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ABSTRACT

This paper analyzes the importance of doctor discretion in medical evaluations. Leveraging comprehensive administrative data and random assignment of doctors to evaluations in workers' compensation insurance, 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 medical evaluations, these decisions are consequential for later claimant outcomes, and doctor effects vary systematically by observed doctor characteristics. In addition, we analyze the relationship between doctor effects 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, some natural questions arise: How much evaluator discretion is there in practice and what are the consequences of this discretion? How does the use of discretion vary across evaluators with different characteristics? How do individuals influence evaluator assignment when given the choice? 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 larger 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. Most state workers' compensation insurance systems allow claimants to choose their own doctor, with little or no restrictions. However, policymakers in many states have debated whether choice should be restricted and roughly a third of 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 regulations in all states specify that such disputes are settled through a second evaluation by a different doctor. There is increasing policy debate about how to assign doctors for these second evaluations, with some states allowing insurers to select doctors while other states use some form of random assignment. 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 training. Thus, ex ante it is unclear how much doctor discretion exists in these evaluations and whether claimants and insurers influence the allocation of doctors based on doctor effects 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 in medical evaluations 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 claimants for medical evaluations that arises through the workers' compensation dispute resolution process. Using this variation, our analysis illustrates there is wide variation across doctors in medical evaluations, these decisions are consequential for later claimant outcomes, and doctor effects systematically vary by observed doctor characteristics. We then analyze the relationship between doctor effects and the behavior of other market participants—claimants and insurers. This analysis sheds light on the impact of market forces on the allocation of evaluators when claimants can select their own doctors, and the potential impact of policy interventions aimed at influencing the allocation of evaluators.

Our study draws on comprehensive administrative data from the Texas workers' compensation insurance program. 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 serves as a gatekeeper for medical care and cash benefit eligibility, 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 cash benefits, and more than half of aggregate workers' compensation costs are attributable to disputed claims. 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. 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 perform 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 the 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. 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. On average, a claimant randomly assigned a doctor with a 10 p.p. higher approval rate for continued benefits (roughly a one standard deviation increase) stays out of work 19.9% longer while receiving income-replacement benefits, is 11.3% more likely to receive permanent impairment benefits, collects an additional $1,691—or a 20.1% increase over the mean—in subsequent cash benefits, experiences a 12.0% increase in subsequent injury-related medical spending, and receives an additional $2,426—or a 16.7% increase—in total workers' compensation benefits, aggregating across post-exam cash benefits and medical spending.

After establishing that the generosity of the assigned doctor 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 rate of assessing claimants as having a continued impairment (and hence being eligible for further cash benefits) is 10.2 percentage points—representing 13.0% 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 following Walters (2024) and Kline, Rose, and Walters (2024) 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 39.5% of denials for continued benefits for disputed claims, while the top quartile of doctors in terms of generosity is only responsible for 9.5% 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, with estimates suggesting doctors whose training focused more on musculoskeletal systems (e.g., doctors of chiropractic, orthopedic specialists) are more generous than other doctors. Moreover, we find doctors with DO credentials are more generous than doctors with MD credentials. Our analysis also suggests some systematic differences across doctors differing in demographic characteristics, with estimates suggesting female doctors and younger doctors are more generous in medical evaluations.

Having established that doctors are influential in claim outcomes and that 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 typically 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 the relationship between doctor generosity—as measured based on the randomized independent medical exams—and interactions with claimants and insurers in the broader workers' compensation setting.

We begin by analyzing the allocation of claimants across doctors. All else equal, claimants likely prefer more generous treating doctors, because, on average, these doctors allow claimants to receive more cash benefits. Given claimants are free to choose their own treating doctors, we might expect that 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 flexibility 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 independent medical 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 and 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 are more likely to have 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 doctors in workers' compensation insurance. A qualitative implication of these findings is that the selection of doctors in this setting is influenced by market forces. To assess the potential quantitative implications of this reallocation, we conduct a simple benchmarking exercise extrapolating from our estimates; the results of this exercise suggest that demand-driven reallocation toward more generous doctors increases workers' compensation cash benefits by roughly 6%. We note that while this demand-driven 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—and more generally, the normative implications of any policy influencing the allocation of doctors—may depend on whether one considers the welfare of claimants or broader measures of social welfare.

While claimants select their own treating doctors, insurers and claimants can both dispute impairment evaluations made by the treating doctor—triggering an independent medical exam. All else equal, insurers have greater incentives to dispute impairment evaluations 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 a 5.7 p.p. increase in the likelihood that an insurer will dispute the cash benefit determination for that claim—or a 66.7% 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, affecting roughly a third of claims with cash benefits, and independent medical exams in some form are used in all states to settle such disputes. 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. This analysis reveals policies narrowing the pool of eligible doctors through imposing restrictions seen in some other states may substantially reduce claimant benefits and program costs. Moreover, our estimates suggest altering the assignment process to move from random assignment to allowing insurers to directly select doctors (as roughly half of state workers' compensation programs allow) could decrease total subsequent workers' compensation benefits by as much as 51%. Additionally, we quantify the "maximum average benefits at stake" when allowing insurers versus claimants to select doctors, with our estimates suggesting the maximum average benefits at stake is $12,893 in subsequent per capita workers' compensation benefits or 93% of the mean. The substantial benefits at stake provide an explanation for the contentious policy debates over doctor choice regulations within state workers' compensation programs.

Our findings also have broader implications for policy beyond independent medical exams. For example, our findings illustrate there is substantial variation across doctors in how they evaluate medical

conditions, despite extensive required training and guidelines encouraging standardization of the evaluation process. By demonstrating that doctors can have substantial impacts on evaluations and associated outcomes, these findings inform 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 scope of practice regulations or 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 play an important role in the market for doctor services and policies aimed at restricting patient choice over doctors—for example, allowing insurers to select doctors directly or to set up narrow networks of doctors—may substantially reduce benefits for patients.

Contributions and 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 government regulated 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 overall 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 contributes 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 government regulated 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.[2]

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

[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.

[2] Moreover, through providing evidence on heterogeneity in decisions among program gatekeepers (doctors in our setting), our work also contributes to a wider literature that has characterized heterogeneity across workers in a range of settings (e.g., see Hoffman and Stanton (2024); Bacher-Hicks and Koedel (2023) for relevant reviews).

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 doctors, 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. Moreover, our estimates suggest the impact of doctor discretion on program costs is large and comparable to impacts induced by behavioral responses to substantial changes in the replacement rate for workers' compensation income benefits—a policy parameter that has been the focus of much of the prior literature on workers' compensation insurance.

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 2010), skill (e.g., Dahlstrand 2024), race (e.g., Alsan, Garrick, and Graziani 2019; Frakes and Gruber 2022), sex (e.g., Cabral and Dillender 2024*a*), or practice setting (e.g., Dahlstrand, Nestour, and Michaels 2025)—on patient outcomes or disparities in outcomes.[3] 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; Beheshti and Neller 2024). While prior work points to important differences in outcomes across 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 doctor 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 novel evidence on the overall scope for doctor discretion in medical evaluations of physical impairments—an initial step in many health care interactions (and all disability 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 analyze 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 literature investigating the relationship between producer 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

[3]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).

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.[4] 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. In the setting of hospital care, prior work has documented some evidence of demand-driven reallocation toward hospitals or surgeons that are better performing, in terms of patient mortality outcomes (e.g., Chandra et al. 2016) and publicly released scorecards (e.g., Cutler, Huckman, and Landrum 2004; Kolstad 2013) or rankings (e.g., Pope 2009). While there has been limited work related to general physician care, a few recent studies document demand is responsive to publicly released patient ratings (e.g., Bensnes and Huitfeldt 2021; Brown et al. 2023) but demand is not responsive to quality measures related to downstream mortality about which patients are uninformed (e.g., Ginja et al. 2022). Our study extends this literature by providing novel evidence documenting demand-driven reallocation toward doctors who are more favorable to patients in medical evaluations. Our findings illustrate the allocation of doctors is influenced by market forces, with evidence suggesting both claimants and insurers influence doctor selections in line with their respective incentives.[5] Moreover, our study quantifies how this demand-driven reallocation shapes outcomes in this market and explores the impact of alternative mechanisms for allocating doctors to patients in this setting.

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. While the coverage, structure, and pricing of workers' compensation insurance are standardized and set by the state, employers typically purchase these policies from private insurers in most 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 insurance follows a "gatekeeper" model, with medical providers overseeing 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.

[4] For example, see Olley and Pakes (1996); Collard-Wexler and De Loecker (2015); Pavcnik (2002).

[5] Our findings also complement recent work by Currie, Li, and Schnell (2023) illustrating that increased competition induced by granting nurse practitioners prescribing authority leads general practice physicians to prescribe more controlled substances—consistent with these doctors shifting care provision toward the preferences of marginal patients. Moreover, 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., Alexander 2020) and across insurance options (e.g., Brown et al. 2014).

