Doctor Discretion in Medical Evaluations *

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Abstract

This paper analyzes the importance of doctor discretion in medical evaluations of physical impairments in the context of workers' compensation insurance. Leveraging comprehensive administrative data from Texas and random assignment of doctors that arises through the dispute resolution process, we identify the scope for doctor discretion in medical evaluations of injured workers and the impacts of this discretion on later claimant outcomes. Our analysis indicates there is wide variation across doctors in the generosity of their medical evaluations, these decisions are consequential for later claimant outcomes, and doctor generosity systematically varies by observed doctor characteristics. In addition, we analyze the relationship between doctor generosity in medical evaluations and market allocation when claimants can select their own doctors. Our findings suggest both claimants and insurers influence the allocation of doctors in line with their respective incentives, indicating market forces shape the distribution of program benefits. Finally, we conclude with supplemental counterfactual analysis and discussion of the policy implications of these findings.

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Individuals are involved in decision-making in many high-stakes environments where expertise is needed to make decisions. For example, judges, doctors, and case managers are charged with evaluating claims and allocating benefits in many government programs. However, faced with the same information, these experts can make different decisions, even when guidelines, training, and professional standards encourage them to make similar decisions. In these settings, a number of natural questions arise: How much evaluator discretion is there in practice and what are the consequences of this discretion? How does evaluator generosity vary with decision-maker characteristics? How do market participants respond to incentives to influence the allocation of evaluators? How do policies surrounding the allocation of evaluators impact outcomes in these programs?

This paper analyzes these questions in the context of workers' compensation insurance—where doctors conduct medical evaluations of physical impairments to determine eligibility for cash benefits. Workers' compensation insurance is state-regulated insurance that provides medical and cash benefits to covered workers who experience a workplace injury. Workers' compensation insurance is one of the largest social insurance programs in the United States. In 2016, workers' compensation insurance paid $62 billion in benefits in the U.S., which was roughly twice the $32 billion paid in benefits for unemployment insurance that year and on par with the benefits paid through the Earned Income Tax Credit program and the Supplemental Nutrition Assistance Program. Despite the large scale of this program, little research has explored how benefits are allocated within this program and the role of doctors in benefit determination.

Doctors serve as gatekeepers in workers' compensation insurance. In addition to overseeing medical care of injured workers, doctors are charged with evaluating the severity of impairments which determines an injured worker's cash benefit eligibility. A key feature of workers' compensation insurance is that claimants play a central role in selecting their own doctors. Historically, most state workers' compensation insurance systems have allowed claimants to choose their own doctor, with little or no restrictions. However, in recent years, policymakers in many states have debated whether choice should be restricted and several states have enacted legislation to restrict claimant choice over doctors—with some states specifying that insurers can select doctors or restrict the pool of doctors from which workers can choose. Moreover, disputes over impairment evaluations are common and there has been increasing policy debate about how to resolve such disputes, with a number of states adopting evaluations by randomly assigned doctors to settle disputes. A fundamental assumption underlying these policy debates is that there is meaningful variation across doctors in impairment evaluations, and hence regulations governing doctor choice could have important consequences for the allocation of benefits. While this assumption is plausible, workers' compensation insurance programs take extensive measures to standardize evaluations— through providing comprehensive medical guidelines for the evaluation of impairments and requiring doctors to regularly participate in related trainings. Thus, ex ante it is unclear how much doctor discretion exists in these evaluations and whether claimants and insurers influence the allocation of evaluators based on evaluator generosity in line with their incentives. Despite the centrality of these issues to current policy debates in workers' compensation insurance and potential implications for broader health care and social insurance settings, little is known about the scope for doctor discretion and how market forces influence the allocation of claimants across doctors. This paper begins to fill this gap.

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 and the impact of this discretion on workers' compensation claimant outcomes. To identify the extent and impact of doctor discretion, we leverage random assignment of doctors to claims that arises through the workers' compensation dispute resolution

process. Using this variation, our analysis illustrates there is wide variation across doctors in the generosity of medical evaluations, these decisions are consequential for later claimant outcomes, and doctor generosity systematically varies by observed doctor characteristics. We then analyze the relationship between doctor generosity 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. To identify the role of doctors, we leverage random assignment of doctors to claims for medical evaluations within the dispute resolution system. While workers' compensation claimants can generally choose their own "treating doctor" who oversees their medical care and serves as a gatekeeper for cash benefits, insurers and injured workers can formally dispute a treating doctor's determination about a worker's continuing eligibility to receive cash disability benefits. Such disputes are common, affecting roughly one-third of claims with such benefits. When a dispute occurs, the Texas Department of Insurance randomly assigns a doctor to perform an independent medical examination—and this doctor's assessment is binding for benefit determination. Medical doctors (MD), doctors of osteopathy (DO), and doctors of chiropractic (DC) can all apply through the Texas Department of Insurance to be included in the list of independent doctors eligible to conduct independent medical exams. The assignment of doctors to these exams is random, among independent doctors available in the county who are eligible to perform the exam. Thus, after controlling for the set of doctors eligible to preform the exam, pre-determined characteristics of the claim should be unrelated to characteristics of the doctor assigned to evaluate the claim—including the generosity of the assigned doctor.

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. Our empirical approach leverages random assignment of independent doctors to claims to assess the role of doctor discretion in evaluating continued impairment in this setting. 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. When examining impacts on claimants evaluated at the randomized exams, we construct a leave-out measure of doctor generosity to avoid issues of reflection. Our analysis uses unique administrative data which includes information on all medical and cash benefits paid for workers' compensation claims in Texas linked to data on independent medical exams. 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 present reduced form evidence illustrating that claimants randomly assigned a more generous independent doctor experience longer durations out of work and receive more benefits. The magnitude of these findings is notable. A claimant randomly assigned a doctor with a 10 p.p. higher approval rate for continued benefits, on average, stays out of work 15.7% longer while receiving income-replacement benefits, is 11.3% more likely to receive permanent impairment benefits, collects an additional $1,234—or a 15.7% increase over the mean—in subsequent cash benefits, experiences a 9.3% increase in subsequent injury-related medical spending, and receives an additional $1,888—or a 13.0% increase—in total workers' compensation benefits, aggregating across post-exam cash benefits and medical spending.

After establishing that doctor generosity impacts later claimant outcomes, we turn toward characterizing the distribution of doctor generosity—to more fully understand the extent of doctor discretion. A key

finding of our study is that generosity in medical evaluations varies substantially across doctors. After accounting for sampling error, the across-doctor standard deviation in the post-exam cash benefit rate is 10.9 percentage points—representing 13.9% of the mean. Further analysis reveals that our measure of doctor generosity is stable over time and across subgroups of claims defined based on baseline claim characteristics.

We further characterize the distribution of doctor generosity, applying empirical bayes deconvolution methods in Kline, Rose, and Walters (2022) based on methods developed by Efron (2016). This analysis reveals there is meaningful variation in generosity across doctors and the distribution is more dispersed among those in the bottom half of doctor generosity. The bottom quartile of doctors in terms of generosity is responsible for nearly 41.1% of denials for continued benefits for disputed claims, while the top quartile of doctors in terms of generosity is only responsible of 11.4% of denials. To further explore variation across doctors, we present descriptive evidence correlating our estimates of doctor effects with observable doctor characteristics. This analysis illustrates that doctor credential and doctor specialty are meaningful predictors of doctor generosity, as are doctor sex and age.

Having established that doctors are influential in claim outcomes and there is substantial variation across doctors in the way they exercise discretion, we turn toward investigating whether and how doctor generosity is related to interactions between doctors and other market participants. A key feature of this market is that claimants can select their own "treating doctors" to oversee their medical care and cash benefit eligibility—outside of the dispute resolution process—and the same doctors who conduct independent medical exams serve as "treating doctors" for other workers' compensation claimants in their standard practice. Using data on all medical and cash benefits for workers' compensation claimants, we explore how doctor generosity—as measured based on the randomized independent medical exams—is related to interactions with claimants and insurers in the broader workers' compensation setting.

We begin by analyzing the allocation of claimants across treating doctors. All else equal, claimants likely prefer more generous doctors, because, on average, these doctors allow claimants to receive more cash benefits. Given claimants are free to choose their own doctors, we might expect competitive forces would lead doctors who are more generous to attract more claimants at a point in time and over time. On the other hand, institutional features may dull these competitive reallocation forces. For example, claimants may lack the knowledge or time to respond to differences in generosity or other correlated doctor characteristics may play a larger role in influencing claimant selections. Ultimately, this is an empirical question. We empirically investigate whether and to what extent more generous doctors attract a greater market share. Specifically, we look at the allocation of claimants across treating doctors and associate this with measures of doctor generosity that we constructed based on the randomized evaluations that those treating doctors conducted.

We find robust evidence that more generous doctors tend to have a greater market share (i.e., more claimants selecting them to serve as a treating doctor) at a point in time. Further, the estimates suggest more generous doctors experience more growth in market share over time. Moreover, we find these correlations are notably stronger among claimants who have more scope for choice (e.g., who live in less concentrated medical markets) and claimants for whom the stakes are higher (e.g., who have more cash benefits on the line). Taken together, this evidence is consistent with an important role of consumer demand in determining the allocation of claimants to doctor evaluators in workers' compensation insurance. While this reallocation leads to substantial increases in evaluated disability and benefits paid, it is unclear if more generous evaluations move the allocation of benefits closer to (or further from) the optimum. Thus, the normative implications of the observed reallocation may depend on whether one considers the welfare of claimants

or broader measures of social welfare.

A qualitative implication of these findings is that the selection of evaluators in this social insurance setting is influenced by market forces. Additionally, extrapolating from these estimates, we present supplemental evidence benchmarking the quantitative importance of this reallocation. These calculations suggest that reallocation of claimants to more generous doctors increased total workers' compensation costs by roughly 4%. Moreover, this estimated aggregate increase in costs due to reallocation is large relative to other policies that have been shown to impact workers' compensation costs. For instance, this estimated 4% increase in workers' compensation costs due to reallocation is nearly half the estimated increase in workers' compensation costs due to behavioral responses among claimants affected by a recent reform that increased weekly income-replacement benefits by an average of 17% (Cabral and Dillender, 2024*b*).

While claimants select their own treating doctor evaluators, insurers and claimants can dispute cash benefit determinations made by the treating doctor—triggering an independent medical exam. All else equal, insurers have greater incentives to dispute cash benefit determinations when a claimant's treating doctor is more generous and thus, if insurers are informed, we would expect the likelihood of an insurer-initiated dispute to be increasing in treating doctor generosity. Supplemental analysis reveals robust evidence in line with this prediction. Specifically, our estimates suggest a one standard deviation increase in treating doctor generosity is associated with an 4.0 pp increase in the likelihood that an insurer will dispute the cash benefit determination for that claim—or a 46.7% increase over the mean rate of disputing claims. In contrast, we find no association between doctor generosity and the likelihood of claimant-initiated disputes.

