Doctors as Gatekeepers in Social Insurance: Evidence from Workers' Compensation Insurance *

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Abstract

In many social insurance programs, eligibility for disability benefits depends on medical evaluations performed by doctors. This paper studies the role of doctors as gatekeepers in workers' compensation insurance and quantifies the discretion they exercise in medical evaluations of physical impairments. Using comprehensive administrative data and random assignment of doctors to independent medical examinations, we identify substantial systematic variation in evaluation decisions across doctors and estimate its consequences for claimant outcomes and program costs. Being evaluated by a one standard-deviation more generous doctor increases subsequent cash benefits by about 20%, compensated time out of work by 20%, injury-related medical spending by 12%, and total workers' compensation costs by 17%. Doctor effects vary meaningfully with observable characteristics. We further examine how discretion interacts with institutional rules and economic incentives when claimants can select their own doctors. More generous doctors attract more claimants, while insurers are more likely to dispute their evaluations, indicating that both parties influence the allocation of gatekeepers in line with their incentives and thereby shape the distribution of program benefits. Finally, we show that alternative evaluator assignment rules can substantially affect claimant outcomes and program costs, underscoring the importance of policies governing the allocation and oversight of gatekeepers in the design of workers' compensation and other disability-related social insurance programs.

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Doctors play a central role in determining access to disability benefits in many social insurance programs worldwide. In the United States, disability arising from workplace injuries is covered by workers' compensation insurance, which provides benefits for lost earnings and medical expenses resulting from job-related injuries. Such injuries are widespread and economically significant: in 2022, approximately three out of every 100 full-time workers experienced an on-the-job injury.[1] Consistent with this prevalence, workers' compensation ranks among the nation's largest social insurance programs. In 2019, it paid $63 billion in benefits—more than twice the amount disbursed through unemployment insurance and comparable to spending on the Earned Income Tax Credit and the Supplemental Nutrition Assistance Program.[2] In workers' compensation, doctors serve as gatekeepers: their assessments of physical impairments determine eligibility for cash benefits. Yet despite the longstanding centrality of these medical evaluations—and growing debate over how doctor evaluators are assigned—little research has examined doctors' gatekeeping role in this large social insurance program or its consequences for claimant outcomes and program costs.

Within workers' compensation insurance, doctors play a central role as both medical providers and gatekeepers to program benefits. Each claimant is evaluated by a doctor who manages medical treatment and assesses the severity of physical impairments as the worker recovers from injury—assessments that directly determine cash benefit eligibility. A defining feature of the system is that injured workers typically have substantial freedom to select this doctor: in most states, claimants may choose their own doctor subject to few restrictions. This degree of choice is the subject of contentious ongoing policy debate.[3] Proponents of choice argue that, as in other health care settings, allowing workers to select their doctors promotes patient-doctor trust and improves medical care.[4] Opponents contend that claimants may strategically seek out doctors who provide more generous impairment ratings, increasing program costs.[5] Reflecting these concerns, impairment evaluations are frequently disputed, and many states have recently revised policies governing doctor choice. Roughly one-third of states have enacted reforms that limit claimant choice by allowing insurers to either directly select doctors or restrict the set of doctors from which the worker can choose. Similar concerns about doctor evaluation consistency and strategic doctor selection arise when impairment evaluations are disputed. Disagreements over impairment assessments are common, and all states require an independent medical evaluation by a second doctor when a dispute arises. There is increasing policy debate over how these doctor evaluators should be assigned, with some states granting insurers selection authority and others relying on random assignment.

At the core of these policy debates is the degree of doctor discretion in evaluating impairments. Policymakers frequently emphasize standardization across doctors as a central goal of workers' compensation systems, often describing consistency in evaluations as a foundational principle.[6] At the same time, there are clear reasons to expect discretion. Evaluating physical impairments is inherently complex, requiring

[1] U.S. Bureau of Labor Statistics 2023

[2] For 2019, aggregate benefits in these programs were: $63.0 billion for workers' compensation insurance (Murphy et al. 2021); $27.3 billion for unemployment insurance (U.S. Department of Labor 2021); $69.6 billion for the Earned Income Tax Credit (U.S. Department of the Treasury 2019); and $55.6 billion for the Supplemental Nutrition Assistance Program (U.S. Department of Agriculture 2020).

[3] According to an organization that tracks workers' compensation insurance legislation, at least eight states had pending legislation regarding doctor choice in workers' compensation insurance in 2025 alone (Evernorth 2025). For discussions of specific policies and policy debates, refer to Esola (2025), Grabell (2015), and Sealover (2025).

[4] See Sponer (2026) for discussion of physician selection models and arguments that employee choice may enhance patient trust and personalized care, and Rummel (2025) on proponents' emphasis on worker choice in legislative debate.

[5] For employer and business perspectives emphasizing cost control and skepticism about expanded choice, see Sealover (2025), which reports insurer and business group arguments that broader choice may complicate care coordination and increase costs.

[6] For instance, in a recent workers' compensation insurance task force meeting, across-doctor consistency in impairment evaluations was described as a "core foundational principle" in workers' compensation insurance medical exams, with the goal being that disability assessments "would remain the same regardless of the [doctor] performing the evaluation" (National Association of Insurance Commissioners 2024).

judgments about recovery trajectories and the extent to which injuries continue to limit work capacity. While stakeholders widely acknowledge the possibility of variation across doctors, beliefs about its magnitude differ sharply: some argue that appropriately trained doctors should reach similar conclusions (e.g., Forst, Friedman, and Chukwu 2010), while others express concern that differences may be substantial (e.g., O'Fallon and Hillson 2005). Despite the centrality of doctors as gatekeepers in workers' compensation and perpetual policy debates about their role, little is known about the extent of doctor discretion in impairment assessments or how such discretion translates into differences in claimant outcomes. Moreover, it is unclear whether, and to what extent, injured workers and insurers influence the allocation of doctors in line with their incentives when choice is available. Quantifying the extent of doctor discretion in impairment evaluations—and how that discretion affects outcomes and interacts with doctor allocation mechanisms—is central to assessing workers' compensation systems and has broader relevance for the design of disability-related social insurance programs.

In this paper, we use data and variation from the Texas workers' compensation insurance system to estimate the extent of doctor discretion in medical evaluations of physical impairments and the impact of this discretion on claimant outcomes and program costs. To identify the extent and impact of doctor discretion, we leverage random assignment of doctors to claimants for medical evaluations that arises through the workers' compensation dispute resolution process. Such disputes are common, affecting roughly one-third of claims with cash benefits, and more than half of aggregate workers' compensation costs are attributable to disputed claims. Using this variation, our analysis illustrates that there is wide variation across doctors in medical evaluations, these decisions are consequential for later claimant outcomes, and doctor effects systematically vary by observed doctor characteristics. We then analyze the relationship between doctor effects and the behavior of other market participants—claimants and insurers. This analysis sheds light on the impact of market forces on the allocation of evaluators when claimants can select their own doctors and the potential impact of policy interventions aimed at influencing the allocation of evaluators.

Our study draws on comprehensive administrative data from the Texas workers' compensation insurance program and exploits random assignment of doctors to claims for medical evaluations within the dispute resolution system. While claimants generally choose their own "treating doctors"—who both manage medical care and determine continued eligibility for cash benefits—insurers and injured workers can formally dispute these determinations. When a dispute occurs, the Texas Department of Insurance randomly assigns an independent doctor from among eligible doctors within the county to perform a binding medical evaluation. If the independent doctor determines the worker has a continued impairment, the worker is eligible for additional cash benefits after the exam; otherwise, the worker's cash benefits end. The random assignment of doctor evaluators allows us to quantify the scope for doctor discretion in evaluating continued impairment. In our analysis, we summarize doctor generosity as the share of claimants the doctor assesses as continually impaired—and therefore eligible for additional cash benefits—at an independent medical exam. We validate our reliance on the regulator's conditional random assignment by illustrating that observable baseline claim characteristics appear uncorrelated with the (leave-out) generosity of the assigned doctor, after conditioning on variables used in the assignment.

We analyze the impacts of being assigned a more generous doctor on downstream outcomes in the three years following the independent medical exam—such as duration out of work recovering from injury, cash disability benefits received, and subsequent medical care—outcomes that may be influenced by assessed benefit eligibility at the independent medical exam but also depend on subsequent actions by claimants, insurers, employers, and the claimant's regular treating doctor. Reduced form estimates indicate that claimants randomly assigned a more generous independent doctor experience longer durations out of work, have more subsequent medical care, and receive more cash disability benefits. The magnitude of these findings is notable. On average, claimants randomly assigned to a doctor with a 10 p.p. higher approval rate for continued benefits (roughly a one standard deviation increase) have 19.9% longer compensated time out of work recovering from injury, are 11.3% more likely to receive permanent impairment benefits, collect an additional $1,650 in subsequent cash benefits (a 20.1% increase over the mean), experience a 12.0% increase in subsequent injury-related medical spending, and incur an additional $2,384—or a 16.6% increase—in total subsequent workers' compensation costs, aggregating across post-exam cash benefits and medical spending.

After establishing that assigned doctor generosity affects claimant outcomes, we characterize the distribution of doctor generosity to better understand the extent of discretion in medical evaluations. Generosity varies substantially across doctors: after accounting for sampling error, the across-doctor standard deviation in the rate of assessing claimants as having a continued impairment is 10.2 p.p., representing 13.0% of the mean. This variation is stable over time and across subgroups of claims defined by baseline characteristics, suggesting it reflects systematic differences in evaluations across doctors. We apply empirical Bayes methods to further characterize this heterogeneity. This analysis illustrates that the distribution of generosity is asymmetric, with substantially greater dispersion among less generous doctors. The bottom quartile of doctors accounts for nearly 39.7% of denials for continued benefits among disputed claims, while the top quartile accounts for only 10.2%. We also present descriptive evidence linking doctor generosity to observable characteristics: generosity is higher among doctors whose training focuses on musculoskeletal systems (e.g., chiropractors and orthopedic specialists) and among doctors with DO credentials relative to MDs, with additional systematic differences by doctor age and sex.

Having established that doctors are influential in claim outcomes and that there is substantial variation across doctors in the way they exercise discretion, we next examine whether doctor generosity shapes interactions with other market participants. Outside the dispute resolution process, claimants are generally free to choose their own treating doctors, and the same doctors who conduct independent medical exams often serve as treating doctors for other workers' compensation claimants. Using comprehensive data on medical and cash benefits, we relate doctor generosity—measured from randomized independent medical exams—to patterns of claimant and insurer behavior in the broader workers' compensation system where claimants can select their own treating doctor.

Whether generosity translates into greater demand is theoretically ambiguous: claimants may prefer more generous doctors, but information frictions, limited choice sets, or correlated provider characteristics may dampen market forces. We find robust evidence that more generous doctors attract more claimants and experience faster growth in market share over time. Our estimates suggest that, on average, a doctor who is one standard deviation more generous has 26% more claimants for whom they serve as the treating doctor and experiences 19 p.p. greater growth in market share over time. These patterns are consistent with demand-driven reallocation, with effects strongest among claimants with greater scope for choice and more at stake. A simple benchmarking exercise suggests that this reallocation toward more generous doctors increases workers' compensation cash benefits substantially. Collectively, these patterns suggest an important role for market forces in doctor selection, though the normative implications of the observed reallocation—and of policies influencing doctor assignment more generally—may depend on whether one considers the welfare of claimants or broader measures of social welfare.

While claimants choose their treating doctors, insurers can dispute impairment evaluations, triggering an independent medical exam. Consistent with insurer incentives, we find that claims involving more generous treating doctors are more likely to face insurer-initiated disputes: a one standard deviation increase in doctor generosity is, on average, associated with a 64% increase in the likelihood of an insurer-initiated dispute.

Finally, we consider the policy implications of our findings for the design of independent medical examination systems in workers' compensation. Independent medical examinations play a central role in resolving disability disputes, affecting roughly one-third of claims with cash benefits and accounting for more than half of aggregate program costs. States differ substantially in how these examinations are structured, particularly in rules governing doctor eligibility and assignment, and these institutional choices are the subject of active policy debate. Using back-of-the-envelope calculations, we examine how changes to eligibility rules and assignment processes—similar to those adopted or under consideration in practice—may affect claimant benefits and program costs. The magnitude of these effects is large and highlights the importance of doctor allocation rules in shaping access to public benefits.

Our findings also have broader implications for the design of workers' compensation and disability-related social insurance programs. We document substantial variation across doctors in how they evaluate medical conditions, despite extensive training and guidelines intended to promote standardized assessments, and show that this discretion generates large differences in access to public benefits and claimant outcomes. Generosity varies systematically with observable doctor characteristics, suggesting that changes in workforce composition or scope-of-practice regulations may meaningfully affect benefit determinations. Moreover, market forces shape doctor allocation: claimants sort toward more generous doctors when choice is available, while insurers are more likely to challenge determinations made by more generous evaluators. Taken together, these findings highlight that doctors' gatekeeping decisions play a central role in determining benefit allocation and program costs, and that institutional rules governing gatekeeper selection can substantially influence access to public benefits and claimant outcomes.

Contributions and Related Literature Our paper makes several contributions. First, it contributes to the literature on workers' compensation insurance and related occupational disability programs. Much of the existing literature has focused on the incentives and behavior of injured workers and employers—for example, by estimating the effects of cash benefit generosity (e.g., Krueger 1990*a*,*b*; Neuhauser and Raphael 2004; Cabral and Dillender 2024*b*), medical benefit generosity (e.g., Powell and Seabury 2018), and firm incentives to reduce costs (e.g., Aizawa, Mommaerts, and Rennane 2023).[7] Despite the central role of doctors in determining benefit eligibility in workers' compensation insurance—and growing policy interest in regulating evaluator assignment—little is known about the extent of doctor discretion in impairment evaluations or its consequences for claimant outcomes and program costs. Our paper begins to fill this gap by providing the first systematic evidence on the role of doctor evaluators in workers' compensation insurance, a major social insurance program in the United States. We show that variation in doctor discretion meaningfully shapes both claimant outcomes and program spending, with effects comparable in magnitude to behavioral responses to substantial changes in the income replacement rate, a central focus of the prior literature. These results highlight doctor discretion as a quantitatively important and previously understudied determinant of claimant outcomes and program costs.

[7] In addition to work on employer and worker incentives, prior research has examined the incidence of program costs or premiums (e.g., Fishback and Kantor 1995; Gruber and Krueger 1991), the rationale for mandated coverage (e.g., Cabral, Cui, and Dworsky 2022), the role of financial incentives among claims administrators (e.g., McInerney 2010), differential impacts of workplace injuries across categories of workers (e.g., Broten, Dworsky, and Powell 2022), consumption smoothing benefits of workers' compensation insurance (e.g., Bronchetti 2012), and interactions with other sources of insurance for medical care or lost earnings (e.g., Dong, Maclean, and Powell 2024; Bronchetti and McInerney 2021; Fomenko and Gruber 2019; Dillender 2015).

Our paper also complements and extends a broader literature on social insurance and social safety net programs. Many of the largest government-regulated programs rely on gatekeepers—such as doctors, caseworkers, hearing officers, or interviewers—to determine benefit eligibility. While prior work has exploited variation in gatekeeper decisions to estimate the effects of benefit receipt on downstream outcomes (e.g., Maestas, Mullen, and Strand 2013; Autor et al. 2019; Silver and Zhang 2022), this literature typically treats gatekeeper discretion as a source of identifying variation rather than as an object of interest in its own right. Our study instead focuses on gatekeeper discretion as a central feature of social insurance systems. We quantify the magnitude of discretion in gatekeeper decisions—accounting for measurement error—and show that it has economically meaningful consequences for claimant outcomes and program spending. We further identify correlates of discretion and assess how institutional rules governing gatekeeper selection may shape these outcomes. Applying this analysis to workers' compensation insurance, we show that gatekeeper discretion is a key determinant of access to public benefits even in large-scale programs with standardized entitlements, and that policies influencing gatekeeper selection can have first-order effects on both the level and distribution of program benefits and claimant outcomes. Our findings also relate to a recent literature showing how aspects of program administration—beyond formal eligibility rules and benefit generosity—shape outcomes in public programs, including features such as prior authorization (e.g., Brot et al. 2023), wait times (e.g., Russo 2024), and proximity to enrollment offices (e.g., Bitler et al. 2025; Deshpande and Li 2019).

In addition, our study provides novel evidence on the scope for doctor discretion in medical decision-making more broadly. Our work complements a growing literature documenting how patient outcomes—and disparities in outcomes—vary across providers with differing characteristics, such as training (e.g., Doyle, Ewer, and Wagner 2010; Chan and Chen 2022), skill (e.g., Dahlstrand 2024), race (e.g., Alsan, Garrick, and Graziani 2019; Frakes and Gruber 2022), sex (e.g., Cabral and Dillender 2024*a*), or practice setting (e.g., Dahlstrand, Nestour, and Michaels 2025).[8] Other related work quantifies provider effects by exploiting variation from physician retirements or relocations (e.g., Molitor 2018; Doyle and Staiger 2021; Badinski et al. 2023). While this literature highlights meaningful differences in outcomes across providers and settings, there is more limited evidence quantifying the overall scope of doctor discretion in medical evaluations.[9] Studying discretion in medical evaluations is challenging for two main reasons. First, patients typically choose their doctors, leading to non-random sorting across providers. Second, observed outcomes often reflect multiple stages of interaction—ranging from evaluation to treatment to adherence—making it difficult to isolate doctor judgment at the evaluation stage. Leveraging features of our setting that mitigate these challenges, we characterize the magnitude of doctor discretion in evaluations of physical impairments, a central input into many health care decisions, including disability determinations. Beyond documenting its extent, we examine how this discretion shapes downstream outcomes, how it varies across a broad range of doctor characteristics, and how it interacts with patient and insurer behavior.

Finally, this paper contributes to the literature on producer performance and market allocation. While prior work—largely in manufacturing—documents a strong link between productivity and market share,

[8]In the hospital context, related work uses quasi-random variation to study the effects of treatment at hospitals with higher spending (Doyle et al. 2015), better average outcomes (Doyle, Graves, and Gruber 2019), or different ownership and organizational structures (Chan, Card, and Taylor 2023).

[9]A related health policy literature examines variability in doctor evaluations of disability, often using patient vignettes or standardized actors, frequently in the context of mental health impairments. These studies typically rely on small samples—one review reports a median of 13 mock patients—and evaluate hypothetical cases that do not mirror real-world disability determinations or allow analysis of many physical impairments (Barth et al. 2017). Findings vary substantially across studies, and this literature generally does not assess systematic differences across doctors or their implications for claimant outcomes or program spending. A recent review concludes that there is "an urgent need for high-quality research conducted in actual insurance settings" (Barth et al. 2017).

the extent to which market forces govern allocation in health care remains less well understood. In hospital settings, prior studies find evidence consistent with demand-driven reallocation toward higher-performing providers based on mortality outcomes (e.g., Chandra et al. 2016) and publicly available scorecards or rankings (e.g., Cutler, Huckman, and Landrum 2004; Kolstad 2013; Pope 2009). Evidence for physician care is more limited, with recent work suggesting demand responds to patient ratings (e.g., Bensnes and Huitfeldt 2021; Brown et al. 2023) but not to less salient quality measures (e.g., Ginja et al. 2025). We extend this literature by showing that market forces operate even in settings where doctors evaluate impairments and act as gatekeepers for disability benefits, generating demand-driven reallocation toward doctors who are more favorable to patients. Our findings indicate that both claimants and insurers influence doctor selection in line with their incentives, and that demand-driven reallocation and doctor assignment mechanisms have meaningful consequences for claimant outcomes and program costs.[10]

1 Background and Data

The data and variation analyzed in this paper come from the Texas workers' compensation insurance system. We begin by providing some background on the setting and then turn to describing the data.

1.1 Background on Setting

Workers' Compensation Insurance Workers' compensation is a state-regulated insurance program that provides benefits to employees who suffer workplace injuries. While program details vary across states, the basic structure of workers' compensation insurance is similar nationwide. Coverage, benefit formulas, and regulatory oversight are set by state law, but in most states employers purchase policies from private insurers. Workers' compensation provides wage replacement benefits when work-related injuries cause temporary or permanent disability and covers all injury-related medical spending at no out-of-pocket cost to the injured worker, regardless of work status or receipt of cash benefits.

Workers' compensation follows a medical gatekeeper model in which doctors oversee both the delivery of medical care and eligibility for cash benefits. Each claimant has a "treating doctor," who both oversees medical care and determines eligibility for cash disability benefits by monitoring recovery progress and work capacity throughout the period following injury. This dual role reflects the structure of disability determination in workers' compensation. Work capacity and cash benefit eligibility are continually evaluated as the worker recovers from injury. Workers' compensation systems assign responsibility for both medical oversight and cash benefit determinations to the treating doctor, reflecting that these doctors already monitor recovery and functional limitations in the course of providing medical care. In addition to billing for medical procedures, treating doctors receive reimbursement for case management services related to their role in monitoring work capacity and benefit eligibility.

In Texas, injured workers may select their own treating doctor, who is typically established as the doctor providing the first non-emergency treatment for the work-related injury. Allowing workers to select their treating doctor mirrors common practice in health care settings, where continuity of care and patient–doctor relationships are emphasized in managing treatment and recovery. Once established, changing treating doctors is difficult and generally requires a documented justification—such as relocation or doctor unavailability—as well as approval from the Texas Department of Insurance. Injured workers typically have access to a wide range of doctors. Reimbursement rates for professional services are generally

[10] These findings complement evidence that increased competition induces physicians to shift care toward patient preferences (Currie, Li, and Schnell 2023) and that insurers and hospitals influence patient allocation in response to financial incentives (e.g., Alexander 2020; Brown et al. 2014).

set above Medicare rates, contributing to high participation rates among primary care doctors and doctors in injury-related specialties. When selecting a treating doctor, workers may draw on multiple sources of information. Providers may engage in direct outreach or maintain publicly accessible profiles indicating their willingness to treat workers' compensation patients, and workers may also rely on prior personal experience, informal networks, online reviews, and injury-specific referrals from coworkers, employers, or legal representatives.

Workers' compensation provides two primary types of cash benefits: temporary income benefits and permanent impairment benefits. Injured workers in Texas are eligible for temporary income benefits after missing seven days of work. These benefits terminate when the earliest of the following occurs: (i) the worker returns to work, (ii) the treating doctor determines the worker has reached "maximum medical improvement" (the point at which healing has plateaued and meaningful further improvement is not expected), or (iii) the statutory maximum duration is reached. In Texas, the statutory maximum duration is 104 weeks, though most spells are substantially shorter. Temporary income benefits replace 70% of the claimant's prior average weekly wage, subject to minimum and maximum amounts. In Texas, temporary income benefit spells average 18 weeks, and nearly all recipients return to work following benefit termination, even when some permanent impairment remains. Using linked workers' compensation and unemployment insurance earnings records, Texas Department of Insurance (2015) documents that 76% of temporary income benefit recipients returned to work within six months of injury and 95% returned within three years among workers injured in 2011.

After temporary income benefits end, workers with lasting impairments may qualify for permanent impairment benefits. The treating doctor determines whether a claimant has reached maximum medical improvement and assigns a permanent impairment rating, expressed as the percentage of whole-body impairment attributable to the injury. Workers with non-zero impairment ratings receive a cash benefit that is a function of the impairment rating and prior wages. In Texas, benefits are calculated as the product of the impairment rating and a statutory wage replacement factor. Permanent impairments in this population are typically modest: among claimants with a non-zero rating, the mean impairment rating is 6%.