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 missing seven days of work, 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", 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. In Texas, temporary income benefit spells average 18 weeks, and nearly all of these beneficiaries return to work when temporary income benefits terminate, regardless of whether they have some degree of partial permanent impairment. Analyzing linked data from workers' compensation insurance and unemployment insurance earnings records, the Texas Department of Insurance (2015) documents that 76% of temporary income benefit recipients returned to work within six months of injury and 95% returned to work within three years of injury among those injured in 2011.

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. Permanent impairments in this population are typically minor and do not prevent the worker from returning to work (potentially with some activity limitations), with the mean claimant rated as 6% impaired (on a scale of 0% to 100%) among claimants having a non-zero permanent impairment rating.

Approximately 20% of workers' compensation claims involve both cash benefits and medical spending, with the remaining 80% of claims involving only medical spending—typically because such claimants do not miss at least seven days of work due to their injury and therefore do not qualify for cash benefits. However, claims with cash benefits are much more costly on average and account for approximately 85% of the aggregate costs in workers' compensation insurance programs.[6]

Independent Medical Evaluations Though the treating doctor serves as the gatekeeper for an injured worker's cash benefits, insurers or injured workers can formally dispute the treating doctor's assessment of a claimant's impairment. Such disputes are common, affecting roughly a third of claims with cash benefits. Moreover, disputed claims tend to be more costly than other claims, with disputed claims accounting for more than half of aggregate workers' compensation program costs.[7] All states have an "independent medical evaluation" system to settle such disputes. Texas relies on medical evaluations performed by independent doctors—referred to as "designated doctors"—to resolve these disputes. While either an insurer or an injured worker can request an independent medical exam if they disagree with the treating doctor's assessment, the vast majority of these exams (85%) are requested by insurers.

Our analysis focuses on independent medical exams where designated doctors are asked to assess the

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

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

workers' "maximum medical improvement" and, if relevant, permanent impairment.[8] In these exams, designated doctors must assess whether the claimant has reached maximum medical improvement—the point at which an injured worker's healing process has slowed and little (or no) further improvement is expected. Because any permanent impairment is evaluated after maximum medical improvement has been reached, designated doctors are nearly always ($> 99.8\%$ of the time) asked to assess both dimensions at the same time if either determination is requested, though the request for the permanent impairment evaluation is only relevant if the designated doctor finds that the injured worker has reached maximum medical improvement. For these exams, designated doctors are instructed to evaluate the claimant's healing trajectory and degree of ongoing disability, taking as given the prior diagnosis of the claimant's injury.[9]

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

The Texas Labor Code outlines the scope of independent medical exams, the information designated doctors can consider, and the reporting requirements for designated doctors. Prior to the independent medical exam, designated doctors are required to review a claimant's medical records, which are supplied by the claimant's treating doctor and insurer. Designated doctors must also consider any medical information supplied by the claimant. Further, the designated doctor is required to conduct a physical examination of the claimant, which often involves range of motion testing or other tests related to the injury. To form an assessment of the injured worker's impairment, the designated doctor compares the information gathered from the physical exam and medical records to disability evaluation guidelines specified by TDI. Designated doctors must justify their decisions based on evidence gathered following the specified guidelines.[10]

Evaluation guidelines acknowledge there is some inherent subjectivity in assessing whether a worker has reached maximum medical improvement (e.g., whether the workers' condition is expected to mean-

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

[9] 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.

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

ingfully 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 professional judgment in these decisions. Note that doctor discretion may be relevant in the evaluation of all types of injuries, 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 more subjective to assess whether the worker is expected to continue to heal from the torn ligament and how the remaining pain, swelling, and reduced mobility limit 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.[11] 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.[12] 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 by controlling for "required doctor credential" by county by exam year-quarter fixed effects. In practice, we define "required doctor credential" as equal to one of four values: any credential for straightforward musculoskeletal injuries of the back and the credential of the assigned doctor (MD, DO, or DC) for all other injuries.[13]

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

[12] 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).

[13] 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

As in other health care settings, doctors in this setting are likely intrinsically motivated to evaluate patients in a way that aligns with medical guidelines and recommendations. Nevertheless, within medical guidelines for evaluating impairments, there may be scope for differences in assessments across doctors if they differ in how they assess the severity of physical impairments and the extent to which particular impairments limit physical activities and work tasks. Outside of independent medical exams, doctor behavior may also be influenced by extrinsic incentives. While doctor compensation has no direct link to evaluated disability or cash benefits patients receive, doctors could face some indirect incentives to be more or less generous toward patients treated in their standard practice. For instance, doctors may want to be more generous to please patients and attract more patients, or doctors may want to be less generous to establish better relationships with insurers—to negotiate more favorable rates or to be included among doctors insurers or employers recommend to injured workers. However, such extrinsic incentives likely play little or no role in independent medical exams, given doctors are randomly assigned, payment rates are set by state statute, and conflict of interest exclusions imply doctors have no ongoing or previous relationships with claimants (or insurers) involved in these exams.

Decisions made by designated doctors at independent medical exams have the potential to influence the benefits claimants receive after an independent medical exam. If the designated doctor determines the worker has a continued impairment on the date of the exam, the worker is eligible to receive further cash benefits. In such cases, future decisions about continued eligibility for cash benefits revert to the worker's normal treating doctor. If instead, the designated doctor determines the worker has no continued impairment, the worker is not eligible to receive further cash benefits. Though designated doctors have sole discretion over whether a claimant is eligible for cash benefits after the independent medical exam, subsequent actions by employers, insurers, treating doctors, and claimants can all influence the final amount of cash benefits that claimants assessed as having a continued disability eventually receive. Since subsequent actions taken by the worker, employer, insurer, and treating doctor may all be influenced by decisions made by the designated doctor in the independent medical exam, we focus on characterizing doctor generosity through the designated doctor's assessment at an initial independent medical exam and summarize impacts on subsequent benefits through considering all benefits received after this exam.[14] See Appendix Section A for more institutional details on independent medical exams.

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 implement-

designated doctors by leveraging the fact that the regulations clearly indicate that designated doctors with any credential can evaluate claims with specified injuries—in particular, back injuries. Though there may be some ambiguity in the required credentials for the evaluation of some types musculoskeletal injuries, the regulations are clear in specifying that back injuries can be evaluated by any designated doctors and we can validate that an assigned doctor's credential appears random among those with back injuries. (See Appendix Table A1.) Thus, we take a conservative approach in defining the "required doctor credential" categorical variable—setting this to be equal to any credential for back injuries and the observed assigned doctor's credential for all other injuries.

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

ing random assignment in 2013, our analysis of independent medical exams focuses on exams that occurred between 2013 and 2019. Beyond our analysis of independent medical exams, we also conduct analysis focusing on the broader set of all claims for which we can identify a claimant's treating doctor.

For all claims—regardless of whether they have a dispute-triggered independent medical exam—the data contain information on cash and medical benefits received. The medical benefit data include detailed information on each medical bill paid for by workers' compensation insurance, such as information on: procedure codes, amount paid, amount charged, diagnoses codes, date and place of service, and information about the provider. The medical data span all types of medical care including physician care, 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).[15] All monetary values are adjusted to 2019 dollars using price information from U.S. Bureau of Labor Statistics (2021). See Appendix Section A for additional details about the data construction.

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

Another component of our analysis focuses on a broader set of claimants: all workers' compensation claimants injured from 2013 to 2019 for whom we can identify their chosen "treating doctor"—the doctor who serves as gatekeeper for their medical and cash benefits.[16] A key feature of our setting is that designated doctors also serve as treating doctors for other claimants in their standard practice. Thus, we use this broader sample of claimants to explore how market forces may influence the selection of treating doctors and whether doctor selection is related to unbiased measures of doctor generosity estimated based on independent medical exams. We refer to this broader sample of claimants as the "all claimants" sample and the treating doctors who are associated with these claimants as the "treating doctor" sample of doctors.

We summarize the sample of designated doctors in Table 1 and compare these doctors to the broader population of treating doctors for workers' compensation patients in Texas, as well as the broader population of doctors in Texas and in the United States. Relative to the population of doctors treating workers' compensation patients, a larger share of designated doctors have a DC credential rather than an MD or DO

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

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

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 benefits—on the date of the independent medical exam.[17] As discussed above, a claimant is eligible for additional cash benefits after an independent medical exam if and only if the designated doctor assesses the claimant as having a continued impairment on the date of the exam. This is a natural measure to focus on for characterizing doctor generosity, as the assessment at the independent medical exam is under the sole control of the designated doctor. Beyond describing the distribution of doctor generosity, we analyze the consequences of being assigned a more or less generous doctor on a broader range of post-exam claim outcomes. In doing so, we consider impacts on post-exam benefits paid and other outcomes during the 36 months after the initial designated doctor exam—a period we observe for all claimants with exams from 2013 to 2019. As discussed above, workers' compensation cash benefits are a function of both the worker's disability and their prior wage. Throughout when we analyze the amount of cash benefits, we focus on a normalized measure of cash benefits where 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 approach ensures our measure of normalized cash benefits reflects disability severity, abstracting from heterogeneity in wages across injured workers. See Appendix A for more details on the construction of this measure.