Next, we consider the policy implications of our findings—starting with the direct implications for workers' compensation policy surrounding independent medical exams. Disputes over benefit determinations are common and independent medical exams are a central part of all state workers' compensation programs. Nevertheless, key aspects of the design of independent medical exams vary across states—including the process for allocating doctors for these exams and the eligibility requirements for doctor evaluators. Motivated by the variation in independent medical exam systems across states and ongoing policy debates over the design of these systems, we conduct simple back-of-the-envelope counterfactual analysis exploring the consequences of two types of potential changes to the independent medical exam system in our setting: (i) implementing further eligibility restrictions for doctors performing these exams and (ii) changing the process for allocating doctors to these exams. [ANALYSIS IN PROGRESS.]

Our findings also have broader implications for policy beyond independent medical exams. For example, our findings demonstrate there is substantial variation across doctors in how they evaluate physical impairments, despite extensive required training and guidelines encouraging standardization of the evaluation process. An implication of this evidence is that not all doctors are the same and the identity of the doctor performing a medical evaluation matters—informing active policy debates over doctor choice policies in workers' compensation insurance, disability insurance, and broader health care settings. Moreover, our findings illustrate that generosity varies substantially across doctors with varying baseline characteristics—such as age, sex, education, and experience. In this way, our findings shed light on the expected impacts from policies impacting the pool of doctors evaluating patients or from broader trends within the doctor workforce. Finally, our analysis suggests that, when given the choice to select their own providers, claimants sort toward doctors who are more generous and insurers are more likely to dispute decisions made by more generous doctors. Taken together, these findings suggest that market forces impact the allocation of patients across doctors and policies aimed at restricting claimant choice over doctors—such as state policies allowing insurers to restrict the set of available doctors or requiring random assignment of

doctors—may substantially reduce benefits paid to claimants.

Related Literature Our paper contributes to several literatures. First, our study provides evidence on the importance of gatekeeper discretion in social insurance and social safety net programs. Several of the largest public programs have a gatekeeper model, where designated evaluators are charged with determining benefit eligibility. Physical impairment and residual work capacity are assessed by doctors in workers' compensation insurance and in many disability insurance programs; caseworkers interview applicants to assess eligibility for the federal Supplemental Nutritional Assistance Program; judges allocate access to Chapter 13 bankruptcy protection; hearing officers adjudicate disputes over unemployment insurance eligibility; and interviewers determine eligibility for the Temporary Assistance for Needy Families program. Prior research has recognized that gatekeepers may exercise discretion in eligibility determinations, with studies leveraging variation in gatekeeper leniency as an instrument to look at the effect of benefit receipt on later outcomes (e.g., Maestas, Mullen, and Strand 2013; Dobbie and Song 2015; Silver and Zhang 2022).[1] However, less is known about the extent of gatekeeper discretion, factors that are associated with gatekeeper generosity, or the impact of policies influencing the allocation of gatekeepers. And this is an important area for further work, given that hundreds of billions of dollars in public program benefits are awarded at the discretion of gatekeepers each year. Our study works to fill this gap through providing a comprehensive assessment of the impact of gatekeepers on claimant outcomes, variation in gatekeeper discretion, correlates of this discretion, and the impacts of gatekeeper allocation in a major public program. In doing so, our paper provides the first evidence on the extent of gatekeeper discretion and the consequences of this discretion for claimant outcomes in workers' compensation insurance—one of the largest social insurance programs in the US and a setting in which gatekeepers play a central role in the distribution of benefits.

Our study also contributes to the wider literature on workers' compensation insurance. Much of the prior research on workers' compensation insurance focuses on estimating behavioral responses to cash benefit generosity (e.g., Cabral and Dillender 2024*b*; Krueger 1990*a*,*b*; Meyer, Viscusi, and Durbin 1995; Neuhauser and Raphael 2004), the impact of medical benefit generosity (e.g., Powell and Seabury 2018), the effect of firm incentives to reduce costs (e.g., Aizawa, Mommaerts, and Rennane 2023), and the incidence of the program or policy premiums (e.g., Fishback and Kantor 1995; Gruber and Krueger 1991). Despite the centrality of doctor evaluators for the distribution of program benefits and growing interest among policymakers in regulating claimant choice of doctor evaluators, no prior work has explored the extent of doctor discretion in this setting or the impact of this discretion on claimant outcomes. This paper contributes to this literature by providing the first evidence on the impact of doctors as program gatekeepers, filling an important gap in this literature and informing ongoing policy debates.

In addition, our study provides novel evidence on the scope for doctor discretion in medical decisions. In this way, our work complements an emerging literature in health care documenting how outcomes vary across patients treated by providers with differing characteristics. For instance, recent work has leveraged random or quasi-random variation to analyze the impact of being matched with a provider with a specified attribute—characterizing the provider's training (e.g., Chan and Chen 2022; Doyle, Ewer, and Wagner

[1] A growing literature has used variation in examiner leniency as an instrument to investigate the impact of a broad range of treatments, including criminal justice punishments and procedures (e.g., Mueller-Smith 2015; Aizer and Doyle 2015), bankruptcy protection (e.g., Dobbie, Goldsmith-Pinkham, and Yang 2017), foster care placements (e.g., Doyle 2007; Bald et al. 2022), foreclosure/evictions (e.g., Collinson et al. 2024; Diamond, Guren, and Tan 2020), and public program benefits (e.g., Cohen 2024; Autor et al. 2019). In health care settings, prior work in this literature has evaluated the impact of hospital quality on patient health (Doyle, Graves, and Gruber, 2019); pneumonia diagnoses on patient health (Chan, Gentzkow, and Yu, 2022); prescriptions for opioids on later opioid abuse (Eichmeyer and Zhang, 2022); psychotherapy on later health and economic outcomes (Blæhr and Søgaard, 2021); and nursing home eligibility on health and health spending (Bakx et al., 2020). See Chyn, Frandsen, and Leslie (2024) for a comprehensive review of this literature.

2010), race (e.g., Alsan, Garrick, and Graziani 2019; Frakes and Gruber 2022), or sex (e.g., Cabral and Dillender 2024*a*)—on patient outcomes or disparities in outcomes.[2] Other recent work has aimed to understand the role of providers on health care outcomes through leveraging variation from provider retirements or relocations (e.g., Molitor 2018; Doyle and Staiger 2021; Badinski et al. 2023; Ginja et al. 2022; Beheshti and Neller 2024). While prior work points to important differences in outcomes among providers with differing characteristics or working in differing settings, little is known about the overall scope for doctor discretion in medical evaluations. This is a challenging topic to analyze for at least two reasons. First, identifying the impact of providers on outcomes is often challenging because patients can typically select their own medical providers and this can result in non-random selection of patients across providers. Second, the role of provider evaluations of medical conditions in influencing outcomes is not always clear as patient-provider interactions are typically complex—often involving a doctor evaluating a patient, a doctor recommending treatment, a patient deciding whether to follow doctor recommendations, and a doctor administering treatment if the patient consents. Two key strengths of our setting allow us to overcome these challenges: the random assignment of providers and the well-defined scope of the medical evaluations we analyze. Through leveraging these strengths, our study provides the first evidence on the overall scope for doctor discretion in medical evaluations—the critical initial step in all health care interactions (and disability eligibility evaluations) and an aspect of these interactions where doctor decision-making is central. Moreover, beyond characterizing the extent of doctor discretion in medical evaluations, we provide novel evidence on the consequences of doctor discretion for later outcomes, correlates of this discretion across a wide range of doctor characteristics, and the relationship between how doctors exercise this discretion and market allocations.

Finally, our paper contributes to a broader literature investigating the relationship between performance and market allocation. Intuitively, we would expect a connection between performance—as perceived by consumers—and market share because competitive forces exert pressure on poorly performing producers to either improve performance or lose market share. Much of the prior work in this area has focused on associating market share with productivity in the manufacturing sector (e.g., Olley and Pakes 1996; Collard-Wexler and De Loecker 2015; Pavcnik 2002). While some have argued market forces may be dulled in health care settings as there may be more barriers to acquiring and acting on information about performance, the extent to which market allocation in health care reflects market forces is an empirical question and there has been little prior related research. An important notable exception is Chandra et al. (2016), who document that observational measures of hospital quality—mean hospital mortality rates for specified health conditions—are correlated with hospital market shares for those conditions, consistent with demand-driven reallocation to higher quality hospitals.[3] Our study extends this literature by investigating the relationship between doctor generosity in medical evaluations and market allocation of patients across doctors. Our findings suggest the allocation of doctors is influenced by market forces, with evidence suggesting both claimants and insurers influence doctor selection in line with their respective incentives.[4]

[2]In the context of hospitals, other related work has leveraged quasi-random variation to identify the impact of being treated at a hospital with higher spending (Doyle et al. 2015), with better mean patient outcomes (Doyle, Graves, and Gruber 2019), or with different ownership/organizational structure (Chan, Card, and Taylor 2023).

[3]In other related work, Chandra et al. (2016) find productivity dispersion is smaller in health care than in the market for ready-mixed concrete, counter to expectations if market forces were dulled in health care relative to other settings. Chandra, Kakani, and Sacarny (2024) document that black patients receive care at lower-performing hospitals than white patients, indicating important differences across market segments in patient sorting across the hospital quality distribution. Other related work has explored the causes and consequences of productivity variation across hospitals (e.g., Chandra and Staiger 2020; Chandra, Colla, and Skinner 2023).

[4]Our finding that insurers are more likely to contest evaluations by more generous doctors complements evidence from prior work documenting that hospitals and insurers respond to financial incentives by influencing the allocation of patients across hospitals (e.g.,

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 a workplace injury. The basic structure of workers' compensation insurance is similar across states. Workers' compensation insurance provides cash benefits when work-related injuries cause temporary or permanent disability. Beyond cash benefits, workers' compensation insurance 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 "gatekeeper" model, with medical providers overseeing the delivery of the delivery of medical care and cash benefit eligibility. Workers' compensation claimants can select their own "treating doctor"—a doctor who is formally charged with managing the claimant's medical care, evaluating the claimant's medical improvement and eligibility for wage replacement benefits, and assessing any permanent impairment resulting from the claimant's injury. Beyond receiving payments for procedures commonly billed in other settings, doctors treating workers' compensation claimants bill for additional "case management services" that are related to their role as a gatekeeper for cash benefits.

Workers' compensation insurance provides two types of cash benefits: temporary income benefits and permanent impairment benefits. Injured workers in Texas are eligible for temporary income benefits after a waiting period of seven days, and temporary income benefits end when the earliest of the following conditions are met: (i) the worker decides to return to work, (ii) the worker's doctor determines he/she has reached "maximum medical improvement" (MMI), and (iii) the statutory maximum duration is met. While the statutory maximum duration in Texas is two years (104 weeks), workers rarely receive temporary income benefits for two years. Temporary income benefits provide partial insurance, replacing 70% of a claimant's prior average weekly wage subject to a maximum and minimum weekly benefit. After temporary income benefits terminate, workers who are still impaired are eligible for permanent impairment benefits. Treating doctors determine whether a claimant has a permanent impairment, and if so, assign a permanent impairment rating—the percentage of permanent impairment of the whole body from the injury. Permanently impaired workers are paid an unconditional cash transfer that is a function of the severity rating of their permanent impairment and their prior average weekly wage, where benefits in Texas are calculated as the product of the claimant's permanent impairment severity rating and the eligible wage replacement rate.