Approximately 20% of workers' compensation claims involve both cash benefits and medical spending; the remaining 80% involve only medical spending, typically because these claimants do not miss at least seven days of work and therefore do not qualify for wage replacement benefits. However, claims involving cash benefits are substantially more costly and account for approximately 85% of aggregate program costs.[11]

Independent Medical Evaluations Though the treating doctor serves as the gatekeeper for an injured worker's cash benefits, insurers or injured workers can formally dispute the treating doctor's assessment of a claimant's continued impairment. Such disputes are common, affecting roughly a third of claims with cash benefits. Moreover, disputed claims tend to be more costly than other claims, with disputed claims accounting for more than half of aggregate workers' compensation program costs.[12] All states have an "independent medical evaluation" system to settle such disputes. Texas relies on medical evaluations performed by independent doctors—referred to as "designated doctors"—to resolve these disputes. While either an insurer or an injured worker can request an independent medical exam if they disagree with the treating doctor's assessment, the vast majority of these exams (85%) are requested by insurers.

[11] We obtain the 85% estimate by dividing the total three-year costs for all 2013 claims receiving cash benefits within their first three years by the total three-year cost for all 2013 claims.

[12] To calculate the share of costs coming from disputed claims, we divide the total three-year costs for all 2013 claims with a dispute through 2019 by the total three-year cost for all 2013 claims. Using this approach, we calculate that disputed claims account for 55% of costs for claims with a 2013 injury year.

Our analysis focuses on independent medical exams where designated doctors are asked to assess workers for "maximum medical improvement" and, if relevant, permanent impairment.[13] In these exams, designated doctors must assess whether the claimant has reached maximum medical improvement—the point at which an injured worker's healing process has slowed and little (or no) further improvement is expected. Because any permanent impairment is evaluated after maximum medical improvement has been reached, designated doctors are nearly always ($>$ 99.8% of the time) asked to assess both dimensions at the same time if either determination is requested, though the request for the permanent impairment evaluation is only relevant if the designated doctor finds that the injured worker has reached maximum medical improvement. For these exams, designated doctors are instructed to evaluate the claimant's healing trajectory and degree of ongoing disability, taking as given the prior diagnosis of the claimant's injury.[14]

Texas maintains a database of designated doctors eligible to perform independent medical exams. Doctors with Medical Doctor (MD), Doctor of Osteopathy (DO), and Doctor of Chiropractic (DC) credentials are eligible to apply to become designated doctors through the Texas Department of Insurance (TDI). Certification as a designated doctor involves completing initial required training through TDI, and designated doctors must re-certify every two years. Designated doctors' evaluations are given presumptive weight, and insurers are mandated to pay cash benefits according to the designated doctor's assessment. When a designated doctor is assigned to a claim, that designated doctor serves as the examiner in the requested independent medical exam and also any subsequent independent medical exams if other disputes arise down the line.[15] The involvement of a designated doctor is limited and defined by statute. Designated doctors are asked to serve as "impartial, objective medical experts" to aid in settling specified claim-related disputes. By law, designated doctors may not have previous or ongoing relationships with claimants beyond independent medical exams and designated doctors are not permitted to recommend or provide treatment to these claimants. Doctors certified to conduct independent medical exams are typical doctors who spend most of their time in their standard practice treating a range of patients, with a small share of their time spent on independent medical exams. Among designated doctors in Texas, the average doctor conducts 24 independent medical exams per year, with a median of 12.

The Texas Labor Code outlines the scope of independent medical exams, the information designated doctors can consider, and the reporting requirements for designated doctors. Prior to the independent medical exam, designated doctors are required to review a claimant's medical records, which are supplied by the claimant's treating doctor and insurer. Designated doctors must also consider any medical information supplied by the claimant. Further, the designated doctor is required to conduct a physical examination of the claimant, which often involves range of motion testing or other tests related to the injury. To form an assessment of the injured worker's impairment, the designated doctor compares the information gathered from the physical exam and medical records to disability evaluation guidelines specified by TDI. Designated doctors must justify their decisions based on evidence gathered following the specified guidelines.[16]

[13] Almost all disputed claims (95.7%) meet this criteria. Although it is rare, independent medical exams can also be requested for other reasons, such as determining whether the impairment was caused by an injury that is compensable under workers' compensation insurance and the extent of the worker's compensable injury.

[14] On the form requesting the independent medical evaluation, the diagnosis describing the claimant's injury is pre-specified, and this diagnosis—including the type of injury and whether the injury is eligible for workers' compensation insurance—is not the subject of the dispute.

[15] Repeat independent medical exams are relatively uncommon: only 12% of claims with an initial exam have a subsequent exam requested within six months. Because later disputes may be shaped by the initial evaluation, we measure generosity based on the initial exam and analyze benefits received thereafter.

[16] According to 28 TAC §127.200(a)(7), designated doctors must apply the American Medical Association Guides for the Evaluation of Permanent Impairment and the Texas Department of Workers' Compensation return-to-work guidelines when appropriate, and designated doctors should also consider the Texas Department of Workers' Compensation treatment guidelines and other evidence-

Among designated doctors eligible to perform independent medical exams in a county, the assignment of designated doctors to claimants is effectively random. When an independent medical exam is requested, claimants are assigned to the next available designated doctor with the appropriate credentials to evaluate the injury from the list of certified designated doctors in the claimant's county.[17] Designated doctors with any credential (MD, DO, or DC) are eligible to evaluate back injuries and most musculoskeletal injuries, while the evaluation of more complex musculoskeletal and non-musculoskeletal injuries—such as those with co-occurring mental and behavioral health disorders—is limited to designated doctors with MD or DO credentials.[18] Because the overwhelming majority of claims are for straightforward musculoskeletal injuries, all designated doctors are eligible to conduct most exams.

Since 2013, TDI has used an automated algorithm to assign designated doctors to claimants that is designed to approximate random assignment. When assigning a designated doctor, the automated system cycles through a confidential list TDI maintains of certified designated doctors in each county, assigning the next available designated doctor in the claimant's county who has the appropriate credentials to assess the claimant's injury. After being assigned, designated doctors move to the bottom of the list. This assignment process is kept confidential, and insurers and claimants cannot observe the order of, or position within, the list of certified designated doctors in each county. Because insurers and claimants do not know which doctor will be assigned next, they cannot time their request to end up with a specific designated doctor. Given this assignment process, the designated doctor assigned to a claimant is random among designated doctors with an appropriate credential to evaluate the claim in the claimant's county. Our empirical analysis isolates conditional random assignment by controlling for "required doctor credential" by county by exam year-quarter fixed effects. In practice, we define "required doctor credential" as equal to one of four values: any credential for straightforward musculoskeletal injuries of the back and the credential of the assigned doctor (MD, DO, or DC) for all other injuries.[19]

As in other health care settings, doctors in this context are likely influenced by intrinsic motivation to evaluate patients in accordance with medical guidelines and professional standards. Nevertheless, even within established guidelines for assessing impairments, there may be scope for variation if doctors differ in how they interpret the severity of physical impairments and the extent to which those impairments limit

based medical guidelines.

[17]Beyond these factors, there are specified exclusions to ensure designated doctors do not have a conflict of interest with the claimant or the claimant's insurer. In particular, the designated doctor cannot have previously treated the claimant and cannot have a contract or agreement with the insurer. Though our baseline analysis does not account for conflict of interest related exclusions, supplemental evidence suggests these are unlikely to affect our results. For example, Table 3 illustrates that baseline claimant characteristics are unrelated to the generosity of the assigned doctor, suggesting our baseline specification may be sufficient for isolating the conditional random assignment. In addition, Appendix Table A2 demonstrates the estimates are nearly identical in specifications that expand the controls to include interactions between our baseline controls and the insurer.

[18]Our analysis excludes the 4% of independent medical exams for claimants with specified diagnoses that the TDI requires an evaluation by an MD or DO with certain board-certified sub-specialties. We make this restriction based on diagnosis codes on the independent medical exam request form. These include rare complex conditions such as traumatic brain injuries or spinal cord injuries. For more details, see 28 TAC §127.130(b).

[19]In this setting, there are multiple ways one could isolate conditional random assignment. For example, an alternative approach to isolate random assignment would be to control for the credential of the assigned designated doctor (known ex post) by county by exam year-quarter fixed effects, as which doctor is assigned is random among designated doctors with that credential in the claimant's county. While this is sufficient to isolate random assignment, a drawback of this alternative approach is that it ignores that many exams could be performed by any designated doctor and thus only allows for the identification of doctor generosity measures that are comparable across doctors with the same credential but not across doctors with differing credentials. In contrast, our approach to isolating conditional random assignment allows us to identify a measure of doctor generosity comparable across all designated doctors by leveraging the fact that the regulations clearly indicate that designated doctors with any credential can evaluate claims with specified injuries—in particular, back injuries. Though there may be some ambiguity in the required credentials for the evaluation of some types musculoskeletal injuries, the regulations are clear in specifying that back injuries can be evaluated by any designated doctors and we can validate that an assigned doctor's credential appears random among those with back injuries. (See Appendix Table A1.) Thus, we take a conservative approach in defining the "required doctor credential" categorical variable—setting this to be equal to any credential for back injuries and the observed assigned doctor's credential for all other injuries.

work-related activities. Outside of independent medical exams, doctor behavior may also reflect extrinsic incentives. Although compensation is not directly tied to evaluated disability or the cash benefits workers' compensation claimants receive, doctors may face indirect incentives to be more or less generous toward claimants in their regular practice. For example, doctors may be more generous to maintain patient satisfaction and attract future referrals, or less generous to cultivate relationships with insurers—whether to negotiate favorable reimbursement rates or to be included among recommended providers insurers or employers recommend to injured workers. In contrast, such incentives are less relevant in independent medical exams, where doctors are randomly assigned, payment rates are set by statute, and conflict-of-interest rules preclude ongoing relationships with claimants or insurers involved in the exam.

Decisions made by designated doctors at independent medical exams have the potential to influence the benefits claimants receive after an independent medical exam. If the designated doctor determines the worker has a continued impairment on the date of the exam, the worker is eligible to receive further cash benefits. In such cases, future decisions about continued eligibility for cash benefits revert to the worker's normal treating doctor. If instead, the designated doctor determines the worker has no continued impairment, the worker is not eligible to receive further cash benefits. Though designated doctors have sole discretion over whether a claimant is eligible for cash benefits after the independent medical exam, subsequent actions by employers, insurers, treating doctors, and claimants can all influence the broader post-exam outcomes we examine, including: compensated duration out of work recovering from injury, total cash benefits, injury-related medical care, and total workers' compensation costs. Since subsequent actions taken by the worker, employer, insurer, and treating doctor may all be influenced by decisions made by the designated doctor in the independent medical exam, we focus on characterizing doctor generosity through the designated doctor's assessment at an initial independent medical exam and summarize impacts on subsequent broader outcomes over the three years following the exam.[20] See Appendix Section A for more institutional details on independent medical exams.

1.2 Data

This project draws on comprehensive administrative data from the Texas Department of Insurance (TDI) obtained through open records request, covering the universe of workers' compensation claims from 2013 to 2019. In addition, we obtained linked data on all independent medical exams that took place from 2005 to 2019. Because our analysis relies on isolating random assignment and TDI introduced the automated algorithm implementing random assignment in 2013, our analysis of independent medical exams focuses on exams that occurred between 2013 and 2019. Beyond our analysis of independent medical exams, we also conduct analysis focusing on the broader set of all claims for which we can identify a claimant's treating doctor.

For all claims—regardless of whether they have a dispute-triggered independent medical exam—the data contain information on cash and medical benefits received. The medical benefit data include detailed information on each medical bill paid for by workers' compensation insurance, such as information on: procedure codes, amount paid, amount charged, diagnoses codes, date and place of service, and information about the provider. The medical data span all types of medical care including physician care, outpa-

[20] As noted above, if an insurer or claimant later requests another independent medical exam, the same designated doctor is called upon to conduct the exam. It is relatively rare for there to be multiple independent medical exams. In our sample, only 12% of claims with independent medical exams have a subsequent independent medical exam requested in the six months after the initial exam. Because any subsequent actions of insurers and workers (including requests for future independent medical exams) may be influenced by the initial independent medical exam, throughout we measure doctor generosity through assessments at an initial independent medical exam and examine impacts on subsequent benefits by considering all benefits received after this exam.

tient care, inpatient care, and prescription drugs. The data also include additional basic information about claimants and their injuries including sex, birth date (year-month), zipcode, and injury date (year-month). For claimants who receive cash benefits, the data include additional information on: the dates the benefits were paid, the type of benefits received, total benefits paid, prior average weekly earnings, and industry. For those with independent medical exams, the data include detailed information on the exam and exam request including the doctor who performed the exam, the date of the exam, the exam requester, and information on the designated doctor's evaluation of the claimant's injury at the exam.

We merge in data on provider characteristics from various sources including the Centers for Medicare & Medicaid Services' (CMS) National Provider Identifier (NPI) registry (CMS 2019b), the Medicare Physician Compare File (CMS 2021), and open records requests to the Texas Board of Chiropractic Examiners (Texas Board of Chiropractic Examiners 2021) and the Texas Medical Board (Texas Medical Board 2014).[21] All monetary values are adjusted to 2019 dollars using price information from U.S. Bureau of Labor Statistics (2021). See Appendix Section A for additional details about the data construction.

Our analysis focuses on a few different samples. Much of our analysis focuses on the sample of claimants with independent medical exams—exams for which designated doctor evaluators are randomly assigned. Throughout, we refer to this sample as the "claimants with independent medical exams" sample and the doctors performing these exams as the "designated doctor" sample of doctors. Our baseline analysis focuses on doctors who performed at least five exams, which yields a final sample of 91,899 independent medical exams performed by 1,076 designated doctors.

Another component of our analysis focuses on a broader set of claimants: all workers' compensation claimants injured from 2013 to 2019 for whom we can identify their chosen "treating doctor"—the doctor who serves as gatekeeper for their medical and cash benefits.[22] A key feature of our setting is that designated doctors also serve as treating doctors for other claimants in their standard practice. Thus, we use this broader sample of claimants to explore how market forces may influence the selection of treating doctors and whether doctor selection is related to unbiased measures of doctor generosity estimated based on independent medical exams. We refer to this broader sample of claimants as the "all claimants" sample and the treating doctors who are associated with these claimants as the "treating doctor" sample of doctors.

We summarize the sample of designated doctors in Table 1 and compare these doctors to the broader population of treating doctors for workers' compensation claimants in Texas, as well as the broader population of doctors in Texas and in the United States. Relative to the population of doctors treating workers' compensation claimants, a larger share of designated doctors have a DC credential rather than an MD or DO credential. Among doctors with MD or DO credentials, the distribution of specialties and the share who graduated from a Top 25 medical school are broadly similar among designated doctors and doctors treating workers' compensation claimants. Compared to doctors overall, doctors treating workers' compensation claimants are more likely to have an orthopedics specialty or DC credential, reflecting expected patterns given the medical needs of injured workers. Among all doctors, doctors in Texas are similar to doctors nationwide.

A key goal of our study is to estimate and analyze variation in doctor generosity, leveraging independent medical exams for identification. We measure doctor generosity as the doctor's impact on whether

[21] In addition, we also use a list of active DCs in Texas compiled by the Texas Board of Chiropractic Examiners (Texas Board of Chiropractic Examiners 2020), in addition to several other crosswalks (CMS 2019a; NBER 2021; United States Census Bureau 2010; Dartmouth Atlas 2013).

[22] We identify treating doctors using bills for case management services that treating doctors are reimbursed for providing. If multiple doctors bill case management services for a claim, we identify the claim's treating doctor as the doctor who has billed the most case management services for the claim.

the claimant is assessed as having a continued impairment—and hence is eligible for subsequent cash benefits—on the date of the independent medical exam.[23] As discussed above, a claimant is eligible for additional cash benefits after an independent medical exam if and only if the designated doctor assesses the claimant as having a continued impairment on the date of the exam. This is a natural measure to focus on for characterizing doctor generosity, as the assessment at the independent medical exam is under the sole control of the designated doctor. Beyond describing the distribution of doctor generosity, we analyze the consequences of being assigned a more or less generous doctor on a broader range of post-exam claim outcomes. In doing so, we consider impacts on post-exam benefits paid and other outcomes during the three years after the initial designated doctor exam—a period we observe for all claimants with exams from 2013 to 2019.

Table 2 provides descriptive statistics both for all claimants and for claimants who received an independent medical exam. Among all claimants, 61% are male and the mean age is 41. Claimants with independent medical exams are broadly similar in terms of these basic demographic characteristics, with 65% male and a mean age of 46. There are a diverse range of injuries, with the largest injury category being sprains and muscle issues—representing 63% of claims with independent medical exams and 46% of all claims. Because independent medical exams are triggered by a dispute related to continued eligibility for cash benefits and claimants must miss at least seven days of work in order to receive cash benefits, we would expect claimants with independent medical exams to have more severe injuries on average than claimants overall. Relative to claimants overall, claimants with independent medical exams are more likely to have initiated treatment for their injury in the Emergency Department, have higher first-day medical spending, have higher rates of cash benefit receipt, and have more medical spending within three years after injury.

Among those with independent medical exams, 78% are assessed as having a continuing disability on the date of the exam—and thus are eligible to receive subsequent cash benefits. After an independent medical exam, the mean total additional cash benefits received is $8,205. Roughly 33% of claimants have compensated time out of work recovering from injury after an exam, while 65% receive permanent impairment benefits. Mean post-exam medical spending is $6,122, and the mean total subsequent workers' compensation costs is $14,327, summing across post-exam medical spending and cash benefits.

2 Impact of Doctors on Claim Outcomes

We begin by estimating the impact of doctors on disability evaluation decisions at independent medical exams and subsequent benefits. Below, we describe our empirical strategy for this analysis and then present the results.

Empirical Strategy We explore the impact of doctors on disability evaluations and subsequent benefits by leveraging random assignment of designated doctors to claimants for independent medical exams. To do so, we estimate the following reduced form specification:

$$y_i = \beta z_{d(i)i} + \mu_{r(i)t(i)c(i)} + \mathbf{X_i \Omega} + \epsilon_i, \tag{1}$$

where i indexes the claimant, $c(i)$ indexes the claimant's county, $d(i)$ indexes the designated doctor assigned to the claimant, $t(i)$ represents the year-quarter of the claimant's independent medical exam, and $r(i)$ indicates doctor credential required to perform the claimant's exam. In this specification, y_i represents the

[23] As discussed above, our analysis throughout focuses on the initial independent medical exam and outcomes relative to the date of that exam.

dependent variable, and $z_{d(i)i}$ is a measure of doctor generosity. To isolate conditional random assignment, this specification also includes fixed effects for doctor credential required for the exam by claimant county by year-quarter of the exam ($\mu_{r(i)t(i)c(i)}$).[24] The specification outlined above accommodates other controls for claimant characteristics ($\mathbf{X_i}$). In our baseline analysis, other controls are limited to fixed effects for year of the claimant's injury, though we demonstrate the robustness of our findings when including additional controls.

The coefficient of interest in this regression is β, which captures the causal effect of being assigned a more generous doctor—as defined through their observed evaluations of continued impairment at independent medical exams—on subsequent claimant outcomes. Because this regression analyzes the relationship between outcomes of claimants at independent medical exams and the assigned doctor's generosity as measured through these same exams, this analysis faces a common challenge in the literature leveraging random assignment of cases to evaluators: small sample correlation between an evaluator's decision in a particular case and the value of the measure of evaluator generosity. To overcome this, we employ a standard leave-one-out strategy in constructing a measure of generosity. Specifically, we construct doctor generosity above, $z_{d(i)i}$, based on doctor decisions in all other claims assigned to the doctor. In our baseline analysis, we measure $z_{d(i)i}$ using the leave-out mean continued impairment rate—the share of claimants assessed as having continued impairment at independent medical exams conducted by doctor $d(i)$ excluding claimant i's exam. Because estimation error in the leave-out mean may lead to downward bias in estimating β, we apply a conventional empirical Bayes shrinkage procedure to the leave-out mean which shrinks the estimated leave-out mean toward the overall mean, in proportion to the estimation error (e.g., Morris 1983).[25]

Within the specification outlined in Equation (1), β represents the impact of being assigned a more generous doctor on claimant outcomes. We consider several outcomes in this analysis. First, we analyze impacts on whether the claimant is assessed as having a continued impairment at the exam (and hence is eligible for further cash benefits)—the outcome parallel to that used to construct the doctor generosity measure—to establish how doctor generosity toward other claimants predicts the doctor's evaluation of the claimant. We then turn to analyzing impacts on outcomes subsequent to the exam. While the assessment of continued impairment is under the direct and full control of the designated doctor, other subsequent outcomes may be directly and indirectly influenced by designated doctor decisions, but may also depend on post-exam behavior of others, including the claimant, the insurer, the claimant's employer, and the claimant's regular treating doctor. These broader subsequent outcomes include: the total additional cash benefits received after the exam, the compensated duration out-of-work recovering from injury after the exam, the claimant's assessed permanent impairment rating, post-exam injury-related medical spending, and total post-exam workers' compensation costs (aggregating across cash benefits and medical spending).

We note that this analysis considers the impact of doctors through estimating how being evaluated by a doctor who makes different decisions about continued impairment at independent medical exams—

[24] Appendix Table A2 demonstrates our findings are very similar in an alternative specification which controls for exam timing in a coarser way through including fixed effects for doctor credential required for the exam by claimant county by year of the exam.

[25] Specifically, the empirical Bayes shrunk estimate is a precision-weighted average between the leave-out mean estimate and the overall mean: $(1-w_i)\hat{z}_{d(i)i} + w_i \frac{1}{N}\sum_{i=1}^{N} \hat{z}_{d(i)i}$, where $w_i = \frac{\hat{s}_i^2}{\hat{s}_i^2+\sigma^2}$; $\hat{z}_{d(i)i}$ is the leave-out mean estimate; $\hat{s}_i^2$ is the square of the standard error of the leave-out mean estimate; and σ^2 is the variance in the distribution of the leave-out mean, estimated as in Morris (1983). Similar estimators have been used extensively in other work in economics (e.g., Kane and Staiger 2008; Chandra et al. 2016; Abaluck et al. 2021). Appendix Table A3 illustrates the robustness of our findings when using an alternative shrinkage procedure based on the distribution of doctor effects we estimate in Section 3 or when ignoring small sample correlation concerns and measuring doctor generosity using the doctor effects estimated in Section 3.

framed as ”doctor generosity” in this discussion—impacts subsequent claim outcomes. An alternative way to explore the impact of doctors on outcomes is to directly estimate the relationship between outcomes and the identity of the doctor—for example, through estimating regressions relating claim outcomes to doctor fixed effects and characterizing differences across doctors through examining properties of these doctor fixed effects. As discussed in Section 3, we also conduct analysis using this alternative approach, and we view these analyses as complementary. Taken together, the results of these analyses indicate that much of the impact of doctors on subsequent claim outcomes is attributable to variation in doctors' decisions about continued impairment at independent medical exams, supporting the use of this as an informative summary measure of doctor generosity in some subsequent analyses.