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

Among those with independent medical exams, 78% are assessed as having a continuing disability on the date of the exam—and thus are eligible to receive subsequent cash benefits. After an independent medical exam, the mean total additional cash benefits received is $8,431. Roughly 33% of claimants receive post-exam income-replacement benefits, while 65% receive permanent impairment benefits. Mean post-exam medical spending is $6,122, and the mean total additional benefits is $14,554, summing across post-exam medical spending and cash benefits.

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

2 Impact of Doctors on Claim Outcomes

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

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

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

where i indexes the claimant, $c(i)$ indexes the claimant's county, $d(i)$ indexes the designated doctor assigned to the claimant, $t(i)$ represents the year-quarter of the claimant's independent medical exam, and $r(i)$ indicates doctor credential required to perform the claimant's exam. In this specification, y_i represents the dependent variable, and $z_{d(i)i}$ is a measure of doctor generosity. To isolate conditional random assignment, this specification also includes fixed effects for doctor credential required for the exam by claimant county by year-quarter of the exam ($\mu_{r(i)t(i)c(i)}$).[18] The specification outlined above accommodates other controls for claimant characteristics ($\mathbf{X_i}$). In our baseline analysis, other controls are limited to fixed effects for year of the claimant's injury, though we demonstrate the robustness of our findings when including additional controls.

The coefficient of interest in this regression is β, which captures the causal effect of being assigned a more generous doctor—as defined through their observed evaluations of continued impairment at independent medical exams—on subsequent claimant outcomes. Because this regression analyzes the relationship between outcomes of claimants at independent medical exams and the assigned doctor's generosity as measured through these same exams, this analysis faces a common challenge in the literature leveraging random assignment of cases to evaluators: small sample correlation between an evaluator's decision in a particular case and the value of the measure of evaluator generosity. To overcome this, we employ a standard leave-one-out strategy in constructing a measure of generosity. Specifically, we construct doctor generosity above, $z_{d(i)i}$, based on doctor decisions in all other claims assigned to the doctor. In our baseline analysis, we measure $z_{d(i)i}$ using the leave-out mean continued impairment rate—the share of claimants assessed as having continued impairment at independent medical exams conducted by doctor $d(i)$ excluding claimant i's exam. Because estimation error in the leave-out mean may lead to downward bias in estimating β, we apply a conventional empirical Bayes shrinkage procedure to the leave-out mean which shrinks the estimated leave-out mean toward the overall mean, in proportion to the estimation error (e.g., Morris 1983).[19]

Within the specification outlined in Equation (1), β represents the impact of being assigned a more generous doctor on claimant outcomes. We consider several outcomes in this analysis. First, we analyze impacts

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

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

on whether the claimant is assessed as having a continued impairment at the exam (and hence is eligible for further cash benefits)—the outcome parallel to that used to construct the doctor generosity measure—to establish how doctor generosity toward other claimants predicts the doctor's evaluation of the claimant. We then turn to analyzing impacts on outcomes subsequent to the exam. While the assessment of continued impairment is under the direct and full control of the designated doctor, other subsequent 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, the claimant's employer, 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, post-exam workers' compensation covered medical spending, and total post-exam workers' compensation benefits (aggregating across cash and medical benefits).

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

Identifying Variation Figure 1 displays a histogram of $z_{d(i)i}$ after partialling out the baseline controls. There is substantial residual variation in $z_{d(i)i}$, with an interquartile range of 10.0 p.p. and an interdecile range of 20.2 p.p. Overlaid on this histogram, Figure 1 Panel A also displays estimates from a non-parametric regression of continued impairment on $z_{d(i)i}$—with both measures residualized using the baseline controls included in Equation (1). The figure indicates the likelihood a claimant is rated as having a continued impairment strongly increases in the leave-out mean from the doctor's other assigned claims, this relationship is roughly linear, and the magnitude of this relationship is approximately one-for-one. For comparison, Figure 1 Panel B displays the analogous estimates instead investigating predicted continued impairment based on baseline (pre-exam) claim characteristics.[20] 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,

[20]To create the measure of predicted continued impairment, we first fit a lasso model of the likelihood that claimants are assessed as having continued impairment during the independent medical exam and then use the fitted values to predict each claimant's likelihood of being assessed as having continued impairment. The lasso model includes indicator variables for day of the week of the first medical treatment, the ICD-9 code for the first medical treatment, insurer, age, gender, injury year-month, and the claim originating in the emergency department.

sex), measures of injury severity (an indicator for whether the claim originated with an emergency department visit, medical spending on the first day of claim), type of injury, an indicator for whether the claimant requested the independent medical exam, industry, and time between injury and independent medical exam request. Table 3 presents these estimates. As expected, $z_{d(i)i}$ is uncorrelated with baseline claimant and injury characteristics, with coefficient estimates that are small and statistically indistinguishable from zero. In addition, Appendix Figure A1 presents the results of an analogous exercise verifying that baseline claim characteristics are also orthogonal to observable doctor characteristics (e.g., age, sex, training). Collectively, this evidence is consistent with expectations and suggests the random assignment of doctors to independent medical exams was implemented as required by state regulation.

Results Table 4 reports the results 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 coefficients on $z_{d(i)i}$ from separate regressions of Equation (1) for the indicated dependent variables. Column 2 reports results from the baseline specification, while the remaining columns report robustness when including further controls. To contextualize magnitudes in our discussion below, we consider the impact of a 10 p.p. increase in doctor generosity—which is roughly equivalent to a one standard deviation increase in doctor generosity based on the unbiased variance estimate of doctor effects discussed in detail in Section 3.1.

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

Table 4 Panel B reports the results for subsequent post-exam claim outcomes. Our discussion of these results focuses on estimates from the baseline specification, though we note the results are similar in alternative specifications including an expanded set of controls reported in the remaining columns. Our estimates indicate that being assigned a doctor who is 10 p.p. more generous leads to an increase in total additional cash benefits of $1,691 or 20.1% of the mean, and this increase is precisely estimated with a 95% confidence interval spanning $1,502 to $1,881. This increase in cash benefits comes from increases in both income-replacement benefits and permanent impairment benefits, with roughly 47% of the increase attributable to temporary income benefits while the remaining 53% is attributable to permanent impairment benefits. Those assigned a designated doctor who is 10 p.p. more generous, on average, experience a 1.56 p.p. (4.7%) increase in the likelihood of receiving any additional income-replacement benefits and stay out of work an additional 1.58 weeks while receiving these benefits—a 19.9% increase beyond the mean additional weeks out of work. Moreover, the estimates indicate that being assigned a designated doctor who is 10 p.p. more generous is associated with a 7.36 p.p. (11.3%) increase in the likelihood of being rated as having a permanent impairment and a 0.70 p.p. increase in the rated degree of permanent impairment (on a scale of 0 to 100), or a 17.3% increase relative to the mean. All of these effects are precisely estimated, with p-values less than 0.001.

While designated doctors only evaluate the injured worker's ongoing degree of impairment (which de-

termines eligibility for cash benefits) and do not recommend or oversee medical care, post-exam workers' compensation medical spending could be indirectly impacted by the generosity of the assigned designated doctor, if cash and medical benefits are complements or the designated doctor's evaluation influences subsequent care decisions of the worker or the worker's regular treating doctor. For example, when claimants stay out of work longer while receiving income-replacement benefits, a claimant's regular treating doctor may recommend more medical care to help the claimant heal to return to work or claimants may be more inclined to follow through with doctor-recommended medical care while out of work longer. Our estimates indicate that those assigned a 10 p.p. more generous designated doctor receive $735 more workers' compensation covered medical care after the exam, representing a 12.0% increase over the mean. This pattern broadly aligns with prior evidence of complementaries between workers' compensation cash benefits and medical spending (Cabral and Dillender, 2024*b*).

We can also evaluate the impact of being assigned a more generous doctor on total subsequent workers' compensation benefits, aggregating across impacts on post-exam medical spending and cash benefits. Our estimates suggest claimants assigned a 10 p.p. more generous designated doctor have $2,426 higher subsequent total workers' compensation benefits, a 16.7% increase over the mean subsequent total workers' compensation benefits.