Independent Medical Evaluations Though the treating doctor is the assigned gatekeeper for cash benefits, insurers or injured workers often formally contest the treating doctor's assessment of a claimant's impairment. As in some other states, 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 evaluation if they disagree with the treating doctor's assessment, the vast majority of these exams (85%) are requested by insurers.

Our analysis focuses on independent medical exams where designated doctors are asked to assess the workers' "maximum medical improvement" (MMI) and, if relevant, permanent impairment. Almost all

Alexander 2020) and across insurance options (e.g., Brown et al. 2014).

disputed claims (95.7%) meet this criteria.[5] In these exams, designated doctors must assess whether the claimant has reached MMI—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 MMI 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 MMI. It is important to note that 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.[6]

Texas maintains a database of designated doctors eligible to perform independent medical evaluations. 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 initially requested independent medical exam and also any subsequent independent medical exams if other disputes arise down the line. The involvement of a designated doctor is limited and defined by statue. 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 theses claimants.

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 mandated to be 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. [7]

Evaluation guidelines emphasize the inherent subjectivity in assessing whether a worker has reached maximum medical improvement (e.g., whether the workers' condition is expected to meaningfully improve with more time, medical treatment, or physical therapy) and the extent of permanent impairment (e.g., the degree to which the worker's activities are permanently limited by having been injured). And training materials for designated doctors indicate that doctors should use their discretion and professional judgment

[5] Although it is rare, independent medical exams can also be requested for other reasons, such as determining whether the impairment was caused by a injury that is compensable under workers' compensation insurance and the extent of the worker's compensable injury.

[6] 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.

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

in these decisions. Importantly, we might expect a large role for doctor discretion in these exams, for any type of injury regardless of the ease in verifying the injury occurred or happened during the course of work activities. For example, while it is simple to verify if a worker has torn a ligament through MRI imaging, it is inherently subjective to assess whether the worker is expected to continue to heal from the torn ligament and how the continuing pain, swelling, and reduced mobility limits the worker's permanent ability to work.

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.[8] 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.[9] Because the overwhelming majority of claims are for straightforward musculoskeletal injuries, all designated doctors are eligible to do 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 through 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 back injuries and the credential of the assigned doctor (MD, DO, or DC) for all other injuries.[10]

[8]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 with the insurer to participate in the insurer's network. 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, the estimates are nearly identical in specifications that expand the controls to include interactions between our baseline controls and insurer.

[9]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).

[10]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 through 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 muskuloskeletal injuries, the regulations are clear in specifying that back injuries can be evaluated by any designated doctors and we can validate that 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

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 continues to be impaired 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 is still impaired but continues to heal 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, by the claimant's treating doctor or the designated doctor.

When a designated doctor decides a claimant has a continued impairment, the designated doctor influences the amount of future benefits at the initial exam through assigning a permanent impairment rating or through 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. Since treating doctors' benefit decisions and any future requests for independent medical exams may be influenced by decisions made by the designated doctor in the initial exam, we focus on characterizing doctor generosity through the designated doctor's assessment at an initial independent medical exam and summarize impacts on subsequent benefits through considering all benefits received after the initial exam. 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 final amount of cash benefits that claimants assessed as having a continued disability eventually receive. However, the assigned designated doctor can still influence the final benefits a claimant receives, both through their initial assessment of the claimant's injury and because the claimant's original designated doctor is responsible for any future independent medical evaluations.

1.2 Data

This project draws on unique administrative data from the Texas Department of Insurance (TDI) obtained through open records requests. These data contain information on claims for the universe of injuries covered by the Texas workers' compensation insurance system occurring 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 designated doctor evaluations focuses on exams that occurred between 2013 and 2019. Beyond our analysis of designated doctor 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 type (CPT codes), amount paid, amount charged, diagnoses codes, date and place of service, and

this to be equal to any credential for back injuries and the observed assigned doctor's credential for all other injuries.

information about the provider. The medical data span all types of medical care including physician care, outpatient 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).[11] 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 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 designated doctor exams" sample and the doctors performing these exams as the "designated doctor" sample of doctors. Our baseline sample includes 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. 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 evaluations. 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 patients in Texas, as well the broader population of doctors in Texas and in the United States. Relative to the population of doctors treating workers' compensation patients, 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 patients. 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 the claimant is assessed as having a continued impairment—and hence is eligible for subsequent cash

[11] In addition, we also use a list of active DCs in Texas complied 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).

benefits—on the date of the independent medical exam.[12] 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 a natural measure of 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 36 months 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 on these basic demographic characteristics, with 65% male and a mean age of 46. There are a diverse range of injuries represented in the sample, with the largest injury category being sprains and muscle issues (63%). Because independent medical exams take place to evaluate cash benefit eligibility 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, and have higher rates of cash benefit receipt and 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 $8,431.[13] Roughly 33% of claimants receive post-exam income-replacement benefits, while 65% receive permanent impairment benefits. Mean post-exam medical spending is $6,122.

2 Impact of Doctors on Claim Outcomes

We begin by estimating the impact of doctors on disability evaluation decisions 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 leveraging random assignment of designated doctors to claimants for independent medical evaluations. 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 preform the claimant's exam. In this specification, y_i represents the dependent variable, and $z_{d(i)i}$ is a measure of doctor generosity. To isolate conditional random assignment,

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

[13] As discussed above, workers' compensation cash benefits are a function of both the worker's disability and their prior wage. Here and throughout when we analyze "total additional cash benefits" we are referring to normalized total additional cash benefits, were we calculate cash benefits that would be paid out based on the average replacement rate for income-replacement and permanent impairment benefits across workers' compensation claimants receiving these benefits.

this specification also includes fixed effects for doctor credential required for the exam by claimant county by year-quarter of the exam ($\mu_{r(i)t(i)c(i)}$). 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 robustness of our findings when including further controls.

Because this regression analyzes the relationship between outcomes of claimants at independent medical exams and doctor 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 the doctor $d(i)$'s independent medical exams excluding claimant i's exam. However, we also conduct robustness analysis that demonstrates the results are virtually identical if we instead construct $z_{d(i)i}$ using the UJIVE estimation approach outlined in Kolesár et al. (2013)—which augments a simple leave-out mean approach by conditioning on the controls included in Equation (1)—or if we instead ignore small sample correlation concerns and measure doctor generosity using the doctor effects estimated in Section 3. See Appendix Table A2 for this analysis.

Within this specification, β represents the impact of doctor generosity on claimant outcomes. We consider a number of 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 claimant's own exam result. We also analyze impacts on other broader subsequent claim outcomes. While the assessment of continued impairment is under the direct and full control of the designated doctor, other subsequent claim 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, and the claimant's regular treating doctor. These broader subsequent claim outcomes include: the total additional cash benefits received after the exam, the duration out-of-work collecting income-replacement benefits after the exam, the claimant's assessed permanent impairment rating, and post-exam workers' compensation covered medical spending.

Identifying Variation Figure 1 displays a histogram of $z_{d(i)i}$ after partialing out the baseline controls. There is substantial residual variation in $z_{d(i)i}$, with an interquartile range of -0.055 to 0.066 and an interdecile range of -0.129 to 0.116. In Figure 1 Panel A , overlaid on this histogram is the non-parametric regression of continued impairment on the leave-out mean of continued impairment ($z_{d(i)i}$)—with both measures residualized using the baseline controls. The figure suggests continued impairment increases roughly linearly with the leave-out mean from the doctor's other assigned claims. For comparison, Figure 1 Panel B displays the analogous non-linear regression with predicted continued impairment based on baseline claim characteristics. 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, 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 of this analysis. 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 coefficient on $z_{d(i)i}$ from a separate regression of Equation (1) for the indicated dependent variable. Column (2) reports results from the baseline specification, while the remaining columns report robustness when including further controls. To contextualize magnitudes in our discussion below, we consider the impact of a 10 p.p. increase in doctor generosity—which is slightly smaller than 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 doctor generosity—based on the share of claimants who are determined to have a continued impairment in the doctor's other exams. The baseline estimates indicate that a 10 p.p. increase in doctor generosity is associated with a 7.62 pp increase in the likelihood that a claimant themselves receives any cash benefits after the exam. This relationship is precisely estimated, with a 95% confidence interval spanning 7.31 to 7.93. The baseline estimates are nearly identical to those reported in the remaining columns, illustrating robustness to the inclusion of further controls for claimant and injury characteristics.

Table 4 Panel B reports the results for subsequent post-exam claim outcomes. Our discussion of these results focuses on estimates from the baseline specification, though we note the results are similar in the alternative specifications including an expanded set of controls. Our estimates indicate that being assigned a doctor that is 10 p.p. more generous leads to an increase in total additional cash benefits of $1,232 or 15.6% of the mean, and this increase is precisely estimated with a 95% confidence interval spanning $1,143 to $1,424. This increase in cash benefits comes from increases in both income-replacement benefits and permanent impairment benefits. Those assigned a designated doctor who is 10 p.p. more generous, on average, experience a 1.29 pp (3.9%) increase in the likelihood of receiving any additional income-replacement benefits and stay out of work an additional 1.25 weeks while receiving these benefits—a 15.7% 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 an 5.72 pp (8.7%) increase in the likelihood of being rated as having a permanent impairment and a 0.5 p.p. increase in the rated degree of permanent impairment (on a scale of 0 to 100), or a 13.3% 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 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 care to help the claimant heal to return to work or claimants may be more inclined to follow through with doctor-recommended care while out of work. Our estimates indicate that those assigned a 10 p.p. more generous designated doctor receive $570 more workers' compensation covered medical care after the exam, representing a 9.3% increase over the mean. This pattern broadly aligns with prior evidence of positive complementaries between workers' compensation cash benefits and medical spending (Cabral and Dillender, 2024*b*).

3 Variation Across Doctors

We next turn toward characterizing how doctors vary in the generosity of their evaluations. This analysis draws on estimates of doctor generosity. Let θ_d represent the generosity of doctor $d \in \{1, .., D\}$. To obtain an estimate for doctor generosity, we estimate the following equation:

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

where our estimate of doctor generosity is equal to the estimated doctor fixed effects in this equation, $\widehat{\theta}_d \equiv \gamma_{d(i)}$. In this specification, we focus on the dependent variable (y_i) indicating that a claimant has been assessed as having a continued impairment on the exam date. 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 injury year in the baseline specification ($\mathbf{X_i}$), and we assess robustness to the inclusion of further controls. Because doctor generosity is 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.

