Does Nurse Staffing Pay Off Where It Is Needed Most? Decision Rights and the Distribution of Staffing Returns

Abstract

Healthcare facilities serving socially deprived communities face a persistent operational challenge: the patients who present the greatest clinical complexity are served by organizations whose environmental constraints yield the lowest returns to staffing investments. A facility bound to the community it serves cannot merge, relocate, or contract its way out of that constraint, which leaves open what does determine whether a clinical resource delivers its value where social need is greatest. We examine whether scope-of-practice provisions in state Nurse Practice Acts, which govern the clinical authority granted to registered nurses, can alter that relationship. Drawing on resource dependence theory, we argue that a critical resource's contribution depends not only on how much of it a facility holds but on the decision rights the environment grants for deploying it. Using a panel of 25,860 facility-year observations from 6,039 U.S. dialysis facilities in 50 states (2015–2019) and an instrumental-variable control-function design, we find that increasing registered nurse staffing relative to patient census improves clinical performance. Where nurses have limited practice authority, community deprivation erodes that positive staffing return, with a move from a low- to a high-deprivation community erasing roughly a third of the quality value of each staffing increase. As statutory authority broadens, the erosion narrows, and where all three permissions are granted the moderation turns positive, so that the staffing return is largest in the communities with the greatest social need. The evidence therefore positions scope-of-practice regulation not merely as a workforce issue but as an institutional condition that determines whether facilities can preserve the quality value of nursing resources across communities with different levels of social need.

Keywords: healthcare operations, workforce capacity, decision rights, scope of practice, resource dependence theory, social determinants of health, dialysis quality

1 Introduction

Every year, more than half a million Americans depend on dialysis to sustain their lives (Johansen et al., 2023), and a large share of them are treated in facilities located in communities characterized by high social deprivation, areas marked by concentrated poverty, limited educational attainment, housing instability, and inadequate access to transportation and nutrition, the conditions that standard indices of community disadvantage are built to summarize (Butler et al., 2013; Singh, 2003). For the facilities that serve these communities, social deprivation is not merely a demographic characteristic of the patient population; it is a structural operational constraint that degrades the returns to every resource the organization deploys. Patients present with greater comorbidity burdens, lower health literacy, and more complex social needs per encounter, while the surrounding community offers fewer complementary resources (reliable transportation, caregiver networks, nutritional support) that sustain treatment adherence between visits (Corbett and Narayanan, 2025; Braveman and Gottlieb, 2014). The result is a persistent quality disadvantage: facilities in high-deprivation

areas consistently report worse clinical outcomes even after adjusting for patient case mix and facility characteristics (Kimmel et al., 2021; Rodriguez et al., 2019). Unlike a manufacturer that can re-source its inputs when local supply conditions deteriorate, or a retailer that can select its trade area and its customer base, a dialysis facility is bound to its community. Consolidation is common in this sector and does bring facilities scale, capital, and administrative capacity, but it does not change the community a facility serves. Acquiring or being acquired gives a facility no less deprived a patient population, and neither alliances nor political action can rapidly alter the socioeconomic conditions constraining its operations. The five inter-organizational dependency-management strategies catalogued by resource dependence theory (RDT), which comprise mergers and vertical integration, joint ventures, boards of directors, political action, and executive succession (Hillman et al., 2009), are all available to dialysis operators as corporate strategies, yet none of them reaches the dependency at issue here. The operational question, then, is not whether social deprivation imposes a constraint but whether any *internal* organizational mechanism can manage a dependency that no external strategy can resolve.

The healthcare operations management (OM) literature has made substantial progress in understanding how staffing and workforce configurations shape clinical outcomes. Foundational work established that workload and staffing intensity directly affect the quality frontier: KC and Terwiesch (2009) demonstrated speed–quality trade-offs under increased workload; Kuntz et al. (2015) identified safety tipping points beyond which insufficient staffing precipitates nonlinear quality declines; Tucker (2004) documented that operational failures, which consume nearly 9% of nurse time, degrade care delivery; and Peng et al. (2023) showed unit-level effects of nurse staffing on turnover and quality within hospitals. In chronic care settings, Li and Benton (2006) established that staffing configurations predict quality in nursing homes, and Bonnett and Heim (2024) demonstrated that the clinical provider mix shapes Triple Aim performance in dialysis. This body of work, however, has predominantly treated the operating environment as homogeneous, estimating *average* staffing–quality relationships that implicitly assume a uniform environmental context. The possibility that the value of operational resources is contingent on the socioeconomic environment in which they are deployed has received remarkably little attention.

That first pattern estimates an average staffing return and leaves the operating environment in the background. A second pattern runs through the work that takes the Triple Aim as its organizing frame. That literature searches for an action capable of moving the three aims together: Roth et al. (2019) identify the hospitals that operate on the productivity frontier, Bonnett and Heim (2024) ask whether a change in clinical provider mix improves Triple Aim performance efficiency, and the Quadruple Aim adds clinician well-being to the ends any such action must serve (Bodenheimer and Sinsky, 2014). What these recommendations share is that the lever is the resource itself, namely which providers to employ, in what mix, and at what cost. Our question comes before that one. Whether a clinical resource delivers its value depends on who is permitted to use it and for what, and in nursing that permission is set by state law rather than by the facility that employs the resource.

A parallel stream has begun to recognize the importance of social determinants of health for operations management. Corbett and Narayanan (2025) called for OM scholarship to engage with social inequities as a first-order operational concern, and empirical work has documented that community-level

disadvantage shapes healthcare utilization patterns, readmission rates, and cost structures in ways that existing operational models fail to capture (Dobrzykowski and McFadden, 2020; Roth et al., 2019). Where staffing and social determinants intersect, recent evidence suggests that operational resources can *buffer* the constraint: Travers et al. (2024) found that nursing home staffing attenuates the adverse impact of neighborhood deprivation on inappropriate antipsychotic use, while Goradia et al. (2025) showed that state government policies interact with local conditions to shape hospital operations performance. Yet this literature has established only that the negative effects of deprivation can be weakened, not that the functional relationship between environmental adversity and operational performance can be fundamentally altered. The question of whether and how an organization can *transform* the operational dependency created by community-level social deprivation remains unanswered.

Resource dependence theory (RDT), the dominant framework for analyzing organizational responses to environmental constraints (Pfeffer and Salancik, 1978), provides a natural starting point, but every mechanism it offers operates between organizations rather than inside one. Subsequent work has refined the distinction between dependency reduction through power restructuring and dependency accommodation through constraint absorption (Casciaro and Piskorski, 2005), yet the theoretical apparatus still stops at the organizational boundary. When the source of dependency is a community-level structural condition that no inter-organizational maneuver can alter, RDT offers no prescription. Hillman et al. (2009) themselves called for research exploring additional strategies through which organizations manage environmental dependencies (p. 1420), but the literature has not identified *intra-organizational* mechanisms through which frontline workers absorb and transform environmental constraints from within. This gap is especially consequential for healthcare OM, where the downstream supply chain is shaped by regulatory and community characteristics beyond organizational control (Dobrzykowski, 2019), and where the "people-centric operations" perspective recognizes that *how* workers deploy their capabilities, not merely how many are available, determines performance (Staats and Gino, 2012; Dobrzykowski and Tarafdar, 2015; Senot et al., 2016).

We address this gap by studying the three-way interaction among registered nurse (RN) staffing intensity, community-level social deprivation, and clinician empowerment in determining clinical quality outcomes at U.S. dialysis facilities. We operationalize clinician empowerment through the scope-of-practice authority granted to RNs under state Nurse Practice Acts, constructing a raw ordinal index (0–3) that captures progressive expansions of autonomous clinical decision-making (the authority to perform a nursing diagnosis, freedom from a continuous-supervision requirement over delegated tasks, and the authority to delegate nursing tasks to licensed practical nurses). Because the zero-permission cell is sparse, the estimating index pools raw levels zero and one and therefore enters the main models on a 1–3 scale; a sensitivity analysis retains all four raw levels. This operationalization aligns empowerment with the theoretical mechanism of worker discretion, the latitude to adaptively reallocate effort and expertise in response to local conditions. It therefore differs from the two measures this literature more often uses, namely survey scales of how empowered nurses report feeling and indicators of a nurse's position in the facility hierarchy; what state law fixes is the set of clinical decisions a nurse may make without another clinician's involvement (Chandrasekaran et al., 2012). What the index records is the statutory practice-authority environment, not what any nurse does inside it. The argument is that a broader legally available response repertoire matters more when external

demands are heterogeneous, an intuition RDT shares with Ashby's (1956) law of requisite variety. Where RNs hold the regulatory authority to match the complexity of patient needs in socially deprived communities, the erosion that deprivation imposes on the staffing return should narrow rather than persist. The paper's move is therefore from resource availability to resource deployability: how much of a critical resource's value survives depends on decision rights the environment confers, not on the quantity of the resource alone.

We estimate this relationship using a panel of 25,860 facility-year observations from 6,039 Medicare-certified dialysis facilities in 50 states over the period 2015–2019. To address the endogeneity of RN staffing decisions, since facilities may adjust staffing in response to anticipated quality outcomes, we employ a control function approach (Wooldridge, 2015) that combines a heteroskedasticity-based instrument (Lewbel, 2012) with an external labor-market wage instrument and a peer staffing instrument drawn from outside the facility's own county, alongside facility fixed effects to absorb time-invariant unobserved heterogeneity. This identification strategy allows us to recover consistent estimates of the causal effect of RN staffing on quality and to test whether that effect varies across levels of social deprivation and empowerment.

Our findings reveal a pattern of *constraint transformation*. RN staffing relative to patient census has a positive average return to quality. At the lowest level of clinician empowerment, social deprivation erodes that return, erasing roughly a third of it between the least and the most deprived communities. As empowerment broadens, the erosion narrows, and where all three permissions are granted the moderation turns positive. Across the observed deprivation distribution, the staffing return remains positive in every evaluated cell, while the three regulatory profiles exchange rank near the middle of the distribution. Thus empowerment changes *where* a given staffing ratio produces its greatest return, not whether that return is positive. The gradient persists when the raw four-level coding is retained, when the outcome is expressed in QIP points, and under an uncorrected fixed-effects estimator, and it is specific to patient-standardized, within-facility resource deployment, the operational quantity our theory concerns.

This study makes three contributions to operations management theory and one to practice. First, we move RDT's account of a critical resource from *availability* to *deployability*. RDT explains why external dependence makes a resource consequential; it has not asked what determines whether an organization may deploy that resource in the way its environment demands. Because state law, not the facility, sets the decision rights governing nursing work, deployment authority is itself an external condition, and the return to a critical resource becomes a joint property of the dependence the organization faces and the authority it has been granted. Second, we show that the effect of an external constraint on resource productivity is not fixed, extending the buffering–bridging framework of Casciaro and Piskorski (2005). The systematic movement from a deprivation penalty under limited authority to no measurable penalty under full authority demonstrates that the functional relationship between environmental adversity and operational performance depends on the regulatory architecture governing deployment, challenging the implicit assumption in RDT and the resource-based view that resource value is inherent. Third, we contribute to the nascent OM literature on social determinants of health (Corbett and Narayanan, 2025) by demonstrating that the operational impact of social deprivation is malleable, shaped by the interaction between the resources a facility holds and the institutional design governing their use. This reframes the policy conversation from compensating for deprivation to *unlocking* the latent productivity of resources already in place.

For practice, our results identify scope-of-practice authority as an operational condition that determines whether a facility preserves the quality return to its RN-to-patient ratio as community need rises. The result does not imply that adding the same absolute number of nurses has the same effect, nor does it establish a realized cost saving. It instead directs managers and policymakers to consider staffing ratios and the authority to deploy skilled labor jointly: resources and regulatory discretion operate as a configuration. For patients receiving dialysis in high-deprivation communities, protecting the return to scarce nursing capacity is an actionable route toward improved quality and a more equitable use of existing resources.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and hypotheses. Section 3 describes the data sources, sample construction, and variable measurement. Section 4 presents the empirical methodology and identification strategy. Section 5 presents the main results, and Section 6 reports the robustness analyses. Section 7 discusses theoretical and practical implications, limitations, and directions for future research.

2 Theory and Hypotheses

Resource dependence theory (RDT) provides a unifying framework for understanding how healthcare organizations manage the critical resources on which their clinical performance depends. At its core, RDT posits that organizations depend on their external environment for resources essential to survival and performance, and must develop strategies to manage these dependencies (Pfeffer and Salancik, 1978). In comprehensive reviews of RDT, scholars have identified five primary strategies through which organizations manage resource dependence: mergers and vertical integration, joint ventures and alliances, boards of directors (interlocking directorates), political action, and executive succession (Hillman et al., 2009). All five strategies operate at the *inter-organizational* level, in that they restructure the organization's relationship with its external environment to reduce dependency.

Healthcare organizations, however, face a distinctive challenge. Dialysis facilities cannot acquire their patient populations through mergers, form alliances to reduce the social deprivation of the communities they serve, or employ political action to rapidly alter the socioeconomic conditions that constrain their operations. In other words, the inter-organizational strategies that dominate the RDT literature are largely unavailable for managing the dependency created by serving socially deprived communities. This raises a fundamental question that the existing RDT literature has not addressed: how do organizations manage resource dependencies when inter-organizational strategies are foreclosed?

We propose that the answer lies in a question RDT has not had to ask when inter-organizational strategies were available: not how much of a critical resource an organization holds, but whether it is permitted to deploy that resource in the way its environment demands. Deployment authority is itself externally determined. State law, not the facility, defines whether a registered nurse may diagnose, delegate, and act without continuous supervision, so the latitude with which a facility can direct its own nursing capacity is a property of the environment on which the facility depends. We develop this argument through three interconnected RDT sub-mechanisms, resource criticality, constraint absorption (incorporating the environmental munificence context), and externally delimited deployment authority, that together link an

external constraint to internal resource deployment and thence to clinical quality outcomes.

2.1 Resource Criticality and the Baseline Resource Effect (H1)

The first link in this causal chain is resource criticality. Pfeffer and Salancik (1978) argued that the importance of a resource to organizational functioning determines the degree to which the organization depends on external entities that control that resource. Casciaro and Piskorski (2005) further refined this argument by demonstrating that dependency is driven not merely by the criticality of a resource, but by the *mutual dependence* between exchange partners (the degree to which both parties rely on each other) and the *power imbalance* between them.

In dialysis facilities, registered nurses (RNs) represent a uniquely critical resource. RNs possess specialized training in nephrology and dialysis procedures, enabling them to manage complex treatments, make critical clinical decisions such as adjusting dialysis settings and administering medications, and identify potential complications during the dialysis process (De Regge et al., 2019; Wheeler et al., 2022; Youn et al., 2022). In many states, regulations mandate that only RNs can perform specific clinical operations, reinforcing the irreplaceability of this resource. The facility's high dependence on RNs, combined with the prevailing shortage of qualified nursing personnel (Benton and Lin, 2011), creates a condition of high resource criticality that directly shapes the organization's performance frontier.

Given this high resource criticality, increasing the availability of RNs should directly enhance clinical quality by expanding the facility's capacity for complex clinical decision-making and patient monitoring. This yields a straightforward prediction grounded in RDT's resource criticality logic:

> *Hypothesis 1 (H1):* A greater RN staffing ratio within a dialysis facility is positively associated with clinical performance.

2.2 Constraint Absorption Failure: When Environmental Scarcity Attenuates Resource Effectiveness (H2)

The second link in the causal chain addresses the *interaction* between internal resource deployment and environmental constraints, a mechanism we term constraint absorption failure, drawing on and extending Casciaro and Piskorski's (2005) concept of constraint absorption. Developing this argument requires first establishing the environmental context in which resource deployment occurs.

Castrogiovanni (1991) introduced the concept of environmental munificence (the degree to which an environment can support sustained growth or absorb the impact of organizational activities) as a critical dimension of the task environment (see also Dess and Beard, 1984). In a munificent environment, organizations have access to abundant external resources that complement their internal operations; in a scarce environment, external constraints impose additional burdens that consume organizational capacity. The social determinants of health (SDoH) represent a critical environmental dimension for healthcare organizations. Communities characterized by high social deprivation, as measured by factors such as poverty, limited education, inadequate housing, and transportation barriers (Berkman et al., 2011; Braveman and Gottlieb, 2014), constitute low-munificence environments for healthcare facilities operating within them.

In such environments, patients arrive with greater comorbidity burdens and lower health literacy, requiring more intensive clinical interventions per patient encounter. Simultaneously, these communities offer fewer complementary resources, such as reliable transportation to appointments, nutritional support programs, and caregiver networks, that would otherwise support treatment adherence and recovery. Areas with greater social deprivation also face heightened difficulty in attracting and retaining healthcare workers (Lehmann et al., 2008; Willis-Shattuck et al., 2008), further compounding the resource scarcity.

The critical question, from an RDT perspective, is not merely whether low environmental munificence directly impairs quality (facility fixed effects absorb the time-invariant component of community deprivation, making a direct-effect test structurally uninformative in panel settings), but rather how low munificence *moderates the effectiveness of the organization's most critical resource*. Casciaro and Piskorski (2005) demonstrated that organizations facing external constraints may be "motivated, but not always capable to manage external dependencies" (p. 168). Their seminal study showed that constraint absorption (the incorporation of an external constraint source into the organization's structure) depends on both the motivation provided by mutual dependence and the capability determined by the power balance. However, their analysis focused exclusively on inter-organizational constraint absorption through mergers and acquisitions: an organization absorbs a constraining entity by acquiring it.

We extend this logic to the intra-organizational level. When a dialysis facility operates in a high-deprivation environment (low munificence) without the structural capacity to absorb the resulting constraints, even increasing its most critical resource, RN staffing, may yield diminishing returns. This occurs because standard operating procedures and rigid task allocations, designed for typical patient populations, cannot accommodate the heightened complexity and variability of patient needs in deprived communities. In such environments, additional RNs may be deployed according to the same standardized protocols, leaving the underlying mismatch between patient needs and care delivery unaddressed. The external constraint is not absorbed but merely endured, reducing the marginal effectiveness of each additional unit of the critical resource.

This mechanism explains why the relationship between resource investment and performance is not constant across environmental conditions. In munificent environments, the resource criticality logic of H1 operates cleanly, and more RNs translate directly into better quality. In scarce environments, however, external constraints attenuate this translation, creating a condition we identify as constraint absorption failure:

> *Hypothesis 2 (H2):* SDoH moderate the effect of RN staffing levels on the clinical outcomes of dialysis facilities, such that higher social deprivation attenuates the positive relationship between RN staffing and clinical performance.

2.3 Externally Delimited Deployment Authority and Resource Deployability (H3)

The final link in the causal chain addresses how organizations can overcome constraint absorption failure. The answer we develop turns on a distinction RDT has not needed to draw: between a critical resource's *availability* and its *deployability*, where deployability is set by decision rights the environment confers rather than by anything the organization accumulates.

The concept of discretion, the latitude of action available to organizational actors, has a rich tradition in strategic management and organizational behavior. Hambrick and Finkelstein (1987) established that managerial discretion varies systematically with environmental, organizational, and individual factors, and Caza (2012) subsequently classified eight distinct domains through which autonomy manifests in organizations. Crossland and Hambrick (2011) then demonstrated that managerial discretion determines the magnitude of leadership effects on organizational performance, establishing that the latitude to act is not merely a contextual factor but an active lever that shapes how dependencies translate into outcomes. Yet this insight has remained confined to executive-level analysis; it has not been extended to front-line workers, nor connected to RDT's core concern with dependency management at the operational level.

Extending it downward requires separating two things the executive literature can leave joined. For a chief executive the latitude to act and the rights that permit it are conferred by the same board, so one word can carry both. For a staff nurse they come apart. The rights that bound what she may decide without another clinician's involvement are written into state statute and are identical for every facility in that state, while the discretion actually exercised within those bounds is a matter of daily practice inside one facility. We hold the two apart for the rest of the paper. The empowerment index measures what state law allows a nurse to decide without another clinician's involvement. The discretion she then exercises inside those bounds is the mechanism the argument runs through, and it is not something our data record.

The operational structure of dialysis facilities makes this gap especially consequential. Federal regulations require a registered nurse to be present at all times during in-center hemodialysis, yet the attending nephrologist is required only to evaluate patients monthly and need not be on-site during treatment (Berns, 2015). The medical director role, while carrying broad quality oversight responsibilities, is estimated at roughly a quarter of a full-time physician position and carries no mandated on-site hours (Schiller, 2015). Empirical evidence confirms this operational reality: nephrologist visit frequency varies primarily across facility practice patterns rather than patient acuity (Erickson et al., 2013), and even policy-induced increases in visit frequency have yielded no measurable improvement in patient survival (Slinin et al., 2012). In practice, the dialysis facility is a physician-absent, nurse-present clinical environment, one in which the registered nurse is the sole clinician continuously available to exercise real-time clinical judgment.