While the baseline analysis described above focuses on cumulative benefits received in the three years after an independent medical exam, Appendix Table A4 reports additional analysis examining the impacts on temporary income benefits and medical spending over alternative time horizons—evaluating impacts during each six-month period during the three years following an exam. This analysis suggests the impacts of being assigned a more generous doctor are largest in the first six months after the independent medical exam, though implied percent impacts are positive and roughly similar across all time periods.[21]

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 of 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, $\widehat{\theta}_d \equiv \gamma_{d(i)}$. Below, we primarily focus on the dependent variable (y_i) indicating that a claimant has been assessed as having a continued impairment by the designated doctor on the exam date, though we conduct supplemental analysis considering a broader range of dependent variables summarizing other claim outcomes after the exam. This specification also includes fixed effects for a claimant's county by required doctor credential by year-quarter of the independent medical exam ($\phi_{r(i)t(i)c(i)}$). Additionally, we control for the year the claimant was injured ($\mathbf{X_i}$), though the estimates are similar if including further controls for other baseline claim characteristics. Because doctor effects are measured by comparing doctors to one another, we identify the vector of doctor fixed effects normalizing the exam-weighted mean doctor effect to zero, and standard errors on these doctor effects are produced by bootstrapping.[22]

[21] The exception is the final six-month period (31-36 months after the exam) for weeks receiving income benefits, where the estimated impact remains positive but is smaller and statistically indistinguishable from zero. Overall, this evidence suggests a more generous doctor increases cash benefits, time out of work, and injury-related medical spending in the short run, with no evidence of offsetting decreases in cash benefits, time out of work, and injury-related medical spending in the medium- to long-run.

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

3.1 Variance Estimation

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

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

Panel B of Table 5 reports the standard deviation based on the exam-weighted variance estimated using this split-sample variance approach. The estimates indicate that there is substantial variation in generosity across doctors. As indicated in the first row of Panel B, the split-sample variance estimator yields an estimated standard deviation of 10.2 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 8.9 and 11.6 with 95% confidence. Appendix Table A5 column (2) reports the standard deviation from an analogous same split-sample variance estimation approach for analyzing the impact of doctors on other subsequent claim outcomes. Based on these estimates, doctors have substantial impacts on claim outcomes across all the subsequent outcomes analyzed. We also assess the robustness of the approach used to obtain an unbiased estimate of the variance of doctor effects. Appendix Table A5 column (3) illustrates that we obtain similar implied standard deviations—for continued impairment and all subsequent claim outcomes—when using an alternative approach to obtain an unbiased variance estimate similar to the approach outlined in Kline, Rose, and Walters (2022).

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

across claimants with different baseline characteristics.

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

The remainder of Panel B reports the standard deviation based on cross-group covariance estimators—considering groups based on claimant age and predicted continued impairment based on baseline characteristics. Comparing exams for claimants above or below the median age, the cross-age-group covariance estimator yields a standard deviation of 10.1 percentage points in continued impairment. Comparing exams above or below the median predicted likelihood of being assessed as having a continued impairment based on baseline characteristics, the cross-predicted-impairment covariance estimator implies a standard deviation of 10.3 percentage points in being assessed as having a continued impairment.[23] The similarity of the standard deviations based on these cross-group covariance estimators to the standard deviation based on the variance estimator suggests doctor generosity is broadly consistent across exams for claimants differing in age and for claimants with differing predicted continued impairment based on baseline characteristics.

3.2 Distribution Across Doctors

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

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

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

Figure 2 Panel A displays the estimated deconvoluted density of the residuals and Panel B displays the resulting marginal distribution of doctor effects, θ_d. The distribution of doctor effects is single-peaked and nearly symmetric near the median, 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

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

substantial variation in doctor effects—with an interquartile range of 15.8 p.p. and an interdecile range of 29.7 p.p.. These are large representing 20.2% and 37.9%, respectively, of the mean rate of being assessed as having a continued impairment.[24]

Based on the deconvoluted distribution, Figure 2 Panel C summarizes the concentration of denials in impairment assessments, similar to a Lorenz curve. Specifically, this figure displays the share of claimants being denied further benefits (i.e., assessed as having no continued impairment at an independent medical exam) attributable to the most generous X% of doctors—where X is indicated on the horizontal axis which displays the share of doctors, ordering doctors from most generous to least generous. The curve is bowed away from the 45-degree reference line, indicating that denials of continued impairment are concentrated among particular doctors. The least generous quartile of doctors is responsible for 39.5% of the denials of continued impairment, while the most generous quartile of doctors is only responsible for 9.5% of continued impairment denials. Based on this figure, we can also visualize another measure of dispersion: the Gini coefficient which is twice the area between the 45-degree line and the indicated curve and ranges from zero (in the case of perfect uniformity) to one (in the case of perfect concentration). The Gini coefficient based on the deconvoluted distribution is 0.26.

3.3 Interpreting Magnitudes

To further interpret magnitudes, we combine the estimates characterizing the distribution of doctor generosity discussed above with estimates from Section 2 on the impact of being assigned a more generous doctor for an independent medical exam. Our estimates suggest doctor discretion substantially impacts subsequent cash benefits and total workers' compensation costs. A one standard deviation increase in the generosity of the assigned doctor is associated with a 20.5% increase in cash benefits and a 17.1% increase in total workers' compensation costs.[25] Moreover, moving from the 25th percentile to the 75th percentile generosity doctor is associated with a 31.9% increase in cash benefits and a 26.5% increase in total workers' compensation costs.

We can benchmark these impacts relative to the impact of the policy parameter most often studied in the prior literature on workers' compensation insurance: the replacement rate for income replacement benefits. To interpret magnitudes, we benchmark the estimated impact of doctor generosity using elasticity estimates from Cabral and Dillender (2024*b*) on the impact of the replacement rate for income benefits on the duration claiming these benefits. Comparing our estimates to these estimates, a one standard deviation more generous doctor increases cash benefits by as much as the behavioral response from a 28.5% increase in the replacement rate for income benefits. Further, moving from a 25th percentile generosity doctor to a

[24]We can contextualize these magnitudes by comparing the estimated range of variation to the ranges estimated in other work analyzing differences in worker effects in other settings. For example, the interdecile range we estimate represents 37.9% of the mean, which is notably larger than the 22% of the mean estimated in Chan, Gentzkow, and Yu (2022) among radiologists evaluating pneumonia cases and the 21% of the mean estimated in Mas and Moretti (2009) among grocery store cashiers. A one standard deviation difference in doctor effects in our setting represents 13% of the mean and 0.24 of the standard deviation of being rated as having a continued impairment, which is smaller than the one standard deviation implied difference of 21% of the mean estimated in Chan and Chen (2022) among doctors in the costs of treating patients in the emergency department and larger than the one standard deviation implied differences of 0.15 and 0.12 standard deviations of student test scores estimated in Staiger and Rockoff (2010) for New York teachers' persistent value added in math and reading, respectively.

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

75th percentile generosity doctor increases cash benefits as much as the behavioral response from a 44.3% increase in the replacement rate for income benefits. This benchmarking exercise illustrates that differences across doctors are as important in influencing program benefits as substantial changes in the policy parameter that has received the most attention in prior academic work on workers' compensation insurance.

4 Correlates of Doctor Generosity

Next, we analyze the relationship between doctor generosity and observed doctor characteristics, by correlating the estimated doctor fixed effects from Equation (2) with observable information about doctors and their prior experience. It is important to note that such relationships may not represent causal impacts. Nevertheless, these correlations are a parsimonious way to summarize the types of doctors who tend to evaluate claimants more or less generously. Figure 3 reports the results from bivariate or multivariate regressions associating doctor generosity with the measure(s) within the indicated characteristic group, along with estimates from multivariate regressions that regress doctor generosity on all measures simultaneously.

We first consider basic doctor demographics. Figure 3 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 0.19 of the standard deviation in doctor effects based on the unbiased variance estimate 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 3 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 0.22 of the standard deviation calculated in Section 3.1.

Next, we turn to correlating generosity with information about doctor background. Patterns in Figure 3 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 (the omitted category), doctors born in Texas have 2.2 p.p. higher continued impairment determinations (p-value 0.026) and doctors born outside the U.S. have 2.8 p.p. lower continued impairment determinations (p-value 0.025). However, doctor birthplace is correlated with other doctor characteristics (e.g., sex, credential, specialty), and the association with birthplace is much smaller and statistically insignificant in multivariate regressions controlling for all doctor measures simultaneously.

We also investigate how doctor 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 (the omitted category). 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 1.22 standard deviations 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 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 with training focused on the musculoskeletal system—those specializing in chiropractic care and orthopedic surgery—are more generous than doctors with more general training—those 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.

Additionally, 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 as having a continued impairment (p-value$<$0.001). Attending a Top 25 medical school is correlated with other doctor characteristics, and this association is small and statistically indistinguishable from zero in multivariate regressions controlling for all doctor measures simultaneously.

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 the 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 3 indicates doctor generosity is negatively associated with both experience measures. The magnitudes suggest an additional year of experience is associated with a 0.7 p.p. decrease in the share of claimants assessed as having a continued impairment (p-value$<$0.001). Moreover, the estimates indicate a doctor with 32 more prior independent medical exams per year (roughly a one standard deviation increase) is associated with a 1.3 p.p. decrease in doctor generosity (p-value 0.006). We note that the analogous estimates from multivariate regressions controlling for all doctor measures at once are notably smaller and statistically indistinguishable from zero.