3.1 Variance Estimation

Test for Dispersion in Doctor Effects We begin by formally testing for variation across doctors by conducting a Pearson χ^2 test of the null hypothesis that all doctors are equally generous—based on estimates of doctor generosity from Equation (2). P-values from this test can be used for inference if each doctor's estimated generosity is normally distributed and centered around the population mean with variance equal to the squared standard error s_d^2. The first row of Table 5 reports the results from this test. These results indicate that we can reject that all doctors are equally generous, with a p-value less 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 key summary statistic of this distribution is the variance of θ_d, which is defined as: $\sigma \equiv \frac{1}{D}\sum_{d=1}^{D}\theta_d^2 - \left(\frac{1}{D}\sum_{d=1}^{D}\theta_d\right)^2$.

A key challenge with estimating σ 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 in this equation leads to upward bias. To address this challenge, we use 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 sampling each doctor's independent medical exams so that a doctor's exams are roughly equally divided across the two subsamples. 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 on this approach.

Panel B of Table 5 reports the standard deviation based on 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 10.6 percentage points 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 8.7 and 12.6 with 95% confidence.

These estimates indicate there is substantial variation across doctors in decisions regarding continued impairment at independent medical exams—and this variation in doctor generosity leads to large differences in claimant outcomes after these exams. We can quantify these differences by combining this variance estimate with the estimates from Table 4. Based on our estimates, a one standard deviation increase in generosity of a claimant's randomly assigned doctor leads to an 8.1 p.p. increase in the likelihood of being evaluated as eligible for continued benefits at the exam. This meaningfully impacts benefits received after the independent medical exam. Being assigned a doctor that is one standard deviation more generous, on average, leads a claimant to stay out of work 1.3 weeks longer while receiving income-replacement benefits, to experience a 6.0 p.p. increase in the likelihood of being rated as permanently impaired, to collect an additional $1,397—or 16.6% increase—in subsequent cash benefits, and to experience a 9.9% increase in subsequent injury-related medical spending.

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 in the first and last half of our sample. Similarly, we estimate a cross-group estimator of the covariance between doctor-by-group generosity—where groups represent groups of claimants with shared characteristics (e.g., above or below median age, above or below median predicted cash benefits). The ratio of the cross-time estimator to $\widehat{\sigma}$ measures the temporal stability of doctor generosity and the ratio of the cross-group estimator to $\widehat{\sigma}$ measures the stability of doctor generosity across claimants from different demographic groups.

Table 5 Panel B reports the results. The cross-time estimator implies standard deviation of 10.4 percentage points for continued impairment, which is nearly equal to the overall standard deviation. The similarity of the standard deviations based on the overall variance estimator and cross-time estimator suggests that doctor generosity is stable over time.

The remainder of Panel B reports the standard deviation based on cross-group estimators—considering groups based on claimant age and predicted cash benefits. Comparing exams for claimants above or below the doctor's median claimant age, the cross-age-group estimator yields a standard deviation of 10.8 percentage points in continued impairment. Comparing exams by predicted benefits, the cross-predicted-benefit estimator implies a standard deviation of 10.1 percentage points being assessed as having a continued impairment. The similarity of the standard deviation among these cross-group estimators to the standard deviation based on the overall split-sample estimator suggests doctor generosity is broadly consistent across exams for claimants from differing groups.

3.2 Distribution Across Doctors

Beyond estimating the variance, we more broadly characterize the distribution of doctor effects using an empirical Bayes deconvolution approach in Kline, Rose, and Walters (2022) based on methods developed by 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. Specifically, this approach begins by considering the distribution of z-scores—the ratio of doctor effects to their standard errors—which is assumed to be a standard normal distribution centered on a doctor-specific mean z-score. Then, the approach estimates the distribution of doctor-specific mean z-scores under flexible parametric assumptions. Finally, the approach recovers the density of the underlying doctor effects under some assumptions on the relationship between the doctor-specific mean z-scores and the standard errors on the doctor effect. See Appendix B.3 for more details on how we implement this approach. As described in the appendix, we estimate this distribution under the constraint that, after adding back in the mean, doctor effects are no larger than one—reflecting the theoretical upper bound that doctors assess all claimants as having a continued impairment—and no smaller than 0.4, which is lower than the lowest empirically observed rate of continued impairment assessment among doctors.

Figure 3 Panel A displays the estimated deconvoluted density of doctor effects for continued impairment, shifted by the mean to ease interpretation. The distribution is single-peaked and nearly symmetric near the mean, though there is a notably longer tail of mass to the left—indicating deviations from the average are larger among doctors who are less generous. Based on this density, there is substantial variation in doctor effects—with an interquartile range of 0.124, representing 15.8% of the mean rate of being assessed as having a continued impairment.

Based on the deconvoluted distribution, Figure 3 Panel B plots a Lorenz curve summarizing the concentration of denials in impairment assessments. Specifically, this figure displays the share of claimants being denied (assessed as having no continued impairment) 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 are responsible for 41.1% of the denials of continued impairment, while the most generous quartile of doctors only responsible for 11.4% 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 Lorenz curve and ranges from zero (in the case of perfect uniformity) to one (in the case of perfect concentration). The Gini coefficient based on the deconvoluted distribution is 0.27.

4 Correlates of Doctor Generosity

Next, we analyze the relationship between doctor generosity and observed doctor characteristics, through 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 2 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.

We first consider basic doctor demographics. Figure 2 indicates older doctors are less generous than younger doctors. The estimates imply that 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 0.18 of the standard deviation in doctor effects based on the overall variance calculated in Section 3.1. Doctor age is correlated with other doctor attributes such as specialty and credential, and the estimated association between doctor generosity and age is more muted in multivariate regressions including all measures. Moreover, the estimates in Figure 2 suggest female doctors are more generous than male doctors. Based on the multivariate regression estimates, female doctors are on average 2.2 p.p. more likely to assess a claimant as having a continued impairment (p-value 0.027) or 0.21 of the standard deviation calculated in Section 3.1.

Next, we turn to correlating generosity with information about doctor background. Patterns in Figure 2 suggest doctors born in Texas are more generous than those born elsewhere in the U.S. and doctors born abroad are less generous than doctors born in the U.S. Compared to doctors born in other states, doctors born in Texas have 1.9 p.p. higher continued impairment determinations (p-value 0.047) and doctors born outside the U.S. have 3.1 p.p. lower continued impairment determinations (p-value 0.013). However, doctor birthplace is correlated with other doctor characteristics (e.g., sex, credential, specialty), and the association with birthplace is much smaller and statistically insignificant in multivariate regressions controlling for all doctor measures simultaneously.

We also investigate how doctor's training is correlated with generosity. Credential is strongly associated with doctor generosity, with the estimates indicating that, on average, doctors with DC credentials are the most generous, followed by doctors with DO credentials, and then doctors with MD credentials. Compared to doctors with MD credentials, doctors with DC credentials have a 12.4 p.p. higher rate of continued impairment determinations (p-value<0.001). This difference is large representing 1.17 standard deviation of doctor generosity based on Section 3.1, and remains statistically significant and is slightly larger in magnitude when controlling for all doctor measures simultaneously. In addition, patterns suggest that doctors with DO credentials are, on average, more generous than doctors with MD credentials, though the magnitude of this difference is slightly less than half of the difference in doctor generosity between those with MD and DC credentials.

Additionally, we investigate how specialty is related to provider generosity. For this analysis, we consider coarse specialty information describing if the doctor specializes in: primary care/internal medicine, chiropractic care, orthopedic surgery, or other specialties—and the multivariate regressions exclude primary care/internal medicine (the most common specialty among MD/DOs) so effects are measured relative to this group. The estimates indicate doctors specializing in chiropractic care and orthopedic surgery are more generous than doctors doctors specializing in primary care/internal medicine. 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)—representing roughly a third of a standard deviation of the overall distribution of doctor effects—and chiropractors are 12.0 p.p. more likely to assess a claimant as having a continued impairment (p-value<0.001). Aside from orthopedic surgeons and chiropractors, doctors with other specialties appear to assess claimants similarly to those with primary care/internal medicine specialties.

Among doctors with MD credentials, we can correlate doctor generosity with the quality of the medical school a doctor attended. Relative to other doctors with MD credentials, doctors with an MD degree from a Top 25 medical school are less generous—being 5.7 p.p. less likely to rate a claimant has having a continued impairment (p-value<0.001). Attending a Top 25 medical school is correlated with other doctor characteristics, and the association with medical school rank and doctor generosity is small and statistically indistinguishable from zero in multivariate regressions controlling for all doctor measures.

Next, we explore the relationship between doctor generosity and features of the doctor's prior experience. For instance, we consider measures characterizing doctor experience with independent medical evaluations focusing on two measures: (i) the number of years the doctor has performed independent medical exams and (ii) the mean number of independent medical exams performed in years the doctor is observed as a designated doctor. Roughly speaking, we would characterize the first measure as capturing experience with these exams while the latter measure captures volume of exams. We construct these measures of designated doctors' prior experience using data from 2005 to 2012—prior to the analysis period which begins in 2013 when the auto-assignment algorithm is adopted.

Figure 2 indicates doctor generosity is negatively associated with experience with independent medical exams, with the magnitudes suggesting an additional year of experience is associated with 1.2 p.p. decrease in the share of claimants assessed as having a continued impairment (p-value$<$0.001). However, this association becomes small and statistically insignificant when analyzing all measures together. The relationship between doctor generosity and volume is positive. For example, the estimates indicate that a doctor with 100 more prior independent medical exams (roughly a 0.32 standard deviation increase) is associated with a 4.0 p.p. decrease in doctor generosity (p-value 0.006)—though the analogous estimate from multivariate regressions controlling for all doctor measures is much smaller and statistically indistinguishable from zero.

Lastly, we investigate the relationship between doctor generosity and disciplinary actions by the Texas Department of Insurance (TDI). The TDI disciplines doctors—with consequences such as suspending doctors' participation in designated doctors exams or in workers' compensation insurance more generally—for various actions, such as providing inappropriate care or failing to submit necessary forms. These disciplinary actions are rare, as only 2.4% of designated doctors are ever disciplined. The patterns in Figure 2 suggest doctor generosity is not strongly associated with disciplinary actions—with associations not significant at conventional levels in either bivariate or multivariate regressions.

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 supplemental evidence examining the relationship between doctor generosity and the behavior of market participants. This analysis leverages the fact that many of the doctors who are responsible for managing medical care and cash benefits for workers' compensation patients 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."

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 it is possible claimants can obtain some information

about doctors through their own experience or through peers or legal representatives, claimants likely have limited ability to assess doctor generosity. Second, claimants my 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 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:

$$y_j = \delta DD_j \times \tilde{\theta}_j + \rho DD_j + \nu_{s(j)m(j)} + \varepsilon_j, \tag{3}$$

where j indexes treating 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 designated doctor exams (described further below), and DD_j indicates that doctor j is certified as a designated doctor in our sample. 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).[14] 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 for doctor j between the first and second halves of the analysis period (Δ_j). Specifically, we construct this measure of mean annual growth rate as the difference in the mean annual number of claims between the second half and first half of the data and then 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 providers.

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 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.