Identifying Variation Figure 1 displays a histogram of $z_{d(i)i}$ after partialling out the baseline controls. There is substantial residual variation in $z_{d(i)i}$, with an interquartile range of 10.0 p.p. and an interdecile range of 20.2 p.p. Overlaid on this histogram, Figure 1 Panel A also displays estimates from a non-parametric regression of continued impairment on $z_{d(i)i}$—with both measures residualized using the baseline controls included in Equation (1). The figure indicates the likelihood a claimant is rated as having a continued impairment strongly increases in the leave-out mean from the doctor's other assigned claims, this relationship is roughly linear, and the magnitude of this relationship is approximately one-for-one. For comparison, Figure 1 Panel B displays the analogous estimates instead investigating predicted continued impairment based on baseline (pre-exam) claim characteristics.[26] As expected given the random assignment of doctors to claims, there is no relationship between predicted continued impairment and $z_{d(i)i}$.

We present further evidence validating the conditional random assignment of doctors to claims. Given the conditional random assignment, pre-determined claimant characteristics should be unrelated to $z_{d(i)i}$ conditional on the included controls. To verify that the assignment of doctors appears random and orthogonal to baseline claim characteristics, we leverage rich data on pre-determined claim characteristics to estimate Equation (1) replacing the dependent variable with baseline claimant and injury characteristics. We examine a wide range of pre-determined claim characteristics including claimant demographics (age, sex), measures of injury severity (an indicator for whether the claim originated with an emergency department visit, medical spending on the first day of claim), type of injury, an indicator for whether the claimant requested the independent medical exam, industry, and time between injury and independent medical exam request. Table 3 presents these estimates. As expected, $z_{d(i)i}$ is uncorrelated with baseline claimant and injury characteristics, with coefficient estimates that are small and statistically indistinguishable from zero. In addition, Appendix Figure A1 presents the results of an analogous exercise verifying that baseline claim characteristics are also orthogonal to observable doctor characteristics (e.g., age, sex, training). Collectively, this evidence is consistent with expectations and suggests the random assignment of doctors to independent medical exams was implemented as required by state regulation.

Results Table 4 reports the results from estimating Equation (1). The mean and standard deviation for the indicated dependent variables are reported in column 1. The remaining columns report regression results where each cell reports the key coefficients on $z_{d(i)i}$ from separate regressions of Equation (1) for the indicated dependent variables. Column 2 reports results from the baseline specification, while the remaining columns report robustness when including further controls. To contextualize magnitudes in our discussion

[26]To create the measure of predicted continued impairment, we first fit a lasso model of the likelihood that claimants are assessed as having continued impairment during the independent medical exam and then use the fitted values to predict each claimant's likelihood of being assessed as having continued impairment. The lasso model includes a quadratic in age and indicator variables for day of the week of first medical treatment, the calendar month of injury, the year of injury, gender, industry, injury type, and the claim originating in the emergency department.

below, we consider the impact of a 10 p.p. increase in doctor generosity—which is roughly equivalent to a one standard deviation increase in doctor generosity based on the unbiased variance estimate of doctor effects discussed in detail in Section 3.1.

Table 4 Panel A reports the results of regressions associating a claimant's own continued impairment determination at the independent medical exam with the assigned doctor's generosity—based on the share of claimants who are determined to have a continued impairment in the doctor's other exams. In line with the nonparametric evidence in Figure 1 Panel A, these estimates indicate that the likelihood a claimant is rated as having continued impairment increases roughly one-for-one with the assigned doctor's generosity. The baseline estimates indicate that a 10 p.p. increase in the assigned doctor's generosity is associated with a 9.65 p.p. increase in the likelihood that a claimant themselves is evaluated as having a continued impairment at their independent medical exam. This relationship is precisely estimated and nearly identical in specifications including further controls for baseline claimant and injury characteristics.

Table 4 Panel B reports the results for subsequent claimant outcomes, measured over the three years after the exam. Our discussion of these results focuses on estimates from the baseline specification, though we note the results are similar in alternative specifications including an expanded set of controls reported in the remaining columns. Our estimates indicate that being assigned a doctor who is 10 p.p. more generous leads to an increase in total additional cash benefits of $1,650 or 20.1% of the mean, and this increase is precisely estimated with a 95% confidence interval spanning $1,451 to $1,848. This increase in cash benefits comes from increases in both income-replacement benefits and permanent impairment benefits, with roughly half of the increase attributable to temporary income benefits and half attributable to permanent impairment benefits. Those assigned a designated doctor who is 10 p.p. more generous, on average, experience a 1.56 p.p. (4.7%) increase in the likelihood of receiving any additional income-replacement benefits and stay out of work an additional 1.58 weeks while receiving these benefits—a 19.9% increase beyond the mean additional weeks out of work. Moreover, the estimates indicate that being assigned a designated doctor who is 10 p.p. more generous is associated with a 7.36 p.p. (11.3%) increase in the likelihood of being rated as having a permanent impairment and a 0.70 p.p. increase in the rated degree of permanent impairment (on a scale of 0 to 100), or a 17.3% increase relative to the mean. All of these effects are precisely estimated, with p-values less than 0.001.

While designated doctors only evaluate the injured worker's ongoing degree of impairment (which determines eligibility for cash benefits) and do not recommend or oversee medical care, post-exam workers' compensation medical spending could be indirectly impacted by the generosity of the assigned designated doctor, if cash and medical benefits are complements or the designated doctor's evaluation influences subsequent care decisions of the worker or the worker's regular treating doctor. For example, when claimants stay out of work longer while receiving income-replacement benefits, a claimant's regular treating doctor may recommend more medical care to help the claimant heal to return to work or claimants may be more inclined to follow through with doctor-recommended medical care while out of work longer. Alternatively, claimants who receive more cash benefits or stay out of work longer immediately following an independent medical exam may experience health improvements that lead to reduced medical spending months later. Our estimates indicate that those assigned a 10 p.p. more generous designated doctor receive $735 more workers' compensation covered medical care after the exam, representing a 12.0% increase over the mean. This pattern broadly aligns with prior evidence of complementaries between workers' compensation cash benefits and medical spending (Cabral and Dillender 2024*b*). We can also evaluate the impact of being assigned a more generous doctor on total subsequent workers' compensation costs, aggregating across impacts on post-exam medical spending and cash benefits. Our estimates suggest claimants assigned a 10 p.p. more generous designated doctor have \$2,384 higher subsequent total workers' compensation costs, a 16.6% increase over the mean subsequent total workers' compensation costs.

As discussed in Section 1, workers' compensation claimants receiving cash benefits in Texas typically return to work when temporary income benefits end regardless of whether they have some degree of partial permanent impairment, and 95% of injured workers receiving cash benefits return to work within three years of injury.[27] Thus, our estimates focusing on cumulative impacts over the three years after an independent medical exam likely capture the first order impacts of doctor discretion on labor supply of injured workers—suggesting workers evaluated by a 10 p.p. more generous doctor, on average, spend about 20% more subsequent time out of work due to their injury.

While the baseline analysis described above focuses on cumulative benefits received in the three years after an independent medical exam, it is possible that these estimates mask offsetting impacts if increases in cash benefits and medical spending immediately after the exam lead to an improvement in health that reduces cash benefits, time out of work, and medical spending in the months or years after the exam. We consider this possibility directly through supplemental analysis exploring dynamic impacts by time since exam. Specifically, Appendix Table A4 reports this analysis which examines cash benefits, compensated time out of work recovering from injury, and injury-related medical spending over alternative time horizons—evaluating impacts during each six-month period during the three years following an exam. These estimates suggest the impacts of being assigned a more generous doctor are largest in the first six months after the independent medical exam, though implied impacts are positive and roughly similar in percent terms across all time periods.[28] Overall, this evidence suggests that being evaluated by a more generous doctor increases cash benefits, time out of work, and injury-related medical spending in the short run, with no evidence of health improvements or offsetting decreases in cash benefits, time out of work, and injury-related medical spending in the medium- to long-run.

Collectively, these estimates suggest that doctors exert substantial influence over the level of social insurance provided to injured workers and the cost of providing that insurance. A 10 p.p. more generous doctor—roughly equivalent to a one standard deviation increase in generosity—is associated, on average, with a 20% increase in cash benefits, a 20% increase in compensated time off work, a 12% increase in subsequent medical spending, and a 17% increase in total workers' compensation costs. These magnitudes imply economically meaningful effects on both claimant outcomes and program expenditures. More broadly, these findings demonstrate that doctor gatekeepers are a central determinant of access to disability benefits, duration out of work, subsequent medical spending, and overall program costs.

3 Variation Across Doctors

We next characterize heterogeneity in doctor generosity. Let θ_d represent the generosity of doctor $d \in \{1, .., D\}$. To obtain an estimate of doctor generosity, we estimate the following equation:

$$y_i = \gamma_{d(i)} + \phi_{r(i)t(i)c(i)} + \mathbf{X_i \Sigma} + e_i, \tag{2}$$

[27]While administrative data releasable to researchers does not allow us to directly analyze labor market outcomes after benefits have terminated, internal research by TDI based on linked workers' compensation insurance data and unemployment insurance earnings records indicates that 76% of temporary income benefit recipients returned to work within six months of injury and 95% returned to work within three years of injury among those injured in 2011 (Texas Department of Insurance 2015).

[28]The exception is the final six-month period (31-36 months after the exam) for weeks receiving income benefits, where the estimated impact remains positive but is smaller and statistically indistinguishable from zero.

where our estimate of doctor generosity is equal to the estimated doctor fixed effects in this equation, $\widehat{\theta}_d \equiv \gamma_{d(i)}$. Below, we primarily focus on the dependent variable (y_i) indicating that a claimant has been assessed as having a continued impairment by the designated doctor on the exam date, though we conduct supplemental analysis considering a broader range of dependent variables summarizing other claim outcomes after the exam. This specification also includes fixed effects for a claimant's county by required doctor credential by year-quarter of the independent medical exam ($\phi_{r(i)t(i)c(i)}$). Additionally, we control for the year the claimant was injured ($\mathbf{X_i}$), though the estimates are similar if including further controls for other baseline claim characteristics. Because doctor effects are measured by comparing doctors to one another, we identify the vector of doctor fixed effects normalizing the exam-weighted mean doctor effect to zero, and standard errors on these doctor effects are produced by bootstrapping.[29]

3.1 Variance Estimation

Test for Dispersion in Doctor Effects We begin by formally testing for variation across doctors by conducting a F-test of the null hypothesis that all doctors are equally generous—based on estimates of doctor generosity from Equation (2). The first row of Table 5 reports the results of this test. These results indicate that we can reject that all doctors are equally generous, with a p-value less than 0.001. Appendix Table A5 column (1) displays analogous tests for all the subsequent claim outcomes analyzed in Section 2 and finds that we can reject equality of doctor effects across all of the subsequent outcomes with p-values smaller than 0.001.

Variance Estimate for Doctor Effects Next, we turn to characterizing the distribution of θ_d in the population of 1,076 designated doctors in our sample. One natural summary statistic of this distribution is the variance of θ_d. A key challenge with estimating the variance is that estimation error leads the $\widehat{\theta}_d$ estimates to be more variable than the true doctor generosity, θ_d. Thus, simply plugging in $\widehat{\theta}_d$ for θ_d to a standard variance formula leads to upward bias. To address this challenge, we use a split-sample approach similar to that used in other work (e.g., Silver 2020; Chan and Chen 2022). Specifically, we re-estimate Equation (2) using two partitions of the data, where these partitions are formed through randomly splitting each doctor's independent medical exams so that a doctor's exams are roughly equally divided across the two partitions. Given the stratified random sampling used to construct these partitions, this estimation yields two noisy estimates of the doctor effects that are plausibly independent, and thus the covariance of these two estimates provides an unbiased estimate of the variance of the doctor effects. See Appendix Section B.2 for more details.

Panel B of Table 5 reports the standard deviation based on the exam-weighted variance estimated using this split-sample variance approach. The estimates indicate that there is substantial variation in generosity across doctors. As indicated in the first row of Panel B, the split-sample variance estimator yields an estimated standard deviation of 10.2 p.p. in being assessed as having continued impairment on the exam date. This standard deviation is precisely estimated, with bootstrapped standard errors allowing us to rule out estimates outside 8.9 and 11.6 with 95% confidence. Appendix Table A5 column (2) reports the standard deviation from an analogous split-sample variance estimation approach for analyzing the impact of doctors on other subsequent claim outcomes. Based on these estimates, doctors have substantial impacts on all the subsequent outcomes analyzed. To assess robustness, we implement an alternative unbiased estimator of the variance of doctor effects, similar to Kline, Rose, and Walters (2022), and find comparable implied standard deviations for continued impairment and subsequent claim outcomes (Appendix Table A5 column

[29] We calculate bootstrapped standard errors using 1,000 iterations.

(3)).

Assessing Stability: Across Time and Claimant Characteristics We turn to investigating the stability of doctor effects across time and across groups of claimants. Building on the split sample approach outlined above, we construct a cross-time estimator measuring the average covariance between doctor generosity estimated using the first and last half of the exams performed by each doctor. Similarly, we estimate a cross-group estimator of the covariance between doctor-by-group generosity—where groups are defined as above or below the median value of a specified characteristic (age or predicted continued impairment) among claimants evaluated by each doctor. The ratio of the cross-time covariance estimate to the overall unbiased variance estimate measures the temporal stability of doctor generosity and the ratio of the cross-group covariance estimate to the overall unbiased variance estimate measures the stability of doctor generosity across claimants with different baseline characteristics.

Table 5 Panel B reports the results. The cross-time covariance estimator implies a standard deviation of 9.9 p.p. for continued impairment, which is very similar to the standard deviation based on the variance estimator. The similarity of the standard deviations based on the variance estimator and cross-time covariance estimator suggests that doctor generosity is stable over time.

The remainder of Panel B reports the standard deviation based on cross-group covariance estimators—considering groups based on claimant age and predicted continued impairment based on baseline characteristics. Comparing claimants above or below the median age, the cross-age covariance estimator yields a standard deviation of 10.1 p.p. in continued impairment. Comparing claimants above or below the median predicted likelihood of being assessed as having a continued impairment, the cross-predicted-impairment covariance estimator implies a standard deviation of 10.3 p.p. in continued impairment.[30] The similarity of these estimates to those from the baseline variance suggests that doctor generosity is broadly consistent across claimants differing in age and baseline predicted impairment.

These findings provide suggestive evidence that generosity is relatively stable within the set of disputed claims. Because disputed claims account for roughly one-third of all claims involving cash benefits, a related question is whether generosity measured among disputed claims reflects doctor behavior more broadly—namely, whether it would remain informative about generosity if all claims were subject to independent medical exams. Appendix Table A6 addresses this by extending the split-sample approach to groups defined by their ex ante likelihood of dispute. Using claims from 2013 to 2019, we first estimate a lasso model predicting dispute probability based on baseline characteristics and use the fitted values to generate ex ante predicted dispute probabilities within the disputed claims sample. We then compute cross–predicted-dispute covariance estimates by splitting claims at the median ex ante predicted dispute probability. We report three specifications: one using only patient characteristics, one adding insurer fixed effects, and one further incorporating treating doctor characteristics.[31] The resulting standard deviations are similar to the baseline variance estimate, indicating that doctor generosity is stable across claims that differ in their ex ante predicted likelihood of dispute and supporting the broader relevance of the generosity measure.

[30] To create the measure of predicted continued impairment, we first fit a lasso model of the likelihood that claimants are assessed as having continued impairment during the independent medical exam that includes a quadratic in age and indicator variables for day of the week of first medical treatment, the calendar month of injury, the year of injury, gender, industry, injury type, and the claim originating in the emergency department. We then use the fitted values of this lasso model to predict claimants' likelihood of being assessed as having continued impairment.

[31] The first model includes a quadratic in age and indicators for day of first medical treatment, calendar month of injury, year of injury, sex, industry, injury type, and whether the claim originated in the emergency department. The second model adds insurer fixed effects. The third adds indicators for treating doctor specialty and sex.

3.2 Distribution Across Doctors

Beyond estimating the variance, we more broadly characterize the distribution of doctor effects using an empirical Bayes deconvolution approach following Walters (2024) and Kline, Rose, and Walters (2024) based on Efron (2016). This approach yields a flexible empirical Bayes prior distribution of the population of doctor effects, taking as an input the estimated doctor effects and associated standard errors. As in many settings, the estimates of interest are correlated with the associated standard errors in our setting based on empirical tests suggested in Walters (2024). Given this, we follow guidance in Walters (2024) to adapt the empirical Bayes deconvolution approach to accommodate this precision dependence, with our approach allowing the mean of the doctor effects conditional on the standard error to depend on the magnitude of the standard error. Specifically, we consider the following model:

$$\theta_d = \phi_1 + \phi_2 r_d \, log \, s_d, \quad r_d | s_d \sim G_r \tag{3}$$

where θ_d is the doctor effect, s_d is the associated standard error, r_d is a residual, and $E[r_d] = 1$. This implies $E[\hat{\theta}_d | s_d] = \phi_1 + \phi_2 log \, s_d$. We estimate ϕ_1 and ϕ_2 by OLS regression and use these estimates to form residuals, $\hat{r}_d = \frac{\hat{\theta}_d - \hat{\phi}_1}{\hat{\phi}_2 \, log \, s_d}$. Then, we estimate G_r using a log-spline deconvolution estimator described in Walters (2024) based on Efron (2016) applied to these residuals, assuming $\hat{r}_d | r_d, s_d \sim \mathcal{N}\big(r_d, \frac{s_d^2}{(\phi_2 \, log \, s_d)^2}\big)$. Using this distribution, we recover the marginal distribution of θ_d by applying a change in variables to the distribution of the residuals combined with the empirical distribution of the standard errors. Appendix B.3 provides more details on this approach.

Figure 2 Panel A displays the estimated deconvoluted density of the residuals and Panel B displays the resulting marginal distribution of doctor effects, θ_d. The distribution of doctor effects is single-peaked and roughly symmetric near the median, though it exhibits a longer left tail, indicating greater dispersion among less generous doctors. Based on this density, there is substantial variation in doctor effects—with an interquartile range of 13.8 p.p. and an interdecile range of 26.5 p.p.. These are large representing 17.6% and 33.9%, respectively, of the mean rate of being assessed as having a continued impairment.[32]

Based on the deconvoluted distribution, Figure 2 Panel C summarizes the concentration of denials in impairment assessments, similar to a Lorenz curve. Specifically, this figure displays the share of claimants being denied further benefits (i.e., assessed as having no continued impairment at an independent medical exam) attributable to the most generous X% of doctors—where X is indicated on the horizontal axis which displays the share of doctors, ordering doctors from most generous to least generous. The curve is bowed away from the 45-degree reference line, indicating that denials of continued impairment are concentrated among particular doctors. The least generous quartile of doctors is responsible for 39.7% of the denials of continued impairment, while the most generous quartile of doctors is only responsible for 10.2% of continued impairment denials. Based on this figure, we can also visualize another measure of dispersion: the Gini coefficient which is twice the area between the 45-degree line and the indicated curve and ranges from zero (in the case of perfect uniformity) to one (in the case of perfect concentration). The Gini coefficient

[32]We can contextualize these magnitudes by comparing the estimated range of variation to the ranges estimated in other work analyzing differences in worker effects in other settings. For example, the interdecile range we estimate represents 33.9% of the mean, which is notably larger than the 22% of the mean estimated in Chan, Gentzkow, and Yu (2022) among radiologists evaluating pneumonia cases and the 21% of the mean estimated in Mas and Moretti (2009) among grocery store cashiers. A one standard deviation difference in doctor effects in our setting represents 13% of the mean and 0.24 of the standard deviation of being rated as having a continued impairment, which is smaller than the one standard deviation implied difference of 21% of the mean estimated in Chan and Chen (2022) among doctors in the costs of treating patients in the emergency department and larger than the one standard deviation implied differences of 0.15 and 0.12 standard deviations of student test scores estimated in Staiger and Rockoff (2010) for New York teachers' persistent value added in math and reading, respectively.

based on the deconvoluted distribution is 0.26.

3.3 Interpreting Magnitudes

To further interpret magnitudes, we combine the estimates characterizing the distribution of doctor generosity discussed above with estimates from Section 2 on the impact of being assigned a more generous doctor for an independent medical exam. Our estimates suggest doctor discretion substantially impacts subsequent cash benefits and total workers' compensation costs. A one standard deviation increase in the generosity of the assigned doctor is associated with a 20.6% increase in cash benefits and a 17.0% increase in total workers' compensation costs.[33] Moreover, moving from the 25th percentile to the 75th percentile generosity doctor is associated with a 27.7% increase in cash benefits and a 22.9% increase in total workers' compensation costs.

We benchmark these impacts against a central policy parameter in the workers' compensation literature: the income replacement rate. Using elasticity estimates from Cabral and Dillender (2024*b*), a one standard deviation increase in doctor generosity raises cash benefits by as much as the behavioral response to a 28.6% increase in the replacement rate. Similarly, moving from a 25th to a 75th percentile generosity doctor increases cash benefits by as much as the behavioral response to a 38.5% increase in the replacement rate. These comparisons indicate that variation across doctors is comparable in magnitude to the behavioral responses to large statutory changes in benefit generosity. We can also benchmark the importance of doctor effects by comparing their explanatory power to that of baseline claim characteristics. Specifically, we compare the partial R^2 from Equation (2) with doctor fixed effects to the partial R^2 from a specification that replaces doctor fixed effects with the set of pre-determined claim observables reported in Table 3. This comparison indicates that doctor effects explain 1.5 times as much variation in exam outcomes as the baseline claim observables.

The large degree of variation across doctors contrasts with the emphasis many workers' compensation systems place on evaluator consistency and suggests that doctor discretion plays a central role in shaping benefit access and program costs.

4 Correlates of Doctor Generosity

Next, we analyze the relationship between doctor generosity and observed doctor characteristics, by correlating the estimated doctor fixed effects from Equation (2) with observable information about doctors and their prior experience. It is important to note that such relationships may not represent causal impacts. Nevertheless, these correlations are a parsimonious way to summarize the types of doctors who tend to evaluate claimants more or less generously.

Figure 3 reports the results from bivariate or multivariate regressions associating doctor generosity with the measure(s) within the indicated characteristic group, along with estimates from multivariate regressions that regress doctor generosity on all measures simultaneously. The discussion below primarily focuses on associations between doctor generosity and individual doctor characteristics, which transparently sum-

[33] Note that an alternative way to characterize the impact of doctors on cash benefits or total workers' compensation costs would be to directly interpret the estimates of the implied standard deviation across doctors for these subsequent claim outcomes from Appendix Table A5. Based on these estimates, a one standard deviation difference across doctors in subsequent cash benefits is 24% of the mean and in total workers' compensation costs is 20% of the mean. Comparing these estimates to the implied impacts on benefits based on the variation in doctor generosity suggests variation in doctor generosity (as measured through continued impairment decisions at independent medical exams) may explain roughly 85% of the overall variation in subsequent claim outcomes across doctors and bootstrapped confidence intervals suggest we cannot statistically reject that all the variation in subsequent outcomes can be explained by variation in doctor generosity. We note that these patterns align with expectations given institutional features and support the use of continued impairment decisions as a summary measure of doctor generosity in this setting.

marize how generosity varies across observable attributes. We note that many doctor characteristics are correlated and a number of these associations attenuate when all observed doctor characteristics are jointly controlled for.