Additionally, we investigate the relationship between doctor generosity and disciplinary actions by either the Texas Department of Insurance (TDI) or by the state professional boards overseeing licensing of these doctors more generally (i.e., the Texas Medical Board or the Texas Board of Chiropractic Examiners). The TDI disciplines doctors—with consequences such as suspending doctors' participation in designated doctor exams or in workers' compensation insurance more generally—for various actions, such as providing inappropriate care or repeatedly failing to submit necessary forms. These disciplinary actions are rare, as only 2.4% of designated doctors are ever disciplined. The patterns in Figure 3 suggest doctor generosity is positively associated with disciplinary actions, though this association is only statistically distinguishable in multivariate regressions (p-value 0.039). In addition to the TDI, state professional boards overseeing the licensing of doctors— the Texas Medical Board and the Texas Board of Chiropractic Examiners—discipline doctors with consequences ranging from fees to license suspension/revocation for various reasons including violating state or federal law, negligence, incompetence, or unprofessional conduct. State board actions

are negatively associated with doctor generosity, though this pattern is not statistically distinguishable from zero and more muted when controlling for all doctors measures at once.

Lastly, we consider the relationship between doctor generosity and patient ratings. For this analysis, we focus on ratings from Healthgrades.com—which is the most common platform on which doctors in our sample are consistently rated. Our analysis focuses on doctors' mean patient ratings, where individual patient ratings on this platform range from 1 (worst) to 5 (best). Approximately half of doctors in our sample have a Healthgrades rating, so regressions with this measure additionally control for an indicator that this measure is missing. The patterns in Figure 3 suggest doctor generosity is positively associated with patient ratings—with a one standard deviation increase in healthgrades.com rating associated with a 2.7 p.p. higher likelihood of assessing claimants as having continued impairments. Patient ratings are correlated with other doctor characteristics, and this association is small and statistically insignificant in 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 evidence examining the relationship between doctor generosity and the behavior of other market participants. This analysis leverages the fact that many of the doctors who serve as gatekeepers for medical care and cash benefits for workers' compensation claimants in their standard practice also are certified as designated doctors eligible to perform independent medical exams. Thus, for these doctors, we are able to observe behavior both when these doctors are randomly assigned to claimants for independent medical exams and when these doctors are in their standard practice treating claimants who have chosen them to serve as their "treating doctor."

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 information conveyed by peers, doctors themselves, or legal representatives, claimants may have limited ability to assess doctor generosity. Second, claimants may have preferences over other provider characteristics (e.g., location, convenience, other attributes), and their choices may be influenced by other parties—such as insurers or employers. Ultimately, it is an empirical question whether patients sort toward providers who are more generous.

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

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

where j indexes doctors, $s(j)$ represents doctor specialty, and $m(j)$ represents the medical market in which the doctor practices. In this equation, $\tilde{\theta}_j$ is a measure of doctor generosity based on independent medical exams (described further below), and DD_j indicates that doctor j is a designated doctor in our sample (i.e., a doctor for whom we can measure generosity).[26] 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).[27] The coefficient of interest is δ, which describes the relationship between the outcomes of interest and doctor generosity among doctors for whom we can identify generosity through random assignment.

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

In this specification, the measure of doctor generosity ($\tilde{\theta}_j$) is based on the doctor fixed effect estimates from Equation (2), which are identified based on the random assignment of designated doctors for independent medical exams. Because measurement error in the doctor generosity measure could lead to downward bias in the associated coefficient estimate, we apply empirical Bayes shrinkage using the deconvoluted distribution estimated in Section 3.2. See Appendix Section B for more details. Additional analysis in Appendix Table A7 illustrates the estimates are very similar if we instead use the unadjusted doctor fixed effects to measure doctor generosity.

Results Table 6 displays the estimates. Panel A column 1 summarizes the baseline estimates testing the static prediction associated with sorting. The estimates indicate more generous doctors have a larger market share, consistent with more generous doctors attracting more claimants at a given point in time. The magnitude is notable, with the estimates indicating a doctor who is one standard deviation more generous has, on average, 28% 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 10% to 46%.

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

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

[27] Appendix Table A6 illustrates the estimates are similar if we use an alternative definition of medical market, based on either counties or Hospital Referral Regions as defined by the Dartmouth Atlas. Refer to Appendix A for more details on identifying and classifying doctor specialties.

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 20 p.p. more growth in their market share over time on average, with a 95% confidence interval spanning 7 p.p. to 34 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 (4) separately for claims in more or less competitive medical markets. For this analysis, we classify medical markets as more or less competitive based on whether the Herfindahl–Hirschman Index (HHI) among doctors treating workers' compensation patients is below or above the median. Table 6 columns 2 and 3 report the estimates. Consistent with 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, on average, a one standard deviation more generous doctor has a market share that is 35% larger (p-value 0.004) and experiences 29 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. Motivated by this, we conduct heterogeneity analysis where we estimate Equation (4) for claimants with above or below median predicted likelihood of receiving cash benefits based on baseline observables.[28] 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 more likely to receive cash benefits. Among claims with above median predicted likelihood of receiving cash benefits, the estimates indicate that, on average, a one standard deviation more generous doctor has a market share that is 24% larger (p-value 0.005) and sees 22 p.p. more market share growth over time (p-value 0.002). For claims with below median predicted likelihood of receiving cash benefits, the estimated relationship is weaker and statistically insignificant.

Collectively, this evidence suggests claimants sort toward more generous providers. One possibility is that this sorting 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

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

other correlated characteristics that claimants generally view favorably—e.g., they may defer more to patients 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.[29] These explanations all suggest that claimant demand is leading to reallocation toward doctors who are more generous in their disability evaluations.

Overall, we interpret the evidence above as consistent with demand-driven reallocation of claimants toward doctors who are more generous in their medical evaluations of physical impairment. A qualitative implication of these findings is that the allocation of doctors to patients is influenced by market forces. We can also conduct back-of-the-envelope calculations to assess the potential quantitative importance of these findings. To do so, we assume the distribution of generosity measured among doctors who conduct independent medical exams reflects the distribution of doctor generosity among all doctors available to treat workers' compensation claimants. Under this assumption, the baseline static estimates (from Table 6 Panel A column 1) combined with the variance estimate from Section 3.1 imply the reallocation of patients toward more generous doctors increases mean doctor generosity by 0.0289. Combining this with the estimates from Table 4 on the implied percent impact of a more generous doctor on total subsequent benefits, this implies that reallocation toward more generous doctors increases aggregate workers' compensation cash benefits by 5.8%. This aggregate implied impact of reallocation on cash benefits is large and of the same order of magnitude as would be induced by increased income benefit durations in response to a sizable change in the replacement rate for income benefits. Benchmarking these estimates against recent elasticity estimates capturing the impact of the workers' compensation income benefit replacement rate on the duration collecting income benefits (Cabral and Dillender, 2024*b*), the estimated 5.8% increase in cash benefits attributable to demand-driven reallocation is equivalent to increased cash benefits resulting from behavioral responses to an 8.1% increase in the replacement rate for income benefits.

5.2 Claim Disputes

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

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

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

where i indexes claimants and $j(i)$ represents claimant i's treating doctor. This specification includes controls for baseline claimant characteristics, Z_i, (sex, age, injury year-month), as well as doctor-level characteristics defined as in Equation (4) above. The key coefficient of interest is γ, which relates outcomes of interest to doctor generosity. In this analysis, we consider three dependent variables: (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. Additional analysis in the appendix illustrates the estimates are similar if we vary the set of geographic or claimant controls (Appendix Table A8) or use unadjusted doctor fixed effects as the measure of doctor generosity (Appendix Table A9).

Results The estimates are displayed in Table 7. Column 1 indicates that claims for which the treating doctor is more generous are more likely to be disputed. The estimate suggests that a claim with a one standard deviation more generous treating doctor, on average, is associated with a 5.8 p.p. increase in the likelihood of being disputed—or 57% of the overall mean rate of disputes. Comparing the estimates in columns 1 and 2, we see this increase in the rate of disputes is attributable to an increase in the likelihood that an insurer disputes the claim; a one standard deviation increase in doctor generosity is associated with a 5.7 p.p. increase in the likelihood that an insurer disputes the claim or 67% of the overall rate of insurer-initiated disputes. In contrast, there is no statistically significant association between doctor generosity and claimant-initiated disputes.

This evidence indicates insurers more often dispute claims managed by more generous treating doctors. One possibility is that insurers have information on which doctors are more generous and target claims managed by these doctors in deciding which claims to dispute. Another possibility is that insurers observe features of claims handled by more generous doctors (e.g., markers that disability evaluations for these claims have been less frequent or strict), and these features—rather than doctor identity itself—lead insurers to more often dispute these claims. We do not take a position on whether the evidence we document reflects insurers targeting doctor identity directly or some other features of claims handled by these doctors that suggest these doctors are being generous in evaluating disability for these claims. All of these explanations suggest insurers use disputes to influence the allocation of evaluators in line with their incentives to reduce costs.