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 29% more claimants for whom the doctor serves as a treating doctor in their standard practice. This relationship is statistically significant, with an implied 95% confidence interval spanning 13% to 45%.

[14] Refer to Appendix A for more details on identifying and classifying doctor specialties.

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 18 p.p. more growth in their market share over time, with a 95% confidence interval spanning 6 p.p. to 31 p.p.

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 aims to test a key comparative static of the demand-based allocation mechanism: when consumers have more choice or are more willing to substitute across producers, then the relationship between producer performance and market allocation should be stronger. We investigate this prediction through heterogeneity analysis, where we re-estimate Equation (3) separately for claims in more or less competitive medical markets. For this analysis, we defined 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 the importance of demand-driven allocation, the estimated relationship between doctor generosity and market allocation is stronger for claims in more competitive markets than for claims in less competitive markets. In more competitive markets, the estimates suggest that a one standard deviation more generous doctor has a market share that is 37% larger (p-value 0.001) and experiences 27 p.p. more growth in their market share over time (p-value 0.001). In contrast, the estimated association in less competitive markets is notably smaller and statistically insignificant.

We conduct a second set of analyses that tests another basic prediction of the demand-based allocation mechanism: the relationship between producer performance and market allocation should be stronger when consumers have more at stake and thus stronger incentives to sort toward producers with better performance from the consumer's perspective. A doctor's generosity in evaluating cash benefit eligibility is only directly relevant for claimants who expect to receive cash benefits—claimants with injuries severe enough to potentially need to miss at least seven days of work—and the stakes associated with doctor generosity are larger for claimants with greater expected cash benefits. Motivated by this, we conduct heterogeneity analysis where we estimate Equation (3) for claimants with above or below median predicted cash benefits. The results are reported in Table 6 columns 4 and 5. The estimates suggest the relationship between doctor generosity and market allocation is stronger among claims with larger expected benefits. Among claims with above median expected benefits, the estimates indicate that a one standard deviation more generous doctor has a market share that is 26% larger (p-value 0.001) and sees 21 p.p. more market share growth over time (p-value 0.001). For claims with below median predicted 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 is driven by claimants who are informed about doctor generosity and sort toward providers based on this information, in line with their incentives. Another possibility is that claimant doctor choices are not motivated by doctor generosity—but instead are based on other characteristics that are correlated with generosity. For example, doctors who are more generous in cash benefit eligibility could also have other correlated characteristics that claimants generally view favorably—e.g., they may defer more to pa-

tients in medical treatment decisions, they could be more empathetic toward patients, they may have better front office staff, etc. 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. 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) imply the reallocation of patients toward more generous doctors increases mean doctor generosity by 0.0306. Combining this with the estimates from Table 4 on the implied percent impact of doctor generosity on total benefits, this implies that reallocation toward more generous doctors increases overall workers' compensation costs by 4.0%. This aggregate implied impact of reallocation on costs is large and of the same order of magnitude as other policies that have been shown to impact workers' compensation costs. For instance, this estimated 4% increase in workers' compensation costs attributable to reallocation is nearly half of the estimated increase in workers' compensation costs due to behavioral responses among claimants affected by a recent reform that increased weekly wage-replacement benefits by an average of 17% (Cabral and Dillender, 2024*b*).

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, more than 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 the the generosity of the claimant's treating doctor.

Given these incentives, we may expect that claims with more generous treating doctors are more often disputed by insurers. However, it is unclear whether such patterns exist in practice, if insurers are imperfectly aware of doctor generosity or other factors that are more important determinants of dispute initiation among insurers. We turn to the data to empirically explore this relationship.

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

$$y_i = \gamma DD_{j(i)} \times \tilde{\theta}_{j(i)} + \phi DD_{j(i)} + \pi Z_i + \mu_{s(j(i))m(j(i))} + e_i, \tag{4}$$

where i indexes claimants and $j(i)$ represents claimant i's treating doctor. This specification includes controls for baseline claimant characteristics, Z_i, (e.g., sex, age, injury year-month), as well as doctor-level characteristics defined as in Equation (3) above. The key coefficient of interest is γ, which relates outcomes of interest to doctor generosity. In this analysis, we consider three dependent variables: (i) an indicator that the claim was disputed, (ii) an indicator that the claim was disputed by the insurer, and (iii) an indicator that the claim was disputed by the claimant.

Results The estimates are displayed in Table 7. Estimates from column (1) indicate that claims for which the treating doctors is more generous are more likely to be disputed. The estimates suggest that a claim with a one standard deviation more generous treating doctor, on average, is associated with a 4.4 p.p. increase in the likelihood of being disputed—or 43% 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 4.0 p.p. increase in the likelihood that an insurer disputes the claim or 47% of the overall rate of insurer-initiated disputes. In contrast, there is no statistically significant association between doctor generosity and claimant-initiated disputes.

5.3 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, to the extent that doctor generosity during independent medical exams predicts doctor generosity when managing cash benefits for their typical patients. However, it is ex ante ambiguous whether we would see these patterns in practice for 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 is not attributable to the impact of doctors. Second, it could be that doctor generosity differs depending on the context 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 (4) 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 on temporary income benefits, permanent impairment rating, and injury-related medical spending. All other included variables are as defined in Equation 4 above, where the coefficient of interest is, γ, captures the relationship between doctor generosity and claimant outcomes among claimants treated by the doctor in their standard practice. We consider specifications both with and without additional controls for baseline claimant observables (e.g., sex, age, injury characteristics) to explore potential differences between unconditional and conditional correlations. In addition, we also analyze potential selection of patients across treating doctors by estimating Equation (4) 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. A one standard-deviation increase in doctor generosity is associated with a 5.2 p.p. increase in the likelihood of receiving any cash benefits (95% CI: 1.2 to 9.2), which represents a 19% 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 $1,459 increase in total cash benefits (95% CI:

574 to 2,344)—which amounts to a 47% 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 4.5 p.p. (95% CI: 0.5 to 8.4) more likely to receive income-replacement benefits—representing a 19% increase over the mean—and remain out of work receiving income-replacement benefits for an additional 2.0 weeks (95% CI: 0.7 to 3.3), which is a 47% increase over the mean duration receiving these benefits. In addition, a one standard deviation more generous doctor is associated with a 4.3 p.p. (95% CI: 1.8 to 6.8) increase in the likelihood of being rated as having any permanent impairment, which represents 37% increase over the mean, and a 0.30 p.p. increase in the permanent impairment rating—representing a 48% 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 $1,207 in injury-related medical spending (95% CI: 359 to 2,054), representing an 30% 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.

To investigate the potential role of selection directly, Appendix Table A4 presents estimates of Equation (4) 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 available baseline characteristics. These estimates reveal no statistically significant relationship between these baseline claimant characteristics and generosity of the treating doctor, with one possible exception: overall predicted cash benefits. Based on the point estimate in Table A4 column 8, a claimant with a one standard deviation more generous treating doctor has on average $159 higher baseline overall predicted cash benefits. While this pattern is consistent with evidence from Table 6 that indicates demand-driven allocation patterns are stronger among claimants who have more at stake (those with higher baseline predicted cash benefits), the point estimate in Table A4 is marginally statistically indistinguishable from zero with a p-value of 0.058 and the magnitude is small—representing less than 10% of the estimated differences in observed spending across patients with a one standard deviation more generous doctor based on Table 4. Overall, Appendix Table A4 suggests differences in baseline observable characteristics across claimants selecting more or less generous treating doctors are limited and do not explain much of the observed association between doctor generosity and observational outcomes among claimants treated in the doctor's standard practice documented in Table 6.

6 Policy Counterfactuals and Discussion

Next, we explore the potential policy implications of our findings. Our findings 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. Motivated by these findings and ongoing related policy debates, we consider the impact of counterfactual

policies influencing the allocation of doctors to claimants for disability evaluations.

We begin by considering the implications of doctor allocation in our empirical setting: independent medical exams. All states use independent medical exam systems to settle disputes over disability evaluations, though key details of these systems differ across states including which doctors are eligible to perform these exams and how doctors are allocated to these exams. We consider back-of-the-envelope counterfactuals characterizing how claimant outcomes and workers' compensation costs could change comparing the doctor allocation system used in Texas to alternative allocation systems—resembling those used in other states. Specifically, we consider two types of counterfactuals: (i) changing the pool of doctors eligible to preform independent exams holding fixed the current assignment process and (ii) changing the current assignment process while holding fixed the set of doctors performing these exams. In analyzing these counterfactuals, we consider the impacts claimant outcomes subsequent to the exam—through combining projected changes in doctor generosity with our estimates of the causal impact of being assigned a more generous doctor from Section 2. Below, our discussion of impacts on claim outcomes focuses on three outcomes: being rated as having a continued impairment, subsequent cash benefits, and subsequent total workers' compensation benefits (the sum of subsequent cash benefits and medical spending).

This analysis draws on the estimated distribution of doctor effects described in Section 3, and this analysis 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).

Alternative Pool of Doctors We first consider the impact of changing the pool of doctors eligible to perform independent medical exams, holding fixed other aspects of the randomized assignment process. Specifically, we consider how claimant outcomes would change if eligibility were limited to a subset of the current doctors performing these exams—-restricting eligibility based on doctor credential, specialty, or experience motivated by restrictions observed in other state workers' compensation programs. This analysis draws on the distribution of doctor effects from Section 3, as well as analogous estimated distributions for subgroups of doctors defined by specified characteristics. [ANALYSIS IN PROGRESS]

Alternative Assignment Process Next, we consider the impact of changing the assignment process from the observed system of randomization in the Texas workers' compensation system to alternative systems that allow insurers or claimants to influence doctor allocation. Motivated by allocation systems seen in other states, we consider alternative allocation systems where insurers or claimants can directly choose a doctor and systems where insurers or claimants can indirectly influence doctor selection—for example, through choosing a doctor from (or striking a doctor from) a randomly selected panel of doctors or by choosing the specialty of the doctor the regulator randomly assigns.

Considering these scenarios requires making some assumption about how claimants and insurers would influence the selection of doctors for these exams if they had the opportunity to do so. In Section 5, we presented evidence on claimant and insurer decisions in the context of treating doctors that suggests insurers and claimants have some knowledge of doctor generosity and act to influence doctor allocation in accordance to their respective incentives. However, because doctors for independent medical exams are randomly assigned in Texas, we cannot provide direct evidence on how claimants and insurers would influence doctor selection in independent medical exams in particular. Our approach is to conduct back-of-the-envelope counterfactual analysis under the assumption that insurers (claimants) select the least (most) generous doctor among the set of available doctors from which they can chose. This assumption is extreme and, in reality, decisions likely deviate from this due to imperfect information about doctor generosity or

other choice frictions. Thus, we interpret estimated changes in outcomes under this assumption as an upper bound on how much giving insurers or claimants influence in doctor selection moves outcomes in the direction of the party being given this influence.