We first consider basic doctor demographics. Older doctors are less generous than younger doctors: a doctor who is 10 years older is, on average, 1.9 p.p. less likely to assess a claimant as having a continued impairment (p-value<0.001), representing 0.19 of the standard deviation in doctor effects based on the unbiased variance estimate in Section 3.1. The estimates also suggest female doctors may be more generous than male doctors. Female doctors are, on average, 1.4 p.p. more likely to assess a claimant as having a continued impairment. This association is similar in magnitude in multivariate regressions, though it is statistically distinguishable from zero only once other doctor characteristics are controlled for.

We then examine doctor birthplace. Doctors born in Texas are more generous than those born in other U.S. states, while doctors born outside the U.S. are less generous. Compared to doctors born in other states, doctors born in Texas have 2.2 p.p. higher continued impairment determinations (p-value 0.026) and doctors born outside the U.S. have 2.8 p.p. lower continued impairment determinations (p-value 0.025). However, doctor birthplace is correlated with other doctor characteristics (e.g., sex, credential, specialty), and the association with birthplace becomes small and statistically indistinguishable from zero in multivariate regressions.

We also investigate how doctor training is correlated with generosity. Credential is strongly associated with doctor generosity: relative to doctors with MD credentials, doctors with DC credentials are 12.4 p.p. more likely to assess a claimant as having a continued impairment (p-value<0.001). This difference is large, representing approximately 1.22 standard deviations of doctor generosity based on the variance estimates in Section 3.1, and remains statistically significant and slightly larger in multivariate regressions. Doctors with DO credentials are also more generous than MDs, though the magnitude is less than half of the difference between those with MD and DC credentials.

We also examine specialty, considering coarse specialty groups: primary care/internal medicine (the most common specialty among MD/DOs), chiropractic care, orthopedic surgery, and other specialties. The estimates indicate that doctors with more specialized training focused on the musculoskeletal system are more generous than doctors with more general training. Relative to doctors specializing in primary care/internal medicine, orthopedic surgeons are 3.6 p.p. more likely to assess a claimant as having a continued impairment (p-value 0.028), while chiropractors are 12.0 p.p. more likely to do so (p-value<0.001). Aside from orthopedic surgeons and chiropractors, doctors in other specialties assess claimants similarly to those in primary care/internal medicine.

In addition, we consider the quality of medical school attended. Among doctors with MD credentials, those who attended a Top 25 medical school are 5.7 p.p. less likely to rate a claimant as having a continued impairment (p-value<0.001). This association is notably smaller and statistically indistinguishable from zero once other doctor characteristics are controlled for.

We next explore how generosity relates to doctors' prior experience with independent medical evaluations. We construct two measures using data from 2005–2012, prior to the analysis period: (i) years of experience performing independent medical exams and (ii) the average annual number of exams performed. Generosity is negatively associated with both measures: an additional year of experience is associated with a 0.7 p.p. lower likelihood of assessing a claimant as having a continued impairment (p-value<0.001), while a one-standard-deviation increase in exam volume (approximately 32 additional exams per year) is associated with a 1.3 p.p. decrease (p-value 0.006). These relationships are substantially smaller and statistically indistinguishable from zero in multivariate regressions.

We also investigate the relationship between doctor generosity and disciplinary actions by either the Texas Department of Insurance (TDI) or by state professional boards overseeing doctor licensing (the Texas Medical Board and the Texas Board of Chiropractic Examiners). The TDI disciplines doctors—through actions such as suspending participation in designated doctor exams or in workers' compensation insurance more generally—for reasons including providing inappropriate care or repeatedly failing to submit required forms. These disciplinary actions are rare, with only 2.4% of designated doctors ever disciplined. Estimates suggest that doctor generosity is positively associated with TDI disciplinary actions, though this association is statistically distinguishable from zero only in multivariate regressions (p-value 0.039). In contrast, disciplinary actions by state professional licensing boards—which may involve penalties ranging from fines to license revocation for violations such as negligence, incompetence, or unprofessional conduct—are negatively associated with doctor generosity. However, these estimates are smaller and statistically indistinguishable from zero, particularly once other doctor characteristics are controlled for.

Finally, we consider the relationship between doctor generosity and patient ratings. We obtain information on patient ratings from Healthgrades.com, the most common platform on which doctors in our sample are consistently rated. Our analysis focuses on doctors' mean patient ratings, where individual patient ratings range from 1 (worst) to 5 (best). Approximately half of doctors in our sample have a Healthgrades.com rating, and regressions including this measure additionally control for an indicator for missing ratings. Doctor generosity is positively associated with patient ratings: a one-standard-deviation increase in ratings is associated with a 2.7 p.p. higher likelihood of assessing a claimant as having a continued impairment. This association is substantially attenuated and statistically insignificant when including controls for other doctor characteristics.

5 Doctor Generosity and Interaction with Market Participants

Evidence summarized in the previous sections establishes that doctors are influential in claimant outcomes, there is substantial variation across doctors in the way they exercise discretion, and some observable characteristics of doctors are significantly associated with the way doctors use this discretion.

Below, we provide evidence examining the relationship between doctor generosity and the behavior of other market participants. This analysis leverages the fact that many of the doctors who serve as gatekeepers for medical care and cash benefits for workers' compensation claimants in their standard practice also are certified as designated doctors eligible to perform independent medical exams. Thus, for these doctors, we are able to observe behavior both when these doctors are randomly assigned to claimants for independent medical exams and when these doctors are in their standard practice treating claimants who have chosen them to serve as their "treating doctor." We note this analysis is premised on the idea that doctor generosity measured in independent medical exams meaningfully predicts the generosity of doctors when treating and evaluating claimants in their standard practice. Section 5.3 below presents supplemental analysis supporting this idea.

5.1 Market Allocation

We begin by examining the relationship between doctor generosity and market allocation. All else equal, claimants would prefer more generous doctors—doctors who are more lenient in their evaluations for cash disability benefit eligibility. Thus, if claimants are informed about doctor generosity and can freely choose among doctors, we might expect claimants to sort toward more generous doctors. However, it is unclear whether such sorting occurs in practice, as a few factors may dampen these forces. First, claimants may have limited information about doctor generosity. While claimants may obtain some information about doctors through their own experience or through information conveyed by peers, doctor marketing, or legal representatives, claimants may have limited ability to assess doctor generosity. Second, claimants may have preferences over other provider characteristics (e.g., location, convenience, other attributes), and their choices may be influenced by other parties—such as insurers or employers. Ultimately, it is an empirical question whether patients sort toward providers who are more generous.

Empirical Strategy We investigate this empirically by examining whether, and to what extent, more generous doctors attract a larger market share of claimants. If patients sort toward more generous doctors, we would expect more generous doctors to have a larger market share at a given point in time and to experience more market share growth over time. We test these predictions empirically by estimating the following equation:

$$y_j = \delta DD_j \times \tilde{\theta}_j + \rho DD_j + \nu_{s(j)m(j)} + \varepsilon_j, \tag{4}$$

where j indexes doctors, $s(j)$ represents doctor specialty, and $m(j)$ represents the medical market in which the doctor practices. In this equation, $\tilde{\theta}_j$ is a measure of doctor generosity based on independent medical exams (described further below), and DD_j indicates that doctor j is a designated doctor in our sample (i.e., a doctor for whom we can measure generosity).[34] To focus on comparisons among doctors qualified to treat the same set of claimants/injuries, this specification includes specialty by medical market fixed effects ($\nu_{s(j)m(j)}$). In the baseline specification, medical markets are Hospital Service Areas (HSAs) as defined by the Dartmouth Atlas, and specialty is a categorical variable for key specialties represented among doctors treating workers' compensation patients (chiropractic, internal or family medicine, orthopedics, physical medicine, emergency medicine, neurology, psychiatry, and other specialty).[35] The coefficient of interest is δ, which describes the relationship between the outcomes of interest and doctor generosity among doctors for whom we can identify generosity through random assignment.

We investigate two different outcome variables: (i) the natural logarithm of the mean annual number of claimants for whom doctor j serves as a treating doctor ($ln(N_j)$) and (ii) the mean annual growth rate in the number of such claimants treated by doctor j between the first and second halves of the analysis period (Δ_j). Specifically, we construct this measure of mean annual growth rate in two steps. First, we take the difference in the mean annual number of claims for whom the doctor serves as the treating doctor between the second half and first half of the analysis period, where claimants are assigned to the first or second half of the analysis period according to their injury date. Second, we divide this difference by the mean annual number of claims for all seven years of the analysis period. These two outcome variables, respectively, test the static and dynamic predictions of sorting toward more generous doctors.

In this specification, the measure of doctor generosity ($\tilde{\theta}_j$) is based on the doctor fixed effect estimates from Equation (2), which are identified based on the random assignment of designated doctors for independent medical exams. Because measurement error in the doctor generosity measure could lead to downward

[34] Doctors who are in our designated doctor sample (i.e., doctors for whom we can measure doctor generosity) represent 17% of all doctors who treat workers' compensation patients as a designated doctor or treating doctor. Beyond doctors for whom we can measure generosity, we include all doctors who treat injured workers in estimating equation 4 as all doctors identify the specialty by medical market fixed effects.

[35] Appendix Table A7 illustrates the estimates are similar if we use an alternative definition of medical market, based on either counties or Hospital Referral Regions as defined by the Dartmouth Atlas. Refer to Appendix A for more details on identifying and classifying doctor specialties.

bias in the associated coefficient estimate, we apply empirical Bayes shrinkage using the deconvoluted distribution estimated in Section 3.2. See Appendix Section B for more details. Additional analysis in Appendix Table A8 illustrates the estimates are very similar if we instead use the unadjusted doctor fixed effects to measure doctor generosity.

Results Table 6 displays the estimates. Panel A column 1 summarizes the baseline estimates testing the static prediction associated with sorting. The estimates indicate more generous doctors have a larger market share, consistent with more generous doctors attracting more claimants at a given point in time. The magnitude is notable, with the estimates indicating a doctor who is one standard deviation more generous has, on average, 26% more claimants for whom the doctor serves as a treating doctor in their standard practice. This relationship is statistically significant, with a p-value of 0.003.

Panel B column 1 displays the baseline estimates exploring the dynamic prediction of sorting. The estimates indicate that doctor generosity is positively related to growth in the number of claimants for whom the doctor serves as a treating doctor, consistent with the notion that more generous doctors attract more claimants over time. Based on these estimates, a doctor who is one standard deviation more generous experiences 19 p.p. more growth in their market share over time on average (p-value 0.005).

While this evidence is consistent with claimants sorting toward more generous providers, we test for more direct evidence that demand-driven allocation is an important mechanism behind these patterns. We view this as particularly important given that intuition suggests there are several factors in health care settings that can work to dampen competitive forces. We provide two sets of related analyses.

The first set of analyses examines a key implication of the demand-based allocation mechanism: when consumers have more choice or greater scope to substitute across producers, the relationship between producer performance and market allocation should be stronger. We explore this implication through heterogeneity analysis, re-estimating Equation (4) separately for claims in more or less competitive medical markets. For this analysis, we classify medical markets as more or less competitive based on whether the Herfindahl–Hirschman Index (HHI) among doctors treating workers' compensation patients is below or above the median. Table 6 columns 2 and 3 report the estimates. Consistent with a demand-driven allocation mechanism, the estimated relationship between doctor generosity and market allocation is stronger for claims in more competitive markets than in less competitive markets. In more competitive markets, a one standard deviation more generous doctor has, on average, a market share that is 34% larger (p-value 0.004) and experiences 28 p.p. more growth in market share over time (p-value 0.001). In less competitive markets, the estimated association is smaller and statistically insignificant.

We conduct a second set of analyses examining another implication of the demand-based allocation mechanism: the relationship between producer performance and market allocation may be stronger when consumers have more at stake and therefore stronger incentives to sort toward producers with performance that aligns with their preferences. A doctor's generosity in evaluating cash benefit eligibility is directly relevant only for claimants who expect to receive cash benefits—those with injuries severe enough to potentially miss at least seven days of work. Motivated by this, we estimate Equation (4) separately for claimants with above- or below-median predicted likelihood of receiving cash benefits based on baseline observables.[36] The results are reported in Table 6 columns 4 and 5. The estimates suggest that the relationship between doctor generosity and market allocation is stronger among claims more likely to receive cash

[36]To create the measure of predicted likelihood of receiving cash benefits, we fit a lasso model of an indicator for receiving cash benefits within the first three years after injury on indicator variables for day of the week of first medical treatment, the ICD-9 code for first medical treatment, age, gender, injury year-month, and whether the claim originated in the emergency department, and then use this model to predict the likelihood of receiving cash benefits in the first three years after injury.

benefits based on baseline information. Among claims with above-median ex ante predicted likelihood of receiving cash benefits, a one standard deviation more generous doctor has, on average, a market share that is 22% larger (p-value 0.009) and experiences 21 p.p. more market share growth over time (p-value 0.003). For claims with below-median ex ante predicted likelihood of receiving cash benefits, the estimated relationship is weaker and statistically insignificant.

Collectively, this evidence suggests claimants sort toward more generous providers. One possibility is that this sorting reflects informed decision-making, with claimants selecting doctors based on differences in generosity in line with their incentives. Alternatively, sorting may arise because claimants choose doctors based on other characteristics that are correlated with generosity. For example, more generous doctors may also possess traits that claimants value more broadly, such as greater deference to patients in treatment decisions, more empathetic bedside manner, or higher-quality office support. We do not take a position on whether the evidence of demand-based allocation we observe is driven by claimants who are actively seeking doctor generosity itself, determinants of doctor generosity, or attributes correlated with doctor generosity.[37] These explanations all suggest that claimant demand is leading to reallocation toward doctors who are more generous in their disability evaluations.

Overall, we interpret the evidence above as consistent with demand-driven reallocation of claimants toward doctors who are more generous in their medical evaluations of physical impairment. A qualitative implication of these findings is that the allocation of doctors to patients is influenced by market forces. We can also conduct back-of-the-envelope calculations to assess the potential quantitative importance of these findings. To do so, we assume the distribution of generosity measured among doctors who conduct independent medical exams reflects the distribution of doctor generosity among all doctors available to treat workers' compensation claimants. Under this assumption, the baseline static estimates (from Table 6 Panel A column 1) combined with the variance estimate from Section 3.1 imply the reallocation of patients toward more generous doctors increases mean doctor generosity by 0.0267. Combining this with the estimates from Table 4 on the implied percent impact of a more generous doctor on total subsequent benefits, this implies that demand-driven reallocation toward more generous doctors increases aggregate workers' compensation cash benefits by 5.4%. This implied increase in aggregate cash benefits is economically meaningful and comparable in magnitude to behavioral responses to sizable changes in statutory benefit generosity. Using elasticity estimates from Cabral and Dillender (2024*b*) on the relationship between the income replacement rate and benefit duration, the 5.4% increase in cash benefits attributable to demand-driven reallocation is equivalent to the impact on benefits from behavioral responses induced by a 7.5% increase in the replacement rate.

5.2 Claim Disputes

Next, we explore the relationship between doctor generosity and insurer-initiated claim disputes. Recall that either insurers or claimants can formally dispute a treating doctor's cash benefit determination, with such disputes triggering an independent medical exam. While either insurers or claimants can file a dispute, roughly 85% of disputes are initiated by insurers. An insurer seeking to minimize costs has the incentive to dispute claims when the insurer believes a claimant's treating doctor is more generous than a randomly selected designated doctor. Thus, an insurer's incentive to dispute a claim is increasing in the generosity of

[37] While we don't take a stand on whether the demand-driven reallocation is caused by claimants actively seeking doctor generosity or some correlated characteristic, we note that the evidence of stronger sorting patterns among claimants more likely to be eligible for cash benefits is consistent with sorting motivated by doctor generosity (or some other doctor characteristic disproportionately relevant to these claimants).

the claimant's treating doctor.

Given these incentives, one might expect claims managed by more generous treating doctors to be disputed more frequently by insurers. However, whether such patterns arise in practice is unclear. Insurers may be imperfectly informed about doctor generosity, and differences in dispute rates could also reflect patient selection across doctors or other claim characteristics that shape dispute initiation. We therefore turn to the data to examine this relationship empirically.

Empirical Strategy Specifically, we estimate the following claim-level specification:

$$y_i = \gamma DD_{j(i)} \times \tilde{\theta}_{j(i)} + \phi DD_{j(i)} + \pi Z_i + \mu_{s(j(i))m(j(i))} + e_i, \tag{5}$$

where i indexes claimants and $j(i)$ represents claimant i's treating doctor. This specification includes controls for baseline claimant characteristics, Z_i, (sex, age, injury year-month), as well as doctor-level characteristics defined as in Equation (4) above. The key coefficient of interest is γ, which relates outcomes of interest to doctor generosity. In this analysis, we consider three dependent variables: an indicator that the claim was disputed, an indicator that the claim was disputed by the insurer, and an indicator that the claim was disputed by the claimant. Additional analysis in the appendix illustrates the estimates are similar if we vary the set of geographic or claimant controls (Appendix Table A9) or use unadjusted doctor fixed effects as the measure of doctor generosity (Appendix Table A10).

Results The estimates are displayed in Table 7. Column 1 indicates that claims for which the treating doctor is more generous are more likely to be disputed. The estimate suggests that a claim with a one standard deviation more generous treating doctor, on average, is associated with a 5.5 p.p. increase in the likelihood of being disputed—or 54% of the overall mean rate of disputes. Comparing the estimates in columns 1 and 2, we see this increase in the rate of disputes is attributable to an increase in the likelihood that an insurer disputes the claim; a one standard deviation increase in doctor generosity is associated with a 5.4 p.p. increase in the likelihood that an insurer disputes the claim or 64% of the overall rate of insurer-initiated disputes. In contrast, there is no statistically significant association between doctor generosity and claimant-initiated disputes.

This evidence indicates that insurers more often dispute claims managed by more generous treating doctors. Several mechanisms could generate this pattern. For example, insurers may have information about which doctors are more generous and target claims managed by these doctors when deciding which cases to dispute. Alternatively, insurers may respond to observable features of claims handled by more generous doctors—such as indicators that disability evaluations have been less frequent or less strict—and these features, rather than doctor identity itself, may increase the likelihood of dispute. While we do not distinguish among these mechanisms, the pattern is consistent with insurers using disputes in ways that influence the allocation of evaluators in line with their cost-containment incentives.

5.3 Observational Claim Outcomes Among Claimants Treated in Standard Practice

Finally, we investigate the relationship between our unbiased measure of doctor generosity and observational outcomes of claimants treated by these doctors in their standard practice. We might expect a positive correlation between doctor generosity in independent medical exams and benefits paid to claimants managed in their standard practice, as doctors conduct similar impairment evaluations in independent medical exams as they do for claimants in their standard practice. However, it is ex ante ambiguous whether we would see these patterns in practice for a few reasons. First, claimants treated in the doctor's standard practice are not randomly assigned and endogenous sorting of claimants across doctors could lead to differences in benefits claimants receive that are not attributable to the impact of doctors. Second, it could be that doctor generosity differs depending on the context of the evaluation, and doctors could evaluate claimants in their standard practice differently than those assigned to them for independent medical exams. Thus, it is an empirical question whether—and to what extent—the unbiased measure of doctor generosity from independent medical exams is associated with observational outcomes of claimants typically treated by these doctors.

Empirical Strategy To conduct this analysis, we estimate Equation (5) described above, replacing the dependent variable with measures of claim outcomes among claimants treated in the doctor's standard practice. We consider a wide range of claim outcomes including indicators for receiving cash benefits (indicators for any cash benefits, temporary income benefits, and permanent impairment benefits), the total cash benefits received, duration out of work receiving temporary income benefits, permanent impairment rating, and injury-related medical spending. In the baseline analysis below, we depart from Equation (5) by omitting controls for claimant characteristics, though we continue to control for year of injury. All other included variables are as defined in Equation (5) above, where the coefficient of interest, γ, captures the relationship between doctor generosity and claimant outcomes among claimants treated by the doctor in their standard practice. In Appendix Table A11, we consider specifications with additional controls for baseline claimant observables—both basic characteristics (e.g., sex, age, injury year-month) and an expanded set of characteristics (e.g., indicators for initial diagnosis of injury, day of the week of first medical treatment, an indicator for the claim originating in the emergency department)—to explore potential differences between unconditional and conditional correlations. In Appendix Table A12, we verify that results are similar if we use unadjusted doctor fixed effects as the measure of doctor generosity. As discussed further below, we also analyze potential selection of patients across treating doctors by estimating Equation (5) replacing the dependent variable with measures of baseline claimant characteristics.

Results Table 8 displays estimates relating doctor generosity and outcomes of injured workers treated in the doctor's standard practice. The estimates suggest claimants with treating doctors who are more generous—as measured through randomly assigned independent medical exams—have substantially higher cash benefits and medical spending. The relationships are economically meaningful and statistically significant, with p-values on the doctor generosity coefficients typically less than 0.01. A one standard deviation increase in doctor generosity is associated with a 6.5 p.p. increase in the likelihood of receiving any cash benefits, which represents a 24% increase over the mean. We observe a similar pattern with total cash benefits, where a one standard deviation increase in doctor generosity is associated with a $2,128 increase in total cash benefits—which amounts to a 71% increase over the mean.

Both temporary income-replacement benefits and permanent impairment benefits are higher among claimants treated by more generous doctors. On average, claimants who have a one standard deviation more generous treating doctor are 5.8 p.p. more likely to receive income-replacement benefits—representing a 24% increase over the mean—and remain out of work receiving income-replacement benefits for an additional 2.6 weeks, which is a 60% increase over the mean duration receiving these benefits. In addition, a one standard deviation more generous doctor is associated with a 5.4 p.p. increase in the likelihood of being rated as having any permanent impairment, which represents a 46% increase over the mean, and a 0.38 p.p. increase in the permanent impairment rating—representing a 60% increase over the mean. Beyond cash benefits, the estimates suggest medical spending is also substantially higher among claimants with more generous treating doctors. The estimates indicate that claimants treated by a one standard deviation more generous treating doctor have, on average, an additional $1,452 in injury-related medical spending, representing a 37% increase relative to the mean.

Overall, the observational evidence in Table 8 suggests claimants who have a more generous treating doctor receive more cash and medical benefits. While these findings are broadly consistent with the causal evidence on the impact of doctors in independent medical exams in Table 4, it is important to emphasize that the estimates in Table 8 do not have a causal interpretation. Claimants can select their own treating doctor and the endogenous selection of claimants across treating doctors could contribute to observed differences in outcomes. Nevertheless, there are at least two additional points worth noting about these estimates. First, the estimated patterns are consistent with doctor generosity being translatable across contexts—given the positive association between doctor generosity measured in independent medical exams and observational outcomes from a doctor's standard practice. Second, the magnitudes of the estimates in percent terms are larger than found in the analysis of independent medical exams. Multiple factors may contribute to these differences. For example, doctors likely have more scope to influence claim outcomes for claimants they regularly evaluate and treat in their standard practice than for claimants they evaluate once through an independent medical exam. In addition, patient selection may reinforce differences across doctors, if patients with more severe injuries tend to select more generous doctors.