5.3 Observational Claim Outcomes Among Claimants Treated in Standard Practice

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

Empirical Strategy To conduct this analysis, we estimate Equation (5) described above, replacing the dependent variable with measures of claim outcomes among claimants treated in the doctor's standard practice. We consider a wide range of claim outcomes including indicators for receiving cash benefits (in-

dicators for any cash benefits, temporary income benefits, and permanent impairment benefits), the total cash benefits received, duration out of work receiving temporary income benefits, permanent impairment rating, and injury-related medical spending. In the baseline analysis below, we depart from Equation (5) by omitting controls for claimant characteristics, though we continue to control for year of injury. All other included variables are as defined in Equation (5) above, where the coefficient of interest, γ, captures the relationship between doctor generosity and claimant outcomes among claimants treated by the doctor in their standard practice. In Appendix Table A10, we consider specifications with additional controls for baseline claimant observables—both basic characteristics (e.g., sex, age, injury year-month) and an expanded set of characteristics (e.g., indicators for initial diagnosis of injury, day of the week of first medical treatment, an indicator for the claim originating in the emergency department)—to explore potential differences between unconditional and conditional correlations. In Appendix Table A11, we verify that results are similar if we use unadjusted doctor fixed effects as the measure of doctor generosity. As discussed further below, we also analyze potential selection of patients across treating doctors by estimating Equation (5) replacing the dependent variable with measures of baseline claimant characteristics.

Results Table 8 displays estimates relating doctor generosity and outcomes of injured workers treated in the doctor's standard practice. The estimates suggest claimants with treating doctors who are more generous—as measured through randomly assigned independent medical exams—have substantially higher cash benefits and medical spending. A one standard deviation increase in doctor generosity is associated with a 7.3 p.p. increase in the likelihood of receiving any cash benefits (95% CI: 2.4 to 12.1), which represents a 27% increase over the mean. We observe a similar pattern with total cash benefits, where a one standard deviation increase in doctor generosity is associated with a $2,031 increase in total cash benefits (95% CI: 938 to 3,125)—which amounts to a 66% 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 6.4 p.p. (95% CI: 1.6 to 11.2) more likely to receive income-replacement benefits—representing a 27% increase over the mean—and remain out of work receiving income-replacement benefits for an additional 2.8 weeks (95% CI: 1.2 to 4.4), which is a 66% increase over the mean duration receiving these benefits. In addition, a one standard deviation more generous doctor is associated with a 6.0 p.p. (95% CI: 2.9 to 9.0) increase in the likelihood of being rated as having any permanent impairment, which represents a 51% increase over the mean, and a 0.42 p.p. (95% CI: 0.21 to 0.62) increase in the permanent impairment rating—representing a 66% 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 $1,611 (95% CI: 516 to 2,707) in injury-related medical spending, representing a 41% increase relative to the mean.

Overall, the observational evidence in Table 8 suggests claimants who have a more generous treating doctor receive more cash and medical benefits. While these findings are broadly consistent with the causal evidence on the impact of doctors in independent medical exams in Table 4, it is important to emphasize that the estimates in Table 8 do not have a causal interpretation. Claimants can select their own treating doctor and the endogenous selection of claimants across treating doctors could contribute to observed differences in outcomes. Nevertheless, there are at least two additional points worth noting about these estimates. First, the estimated patterns are consistent with doctor generosity being translatable across contexts—given the positive association between doctor generosity measured in independent medical exams and observational

outcomes from a doctor's standard practice. Second, the magnitudes of the estimates in percent terms are larger than found in the analysis of independent medical exams. Multiple factors may contribute to these differences. For example, doctors likely have more scope to influence claim outcomes for claimants they regularly evaluate and treat in their standard practice than for claimants they evaluate once through an independent medical exam. In addition, patient selection may reinforce differences across doctors, if patients with more severe injuries tend to select more generous doctors.

To investigate the potential role of selection directly, Appendix Table A12 presents estimates of Equation (5) replacing the dependent variable with measures of baseline claimant characteristics, including basic demographics (sex and age), characteristics of the claimants' zipcode (above median average income, above median share Hispanic), baseline injury characteristics (injury type, first-day medical spending), and overall predicted cash benefits based on baseline characteristics. These estimates reveal no statistically significant relationship between baseline claimant characteristics and the generosity of the treating doctor, though the estimates indicate a suggestive association with predicted cash benefits based on baseline claim characteristics (p-value 0.077).[30,31] Based on the point estimate in Appendix Table A12 column 6, a claimant with a one standard deviation more generous treating doctor has on average $155 higher baseline predicted cash benefits. Note this is consistent with incentives in this context and evidence from Table 6 that indicates patterns consistent with demand-driven reallocation are stronger among claimants who have more at stake (those more likely to receive cash benefits based on baseline characteristics). That said, the magnitude of this association is small—representing 7.6% of the estimated differences in observed spending across patients with a one standard deviation more generous doctor based on Table 8—and the estimate is not statistically significant based on conventional thresholds. Moreover, Appendix Table A10 illustrates the estimates relating observational outcomes and the unbiased measure of doctor generosity (in Table 8) are similar when controlling for a wide range of baseline claim characteristics.

Overall, this evidence suggests that, while differences in baseline observable characteristics across claimants selecting more or less generous treating doctors are broadly consistent with our evidence on market allocation, these differences are quantitatively modest and do not explain much of the observed association between doctor generosity and observational outcomes among claimants treated in the doctor's standard practice documented in Table 8. Additionally, we assess the potential role of selection on unobservables in explaining patterns in the observational data, drawing on methods in Oster (2019). See Appendix Table A13 for this analysis. Overall, this analysis suggests the overall pattern in the observational data—that patient outcomes such as cash disability benefits and medical spending are positively associated with doctor generosity—persists under a wide range of reasonable assumptions on selection on unobservables. In this way, this evidence suggests doctor generosity measured in independent medical exams is broadly reflective of doctor generosity in similar exams performed by doctors regularly treating claimants in their standard practice. Moreover, this evidence suggests that—even in the presence of endogenous sorting of claimants across doctors—observational evidence on claimant outcomes may be an informative (albeit noisy) signal about doctor generosity that could potentially influence claimant and in-

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

[31] Aside from the association with predicted cash benefits, the only other baseline claimant characteristics with evidence of a possible positive association with doctor generosity is an indicator for the claimant's residential zipcode having above median average income. While this association has a p-value of 0.087 and should be interpreted with caution, this positive association could be consistent with claimants from higher income zipcodes having better access to information on doctor generosity or more flexibility to act on this information.

surer decisions.

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 discuss the broader implications of our findings for policy in workers' compensation insurance, health care, and related social insurance settings further in the conclusion. We now turn to using our estimates to consider the direct implications of our findings for policy related to our empirical setting: independent medical exams in workers' compensation insurance. All states use independent medical exam systems to settle disputes over disability evaluations, though key details of these systems vary 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 perform independent exams and (ii) changing the current assignment process.

In analyzing these counterfactuals, we consider the impacts on claimant outcomes subsequent to the exam—by combining projected changes in doctor generosity with our estimates of the causal impact of being assigned a more generous doctor from Section 2. 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). Our analysis focuses on the impacts on subsequent claimant benefits and program costs. While more generous doctors' evaluations substantially increase both claimant benefits and program costs, it is unclear whether evaluations from more generous doctors are closer to or further from the optimum than evaluations from less generous doctors. Thus, policies that shift claimants toward more generous doctors may have different normative implications depending on whether one focuses on claimant welfare or broader measures of social welfare.[32]

We summarize the basic setup of this counterfactual analysis below and provide the full details in Appendix Section C. This analysis considers the universe of claims with independent medical exams observed over the analysis period. By holding fixed the set of claims, these counterfactuals do not capture any general

[32]It is beyond the scope of our paper to calculate the optimal generosity of doctors. In this setting, we do not have an objective measure of true disability (that is plausibly not directly affected by designated doctor evaluations) to measure doctor evaluations against. Moreover, even if such a measure were available, it would not be straightforward to calculate the optimal generosity of doctors (and hence optimal benefits). If one considers broader measures of social welfare, the optimal level of doctor generosity would trade off the value of risk-protection injured workers gain from increased cash benefits, time out of work, and medical spending when being evaluated by a more generous doctor against any distortions potentially induced by these increases. While having a more generous doctor provides workers more complete insurance against losses associated with their workplace injuries, the ex-ante value of the consumption smoothing benefits, additional recovery time, or medical care for injured workers on this margin is unclear. Moreover, it is difficult to characterize potential distortions that result from having a more generous doctor. For instance, it is not straightforward to interpret changes in time out of work from a social welfare perspective, as changes in this setting are driven by differences in doctor decisions. Importantly, this differs from changes in time out of work induced by changes in worker incentives (e.g., changes in the replacement rate for income benefits), which some prior work characterizes as moral hazard. In contrast, changes in time out of work in this setting are induced by differences in doctor generosity—and hence differences in external constraints on worker decisions. Overall, it is ex ante unclear if relaxing these constraints improves or harms social welfare. Given this, our analysis focuses on analyzing impacts on workers' compensation cash benefits and overall costs.

equilibrium adjustments (e.g., changes in which claims are disputed). For each doctor eligibility restriction considered, we first construct the pool of doctors available in each county by drawing from the associated distribution of doctor generosity—either the distribution of doctor effects from Section 3 or the analogous estimated distribution for the subgroup of doctors defined by specified eligibility restriction—where the number of draws is based on the number of designated doctors in the county. Among available doctors, doctors are allocated to claims according to the indicated allocation mechanism considered in the particular counterfactual. In each counterfactual considered, we simulate outcomes for claims using the assigned doctor generosity and the estimated impacts of being assigned a more generous doctor from Table 4. Tables summarizing results from these counterfactuals report the mean of claim outcomes as well as the standard deviation across claims, in addition to bootstrapped standard errors for these statistics based on 1,000 iterations.