This structural reality sharpens the question of how clearly the nurse's decision-making authority is defined. Substitutes-for-leadership theory (Kerr and Jermier, 1978) holds that when formal authority is explicitly codified and delegated to front-line workers, organizational structure can functionally replace the absent leader's directive role. The theory's premise, however, is that the delegation must be unambiguous. When it is not, that is, when state regulations neither explicitly authorize nor explicitly prohibit independent nursing actions such as performing a nursing diagnosis, supervising, and delegating tasks, front-line workers confront the condition that role theory identifies as role ambiguity: uncertainty not about workload or competing demands, but about the boundaries of one's own decision-making authority (Rizzo et al., 1970; Kahn et al., 1964). Spreitzer (1996) demonstrated that role ambiguity is among the strongest negative predictors of psychological empowerment, and recent evidence in nursing confirms that boundary uncertainty, independent of workload, is a primary driver of emotional exhaustion and moral distress (Wang et al., 2023; Lamiani et al., 2017). The problem these nurses face is not that they are told "no"; it is that they are never

told "yes."

Conversely, when scope-of-practice provisions explicitly grant registered nurses the authority to perform a nursing diagnosis, to supervise, and to delegate, they resolve the very ambiguity that undermines empowerment. Clear regulatory boundaries provide what Kanter's (1977) framework identifies as formal power, the structural precondition for psychological empowerment. Spreitzer (1995) conceptualized this downstream cognition as comprising meaning, competence, self-determination, and impact, which is the felt experience of having not only the authorization but also the confidence to act. Laschinger et al. (2001) validated this structural-to-psychological pathway in a nursing population, showing that access to formal power predicts psychological empowerment, which in turn shapes clinical engagement. Poghosyan et al. (2022) extended this evidence across six U.S. states, finding that nurse practitioners in full-practice-authority jurisdictions reported substantially greater professional visibility and organizational support than those in restricted or ambiguously regulated environments. The mechanism, then, is not simply that broader authority gives nurses more tasks to perform; it is that explicit regulatory authority creates the conditions under which a physician-absent workplace becomes an enabling practice environment rather than one characterized by role ambiguity and constrained judgment. One boundary of the design follows directly from this. What we measure is the state-law decision-rights environment in which nurses work, and nothing more. Realized discretion, actual delegation, the reallocation of clinical attention, and the psychological states this literature describes are the pathway the law opens, and the paper does not claim to observe any of them.

Two external conditions therefore meet inside the facility. Community deprivation creates the dependence and the instability under which care must be delivered, and state law delimits the decision rights with which the facility may respond. Neither is chosen by the organization; both are properties of the environment whose control over the organization RDT takes as its subject. What the organization does is convert a critical resource into care under whatever authority it has been granted. Where state law permits registered nurses to delegate routine tasks to licensed practical nurses (LPNs) and patient care technicians (PCTs), the practice environment is more enabling, and the same nursing capacity can be directed toward the specific challenges of the patient population. In high-deprivation environments, that latitude is what would allow adjusting care priorities, initiating social service referrals, modifying treatment plans, and redistributing attention toward the most complex cases, none of which alters the facility's external environment.

The resource-based view might appear to be the natural frame for a mechanism that operates inside the organization (Wernerfelt, 1984; Barney, 1991). The feature that keeps the argument within RDT is where the authority comes from: the decision rights our index measures are not an internally accumulated capability but a grant of the state's regulatory environment, external to every facility and beyond any facility's control. What the organization does is deploy an externally conferred authority against an externally imposed constraint; both sides of the mechanism are properties of the environment whose control over the organization RDT takes as its subject (Pfeffer and Salancik, 1978). The complementary question the resource-based view would ask, how facilities differ in converting the same statutory authority into performance, concerns internal heterogeneity that our state-level measure holds fixed and our facility fixed effects absorb. The distinction can be put more simply. A resource-based account varies the resource; here the resource is held fixed and the permission to deploy it is what varies. The lever in this argument is not the resource at all, which is why

the theory that governs it is one about external control rather than one about internal endowments.

The theoretical move is therefore from resource availability to resource deployability, and from an average resource effect to returns that differ with the external conditions under which the resource is deployed. Whereas Casciaro and Piskorski's (2005) constraint absorption *eliminates* the source of an external constraint by incorporating it into the organization's structure (through merger and acquisition), the deployment argument leaves the constraint fully intact and asks what the organization is permitted to do in its presence. The social deprivation of the community does not diminish, and neither the facility's dependence on its community nor its subordination to state law is relaxed. What varies across facilities is how much of a scarce clinical resource's value survives that dependence. Davis and Cobb (2010), reviewing RDT's prospects, observe that the theory's most productive development lies in taking seriously how external control conditions organizational action rather than in cataloguing further responses to it.

Critically, this mechanism predicts an asymmetric effect of empowerment across environmental conditions. In munificent (low-deprivation) environments, where constraint absorption failure is absent, empowerment provides limited additional benefit, because there are few external constraints requiring adaptive resource reallocation, and the coordination costs of expanded discretion may partially offset any gains. In scarce (high-deprivation) environments, however, empowerment directly addresses the constraint absorption failure identified in H2 by enabling the adaptive deployment of the critical resource. This asymmetry echoes the broader finding that discretion is most consequential under conditions of high environmental complexity (Hambrick and Finkelstein, 1987; Crossland and Hambrick, 2011), extended here from executive to front-line clinician discretion. The prediction follows that empowerment restores, and potentially enhances, the resource effectiveness that environmental scarcity would otherwise attenuate:

> *Hypothesis 3 (H3):* Higher levels of RN empowerment will lessen the negative moderating impact of SDoH on the association between the RN staffing ratio and clinical performance.

2.3.1 Which dimensions of discretion carry the mechanism

H3 treats empowerment as the overall breadth of statutory authority. The three permissions are not, however, three interchangeable units of that breadth, because each one enlarges a different part of what a nurse may do. What regulates a varied environment, in Ashby's (1956) sense, is the repertoire of responses the clinician may actually deploy, and each permission enlarges a different part of what a registered nurse may do on a dialysis floor. Nursing diagnosis authority lets the nurse assess a patient and identify what nursing interventions may be needed, separating the potential complication that needs her judgment from the routine care that does not, without waiting for a physician to make that call. LPN delegation authority lets her hand the routine, protocol-driven work, stable maintenance treatments, monitoring, and documentation, to a licensed practical nurse. Freedom from a continuous-supervision requirement determines whether that handoff frees her at all. On a treatment floor where the physician is present only intermittently, the RN is the one clinician continuously available to exercise real-time judgment. If the law requires her to watch a delegated treatment from start to finish, handing that treatment to an LPN gives her back none of her own time.

Because the three permissions govern one connected piece of nursing work, deciding what a patient needs, moving routine treatments to the LPN, and letting the delegated work proceed without having to

continuously monitor it, their contributions reinforce one another. A nurse who may delegate but must continuously supervise every delegated task has moved the work to the LPN's hands without moving it off her own watch. A nurse relieved of the supervision requirement but barred from delegating has no routine work to release in the first place. And knowing which patient needs her judgment changes little unless the routine work can move off her hands. Each added permission therefore contributes on its own and raises the value of the permissions already granted, which is why the breadth of authority that H3 counts is the relevant axis. As breadth grows, the deprivation penalty on staffing returns should narrow. This reasoning carries three observable implications for the provision-level evidence. The composite gradient across empowerment levels should rise with each added permission, as H3 tests. The incremental association of any single permission, holding the other two fixed, should be modest. And a permission's increment should be larger in the presence of its counterparts. The three provisions are parallel grants in state law, and a state may confer any one of them without first conferring another. These implications therefore concern how the associations vary with one another, not a sequence in which a state must grant them.

Equal standing in state law does not imply equal operational weight. In dialysis the three permissions do not matter equally. Most dialysis care consists of protocol-driven maintenance runs, so the permission that moves that work to the LPN does the most. A handoff releases RN attention only when the nurse need not remain at the chairside supervising it, so freedom from the continuous-supervision requirement comes next. The diagnosis needs of a standing dialysis census are narrow and largely protocol-coded, so diagnosis authority adds least. Holding the other permissions fixed, the incremental association should therefore be largest for LPN delegation authority, intermediate for freedom from continuous supervision, and smallest for diagnosis authority. The same logic runs pair by pair. Delegation and freedom from supervision, the two permissions that determine whether routine work actually moves off the RN during a treatment day, should reinforce each other in both directions. Diagnosis authority should raise the value of the delegation it directs rather than act on its own. And diagnosis paired with supervision freedom alone, when the nurse still cannot delegate, should produce no joint gain. The permissions are parallel grants in law; the mechanism joins them in function. The provision-level analysis in Section 5 examines this reinforcement structure and this ordering directly.

2.4 Summary of the Causal Chain

The three hypotheses form a unified causal chain grounded in resource dependence theory. H1 establishes the baseline resource effect through *resource criticality*: RN staffing is the critical resource upon which dialysis facility performance depends. H2 introduces the environmental context through *environmental munificence* and identifies the resulting *constraint absorption failure*: community-level social deprivation constitutes a low-munificence environment that attenuates the returns to even the most critical resource. H3 completes the chain with *externally delimited deployment authority*: because state law determines the decision rights with which nursing capacity can be directed, the same critical resource converts into quality at different rates depending on how enabling that statutory environment is.

Figure 1 summarizes this theoretical framework. The progressive logic, from resource criticality through constraint absorption failure (incorporating the environmental munificence context) to externally

delimited deployment authority, yields testable predictions about a question RDT poses but has not answered for a resource the organization already holds: what external dependence does to the value of that resource, and what determines how much of that value survives.

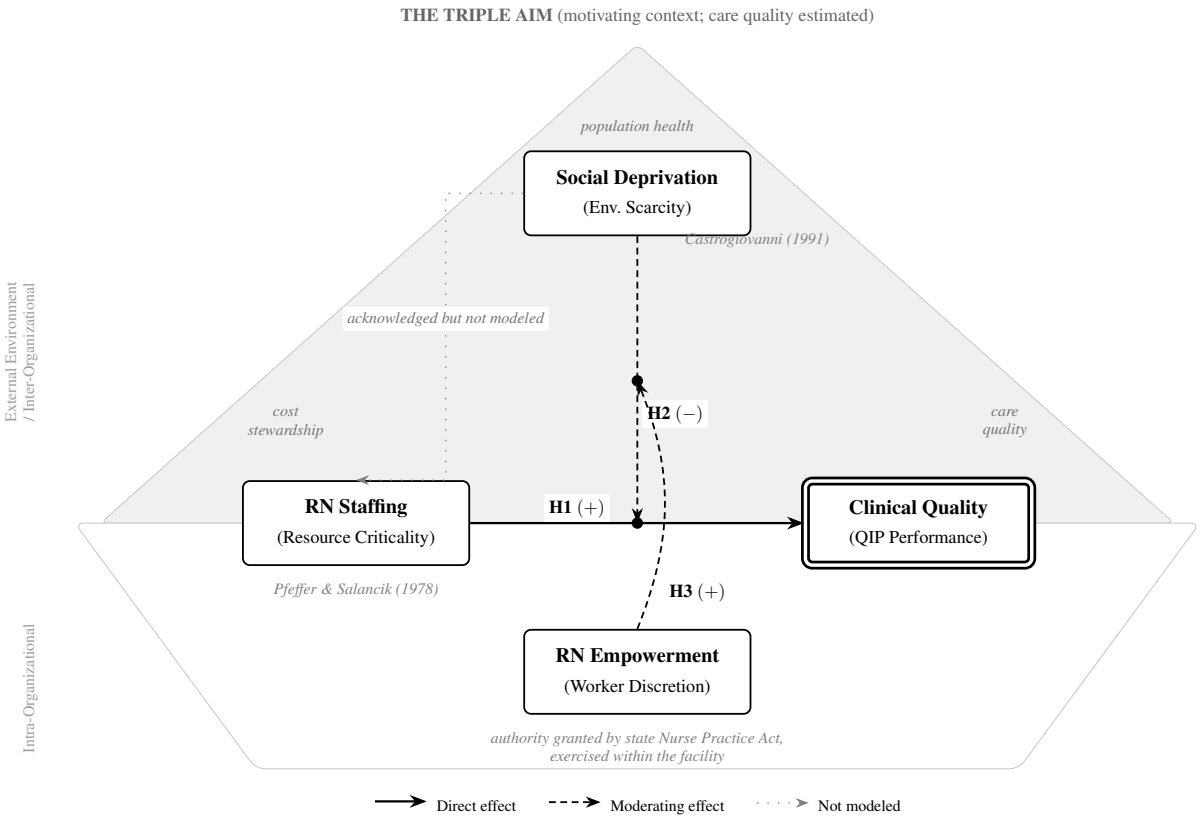


Figure 1: Conceptual framework. The upper triangle spans the external environment and the inter-organizational level at which the dependency-management strategies catalogued by resource dependence theory would operate and are, for a facility bound to its community, foreclosed. Its vertices are labeled with the three aims, which motivate the setting rather than being jointly tested here: care quality at the right base is the directly estimated outcome, population health at the apex enters as the community deprivation context in which RN staffing is committed, and cost stewardship at the left base is an implication of the estimated margin rather than a measured quantity. The inverted trapezoid is the intra-organizational level, where the practice authority granted by state Nurse Practice Acts is exercised. RN staffing and clinical quality sit on the boundary between the two because they are shaped by the external environment and observed within the facility. H1 is the staffing return, H2 its moderation by deprivation, and H3 the moderation of that moderation by empowerment. The empowerment measure records the decision rights state law confers; realized clinical discretion and work reallocation are the mechanism those rights permit and are not observed here.

Table 1 positions this study within the healthcare operations literature along two dimensions: the theoretical mechanisms examined and the identification strategy employed. The theoretical columns track coverage of the causal chain developed above, namely whether each study examines community-level social determinants as environmental constraints, tests the interaction between staffing and environmental condi-

tions, and incorporates worker discretion through scope-of-practice regulation. The final theoretical column identifies studies that test the complete three-way mechanism through which worker discretion resolves constraint absorption failure. As the table reveals, no prior study has tested this full causal chain in any healthcare setting.

Table 1: Literature Positioning: Theoretical Mechanisms and Identification Strategy

			Theoretical Mechanisms				*Identification*
Study	**Journal**	**Setting**	**SDoH**	**Staff. × Env.**	**W. Disc.**	**3-Way**	**Approach**
Hospital							
Aiken et al. (2002)	JAMA	Hospital					n/a
Needleman et al. (2002)	NEJM	Hospital					n/a
Tucker (2004)	JOM	Hospital					n/a
KC & Terwiesch (2009)	MS	Hospital					n/a
Kuntz et al. (2015)	MS	Hospital					Selection model
Senot et al. (2016)	POMS	Hospital			✓		n/a
Peng et al. (2023)	JOM	Hospital		✓			Panel FE
Nursing Home & Long-Term Care							
Park & Stearns (2009)	HSR	Nurs. Home			✓		n/a
Travers et al. (2024)	JAMA NO	Nurs. Home	✓	✓			n/a
Outpatient / Dialysis							
Thomas-Hawkins et al. (2008)	NNJ	Dialysis					n/a
This study	**JOM**	**Dialysis**	✓	✓	✓	✓	**Facility FE + CF (3 IVs)**

Notes. Mechanism columns trace the RDT causal chain: **SDoH**, community social determinants as an environmental constraint; **Staff. × Env.**, staffing–environment interaction; **W. Disc.**, scope-of-practice regulation or worker empowerment; **3-Way**, the full staffing × environment × empowerment interaction. *Approach* names the study's strategy for unobserved heterogeneity and endogeneity where one is employed; n/a indicates none reported. CF = control function; FE = fixed effects.

What the unmarked rows share. Six of the ten prior studies carry no mechanism mark: Aiken et al. (2002), Needleman et al. (2002), Tucker (2004), KC and Terwiesch (2009), Kuntz et al. (2015), and Thomas-Hawkins et al. (2008). They are not a residual category. Each estimates an *average* staffing or workload effect on quality in which the community environment, where it appears at all, is a control to be partialled out rather than a condition that changes the effect's size. The four partially marked rows relax that in one direction only: Senot et al. (2016) and Park and Stearns (2009) add worker discretion, Peng et al. (2023) adds a staffing–environment interaction, and Travers et al. (2024) adds both without the discretion channel. What no row combines is an environment that conditions the staffing return and a regulatory permission that conditions that conditioning, which is the cell this study occupies.

Journals: JAMA = *J. American Medical Assoc.*; NEJM = *New England J. Med.*; JOM = *J. Operations Management*; MS = *Management Science*; POMS = *Production & Operations Management*; HSR = *Health Services Research*; JAMA NO = *JAMA Network Open*; NNJ = *Nephrology Nursing J.*

3 Data and Variables

3.1 Data Sources and Sample Construction

Our analysis integrates five data sources covering U.S. dialysis facilities from 2015 to 2019:

1. **CMS Dialysis Facility Compare (DFC).** The Centers for Medicare & Medicaid Services publishes annual facility-level data including Quality Incentive Program (QIP) scores (Centers for Medicare & Medicaid Services, 2024), patient census, facility characteristics (stations, certification date, ownership, chain affiliation), and clinical measures (standardized hospitalization ratio, standardized mortality ratio, infection rates).

2. **Healthcare Cost Report Information System (HCRIS).** Medicare cost reports provide annual full-time-equivalent staffing counts by occupational category, including RNs, LPNs, patient care technicians, physicians, management and administrative staff, nurse aides, and social workers, together with facility drug and laboratory expenses.

3. **Social Deprivation Index (SDI).** County-level composite index of area-level socioeconomic deprivation based on seven demographic characteristics from the American Community Survey, including percent living in poverty, percent with less than 12 years of education, percent single-parent households, percent living in rented housing units, percent living in overcrowded housing, percent of households without a car, and percent non-employed adults under 65 (Butler et al., 2013). The SDI exhibits high temporal stability ($r = 0.993$ across adjacent years in the estimation sample), supporting its use as a structural community characteristic.

4. **Bureau of Labor Statistics (BLS) OEWS.** MSA-level mean hourly wages for registered nurses, used as an external instrumental variable in the main identification strategy.

5. **State Nurse Practice Acts (NPAs).** Coded from the LawAtlas *Registered Nurse Scope of Practice* legal dataset (Center for Public Health Law Research, Temple University; laws in effect as of August 1, 2015), providing the three binary indicators underlying the empowerment index. Federal ESRD regulation assigns the scope of nursing practice in dialysis facilities to state law: the Conditions for Coverage require that care be provided in accordance with each state's Nurse Practice Act (42 C.F.R. §494.140), which makes the state statute the binding source of the authority our index measures (Centers for Medicare & Medicaid Services, 2008).

The uniform screens summarized in Figure 3, which require a valid measurement-period QIP score, complete measurement on the staffing, deprivation, wage, and original control variables, and a deprivation series free of implausible year-to-year jumps, yield 25,963 facility-year observations before the expanded operational controls are imposed. Requiring completeness on those controls and the separate log-patient-census scale control removes 103 rows; the two network-pool leave-one-out excluded instruments (Section 4) are defined for every remaining observation, leaving a common main-model estimation sample of $N = 25{,}860$ facility-year observations from 6,039 facilities in 50 states. The sample applies no influence-based observation deletion. To limit the influence of extreme values, we winsorize the RN-to-patient ratio at its 5th and 95th percentiles and trim the log QIP score below its 1st percentile and above its 96th percentile, following standard practice in staffing-ratio analyses (KC and Terwiesch, 2009). QIP scores are indexed throughout by the calendar year of their measurement period (the payment-year label under which CMS releases each score is an administrative label, not a measurement date). Figure 3 reports the full sample flow, and Table A2 defines every variable and its source.

3.2 Nurse Empowerment Measurement

We construct the nurse empowerment index Emp_i from three dimensions of state registered-nurse scope-of-practice law, coded directly from the *Registered Nurse Scope of Practice* legal dataset compiled by the

Center for Public Health Law Research at Temple University and published on LawAtlas (laws in effect as of August 1, 2015; Center for Public Health Law Research, 2017). The three indicators correspond to three named items of that dataset (the nursing-diagnosis item, the continuous-supervision item, and the LPN-delegatee item), and Appendix A reports the coded values for all 51 jurisdictions so that the construction is fully reproducible from the cited source. These dimensions capture the extent to which state law enables nurses to exercise autonomous clinical judgment:

1. **Nursing diagnosis authority (R_a).** Whether state law authorizes RNs to perform a nursing diagnosis when assessing patient conditions, which the source coding distinguishes from a medical diagnosis reserved to physicians. Thirty-five states and the District of Columbia grant this authority, that is, 36 of the 51 coded jurisdictions.