To investigate the potential role of selection directly, Appendix Table A13 presents estimates of Equation (5) replacing the dependent variable with measures of baseline claimant characteristics, including basic demographics (sex and age), characteristics of the claimants' zipcode (above median average income, above median share Hispanic), baseline injury characteristics (injury type, first-day medical spending), and overall predicted cash benefits based on baseline characteristics. The only statistically significant coefficient is on the indicator variable for the claimant's residential zipcode having above median average income (p-value 0.050), suggesting a claimant with a one standard deviation more generous treating doctor is 3.8 p.p. more likely to live in a zipcode with an average income above the median. This positive association could be consistent with claimants from higher income zipcodes having better access to information on doctor generosity or more flexibility to act on this information. The estimates also indicate a suggestive association with predicted cash benefits based on baseline claim characteristics (p-value 0.102).[38] Based on the point estimate in Appendix Table A13 column 6, a claimant with a one standard deviation more generous treating doctor has on average $149 higher baseline predicted cash benefits. Note this is consistent with incentives in this context and evidence from Table 6 that indicates patterns consistent with demand-driven reallocation are stronger among claimants who have more at stake (those more likely to receive cash benefits based on baseline characteristics). That said, the magnitude of this association is modest relative to the overall correlation between doctor generosity and observed outcomes. It accounts for only 7.0% of the estimated difference in spending across patients assigned to a one standard deviation more generous doctor (Table 8), and the estimate is not statistically significant at conventional levels. Moreover, Appendix Table A11 illustrates the estimates relating observational outcomes and the unbiased measure of doctor generosity (in Table 8) are similar when controlling for a wide range of baseline claim characteristics.

Overall, this evidence suggests that, while differences in baseline observable characteristics across claimants selecting more or less generous treating doctors are broadly consistent with our evidence on market allocation, these differences are quantitatively modest and do not explain much of the observed

[38]The measure of predicted cash benefits comes from first fitting a lasso model of claimants' cash benefits within the first three years of claims with baseline characteristics and then using the lasso model to predict cash benefits. The lasso model includes indicator variables for the following: day of the week of the first medical treatment, the ICD-9 code for the first medical treatment, age, gender, injury year-month, and the claim originating in the emergency department.

association between doctor generosity and observational outcomes among claimants treated in the doctor's standard practice documented in Table 8. Additionally, we assess the potential role of selection on unobservables in explaining patterns in the observational data, drawing on methods in Oster (2019). See Appendix Table A14 for this analysis. Overall, this analysis suggests the overall pattern in the observational data—that patient outcomes such as cash disability benefits and medical spending are positively associated with doctor generosity—persists under a wide range of reasonable assumptions on selection on unobservables. In this way, this evidence suggests doctor generosity measured in independent medical exams is broadly reflective of doctor generosity in similar exams performed by doctors regularly treating claimants in their standard practice. Moreover, this evidence suggests that—even in the presence of endogenous sorting of claimants across doctors—observational evidence on claimant outcomes may be an informative (albeit noisy) signal about doctor generosity that could potentially influence claimant and insurer decisions.

6 Policy Counterfactuals and Discussion

Next, we explore the potential policy implications of our findings. Our results indicate there is substantial scope for doctor discretion in disability evaluations, this discretion has large impacts on claimant outcomes, and claimant benefits increase (decrease) when claimants (insurers) can influence the allocation of doctors. These findings speak directly to ongoing policy debates in many state workers' compensation programs over doctor selection, the degree of standardization in disability evaluations, and the scope of injured worker choice. States vary substantially along these dimensions, and policymakers continue to reconsider and revise these rules.[39] Motivated by this institutional variation and ongoing debate, we conduct a set of simple policy counterfactuals examining how alternative rules governing doctor eligibility and assignment may affect outcomes.

This analysis focuses on the direct implications for independent medical examinations in workers' compensation insurance. All states use independent medical exam systems to resolve disputes over disability evaluations, though key features vary, including which doctors are eligible to perform these exams and how they are allocated to exams. States differ in the degree of influence claimants or insurers have over doctor selection and in whether doctor eligibility is restricted by credential, specialty, or experience. The consequences of these design choices are actively debated in legislative and regulatory settings. We characterize how claimant outcomes and program costs would change under alternative eligibility and assignment rules resembling those used in other states, focusing on (i) changes to eligibility rules governing which doctors may conduct independent medical exams and (ii) changes to the assignment process.

In this analysis, we estimate changes in claimant outcomes by combining projected changes in doctor allocation with our estimated causal effects of being assigned a more generous doctor from Section 2. We summarize the structure of this analysis here and provide full details in Appendix Section C. The analysis holds fixed the universe of claims with independent medical exams observed over the study period. We focus on characterizing impacts on three outcomes: continued impairment assessments, subsequent cash benefits, and total subsequent workers' compensation costs (cash benefits plus medical spending). For each eligibility restriction considered, we construct the pool of available doctors in each county by drawing from the relevant estimated distribution of doctor generosity—either the full distribution from Section 3 or the estimated distribution for the subgroup defined by the eligibility restriction—with the number of draws

[39]Several states had pending legislation addressing doctor choice in workers' compensation in 2025 (Evernorth 2025). For examples of related policy discussions, see Esola (2025), Grabell (2015), and Sealover (2025).

corresponding to the number of designated doctors in the county. Doctors are then allocated to claims according to the specified assignment rule. For each simulated assignment, we project outcomes using assigned doctor generosity and the estimated causal impacts from Table 4. For this analysis, we report means and standard deviations of claim outcomes, along with bootstrapped standard errors based on 1,000 iterations.

We highlight three considerations that inform the interpretation of this analysis. First, the analysis holds fixed the set of claims with independent medical exams and abstracts from potential general equilibrium responses, such as changes in dispute frequency. Many of the policies we consider make independent medical exams more favorable to insurers on average; if insurers were to respond by requesting exams more frequently, extrapolating from these estimates would understate the implied aggregate reductions in program-wide costs. Second, as discussed below, the analysis considering alternative assignment processes relies on simplifying assumptions about how claimants and insurers would behave if granted greater influence over evaluator selection. These assumptions are intended to characterize the potential magnitude of the stakes involved in alternative allocation systems rather than to provide precise behavioral predictions. Third, our analysis focuses on characterizing impacts on claimant outcomes and program costs. While more generous evaluations increase both claimant benefits and program costs, it is unclear whether more or less generous evaluations are closer to a social optimum. Accordingly, the welfare implications depend on how one weighs claimant welfare against broader measures of social welfare.[40]

Alternative Eligibility Restrictions We first consider the impact of changing the pool of doctors eligible to perform independent medical exams, holding fixed the randomized assignment process. Specifically, we examine how claimant outcomes would change if eligibility were limited to a subset of currently eligible doctors—based on credential, specialty, or experience—motivated by restrictions observed in other state workers' compensation programs.

Table 9 reports the results. Panel A presents the mean and standard deviations of claim outcomes under the baseline scenario, where the full set of independent medical exam doctors is eligible (column 1), and under alternative scenarios in which eligibility is restricted to indicated subsets of doctors (remaining columns). Panel B reports differences in mean outcomes between each alternative scenario and the baseline, along with associated standard errors. When the full set of doctors is eligible, 77.3% of claimants are assessed as having a continuing impairment; these claimants have, on average, $8,022 in subsequent cash benefits and $14,064 in total subsequent workers' compensation costs. We next assess how these outcomes change under alternative eligibility restrictions.

Most states allow doctors with MD, DO, or DC credentials to serve as evaluators for independent medical exams, though some restrict eligibility to only those with MD or DO credentials. There is ongoing debate in several states about whether DCs should be permitted to conduct independent medical evaluations.[41] Column 2 reports how outcomes would change under such a restriction. The results indicate that

[40]It is beyond the scope of our paper to characterize the optimal level of doctor generosity. In this setting, we lack an objective measure of true disability that is plausibly independent of designated doctor evaluations. Even if such a measure were available, determining the optimal level of generosity—and hence optimal benefits—would require weighing the insurance value of increased cash benefits, time out of work, and medical spending against any associated distortions. While more generous evaluations provide more complete insurance against workplace injury losses, the ex-ante value of additional consumption smoothing, recovery time, or medical care at this margin is unclear. Characterizing potential distortions is also challenging, particularly because changes in time out of work, cash benefits, and medical spending reflect differences in doctor decisions rather than worker incentives. Whether relaxing these external constraints improves or harms social welfare is therefore ambiguous. Given these challenges, we focus on impacts on claimant outcomes and overall program costs.

[41]Some states have debated or changed rules about which providers may serve as independent medical examiners in workers' compensation. For example, in Oklahoma State Chiropractic Independent Physicians Association v. Fallin (Oklahoma Supreme Court 2011), the Oklahoma Supreme Court struck down a statutory restriction that limited eligibility to conduct independent medical exams

cash benefits and program costs decline substantially if doctors with DC credentials are excluded. Relative to the baseline, excluding DCs leads to a 6.8 p.p. (8.8%) decrease in the share of claimants assessed as having a continued impairment, a $1,159 (14.4%) decrease in subsequent cash benefits, and a $1,675 (11.9%) decrease in total subsequent workers' compensation costs.

Another potential policy is to restrict eligibility by doctor specialty. Motivated by regulations in some states highlighting the role of orthopedic surgeons, column 3 reports outcomes when eligibility is limited to orthopedic surgeons. Claimant benefits decrease under this restriction, though the magnitudes are more modest. Relative to the baseline, limiting eligibility to orthopedic surgeons reduces the share assessed as having a continued impairment by 4.4 p.p. (5.6%), decreases cash benefits by $744 (9.3%), and reduces total workers' compensation spending by $1,075 (7.6%). On average, orthopedic surgeons are more generous than doctors with MD or DO credentials overall, though less generous than doctors with DC credentials (Figure 3). Consistent with this, mean claimant benefits in column 3 exceed those in column 2.

Some states restrict eligibility based on other doctor characteristics, such as training, affiliation, and experience. For example, some states require doctors for these exams to have some minimum number of years treating injured workers in their standard practice. Column 4 examines one such restriction, limiting eligibility to doctors with at least three prior years of experience treating workers' compensation claimants. This restriction reduces workers' compensation costs, leading to a 2.4 p.p. (3.1%) decrease in continued impairment assessments, a $404 (5.0%) decrease in subsequent cash benefits, and a $585 (4.2%) decrease in total subsequent workers' compensation spending.

Taken together, these exercises indicate that eligibility rules governing who may conduct independent medical exams can meaningfully affect claimant outcomes and program costs. Differences in required credential, specialty, or experience—features often specified in statute or regulation—translate into nontrivial shifts in benefit levels. These findings underscore that eligibility restrictions are an important feature of the institutional design of independent medical examination systems.

Alternative Assignment Process Next, we consider how outcomes would change under alternative assignment systems that allow insurers or claimants to influence doctor allocation. These scenarios reflect assignment approaches used in practice and debated in policy discussions. We consider systems in which insurers or claimants directly select doctors, as well as systems where they influence selection indirectly (for example, by specifying the specialty of the assigned doctor or by choosing from or striking doctors within a randomly selected panel).

Evaluating these scenarios requires assumptions about how claimants and insurers would influence the selection of doctors for these exams if they had the opportunity to do so. Because independent medical exam doctors are randomly assigned in Texas, we do not observe how claimants or insurers would behave under alternative regimes. We therefore conduct this analysis under the assumption that insurers (claimants) select the least (most) generous doctor from the available set in the indicated scenario. Under this assumption, the analysis considering these scenarios provides an upper bound on how much allowing one party to influence doctor selection could shift outcomes in that party's favor.

The process for assigning doctors to independent medical evaluations varies widely across states. In 22 states, the regulator plays a role in assigning doctors to independent medical exams. Among these states with administrative assignment, some rely on explicit random assignment, though the details differ. For example, some assign a randomly selected doctor from an approved list (as in Texas), while others use more complex assignment systems. In California, for instance, the regulator draws a random panel of three

to MDs and DOs, excluding DCs.

doctors. If the claimant is unrepresented, they select one; if represented, the insurer and claimant each strikes one, and the remaining doctor performs the exam.[42] States with administrative assignment also vary in whether insurers may specify the specialty of the assigned doctor. In the remaining 28 states, 25 allow insurers to directly select the doctor for an independent medical exam, while three permit the exam requester—which is usually the insurer but sometimes the injured worker—to select the doctor. These institutional differences are the subject of ongoing debate in many state workers' compensation programs.

Motivated by the wide range of allocation systems observed across states and ongoing policy debates, we explore the consequences of alternative assignment rules. Table 10 reports outcomes under the current random assignment system (column 1) and under alternative allocation systems (remaining columns). Columns 2 and 3 consider systems in which the insurer or claimant, respectively, selects the evaluating doctor. Relative to the current system, allowing insurers to select evaluators could substantially reduce benefits and program costs: a 35.0 p.p. (45.3%) decrease in the share assessed with continued impairment, a \$5,985 (74.6%) decrease in cash benefits, and an \$8,650 (61.5%) decrease in total workers' compensation costs. Conversely, allowing claimants to select evaluators could substantially increase benefits and costs, leading to a 21.6 p.p. (28.0%) increase in the share assessed with continued impairment, a \$3,694 (46.0%) increase in cash benefits, and a \$5,340 (38.0%) increase in total costs. These estimates should be interpreted as upper bounds under the behavioral assumptions described above. The difference between these two scenarios therefore provides an estimate of the maximum average benefits at stake under alternative assignment systems. Holding the pool of doctors fixed, the implied maximum average difference is \$9,679 in cash benefits and \$13,989 in total workers' compensation costs. These magnitudes are large and roughly comparable to the mean subsequent cash benefits and total costs in the sample. Overall, these findings highlight that who selects the evaluating doctor can have large effects on claimant benefits and program costs, helping explain the intensity of policy debates over doctor choice in workers' compensation systems.

Some states allow insurers to indirectly influence doctor selection by specifying the specialty of the assigned evaluator. Column 4 examines one such allocation system, in which the regulator continues to randomly assign a doctor but the insurer specifies the specialty. For this exercise, we assume the insurer selects the specialty that is least generous on average among eligible doctors. Based on Figure 3, primary care/internal medicine is the least generous specialty group on average, so this assumption corresponds to insurers selecting primary care/internal medicine. The estimates indicate that allowing insurers to specify specialty can substantially shift outcomes, leading to a 7.3 p.p. (9.4%) decrease in the share assessed as having a continued impairment, a \$1,247 (15.5%) decrease in cash benefits, and a \$1,803 (12.8%) decrease in total workers' compensation costs. These effects amount to roughly one-fifth of the reductions observed under direct insurer selection (Column 2), indicating that allowing insurers to indirectly influence doctor assignment through specialty selection generates a meaningful share of the maximum potential shift in outcomes.

Finally, we consider alternative allocation systems with some form of random assignment inspired by systems used in other states. Specifically, we consider systems where the regulator randomly selects a panel of three doctors, and one of these doctors is assigned to conduct the exam. In column 5, the claimant chooses the doctor from the panel; in column 6, the claimant and insurer each strike one doctor, leaving the remaining doctor to conduct the exam—which, under our assumptions, is equivalent to assigning the median-generosity doctor from the three-doctor panel. Based on the estimates in column 5, allowing claimants to choose among a randomly selected panel of doctors leads to increased benefits—an 8.5 p.p.

[42] See California Labor Code §4062.2.

(or 11.0%) increase in the share assessed with continued impairment, a $1,453 (or 18.1%) increase in subsequent cash benefits, and a $2,101 (or 14.9%) increase in subsequent total workers' compensation costs. This increase is notably smaller than when claimants have unconstrained choice among available doctors in the county. Estimates in column 6 suggest that allowing each party to strike one doctor from the panel yields mean outcomes similar to random assignment of a single doctor, but substantially reduces dispersion across claimants. In particular, the standard deviation of subsequent claim outcomes declines by roughly one-third. This reduction in dispersion suggests that relatively modest modifications to the assignment process have the potential to meaningfully increase consistency across evaluations, even when mean outcomes remain similar. Because consistency across evaluators is often a stated objective in the design of independent medical examination systems, this finding underscores the importance of assignment rules in promoting that objective.

7 Conclusion

Our paper studies how discretion exercised by individual gatekeepers shapes the implementation of social insurance. Leveraging comprehensive administrative data from the Texas workers' compensation system and the random assignment of doctor evaluators to independent medical exams, we document substantial scope for doctor discretion in medical evaluations, show that this discretion materially affects claimant outcomes, and demonstrate that generosity varies systematically across doctors. We further examine how discretion interacts with allocation mechanisms when claimants can select their own evaluators. Both claimants and insurers influence the assignment of doctors in line with their incentives, indicating that market forces shape the distribution of program benefits. Finally, we consider the impacts of alternative assignment rules.

Government-regulated programs distribute billions of dollars in benefits each year at the discretion of gatekeepers. Although such programs are typically designed with standardized evaluation processes in mind, individual gatekeepers exercise judgment in determining eligibility. Our study provides new evidence quantifying the scope and consequences of this discretion in a major social insurance program—workers' compensation insurance. We find that doctors have substantial discretion in evaluating physical impairments, and that this discretion has economically meaningful effects on subsequent outcomes. For example, being assigned a doctor who is one standard deviation more generous increases compensated time out of work by 20%, total cash benefits by 20%, injury-related medical spending by 12%, and total workers' compensation costs by 17%. When claimants can influence the allocation of evaluators, they sort toward more generous doctors, while insurers are more likely to object to evaluations performed by more generous doctors. These patterns highlight the role of market forces in shaping the allocation of doctors, and our estimates suggest that demand-driven reallocation meaningfully increases claimant benefits and program costs. Because independent medical exams affect roughly one-third of workers' compensation claims with cash benefits, policies governing doctor assignment in these exams have first-order implications for both claimants and program expenditures. Our counterfactual analysis illustrates the potential consequences of alternative allocation systems used in other states, including systems that allow insurers to influence doctor assignment or restrict the pool of eligible evaluators.

Our findings have broader implications for workers' compensation insurance and related disability programs. We document substantial variation in how doctors evaluate physical impairments, even in environments with extensive training and formal guidelines. This variation implies that the identity of the evaluating gatekeeper can substantially affect both determinations and downstream outcomes. As a result, programs that appear to offer standardized benefits may in practice deliver markedly different outcomes depending on who evaluates a claim. Our results also show that doctor generosity varies systematically with observable doctor characteristics, informing debates about credentialing requirements, scope-of-practice regulations, and doctor workforce composition. When patients have discretion over evaluator selection, they sort toward more generous doctors, while insurers respond strategically. Policies that govern how evaluators are assigned therefore play a central role in determining both equity and program costs.

More generally, our findings speak to the role of gatekeepers in government-regulated programs. Even when eligibility rules are formally standardized, meaningful discretion often resides with individual gatekeepers. The effective design of social insurance programs thus depends not only on written rules, but also on how authority over eligibility is allocated and constrained. When discretion shapes the allocation of benefits, assignment mechanisms become central policy instruments that influence both the level and distribution of public benefits. Our findings highlight how when standardized public programs are implemented by heterogeneous agents, the structure of delegated authority can be a first-order determinant of program outcomes.

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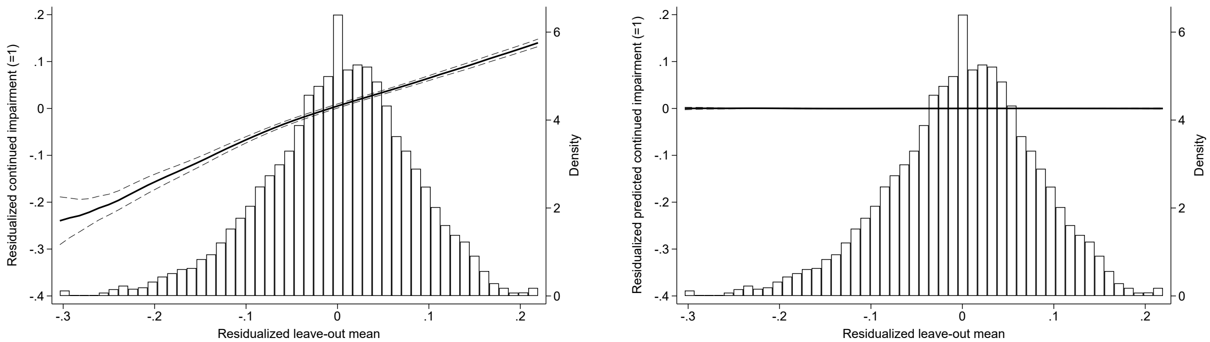
Figure 1: Distribution of Leave-Out Generosity Measure and Likelihood of Being Rated as Having Continued Impairment on Exam Date

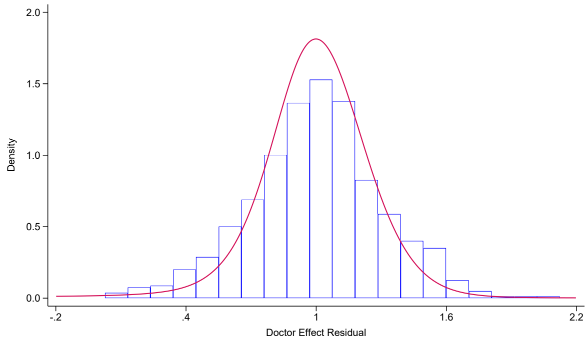


(a) Likelihood of Rated as Having Continued Impairment on Leave-Out Generosity Measure

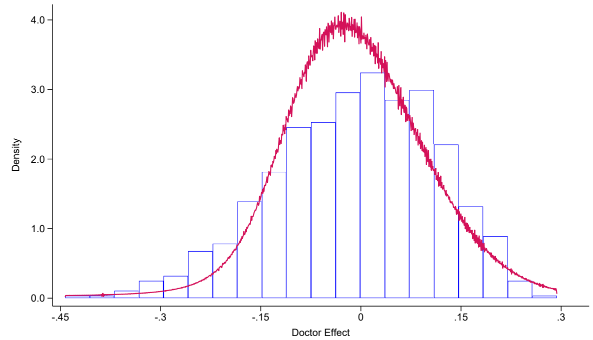
(b) Predicted Likelihood of Rated as Having Continued Impairment on Leave-Out Generosity Measure

Notes: This figure displays the distribution of the residualized leave-out generosity measure, along with its impact on claimants' likelihood of being rated as having continued impairment on the exam date (Panel A) and its impact on claimants' predicted likelihood of being rated as having continued impairment on the exam date based on baseline observables (Panel B). The leave-out generosity measure and the dependent variables are residualized for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. The solid lines are generated by local linear regressions of the residualized dependent variables on the residualized leave-out measure and correspond to the left vertical axis, while the histograms correspond to the right vertical axis. Dashed lines represent 95% confidence intervals calculated from standard errors clustered at the doctor level.

