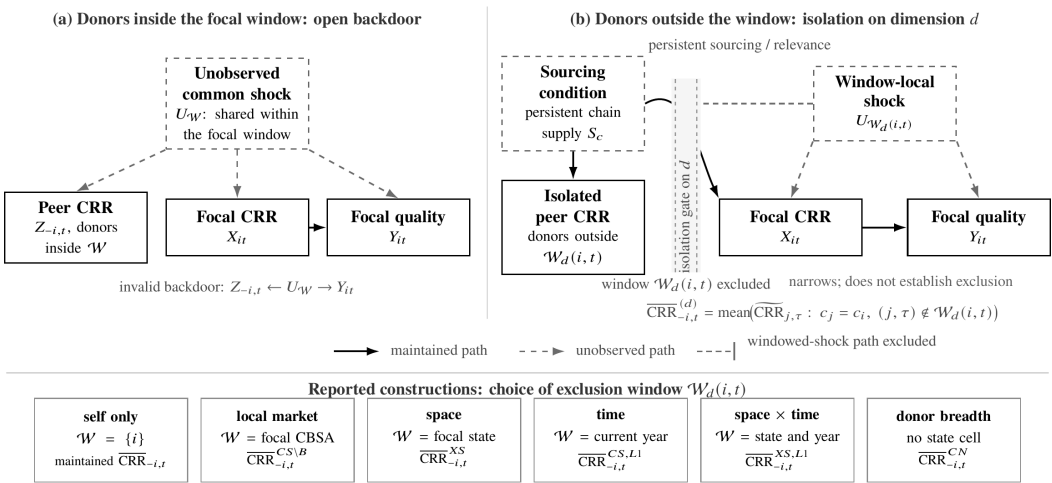


FIGURE A.1 Schematic illustration of the peer-LOO construction family. Panel (a) depicts the common-shock concern when donor peers share the focal facility’s environment; panel (b) depicts the isolation logic, with donors drawn from outside an exclusion window $W_d(i, t)$ on the relevant dimension. The bottom strip illustrates the maintained construction and five alternative exclusion windows. Each construction narrows the corresponding pathway rather than establishing exclusion.

TABLE A.6 Common-Shock Robustness Checks

Specification	Joint F	$\widetilde{CRR}^2$ (H1)	TP	θ_{SI} (H2b)	θ_{PS} (H3b)
Chain-state LOO (maintained)	223.1	−5.440	6.9%	7.476 ($p = 0.03$)	−6.001 ($p = 0.05$)
State×year FE	154.8	−4.538	5.5%	6.890 ($p = 0.08$)	−5.639 ($p = 0.08$)
Chain-state LOO, excl. own CBSA	149.2	−5.468	6.8%	7.874 ($p = 0.06$)	−5.581 ($p = 0.07$)

Notes: All rows retain the peer-plus-HBIV control-function system. The state×year row changes only the absorbed fixed effects; the CBSA row changes only the peer donor pool. The $\widetilde{CRR}^2$ curvature is negative and significant ($p < 0.01$) in every row; H2a remains supported and H3a remains unsupported. We also examined alternative conventional evaluation values; in the maintained specification, the conditional quadratic coefficient remains negative from the 10th through the 90th percentile of each moderator (Table A.7). Turning-point-shift inference is based on 1,000 facility-clustered bootstrap replications. Cluster-robust standard errors.

TABLE A.7 Conditional Curvature at Alternative Conventional Moderator Values

Moderator level	Conditional curvature
<i>Panel A. Support intensity (Model 2)</i>	
SI, 10th percentile	−0.331
SI, 90th percentile	−15.369
<i>Panel B. Patient severity (Model 3)</i>	
PS, 10th percentile	−6.562
PS, 90th percentile	−3.623

Notes: Point evaluations of the conditional quadratic coefficient from the Table 5 estimates at the 10th and 90th percentiles of each moderator. All evaluations are negative. Quartile and mean evaluations with delta-method standard errors appear in Table 6. Other conventional values, including ± 1 SD, yield the same conclusion (available upon request).