The process of assigning doctors for 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 states rely on explicit random assignment, though the details of these assignment processes vary. For example, some states assign a randomly selected doctor from an approved list to preform the exam (as in Texas), while other states have more complex systems where the regulator randomly selects a panel of three doctors from an approved list, allows insurers and claimants to each strike one, and then assigns the remaining doctor in the panel to perform the exam. Moreover, states with administrative assignment vary in whether they allow insurers or the party requesting the exam to specify the specialty of the assigned doctor. In the remaining 28 states, 25 allow the insurer to select the doctor for an independent medical exam, while two allow the exam requester—which is usually the insurer but sometimes the injured worker—to select the doctor. Even among states that specify that insurers control doctor selection, relevant state statutes often recognize this feature could disadvantage injured workers, with many of these states stipulating that injured workers are entitled to have a doctor or other observer (e.g. attorney, advocate) of their own selection present at an independent medical exam. There are ongoing debates in many state workers' compensation programs about the structure of the assignment process for these exams.

Motivated by the wide range of allocation systems observed across states and ongoing related policy debates, we explore the consequences of different allocation systems. [ANALYSIS IN PROGRESS]

7 Conclusion

Our paper analyzes the importance of doctor discretion in medical evaluations. We leverage comprehensive administrative data from Texas workers' compensation insurance and random assignment of doctors to injury exams which happens through the claim dispute resolution system. Our analysis illustrates there is substantial variation scope for doctor discretion in these medical evaluations, these decisions have meaningful impacts on claimants' later outcomes, and doctor generosity in these decisions varies systematically across doctors with differing baseline characteristics. Moreover, we analyze how doctor generosity in medical evaluations is associated with market allocation when claimants can select their own doctors. This analysis indicates both claimants and insurers influence the allocation of doctors in line with their respective incentives, suggesting market forces shape the distributed program benefits. We conclude by presenting supplemental counterfactual analysis which provide context on the implications of our findings for ongoing policy debates.

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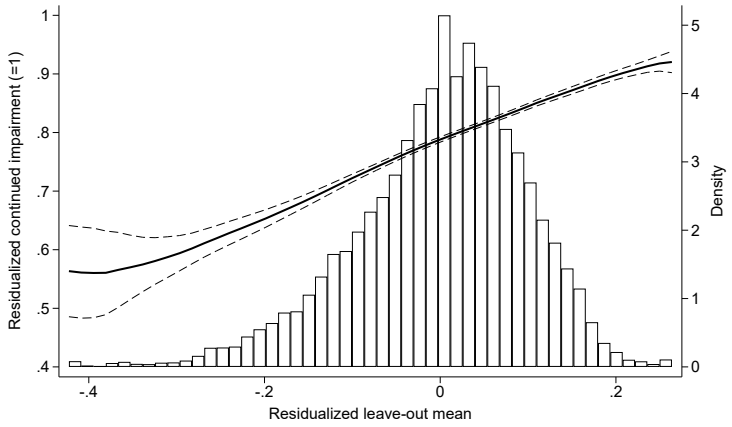
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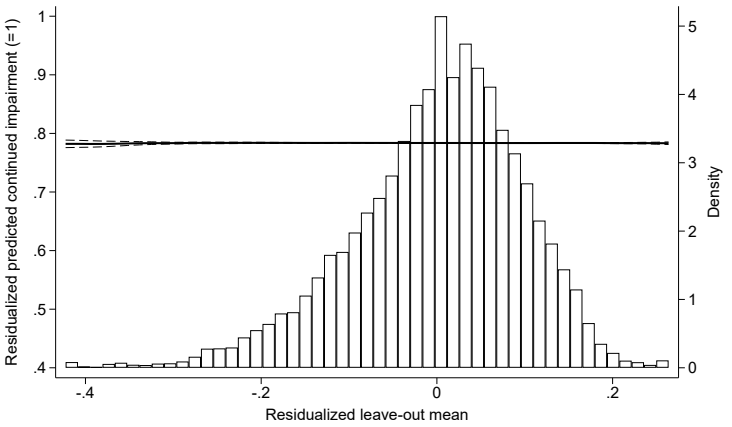
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Figure 1: Distribution of Leave-Out Generosity Measure and Likelihood of Being Rated as Having Continued Impairment on Exam Date



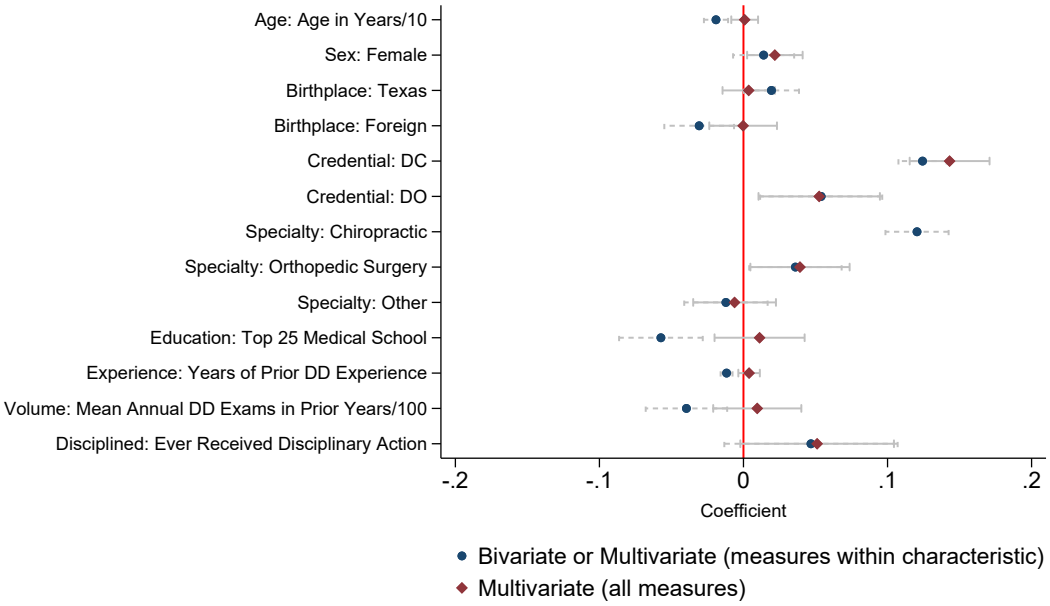
(a) Likelihood of Rated as Having Continued Impairment on Leave-Out Generosity Measure



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

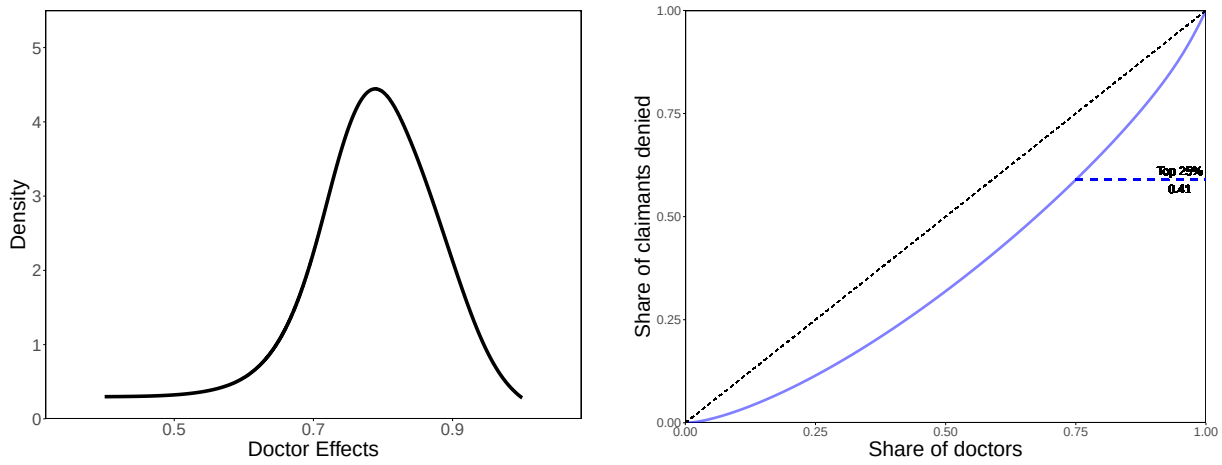
Notes: This figure displays the distribution of the residualized leave-out generosity measure, along with its impact on claimants' likelihood of being rated as having continued impairment on the exam date (Panel A) and its impact on claimants' predicted likelihood of being rated as having continued impairment on the exam date (Panel B). The leave-out generosity measure and the dependent variables are residualized for injury year and the doctor credential required to preform 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 right vertical. Dashed lines represent 95% confidence intervals calculated from standard errors clustered at the doctor level.

Figure 2: 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.

Figure 3: Distribution of Doctor Effects



(a) Distribution of Doctor Effects for Continued Impairment (shifted by mean)

(b) Share of Denials attributable to Doctors

Notes: Panel A reports the deconvoluted distribution of doctor effects on an indicator for continued impairment, shifted by the overall mean of continued impairment to facilitate interpretation. See Appendix Section B.3 for more details on this estimation. Panel B reports an associated Lorenz curve summarizing the concentration of denials in 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.

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 the National Plan and Provider Enumeration System (NPPES) data through 2019. Information on age 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
Recieves Income-Replacement Benefits within three years of injury	0.19	0.83
Recieves Permanent Impairment Benefits within three years of injury	0.09	0.65
Injury Type:	0.15	0.09
Contusion	0.06	0.15
Fracture	0.10	0.02
Sprain or Muscle Issue	0.46	0.63
Other	0.23	0.10
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	-	8,431
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 Benefits	-	14,554

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	0.011	(0.017)	[0.503]
Age	0.397	(0.429)	[0.355]
ED Claim	-0.004	(0.018)	[0.824]
Log(First-Day Medical Spending)	0.028	(0.047)	[0.556]
Log(Med Spending Prior to Exam Request)	0.001	(0.039)	[0.970]
Log(Weeks from Injury to Exam Request)	0.009	(0.020)	[0.659]
Claimant Contested	-0.004	(0.011)	[0.721]
Injury Type:			
Contusion	-0.004	(0.011)	[0.753]
Fracture	-0.001	(0.015)	[0.929]
Laceration	-0.004	(0.006)	[0.487]
Sprain or Muscle Issue	0.005	(0.018)	[0.767]
F-Statistic for All Variables in Multivariate Regression	0.401		

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 preform 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 in 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 is for the joint hypothesis that the coefficients on all the variables listed in the table are zero.

Table 4: Effect of Doctor Generosity

	Dependent Variable Mean and Std Dev	Leave-Out Doctor Generosity, $z_{d(i)t}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.762	0.761	0.762
	(0.412)	(0.016)	(0.016)	(0.016)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,431	13,178	13,170	13,163
	(14,038)	(734)	(732)	(729)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.129	0.129	0.128
	(0.471)	(0.023)	(0.023)	(0.022)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	12.479	12.503	12.473
	(18.56)	(0.964)	(0.962)	(0.950)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.572	0.570	0.571
	(0.476)	(0.021)	(0.021)	(0.021)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	5.382	5.360	5.368
	(5.670)	(0.270)	(0.267)	(0.265)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	5,698	5,719	5,702
	(12,936)	(589)	(584)	(579)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Benefits	14,554	18,876	18,889	18,865
	(24,136)	(1,234)	(1,228)	(1,220)
		[<0.001]	[<0.001]	[<0.001]
Controls:				
Baseline		x	x	x
Claimant Demographics			x	x
Injury Type				x

Notes: This table displays estimates of the coefficients on the leave-out measure of doctor generosity from separate OLS regressions of Equation (1) where the dependent variable is indicated in the corresponding row. All regressions include the baseline controls for injury year and the doctor credential required to preform 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 injury type. 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.