2. **Freedom from a continuous-supervision requirement (R_b).** Whether state law does *not* require the RN to maintain continuous supervision over delegated nursing tasks. This latitude lets the RN extend clinical reach without constant monitoring of every delegated task. Thirty-three states, and no other jurisdiction, impose no continuous-supervision requirement.

3. **LPN delegation authority (R_c).** Whether the state's delegation provision names licensed practical nurses (LPNs), whose title is licensed vocational nurse (LVN) in California and Texas for the same credential, as eligible delegatees of nursing tasks, enabling the RN to focus on higher-acuity clinical functions. Twenty-eight states grant this authority. The construct this item measures is delegation authority; LPNs are the delegatee class the statute names, and Section 6.1 shows that the provision's estimated effect does not run through the facility's LPN headcount.

The raw empowerment index sums these three binary indicators: $Emp_i^{raw} = R_{a,i} + R_{b,i} + R_{c,i}$, yielding an ordinal variable with values 0 (no dimensions), 1 (one dimension), 2 (two dimensions), or 3 (all three dimensions). This additive construction treats each NPA provision as an incremental expansion of the nurse's operational authority. In the estimation sample, the raw counts are 491, 8,645, 11,378, and 5,346 facility-years at levels 0 through 3, respectively (1.90%, 33.43%, 44.00%, and 20.67%). Because the raw zero-permission cell is sparse, the main interaction uses the analysis coding $Emp_i = \max(Emp_i^{raw}, 1)$. Thus its analysis levels 1, 2, and 3 contain 9,136, 11,378, and 5,346 facility-years, respectively. The raw 0–3 measure remains visible in the descriptive statistics; no observations are removed by this recoding.

The empowerment provisions are measured from the 2015 LawAtlas cross section and enter the panel as state-level, time-invariant indicators, so the main effect of empowerment is absorbed by the facility fixed effects. Empowerment enters the model exclusively through its interactions with the time-varying staffing and deprivation variables, identifying the moderating effect from within-facility variation in staffing and SDI conditional on the state's regulatory environment. Figure 2 displays the distribution of the composite empowerment index across all 51 jurisdictions (the 50 states and the District of Columbia), generated directly from the state-level coding reported in Appendix A.

As coding sensitivities, we retain the raw 0–3 index rather than pooling the sparse zero cell (Section 6) and estimate free-shape specifications for both the three main analysis levels and all four raw levels

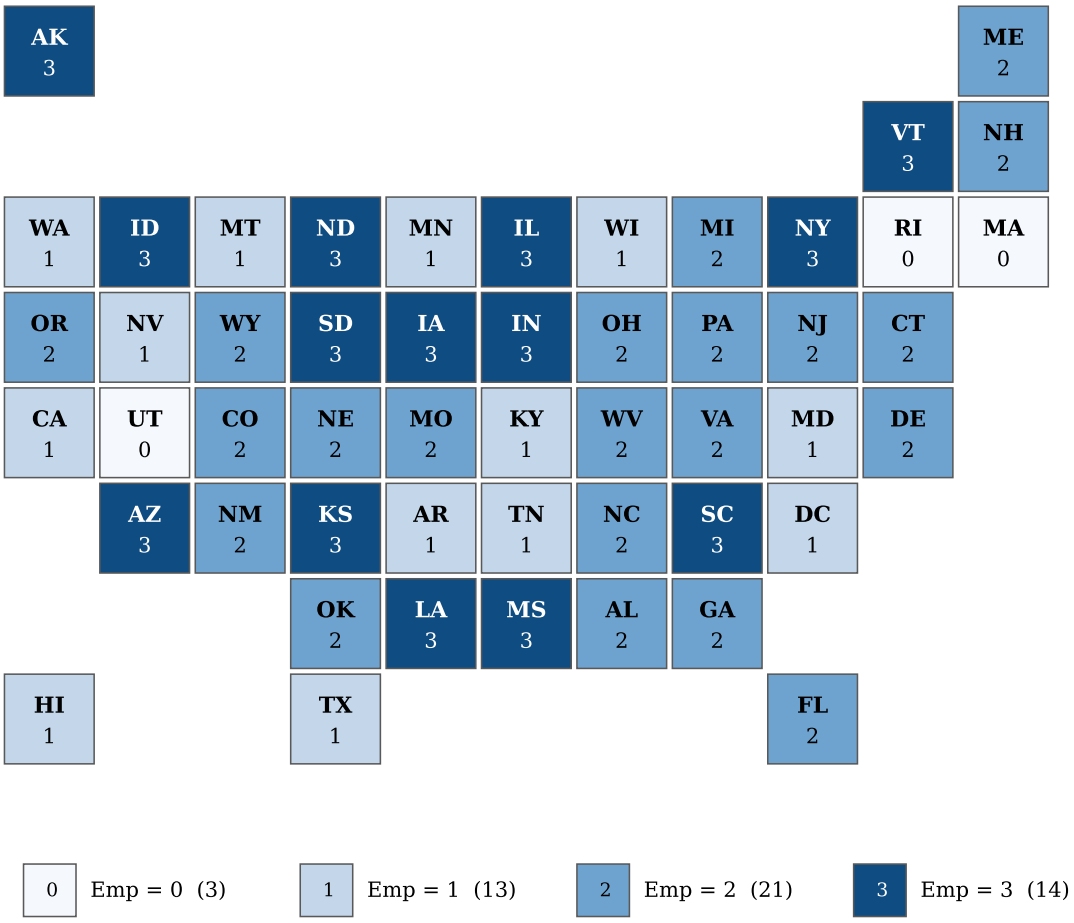


Figure 2: Geographic distribution of the RN scope-of-practice composite index across the 50 U.S. states and the District of Columbia. Each tile prints the jurisdiction's abbreviation and its index value, so the full distribution (*Emp* = 0: 3; *Emp* = 1: 13; *Emp* = 2: 21; *Emp* = 3: 14 jurisdictions) can be counted directly from the figure; shading encodes the same value redundantly, with darker tiles indicating broader scope of practice. The index sums three binary provisions from the LawAtlas Registered Nurse Scope of Practice dataset (laws as of August 1, 2015): (1) nursing diagnosis authority, (2) delegation to licensed practical nurses, and (3) freedom from a continuous-supervision requirement. The figure is generated from the same state-level coding reported in Appendix A.

(Section 5.4). The post-hoc analysis also replaces the composite with the individual statutory dimensions and their eight observed legal configurations.

3.3 Sample Construction

Figure 3 summarizes the sample construction process. We begin with 35,096 facility-year observations (7,019 unique facilities) from the merged CMS Dialysis Facility Compare and HCRIS Cost Report files for 2015–2019. We apply uniform, rule-based screens that target observations inconsistent with valid measurement

rather than selected case by case. Requiring a valid measurement-period QIP score and trimming the log score at the 1st and 96th percentiles yields 31,266 observations; requiring complete staffing, deprivation, wage, and original control variables yields 26,420; and excluding facilities whose maximum absolute year-to-year change in log SDI exceeds 0.6 yields the 25,963-observation construction sample. Requiring completeness on the expanded operational controls then removes 103 rows; the two network-pool leave-one-out excluded instruments are defined for every remaining observation, yielding the common main-model sample of $N = 25{,}860$ facility-year observations from 6,039 facilities. The panel is unbalanced: facilities contribute 4.282 years on average, with 4,867, 5,144, 5,213, 5,369, and 5,267 observations in 2015 through 2019, respectively. Models 1–3 use this common sample; the diagnostic 2SLS routine reports its own smaller usable within-panel sample, which Section 4.6 reports separately.

Deprivation and measured performance are already associated in this sample before any model is fitted. Of the 2,788 facility-years that fall in the bottom tenth of their own year's QIP distribution, 61.3 percent serve counties above the sample median on the deprivation index, against the 50 percent an even split would give. The facilities the payment program penalizes are therefore drawn disproportionately from the communities the deprivation measure identifies, which is the descriptive fact the interaction analysis then conditions on.

3.4 Descriptive Statistics

Table 2 presents descriptive statistics and distributional percentiles for all variables in the main-model sample, along with pairwise correlations for the focal variables, scale control, baseline controls, and wage instrument. Table 3 further describes the panel and reports both the raw empowerment distribution and the bottom-coded analysis distribution. The modal raw category is two dimensions (44.00%), while the raw zero-permission cell contains only 1.90% of facility-years. This sparse cell motivates the transparent pooling of raw levels 0 and 1 in the main interaction. The post-hoc free-shape analysis in Section 5.4 reports both that three-level coding and the unpooled four-level alternative, including the most-constrained group explicitly.

4 Empirical Methodology

4.1 Model Specification

Our empirical analysis estimates the effect of registered nurse (RN) staffing intensity on dialysis service quality while accounting for unobserved facility heterogeneity, facility scale, and the potential endogeneity of staffing decisions. Let $X_{1,it} = \ln(100 \times RN\,FTE_{it}/Patient\,Census_{it})$, $X_{2,it} = \ln(SDI_{it})$, and $S_{it} =$

Table 2: Descriptive Statistics, Percentiles, and Pairwise Correlations

	Variable	Mean	S.D.	P1	Median	P99
Panel A: Descriptive statistics and distributional percentiles						
(1)	ln(QIP Score)	4.123	0.204	3.497	4.159	4.443
(2)	ln(RN Staffing)	1.685	0.493	0.838	1.656	2.909
(3)	ln(SDI)	3.789	0.823	0.693	4.060	4.595
(4a)	Raw Empowerment	1.834	0.768	0.000	2.000	3.000
(4)	Analysis Empowerment	1.853	0.734	1.000	2.000	3.000
(5)	ln(Patient Census)	4.286	0.697	2.303	4.369	5.602
(6)	Stations	18.757	8.004	0.000	18.000	45.000
(7)	Patient Severity	16.673	11.531	0.000	14.000	60.000
(8)	Years Certified	16.937	10.205	2.000	16.000	41.000
(9)	Physicians (FTE)	0.179	1.450	0.000	0.250	1.000
(10)	Technicians (FTE)	7.010	8.068	0.000	5.980	24.390
(11)	Management (FTE)	0.761	1.411	0.000	0.130	4.670
(12)	LPNs (FTE)	0.795	3.205	0.000	0.310	5.430
(13)	Chain-Owned	0.936	0.245	0.000	1.000	1.000
(13a)	For-Profit	0.926	0.262	0.000	1.000	1.000
(14)	ln(RN Wage)	3.542	0.175	3.268	3.503	4.091
(15)	Nurse Aides (FTE)	0.388	1.720	0.000	0.000	9.200
(16)	Social Workers (FTE)	0.744	0.682	0.060	0.650	2.380
(17)	Drug Expense/1,000	445.936	291.701	69.633	379.596	1464.139
(18)	Laboratory Expense/1,000	98.874	68.487	14.512	81.997	334.170
(19)	Late Shift	0.188	0.390	0.000	0.000	1.000
(20)	In-Center Hemodialysis	0.981	0.136	0.000	1.000	1.000
(21)	Home Hemodialysis Training	0.295	0.456	0.000	0.000	1.000

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel B: Pairwise correlations for focal variables, scale, baseline controls, and the wage instrument														
(1) ln(QIP Score)														
(2) ln(RN Staffing)	.110*													
(3) ln(SDI)	−.112*	−.046*												
(4) Analysis Empowerment	−.025*	−.053*	−.035*											
(5) ln(Patient Census)	−.229*	−.503*	.126*	−.021*										
(6) Stations	−.143*	−.155*	.174*	−.053*	.574*									
(7) Patient Severity	−.190*	−.048*	.012	.067*	.004	−.060*								
(8) Years Certified	−.070*	−.170*	.079*	.014*	.353*	.368*	−.113*							
(9) Physicians (FTE)	−.027*	.045*	.000	−.013*	.003	−.015*	.054*	−.006						
(10) Technicians (FTE)	−.087*	.040*	.092*	−.039*	.359*	.378*	.008	.161*	.341*					
(11) Management (FTE)	−.068*	.019*	.028*	.002	.139*	.147*	−.017*	.094*	.261*	.577*				
(12) LPNs (FTE)	−.042*	.006	.046*	−.011	.103*	.117*	−.008	.056*	−.005	.101*	.042*			
(13) Chain-Owned	.116*	−.059*	−.022*	−.070*	−.015*	−.010	−.115*	.033*	−.098*	−.086*	−.061*	−.038*		
(14) ln(RN Wage)	−.007	.162*	.036*	−.366*	.106*	.093*	−.065*	−.022*	.017*	.186*	.014*	−.021*	−.026*	
(13a) For-Profit	−.001	−.104*	.016*	.034*	−.006	−.072*	.081*	−.099*	.014*	−.045*	.050*	−.004	.230*	−.018*

Notes. N = 25,860 facility-year observations from 6,039 facilities in 50 states, 2015–2019. Panel A reports the Model 3 estimation-sample statistics, rounded to three decimals. P1, Median, and P99 denote the 1st, 50th, and 99th percentiles. Raw Empowerment is the 0–3 legal index; Analysis Empowerment is $\max(Emp^{raw}, 1)$. RN Staffing is RN FTEs per 100 patients, with the underlying ratio winsorized at the 5th and 95th percentiles. RN Wage is shown in logs here but enters the first stage in levels. The expanded operational controls (15)–(21) are summarized in Panel A; Panel B reports the correlation block produced for variables (1)–(14). $^{*}p < .05$ (two-tailed).

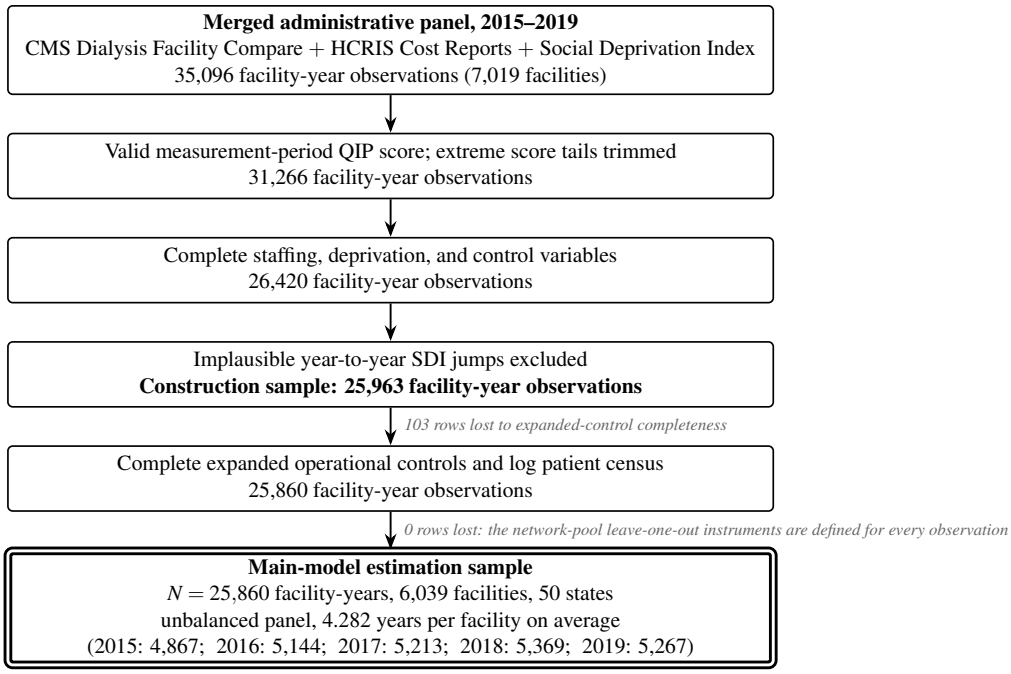


Figure 3: Sample construction. Three publicly available administrative data sources (CMS Dialysis Facility Compare, HCRIS Cost Reports, and the Robert Graham Center Social Deprivation Index) are merged into a panel of 35,096 facility-year observations. Requiring a valid measurement-period QIP score and applying the prespecified score trim yields 31,266 observations; requiring complete core covariates yields 26,420; and the SDI-jump screen yields a construction sample of 25,963. Requiring the expanded operational controls removes 103 rows; the two network-pool leave-one-out excluded instruments are defined for every remaining observation, yielding the main-model sample of $N = 25{,}860$ facility-years from 6,039 facilities (unbalanced panel; 4.282 years per facility on average).

Table 3: Sample Description: Empowerment Distribution

	Statutory permissions granted (raw 0–3 index)			
	0 (none)	1	2	3 (all three)
Facility-years	491	8,645	11,378	5,346
Share of sample (%)	1.90	33.43	44.00	20.67
Analysis coding, $Emp = \max(Emp^{raw}, 1)$	$Emp = 1$: 9,136 (35.33%)		11,378 (44.00%)	5,346 (20.67%)

Notes. Panel data of Medicare-certified dialysis facilities: 25,860 facility-year observations from 6,039 facilities in 50 states, 2015–2019, 4.282 years per facility on average (unbalanced panel; Figure 3). Empowerment dimensions: (1) RN diagnosis authority, (2) freedom from continuous supervision, (3) LPN delegation authority. The main analysis pools the sparse raw level 0 with level 1 but does not remove those observations; see Section 3.2 for coding details. Log-scale analysis variables (mean, SD): ln(*RN FTE/patient census* × 100) 1.685 (0.493); ln(*SDI*) 3.789 (0.823); ln(*QIP*) 4.123 (0.204); ln(*patient census*) 4.286 (0.697). QIP = Quality Incentive Program total performance score. SDI = Social Deprivation Index (county-level).

ln(*Patient Census*$_{it}$). We estimate three progressively richer models:

$$\ln(Y_{it}) = \alpha_i + \gamma_t + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \kappa S_{it} + \boldsymbol{\delta}'\mathbf{C}_{it} + \varepsilon_{it} \tag{1}$$

$$\ln(Y_{it}) = \alpha_i + \gamma_t + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 (X_{1,it} \times X_{2,it}) + \kappa S_{it} + \boldsymbol{\delta}'\mathbf{C}_{it} + \varepsilon_{it} \tag{2}$$

$$\begin{aligned}\ln(Y_{it}) = {} & \alpha_i + \gamma_t + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 (X_{1,it} \times X_{2,it}) \\ & + \beta_4 (X_{1,it} \times Emp_i) + \beta_5 (X_{2,it} \times Emp_i) \\ & + \beta_6 (X_{1,it} \times X_{2,it} \times Emp_i) + \kappa S_{it} + \boldsymbol{\delta}'\mathbf{C}_{it} + \varepsilon_{it}\end{aligned} \tag{3}$$

Here, Y_{it} is the ESRD Quality Incentive Program (QIP) total performance score for facility i measured over year t. CMS releases the score under a later payment-year label; throughout the paper, we index it by the calendar year of its measurement period. The raw state-law index is $Emp_i^{raw} = R_{a,i} + R_{b,i} + R_{c,i}$. Because only 491 facility-years, 1.90% of the sample, occupy raw level 0, the main specification transparently uses $Emp_i = \max(Emp_i^{raw}, 1)$, so the analysis levels are 1, 2, and 3. This coding pools the sparse raw 0 cell with level 1 but drops no observations.

The vector $\mathbf{C}_{it}$ contains dialysis stations, patient severity, years certified, physician FTEs, patient care technician FTEs, management and administrative FTEs, LPN FTEs, recorded ownership type, chain affiliation, nurse-aide FTEs, social-worker FTEs, drug expense per 1,000, laboratory expense per 1,000, a late-shift indicator, and indicators for offering in-center hemodialysis and home-hemodialysis training. Log patient census enters separately so that the RN-to-patient intensity coefficient is not asked to absorb facility scale. Recorded ownership type enters as a control rather than being absorbed: it changes for 253 facility-years in the estimation panel, so the facility fixed effects do not remove it. Chain affiliation, which changes for 3,191 facility-years, is the second ownership-structure control. The QIP score, RN staffing ratio, SDI, and patient census enter in natural logs; the remaining controls enter in levels. The BLS MSA RN wage also enters the first stage in levels. Standard errors are two-way clustered by facility and by chain organization throughout, so that inference is robust both to within-facility serial correlation and to correlated shocks across facilities under common ownership (Cameron and Miller, 2015). Chain affiliation is measured year by year, and all independently owned facilities are pooled into a single cluster; the main sample contains 88 chain clusters. Each displayed structural equation is augmented in estimation by the corresponding first-stage residual, as described below.