TABLE A.8 Alternative Heteroskedasticity Driver

Statistic	Support-staffing driver, log(other_total)
Excluded-instrument joint F	58.5
Heteroskedasticity-driver first-stage loading	−1.688
Peer-instrument first-stage loading	0.233
$\widetilde{CRR}^2$ curvature (H1)	−2.408 ($p = 0.08$)
Turning-point shift θ_{SI} (H2b)	5.431 ($p = 0.02$)
Turning-point shift θ_{PS} (H3b)	−3.454 ($p = 0.10$)

Notes: The management-staffing heteroskedasticity driver of the maintained specification is replaced by a support-staffing measure, the log of total support (“Other”) staffing reported on the cost report; management staffing is retained as a control. The negative $\widetilde{CRR}^2$ curvature and the supported turning-point shifts are reproduced. Cluster-robust standard errors; turning-point-shift inference is based on 1,000 facility-clustered bootstrap replications.

APPENDIX SECTION A.4 | Residual Structure of the Control Function: Derivation and Tests

The structural model of Section 5.1 is shown as

$$\widetilde{CQ}_{it} = \beta_1 \widetilde{CRR}_{it} + \beta_2 \widetilde{CRR}_{it}^2 + \gamma^T \mathbf{G}_{it} + \theta^T \mathbf{W}_{it} + \alpha_i + \delta_t + e_{it}, \tag{A.1}$$

where $\mathbf{G}_{it}$ captures the moderator's main effects and, in the moderation models, the interaction terms, with $E[e_{it} | \widetilde{CRR}_{it}, \mathbf{W}_{it}] \neq 0$. Eq. (8) estimates one reduced-form residual, v_{it} , for the endogenous contract RN ratio.

Wooldridge (2015) shows that a single reduced-form residual controls for the endogeneity of nonlinear functions of a single endogenous regressor when the structural error $E[e_{it} | \mathbf{Z}_{it}, \mathbf{W}_{it}, v_{it}] = \rho v_{it}$. This condition fits our design because contract RN use is the only endogenous staffing choice; the square and moderator interactions are deterministic functions used to represent curvature and conditional curvature. We therefore estimate the structural models with one residual, $\hat{v}_{it}$, and evaluate whether additional residual terms are needed as specification checks rather than as part of the maintained estimator.

We adopt the single-residual structure with variable-addition tests (Rivers and Vuong, 1988). First, we add a squared residual, $\hat{v}_{it}^2$, to test whether the correction is linear in the reduced-form innovation (Wooldridge, 2015). Second, we add residual-by-moderator terms in the moderation models to test whether the correction varies with support intensity or patient severity.

The single control-function residual is significant in the baseline model ($\rho = 2.466, p < 0.01$), providing a regression-based endogeneity test for contract RN use. Adding a squared residual does not alter this conclusion: the level residual remains significant ($p < 0.01$), while the squared residual is not significant ($p = 0.19$), supporting a linear residual correction for the contract RN source. The residual-by-support-intensity term is not significant in the support-intensity model ($p = 0.50$), so support intensity does not require an additional residual correction. We use a single linear residual for the contract RN source in all structural models, and separately subject patient severity to the lagged-severity two-residual control-function check reported in Section 7.5.

APPENDIX SECTION A.5 | Cost–Quality Analysis

This appendix documents the construction of the cost–quality efficiency map in Figure 5. We consider a representative facility calibrated to sample means: $\bar{N} = 5$ essential clinical staff (sample mean = 4.99) and $\bar{P} = 115$ total patients (sample mean = 115). Wage assumptions are based on the Bureau of Labor Statistics (2023–2024) and industry benchmarks (U.S. Bureau of Labor Statistics, 2024; Advisory Board, 2022): $w_{PRN} = \$89,000$ for each permanent RN, $w_{PCT} = \$47,000$ for each PCT, and $w_{CRN} = \$178,000$ for each contract RN.