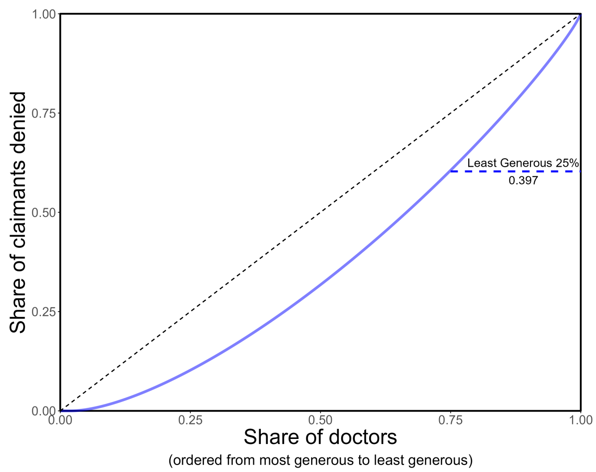
Figure 2: Distribution of Doctor Effects



(a) Distribution of Doctor Effect Residuals



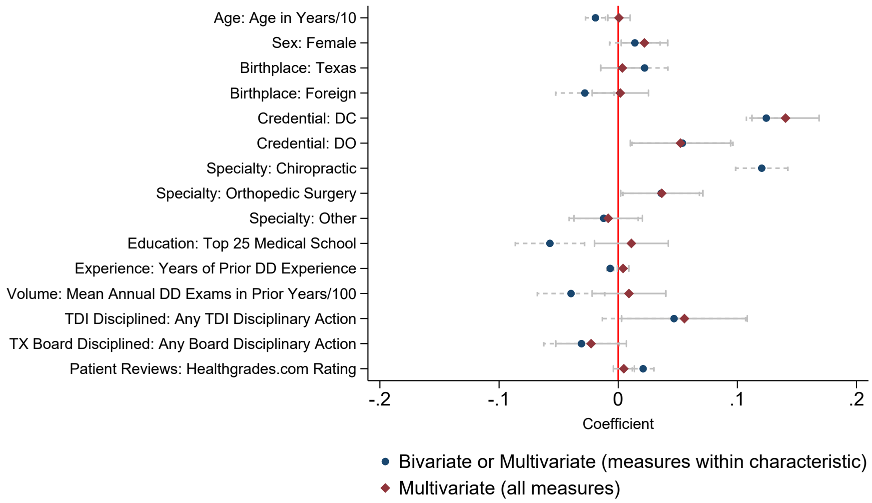
(b) Distribution of Doctor Effects



(c) Share of Denials Attributable to Doctors

Notes: Panel A reports the deconvoluted distribution of doctor effect residuals (solid line) overlaid on a histogram of the underlying empirical residuals (hollow bars), while Panel B reports the implied distribution of doctor effects (solid line) based on a change in variables applied to the distribution of residuals overlaid on a histogram of the underlying doctor effect estimates (hollow bars). As discussed in Appendix Section B.3, we calibrate maximum likelihood penalty parameters so that the implied variance from the deconvoluted distribution of residuals matches an unbiased variance estimate of r_d. The implied standard deviation of doctor effects based on the estimated distribution is 0.106, which is close to the implied standard deviation of 0.103 based on an unbiased split-sample variance estimate of θ_d. See Appendix Section B.3 for more details on this estimation. Panel C summarizes the concentration of denials in continued impairment assessments. In this panel, the horizontal axis displays the share of doctors where doctors are ordered from most generous to least generous, while the vertical axis displays the share of denials of continued benefits attributable to the most generous X% of doctors—where X is indicated on the horizontal axis.

Figure 3: Correlates of Doctor Effects



Notes: This figure displays coefficients from regressions of doctor effects estimated from Equation (2) on measures of doctor characteristics. The coefficients indicated by blue circles are from separate bivariate or multivariate regressions of the variable(s) for the characteristic indicated in the first part of the label. The coefficients indicated by red diamonds are from a single regression that includes all variables in the figure. Note this figure omits the multivariate coefficient for chiropractic specialty as this variable is equivalent to the indicator for doctor of chiropractic credential. 95% confidence intervals calculated using robust standard errors are shown along with the point estimates.

Table 1: Descriptive Statistics—Doctors

	Designated Doctors (1)	Texas Doctors Treating Injured Workers (2)	All Texas Doctors (3)	All U.S. Doctors (4)
MDs/DOs	49%	85%	91%	92%
Share Male	80%	76%	66%	66%
Mean Years Experience	33.92	23.41	25.42	21.57
Specialty:				
Internal or Family Medicine	47%	48%	38%	40%
Orthopedics	20%	25%	7%	7%
Other	34%	27%	55%	53%
Top 25 Medical School	47%	48%	38%	40%
DCs				
Share Male	81%	81%	72%	72%
Mean Years Experience	18.59	18.28	14.59	18.22
N	1,076	5,821	64,729	1,022,276

Notes: This table compares characteristics of doctors who perform independent medical exams to characteristics of broader populations of doctors. Column 1 displays information on our sample of designated doctors: doctors who performed at least five independent medical exams from 2013 to 2019 in doctor exam data from the TDI. Column 2 displays information on doctors who serve as treating doctors for workers injured from 2013 to 2019 in the Texas workers' compensation insurance medical data. Columns 3 and 4 display information on all doctors in Texas (in column 3) and nationwide (in column 4) based on the National Plan and Provider Enumeration System (NPPES) data through 2019. Information on years of experience and specialty comes from the NPPES data. Information on medical schools attended comes from the Medicare Physician Compare File, and we merge in information on medical schools' average research ranking in the U.S. News and World Report from 2010 to 2017 as reported in Schnell and Currie (2018). If an observation is missing information for a characteristic, that observation is excluded from the percent calculation so total percents sum to 100.

Table 2: Descriptive Statistics—Claimants

	All Claimants	Claimants with Independent Medical Exams
	(1)	(2)
Panel A. Claim Characteristics		
Male	0.61	0.65
Age	41.13	45.54
Claim Initiated with ED Visit	0.27	0.34
First-Day Medical Spending	585	1,114
Receives Income-Replacement Benefits within Three Years of Injury	0.19	0.83
Receives Permanent Impairment Benefits within Three Years of Injury	0.09	0.65
Injury Type:		
Contusion	0.15	0.09
Sprain or Muscle Issue	0.46	0.63
Other	0.39	0.27
Panel B. Characteristics of Claims with Independent Medical Exams		
Rated as Having Continued Impairment on Exam Date	-	0.78
Post-Exam Claim Outcomes (within Three Years after Exam)		
Total Additional Cash Benefits	-	8,205
Any Income-Replacement Benefits	-	0.33
Weeks Receiving Income-Replacement Benefits	-	7.94
Any Permanent Impairment Benefits	-	0.65
Permanent Impairment Rating	-	4.05
Medical Spending	-	6,122
Total Additional Workers' Compensation Benefits	-	14,327

Notes: This table compares all claimants injured from 2013 to 2019 (in column 1) to the baseline sample of claimants with independent medical exams (in column 2). The baseline sample of claimants with independent medical exams includes 91,899 claims for injuries occurring from 2013 to 2019 that had an independent medical exam by the end of 2019 and were evaluated by a doctor who performed at least five independent medical exams during the analysis period. All dollar values are CPI-U adjusted to 2019 dollars.

Table 3: Balance

	Leave-Out Doctor Generosity, $z_{d(i)i}$		
	coefficient	std error	p-value
	(1)	(2)	(3)
Male Claimant	0.006	(0.020)	[0.786]
Age	0.345	(0.530)	[0.516]
ED Claim	-0.010	(0.023)	[0.655]
Log(First-Day Medical Spending)	0.035	(0.060)	[0.558]
Log(Med Spending Prior to Exam Request)	-0.007	(0.047)	[0.887]
Log(Weeks from Injury to Exam Request)	0.003	(0.025)	[0.899]
Claimant Contested	0.002	(0.013)	[0.858]
Injury Type:			
Contusion	-0.002	(0.014)	[0.894]
Sprain or Muscle Issue	-0.003	(0.023)	[0.907]
Other	0.005	(0.020)	[0.824]
Industry:			
Agriculture/Forestry/Fishing/Hunting	-0.001	(0.004)	[0.785]
Arts/Entertainment/Accommodation/Food Services	0.006	(0.009)	[0.541]
Information/Finance/Real Estate/Professional Services	-0.012	(0.012)	[0.308]
Health Care/Educational Services	0.014	(0.015)	[0.355]
Manufacturing	0.013	(0.014)	[0.351]
Mining/Utilities/Construction	-0.019	(0.015)	[0.220]
Public Administration/Other Services	-0.008	(0.020)	[0.709]
Wholesale Trade/Retail Trade/Transportation	0.007	(0.019)	[0.716]
F-test for All Variables in Multivariate Regression [p-value]	0.564 [0.912]		

Notes: This table displays estimates of the coefficients on the leave-out measure of doctor generosity from OLS regressions of Equation (1) that control for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. Each row represents a separate regression with the dependent variable as indicated in the table. This analysis uses the baseline sample of claimants with independent medical exams (N = 91,899 claims) summarized in Table 2. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets. For the F-statistic shown at the bottom of the table, we regress leave-out-generosity on the baseline controls and on all the variables listed in the table. The F-statistic (and associated p-value) is for the joint hypothesis that the coefficients on all the variables listed in the table are zero.

Table 4: Impact of an Evaluation by a More Generous Doctor

	Dependent Variable Mean and Std Dev	Leave-Out Doctor Generosity, $z_{d(i)i}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.965	0.962
	(0.412)	(0.014)	(0.014)	(0.013)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,205	16,497	16,506	16,353
	(15,045)	(1,012)	(1,004)	(965)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.157	0.153
	(0.471)	(0.030)	(0.030)	(0.029)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	15.863	15.704
	(18.56)	(1.261)	(1.258)	(1.216)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	4,046	8,194	8,215	8,131
	(10,824)	(686)	(681)	(661)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.735	0.734
	(0.476)	(0.024)	(0.024)	(0.023)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	6.992	6.947
	(5.670)	(0.345)	(0.341)	(0.332)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,159	8,303.030	8,291.219	8,221.822
	(7,654)	(510.461)	(507.484)	(483.297)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	7,385.971	7,144.480
	(12,936)	(760.453)	(753.379)	(719.236)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,327	23,843.973	23,891.994	23,497.488
	(24,729)	(1,647.617)	(1,631.910)	(1,551.128)
		[<0.001]	[<0.001]	[<0.001]
Controls:				
Baseline		x	x	x
Claimant Demographics			x	x
Injury Diagnosis				x

Notes: Columns 2 through 4 of this table display estimates of the coefficients on the leave-out measure of doctor generosity described in Section 2 from separate OLS regressions of Equation (1) where the dependent variable is indicated in the corresponding row. Column 1 summarizes the mean and standard deviation of the indicated dependent variable. All regressions include the baseline controls for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. The regressions in columns 3 and 4 also control for claimants' age and gender, while the regressions in column 4 further control for initial injury diagnosis through indicators for three-digit ICD-9 diagnoses codes reported on the first date the injury was treated. This analysis uses the baseline sample of claimants with independent medical exams (N = 91,899 claims) summarized in Table 2. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table 5: Variation Across Doctors

	Rated as Having Continued Impairment (1)
Panel A	
F-test for Heterogeneity	4.835
	[<0.001]
Panel B	
Standard Deviation Based on Split Sample…	
Variance Estimator	0.102
	(0.007)
Cross-Time Covariance Estimator	0.099
	(0.007)
Cross-Age-Group Covariance Estimator	0.101
	(0.006)
Cross-Predicted-Impairment Covariance Estimator	0.103
	(0.006)

Notes: This table displays estimated standard deviations of doctor generosity and tests for heterogeneity in doctor generosity. Panel A displays the F-test statistic and associated p-value from a test of the null hypothesis of no heterogeneity in doctor generosity (i.e., that all doctor effects are jointly zero). Panel B displays the standard deviation of the variance estimator described in Section 3.1, as well as standard deviations from cross-time, cross-age-group, and cross-predicted-continued-impairment covariances between doctor-by-time, doctor-by-age, and doctor-by-predicted-continued-impairment differences in generosity.

Table 6: Relationship Between Doctor Generosity and Patient Volume

	(1)	(2)	(3)	(4)	(5)
			Panel A: Static. Dep Var: ln(N)		
DD X $\tilde{\theta}$	2.555	3.283	1.579	2.152	0.916
	(0.869)	(1.129)	(1.382)	(0.827)	(1.090)
	[0.003]	[0.004]	[0.253]	[0.009]	[0.401]
			Panel B: Dynamic. Dep Var: Δ		
DD X $\tilde{\theta}$	1.856	2.715	0.486	2.022	1.464
	(0.663)	(0.850)	(1.070)	(0.677)	(0.906)
	[0.005]	[0.001]	[0.650]	[0.003]	[0.106]
Sample Restriction	None	Medical Market HHI< Median	Medical Market HHI> Median	None	None
Claims used to Construct Dependent Variable	All Claims	All Claims	All Claims	Claims with Predicted Cash Benefits> Median	Claims with Predicted Cash Benefits< Median

Notes: This table displays estimates of the coefficients on doctor generosity from OLS regressions of Equation (4), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure and an indicator for the doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). The coefficient in each column is from a separate regression that includes controls for provider specialty by HSA fixed effects and an indicator for the doctor having a generosity measure. The dependent variable in Panel A is the natural log of the total number of claimants for whom the doctor serves as the treating doctor during the analysis period, while the dependent variable in Panel B is the mean annual growth rate from the first half of the analysis period to the second half of the analysis period in the number of claimants for whom the doctor is the treating doctor as defined in Section 5. The sample contains 5,821 doctors identified as being treating doctors for workers injured from 2013 to 2019. Robust standard errors are reported in parentheses, and p-values are reported in brackets.

Table 7: Relationship Between Doctor Generosity and Likelihood Claim Is Contested

	Independent Medical Exam is Requested	Insurer Requests Independent Medical Exam	Claimant Requests Independent Medical Exam
	(1)	(2)	(3)
DD X $\tilde{\theta}$	0.535	0.530	0.017
	(0.160)	(0.139)	(0.037)
	[0.001]	[<0.001]	[0.646]
Dependent Variable			
Mean	0.101	0.085	0.017
Standard Deviation	0.301	0.279	0.128

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for injury year-month fixed effects, patient's age, patient's sex, provider specialty by HSA fixed effects, and an indicator for the patient being treated by a doctor who has a generosity measure. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table 8: Relationship Between Doctor Generosity and Observational Outcomes

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD X $\tilde{\theta}$	0.631	20,798.395	0.563	25.223	0.524	3.705	14,197.431
	(0.228)	(5,902.926)	(0.226)	(7.832)	(0.148)	(0.979)	(5,276.059)
	[0.006]	[<0.001]	[0.013]	[0.001]	[<0.001]	[<0.001]	[0.007]
Dependent Variable							
Mean	0.269	3,012	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	10,384	0.428	14.09	0.321	2.467	8,266

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for injury year, provider specialty by HSA fixed effects, and an indicator for the patient being treated by a doctor who has a generosity measure. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table 9: Policy Counterfactuals: Alternative Pool of Doctors

	Doctors eligible to perform exams							
	All Observed Doctors (Baseline)		Doctors with MD or DO credentials		Doctors specializing in orthopedic surgery		Doctors with at least three years experience	
	(1)		(2)		(3)		(4)	
Panel A. Mean and Standard Deviation of Outcomes	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Rated as Having Continued Impairment	0.773	0.101	0.705	0.081	0.730	0.071	0.750	0.105
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Total Additional Cash Benefits	8,022	1,732	6,863	1,381	7,279	1,210	7,618	1,794
	(17.6)	(13.1)	(22.6)	(19.8)	(43.0)	(25.9)	(28.3)	(22.6)
Total Additional Workers' Compensation Costs	14,064	2,503	12,389	1,996	12,989	1,749	13,479	2,593
	(25.4)	(18.9)	(32.7)	(28.6)	(62.2)	(37.4)	(40.9)	(32.7)
Panel B. Mean Difference in Outcomes Relative to Baseline								
Rated as Having Continued Impairment	-		-0.068		-0.044		-0.024	
	-		(0.00005)		(0.00009)		(0.00006)	
Total Additional Cash Benefits	-		-1,159		-744		-404	
	-		(0.9)		(1.5)		(1.1)	
Total Additional Workers' Compensation Benefits	-		-1,675		-1,075		-585	
	-		(1.3)		(2.1)		(1.5)	

Notes: This table summarizes policy counterfactuals that vary the pool of doctors who are eligible to perform independent medical exams while holding fixed the assignment process. The analysis draws on the causal impact of being assigned a more generous doctor from Section 2 and the deconvoluted distribution of doctor effects described in Section 3. See Section 6 and Appendix Section C for more details.

Table 10: Policy Counterfactuals: Alternative Assignment Process

	Regulator Selects… one random doctor and assigns this doctor (Baseline)		Insurer Selects		Claimant Selects		one random doctor from specialty indicated by insurer and assigns this doctor		Regulator Selects… random panel of three doctors from which claimant chooses doctor		random panel of three doctors from which each party strikes one and remaining is assigned	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. Mean and Standard Deviation of Outcomes	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Rated as Having Continued Impairment	0.773	0.101	0.423	0.071	0.989	0.015	0.700	0.078	0.858	0.075	0.773	0.067
	(0.0010)	(0.0008)	(0.0065)	(0.0029)	(0.0003)	(0.0010)	(0.0018)	(0.0014)	(0.0011)	(0.0005)	(0.0010)	(0.0005)
Total Additional Cash Benefits	8,022	1,732	2,038	1,205	11,717	254	6,775	1,337	9,476	1,277	8,020	1,148
	(17.6)	(13.1)	(111.9)	(50.4)	(5.7)	(17.7)	(30.7)	(23.4)	(19.5)	(9.1)	(16.9)	(9.2)
Total Additional Workers' Compensation Costs	14,064	2,503	5,414	1,742	19,403	366	12,261	1,933	16,165	1,846	14,061	1,659
	(25.4)	(18.9)	(161.7)	(72.9)	(8.2)	(25.6)	(44.4)	(33.8)	(28.2)	(13.2)	(24.4)	(13.3)
Panel B. Mean Difference in Outcomes Relative to Baseline												
Rated as Having Continued Impairment	-		-0.350		0.216		-0.073		0.085		0.000	
	-		(0.00021)		(0.00003)		(0.00007)		(0.00005)		(0.00005)	
Total Additional Cash Benefits	-		-5,985		3,694		-1,247		1,453		-2	
	-		(3.6)		(0.6)		(1.1)		(0.8)		(0.8)	
Total Additional Workers' Compensation Benefits	-		-8,650		5,340		-1,803		2,101		-3	
	-		(5.2)		(0.8)		(1.6)		(1.2)		(1.1)	

Notes: This table summarizes policy counterfactuals that vary the process for assigning doctors to perform independent medical exams. The analysis draws on the causal impact of being assigned a more generous doctor from Section 2 and the deconvoluted distribution of doctor effects described in Section 3. See Section 6 and Appendix Section C for more details.

FOR ONLINE PUBLICATION

APPENDIX

A Additional Details on Setting and Data

Additional Information on Independent Medical Exams In the text, we summarize how decisions by designated doctors influence the receipt of benefits after an independent medical exam. Below, we provide more related details.

Decisions by designated doctors influence the cash benefits claimants receive after an independent medical exam. The claimant is eligible for further cash benefits after the exam if and only if the designated doctor determines that the claimant has a continued impairment on the date of the exam. If the designated doctor determines the claimant continues to be impaired on the date of the exam, the claimant is eligible for further cash benefits and the type of benefits the claimant receives depends on the healing trajectory of the claimant's injury. If the designated doctor decides the claimant has a continuing impairment but that the claimant has reached maximum medical improvement (i.e., the doctor determines that healing from the claimant's injury has reached a permanent plateau), the designated doctor assigns the claimant a permanent impairment rating and the claimant receives unconditional cash benefits that depend on this rating. If the designated doctor determines the claimant has a continued impairment but is still healing from the injury, the claimant is eligible to continue receiving temporary income benefits while out of work from the injury and can be assessed for permanent impairment in the future.

When a designated doctor decides a claimant has a continued impairment, the designated doctor influences the amount of future benefits at the initial exam by assigning a permanent impairment rating or by assigning a future date at which maximum medical improvement will be reached. If designated doctors determine the claimant is still healing from the injury and declines to provide a future date at which maximum medical improvement will be reached, future benefit decisions revert to the claimant's treating doctor, unless and until the insurer or claimant requests another designated doctor evaluation. Typically, future decisions are governed by the workers' normal treating doctor. In our data, only 12% of claims with independent medical exams have a subsequent independent medical exam requested in the six months after the initial exam. While designated doctors have sole discretion over whether a claimant is eligible for cash benefits after the independent medical exam, subsequent actions by employers, insurers, treating doctors, and claimants can all influence the broader post-exam outcomes we examine, including: compensated duration out of work recovering from injury, total cash benefits, injury-related medical care, and total workers' compensation costs. Because subsequent actions taken by the worker, employer, insurer, and treating doctor may all be influenced by decisions made by the designated doctor in the independent medical exam, we focus on characterizing doctor generosity through the designated doctor's assessment at an initial independent medical exam and summarize impacts on subsequent broader outcomes over the three years following the exam.

Information on Initial Diagnoses and County We identify claimant county using information on claimants' zipcode from the medical data. We exclude the small numbers of claims with missing county information (1.8%) or for people who reside outside of Texas (1.0%).

We classify injuries as being contusions, sprains or muscle issues, or other injuries based on the most commonly listed ICD-9 code of the earliest medical treatment. We use this injury classification when testing for balance and some supplemental analysis. For bills that list ICD-10 codes, we convert ICD-10 codes to ICD-9 codes using a crosswalk from the Centers for Medicare & Medicaid Services (CMS) so that we have consistent definitions of injuries over time.

Additional Details on Doctors The analysis of independent medical exams focuses on the 99.6% of exams performed by medical doctors (MD), doctors of osteopathy (DO), and doctors of chiropractic (DC); this excludes the 0.4% of exams performed by providers with other credentials (e.g., nurse practitioners and physical therapists). We identify doctors' National Provider Identifiers (NPI) from the medical claims data and exclude the 2% of exams performed by doctors with missing NPIs.

For the analysis of treating doctors, we identify a claimant's treating doctor as the doctor who bills the most case management services for the claimant. As with the designated doctor analysis, we focus on treating doctors with MD, DO, or DC credentials and with non-missing NPI information, and we focus on doctors in Texas who treat claimants residing in Texas.

For both samples of doctors, we create the specialty variables using information on taxonomy codes from the National Plan and Provider Enumeration System (NPPES). We identify doctors' Hospital Service Areas (HSAs) by merging doctors' most commonly billed zipcode in the medical claims data to the zipcode to HSA crosswalk from Dartmouth Atlas (2013).

Identifying Doctor Specialty Our specialty measure is based on the first four digits of the provider taxonomy codes obtained from CMS 2019b. The first four digits associated with each specialty are as follows: chiropractic: 111N; internal or family medicine: 207Q, 207R, 2083, and 208D; orthopedics: 207X and 2086; physical medicine: 2081; emergency medicine: 207P; neurology: 2084; psychiatry: 207W and 3902; and other specialty: all other four-digit taxonomy codes.

B Distribution of Doctor Effects

In this appendix section, we provide further details on how we estimate doctor effects and various features of the distribution of these effects.

B.1 Estimating Doctor Effects

We estimate doctor effects as described in Section 3. We let θ_d denote the generosity of doctor $d \in \{1, .., D\}$ and estimate these using the following specification:

$$y_i = \gamma_{d(i)} + \phi_{r(i)t(i)c(i)} + \mathbf{X_i}\mathbf{\Sigma} + e_i, \tag{6}$$

where $\hat{\theta}_d \equiv \gamma_{d(i)}$ is our measure of doctor effects (also referred to as "doctor generosity" throughout). The dependent variable is an indicator for the claimant having been assessed as having a continued impairment on the date of the independent medical exam. This equation also includes fixed effects for the claimant's county by required doctor credential by year-quarter of the independent medical exam ($\phi_{r(i)t(i)c(i)}$) and controls for injury year ($\mathbf{X_i}$). Since doctor effects are identified by comparing doctors to one another, we normalize the exam-weighted mean doctor effect to zero. We calculate standard errors on these doctor effects through bootstrapping.