Model (1) is the designated test of the average RN staffing–quality relationship (H1). The coefficient β_1 is an elasticity conditional on SDI, facility scale, the expanded control set, and facility and year effects.

Model (2) introduces the county-level SDI (in logs) and its interaction with RN staffing to test whether the marginal quality return to skilled nursing varies with socioeconomic context (H2). The marginal effect of RN staffing becomes $\beta_1 + \beta_3 \ln(SDI)$, allowing us to evaluate whether facilities serving more deprived communities derive greater or lesser benefit from RN-intensive staffing.

Model (3) introduces the three-way interaction among RN staffing, SDI, and nurse empowerment (H3). Rather than estimating separate regressions within empowerment strata, we model the 1–3 analysis index as an ordinal moderator interacted with all components of the staffing–deprivation relationship. The coefficient β_6 tests whether the SDI moderation of the staffing–quality relationship changes with empowerment. The net moderation at an observed analysis level $e \in \{1, 2, 3\}$ is:

$$\left.\frac{\partial^2 \ln Y}{\partial X_1 \, \partial X_2}\right|_{Emp=e} = \beta_3 + \beta_6 \cdot e \tag{4}$$

A positive β_6 indicates that broader statutory practice authority progressively shifts the SDI moderation upward, from a regime in which deprivation attenuates the staffing return toward one in which it does not, consistent with the theoretical prediction that a broader legally available response repertoire permits nurses to deploy their clinical expertise more effectively in complex, resource-constrained environments.

The full marginal effect of RN staffing at empowerment level e and SDI level x is:

$$\left.\frac{\partial \ln Y}{\partial X_1}\right|_{Emp=e,\ X_2=x} = \beta_1 + \beta_4 \cdot e + (\beta_3 + \beta_6 \cdot e)\, x \tag{5}$$

This expression forms the basis for the Johnson–Neyman (J-N) analysis presented in the Results section (Johnson and Neyman, 1936; Spiller et al., 2013). Following the marginal-effects approach recommended by Brambor et al. (2006) and Busenbark et al. (2022), we plot Equation (5) as a function of X_2 for each empowerment level, with 90% confidence bands computed via the delta method.

The progressive specification strategy follows the hierarchical approach recommended by Aiken and West (1991) and Dawson (2014) for testing moderated moderation. Model (2) reports the two-way interaction pooled across authority regimes. Model (3) then tests H3 and characterizes the two-way interaction at each observed empowerment level through $\beta_3 + \beta_6 e$. Because the main coding begins at $e = 1$, the standalone β_3 in Model 3 is the algebraic value at the unobserved point $e = 0$ and is not interpreted as an observed reference-group effect. H2 predicts attenuation where practice authority is limited, so its designated test is the net moderation $\beta_3 + \beta_6$ evaluated at the lowest observed authority level. The pooled Model 2 coefficient averages that regime against the expanded-authority regimes and is therefore an average of quantities the theory predicts will differ in sign (Dawson, 2014; Chuang et al., 2019); it is reported for completeness alongside the observed-level test.

The post-hoc heterogeneity analyses relax the index structure without changing the estimator. First, categorical specifications give each empowerment level its own X_1, X_2, and X_1X_2 terms. We estimate one version on the three main analysis levels and a second on the four raw levels, thereby retaining the zero-permission cell separately. Second, we replace the composite score with the three binary provisions R_a, R_b, and R_c in one mutually adjusted model. For each provision, the model includes X_1R_j, X_2R_j, and $X_1X_2R_j$; the time-invariant provision levels are absorbed by facility fixed effects. The coefficient on $X_1X_2R_j$ therefore estimates the provision-specific increment in the staffing–deprivation moderation while holding the other two provisions' complete lower-order hierarchies fixed. The model retains the patient-census control, expanded controls, facility and year fixed effects, and the three-instrument, single-residual control function, and carries the same facility-by-chain two-way inference as the main models. We also estimate one saturated model that assigns its own staffing-by-deprivation term to each of the eight statutory configurations, which lets the provisions be read jointly rather than one at a time. This analysis diagnoses where H3's composite gradient is concentrated; it is not an additional confirmatory hypothesis or a policy treatment-effect estimate.

4.2 Estimator Selection

Random effects requires unobserved facility heterogeneity α_i to be uncorrelated with the regressors. That condition is implausible here because persistent facility attributes, such as organizational culture, managerial capability, and local competitive intensity, shape both staffing decisions and quality outcomes. We therefore adopt the within estimator (fixed effects) throughout, which absorbs all time-invariant facility-level confounders and identifies the staffing–quality relationship exclusively from within-facility variation over time. Year fixed effects γ_t capture macroeconomic trends, industry-wide regulatory changes, and other temporal

shocks common to all facilities in a given year. While the within estimator eliminates time-invariant confounders, it does not resolve endogeneity arising from the simultaneous determination of staffing and quality within a facility over time.

4.3 Endogeneity and the Control Function Approach

Identification starts from an accounting of where endogeneity can enter the estimating equations, because the source of each concern dictates the response to it. Table 4 states this accounting term by term: the economic origin of each threat, the design element that answers it, and the diagnostic that certifies the answer, with the section where each certificate is reported. Three features of the design follow directly from the sources rather than from convention. First, the structurally endogenous regressor is RN staffing; the deprivation index is a county attribute and the empowerment index a predetermined state-law attribute. The interaction terms inherit staffing's endogeneity, so we use a single control-function residual rather than treating every product term as a separate endogenous variable. Second, the maintained first stage uses three excluded instruments: one Lewbel instrument formed from year-demeaned years certified and the auxiliary-OLS residual (Lewbel, 2012), the external cross-market RN wage within the facility's ESRD Network, and a same-Network leave-own-county-out peer staffing measure. Third, the moderators cannot readily be moved by one facility's current outcome: no single facility determines its county SDI, and the empowerment coding is fixed from statutes in force as of August 1, 2015. These timing and level-of- aggregation features support the single-residual correction; Section 6.2 reports complementary estimator checks.

The central identification challenge is the potential for simultaneous determination of RN staffing and service quality. Facilities that observe deteriorating quality may respond by increasing their RN staffing intensity, while facilities achieving strong performance may reallocate nursing resources to other operational priorities. If staffing decisions are partly a function of quality outcomes, the within-estimator coefficient β_1 will be biased. Whether reverse causality generates upward or downward bias depends on the nature of the managerial response. If facilities increase RN staffing in reaction to poor quality (a corrective response), the OLS estimate of β_1 will be attenuated toward zero or may even reverse sign, leading the analyst to underestimate the true benefit of skilled nursing (Konetzka et al., 2008).

This simultaneity concern is well recognized in the healthcare operations literature (KC and Terwiesch, 2009; Kuntz et al., 2015; Lu and Lu, 2017a), where staffing levels and quality outcomes are understood to be jointly determined within an ongoing operational feedback loop. To address this endogeneity, we employ a control function (CF) approach (Wooldridge, 2015) rather than standard two-stage least squares (2SLS). The CF approach is preferred in our context because, as Wooldridge (2015) demonstrates, it provides consistent estimates of interaction effects involving the endogenous regressor, a binding requirement given that our hypotheses center on interactions between RN staffing, SDI, and empowerment. Standard 2SLS can produce inconsistent estimates of interaction coefficients when the endogenous variable enters multiplicatively.

Table 4: Sources of Endogeneity and the Identification Design They Dictate

Term	Source of the concern	Design response	Certifying diagnostic
$\ln(RN)$	Reverse causality (staffing adjusts to observed quality); omitted managerial quality; measurement error in a ratio of noisy counts	Single-residual control function; year-demeaned years-certified Lewbel instrument, the external cross-market RN wage within the ESRD Network, and the same-Network leave-own-county-out peer staffing measure	Excluded-IV $F(3) = 67.148$ in Model 1; diagnostic 2SLS KP $F = 22.174$ and Hansen $J = 2.676$ ($p = .262$); $\hat{v} < 0$ and significant in every model (Table 5)
$\ln(SDI)$	Residential sorting; area-level shocks	Predetermined county-level environmental constraint; facility fixed effects absorb location; within-facility identification	County-level aggregation and adjacent-year stability ($r = 0.993$; Section 6.3)
Emp	Policy endogeneity (states could legislate in response to staffing or quality conditions)	Statutory index predetermined (laws in effect August 1, 2015), time-invariant, enters only through interactions	Full coding provenance in Appendix A; raw 0–3 coding sensitivity in Section 6.1
Interactions (incl. the three-way)	Inherit staffing's endogeneity	Single-residual CF for the staffing channel; county-level SDI and the predetermined statutory index supply the moderator timing and aggregation argument (Bun and Harrison, 2019; Nizalova and Murtazashvili, 2016)	Interacted-residual block $F(3) = 0.48$ ($p = .70$); three-way 0.011 with a second residual for the deprivation index (Section 6.2)
Unobserved facility trajectory	Loads on both staffing and the outcome	Facility and year fixed effects; coefficient-stability bounds	Oster $\delta = 2.31$ (Section 6.2)
Outcome timing	Payment-year label is not the measurement date	Outcome indexed by its measurement period	Source-date alignment documented in the data construction (Section 3)

Notes. Each row names the economic source of one identification concern, the design element that responds to it, and the diagnostic that certifies the response, with the section in which the certificate is reported.

4.4 Excluded Instrument Construction

The maintained specification uses three excluded instruments for RN staffing: one heteroskedasticity-based instrument constructed following Lewbel (2012), the BLS cross-market mean hourly RN wage within the facility's ESRD Network, and a same-Network leave-own-county-out peer staffing measure. The heteroskedasticity-based instrument is built as follows:

1. **Auxiliary OLS.** On the 25,963-observation construction sample, regress $X_{1,it}$ on $X_{2,it}$, stations, severity, years certified, physician FTEs, technician FTEs, management FTEs, LPN FTEs, chain affiliation, and year indicators; retrieve the residual $\hat{u}_{it}$. The external wage instrument is excluded from this auxiliary regression and enters only the subsequent fixed-effects first stage.

2. **Year demeaning.** Center years certified on its calendar-year mean:

$$\widetilde{Z}_{it} = YearsCertified_{it} - \overline{YearsCertified}_{t}.$$

   This is year demeaning, not facility demeaning.

3. **Instrument formation.** Form the excluded heteroskedasticity-based instrument $H_{it}^{YC} = \widetilde{Z}_{it}\hat{u}_{it}$.

Both remaining instruments pool over the facility's CMS ESRD Network, so it is worth stating exactly which units enter a donor pool. The ESRD Networks are the administrative geography CMS uses for quality oversight, and each is a fixed group of whole states and territories. Two of the eighteen Networks partition a single state, California, so a state-level assignment yields seventeen distinct pools; these hold from one state (New York, Florida, Texas, Illinois) to six (Network 1: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), with a median of three. A donor pool is therefore not a within-state average. It contains the other markets, or the other counties, of every state assigned to that Network, minus the focal facility's own excluded window. Because the statutory provisions are state-level and time-invariant here, a pool that reaches across state lines is what makes the instrument independent of the facility's own regulatory environment, which the facility fixed effects have already absorbed.

The second excluded instrument, w_{it}^{RN}, is the BLS mean hourly RN wage averaged over all other labor markets in the facility's CMS ESRD Network and year, leaving out the facility's own market, and enters in levels. It captures regional labor-market variation in the supply price of registered nursing while excluding the facility's own market from the measure. The window is the metropolitan market rather than the county because the market is the unit at which wages are set: a labor-market shock, a local nursing shortage for example, operates on the market as a whole, so removing only the county would leave the rest of the shared market inside the donor pool. The Network pool, the CMS quality-oversight geography that groups contiguous states, guarantees that a second labor market exists for every facility; a state-level pool leaves the instrument undefined wherever BLS coverage reduces a state to a single wage market, which deletes entire states, including two of the three zero-permission states, from the estimation sample. Area nursing wages have been used to instrument facility staffing inputs in recent facility-quality studies (Pradhan et al., 2025; Ghiasi et al., 2026); our leave-own-market-out measure applies the same supply-side logic at a broader labor-market level. Because the statutory practice provisions are time-invariant over the panel, the facility fixed effects absorb each facility's own regulatory environment, so the cross-market wage variation identifies the staffing response rather than differences in practice regimes.

The third excluded instrument, z_{it}^{CTY}, is the mean RN staffing ratio of all other facilities in the same ESRD Network and year that lie outside the focal facility's own county. It carries regional staffing-market conditions that move a facility's own staffing without passing through that facility's county-level quality environment, and the leave-own-county-out construction removes the mechanical component that a within-county peer average would share with the focal facility's own local conditions. Here the window is the county rather than the market because the county is the unit at which the quality-relevant community environment, including the SDI itself, is measured; the donors that remain carry Network staffing conditions without the focal county's own environment. Each instrument's window therefore matches the geographic footprint of the shock it excises. The two windows also correspond to the levels at which the source data are published: the BLS reports RN wages by metropolitan market, and the deprivation index is published at the county level, so each exclusion window follows the official geography of its own variable rather than a discretionary partition. That the two instruments operate at different official levels is itself a safeguard, since a shock local to any single geography cannot enter both instruments through a shared window.

Figure 4 states what the exclusion window is for. Panel (a) is the design without one: a peer or wage average taken inside the facility's own market and county is moved by the same unobserved local shock that moves the facility's own staffing and its own quality, which leaves the backdoor from instrument to outcome open. Panel (b) is the design we use, in which the donors lie outside that window, so the only channel left to them is the Network-wide condition. The two instruments differ only in which window they excise, the own MSA for the wage and the own county for peer staffing, because the two confounding channels live at different geographies. The window narrows each channel without by itself establishing exclusion.

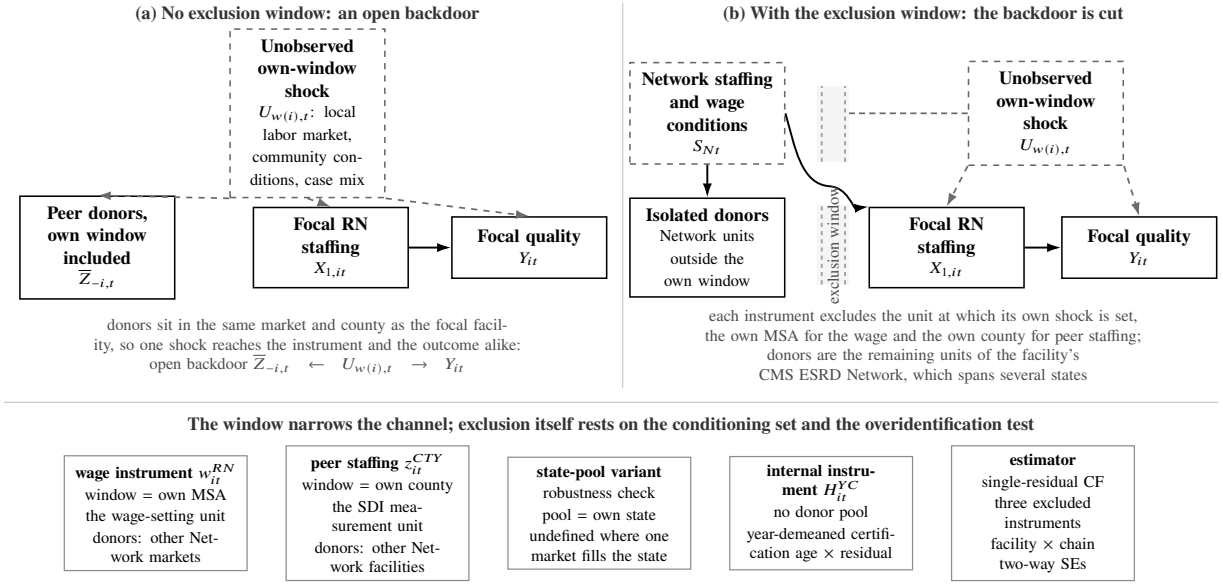


Figure 4: Why the leave-one-out window exists. Panel (a) shows the design without an exclusion window: the donor average is drawn from the facility's own market and county, so a single unobserved local shock reaches the instrument, the facility's staffing, and its quality alike, and the backdoor from instrument to outcome stays open. Panel (b) shows the maintained design: donors are the units of the facility's CMS ESRD Network that lie outside the excluded window, the gate cuts the shock's path into the donor pool, and the only channel that survives to the instrument is the Network-wide staffing and wage condition. Each of the two instruments excises the unit at which its own shock is set, the own metropolitan market for the wage because that is where wages are set, and the own county for peer staffing because that is where the quality-relevant community environment, the SDI included, is measured. The window narrows that channel; exclusion itself rests on the conditioning set and the diagnostics of Table 5. The bottom strip lists the reported constructions: the two maintained Network-pool instruments, the state-pool variant carried as a robustness check, the internal heteroskedasticity-based instrument, which uses no donor pool, and the estimator that combines them.

We restrict the main instrument set to these three excluded variables. This restriction limits instrument proliferation relative to the 25,860-observation main-model sample (Bekker, 1994), and the overidentification test does not reject the retained set (Table 5). As with any heteroskedasticity-based identification design, validity requires the relevant heteroskedasticity moment conditions in addition to relevance (Lewbel, 2012; Baum and Lewbel, 2019).

4.5 Control Function Estimation

We implement the CF approach in two stages. In the **first stage** for model m, we regress $X_{1,it}$ on the years-certified Lewbel instrument, the Network cross-market RN wage, the same-Network leave-own-county-out peer staffing measure, the model-specific exogenous terms, and facility and year fixed effects:

$$X_{1,it} = \alpha_i^{(1)} + \gamma_t^{(1)} + \pi_1 H_{it}^{YC} + \pi_2 w_{it}^{RN} + \pi_3 z_{it}^{CTY} + \boldsymbol{\phi}' \mathbf{W}_{it}^{(m)} + \nu_{it}^{(m)}, \tag{6}$$

where $\mathbf{W}_{it}^{(m)}$ contains log patient census, log SDI, and the full expanded control set; Model 3 additionally includes $X_{2,it} \times Emp_i$. Models 1 and 2 share the same first stage and residual. The joint excluded-instrument statistic is $F(3) = 67.148$ for Models 1 and 2 and $F(3) = 67.310$ for Model 3.

In the **second stage**, we include the first-stage residual $\hat{v}_{it}$ as an additional regressor in the structural equation alongside the original (endogenous) $\ln(RN_{it})$. A statistically significant coefficient on $\hat{v}_{it}^{(m)}$ indicates endogeneity of RN staffing (Wooldridge, 2015). The residual coefficient is negative and significant in every specification: -0.174 ($p = .002$) in Model 1, -0.176 ($p = .002$) in Model 2, and -0.173 ($p = .002$) in Model 3. Thus the unobserved component that raises RN staffing is associated with lower contemporaneous quality, a pattern consistent with corrective staffing responses to adverse quality shocks and downward bias in an uncorrected within estimate. We therefore retain the CF specification as the preferred estimator and report the FE-OLS estimates as a same-sample comparison (Section 6).

Relative to the standard Durbin–Wu–Hausman test, the CF residual is directly interpretable in sign and magnitude and remains valid in the interaction specifications of Models (2)–(3) (Pal et al., 2024); Table 5 reports these estimates.

4.6 First-Stage Diagnostics

Table 5 reports the first stage alongside the structural estimates it identifies, and separates both from the diagnostic 2SLS statistics in its Panel C, which are computed on a smaller usable within-panel sample.

The three excluded instruments are jointly relevant in the main Model 1 first stage ($F(3) = 67.148$). In the diagnostic 2SLS run, the Kleibergen–Paap statistic is 22.174 and the Hansen test does not reject the three-instrument set ($J = 2.676$, $p = .262$). These diagnostics are reported under the routine's own facility-cluster convention on its $N = 25{,}499$ observations and 5,678 facilities, not relabeled as the 25,860-observation CF sample or as carrying the main models' two-way variance estimator. The negative and significant CF residual in every model is consistent with facilities increasing RN staffing in response to adverse unobserved quality conditions; the corrected coefficients are therefore the paper's preferred estimates.

All estimation is performed in Stata 19/MP. Instrument diagnostics are computed via `ivreg2` and `xtivreg2` (Baum et al., 2007); marginal effects and Johnson–Neyman 90% confidence bands are computed via the delta method.