Using these inputs, we calculate both quality outcomes and total labor costs as functions of CRR and SI. Specifically, we vary CRR from 0 to 0.20 in increments of 0.005 and SI from 0.025 to 0.20 in increments of 0.005. For each point on the grid, quality is calculated using Model (2) in Table 5, and total labor cost is computed as:

$$\text{Cost} = \bar{N} \cdot \text{CRR} \cdot w_{CRN} + \bar{N} \cdot (1 - \text{CRR}) \cdot w_{PRN} + \bar{P} \cdot \text{SI} \cdot w_{PCT}. \quad (\text{A.2})$$

For interpretive context, a 0.01 increase in CRR is associated with an increase of approximately \$4,450 in costs, while a 0.01 increase in SI corresponds to an increase of approximately \$54,050.

These results are intended as an illustrative reference rather than a prescriptive optimization rule. The efficiency map in Figure 5 translates our empirical patterns into an interpretable cost–quality trade-off under representative staffing and wage assumptions, helping practitioners understand how different combinations of CRR and SI can deliver comparable quality outcomes with different cost implications.

In practice, the most attractive region on the map will depend on facility-specific conditions such as local labor costs, staffing availability, patient mix, and operational constraints. Managers can adapt the same procedure by substituting facility-specific inputs (e.g., wages, baseline staffing, and patient volume) and conducting simple sensitivity analyses. Used in this way, the framework offers a transparent “what-if” tool to benchmark alternative staffing configurations and evaluate locally efficient choices consistent with the empirical relationships documented in this study.

APPENDIX SECTION A.6 | Robustness Checks for Alternative Dependent Variable Constructions

Table A.9 re-estimates the full control-function specification, with its own lagged-outcome controls, heteroskedasticity auxiliary, and first stage, on the standardized composite $z(Kt/V) + z(BSI)$ as the dependent variable.

TABLE A.9 Standardized-Composite Outcome: Full Control-Function Specification with Bootstrap Inference

Variable	First stage	(1) Main	(2) SI moderation	(3) PS moderation
<i>Panel A. Excluded instruments (first stage)</i>				
Peer instrument L	0.135*** (0.052)			
HBIV instrument H	−0.845*** (0.084)			
<i>Panel B. Structural estimates (bootstrap)</i>				
CRR		3.086* (1.719)	3.698* (1.887)	2.805 (1.779)
$\widehat{CRR}^2$		−23.823*** (7.641)	−30.338*** (10.286)	−22.885*** (7.815)
$\widetilde{SI}$	−0.002** (0.001)	0.429*** (0.057)	0.440*** (0.057)	0.439*** (0.056)
$\widetilde{PS}$	−0.000 (0.000)	−0.153*** (0.030)	−0.154*** (0.030)	−0.160*** (0.031)
$\widehat{CRR} \times \widetilde{SI}$			6.978** (3.224)	
$\widehat{CRR}^2 \times \widetilde{SI}$			−34.006** (16.043)	
$\widehat{CRR} \times \widetilde{PS}$				−5.756** (2.755)
$\widehat{CRR}^2 \times \widetilde{PS}$				9.187 (10.045)
Control-function residual (ρ)		8.286*** (2.089)	9.329*** (1.864)	8.442*** (1.865)
<i>Panel C. Turning Point shift tests (bootstrap)</i>				
H2b: Turning Point shift, θ_{SI}			88.644* (63.230)	
H3b: Turning Point shift, θ_{PS}				−107.608** (60.174)
<i>Panel D. Diagnostics and sample</i>				
Controls	✓	✓	✓	✓
Facility FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Single control-function residual		✓	✓	✓
Excluded-instrument joint F	222.20			
F -statistics	102.67	14.51	13.39	13.63
Observations		14,749		
Facilities		3,914		
Chi-square	1642.67***	2801.48***	2817.66***	2831.18***

Notes: The outcome is $z(Kt/V) + z(BSI)$; its control function is rebuilt.