Given the conditional random assignment of doctors to exams, γ_d estimates from Equation (6) should provide unbiased estimates of the assigned doctor's impact on the assessment of continued impairment in these exams. Supplemental analysis suggests the included controls are sufficient to isolate conditional random assignment. Appendix Figure A1 shows that claimant characteristics are balanced across average doctor characteristics (e.g., age, gender, credential) conditional on the included baseline controls. Additionally, we estimate a variant of Equation (6) replacing the dependent variable with the predicted value of being assessed as having a continued impairment, where this prediction is based on baseline observables. The associated F-statistic for joint significance of the doctor effects in this estimation is 1.033 with a p-value of 0.223. This is much smaller than the F-statistic for joint significance of the doctor effects using the actual assessment of continued impairment (4.835, with a p-value less than 0.001). This evidence supports our use of the baseline specification in isolating the conditional random assignment in this setting.

B.2 Estimating Variance of Doctor Effects

We estimate the variance of doctor effects θ_d, which is defined as: $\sigma \equiv \frac{1}{D}\sum_{d=1}^{D}\theta_d^2 - \left(\frac{1}{D}\sum_{d=1}^{D}\theta_d\right)^2$. If we simply plug in our doctor effect estimates in this equation, we obtain a variance of 0.013 and an implied standard deviation of 0.115. However, this is an upward biased estimate of the true variance, due to sampling error in the estimation for doctor effects. To obtain an unbiased estimate of the variance, we leverage a split-sample approach similar to approaches leveraged in other studies (e.g., Silver 2020; Chan and Chen 2022). To implement this approach, we re-estimate Equation (6) using two partitions of the data, where these partitions are constructed by randomly sampling a doctor's independent medical exam so that a doctor's exams are roughly equally divided across the two partitions. This procedure produces two noisy estimates of the doctor effects: $\hat{\theta}_{d,a}$ and $\hat{\theta}_{d,b}$ from partitions a and b respectively. Dropping the d subscript for simplicity, we can express these estimates as:

$$\hat{\theta}_p = \theta + \epsilon_p, \qquad p \in \{a, b\}, \tag{7}$$

where p denotes partition and ϵ_p represents sampling error in the partition-specific estimates such that $Cov(\theta, \epsilon_p) = 0$. Because these partitions are formed through stratified random sub-sampling, these two estimates are plausibly independent, and hence ϵ_a and ϵ_b are uncorrelated ($Cov(\epsilon_a, \epsilon_b) = 0$). Thus, the covariance between these two estimates provides an unbiased estimate of the variance of the doctor effects:

$$\begin{aligned} Cov(\widehat{\theta}_a, \widehat{\theta}_b) &= Cov(\theta + \epsilon_a, \theta + \epsilon_b) & (8) \\ &= Cov(\theta, \theta) + Cov(\theta, \epsilon_b) + Cov(\epsilon_a, \theta) + Cov(\epsilon_a, \epsilon_b) & (9) \\ &= Var(\theta). \end{aligned}$$

As reported in Table 5 of the text, the standard deviation based on this unbiased variance estimate of doctor effects is 0.102. This is roughly 89% of the naive implied standard deviation that does not account for sampling error. In Appendix Table A5, we demonstrate we obtain a similar implied standard deviation of 0.105 if we use an alternative strategy to calculate an unbiased variance estimate similar to that in Kline, Rose, and Walters (2022).

B.3 Estimating the Distribution of Doctor Effects

To characterize the population distribution of doctor effects, we apply an approach following Walters (2024) and Kline, Rose, and Walters (2024) based on Efron (2016). This approach produces a flexible empirical Bayes prior distribution of the population of doctor effects, taking as inputs the estimated doctor effects and associated standard errors. As in many settings, the estimates of interest are correlated with the associated standard errors in our setting. Specifically, following tests recommended in Walters (2024), we empirically assess potential dependence by regressing $\hat{\theta}_d$ on $log\ s_d$, which yields a coefficient of -0.123 with a robust standard error of 0.009.

Motivated by this and in line with guidance in Walters (2024), we estimate a model of dependence between the doctor effects and standard errors, then deconvolve residuals from this model. Specifically, we consider the following model:

$$\theta_d = \phi_1 + \phi_2 r_d \, log\ s_d, \quad r_d | s_d \sim G_r \tag{10}$$

where θ_d is the doctor effect, s_d is the associated standard error, r_d is the residual, and $E[r_d] = 1$. This model implies $E[\hat{\theta}_d | s_d] = \phi_1 + \phi_2 \, log\ s_d$. We estimate ϕ_1 and ϕ_2 by OLS regression and use these estimates to form residuals, $\hat{r}_d = \frac{\hat{\theta}_d - \hat{\phi}_1}{\hat{\phi}_2 \, log\ s_d}$.

We then estimate G_r using a log-spline deconvolution estimator described in Walters (2024) based on Efron (2016) applied to these residuals, assuming $\hat{r}_d | r_d, s_d \sim \mathcal{N}\big(r_d, \frac{s_d^2}{(\phi_2 \, log\ s_d)^2}\big)$. This procedure approximates G_r with a smooth log density parameterized by a natural cubic spline, where the parameters of this spline are estimated via penalized maximum likelihood. As in Walters (2024), we calibrate penalty parameter in the maximum likelihood estimation so that the implied variance from the deconvoluted distribution matches an unbiased variance estimate of r_d.[1] In practice, we select the other log-spline tuning parameters by setting the number of spline knots to five and using 1,000 equally spaced support points over the range of r considered, where we constrain this range to span from the minimum to the maximum implied value of r evaluated at the empirical minimum and maximum of θ, respectively.[2]

Using this distribution, we recover the marginal distribution of θ_d by applying a change in variables to the distribution of the residuals combined with the empirical distribution of the standard errors, where we constrain the range of this distribution to the empirical range of $\hat{\theta}_d$. Figure 2 Panel A in the text displays the

[1] Note that we estimate the unbiased variance of r_d following a split-sample approach similar to that used to estimate the unbiased variance of θ_d.

[2] Specifically, the range of r considered is $[min_d(\frac{min_d(\hat{\theta}_d) - \hat{\phi}_1}{\hat{\phi}_2 \, log\ s_d}), max_d(\frac{max_d(\hat{\theta}_d) - \hat{\phi}_1}{\hat{\phi}_2 \, log\ s_d})]$. To avoid the inclusion of noisy estimates of doctor effects, our deconvolution excludes doctors with less than 20 independent medical exams. We note that the implied standard deviation of doctor effects in this restricted sample used in the deconvolution (0.103) is nearly identical to that reported in Table 5 for the full sample (0.102).

deconvoluted distribution of the residuals, and Panel B displays the implied distribution of doctor effects. Figure 2 Panel C plots an associated curve summarizing the concentration of denials in impairment assessments. As reported in the text, the estimates imply the least generous 25% of doctors are responsible for 39.7% of the denials of continued impairment, while the most generous 25% of doctors are only responsible for 10.2% of continued impairment denials.

B.4 Empirical Bayes Posteriors of Doctor Effects

We calculate empirical Bayes posteriors of doctor effects as in Walters (2024). Specifically, we compute the posterior mean residuals $\hat{r}_d^*$ and then transform these to predict θ_d according to Equation (10). See Appendix Figure A2 comparing histograms of the doctor effects and empirical Bayes posteriors.

C Policy Counterfactuals: Additional Details

As described in Section 6, we use our estimates to analyze policy counterfactuals related to independent medical exams. Specifically, we consider two types of policy counterfactuals: (i) changing the pool of doctors eligible to perform independent exams and (ii) changing the current assignment process.

In these counterfactuals, we consider the impacts on claimant outcomes subsequent to the exam—by combining projected changes in doctor generosity with our estimates of the causal impact of being assigned a more generous doctor from Section 2. We consider impacts on three outcomes: being rated as having a continued impairment, subsequent cash benefits, and subsequent total workers' compensation costs (the sum of subsequent cash benefits and medical spending). This analysis draws on the estimated distribution of doctor effects described in Section 3 and holds fixed the set of claims for which an independent medical exam is requested—meaning these counterfactuals do not capture any general equilibrium adjustments (e.g., changes in which claims are disputed). Counterfactuals analyzing the impact of changing the pool of eligible doctors draw on analogous distributions we estimate for subsets of doctors—using the same approach outlined in Appendix Section B.3. Appendix Figure A3 displays estimated distributions for the subsets of doctors we consider, where this figure displays the estimated distributions for doctor effect residuals and the implied distribution of doctor effects side-by-side for the indicated subsets of doctors.

Below, we provide more details on the setup of the counterfactuals. In these counterfactuals, we estimate impacts on outcomes for the population of claims with independent medical exams observed over the analysis period, where claims are distributed across counties as observed in the data. For each doctor eligibility criteria considered, we begin by defining the pool of doctors available in each county, where we construct this pool by drawing from the estimated distribution of doctor effects corresponding to doctors eligible to perform the exams. When constructing the pools of doctors for each county, the number of draws in a given county corresponds to the observed number of distinct independent doctors in the county over our analysis period, setting a floor on this value of ten to ensure a nontrivial pool of available doctors in the few counties with only a handful of exams during the analysis period.

Counterfactuals Varying Eligibility Criteria For each claim, we randomly assign one doctor from the claim's county from the constructed pool of available doctors meeting the relevant eligibility criteria, as defined above. We then simulate outcomes for each claim using the associated doctor effect and the estimates from Table 4, where the simulated outcomes are defined as: $\hat{y}_i \equiv \bar{y} + \theta_{d(i)}\hat{\beta}_y$, where $\theta_{d(i)}$ is the doctor effect of the doctor assigned to claim i, $\hat{\beta}_y$ is the coefficient estimate for outcome y, $\bar{y}$ is the mean of outcome y.

Counterfactuals Varying Allocation Process For these counterfactuals, the process we followed for assigning doctors to claims in each of the allocation systems considered is outlined below.

- **Baseline.** For each claim, randomly assign one doctor from the constructed pool of doctors available in the claim's county (as described above).
- **Insurer selects a doctor.** For each claim, assign the doctor who is the least generous from the pool of doctors available in the claim's county (as described above).
- **Claimant selects a doctor.** For each claim, assign the doctor who is the most generous from the pool of doctors available in the claim's county (as described above).

- **Regulator selects a randomly assigned doctor with specialty chosen by insurer.** For each claim, randomly assign one doctor from the constructed pool of doctors available in the claim's county who specialize in primary care/internal medicine (as described above). (Note: Analysis reported in the paper indicates primary care/internal medicine is the least generous specialty on average.)

- **Regulator randomly selects a panel of three doctors from which claimant chooses a doctor.** For each claim, randomly select three distinct doctors from the constructed pool of available doctors in the claim's county (as described above), and assign the most generous among these three doctors.

- **Regulator randomly selects a panel of three doctors from which each party strikes one and the remaining doctor assigned.** For each claim, randomly select three distinct doctors from the constructed pool of available doctors in claim's county (as described above), and assign the median generosity doctor among these three doctors.

For each counterfactual considered, we then simulate outcomes for each claim using the associated doctor effect and the estimates from Table 4, where the simulated outcomes are defined as: $\hat{y}_i \equiv \bar{y} + \theta_{d(i)}\hat{\beta}_y$, where $\theta_{d(i)}$ is the doctor effect of the doctor assigned to claim i, $\hat{\beta}_y$ is the coefficient estimate for outcome y, $\bar{y}$ is the mean of outcome y.

Table A1: Balance for Exams All Doctors Can Perform

	Indicator Doctor Credential DC		
	coefficient	std error	p-value
	(1)	(2)	(3)
Male Claimant	0.010	(0.023)	[0.667]
Age	-0.706	(0.551)	[0.201]
ED Claim	-0.028	(0.021)	[0.171]
Log(First-Day Medical Spending)	-0.027	(0.047)	[0.568]
Log(Med Spending Prior to Exam Request)	-0.032	(0.041)	[0.434]
Log(Weeks from Injury to Exam Request)	0.006	(0.027)	[0.821]
Claimant Contested	-0.019	(0.015)	[0.200]
Injury Type:			
Contusion	0.001	(0.009)	[0.903]
Sprain or Muscle Issue	0.009	(0.013)	[0.489]
Other	-0.010	(0.009)	[0.293]
Industry:			
Agriculture/Forestry/Fishing/Hunting	-0.004	(0.004)	[0.341]
Arts/Entertainment/Accommodation/Food Services	-0.005	(0.010)	[0.647]
Information/Finance/Real Estate/Professional Services	-0.006	(0.014)	[0.664]
Health Care/Educational Services	-0.010	(0.017)	[0.547]
Manufacturing	0.012	(0.017)	[0.473]
Mining/Utilities/Construction	-0.001	(0.016)	[0.935]
Public Administration/Other Services	-0.024	(0.021)	[0.244]
Wholesale Trade/Retail Trade/Transportation	0.039	(0.021)	[0.061]
F-test for All Variables in Multivariate Regression [p-value]	0.733 [0.763]		

Notes: This table displays estimates of coefficients on an indicator variable for doctors having a DC credential from OLS regressions that control for injury year, claimant county by exam year-quarter fixed effects, and an indicator variable for doctors having a DO credential. Each row represents a separate regression with the dependent variable as indicated in the table. This analysis uses the sample of claimants with independent medical exams for straightforward musculoskeletal injuries of the back—a category of injury for which state law explicitly stipulates independent exams can be performed by doctors with any credential (N = 5,631 claims). Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets. For the F-statistic shown in the bottom of the table, we regress an indicator for the doctor having a DC credential on the baseline controls and on all the variables listed in the table. The F-statistic (and associated p-value) is for the joint hypothesis that the coefficients on all the variables listed in the table are zero.

Table A2: Impact of an Evaluation by a More Generous Doctor—Alternate Controls

	Dependent Variable Mean and Std Dev	Leave-Out Doctor Generosity, $z_{d(i)i}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.979	0.985
	(0.412)	(0.014)	(0.013)	(0.024)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,205	16,497	16,648	17,674
	(15,045)	(1,012)	(1,035)	(1,113)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.163	0.209
	(0.471)	(0.030)	(0.029)	(0.036)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	15.792	17.234
	(18.56)	(1.261)	(1.279)	(1.447)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	4,046	8,194	8,236	8,658
	(10,824)	(686)	(700)	(806)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.747	0.766
	(0.476)	(0.024)	(0.024)	(0.031)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	7.150	7.641
	(5.670)	(0.345)	(0.340)	(0.386)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,159	8,303.030	8,412.129	9,015.867
	(7,654)	(510.461)	(512.116)	(531.774)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	7,297.685	7,686.307
	(12,936)	(760.453)	(747.443)	(830.975)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,327	23,843.973	23,945.352	25,360.180
	(24,729)	(1,647.617)	(1,660.293)	(1,776.988)
		[<0.001]	[<0.001]	[<0.001]
Controls:				
Baseline: Required credential X county X exam year-quarter		x		
Required credential X county X exam year			x	
Required credential X county X exam year-quarter X insurer				x

Notes: Columns 2 through 4 of this table display estimates of the coefficients on the leave-out measure of doctor generosity described in Section 2 from separate OLS regressions of Equation (1) where the dependent variable is indicated in the corresponding row. Column 1 summarizes the mean and standard deviation of the indicated dependent variable. All regressions include the baseline controls for injury year. Column 2 reports results from the baseline specification, which additionally controls for required credential by claimant county by exam year-quarter. The regressions in columns 3 and 4 consider alternative additional controls: required credential by claimant county by exam year (column 3) and required credential by claimant county by exam year-quarter by insurer (in column 4). This analysis uses the baseline sample of claimants with independent medical exams (N = 91,899 claims) summarized in Table 2. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A3: Impact of an Evaluation by a More Generous Doctor—Alternate Specifications

	Dependent Variable Mean and Std Dev	Doctor Generosity, $z_{d(i)i}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.877	1.000
	(0.412)	(0.014)	(0.017)	(0.005)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,205	16,497.336	14,903.627	14,871.377
	(15,045)	(1,012.363)	(935.187)	(790.409)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.130	0.175
	(0.471)	(0.030)	(0.028)	(0.024)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	14.074	14.578
	(18.56)	(1.261)	(1.184)	(0.991)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	4,046	8,194.306	7,441.191	7,467.638
	(10,824)	(685.886)	(641.879)	(535.955)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.677	0.733
	(0.476)	(0.024)	(0.023)	(0.018)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	6.344	6.342
	(5.670)	(0.345)	(0.318)	(0.274)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,159	8,303.030	7,462.436	7,403.739
	(7,654)	(510.461)	(467.781)	(398.686)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	6,297.187	6,993.067
	(12,936)	(760.453)	(703.867)	(605.576)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,327	23,843.973	21,200.812	21,864.443
	(24,729)	(1,647.617)	(1,518.484)	(1,291.995)
		[<0.001]	[<0.001]	[<0.001]
Doctor Generosity Measure				
Baseline		x		
Alternative: Leave-Out Mean Shrunk Using Deconvoluted Distribution			x	
Alternative: Doctor Effects Estimated in Section 3				x

Notes: Columns 2 through 4 of this table display estimates of the coefficients on the indicated measure of doctor generosity from separate OLS regressions of Equation (1) where the dependent variable is indicated in the corresponding row. Column 1 summarizes the mean and standard deviation of the indicated dependent variable. All regressions include the baseline controls for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. Column 2 reports the baseline results for reference. Columns 3 and 4 report results from specifications using alternative measures of doctor generosity. Specifically, Column 3 reports results from a specification using a measure of doctor generosity obtained by applying an empirical Bayes shrinkage procedure to the de-meaned leave-out continued impairment rate using the deconvoluted distribution estimated in Section 3.2, while column 4 reports results from a specification using the doctor fixed effects from Equation (2) as the measure of doctor generosity. This analysis uses the baseline sample of claimants with independent medical exams (N = 91,899 claims) summarized in Table 2. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A4: Impact of an Evaluation by a More Generous Doctor: Outcomes Measured over Different Horizons

	Panel A: Cash Benefits					
	0-6 months	7-12 months	13-18 months	19-24 months	25-30 months	31-36 months
	(1)	(2)	(3)	(4)	(5)	(6)
Doctor Generosity, $Z_{d(i)i}$	7,154.222	4,828.202	2,485.023	1,345.529	517.623	166.644
	(351.763)	(332.695)	(219.150)	(137.871)	(70.560)	(39.285)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Dependent Variable						
Mean	4,290	2,084	1,068	514	184	65
Standard Deviation	6,004	4,956	3,627	2,437	1,424	883
Implied % Impact for One Std. Dev.	17%	24%	24%	27%	29%	26%

	Panel B: Weeks out of Work Receiving Income Benefits					
	0-6 months	7-12 months	13-18 months	19-24 months	25-30 months	31-36 months
	(1)	(2)	(3)	(4)	(5)	(6)
Doctor Generosity, $Z_{d(i)i}$	7.998	5.323	2.051	0.389	0.047	0.005
	(0.622)	(0.422)	(0.250)	(0.076)	(0.025)	(0.016)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.064]	[0.740]
Dependent Variable						
Mean	4.465	2.283	0.980	0.182	0.020	0.009
Standard Deviation	8.818	6.860	4.441	1.614	0.639	0.450
Implied % Impact for One Std. Dev.	18%	24%	21%	22%	24%	6%

	Panel C: Medical Spending					
	0-6 months	7-12 months	13-18 months	19-24 months	25-30 months	31-36 months
	(1)	(2)	(3)	(4)	(5)	(6)
Doctor Generosity, $Z_{d(i)i}$	2,582.034	2,128.169	1,373.600	817.342	307.590	293.362
	(303.263)	(258.018)	(186.709)	(152.252)	(110.127)	(80.220)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.005]	[<0.001]
Dependent Variable						
Mean	2,760	1,613	909	557	310	199
Standard Deviation	5,887	5,074	3,946	3,190	2,897	1,990
Implied % Impact for One Std. Dev.	10%	13%	15%	15%	10%	15%

Notes: This table displays estimates of the coefficients on the leave-out measure of doctor generosity described in Section 2 from separate OLS regressions of Equation (1) with dependent variables indicated in the panels as measured at various points in time after the exam. Panel A displays estimates for weeks of income replacement benefits, while Panel B displays estimates for medical spending. All regressions include the baseline controls for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. This analysis uses the baseline sample of claimants with independent medical exams (N = 91,899 claims) summarized in Table 2. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A5: Variation Across Doctors Across Different Outcome Measures

	F-test for Heterogeneity	Standard Deviation Based on Split-Sample Variance Estimator	Standard Deviation Based on Variance Estimated Using Approach as in KRW (2022)
	(1)	(2)	(3)
Rated as Having Continued Impairment on Exam Date	4.835	0.102	0.105
	[<0.001]	(0.007)	(0.003)
Total Additional Cash Benefits	2.222	2,031	2,070
	[<0.001]	(214)	(120)
Any Income-Replacement Benefits	1.658	0.048	0.050
	[<0.001]	(0.010)	(0.004)
Weeks Receiving Income-Replacement Benefits	2.289	2.339	2.596
	[<0.001]	(0.235)	(0.138)
Amount of Income-Replacement Benefits	1.899	1,242.859	1,357.547
	[<0.001]	(140.072)	(83.663)
Any Permanent Impairment Benefits	2.892	0.082	0.086
	[<0.001]	(0.007)	(0.003)
Permanent Impairment Rating	2.372	0.734	0.804
	[<0.001]	(0.087)	(0.041)
Amount of Permanent Impairment Benefits	2.154	1,062.711	1,026.074
	[<0.001]	(176.074)	(57.248)
Medical Spending	1.638	1,094	1,190
	[<0.001]	(246)	(78)
Total Additional Workers' Compensation Benefits	2.100	2,983	3,149
	[<0.001]	(346)	(172)

Notes: This table displays estimated standard deviations of doctor effects and tests for heterogeneity in doctor effects for the claim outcome measures indicated in the row. Column 1 displays the F-test statistic and associated p-value from a test of the null hypothesis of no heterogeneity in doctor generosity (i.e., that all doctor effects are jointly zero). Column 2 displays the standard deviation of the split-sample variance estimator described in Section 3.1. Column 3 displays the standard deviation of the variance estimator based on an approach as in Kline, Rose, and Walters (2022).

Table A6: Variation Across Doctors, by Ex Ante Predicted Dispute Likelihood

	Rated as Having Continued Impairment
	(1)
Standard Deviation Based on Split Sample…	
Variance Estimator	0.102
	(0.007)
Cross-Predicted-Dispute-Likelihood Covariance Estimator (prediction using claimant information)	0.103
	(0.006)
Cross-Predicted-Dispute-Likelihood Covariance Estimator (+ insurer fixed effects)	0.100
	(0.006)
Cross-Predicted-Dispute-Likelihood Covariance Estimator (+ treating doctor information)	0.104
	(0.006)

Notes: This table displays the standard deviation of the baseline variance estimator described in Section 3.1, as well as standard deviations from cross-predicted-dispute-likelihood covariances between doctor-by-predicted-dispute-likelihood differences in generosity. To create the measure of ex ante predicted dispute likelihood, we first fit a lasso model of the likelihood that claims are disputed based on baseline claim characteristics using the broader sample of all claims from 2013 to 2019 and then use the fitted values to predict each claim's ex ante likelihood of being disputed. The first prediction model includes a quadratic in age and indicator variables for day of the week of first medical treatment, the calendar month of injury, the year of injury, sex, industry, injury type, and the claim originating in the emergency department. The second prediction model includes insurer fixed effects in addition to patient characteristics. The third prediction model includes indicator variables for treating doctor specialty and sex in addition to patient characteristics and insurer fixed effects.