5 Results

5.1 Main Regression Results

Table 5 reports the three control-function (CF) specifications. Each model uses facility and year fixed effects, standard errors two-way clustered by facility and chain, and one first-stage residual for the endogenous RN staffing ratio. The excluded instruments, a heteroskedasticity-based instrument formed from certification age, the cross-market RN wage within the facility's ESRD Network, and the same-Network leave-own-county-out peer staffing measure, are jointly relevant in every first stage ($F(3) = 67.148$ in Models 1–2 and $F(3) = 67.310$ in Model 3). The CF residual is negative and significant throughout, indicating that the uncorrected within-facility association understates the staffing return. The diagnostic fixed-effects 2SLS estimate for Model 1 reproduces the CF point estimate; under the facility-cluster convention native to that routine its Kleibergen–Paap statistic is 22.174 and the Hansen test does not reject the three-instrument set ($J = 2.676$, $p = .262$). The 2SLS diagnostic uses 25,499 nonsingleton observations from 5,678 facilities, whereas the CF models retain 25,860 facility-years from 6,039 facilities.

Hypothesis 1: RN Staffing and Quality (Model 1). Model 1 is the designated test of H1 because it estimates the staffing effect without conditioning it on higher-order interactions. The coefficient on the RN-to-patient ratio is positive and statistically significant ($\hat{\beta}_1 = 0.157$, SE = 0.067, $p = .021$). Thus a ten-percent increase in RN staffing per patient is associated with approximately a 1.5-percent increase in the QIP score, holding facility scale, the expanded control set, and facility and year effects constant. The diagnostic 2SLS coefficient is identical to three decimal places (0.157, SE = 0.054, $p = .004$). **Hypothesis 1 is supported.**

Hypothesis 2: Community Deprivation as a Moderator. Model 3 supplies the designated test of H2 on the observed authority surface. At the lowest observed authority level the staffing-by-deprivation moderation is negative and significant (−0.017, SE = 0.009, $p = .047$), so deprivation attenuates the staffing–quality relationship where practice authority is limited. **Hypothesis 2 is supported.** The pooled Model 2 estimate averages this regime against the expanded-authority regimes and is correspondingly small and not distinguishable from zero (−0.007, SE = 0.005, $p = .127$), exactly the pattern expected when a negative moderation under limited authority and a positive shift under expanded authority are averaged together (Dawson, 2014; Chuang et al., 2019). The pooled term is therefore reported for completeness rather than used as the test of H2.

Hypothesis 3: Moderated moderation (Model 3). Model 3 reveals the heterogeneity masked by the pooled two-way estimate. The three-way coefficient is positive and significant (0.011, SE = 0.005, $p = .035$): every one-level increase in empowerment shifts the deprivation moderation of the staffing return upward by about 0.011. **Hypothesis 3 is supported.**

The lower-order staffing-by-deprivation coefficient in Model 3 is evaluated at $Emp = 0$, which lies outside the support of the analysis coding and therefore is not itself an observed-regime test. Its value is

Table 5: RN Staffing and Dialysis Service Quality: First Stage, Control-Function Estimates, and Instrument Diagnostics

	Model 1 Main Effect	**Model 2** Two-Way	**Model 3** Three-Way
Panel A. First stage. Dependent variable: ln(*RN*)			
Years-certified heteroskedasticity-based IV, H^{YC}	0.0056***	0.0056***	0.0056***
	(0.0005)	(0.0005)	(0.0005)
Network cross-market RN wage, w^{RN}	0.0015	0.0015	0.0019
	(0.0032)	(0.0032)	(0.0033)
Network leave-own-county-out peer staffing, z^{CTY}	5.651***	5.651***	5.649***
	(0.647)	(0.647)	(0.647)
Excluded-instrument $F(3)$	67.148	67.148	67.310
Number of excluded instruments	3	3	3
First-stage N / facilities	25,860 / 6,039	25,860 / 6,039	25,860 / 6,039
Panel B. Second stage. Dependent variable: ln(*QIP score*)			
ln(*RN*)	0.157**	0.186**	0.271**
	(0.067)	(0.080)	(0.114)
ln(*Patient census*)	0.118**	0.119**	0.117**
	(0.049)	(0.050)	(0.049)
ln(*SDI*)	0.031***	0.044***	0.046
	(0.011)	(0.011)	(0.030)
ln(*RN*) × ln(*SDI*)		-0.007	-0.029**
		(0.005)	(0.014)
ln(*RN*) × *Emp*			-0.047**
			(0.020)
ln(*SDI*) × *Emp*			-0.001
			(0.016)
ln(*RN*) × ln(*SDI*) × *Emp*			0.011**
			(0.005)
CF residual $\hat{v}$	-0.174***	-0.176***	-0.173***
	(0.055)	(0.056)	(0.055)
R^2_{within}	0.178	0.178	0.178
N	25,860	25,860	25,860
Facilities	6,039	6,039	6,039
Panel C. Diagnostic 2SLS for the maintained instrument set (facility-cluster convention)			
Kleibergen–Paap rk Wald F		22.174	
Hansen J		2.676 (p = .262)	
Diagnostic N		25,499	
Diagnostic facilities		5,678	

Notes. RN staffing is RN FTEs per 100 patients; *Emp* $\in \{1, 2, 3\}$ pools the raw zero-permission cell with level one. Every model carries facility and year fixed effects, the controls of Table A2 including log patient census, and one CF residual. Models 1–2 share a first stage; Model 3's adds ln(*SDI*) × *Emp*. The instruments are jointly relevant throughout, and the wage term is individually weak; first-stage inference is conventional, matching the reported F. Because the control function has one endogenous regressor and one shared first stage, the Panel C diagnostic is defined at the level of the instrument set and applies to all three models. It is the no-interaction 2SLS run, which drops 361 singleton observations and uses that routine's facility-cluster convention, so its N and its variance estimator are not those of the CF models. **Clustered standard errors in parentheses, two-way by facility and by chain organization** (Cameron and Miller, 2015). $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

−0.029 (SE = 0.014, $p = .037$). The observed-level quantities are the linear combinations reported above and in Table 6.

The coefficient on $\ln(RN) \times Emp$ is negative (−0.047, $p = .022$), whereas the SDI-by-empowerment coefficient is near zero (−0.001). Because $\ln(SDI)$ enters in levels rather than mean-centered form, this coefficient is the shift in the staffing slope per empowerment dimension evaluated at $\ln(SDI) = 0$, that is, at a county deprivation index of one, and not at the sample mean. It is therefore a conditional quantity at a specific point of the deprivation distribution, and it carries no interpretation on its own. The operational meaning of the interaction terms emerges from the net moderation and staffing-slope profiles below.

5.2 Marginal Effects by Empowerment Level

Table 6 evaluates Equation (4) at each observed analysis level. The deprivation moderation rises monotonically with empowerment, from a significant negative value under limited authority (−0.017, $p = .047$) through a smaller intermediate value (−0.006) to a value at full authority that is no longer distinguishable from zero (0.006), and the Δ(Emp 3 − Emp 1) contrast is significant ($p = .035$).

Table 6: Net SDI Moderation of the Staffing–Quality Relationship by Empowerment Level

$\partial^2 \ln Y / \partial X_1 \, \partial X_2$ at:	$\hat{\beta}$	SE	p
Emp = 1 (low)	-0.017**	(0.009)	.047
Emp = 2 (middle)	-0.006	(0.005)	.202
Emp = 3 (high)	0.006	(0.005)	.263
Per-level three-way gradient	0.011**	(0.005)	.035
Δ(Emp 3 − Emp 1)	0.023**	(0.011)	.035

Notes. Net moderation is $\hat{\beta}_3 + e\hat{\beta}_6$ from Model 3. $\Delta(a - b)$ denotes the difference between the net moderation at level a and level b; Δ(Emp 3 − Emp 1) equals $2\hat{\beta}_6$. The analysis index pools the raw zero-permission cell with raw level one. **Clustered standard errors**, two-way by facility and chain. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Expressing the outcome in QIP points yields the same pattern. The level-three-minus-level-one swing in the deprivation margin is 0.532 points ($p = .076$) for simultaneous one-standard-deviation changes in staffing and deprivation. That swing decomposes into −0.359 QIP points at empowerment level one and +0.173 points at level three. These translations describe the deprivation margin of the staffing return; they are not estimates of a direct policy effect on the QIP score. In managerial terms the regimes differ sharply: under limited authority, moving from the least to the most deprived county erases thirty-two percent of the staffing return, a swing equal to more than two-fifths of the average return itself, whereas under full authority the same move raises the return by about a sixth.

5.3 Johnson–Neyman Analysis

The staffing-return profiles provide a complementary view. We evaluate the marginal staffing effect of Equation (5) across nine percentiles of observed deprivation for each empowerment level. All 27 estimated staffing slopes are positive, ranging from 0.135 to 0.212, and all have $p \leq .032$; because every evaluated



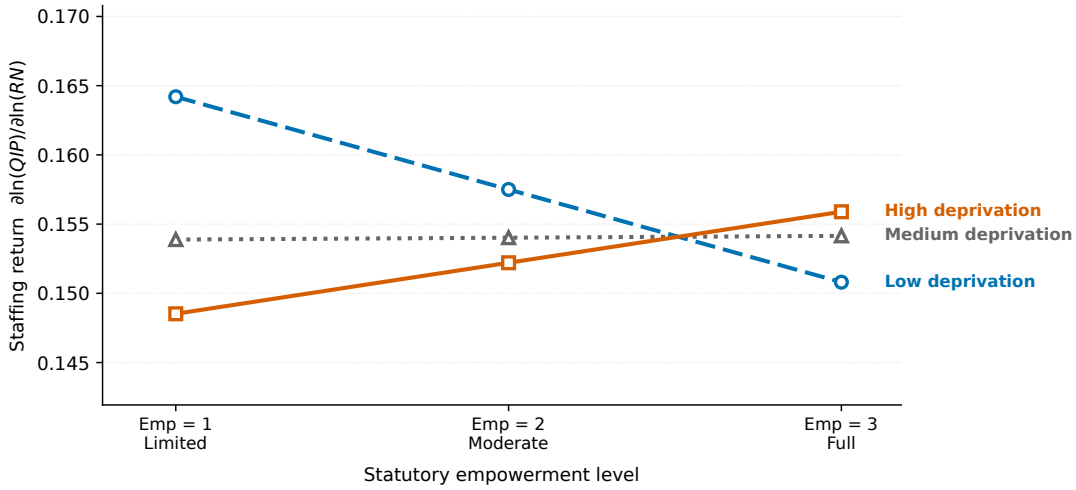
Figure 5: How empowerment changes the deprivation moderation of the staffing return. Circles show the linearly constrained estimates from Table 6; squares show the three-level free-shape estimates from Panel A of Table 7. The constrained gradient moves upward monotonically, while the free-shape estimates locate the principal contrast between the highest authority regime and the two lower regimes. Whiskers are 90% confidence intervals.

slope clears zero, no Johnson–Neyman transition point falls inside the observed deprivation range. At level one, the slope declines from 0.212 at the first deprivation percentile to 0.145 at the 99th. At level two it changes from 0.174 to 0.151. At level three it rises from 0.135 to 0.157. The profiles converge and exchange rank near the median. Empowerment therefore reallocates a positive staffing return across the deprivation distribution; it does not turn a harmful staffing effect into a beneficial one.

The raw four-level coding reaches the same substantive conclusion. The linear raw specification reproduces the gradient (three-way 0.011, $p = .025$), and its most-constrained-level moderation is negative and significant (-0.028, $p = .027$), so the deprivation penalty is sharpest where no statutory authority is granted. Because the network-pool leave-one-out instruments are defined for every construction-sample observation, the raw zero-permission cell retains its full 491 facility-years, and its cell-level free-form estimate is reported directly in Panel B of Table 7; the joint heterogeneity across the raw levels is significant ($F(3) = 5.339$, $p = .002$). The evaluated staffing return is positive and significant at every raw level, including the most-constrained cell, where it runs from 0.162 at the 25th deprivation percentile to 0.117 at the 75th ($p \leq .020$ throughout); at median deprivation the four raw levels return 0.132, 0.153, 0.142, and 0.154, each significant at $p \leq .034$.

Figure 6 shows what that reallocation looks like. Reading the same estimates by empowerment level rather than by deprivation makes the exchange of rank explicit. Under limited authority the staffing return is larger in the less deprived counties and smaller in the more deprived; under full authority the ordering is reversed. The two profiles cross between the second and third empowerment level, and the return at median

deprivation is essentially unchanged across the three levels, which is what a rotation around the middle of the deprivation distribution implies.



Lines evaluate the return at the 25th, 50th, and 75th percentiles of county deprivation.
Every plotted staffing return is positive and significant (largest p = .029); empowerment shift in the deprivation moderation +0.023 (p = .035).
Standard errors two-way clustered by facility and chain.

Figure 6: Johnson–Neyman analysis of the three-way interaction. The vertical axis is the staffing return $\partial \ln Y / \partial X_1$ from Equation (5), computed from the Model 3 estimates in Table 5; the horizontal axis is the analysis empowerment level; each line evaluates the return at the 25th, 50th, or 75th percentile of county deprivation. At limited authority the return runs from 0.163 in the less deprived counties to 0.147 in the more deprived, and at full authority that ordering reverses, from 0.149 to 0.154. Every plotted return is positive and statistically distinguishable from zero, so no Johnson–Neyman transition point lies within the observed deprivation range. The change in the deprivation moderation from the first empowerment level to the third is the contrast reported in Table 6. **Clustered standard errors**, two-way by facility and chain.

5.4 Post-Hoc Heterogeneity Analysis

The main model imposes a linear empowerment gradient and pools the sparse zero-permission cell with level one. We relax both restrictions in stages. Panel A of Table 7 lets each of the three analysis levels carry its own moderation effect. Panel B restores the raw zero-permission group and estimates all four levels freely, so that the most-constrained comparison is read directly off its own cell rather than extrapolated by the linear model to a level outside its analysis support.

Reading the two panels together explains a feature of Panel A that would otherwise look like a weakness. In the linear model the deprivation moderation at analysis level one is −0.017 (p = .047), while the free-shape estimate for the same level is −0.013 and not significant (p = .132). The two differ for a reason visible in Panel B: analysis level one is a pooled cell that averages the 491 facility-years with no statutory authority, whose moderation is −0.050 (p = .044), together with the 8,645 facility-years holding exactly one permission, whose moderation is −0.011 (p = .184). Freeing the shape therefore does not weaken the low-authority evidence; it separates the pooled cell and shows that the deprivation penalty concentrates in

the group that holds no permission at all. The linear model remains the designated test of H2 because it was specified before estimation, and the free-shape panels are reported as the diagnostic that locates where its low-authority quantity comes from.

Table 7: Post-Hoc Heterogeneity Analysis: Free-Shape Moderation by Empowerment Level

$\partial^2 \ln Y / \partial X_1 \, \partial X_2$ or contrast:	$\hat{\beta}$	SE	p
Panel A: Main three-level analysis coding			
Emp = 1 (low)	-0.013	(0.009)	.132
Emp = 2 (middle)	-0.014*	(0.007)	.064
Emp = 3 (high)	0.012**	(0.006)	.050
Δ(Emp 2 − Emp 1)	-0.001	(0.009)	.953
Δ(Emp 3 − Emp 1)	0.026**	(0.010)	.014
Panel B: Raw four-level coding, including the most-constrained level			
Emp = 0 (none)	-0.050**	(0.025)	.044
Emp = 1 (one dimension)	-0.011	(0.008)	.183
Emp = 2 (two dimensions)	-0.014*	(0.007)	.064
Emp = 3 (all three)	0.012**	(0.006)	.050
Δ(Emp 3 − Emp 0)	0.062**	(0.024)	.010
Δ(Emp 3 − Emp 1)	0.023**	(0.010)	.028
Joint heterogeneity block, $F(3)$	5.339***		.002

Notes. Each level receives its own staffing, deprivation, and staffing-by-deprivation terms. Both panels use the same three-instrument, single-residual CF design, facility and year fixed effects, expanded controls, and 25,860-observation sample as Table 5, with **clustered standard errors**, two-way by facility and chain. The raw zero-permission cell contains 491 facility-years from the three states granting none of the measured provisions. The equal-step restriction implicit in a linear raw 0–3 score is rejected under this inference ($F(2) = 4.973$, $p = .009$), which is why the composite gradient is reported alongside the free-shape estimates rather than in place of them. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

We next replace the composite score with the three statutory provisions themselves. The reinforcement structure developed in Section 2.3 carries three implications for this decomposition. The composite gradient should be monotone in breadth, as the empowerment-level results above establish; no single permission, held against the other two, should carry a dominant share of the heterogeneity; and each permission's increment should be larger in the presence of its counterparts. Table 8 reports the provision-level tests on the main sample and machinery.

The decomposition supports the first two implications and qualifies the third. In Panel A the mutually adjusted increments follow the predicted order: delegation, the permission that moves routine work to the LPN, carries the largest and individually significant increment (0.018, $p = .018$), with supervision freedom intermediate (0.012) and diagnosis authority smallest (0.004). The three increments are jointly significant ($F(3) = 4.523$, $p = .005$) but are not statistically distinguishable from one another ($F(2) = 1.880$, $p = .159$), so no single permission can be identified as dominant. Panel B reports the pairwise structure. Delegation and supervision freedom, the two permissions that determine whether routine treatments actually move off the RN, each carry a significant increment in the presence of the other: delegation's increment is significant where nurses are also free of continuous supervision (0.028, $p < .001$), supervision freedom's is significant where delegation is available (0.022, $p < .001$), and neither increment is distinguishable from zero without the other (0.003 and −0.004). Delegation's increment is likewise significant where the nurse may also

Table 8: Between-Dimension Structure of the Empowerment Provisions

	Estimate	SE	p
Panel A. Mutually adjusted provision increments			
R_a: Diagnosis authority	0.004	(0.008)	.618
R_b: Freedom from continuous supervision	0.012	(0.008)	.156
R_c: LPN delegation authority	0.018^{**}	(0.008)	.018
Equality of the three increments	$F(2) = 1.880$		.159
Joint significance of the three increments	$F(3) = 4.523^{***}$		.005
Panel B. Pairwise conditional increments			
Supervision freedom with delegation ($R_b \times R_c$)			
R_c increment with R_b	0.028^{***}	(0.008)	<.001
R_c increment without R_b	0.003	(0.015)	.851
R_b increment with R_c	0.022^{***}	(0.006)	<.001
R_b increment without R_c	−0.004	(0.016)	.813
Diagnosis with delegation ($R_a \times R_c$)			
R_c increment with R_a	0.024^{**}	(0.010)	.014
R_c increment without R_a	0.009	(0.011)	.431
R_a increment with R_c	0.014	(0.010)	.201
R_a increment without R_c	−0.002	(0.011)	.880
Diagnosis with supervision freedom ($R_a \times R_b$)			
R_b increment without R_a	0.024^{**}	(0.011)	.030
R_b increment with R_a	0.006	(0.010)	.537
R_a increment with R_b	−0.005	(0.009)	.582
R_a increment without R_b	0.013	(0.011)	.245
Panel C. Net deprivation moderation by statutory configuration			
None of the three granted	-0.050^{**}	(0.024)	.044
R_c only	−0.018	(0.013)	.166
R_b only	−0.010	(0.010)	.332
$R_b + R_c$	−0.003	(0.008)	.734
R_a only	−0.011	(0.012)	.374
$R_a + R_c$	−0.012	(0.007)	.102
$R_a + R_b$	-0.024^{*}	(0.013)	.064
All three granted	0.012^{**}	(0.006)	.050
Panel D. Contrasts with the full statutory bundle			
Δ(All three − none)	0.062^{**}	(0.024)	.010
Δ(All three − R_a+R_b): adding R_c	0.036^{**}	(0.015)	.015
Δ(All three − R_a+R_c): adding R_b	0.024^{***}	(0.007)	.001
Δ(All three − R_b+R_c): adding R_a	0.015	(0.012)	.216

Notes. Panel A reports the coefficients on $\ln(RN) \times \ln(SDI) \times R_j$ from one model that includes R_a, R_b, and R_c simultaneously, together with $\ln(RN) \times R_j$ and $\ln(SDI) \times R_j$ for every provision. Panel B estimates, for each pair of provisions, one model carrying both provisions and their product with the full interaction hierarchy, and reports each provision's increment at the two values of its partner. Panels C and D estimate the net $\ln(RN) \times \ln(SDI)$ moderation separately for each of the eight statutory configurations observed in the data, from one saturated configuration model. The most-constrained configuration contains 491 facility-years from the three states granting none of the measured provisions. All models use the main sample (N = 25,860; 6,039 facilities), expanded controls, facility and year fixed effects, the same three excluded instruments and single-residual control function as Table 5, and **clustered standard errors**, two-way by facility and chain. These are exploratory conditional associations, not provision-level treatment effects, and the configurations are not ordered. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

decide what each patient needs (0.024, p = .014), whereas diagnosis authority contributes little in either pairing (0.013 with delegation, −0.001 without). The one pairing that leaves the nurse unable to delegate, diagnosis with supervision freedom, produces no significant joint increment, and that configuration carries the deepest partial-cell penalty in Panel C. Panel C places the eight statutory configurations on a common footing. The deprivation penalty is significant in the most-constrained configuration (−0.050, p = .044) and in the R_a + R_b configuration, the full-bundle estimate is positive and significant (0.012, p = .050), and the remaining cells are not distinguishable from zero. Panel D reports the contrasts with the full