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.

Table 9 reports the results. Panel A of Table 9 reports the mean and standard deviations of claim outcomes, for the baseline scenario where the full set of independent medical doctors is eligible to perform these exams (in column 1) and in counterfactual scenarios where the indicated subsets of independent medical doctors are eligible to perform these exams (in the remaining columns). Panel B of Table 9 reports differences in mean outcomes between the counterfactual and baseline scenarios, as well as associated standard errors. When the full set of doctors is eligible to perform independent medical exams, 75.7% of claimants are assessed as having a continuing impairment—with these claimants on average receiving $7,963 in subsequent cash benefits and $13,883 in subsequent total workers' compensation benefits. We assess how these outcomes change when restricting the set of doctors eligible to perform these exams.

While most states allow doctors with MD, DO, or DC credentials to serve as evaluators for independent medical exams, some states restrict eligibility to doctors with MD or DO credentials. Column 2 of Table 9 reports how claim outcomes would change with such a restriction. The results indicate that claimant benefits—and hence program costs—go down substantially if doctors with DC credentials are excluded from independent medical exams. Relative to the baseline scenario, excluding doctors with DC credentials from independent medical exams would lead to a 5.7 p.p. (or 7.5%) decrease in the share of claimants assessed as having continued impairment, a $998 (or 12.5%) decrease in subsequent cash benefits, and a $1,431 (or 10.3%) decrease in subsequent total workers' compensation benefits.

Another potential policy is to impose particular restrictions on physician specialty. Motivated by regulations in some states highlighting the role of orthopedic surgeons, column 3 reports outcomes under the scenario with eligibility limited to orthopedic surgeons. Claimant benefits decrease when eligibility is limited to those specializing in orthopedic surgery—though these differences are more modest. Compared to the baseline scenario, restricting eligibility to orthopedic surgeons decreases the share assessed as having continued impairment by 2.5 p.p. (or 3.3%), decreases cash benefits by $435 (or 5.5%), and decreases total workers' compensation spending by $624 (or 4.5%). On average, orthopedic surgeons are more generous than the population of doctors with MD or DO credentials, though they are less generous than doctors with DC credentials. Thus, mean claimant benefits are notably larger in column 3 relative to column 2.

Some states restrict eligibility based on other doctor characteristics, such as doctor's training, affilia-

tion, and past experience. For example, some states require doctors for these exams to have some minimum length of experience treating injured workers in their standard practice. Column 4 investigates the impact of one such restriction, where eligibility is limited to doctors with at least three prior years of experience treating workers' compensation claimants. Imposing this restriction leads to a decrease in workers' compensation benefits, with a 1.9 p.p. (or 2.4%) decrease in continued impairment assessments, a $324 (or 4.1%) decrease in subsequent cash benefits, and a $465 (or 3.4%) decrease in subsequent total workers' compensation spending.

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 is consistent with insurers and claimants having some knowledge of doctor generosity and acting 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 choose. 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 perform 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 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 three allow the exam requester—which is usually the insurer but sometimes the injured worker—to select the doctor.[33] 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. Table 10 presents the findings from

[33]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.

this analysis, describing outcomes under the current random assignment process in column 1 for reference and alternative allocation systems in the remaining columns. Columns 2 and 3 describe the impact of an allocation system that leaves the choice of doctor to the insurer or claimant, respectively. Compared to the current system, allowing insurers to select doctor evaluators could result in much lower benefits and program costs: a 28.0 p.p (or 37.0%) decrease in the share assessed with continued impairment, a $4,913 (or 61.7%) decrease in subsequent cash benefits, and a $7,047 (or 50.8%) decrease in subsequent total workers' compensation benefits. Conversely, allowing claimants to select doctor evaluators has the potential to greatly increase benefits and program costs, leading to a 23.3 p.p (or 30.7%) increase in share with continued impairment, a $4,075 (or 51.2%) increase in subsequent cash benefits, and a $5,846 (or 42.1%) increase in subsequent total workers' compensation benefits. Both of these represent an upper bound on how much benefits would change in the direction of the party being given choice over doctors given the assumptions underlying the analysis, meaning one can interpret the difference between these two scenarios as the "maximum average benefits at stake" comparing different assignment systems. Fixing the pool of doctors, the maximum average benefits at stake is $8,988 in subsequent cash benefits (112.9% of the mean) and $12,893 in total subsequent workers' compensation costs (92.9% of the mean). These findings highlight that who chooses the evaluating doctor can have large impacts on claimant benefits and program costs, offering an explanation for the contentious policy debates in many states over regulations regarding doctor choice in workers' compensation insurance.

Some states allow insurers to indirectly influence the choice of doctor through specifying the specialty of the doctor the regulator assigns. Column 4 considers one such allocation process where the regulator continues to randomly assign a doctor to perform the exam but the insurer specifies the specialty of the assigned doctor, where we assume the insurer selects the specialty that is least generous on average among doctors eligible to evaluate a claimant. Based on the estimates in Figure 3, "primary care/internal medicine" is the least generous specialty group on average, and thus this assumption amounts to insurers selecting primary care/internal medicine. The estimates indicate that allowing insurers to specify specialty can substantially move outcomes—leading to a 6.1 p.p. (8.1%) decrease in share assessed as continually impaired, a $1,071 (or 13.4%) decrease in subsequent cash benefits, and a $1,536 (or 11.1%) decrease in subsequent total workers' compensation benefits.

Finally, we consider alternative allocation systems with some form of random assignment inspired by systems used in other states. Specifically, we consider systems where the regulator randomly selects a panel of three doctors, and one of these doctors is assigned to the exam, where this doctor either: is chosen by the claimant (column 5) or is the remaining doctor after the claimant and the insurer each strike one (column 6)—which under our assumptions is equivalent to assigning the median generosity doctor among the randomly sampled three doctor panel. Based on the estimates in column 5, allowing claimants to choose among a randomly selected panel of doctors leads to increased benefits—a 9.4 p.p (or 12.4%) increase in share with continued impairment, a $1,639 (or 20.6%) increase in subsequent cash benefits, and a $2,351 (or 16.9%) increase in subsequent total workers' compensation benefits. This increase in benefits is notably smaller than when claimants have unconstrained choice among available doctors in the county. Estimates in column 6 suggest that allowing claimants and insurers to each strike a doctor from a randomly selected panel leads to similar mean outcomes as randomly assigning a single doctor—though such a system leads to a substantial decrease in the variance of outcomes across claimants relative to a single doctor assignment system. Based on the estimates in column 6, allowing claimants and insurers to each strike a doctor from three randomly selected doctors decreases the standard deviation of subsequent claim outcomes by 30%.

7 Conclusion

Our paper analyzes the importance of doctor discretion in medical evaluations. We leverage comprehensive administrative data from the 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 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 distributed program benefits. We conclude by presenting supplemental counterfactual analysis which provides context on the implications of our findings for ongoing policy debates.

Government regulated programs distribute billions of dollars in benefits each year at the discretion of gatekeepers. And while such programs are typically designed with a standardized claim evaluation process in mind, individual gatekeepers are human and may exercise discretion and judgment in assessing eligibility for program benefits. Our study provides novel evidence quantifying the scope for gatekeeper discretion and the consequences of this discretion in a major social insurance program—workers' compensation insurance. Our estimates indicate that doctors have a large degree of discretion in evaluating physical impairments, and this discretion impacts claimant outcomes substantially. For example, we find that being assigned a one standard deviation more generous doctor for a workers' compensation insurance independent medical exam increases total subsequent workers' compensation benefits by 17%. Moreover, we find that when claimants are given the opportunity to influence the allocation of doctor evaluators, they sort toward more generous doctors in line with their incentives and insurers are more likely to object to disability evaluations performed by more generous doctors. This evidence highlights the importance of market forces in the allocation of doctors, and the magnitudes of our estimates suggest demand-driven reallocation is responsible for substantial increases in claimant benefits and program costs. Our findings have direct implications for the allocation of doctors for independent medical exams, which affect roughly a third of claims with cash benefits. Through back-of-the-envelope counterfactual analysis, we illustrate the potential consequences for claimant benefits and program costs of alternative allocation systems used in some other states—such as those allowing insurers to influence doctor assignment or restricting doctors eligible to perform these exams.