Panel A uses cluster-robust standard errors; Panels B–C use bootstrap standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX SECTION A.7 | Sample-Composition Robustness Estimates

Table A.10 reports the estimates behind the sample-composition and boundary-year checks of Section 7.2: the modality subsample in column (1), the boundary-year panels in columns (2) and (3), and the earlier-baseline specification in column (4).

TABLE A.10 Sample-Composition Robustness: Modality Subsample and Boundary-Year Panels

	(1) Modality subsample	(2) Excluding final year	(3) Excluding initial year	(4) Earlier baseline
$\widehat{CRR}$	0.719 (0.06)	0.801 (0.10)	0.747 (0.05)	0.560 (0.11)
$\widehat{CRR}^2$	-5.357 (0.001)	-6.396 (0.003)	-5.586 (<0.001)	-4.303 (0.004)
Control-function residual (ρ)	2.432 (<0.001)	2.099 (<0.001)	2.629 (<0.001)	1.938 (<0.001)
Excluded-instrument joint F	223.9	140.5	226.7	380.2
$\widehat{CRR}^2 \times \widehat{SI}$	-11.231 (<0.001)	-13.950 (<0.001)	-10.741 (0.001)	-8.765 (0.003)
Turning Point shift, θ_{SI}	7.513 ($p < 0.1$)	12.420 ($p < 0.1$)	7.290 ($p < 0.1$)	4.465 ($p < 0.1$)
$\widehat{CRR}^2 \times \widehat{PS}$	2.041 (0.32)	-6.406 (0.08)	2.108 (0.30)	1.438 (0.47)
Turning Point shift, θ_{PS}	-5.872 ($p < 0.1$)	-3.377 ($p < 0.1$)	-6.192 ($p < 0.1$)	-4.026 ($p < 0.1$)

Notes: Columns vary modality, boundary years, and the baseline specification under the FE-CF design.

Parentheses report two-sided p -values; turning-point-shift p -values use 1,000 facility-clustered bootstrap replications, and the excluded-instrument F is cluster-robust.

APPENDIX SECTION A.8 | Negative-Control and Outcome-Proxy OVB Analysis

Let U denote an unobserved facility condition, such as operational distress, which survives the controls and fixed effects and may affect contract RN use, the moderators, and clinical quality. The main identification strategy removes the modeled endogenous component of contract RN use through the control function, and Section 7.5 separately checks potential reverse causality in patient severity through a lagged-moderator control function. The remaining omitted-variable-bias concern is narrower: whether a residual facility condition both remains after these corrections and is aligned with the moderator contrast in a way that reproduces the curvature or supported interaction terms. The negative-control framework (Lipsitch et al., 2010) evaluates this shared-confounding channel. A negative-control outcome (NCO) is affected by U but not by the theorized RN–PCT coordination mechanism. If the inverted-U in clinical quality were driven by U , the same curvature should appear in the NCO. A flat NCO therefore provides evidence against U as the driver of the curvature, conditional on the NCO exclusion and shared-confounder assumptions.

Coefficient-stability sensitivity. We first implement Oster-style coefficient-stability diagnostics on the fixed-effects control-function models. For the main curvature term, the Oster δ required to move the estimate to zero is 20.47; for the support-intensity curvature-moderation term, the corresponding δ is 272.60. For the supported linear interaction terms, adding observed controls moves the coefficients away from zero rather than toward zero. These diagnostics do not replace the IV control function, but they show that the remaining within-facility omitted-variable channel would need to be unusually strong to explain away the load-bearing curvature and supported moderation estimates.

Negative-control outcomes. We use two NCOs that are adjacent to general facility functioning but outside the theorized RN–PCT coordination pathway. The first is the ICH CAHPS caring-and-communication achievement measure. Estimating the structural specification with this NCO as the dependent variable yields $\beta_2 = 0.098$ ($p = 0.78$). The second NCO is the standardized readmission ratio, which is likewise flat in $\widehat{CRR}$ ($\beta_2 = 1.618$, $p = 0.91$). Neither negative control reproduces the curvature observed in the clinical-quality outcome.