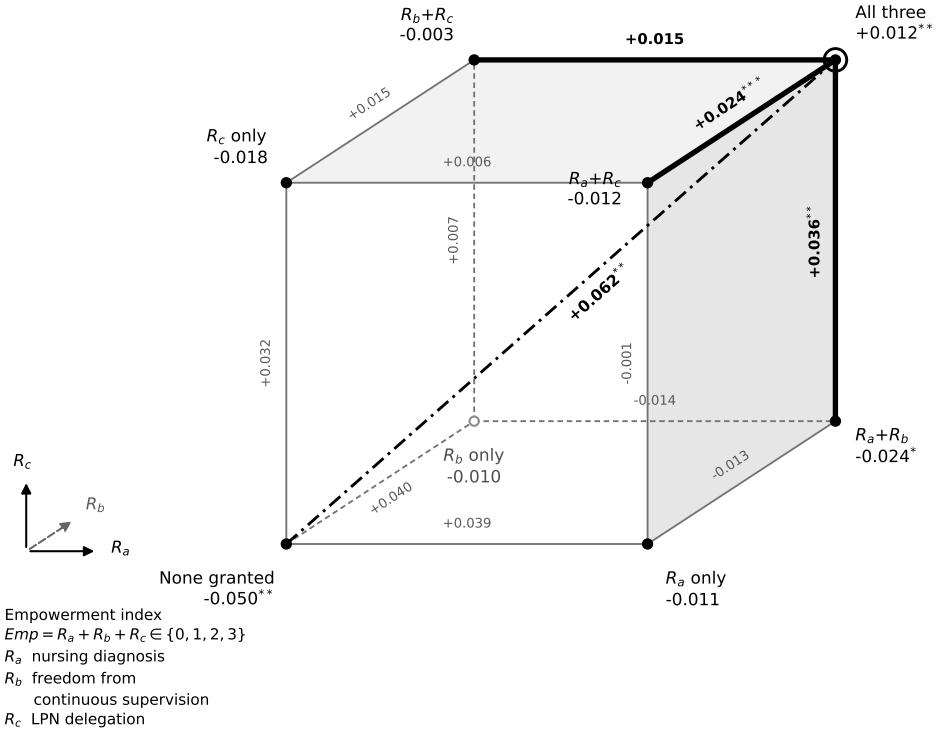


Figure 7: The provision cube. The three scope-of-practice provisions form a $2 \times 2 \times 2$ design, so the eight observed statutory configurations are its vertices and their sum is the empowerment index $Emp = R_a+R_b+R_c$: a configuration's level is how many permissions separate it from the origin, and the four levels are the cube's layers. Vertices report the net deprivation moderation $\partial^2 \ln Y / \partial X_1 \, \partial X_2$ estimated for that configuration from the saturated configuration model (Table 8, Panel C); each edge reports the change in that moderation from granting one further permission with the other two held fixed. The three heavy edges into the completed bundle and the interior diagonal running from no authority to it (Δ(All three − none) = +0.062, $p = .010$) are Panel D's reported contrasts; the completed bundle is the only vertex whose point estimate lies above zero. The delegation-completing edge (+0.036, $p = .015$) is sensitive to the statutory coding of two states (Section 6.1); the supervision-completing edge (+0.024, $p = .001$) is not. The rear lower-left vertex is occluded by the front face and its edges are dashed. Estimates use the main sample (N = 25,860; 6,039 facilities), expanded controls, facility and year fixed effects, and the three-instrument single-residual control function, with standard errors two-way clustered by facility and chain as reported in Table 8. These are exploratory conditional associations, not provision-level treatment effects. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

bundle. Adding supervision freedom to the diagnosis-plus-delegation configuration ($p = .001$) and adding delegation to the diagnosis-plus-supervision configuration ($p = .015$) are both significant, while adding diagnosis authority to the supervision-plus-delegation configuration is not ($p = .216$). The full bundle also clears the most-constrained benchmark directly: with the zero-permission cell restored to its full 491 facility-years, Δ(All three − none) is positive and significant (+0.062, $p = .010$), so the configuration granting all

three permissions differs from the configuration granting none at both ends of the gradient. Two further limits bound the reading of Panel D. Section 6.1 shows that the delegation contrast is sensitive to the statutory coding of two states, whereas the supervision-freedom contrast is not. And because the configurations are parallel statutory bundles rather than stages of a sequence, these contrasts describe localized heterogeneity rather than a completion path. Figure 7 draws the eight configurations as the provision cube, with Panel D's contrasts on its completion edges and its interior diagonal. The decomposition therefore explains the composite gradient rather than replacing it, and H3's composite-index test remains the governing result.

5.5 Summary of Hypothesis Tests

Table 9: Summary of Hypothesis Tests

	Hypothesis	**Governing test**	**Result**
H1	RN staffing ratio improves quality	Model 1: 0.157 (SE = 0.067, p = .021)	*Supported*
H2	Deprivation attenuates the staffing return	Model 3 net moderation at Emp = 1: −0.017 (SE = 0.009, p = .047)	*Supported*
H3	Empowerment lessens the deprivation moderation	Model 3 three-way gradient: 0.011 (SE = 0.005, p = .035)	*Supported*

Notes. H1 is tested by the no-interaction model; H2 by the net staffing-by-deprivation moderation at the lowest observed authority level in Model 3; and H3 by the per-level change in that moderation in Model 3. The Model 3 lower-order interaction at *Emp* = 0 lies outside the analysis support and is not used as a test of H2. The pooled Model 2 interaction averages across authority regimes and is reported in Table 5 for completeness.

6 Robustness Checks

We assess the sensitivity of our main findings in three groups. Measurement robustness covers the coding and weighting of the empowerment construct, the statutory coding of two boundary states, the outcome scale, an independent outcome measure, and alternative staffing constructions. Estimation and instrument robustness covers the control-function correction, the estimator and panel design, the instrument pool, and coefficient stability under unobservable selection. Temporal stability covers the persistence of the SDI moderator and the year fixed-effect pattern. The staffing return of H1 holds under every construction of the RN input we examine. The empowerment gradient of H3 reproduces in sign across the coding, weighting, outcome-scale and estimator checks, and is estimated on the demand-normalized staffing ratio, which is the quantity the mechanism concerns.

6.1 Measurement Robustness

Empowerment index coding and weighting. The main analysis pools the sparse raw zero-permission cell with level one. Retaining the raw 0–3 coding instead yields a three-way coefficient of 0.011 (SE = 0.005, p = .025), and the net deprivation moderation progresses from −0.028 at raw level zero (p = .027) through −0.017 (p = .038) and −0.005 (p = .224) to +0.006 at level three. Pooling the two lowest cells therefore improves support for the gradient without creating it.

The equal-weight index also survives prevalence standardization. Standardizing each binary permission by its source-verified state adoption rate before summing yields a positive three-way coefficient of 0.005 (SE = 0.002, $p = .031$); using the adoption rates a reader might instead take from the published counts yields 0.005 (SE = 0.002, $p = .039$); and standardizing within each year rather than once for the panel yields 0.005 (SE = 0.002, $p = .031$). The standardized index carries the same conclusion on the untransformed outcome: in QIP points its three-way coefficient is 0.296 (SE = 0.154, $p = .058$), against 0.653 (SE = 0.365, $p = .077$) for the equal-weight index. The coefficient scale changes because the index units change, spanning about 6.3 rather than 3; the substantive conclusion does not. We retain the equal-weight construction because the construct is the breadth of statutory authority, in which each permission contributes one unit, whereas prevalence weighting would make regulatory rarity part of the construct.

Dropping a dimension rather than reweighting it gives a third view of the coding. Rebuilding the index from each pair of provisions in turn yields three-way coefficients of 0.005 (SE = 0.006, $p = .363$) for diagnosis with supervision freedom, 0.012 (SE = 0.007, $p = .089$) for diagnosis with delegation, and 0.015 (SE = 0.005, $p = .002$) for supervision freedom with delegation. The index does not depend on any one provision being present, and the ordering of the three two-dimensional versions is the ordering the provision-level analysis of Section 5.4 reports independently: the pair that carries the gradient is supervision freedom with delegation, and diagnosis authority is the dimension whose removal costs least.

The delegation provision and the delegatee it names. The third provision is coded from a statutory item that names licensed practical nurses as eligible delegatees, which raises the question whether the mechanism is delegation authority or the presence of that particular delegatee. The data separate the two. LPN staffing is positive in 68.2 percent of facility-years, and the composite gradient is the same on both sides of that divide: 0.011 ($p = .140$) where the facility employs no LPN and 0.011 ($p = .075$) where it employs at least one. Estimating the delegation provision's own three-way term the same way gives 0.015 in both subsamples ($p = .401$ and $p = .208$). Letting delegatee capacity enter continuously, the provision's three-way coefficient is 0.025 ($p = .016$) evaluated at no LPN capacity and declines with it (−0.016 per log LPN FTE, $p = .019$), so the permission does the most work where the RN's own time is most binding. What varies with the statute is therefore the authority to redeploy work, not the stock of a particular delegatee, which is what a deployment-authority account predicts and a headcount account does not.

Sensitivity to the coding of two states. Two states, Missouri and Pennsylvania, sit at the boundary of the continuous-supervision provision, and together they supply 1,790 of the 25,860 facility-years in the sample (628 and 1,162 respectively). We therefore re-estimate the full apparatus under two alternatives to the LawAtlas baseline coding: recoding both states from granted to not granted on R_b, and excluding both states entirely. Table 10 reports the result.

The result the paper rests on is unaffected. H1, the formal Model 3 staffing-by-deprivation coefficient, the H3 gradient, the low-to-high empowerment shift, the adoption-rate standardized index, and the joint provision block all remain significant in all three columns. Recoding the two states strengthens every one of them except the H1 staffing return, which is unchanged because Model 1 does not use the empowerment

Table 10: Robustness: Alternative Statutory Coding of Missouri and Pennsylvania

Quantity	Baseline	R_b recoded to 0	States excluded
H1: staffing return	0.157**	0.157**	0.186***
Model 3 lower-order, Emp = 0	-0.029**	-0.033***	-0.027*
Net moderation at Emp = 1	-0.017**	-0.018***	-0.014
H3: three-way gradient	0.011**	0.015***	0.012**
Δ(Emp 3 − Emp 1) shift	0.023**	0.029***	0.025**
Adoption-rate standardized index	0.005**	0.007***	0.006**
Joint provision block, $F(3)$	4.523***	15.897***	3.053**
N	25,860	25,860	24,070
Facilities	6,039	6,039	5,615
States	50	50	48
Chain clusters	88	88	83

Notes. All three columns use the main Model 3 specification, facility and year fixed effects, the same three excluded instruments and single-residual control function, and **clustered standard errors**, two-way by facility and chain. The LawAtlas baseline coding remains the main specification; the alternatives are sensitivity analyses. *$p < .10$; **$p < .05$; ***$p < .01$.

coding. The one quantity that does move is the net moderation evaluated at the lowest observed authority level, which is significant in the baseline ($p = .047$) and under recoding ($p = .009$) but not when both states are dropped ($p = .113$). Excluding two states removes 7% of the sample and 2 of 50 states from a quantity already evaluated at the edge of the authority distribution, so the composite gradient that H3 tests, rather than the endpoint evaluation, is the inference the paper carries.

The coding also matters for one provision-level contrast. Missouri and Pennsylvania supply roughly 29% of the observations in the $R_a + R_b$ configuration, so both alternatives move that cell from −0.024 ($p = .064$) to about −0.017 ($p = .451$). The contrast between the full bundle and that configuration therefore falls from 0.036 ($p = .015$) to 0.030 ($p = .183$). The contrast between the full bundle and the diagnosis-plus-delegation configuration is unaffected in both alternatives (0.024, $p \leq .001$ throughout), because neither the $R_a + R_c$ nor the full-bundle cell contains these states. Section 5.4 reports the provision-level evidence with this distinction in view.

Alternative outcome scale. Replacing the log outcome with the QIP score in points yields a positive three-way coefficient of 0.653 (SE = 0.365, $p = .077$), and the endpoint swing in the deprivation margin between analysis levels one and three is 0.530 QIP points ($p = .077$), matching the point-scale translation reported with the marginal effects in Section 5. The gradient is therefore not an artifact of the log transformation, and it is material on the scale on which the payment program itself scores facilities.

Alternative outcome measures. To assess whether the empowerment gradient generalizes beyond the QIP composite, we re-estimate Model 3 on an independent clinical indicator, the facility hypercalcemia rate (the share of patients with serum calcium above the clinical threshold), for the 17,331 facility-years with a positive rate. Because a lower rate indicates better mineral-metabolism management, the predicted signs reverse. The estimates reproduce the pattern. Under limited authority, deprivation significantly worsens the staffing relationship with calcium management (+0.054, $p = .007$); the adverse moderation shrinks at the middle level (+0.024, $p = .054$) and is gone at full authority (−0.005, $p = .851$), with the three-way coefficient carrying the predicted negative sign (−0.030, SE = 0.021, $p = .168$). The raw four-level shape

anchors the same conclusion at both ends: the adverse moderation is largest in the zero-permission cell (+0.125, $p = .029$), and Δ(All three − none) is negative and significant (−0.151, $p = .013$). An independent clinical dimension thus shows the same movement as the QIP composite: the deprivation penalty on staffing effectiveness is a limited-authority phenomenon.

Alternative staffing constructions. The staffing measure is RN capacity per one hundred patients with facility scale controlled separately, since an absolute headcount can be confounded with facility size. Table 11 re-estimates the staffing return on that measure and on two alternatives raised in review: the absolute RN count, and the RN share of the bedside nursing team, defined as registered nurses over the sum of registered nurses, licensed practical nurses, and patient care technicians. Those three roles are the ones among which nursing work moves; the physician FTE is not in that pool, which is the premise of the setting, and it remains a control.

The return is positive and significant on all three constructions. It is worth being explicit about why the first two rows are close rather than independent. Because log patient census is already in the equation, the coefficient on the absolute count and the coefficient on the ratio are the same parameter, and the size confound the review identified is handled by conditioning on census rather than by choosing between the two measures; the rows differ only through whether the winsorization is applied to the count or to the ratio. The bedside-share row is an independent construction, and it carries ln(*bedside total*) as well, since ln(*RN share*) = ln(*RN*) − ln(*bedside total*) and without that term the coefficient would mix an increase in registered nurses with a reduction in everyone else. Its excluded instruments are appreciably weaker than in the other two rows, which the table reports.

Table 11: Robustness: The Staffing Return under Alternative RN Staffing Constructions

RN input	Staffing return	Clustered SE	First-stage $F(3)$	N
RN FTE per 100 patients (focal)	0.157^{**}	(0.067)	67.1	25,860
Absolute RN FTE count	0.176^{**}	(0.072)	59.7	25,860
RN share of bedside nursing team	0.786^{*}	(0.458)	6.3	25,829

Notes. The staffing return is the Model 1 coefficient, the designated test of H1. Every row uses the same three excluded instruments, the same expanded control set, facility and year fixed effects, and **clustered standard errors**, two-way by facility and chain. Log patient census is in every equation, which is why the first two rows estimate the same parameter and differ only in the winsorization basis. The bedside denominator is *RN + LPN + technicians*, and that row additionally controls ln(*bedside total*); the physician FTE is a control in every column, not a denominator component. That row uses $N = 25{,}829$ because 31 observations lack a positive registered-nurse count or a positive bedside denominator. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

6.2 Estimation and Instrument Robustness

Alternative estimation methods. Table 12 addresses four questions: whether the gradient depends on the control-function correction, whether it is identified by the within-facility comparison the design targets, whether the three-instrument set is supported by the level-model diagnostics and by IV estimators with different finite-sample behavior, and whether the inference depends on the clustering scheme.

The fixed-effects estimates answer the first question. The FE-OLS coefficient (0.012, $p = .037$)

Table 12: Robustness: Alternative Estimation Methods

Check	Estimate	Clustered SE/statistic	p
Panel A: Three-way coefficient by estimator			
FE + CF (main)	0.011^{**}	(0.005)	.035
FE-OLS (no CF correction)	0.012^{**}	(0.005)	.037
Random effects[a]	0.002	(0.002)	.256
Pooled OLS	0.002	(0.002)	.332
Panel B: Model 1 instrument diagnostics and IV estimators			
Diagnostic FE-2SLS, ln(RN)	0.157^{***}	(0.054)	.004
FE-LIML, ln(RN)	0.160^{***}	(0.055)	.004
FE two-step GMM, ln(RN)	0.157^{***}	(0.053)	.004
Kleibergen–Paap rk Wald F	22.174		
Kleibergen–Paap rk LM, $\chi^2(3)$	62.140		$< .001$
Hansen J, $\chi^2(2)$	2.676		.262
Panel C: Three-way coefficient by clustering scheme			
Facility only	0.011^{**}	(0.005)	.036
State only	0.011^{**}	(0.006)	.043
Chain only	0.011^{*}	(0.006)	.058
Facility × chain (main)	0.011^{**}	(0.005)	.035
Facility × state	0.011^{**}	(0.006)	.043

Notes. Panels A and C use the Model 3 variables and the 25,860-observation analysis sample. [a] Panel A rows carry the two-way facility-by-chain estimator except random effects, which admits one cluster variable and is clustered by facility; chain is unavailable to it because chain affiliation is time-varying, so facilities are not nested within chains, the same feature that motivates two-way clustering elsewhere. Panel B is the no-interaction level model; the IV routines drop 361 singleton observations, so they use N = 25,499 and 5,678 facilities under that routine's facility-cluster convention. In Panel C the point estimate is invariant by construction and only the variance estimator changes; the year dimension is not used as a cluster because it has five levels. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

is close to the main CF estimate, so the gradient is present in the raw within-facility variation and is not produced by the correction. Random-effects and pooled estimates are near zero, confirming the importance of the panel design: between-facility comparisons mix the staffing–quality relationship with persistent facility differences that the fixed effects are there to remove.

Panel B answers the third question on the level model. Limited-information maximum likelihood and two-step GMM, which respond differently to weak instruments and to heteroskedasticity than 2SLS does, return 0.160 and 0.157 against the 2SLS estimate of 0.157, and the Hansen test does not reject under any of them. Panel C answers the fourth. Because the point estimate does not depend on the variance estimator, the question is only whether the inference does: clustering on facility alone, on state alone, on chain alone, on facility and chain, or on facility and state leaves the three-way coefficient significant in every case, with p between .035 and .058. The scheme of record, facility by chain, is neither the most nor the least favorable of the five.

The correction itself operates through the staffing level alone: allowing the first-stage residual to enter through the deprivation and empowerment interactions as well leaves the added terms jointly insignificant ($F(3) = 0.48$, $p = .70$). This is the configuration in which interaction coefficients are estimated consistently even where the level coefficient requires correction (Bun and Harrison, 2019), and its mirror case, a corrected staffing term interacted with a moderator that might itself respond to facility quality, is covered by Nizalova and Murtazashvili (2016), whose condition is that the moderator not drive the treatment in reverse. The county-level index gives that condition institutional footing, and a direct check supports it: assigning the

deprivation index its own first stage, with the leave-out-county state-year deprivation mean as the excluded instrument (first-stage $F = 881$), and entering the second residual alongside the first leaves the three-way coefficient at 0.011 ($p = .037$, $N = 25{,}855$), with the deprivation residual itself not significant ($p = .143$).

The level-model diagnostics answer the third question. The diagnostic 2SLS estimate coincides with the CF estimate to three decimal places, the Kleibergen–Paap Wald statistic indicates relevance, the underidentification test rejects decisively, and the Hansen test does not reject the three-instrument set ($p = .262$). The instrument set the paper maintains is therefore both relevant and unrejected by the overidentification test.

Alternative wage-instrument construction. The maintained leave-one-out instruments pool over the facility's CMS ESRD Network, the administrative region through which CMS organizes dialysis care. The Network is defined for every facility by the same federal source that defines the facility universe, it applies one uniform rule to every observation, and its pool guarantees a second labor market and an out-of-county peer group everywhere, so the instruments are defined on the full construction sample.