Table 5: Variation Across Doctors

	Rated as Having Continued Impairment
	(1)
Panel A	
χ^2 test of heterogeneity	10,013
	[<0.001]
Panel B	
Standard Deviation Based on Split Sample…	
Variance Estimator	0.106
	(0.010)
Cross-Time Covariance Estimator	0.104
	(0.010)
Cross-Age-Group Covariance Estimator	0.108
	(0.008)
Cross-Predicted-Benefits Covariance Estimator	0.101
	(0.011)

Notes: This table displays estimated standard deviations of doctor generosity and tests for heterogeneity in doctor generosity. Panel A displays the χ^2 test statistic and associated p-value from a test of the null hypothesis of no heterogeneity in doctor generosity. 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-sex covariances between doctor-by-time, doctor-by-age, and doctor-by-sex 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 $\tilde{\theta}$	2.715	3.529	1.571	2.418	1.072
	(0.771)	(1.020)	(1.189)	(0.741)	(0.963)
	[<0.001]	[0.001]	[0.187]	[0.001]	[0.266]
			Panel B: Dynamic. Dep Var: Δ		
DD X $\tilde{\theta}$	1.726	2.584	0.449	1.948	1.270
	(0.589)	(0.768)	(0.921)	(0.609)	(0.802)
	[0.003]	[0.001]	[0.626]	[0.001]	[0.114]
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 (3), 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 Contested Claims

	Independent Medical Exam is Requested	Insurer Requests Independent Medical Exam	Claimant Requests Indpendent Medical Exam
	(1)	(2)	(3)
DD X $\tilde{\theta}$	0.413	0.378	0.045
	(0.130)	(0.113)	(0.028)
	[0.002]	[0.001]	[0.108]
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 (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 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. 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 Benefits

	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 $\tilde{\theta}$	0.489	13,745.056	0.424	19.017	0.407	2.843	11,362.981
	(0.194)	(4,252.578)	(0.189)	(6.190)	(0.120)	(0.811)	(4,072.089)
	[0.012]	[0.001]	[0.025]	[0.002]	[0.001]	[<0.001]	[0.005]
Dependent Variable							
Mean	0.269	3076	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	9504	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 (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 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. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

FOR ONLINE PUBLICATION

APPENDIX

A Additional Details on Data

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, fractures, or sprains or muscle issues based on the most commonly listed ICD-9 code of the earliest medical treatment. We use this injury classification when testing for balance and as supplemental controls. 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.

Construction of Normalized Additional Benefits Measure We assess the value of cash benefits received after exams by creating a "normalized additional benefits" measure—which captures the dollar value of disability benefits removing the influence of a claimant's own prior earnings. Specifically, this measure captures the total cash benefits received in the three years after exams valued at the mean benefit rate for each benefit type based on the population-wide distribution of pre-injury wages. To create this measure, we first calculate the mean, inflation-adjusted weekly benefit rate separately for temporary income-replacement benefits and permanent impairment benefits using the populations of claimants receiving each type of benefit injured from 2013 to 2019. We then multiply the mean benefit rate for each type of benefit by the number of weeks claimants received benefits. Finally, we add these two amounts to calculate the total normalized additional cash benefits.

Predicting Cash Benefits with Lasso Model To create the measure of predicted cash benefits, we first fit a lasso model of the likelihood that claimants are assessed as having continued impairment during the independent medical exam. We then predict claimants' likelihood of being assessed as having continued impairment based on this lasso model. For the lasso model, we include indicator variables for day of the week of first medical treatment, the ICD-9 code for first medical treatment, insurer, age, gender, injury year-month, and the claim originating in the emergency department.

B Distribution of Doctor Effects

In this appendix section, we describe 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. Let θ_d denote the generosity of doctor $d \in \{1, .., D\}$. We estimate these using the following specification:

$$y_i = \gamma_{d(i)} + \phi_{r(i)t(i)c(i)} + \mathbf{X_i}\mathbf{\Sigma} + e_i, \tag{5}$$

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 effecs 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 (5) 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.

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 an variance of 0.022 and implied standard deviation of 0.148. 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 (5) 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:

$$\hat{\theta}_p = \theta + \epsilon_p, \qquad p \in \{a, b\}, \tag{6}$$

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:

$$\begin{aligned} Cov(\hat{\theta}_a, \widehat{\theta}_b) &= Cov(\theta + \epsilon_a, \theta + \epsilon_b) && (7)\\ &= Cov(\theta, \theta) + Cov(\theta, \epsilon_b) + Cov(\epsilon_a, \theta) + Cov(\epsilon_a, \epsilon_b) && (8)\\ &= Var(\theta). \end{aligned}$$

As reported in Table 5 of the text, the standard deviation based on this unbiased variance estimate of doctor effects is 0.106. This is roughly 72% of the naive implied standard deviation that does not account for sampling error.

B.3 Estimating Distribution of Doctor Effects

To characterize the population distribution of doctor effects, we apply an approach used in Kline, Rose, and Walters (2022) based on Efron (2016). For the baseline approach in Kline, Rose, and Walters (2022), the key

inputs are the doctor effect estimates ($\hat{\theta}_d$) and associated standard errors (s_d) described in Appendix Section B.1 above. Suppose the distribution of doctor z-scores ($z_d = \frac{\theta_d}{s_d}$) can be described as:

$$z_d|\nu_d \sim N(c_d, 1), \qquad \nu_d \sim G, \tag{9}$$

where ν_d is the population analogue of z_d.

The approach first applies the Efron (2016) deconvolution procedure to obtain an estimates of the distribution of provider z-scores $\hat{G}$ with associated density $\hat{g}$. This procedure assumes G belongs to an exponential family flexibly parameterized by a fifth order spline, where the parameters of this spline are estimated via penalized maximum likelihood. Assuming s_d is independent of ν_d, one can then estimate the distribution of doctor effects $\hat{F}$ with density function $\hat{f}$ at each point x:

$$\hat{f}(x) = \frac{1}{D}\sum_{d=1}^{D}\frac{1}{s_d}\hat{g}(\frac{x}{s_d}). \tag{10}$$

We aim to use deconvolution to estimate the distribution of doctor effects in the assessment of continued impairment. However, the independence assumption referenced above may not hold in this setting. To see this, note that there is a theoretical upper bound on doctor generosity—as the maximum share of patients a doctor can evaluate as having a continued impairment is one.[1] Thus, as a doctor's true generosity approaches this upper bound, the associated standard error on an estimate of doctor generosity will be smaller, pointing to a likely dependence between ν_d and s_d. Given this, our baseline estimation of the distribution of doctor effects amends the approach described above using using a variance stabilization transformation—an alternative approach outlined in Kline, Rose, and Walters (2022) that allows for dependence between ν_d and s_d. Below, we summarize how we apply this variance stabilization approach in our setting.

This approach relies on assuming a parametric model of dependence between doctor-specific variances and the underlying doctor effects, $s_d^2 = k(\theta_d)$. Suppose $y(t) = \int_\infty^t k(x)^{-1/2}dx$, and hence $\frac{d}{dt}y(t) = k(t)^{-1/2}$. Based on the reasoning behind the delta method, $y(\hat{\theta}_d)|\theta_d \sim \mathcal{N}(y(\theta_d), 1)$. One can estimate the population distribution of θ_d by applying the Efron (2016) deconvolution estimator to the transformed estimates $y(\theta_d)$ using the change of variables $\hat{f}(x) = \hat{f}_y(x)k'(x)$, where $\hat{f}_y(x)$ is the estimated density of y.

We implement this approach by assuming a quadratic relationship between the squared standard errors and the doctor effects: $k(\theta) = \beta_0 + \beta_1\theta + \beta_2\theta^2$, for $\theta \in \mathcal{S}$ where $\mathcal{S}$ is the support of the doctor effects. We use a split-sample instrumental variables approach to estimate this equation. Specifically, we randomly split the sample into two partitions, $l \in \{0, 1\}$, and approximate θ_d and θ_d^2 with $\hat{\theta}_{dl}$ and $\hat{\theta}_{dl}^2 - s_{dl}^2$, respectively, where $\hat{\theta}_{dl}$ and s_{dl} are the doctor effect estimates and standard errors, respectively, from partition l. We obtain estimates of the parameters in the quadratic equation $(\beta_0, \beta_1, \beta_2)$ from regressing s_{dl}^2 on $\hat{\theta}_{dl}$ and $\hat{\theta}_{dl}^2 - s_{dl}^2$, where we instrument for these using $\hat{\theta}_{d(l)}$ and $\hat{\theta}_{d(l)}^2 - s_{d(l)}^2$ from the other partition (i.e., $(l) = 1 - l$).

Similar to Kline, Rose, and Walters (2022), we calibrate the regularization parameter in the maximum likelihood estimation so that the variance of the deconvoluded distribution matches the split-sample variance described in Appendix Section B.2 above.[2] Figure 3 Panel A in the text displays the deconvoluted distribution of doctor effects using the variance stabilization approach, where displayed estimates are shifted by the mean to ease interpretation. Figure 3 Panel B plots an associated Lorenz 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 41.1% of the denials of continued impairment, while the most generous 25% of doctors only responsible for 11.4% of continued impairment denials.

For comparison, Appendix Figure A2 presents estimates of the distribution of doctor effects using an alternative method—the primary devolution method in Kline, Rose, and Walters (2022) that assumes independence between ν_d and s_d. The key take-aways from this figure are very similar as those from the baseline approach described in the text (and reported in Figure 3). For instance, based on this alternative approach,

[1] There is also a theoretical lower bound on doctor effects—the share of patients with continued impairments cannot be below zero—but this is well outside the empirically relevant range given the minimum observed doctor share with continued impairment exceeds 0.4.

[2] As described in the text, we restrict the support of doctor effects such that the range, after adding back in the mean, is $[0.4, 1]$.

the estimates imply the least generous 25% of doctors are responsible for 41.0% of the denials of continued impairment, while the most generous 25% of doctors only responsible for 10.8% of continued impairment denials.

B.4 Doctor Effects

We calculate empirical Bayes posteriors of doctor effects as in Kline, Rose, and Walters (2022):

$$\bar{\theta}_d = s_d \frac{\int x\phi(z_d - x)g(x)dx}{\int \phi(z_d - x)g(x)dx}, \tag{11}$$

where the function ϕ represent the standard normal density.