Outcome-proxy adjustment. We next implement a proximal outcome-proxy adjustment. Let P_{it} denote an outcome-

confounding proxy, operationalized by a negative-control outcome. We estimate

$$\widetilde{CQ}_{it} = \beta_1 \widetilde{CRR}_{it} + \beta_2 \widetilde{CRR}_{it}^2 + \lambda P_{it} + \rho \hat{v}_{it} + \theta^T \mathbf{W}_{it} + \alpha_i + \delta_t + e_{it}, \quad (\text{A.3})$$

where $\hat{v}_{it}$ is the CRR control-function residual. The logic follows proximal causal inference (Tchetgen Tchetgen et al., 2024): if an unobserved facility condition drives both the primary outcome and the NCO, conditioning on the outcome-confounding proxy should absorb part of that residual channel. If the main curvature were primarily an omitted-variable artifact, the curvature should attenuate once P_{it} is included. Instead, using the ICH CAHPS caring-and-communication proxy, the adjusted curvature remains negative and significant ($\beta_2 = -4.339$, $p = 0.02$), with an interior turning point at a 5.4% contract RN ratio. Using the standardized readmission-ratio proxy yields the same conclusion ($\beta_2 = -5.439$, $p < 0.01$; turning point 6.9%).

Connection to moderated endogeneity. The outcome-proxy adjustment complements the interaction result in Nizalova and Murtazashvili (2014). Once the endogenous component of $\widetilde{CRR}_{it}$ is controlled through $\hat{v}_{it}$, the remaining condition for interpreting the interaction terms is that the moderators' unobserved determinants not co-move with the residual CRR selection component across the moderation contrast. For patient severity, we further estimate a two-residual control-function model in which lagged severity instruments current severity and a second residual is added to Model (3) alongside the CRR residual. This one-residual-per-endogenous-source construction follows recent OM applications that jointly include source-specific first-stage corrections (Pal et al., 2024; Sharma et al., 2024). The lagged severity first stage is strong ($F = 71.08$), and the supported severity interaction remains negative and significant ($\widetilde{CRR} \times \widetilde{PS} = -1.475$, $p < 0.01$), close to the maintained estimate (-1.43 , $p < 0.1$). The logic of the sequence is therefore precise: the first residual addresses the endogenous CRR, the second residual checks potential moderator feedback, and the negative-control/proxy layer checks whether a remaining moderator-linked omitted facility condition is still strong enough to reproduce the result. Here, the answer is not. The same lagged-instrument construction applied to support intensity (first stage $F = 17.8$) likewise leaves both supported SI interactions essentially unchanged (2.52, $p < 0.01$; -10.95 , $p < 0.01$), so the conclusion extends to both moderators.

Scope. These analyses are falsification and sensitivity checks, not replacement estimators for the main structural results. The negative-control rows check whether the curvature appears where the theory says it should not. The outcome-proxy rows check whether conditioning on an observed proxy for the residual confounding channel removes the curvature. Neither occurs. We therefore retain the IV control-function estimates as the main estimates and interpret the OVB analysis as corroborating evidence that residual facility-level confounding is unlikely to be the source of the inverted-U or the supported moderation results.

APPENDIX SECTION A.9 | Two-Stage Least Squares Benchmark

We estimate the structural model by 2SLS with the identical instrument set, treating $\widetilde{CRR}_{it}$ and $\widetilde{CRR}_{it}^2$ as separate endogenous regressors instrumented by the excluded instruments together with the squared external peer instrument. This system avoids the forbidden regression that Wooldridge (2010) cautions against, which would substitute fitted values into the nonlinear terms. Its cost is strength: the level and squared terms draw on the same instrument variation and are highly collinear, so the first-stage F-statistic for the quadratic equation falls below the Stock-Yogo threshold of 19.93, and both 2SLS coefficients are statistically indistinguishable from zero ($p = 0.28$ for each). Weak-instrument-robust Anderson-Rubin inference in this framework is consistent with the control-function conclusions. The control function estimator, which uses the same instruments without separate projections for the square, produces the stable curvature estimates reported in the main analysis.