A state-pool variant of the same leave-one-out logic uses only the markets in the facility's own state and year. The two pools sit at the same administrative tier, the Network being the CMS grouping of contiguous states and the state pool its single-state restriction, so the two constructions embody the same exclusion logic and differ only in the membership of the averaging pool. The state pool's one structural feature is that a state containing a single labor market has no other member to average over, so the wage instrument is undefined there: this removes 742 facility-years across Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, and South Dakota, including two of the three zero-permission states that anchor the raw empowerment distribution.

Re-estimating the model on the state-pool construction and the 25,118-observation subframe on which it is defined reproduces every estimate the paper reports: the three-way coefficient is 0.011 (SE = 0.005, $p = .042$), against 0.012 (SE = 0.005, $p = .035$) in the maintained specification; the net deprivation moderation at the lowest observed authority level is −0.016 (SE = 0.009, $p = .064$), against −0.017 (SE = 0.009, $p = .047$); the excluded instruments remain jointly relevant, $F(3) = 76.926$; the Kleibergen–Paap statistic is 24.019; and the Hansen test does not reject ($p = .862$). The pool choice therefore determines which facilities the sample retains, not what the model estimates on the facilities the two constructions share.

Unobservable selection and coefficient stability. To quantify how much selection on unobservables would be required to overturn the three-way coefficient, we compute the Oster (2019) bounds, holding the constituent interaction terms and the year effects in both the uncontrolled and controlled models so that the exercise isolates the control set (facility fixed effects, the facility controls, and the first-stage residual). Moving from the uncontrolled to the fully controlled model moves the coefficient away from zero (from 0.010 to 0.011) while R^2 rises from 0.11 to 0.61; the bias-adjusted coefficient at equal selection ($\delta = 1$, $R_{\max} = 1.3\tilde{R}$) is 0.015, same-signed and larger than the estimate; and the selection on unobservables required to drive the coefficient to zero is $\delta = 2.29$ under Oster's recommended $R_{\max}$ convention (1.05 under the most demanding $R_{\max} = 1$). Because adding the observed controls moves the estimate away from zero, proportional selection

on unobservables would, if anything, raise it.

6.3 Temporal Stability

SDI temporal stability. Our identification strategy treats the county-level SDI as a quasi-stable contextual moderator. On the estimation sample, the adjacent-year autocorrelation of the SDI at the facility level is $r = 0.993$, reflecting the structural nature of the index's components, poverty rates, educational attainment, and housing characteristics, which are unresponsive to any individual facility's decisions. This stability supports interpreting the interaction terms as genuine cross-level moderation by a persistent community condition rather than co-movement with facility-level shocks.

Year fixed-effect patterns. The year fixed effects place QIP scores below the 2015 baseline in every subsequent year: -0.121 in 2016, -0.053 in 2017, -0.135 in 2018, and -0.190 in 2019, all $p < .001$. The path is not monotone, and the level shift is consistent with recalibration of the QIP scoring environment over the period rather than with a trend. Because the year fixed effects absorb these aggregate shifts, the estimated coefficients on staffing, SDI, empowerment, and their interactions are identified from within-year, within-facility variation and are not contaminated by the secular scoring trend.

7 Discussion

This study asks whether regulatory authority changes the operational value of scarce nursing capacity in dialysis facilities serving socially deprived communities. Three findings answer that question. First, increasing RN staffing relative to patient census is associated with better clinical performance in the designated no-interaction model. Second, under limited practice authority, deprivation significantly erodes that positive staffing return. Third, the erosion narrows as empowerment rises and is gone at the highest level, with a significant low-versus-high contrast; in the configuration granting all three permissions the moderation turns positive. Across the observed deprivation distribution, every evaluated staffing return remains positive, and the regulatory profiles exchange rank near the median. Empowerment therefore changes the distribution of a beneficial staffing return rather than converting staffing from harmful to beneficial.

The supporting analyses reinforce this reading. The empowerment gradient survives the raw four-level coding, including a separately estimated most-constrained group, a QIP-points outcome, fixed-effects estimation without the control-function correction, each of five clustering schemes, and both alternative codings of the two states whose continuous-supervision status is contestable; on an independent clinical outcome it reproduces in sign, with the endpoint contrast significant and the composite gradient not. The provision-level analysis is consistent with permissions that work together rather than separately. Delegation and freedom from continuous supervision, the two permissions that determine whether routine treatments actually move from the RN to the LPN during a treatment day, each carry a significant increment only in the presence of the other. Diagnosis authority adds little in either pairing. The one pairing that leaves the nurse unable to delegate, diagnosis with supervision freedom, produces no significant joint increment and carries the deepest remaining penalty among the partial configurations. In Ashby's terms, a statute enlarges

a facility's usable responses when the nurse can decide what a patient needs, move the routine work to the LPN, and let that work proceed without standing over it. These are parallel grants in law, and the evidence describes how their associations vary with one another rather than a sequence in which they must be acquired or a ranking among them. The operative quantity throughout is patient-standardized RN capacity deployed within facilities, and the dimension results refine the proposed mechanism without replacing the composite H3 test, which remains the governing inference.

7.1 Theoretical Contributions

An empirical study contributes to operations theory by testing the claims an established theory makes or by deriving insights that inform the theory itself (Bendoly and Oliva, 2025). The findings here do both. The hypothesis tests confirm predictions built from RDT, and the pattern of results adds three claims the theory did not previously carry.

7.1.1 From Resource Availability to Resource Deployability

The inter-organizational strategies catalogued by Hillman et al. (2009) are difficult to deploy against a community-level constraint. A dialysis facility cannot merge away local poverty, change its patient population without abandoning its service mission, or rapidly create the transportation, nutrition, and caregiver resources its patients lack. What our study shows is that the value of the critical resource such a facility does hold is not fixed either. It depends on the decision rights the state grants for deploying that resource. By setting the domain in which frontline clinicians may exercise professional judgment, regulation changes how a fixed pool of expertise can respond to environmental demands without changing the source of those demands (Dobrzykowski, 2019). Both sides of that mechanism are external to the facility: the community creates the dependence, and the statute delimits the response. RDT is therefore the theory that explains the finding, and the finding extends what RDT says about a critical resource from its availability to its deployability.

This result extends research on discretion and operational performance. Managerial discretion conditions leadership effects at the top of the organization (Crossland and Hambrick, 2011), while bottom-up autonomy can improve healthcare quality closer to the work itself (Senot et al., 2016). We locate the relevant discretion at the resource–environment interface: the RN who repeatedly encounters patients whose clinical routines are disrupted by transportation, nutrition, housing, or caregiving constraints. Regulatory authority matters because it determines which responses that worker may initiate without waiting for another organizational layer.

7.1.2 Constraint Impact Absorption: From Buffering to Transformation

The second contribution refines the idea of constraint absorption. A simple buffering account would predict that empowerment weakens deprivation's adverse effect. The observed pattern is that the deprivation moderation moves from significantly negative at low authority to a value at high authority that is no longer distinguishable from zero, and the high-versus-low contrast is statistically distinguishable. What the evidence

supports is this *change in the gradient*, a reordering of where resource value is produced, not a claim that deprivation itself becomes beneficial.

This distinction matters theoretically. The data show that a regulatory capability can prevent an environmental constraint from progressively destroying the return to an operating resource. They do not show that deprivation itself creates value, nor that the most deprived facilities receive a uniformly larger return. Indeed, every staffing-return estimate is positive. What changes is their ordering: limited-authority facilities begin with the highest return at the low-deprivation margin and lose ground as deprivation rises, while high-authority facilities begin lower and preserve more of their return. Transformation is therefore a redistribution of where nursing capacity is most productive.

This formulation extends the buffering–bridging logic of resource dependence theory (Casciaro and Piskorski, 2005). When an external dependency cannot be eliminated, internal authority can alter its operational incidence. The organization still faces deprivation, but the effect of that deprivation on resource productivity is no longer fixed. The result therefore concerns what external control does to the value of a resource an organization already holds, a question RDT poses and has answered mainly for the acquisition of resources rather than for their deployment.

7.1.3 Resource Value Contingency Through Requisite Variety

Ashby's law of requisite variety provides the mechanism for the gradient: a response repertoire must match the variety of disturbances it confronts. High-deprivation communities expose facilities to more heterogeneous barriers to treatment adherence. RN authority expands the set of clinically informed responses available at the point of care, allowing the facility to preserve the contribution of its nursing capacity as those barriers accumulate (Ashby, 1956; Staats and Gino, 2012).

The staffing-measure boundary makes this contribution more specific. Empowerment does not moderate the return to absolute RN headcount in the same way, and it does not moderate an RN occupational share. It moderates RN capacity relative to patient load, after patient census is entered separately. In other words, the theoretically relevant resource is not a stock of labor detached from demand; it is service capacity per unit of operational need. This result connects worker discretion to a core OM concern, the matching of capacity to demand, and clarifies why regulatory authority and staffing ratios must be analyzed jointly.

The point also qualifies a broad resource-based interpretation. Resource value is neither fully inherent in a resource nor determined by the environment alone. It is jointly configured by quantity relative to demand, the environmental variety confronting that quantity, and the rules governing deployment. Similar relationships may arise wherever skilled frontline workers serve heterogeneous demand under externally imposed limits on discretion.

7.2 What the Evidence Does and Does Not Establish

The Triple Aim (care quality, population health, and cost stewardship) (Berwick et al., 2008) motivates the application, but the evidence speaks to its components with different force, and we do not present this study as a joint test of the three aims. The design estimates one outcome equation; the other two aims enter as context and as implication. Quality is observed directly. Equity appears as the deprivation gradient in the

return to staffing. Cost is not observed as an outcome and therefore enters only as an operational implication of preserving value from an existing staffing ratio.

The relation to that literature is a division of labor rather than a substitution. Work that places the Triple Aim at the center has looked for an action that moves the three aims together. Roth et al. (2019) identify the hospitals that sit on the productivity frontier, Bonnett and Heim (2024) ask whether a change in clinical provider mix improves Triple Aim performance efficiency, and the Quadruple Aim adds clinician well-being to the ends such an action must serve (Bodenheimer and Sinsky, 2014). Those recommendations differ in content but agree in form: the lever is the resource, and the recommendation concerns which resources to hold and in what proportion. Our question comes before that one. A resource can be used well only where someone is permitted to use it, and permission is not a property of the resource. Locating the contribution on that side of the problem is what makes the finding portable. It says nothing about which staffing mix a facility should buy, and it says that whichever mix a facility holds will return more or less of its value depending on the decision rights under which it is deployed, with the difference concentrated in the communities whose operating conditions vary most.

Care quality. The no-interaction model shows a positive return to RN staffing per patient, consistent with the healthcare staffing literature (Kuntz et al., 2015; KC and Terwiesch, 2009; Peng et al., 2023). The moderated model then identifies a regulatory condition under which that return is more or less exposed to community deprivation.

Population health equity. Facilities serving high-deprivation communities begin from a more difficult operating environment. Under limited authority, the return to an incremental staffing ratio erodes as deprivation rises. Expanded authority significantly narrows that gradient. This does not by itself demonstrate population-health improvement, but it identifies an operational channel through which a common quality investment can become less unequal across communities, answering calls to incorporate equity into OM analysis (Corbett and Narayanan, 2025).

Cost stewardship. The analysis does not estimate savings, implementation costs, or a policy treatment effect. It shows that the same change in patient-standardized nursing capacity has different predicted quality returns under different regulatory regimes. On the QIP-points scale, the high-versus-low authority difference in the deprivation margin is about half a point for simultaneous one-standard-deviation changes in staffing and deprivation. Managers should read this as a capacity-productivity comparison, not as an accounting estimate.

7.3 Practical Implications

For facility managers. Staffing plans should distinguish headcount from capacity relative to patient load. What this study estimates is the return to registered-nurse capacity per unit of patient demand, and that is the quantity a manager can act on. A manager confronting rising community complexity should therefore monitor whether patient-standardized RN capacity is being preserved and whether facility procedures allow nurses to exercise the authority already available under state law. Adding staff without attending to demand and deployment rules is not the intervention tested here.

What authority is worth can be put in the operator's own units. In the most deprived communities

the staffing returns reported in Section 5.3 imply that a facility under the restrictive regime must raise RN capacity by about seven percent more than one with the full bundle of permissions to obtain the same proportional quality gain. On the sample averages, roughly five RN full-time equivalents for about ninety patients at a mean BLS wage near $35 an hour, the RN payroll is about $351,000 a year, so that gap is roughly $25,000 a year per facility, about a third of one nurse. It widens to about $30,000 in the very most deprived counties. Across the 1,217 facilities in our sample that both serve above-median-deprivation communities and sit in the most restrictive authority regime, the same gap comes to roughly $31 million a year. These are translations of estimated returns into payroll units at sample means rather than measured savings, and what they price is the authority environment, not the staffing decision: the same capacity addition buys more where the law permits more.

For state policymakers. Scope-of-practice rules shape the operating conditions under which nursing capacity produces quality. The room for reform is wide: on the verified coding reported in Appendix A, 36 of the 50 states withhold at least one of the three permissions, and 14 grant all three. The evidence supports evaluating reforms as part of a capacity system: authority, staffing relative to patient demand, and the complexity of the served community. The exploratory provision results direct attention to the breadth of authority rather than to any single reform. The deprivation penalty narrows as authority broadens, and in the configuration in which all three permissions are granted it reverses, with the net moderation turning positive and significant. The provision estimates are conditional associations rather than a causal ranking of individual reforms; the policy-relevant conclusion is that the breadth of authority conditions how deprivation bears on the staffing return, not that any one permission should be reformed first. The payment stakes concentrate where authority is most binding: facilities in the bottom tenth of their year's QIP distribution are drawn disproportionately from above-median-deprivation communities, as Section 5 reports. Broadening statutory authority is the one lever in this capacity system that carries no direct fiscal cost to facilities.

For federal regulators. Quality programs compare facilities that operate under different state rules and community constraints, and the QIP attaches payment to the comparison, reducing Medicare payments by up to two percent for facilities scoring below the yearly performance standard (Centers for Medicare & Medicaid Services, 2024). Our findings suggest that identical changes in RN-to-patient capacity need not yield identical quality returns across those environments. Regulators can use that insight to interpret performance heterogeneity and to encourage states and providers to examine regulatory barriers alongside staffing shortages. The estimates do not justify mechanically adjusting QIP scores for scope-of-practice law; such a policy would require a separate analysis of incentives and incidence.

7.4 Boundary Conditions of the Mechanism

The mechanism we identify operates through the release of clinical authority, and the same release carries risks that bound where the policy implication holds. First, case complexity. Requisite variety presumes that the regulator's repertoire is adequate to the disturbances it meets. For clinical presentations outside what registered nurses are trained and licensed to manage, the argument predicts no benefit from reduced

oversight, and physician involvement remains the appropriate regulator of care (Berns, 2015). Our setting limits this exposure, because the permissions studied here move protocol-driven maintenance work rather than complex medical management, but the boundary belongs to the theory itself. Second, the burden on the nurse. Authority to act is also responsibility to decide, carried by the clinician who is already continuously present, and the nursing literature associates expanded responsibility without commensurate support with exhaustion and moral distress (Wang et al., 2023; Lamiani et al., 2017). This is the risk that motivated the addition of clinician well-being as a fourth aim (Bodenheimer and Sinsky, 2014), and it is the cost against which any gain we report has to be set. A scope-of-practice provision does not by itself supply the staffing, training, or decision support that make expanded authority sustainable; our focal interaction pairs authority with staffing capacity for precisely this reason. Third, what the outcome can register. The QIP composite would not detect an increase in errors concentrated in rare complex cases, or a deterioration in nurse well-being, on the time scale we observe. Adverse-event and workforce outcomes are therefore the most consequential direction for follow-on work.

7.5 Conclusion

Several structural limitations frame the interpretation. First, the result concerns the theoretically motivated staffing measure, RN capacity per patient with facility scale controlled separately. Future work should examine which demand denominators best capture workload in other service settings and whether task-level demand measures sharpen the capacity mechanism.

Second, the evidence comes from within-facility variation in a five-year observational panel. Longer panels and observed regulatory changes would help separate persistent facility trajectories from changes in scope-of-practice regimes.

Third, the empowerment variable captures legal authority rather than actual use of that authority inside a facility. Policies, supervision norms, training, and psychological safety may determine whether nurses exercise the discretion a statute permits. Combining the statutory measure with facility surveys or workflow data would test the mechanism directly and identify the organizational complements required for legal authority to become operational discretion.

Finally, dialysis is a longitudinal, protocolized setting in which nurses repeatedly observe the same patients. The requisite-variety mechanism may be strongest where clinicians accumulate tacit knowledge and can adapt care over time. Research in oncology infusion, long-term care, and home health could test whether the same authority-by-capacity relationship appears in other settings with repeated service and heterogeneous social needs (KC et al., 2020; Keskinocak and Savva, 2020; Lu and Lu, 2017b).

Within those boundaries, the conclusion stands. Clinician empowerment changes how community deprivation bears on the quality value of RN capacity. The positive return to RN staffing per patient erodes under limited authority but is progressively preserved as authority expands. Statutory practice authority determines how much of a critical resource's value survives external dependence, and it does so only when paired with capacity measured relative to operating demand. For healthcare operations, resources, demand, and authority are not separable levers; their configuration determines whether scarce clinical expertise retains its value where community constraints are greatest.

References

Leoni S. Aiken and Stephen G. West. *Multiple Regression: Testing and Interpreting Interactions*. Sage Publications, Newbury Park, CA, 1991.

Linda H. Aiken, Sean P. Clarke, Douglas M. Sloane, Julie Sochalski, and Jeffrey H. Silber. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *JAMA*, 288(16):1987–1993, 2002.

W. Ross Ashby. *An Introduction to Cybernetics*. Chapman & Hall, London, 1956.

Jay Barney. Firm resources and sustained competitive advantage. *Journal of Management*, 17(1):99–120, 1991.

Christopher F. Baum and Arthur Lewbel. Advice on using heteroskedasticity-based identification. *Stata Journal*, 19(4):757–767, 2019.

Christopher F. Baum, Mark E. Schaffer, and Steven Stillman. Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *Stata Journal*, 7(4):465–506, 2007.

Paul A. Bekker. Alternative approximations to the distributions of instrumental variable estimators. *Econometrica*, 62(3):657–681, 1994.

Elliot Bendoly and Rogelio Oliva. Meaningful theoretical pathways for research contributions. *Journal of Operations Management*, 71(1):4–10, 2025.

W. C. Benton and Chin-Yao Lin. Nurse staffing as a critical resource: A review and analysis. *Production and Operations Management*, 20(6):892–909, 2011.

Lisa F. Berkman, Ichiro Kawachi, and M. Maria Glymour. Social epidemiology. *Oxford University Press*, 2011.

Jeffrey S. Berns. The evolving role of the medical director of a dialysis facility. *Clinical Journal of the American Society of Nephrology*, 10(2):326–330, 2015.

Donald M. Berwick, Thomas W. Nolan, and John Whittington. The triple aim: Care, health, and cost. *Health Affairs*, 27(3):759–769, 2008.

Thomas Bodenheimer and Christine Sinsky. From triple to quadruple aim: Care of the patient requires care of the provider. *The Annals of Family Medicine*, 12(6):573–576, 2014.

John P. Bonnett and Gregory R. Heim. Do mid-level providers enhance hospital cost per discharge or triple aim performance efficiency? *Journal of Operations Management*, 70(5):793–830, 2024.

Thomas Brambor, William Roberts Clark, and Matt Golder. Understanding interaction models: Improving empirical analyses. *Political Analysis*, 14(1):63–82, 2006.

Paula Braveman and Laura Gottlieb. The social determinants of health: It's time to consider the causes of the causes. *Public Health Reports*, 129(Suppl 2):19–31, 2014.

Maurice J. G. Bun and Teresa D. Harrison. OLS and IV estimation of regression models including endogenous interaction terms. *Econometric Reviews*, 38(7):814–827, 2019.

John R. Busenbark, Scott D. Graffin, R. Jeff Campbell, and Eun-Hee Lee. A marginal effects approach to interpreting main effects and moderation. *Organizational Research Methods*, 25(1):147–169, 2022.

Declan C. Butler, Stephen Petterson, Robert L. Phillips, and Andrew W. Bazemore. Measures of social deprivation that predict health care access and need within a rational area of primary care service delivery. *Health Services Research*, 48(2pt1):539–559, 2013.

A. Colin Cameron and Douglas L. Miller. A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50(2):317–372, 2015.

Tiziana Casciaro and Miko laj Jan Piskorski. Power imbalance, mutual dependence, and constraint absorption: A closer look at resource dependence theory. *Administrative Science Quarterly*, 50(2):167–199, 2005.