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]
Fracture	0.000	(0.002)	[0.995]
Laceration	-0.004	(0.003)	[0.278]
Sprain or Muscle Issue	0.009	(0.013)	[0.489]

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 injuries that state law explicitly stipulates can be preformed by doctors with any credential (N= 5,631 claims). Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A2: Effect of Doctor Generosity—Alternate Specifications

	Dependent Variable Mean and Std Dev	Doctor Generosity, $Z_{d(i)i}$			
	(1)	(2)	(3)	(4)	(5)
Panel A. Continued Impairment					
Rated as Having Continued Impairment on Exam Date	0.784	0.762	0.724	1.000	1.174
	(0.412)	(0.016)	(0.014)	(0.005)	(0.011)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes					
Total Additional Cash Benefits	8,431	13,177.933	12,427.271	15,341.515	18,208.914
	(14,038)	(734.437)	(716.514)	(766.475)	(995.772)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.129	0.131	0.175	0.203
	(0.471)	(0.023)	(0.022)	(0.024)	(0.030)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	12.479	11.989	14.578	17.291
	(18.56)	(0.964)	(0.924)	(0.991)	(1.256)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.572	0.540	0.733	0.870
	(0.476)	(0.021)	(0.019)	(0.018)	(0.021)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	5.382	4.981	6.342	7.564
	(5.670)	(0.270)	(0.260)	(0.274)	(0.342)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	5,697.969	5,221.741	6,993.067	8,241.755
	(12,936)	(588.938)	(572.005)	(605.576)	(753.780)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Total Additional Benefits	14,554	18,875.902	17,649.012	22,334.582	26,450.670
	(24,136)	(1,234.446)	(1,206.234)	(1,283.458)	(1,648.106)
		[<0.001]	[<0.001]	[<0.001]	[<0.001]
Doctor Generosity Measure:					
Baseline: Leave-Out Mean		x			
Alternative: UJIVE approach			x		
Alternative: Doctor Effects Estimated in Section 4				x	
Alternative: Shrunk Doctor Effects Estimated in Section 4					x

Notes: This table displays estimates of the coefficients on doctor generosity from OLS regressions of Equation (1) that control for injury year and the doctor credential required to preform the claimant's exam interacted with claimant county and exam year-quarter. Each row displays coefficients from four separate regressions with the generosity measure 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.

Table A3: Effect of Doctor Generosity—Alternate Controls

	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	0.762	0.778	0.771
	(0.412)	(0.016)	(0.016)	(0.023)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,431	13,177.933	13,247.473	14,439.042
	(14,038)	(734.437)	(741.766)	(830.460)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.129	0.130	0.170
	(0.471)	(0.023)	(0.022)	(0.028)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	12.479	12.380	13.588
	(18.56)	(0.964)	(0.974)	(1.136)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.572	0.587	0.595
	(0.476)	(0.021)	(0.021)	(0.027)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	5.382	5.536	5.825
	(5.670)	(0.270)	(0.267)	(0.328)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	5,697.969	5,677.006	6,030.699
	(12,936)	(588.938)	(576.559)	(670.454)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Benefits	14,554	18,875.902	18,924.479	20,469.740
	(24,136)	(1,234.446)	(1,230.067)	(1,381.679)
		[<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: This table displays estimates of the coefficients on doctor generosity from OLS regressions of Equation (1) that control for injury year. Each row displays coefficients from four separate regressions with the generosity measure 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.

Table A4: 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 $\tilde{\theta}$	0.068	0.514	0.199	0.024	0.163	1,500.044	0.057
	(0.118)	(1.660)	(0.174)	(0.134)	(0.107)	(789.979)	(0.152)
	[0.564]	[0.757]	[0.252]	[0.856]	[0.129]	[0.058]	[0.710]
Dependent Variable							
Mean	0.605	41.98	0.501	0.501	0.487	2,911	5.827
Standard Deviation	0.489	13.31	0.500	0.500	0.500	2,657	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 (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 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. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A5: Relationship Between Doctor Generosity and Patient Volume—Alternate Specifications

	Static			Dynamic		
	Dep Var: ln(N)			Dep Var: Δ		
DD X θ	2.725	2.546	2.745	1.720	1.556	1.744
	(0.771)	(0.734)	(0.760)	(0.588)	(0.565)	(0.580)
	[<0.001]	[0.001]	[<0.001]	[0.003]	[0.006]	[0.003]
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 (3), 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 A6: Relationship Between Doctor Generosity and Contested Claims—Alternate Specifications

	Independent Medical Exam is Requested			Insurer Requests Independent Medical Exam			Claimant Requests Independent Medical Exam		
	(1)	(2)	(4)	(5)	(6)	(8)	(9)	(10)	(12)
DD X θ	0.412	0.384	0.390	0.380	0.356	0.364	0.041	0.037	0.035
	(0.130)	(0.118)	(0.120)	(0.113)	(0.103)	(0.105)	(0.028)	(0.027)	(0.025)
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.147]	[0.167]	[0.162]
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	

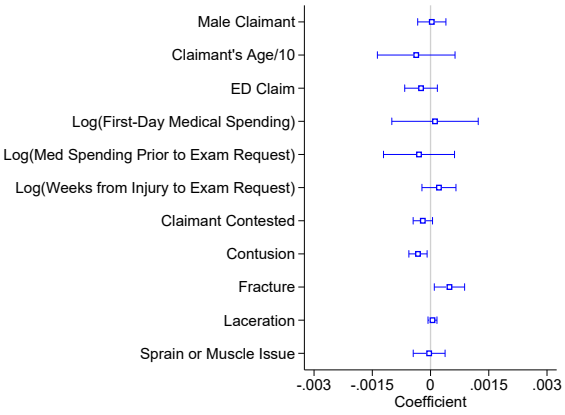
Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (4), where the measure of doctor generosity is calculated using Empirical Bayes shrinkage on the coefficients from 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 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. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A7: Relationship Between Doctor Generosity and Benefits—Alternate Specifications

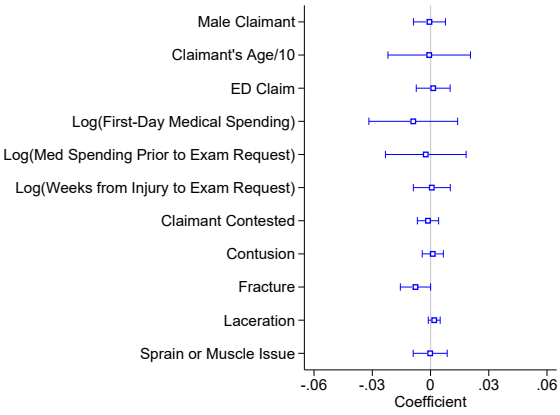
	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline Specification							
DD X θ	0.484	12,943.325	0.415	18.863	0.413	2.853	10,874.421
	(0.194)	(4,027.926)	(0.189)	(6.193)	(0.118)	(0.808)	(3,908.519)
	[0.013]	[0.001]	[0.028]	[0.002]	[<0.001]	[<0.001]	[0.005]
Panel B: Including Additional Claimant Controls							
DD X θ	0.405	12,009.276	0.342	17.512	0.386	2.643	9,633.727
	(0.163)	(3,625.831)	(0.160)	(5.617)	(0.105)	(0.715)	(3,454.614)
	[0.013]	[0.001]	[0.033]	[0.002]	[<0.001]	[<0.001]	[0.005]
Dependent Variable							
Mean	0.269	2,911	0.241	4.276	0.117	0.630	3,812
Standard Deviation	0.443	8,995	0.428	14.09	0.321	2.467	7,938

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 (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 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. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

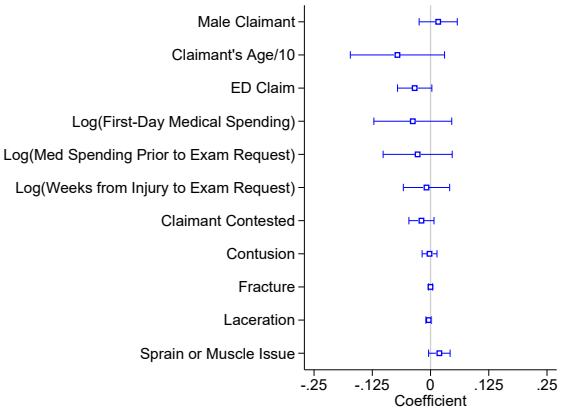
Figure A1: Balance of Claimant Characteristics across Designated Doctor Characteristics



(a) Doctor Age



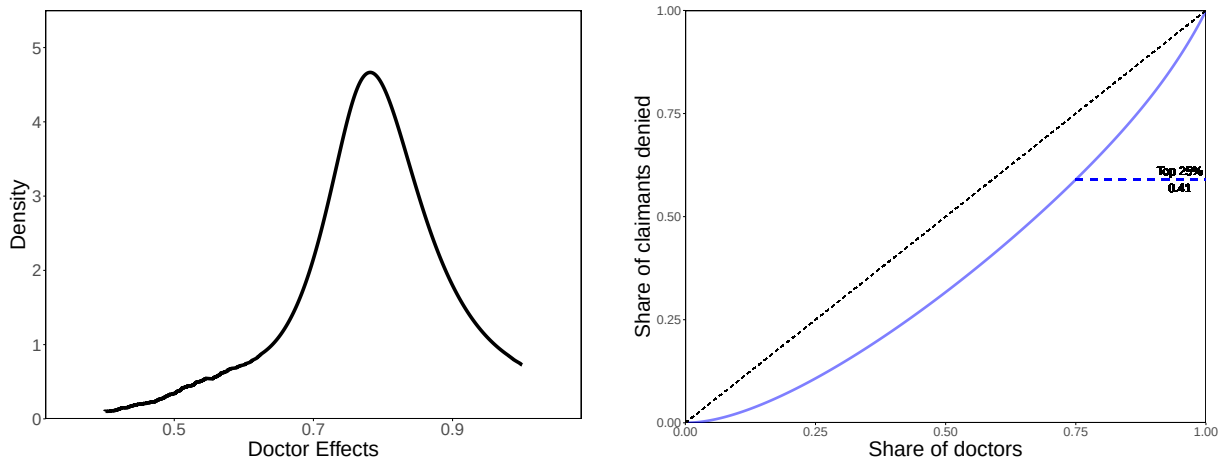
(b) Doctor Female



(c) Doctor DC

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 being a DC (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 preform the claimant's exam interacted with claimant county and exam year-quarter. Standard errors clustered at the doctor level.

Figure A2: Distribution of Doctor Effects: Alternative Approach



(a) Distribution of Doctor Effects for Continued Impairment (shifted by mean)

(b) Share of Denials attributable to Doctors

Notes: This figure displays estimate of the distribution of doctor effects from an alternative deconvolution procedure that assumes independence between ν_d and s_d. See Appendix Section B.3 for more details on this estimation. Panel A reports the deconvoluted distribution of doctor effects on an indicator for continued impairment, shifted by the overall mean of continued impairment to facilitate interpretation. Panel B reports an associated Lorenz curve summarizing the concentration of denials in 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.