Table A7: Relationship Between Doctor Generosity and Patient Volume—Alternate Specifications

	Static			Dynamic		
	Dep Var: ln(N)			Dep Var: Δ		
	(1)	(2)	(3)	(4)	(5)	(6)
DD X $\tilde{\theta}$	2.555	2.453	2.407	1.856	1.753	1.858
	(0.869)	(0.834)	(0.860)	(0.663)	(0.642)	(0.656)
	[0.003]	[0.003]	[0.005]	[0.005]	[0.006]	[0.005]
Controls						
Specialty X HSA (Baseline)	x			x		
Specialty X HRR		x			x	
Specialty X County			x			x

Notes: This table displays estimates of the coefficients on doctor generosity from OLS regressions of Equation (4), where the measure of doctor generosity is calculated using empirical Bayes shrinkage with the deconvoluted distribution estimated in Section 3 on the coefficients from Equation (2). The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure and an indicator for the doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). The coefficient in each column is from a separate regression that includes an indicator for the doctor having a generosity measure and the controls indicated in the table. The dependent variable for columns 1 through 3 is the natural log of the total number of claimants for whom the doctor serves as the treating doctor during the analysis period, while the dependent variable in columns 4 through 6 is the mean annual growth rate from the first half of the analysis period to the second half of the analysis period in the number of claimants for whom the doctor is the treating doctor as defined in Section 5. The sample contains 5,821 doctors identified as being treating doctors for workers injured from 2013 to 2019. Robust standard errors are reported in parentheses, and p-values are reported in brackets.

Table A8: Relationship Between Doctor Generosity and Patient Volume—Unadjusted Doctor Effects

	(1)	(2)	(3)	(4)	(5)
			Panel A: Static. Dep Var: ln(N)		
DD X $\tilde{\theta}$	2.447	3.085	1.527	2.324	1.632
	(0.611)	(0.806)	(0.945)	(0.586)	(0.773)
	[<0.001]	[<0.001]	[0.106]	[<0.001]	[0.035]
			Panel B: Dynamic. Dep Var: Δ		
DD X $\tilde{\theta}$	1.367	2.047	0.342	1.529	1.119
	(0.466)	(0.608)	(0.732)	(0.480)	(0.643)
	[0.003]	[0.001]	[0.641]	[0.001]	[0.082]
Sample Restriction	None	Medical Market HHI< Median	Medical Market HHI> Median	None	None
Claims used to Construct Dependent Variable	All Claims	All Claims	All Claims	Claims with Predicted Cash Benefits> Median	Claims with Predicted Cash Benefits< Median

Notes: This table displays estimates of the coefficients on doctor generosity from OLS regressions of Equation (4), where the measure of doctor generosity is calculated using the unadjusted coefficients from Equation (2). The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure and an indicator for the doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). The coefficient in each column is from a separate regression that includes controls for provider specialty by HSA fixed effects and an indicator for the doctor having a generosity measure. The dependent variable in Panel A is the natural log of the total number of claimants for whom the doctor serves as the treating doctor during the analysis period, while the dependent variable in Panel B is the mean annual growth rate from the first half of the analysis period to the second half of the analysis period in the number of claimants for whom the doctor is the treating doctor as defined in Section 5. The sample contains 5,821 doctors identified as being treating doctors for workers injured from 2013 to 2019. Robust standard errors are reported in parentheses, and p-values are reported in brackets.

Table A9: Relationship Between Doctor Generosity and Likelihood Claim is Contested—Alternate Specifications

	Independent Medical Exam is Requested			Insurer Requests Independent Medical Exam			Claimant Requests Independent Medical Exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DD X $\tilde{\theta}$	0.535	0.498	0.528	0.530	0.499	0.528	0.017	0.012	0.012
	(0.160)	(0.146)	(0.154)	(0.139)	(0.128)	(0.135)	(0.037)	(0.036)	(0.035)
	[0.001]	[0.001]	[0.001]	[<0.001]	[<0.001]	[<0.001]	[0.646]	[0.736]	[0.725]
Controls									
Injury Year-Month, Claimant Sex and Age	x	x	x	x	x	x	x	x	x
Specialty X HSA	x	x		x	x		x	x	
Specialty X HRR			x			x			x
Additional Claimant Characteristics		x			x			x	

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for an indicator for the patient being treated by a doctor who has a generosity measure and the controls indicated in the table. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A10: Relationship Between Doctor Generosity and Likelihood Claim is Contested—Unadjusted Doctor Effects

	Independent Medical Exam is Requested	Insurer Requests Independent Medical Exam	Claimant Requests Independent Medical Exam
	(1)	(2)	(3)
DD X $\tilde{\theta}$	0.310	0.280	0.036
	(0.104)	(0.089)	(0.023)
	[0.003]	[0.002]	[0.118]
Dependent Variable			
Mean	0.101	0.085	0.017
Standard Deviation	0.301	0.279	0.128

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using the unadjusted coefficients from Equation (2). The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for injury year-month fixed effects, patient's age, patient's sex, provider specialty by HSA fixed effects, and an indicator for the patient being treated by a doctor who has a generosity measure. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A11: Relationship Between Doctor Generosity and Observational Outcomes—Alternate Specifications

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline Specification							
DD X $\tilde{\theta}$	0.631	20,798.395	0.563	25.223	0.524	3.705	14,197.431
	(0.228)	(5,902.926)	(0.226)	(7.832)	(0.148)	(0.979)	(5,276.059)
	[0.006]	[<0.001]	[0.013]	[0.001]	[<0.001]	[<0.001]	[0.007]
Panel B: Including Basic Claimant Controls							
DD X $\tilde{\theta}$	0.631	20,725.510	0.562	25.128	0.524	3.706	14,169.184
	(0.221)	(5,696.335)	(0.219)	(7.632)	(0.144)	(0.950)	(5,141.990)
	[0.004]	[<0.001]	[0.010]	[0.001]	[<0.001]	[<0.001]	[0.006]
Panel C: Including Expanded Claimant Controls							
DD X $\tilde{\theta}$	0.537	19,371.951	0.471	23.293	0.492	3.450	12,585.068
	(0.187)	(5,228.663)	(0.187)	(6.995)	(0.129)	(0.852)	(4,641.200)
	[0.004]	[<0.001]	[0.012]	[0.001]	[<0.001]	[<0.001]	[0.007]
Dependent Variable							
Mean	0.269	3,012	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	10,384	0.428	14.09	0.321	2.467	8,266

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for an indicator for the patient being treated by a doctor who has a generosity measure and provider specialty by HSA fixed effects. The regressions for Panel A also include controls for injury year fixed effects. The regressions for Panel B include controls for injury year-month fixed effects, patient's age, and patient's sex. The regressions for Panel C include the controls in Panel B, as well as controls for the day of the week of the first medical treatment, the ICD-9 code of the first medical treatment, and an indicator variable for the claim originating in the emergency department. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A12: Relationship Between Doctor Generosity and and Observational Outcomes—Unadjusted Doctor Effects

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD X $\tilde{\theta}$	0.382	11,471.555	0.330	14.569	0.310	2.169	8,830.071
	(0.155)	(3,694.303)	(0.151)	(4.947)	(0.096)	(0.655)	(3,229.179)
	[0.014]	[0.002]	[0.029]	[0.003]	[0.001]	[0.001]	[0.006]
Dependent Variable							
Mean	0.269	3,012	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	10,384	0.428	14.09	0.321	2.467	8,266

Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using the unadjusted coefficients from Equation (2). The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for injury year, provider specialty by HSA fixed effects, and an indicator for the patient being treated by a doctor who has a generosity measure. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A13: Relationship Between Doctor Generosity and Claimant Characteristics

	Demographics		Characteristics of Claimant's Zipcode		Baseline Injury Characteristics		
	Male	Age	Above Median Average Income	Above Median Share White, non-Hispanic	Sprain or Muscle Issue	Predicted Cash Benefits	Log(First Day Medical Spending)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD X $\tilde{\theta}$	0.008	-0.563	0.369	0.167	0.215	1,458.744	0.162
	(0.182)	(2.537)	(0.188)	(0.157)	(0.150)	(891.385)	(0.200)
	[0.964]	[0.825]	[0.050]	[0.288]	[0.151]	[0.102]	[0.417]
Dependent Variable							
Mean	0.605	41.98	0.501	0.501	0.487	3,012	5.867
Standard Deviation	0.489	13.31	0.500	0.500	0.500	2,928	0.816

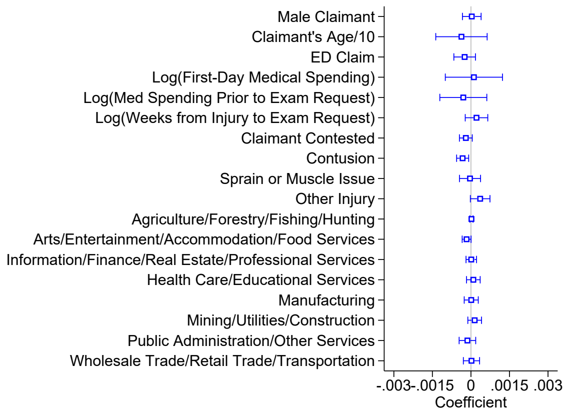
Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). These regressions include controls for injury year fixed effects, provider specialty by HSA fixed effects, and an indicator for the patient being treated by a doctor who has a generosity measure. The sample contains 825,787 claims for workers injured from 2013 to 2019. Robust standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets. The information on characteristics of zipcodes used in columns 3 and 4 comes from the IPUMS National Historical Geographic Information System (Manson et al. 2024).

Table A14: Relationship Between Doctor Generosity and Observational Outcomes—Robustness to Selection

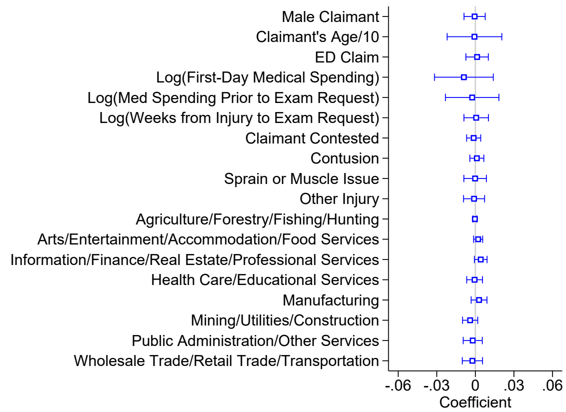
	Dependent Variable		Baseline Effect (Std. Error) [R^2]			Controlled Effect (Std. Error) [R^2]			Bias-Adjusted β [if equal selection on unobservables and observables, δ=1]	Selection (δ) on unobservables relative to observables needed to make β=0
	mean	std dev	coef	std err	R^2	coef	std err	R^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Any Cash Benefits	0.269	0.443	0.631	(0.228)	[0.002]	0.537	(0.187)	[0.114]	0.507	17.896
Total Cash Benefits	3,012.015	10,383.707	20,798.395	(5,902.926)	[0.003]	19,371.952	(5,228.663)	[0.071]	18,926.505	40.402
Any Temporary Income-Replacement Benefits	0.241	0.428	0.563	(0.226)	[0.002]	0.471	(0.187)	[0.103]	0.442	16.139
Temporary Income-Replacement Benefit Duration	4.276	14.087	25.223	(7.832)	[0.002]	23.293	(6.995)	[0.054]	22.686	35.755
Any Permanent Impairment Benefits	0.117	0.321	0.524	(0.148)	[0.003]	0.492	(0.129)	[0.074]	0.482	47.035
Permanent Impairment Rating	0.630	2.467	3.705	(0.979)	[0.002]	3.450	(0.852)	[0.064]	3.374	42.720
Medical Spending	3,969.038	8,265.971	14,197.431	(5,276.059)	[0.003]	12,585.069	(4,641.200)	[0.138]	12,098.059	25.039

Notes: This table displays robustness analysis assessing the potential role of selection on unobservables following methods outlined in Oster (2019). Each row indicates the dependent variable relevant in the indicated regressions. The coefficient estimates are from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from Equation (2) with the deconvoluted distribution from Section 3. The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure for the patient's treating doctor and an indicator for that doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). The baseline regressions (referenced in columns 3 through 5) include controls for an indicator for the patient being treated by a doctor who has a generosity measure, provider specialty by HSA fixed effects, and injury year fixed effects. The controlled regressions (referenced in columns 6 through 8) supplement the baseline specification with controls for injury year-month fixed effects, patient's age, patient's sex, the day of the week of the first medical treatment, the ICD-9 code of the first medical treatment, and an indicator variable for the claim originating in the emergency department. Column 9 reports the bias-adjusted coefficient assuming equal selection on unobservables and observables ($\delta = 1$ in the Oster (2019) framework). Column 10 reports the degree of selection on unobservables relative to observables that would be needed for selection to explain away the entire relationship between the dependent variable and doctor generosity estimated in the baseline regression (the coefficient reported in column 3). Following guidance in Oster (2019), the calculations in columns 9 and 10 assume the maximum R^2 from a hypothetical regression with the full set of observables and unobservables would be 1.3 times the R^2 from the controlled regression (reported in column 8). The sample contains 825,787 claims for workers injured from 2013 to 2019.

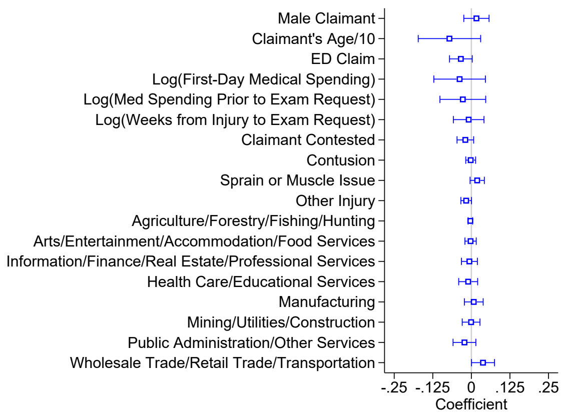
Figure A1: Balance of Claimant Characteristics across Designated Doctor Characteristics



(a) Doctor Age



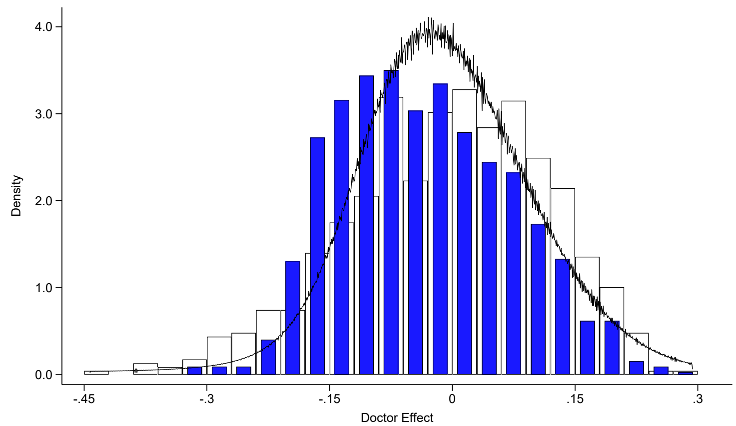
(b) Doctor Female



(c) Doctor DC credential

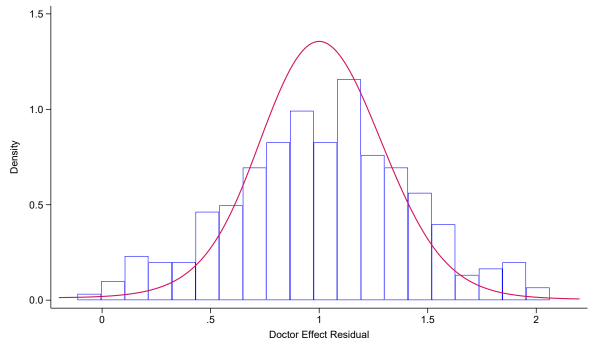
Notes: This figure displays coefficients and estimated 95% confidence intervals from separate regressions of each claimant characteristic listed on the vertical axis on the provider characteristic indicated in the panel: doctor age (Panel A), an indicator variable for the doctor being female (Panel B), and an indicator variable for the doctor has a DC credential (Panel C). Each marker is from a separate regression with the indicated dependent variable. These regressions include the baseline controls for the claimant's injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. 95% confidence intervals calculated using standard errors clustered at the doctor level are shown along with the point estimates.

Figure A2: Distribution of Doctor Effects Before and After Empirical Bayes Shrinkage

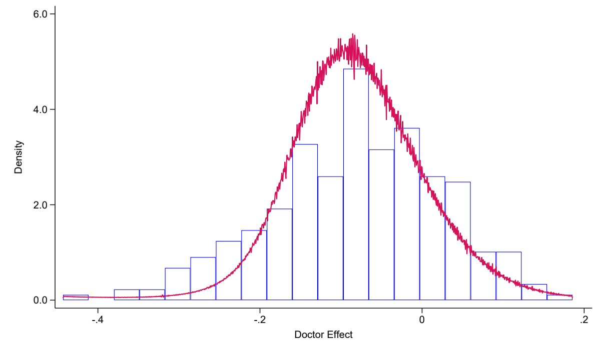


Notes: This figure displays the implied distribution of doctor effects (solid line) based on a change in variables applied to the deconvoluted distribution of residuals, overlaid on a histogram of the estimated doctor effects (hollow bars) and a histogram of the doctor effects after applying empirical Bayes shrinkage based on the implied distribution of doctor effects (solid bars). See Appendix Section B for more details.

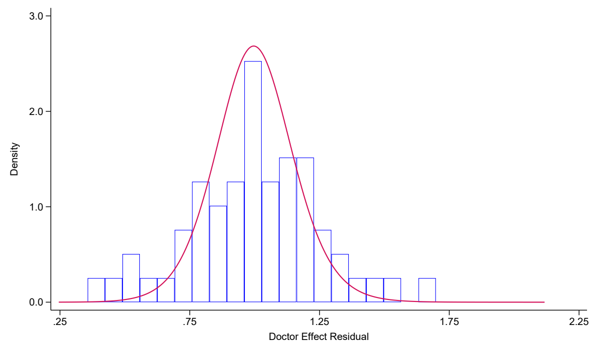
Figure A3: Distribution of Doctor Effects by Subgroup



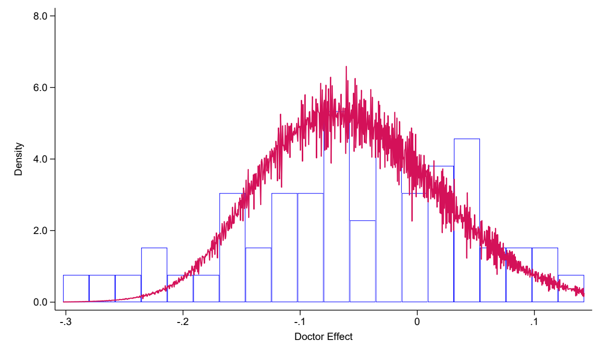
(a) Doctor Effect Residual: MD/DO Credential



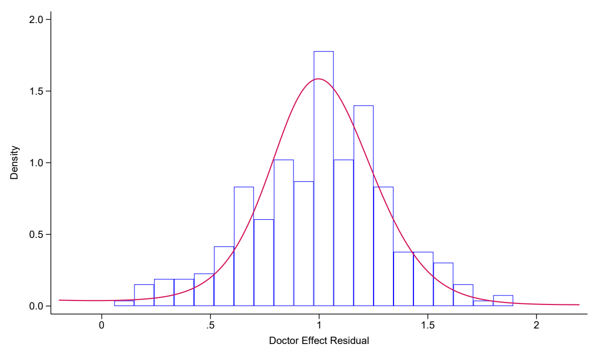
(b) Doctor Effect: MD/DO Credential



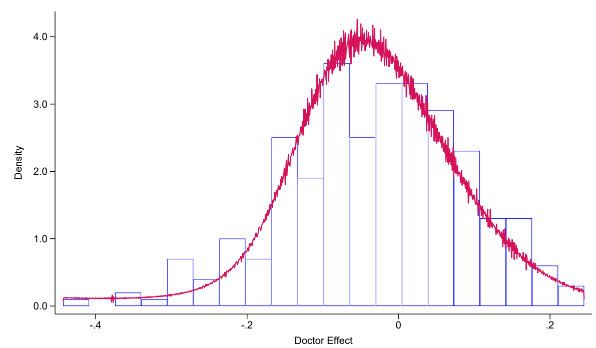
(c) Doctor Effect Residual: Orthopedic Surgery



(d) Doctor Effect: Orthopedic Surgery

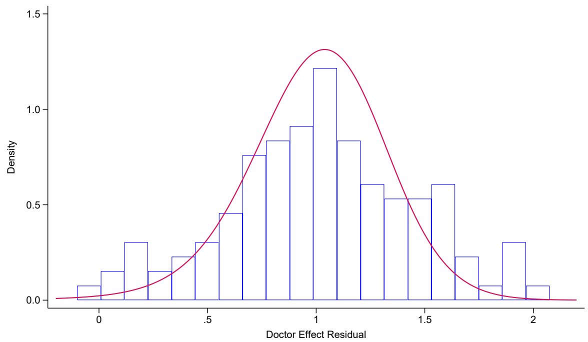


(e) Doctor Effect Residual: More Than Three Years Experience

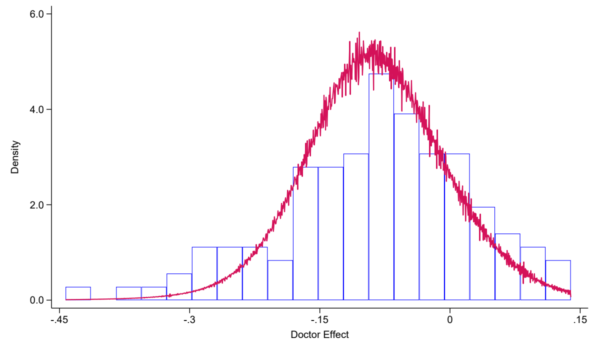


(f) Doctor Effect: More Than Three Years Experience

Figure A3: Distribution of Doctor Effects by Subgroup (cont.)



(g) Doctor Effect Residual: Primary Care



(h) Doctor Effect: Primary Care

Notes: For the indicated subgroups of doctors, this figure displays sets of panels depicting the deconvoluted distribution of doctor effect residuals (left panel) and the associated implied distribution of doctor effects (right panel) based on a change in variables applied to the distribution of residuals. These distributions overlay the associated histogram of the underlying empirical residuals and estimated doctor effects, respectively. The implied standard deviations of doctor effects based on the estimated distributions (MD/DO Credential: 0.078, Orthopedic Surgery: 0.068, More Than Three Years Experience: 0.103, and Primary Care: 0.086) broadly align with the implied standard deviations based on unbiased split-sample variance estimates of doctor effects for these subgroups (MD/DO Credential: 0.084, Orthopedic Surgery: 0.073, More Than Three Years Experience: 0.109, and Primary Care: 0.081). See Appendix Section B.3 for more details on this estimation.