Gary J. Castrogiovanni. Environmental munificence: A theoretical assessment. *Academy of Management Review*, 16(3):542–565, 1991.

Arran Caza. Typology of the eight domains of discretion in organizations. *Journal of Management Studies*, 49(1):144–177, 2012.

Center for Public Health Law Research. Registered nurse scope of practice. LawAtlas Policy Surveillance Program, Temple University Beasley School of Law, 2017. Cross-sectional legal dataset; state laws in effect as of August 1, 2015. Available at https://lawatlas.org/datasets/registered-nurse-scope-of-practice-1509027306.

Centers for Medicare & Medicaid Services. Conditions for coverage for End-Stage Renal Disease facilities, 42 C.F.R. § 494.140. Code of Federal Regulations, 2008. Available at https://www.ecfr.gov/current/title-42/chapter-IV/subchapter-G/part-494.

Centers for Medicare & Medicaid Services. End-stage renal disease quality incentive program, 2024. URL https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/ESRDQIP. Accessed: December 2024.

Aravind Chandrasekaran, Claire Senot, and Kenneth K. Boyer. Process management impact on clinical and experiential quality: Managing tensions between safe and patient-centered healthcare. *Manufacturing & Service Operations Management*, 14(4):548–566, 2012.

Aichia Chuang, Catherine K. Lam, Chi-Sum Wong, and Junqi Zhu. Three-way interactions in management research. *Asia Pacific Journal of Management*, 36:1–25, 2019.

Charles J. Corbett and Sriram Narayanan. Diversity, equity and inclusion and operations management: Critical linkages and research opportunities. *Production and Operations Management*, 34(3):310–330, 2025.

Craig Crossland and Donald C. Hambrick. Differences in managerial discretion across countries: How nation-level institutions affect the degree to which CEOs matter. *Strategic Management Journal*, 32(8): 797–819, 2011.

Gerald F. Davis and J. Adam Cobb. Resource dependence theory: Past and future. *Research in the Sociology of Organizations*, 28:21–42, 2010.

Jeremy F. Dawson. Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, 29(1):1–19, 2014.

Melissa De Regge, Kaat De Pourcq, Céline Van de Voorde, Koen Van den Heede, Paul Gemmel, and Kristof Eeckloo. The introduction of hospital process orientation in dialysis centers: A multiple case study. *BMC Health Services Research*, 19(1):1–12, 2019.

Gregory G. Dess and Donald W. Beard. Dimensions of organizational task environments. *Administrative Science Quarterly*, 29(1):52–73, 1984.

David D. Dobrzykowski. Understanding the downstream healthcare supply chain: Unpacking regulatory and industry characteristics. *Journal of Supply Chain Management*, 55(2):26–46, 2019.

David D. Dobrzykowski and Kathleen L. McFadden. Examining governance in hospital operations: The effects of trust and physician employment in achieving efficiency and patient satisfaction. *Decision Sciences*, 51(1):74–109, 2020.

David D. Dobrzykowski and Monideepa Tarafdar. Understanding information exchange in healthcare operations: Evidence from hospitals and patients. *Journal of Operations Management*, 36:201–214, 2015.

Kevin F. Erickson, Kai Bun Tan, Wolfgang C. Winkelmayer, Glenn M. Chertow, and Jay Bhattacharya. Variation in nephrologist visits to patients on hemodialysis across dialysis facilities and geographic locations. *Clinical Journal of the American Society of Nephrology*, 8(6):987–994, 2013.

Akbar Ghiasi, Rohit Pradhan, Gregory Orewa, and Robert Weech-Maldonado. Higher nursing staff wages are associated with lower operating margins in nursing homes: An instrumental variable analysis. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 63, 2026.

Deepa Goradia, Sriram Narayanan, and Shawnee Vickery. The effects of state government policy on operations performance in the hospital industry. *Production and Operations Management*, 2025. Advance online publication.

Donald C. Hambrick and Sydney Finkelstein. Managerial discretion: A bridge between polar views of organizational outcomes. *Research in Organizational Behavior*, 9:369–406, 1987.

Amy J. Hillman, Michael C. Withers, and Brian J. Collins. Resource dependence theory: A review. *Journal of Management*, 35(6):1404–1427, 2009.

Kirsten L. Johansen, Glenn M. Chertow, David T. Gilbertson, Areef Ishani, Ajay Israni, Elaine Ku, Shuling Li, Suying Li, Jiannong Liu, Gregorio T. Obrador, Ivonne Schulman, Kevin Chan, Kevin C. Abbott, Ann M. O'Hare, Neil R. Powe, Nicholas S. Roetker, Jennifer S. Scherer, Wendy St. Peter, Jon Snyder, Wolfgang C. Winkelmayer, Susan P.Y. Wong, and James B. Wetmore. Us renal data system 2022 annual data report: Epidemiology of kidney disease in the united states. *American Journal of Kidney Diseases*, 81(3):A8–A11, March 2023. ISSN 0272-6386. doi: 10.1053/j.ajkd.2022.12.001. URL http://dx.doi.org/10.1053/j.ajkd.2022.12.001.

Palmer O. Johnson and Jerzy Neyman. Tests of certain linear hypotheses and their application to some educational problems. *Statistical Research Memoirs*, 1:57–93, 1936.

Robert L. Kahn, Donald M. Wolfe, Robert P. Quinn, J. Diedrick Snoek, and Robert A. Rosenthal. *Organizational Stress: Studies in Role Conflict and Ambiguity*. Wiley, New York, 1964.

Rosabeth Moss Kanter. *Men and Women of the Corporation*. Basic Books, New York, 1977.

Diwas Singh KC and Christian Terwiesch. Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science*, 55(9):1486–1498, 2009.

Diwas Singh KC, Stefan Scholtes, and Christian Terwiesch. Empirical research in healthcare operations: Past research, present understanding, and future opportunities. *Manufacturing & Service Operations Management*, 22(1):73–83, 2020.

Steven Kerr and John M. Jermier. Substitutes for leadership: Their meaning and measurement. *Organizational Behavior and Human Performance*, 22(3):375–403, 1978.

Pinar Keskinocak and Nicos Savva. A review of the healthcare-management (modeling) literature published in manufacturing & service operations management. *Manufacturing & Service Operations Management*, 22(1):59–72, 2020.

Paul L. Kimmel, Chyng-Wen Fwu, Kevin C. Abbott, Jerry Ratner, and Paul W. Eggers. Racial disparities in poverty account for mortality differences in US medicare beneficiaries. *SSM–Population Health*, 13: 100745, 2021.

R. Tamara Konetzka, Sally C. Stearns, and Jeongyoung Park. The staffing–outcomes relationship in nursing homes. *Health Services Research*, 43(3):1025–1042, 2008.

Ludwig Kuntz, Roman Mennicken, and Stefan Scholtes. Stress on the ward: Evidence of safety tipping points in hospitals. *Management Science*, 61(4):754–771, 2015.

Giulia Lamiani, Lidia Borghi, and Piergiorgio Argentero. When healthcare professionals cannot do the right thing: A systematic review of moral distress and its correlates. *Journal of Health Psychology*, 22(1): 51–67, 2017.

Heather K. Spence Laschinger, Joan Finegan, Judith Shamian, and Piotr Wilk. Impact of structural and psychological empowerment on job strain in nursing work settings: Expanding Kanter's model. *Journal of Nursing Administration*, 31(5):260–272, 2001.

Uta Lehmann, Marjolein Dieleman, and Tim Martineau. Staffing remote rural areas in middle- and low-income countries: A literature review of attraction and retention. *BMC Health Services Research*, 8(1): 19, 2008.

Arthur Lewbel. Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80, 2012.

Ling X. Li and W. C. Benton. Hospital technology and nurse staffing management decisions. *Journal of Operations Management*, 24(5):676–691, 2006.

Susan F. Lu and Lauren Xiaoyuan Lu. Do mandatory overtime laws improve quality? staffing decisions and operational flexibility of nursing homes. *Management Science*, 63(11):3566–3585, 2017a. Published online 2016, print 2017; cited as Lu2018 in methods section.

Susan F. Lu and Lauren Xiaoyuan Lu. Do mandatory overtime laws improve quality? staffing decisions and operational flexibility of nursing homes. *Management Science*, 63(11):3566–3585, 2017b.

Jack Needleman, Peter Buerhaus, Soeren Mattke, Maureen Stewart, and Katya Zelevinsky. Nurse-staffing levels and the quality of care in hospitals. *New England Journal of Medicine*, 346(22):1715–1722, 2002.

Olena Y. Nizalova and Irina Murtazashvili. Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5(1):71–77, 2016.

Emily Oster. Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204, 2019.

Raktim Pal, Anand Nair, and Minhao Zuo. Collaborative dynamics in open source software development: Unveiling the influence of team interaction and the role of project manager. *Journal of Operations Management*, 70(8):1398–1423, 2024.

David Xiaosong Peng, Huaxia Ye, Xin Ding, and Aravind Chandrasekaran. The impact of nurse staffing on turnover and quality: An empirical examination of nursing care within hospital units. *Journal of Operations Management*, 69(7):1124–1152, 2023.

Jeffrey Pfeffer and Gerald R. Salancik. *The External Control of Organizations: A Resource Dependence Perspective*. Harper & Row, New York, 1978.

Lusine Poghosyan, Allison A. Norful, and Miriam Laugesen. State-level scope of practice regulations impact nurse practitioner work environments. *Research in Nursing & Health*, 45(5):569–581, 2022.

Rohit Pradhan, Akbar Ghiasi, and Robert Weech-Maldonado. The impact of nursing staff wages on nursing home quality: An instrumental variable approach. *Journal of the American Medical Directors Association*, 26(8):105705, 2025.

John R. Rizzo, Robert J. House, and Sidney I. Lirtzman. Role conflict and ambiguity in complex organizations. *Administrative Science Quarterly*, 15(2):150–163, 1970.

Robert A. Rodriguez, Saunak Sen, Kalyan Mehta, Sharon Moody-Ayers, Peter Bacchetti, and Ann M. O'Hare. Geography matters: Relationships among urban residential segregation, dialysis facility characteristics, and patient outcomes. *Annals of Internal Medicine*, 171(4):242–250, 2019.

Aleda V. Roth, Anita L. Tucker, Sriram Venkataraman, and Jon A. Chilingerian. Being on the productivity frontier: Identifying "triple aim performance" hospitals. *Production and Operations Management*, 28(9): 2165–2183, 2019.

Brigitte Schiller. The medical director and quality requirements in the dialysis facility. *Clinical Journal of the American Society of Nephrology*, 10(3):493–499, 2015.

Claire Senot, Aravind Chandrasekaran, and Peter T. Ward. Role of bottom-up decision processes in improving the quality of health care delivery: A contingency perspective. *Production and Operations Management*, 25(3):458–476, 2016.

Gurwinder K. Singh. Area deprivation and widening inequalities in US mortality, 1969–1998. *American Journal of Public Health*, 93(7):1137–1143, 2003.

Yelena Slinin, Haifeng Guo, Shuling Li, Jiannong Liu, Kristine Ensrud, David T. Gilbertson, Allan J. Collins, and Areef Ishani. Association of provider-patient visit frequency and patient outcomes on hemodialysis. *Journal of the American Society of Nephrology*, 23(9):1560–1567, 2012.

Stephen A. Spiller, Gavan J. Fitzsimons, John G. Lynch, and Gary H. McClelland. Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of Marketing Research*, 50(2):277–288, 2013.

Gretchen M. Spreitzer. Psychological empowerment in the workplace: Dimensions, measurement, and validation. *Academy of Management Journal*, 38(5):1442–1465, 1995.

Gretchen M. Spreitzer. Social structural characteristics of psychological empowerment. *Academy of Management Journal*, 39(2):483–504, 1996.

Bradley R. Staats and Francesca Gino. Specialization and variety in repetitive tasks: Evidence from a Japanese bank. *Management Science*, 58(6):1141–1159, 2012.

Jasmine L. Travers, Erinn M. Hade, Steven Friedman, Aasha Raval, Kimberly Hadson, and Jason R. Falvey. Staffing and antipsychotic medication use in nursing homes and neighborhood deprivation. *JAMA Network Open*, 7(4):e248322, 2024.

Anita L. Tucker. The impact of operational failures on hospital nurses and their patients. *Journal of Operations Management*, 22(2):151–169, 2004.

Yue Wang, Hui Zhang, et al. Role ambiguity, emotional exhaustion and work alienation among Chinese nurses. *BMC Psychiatry*, 23:article 456, 2023.

Birger Wernerfelt. A resource-based view of the firm. *Strategic Management Journal*, 5(2):171–180, 1984.

Derek Wheeler, Brenda Szymanski, Amanda Peguero, Zenobia Lathara, and Sara Breckenridge-Sproat. Expanding the role of nurses in dialysis: Opportunities and challenges. *Nephrology Nursing Journal*, 49 (3):213–224, 2022.

Mischa Willis-Shattuck, Posy Bidwell, Steve Thomas, Laura Wyness, Duane Blaauw, and Prudence Ditlopo. Motivation and retention of health workers in developing countries: A systematic review. *BMC Health Services Research*, 8(1):247, 2008.

Jeffrey M. Wooldridge. Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445, 2015.

Nara Youn, Malek Maalouf, Noah Borgman, and Monther Al Shorman. Dialysis nursing workforce: Challenges, solutions, and future directions. *Nephrology Nursing Journal*, 49(5):415–426, 2022.

A State Scope-of-Practice Coding

Table A1 reports the coded value of each empowerment dimension for all 51 jurisdictions in the LawAtlas *Registered Nurse Scope of Practice* dataset (laws in effect as of August 1, 2015). The three indicators are coded from three named items of the source dataset: R_a from the item recording whether the RN may perform a nursing diagnosis, R_b as the complement of the item recording whether the RN must provide continuous supervision over delegated tasks, and R_c from the item recording whether the LPN is named as an eligible delegatee in the state's delegation provision. The published data file (`201599_Registered_Nurse_Scope_of_Practice_Data`) is available from the LawAtlas Policy Surveillance Program, and the coding reported here reproduces it for all 51 jurisdictions.

B Variable Definitions

Table A2 defines every variable used in the analysis, with its source and construction rule.

Table A1: State Scope-of-Practice Coding Underlying the Empowerment Index

State	R_a	R_b	R_c	*Emp*	State	R_a	R_b	R_c	*Emp*
AK	1	1	1	3	MT	0	0	1	1
AL	0	1	1	2	NC	1	1	0	2
AR	0	1	0	1	ND	1	1	1	3
AZ	1	1	1	3	NE	1	1	0	2
CA	0	1	0	1	NH	1	1	0	2
CO	1	0	1	2	NJ	1	0	1	2
CT	1	1	0	2	NM	1	0	1	2
DC	1	0	0	1	NV	1	0	0	1
DE	1	1	0	2	NY	1	1	1	3
FL	1	1	0	2	OH	0	1	1	2
GA	1	1	0	2	OK	1	0	1	2
HI	0	1	0	1	OR	1	0	1	2
IA	1	1	1	3	PA	1	1	0	2
ID	1	1	1	3	RI	0	0	0	0
IL	1	1	1	3	SC	1	1	1	3
IN	1	1	1	3	SD	1	1	1	3
KS	1	1	1	3	TN	0	1	0	1
KY	1	0	0	1	TX	1	0	0	1
LA	1	1	1	3	UT	0	0	0	0
MA	0	0	0	0	VA	0	1	1	2
MD	1	0	0	1	VT	1	1	1	3
ME	1	0	1	2	WA	1	0	0	1
MI	0	1	1	2	WI	0	0	1	1
MN	0	1	0	1	WV	0	1	1	2
MO	1	1	0	2	WY	1	0	1	2
MS	1	1	1	3					

Notes. Coded from the LawAtlas *Registered Nurse Scope of Practice* dataset (laws in effect as of August 1, 2015). $R_a = 1$ if the state authorizes RNs to perform a nursing diagnosis; $R_b = 1$ if the state does NOT require the RN to maintain continuous supervision over delegated nursing tasks; $R_c = 1$ if the state's delegation provision names LPNs as eligible delegatees. $Emp = R_a + R_b + R_c$. Jurisdiction counts: $R_a = 1$ in 36, $R_b = 1$ in 33, $R_c = 1$ in 28 of 51 jurisdictions (50 states plus DC); *Emp* distribution 3 / 13 / 21 / 14. DC (*Emp* = 1) does not appear in the estimation sample.

Table A2: Variable Definitions and Data Sources

Variable	Definition	Source
ln(QIP Score)	ESRD Quality Incentive Program total performance score (0–100 composite), indexed by the calendar year of its measurement period; natural log	CMS ESRD QIP
ln(RN Staffing)	Registered-nurse FTEs per 100 patients, $\ln(100 \times$ RN FTE/patient census); the underlying ratio is winsorized at the 5th and 95th percentiles	HCRIS (RN FTEs); CMS facility panel (census)
ln(SDI)	County-level Social Deprivation Index (1–100 composite of seven ACS socioeconomic indicators); natural log	Robert Graham Center
Raw Empowerment (Emp^{raw})	Sum of diagnosis authority (R_a), freedom from a continuous-supervision requirement (R_b), and LPN delegation authority (R_c); ordinal 0–3 and time-invariant	LawAtlas RN Scope of Practice (laws as of Aug. 1, 2015)
Analysis Empowerment (Emp)	Main-model coding $\max(Emp^{raw}, 1)$; ordinal 1–3. The sparse raw level 0 is pooled with level 1, without deleting observations	Constructed from LawAtlas indicators
ln(Patient Census)	Facility patient census; natural log; included separately from the RN-to-patient ratio to control for facility scale	CMS facility panel
Stations	Number of certified dialysis stations	DFC
Patient Severity	Percent of patients with hemoglobin <10 g/dL plus percent with hemoglobin >12 g/dL	DFC clinical measures
Years Certified	Years since initial CMS certification	DFC
Physicians (FTE)	Physician full-time equivalents	HCRIS Cost Reports
Technicians (FTE)	Patient care technician full-time equivalents	HCRIS Cost Reports
Management (FTE)	Management and administrative full-time equivalents	HCRIS Cost Reports
LPNs (FTE)	Licensed practical nurse full-time equivalents	HCRIS Cost Reports
Chain-Owned	Indicator equal to one if the facility is chain-affiliated	DFC
For-Profit	Indicator equal to one if the facility is for-profit	DFC
Nurse Aides (FTE)	Nurse-aide full-time equivalents	HCRIS Cost Reports
Social Workers (FTE)	Social-worker full-time equivalents	HCRIS Cost Reports
Drug Expense/1,000	Facility drug expense divided by 1,000	HCRIS Cost Reports
Laboratory Expense/1,000	Facility laboratory expense divided by 1,000	HCRIS Cost Reports
Late Shift	Indicator for operation of a late dialysis shift	CMS facility panel
In-Center Hemodialysis	Indicator that the facility offers in-center hemodialysis	CMS facility panel
Home Hemodialysis Training	Indicator that the facility offers home-hemodialysis training	CMS facility panel
BLS RN Wage	MSA-level mean hourly registered-nurse wage; the facility's own market value is reported here, while the excluded instrument is the leave-own-market-out mean over the other markets of the facility's CMS ESRD Network and enters the first stage in levels. Its natural log is shown only in the descriptive table	BLS OEWS
Years-Certified Lewbel IV	Year-demeaned years certified multiplied by the auxiliary-OLS residual: $[YearsCertified_{it} - \overline{YearsCertified_t}]\hat{u}_{it}$	Constructed from DFC and the analysis data
Network Cross-Market RN Wage IV, w^{RN}	Mean hourly RN wage across all other labor markets in the facility's CMS ESRD Network and year, excluding the facility's own market. A Network is a fixed group of whole states, so the donor pool spans state lines	Constructed from BLS OEWS
Network Leave-Own-County-Out Peer Staffing IV, z^{CTY}	Mean RN-to-patient ratio of all facilities in the facility's CMS ESRD Network and year located outside its own county, again pooling across the states assigned to that Network	Constructed from DFC and the analysis data

Notes. DFC = CMS Dialysis Facility Compare; HCRIS = Healthcare Cost Report Information System; ACS = American Community Survey; BLS OEWS = Bureau of Labor Statistics Occupational Employment and Wage Statistics. The main first stage has three excluded instruments: the years-certified Lewbel instrument, the Network cross-market RN wage, and the Network leave-own-county-out peer staffing measure; a state-pool variant of the latter two is carried only as the robustness check of Section 6.2. Recorded ownership type is absorbed by the facility fixed effects and is therefore not listed as an estimated control. All expanded operational controls enter in levels except log patient census; drug and laboratory expenses are scaled by 1,000.