More generally, our findings provide broader insights that can inform policy in workers' compensation insurance, health care, and related social insurance settings. First, our findings demonstrate there is substantial variation across doctors in how they evaluate physical impairments, even in settings with extensive training and guidelines promoting consistency in evaluations. This evidence suggests the identity of the doctor conducting a medical evaluation can have substantial impacts on evaluations and associated outcomes, informing ongoing policy discussions about doctor choice in workers' compensation insurance, disability insurance, and broader health care settings. Second, our results illustrate doctor generosity varies across doctors with differing baseline characteristics—such as sex, age, credential, and experience. In this way, our results inform policy discussions about regulations governing doctor qualifications (e.g., scope of practice regulations), as well as the impacts of broader trends in the health care workforce. Finally, our estimates illustrate that patients—when given the choice—sort toward doctors who are more generous, and insurers are more likely to dispute decisions by more generous doctors. Taken together, these findings sug-

gest market forces influence the market for doctors and policies that limit patient choice over doctors, such as regulations allowing insurers to directly select doctors or restrict patient choice to a specified narrow network of doctors, could substantially impact patient outcomes and overall costs.

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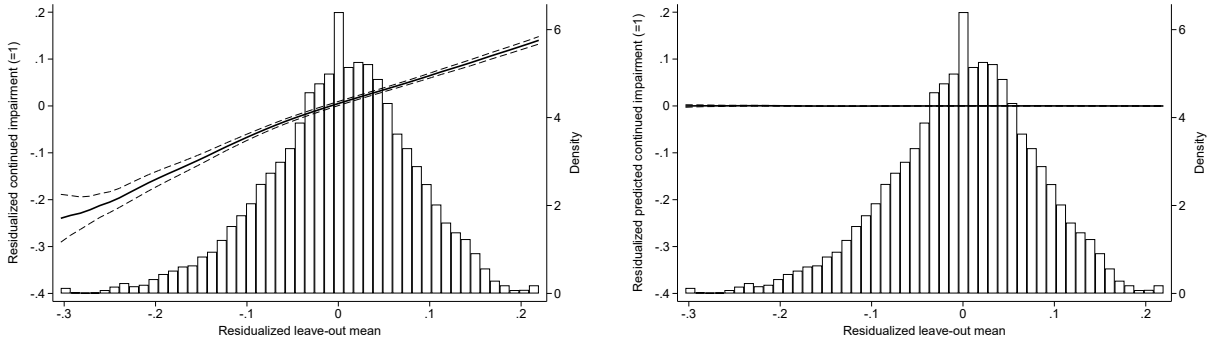
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Figure 1: Distribution of Leave-Out Generosity Measure and Likelihood of Being Rated as Having Continued Impairment on Exam Date

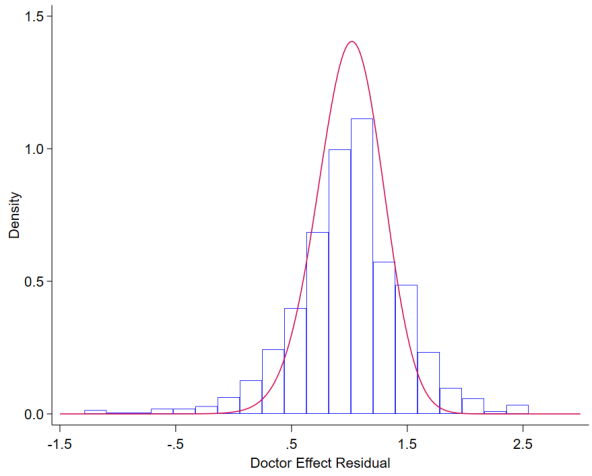


(a) Likelihood of Rated as Having Continued Impairment on Leave-Out Generosity Measure

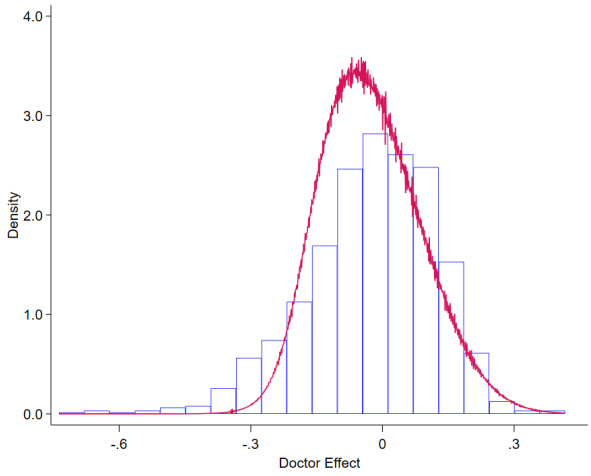
(b) Predicted Likelihood of Rated as Having Continued Impairment on Leave-Out Generosity Measure

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 based on baseline observables (Panel B). The leave-out generosity measure and the dependent variables are residualized for injury year and the doctor credential required to perform the claimant's exam interacted with claimant county and exam year-quarter. The solid lines are generated by local linear regressions of the residualized dependent variables on the residualized leave-out measure and correspond to the left vertical axis, while the histograms correspond to the right vertical axis. Dashed lines represent 95% confidence intervals calculated from standard errors clustered at the doctor level.

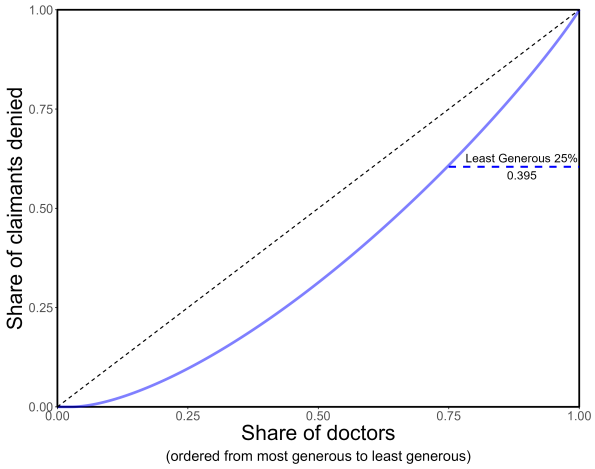
Figure 2: Distribution of Doctor Effects



(a) Distribution of Doctor Effect Residuals



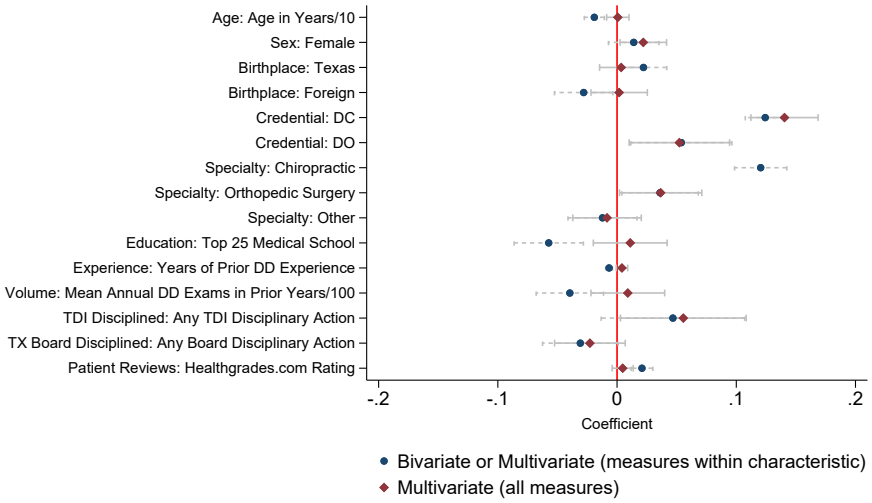
(b) Distribution of Doctor Effects



(c) Share of Denials Attributable to Doctors

Notes: Panel A reports the deconvoluted distribution of doctor effect residuals (solid line) overlaid on a histogram of the underlying empirical residuals (hollow bars), while Panel B reports the implied distribution of doctor effects (solid line) based on a change in variables applied to the distribution of residuals overlaid on a histogram of the underlying doctor effect estimates (hollow bars). See Appendix Section B.3 for more details on this estimation. Panel C summarizes the concentration of denials in continued impairment assessments. In this panel, the horizontal axis displays the share of doctors where doctors are ordered from most generous to least generous, while the vertical axis displays the share of denials of continued benefits attributable to the most generous X% of doctors—where X is indicated on the horizontal axis.

Figure 3: Correlates of Doctor Effects



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

Table 1: Descriptive Statistics—Doctors

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

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

Table 2: Descriptive Statistics—Claimants

	All Claimants	Claimants with Independent Medical Exams
	(1)	(2)
Panel A. Claim Characteristics		
Male	0.61	0.65
Age	41.13	45.54
Claim Initiated with ED Visit	0.27	0.34
First-Day Medical Spending	585	1,114
Receives Income-Replacement Benefits within Three Years of Injury	0.19	0.83
Receives Permanent Impairment Benefits within Three Years of Injury	0.09	0.65
Injury Type:		
Contusion	0.15	0.09
Sprain or Muscle Issue	0.46	0.63
Other	0.39	0.27
Panel B. Characteristics of Claims with Independent Medical Exams		
Rated as Having Continued Impairment on Exam Date	-	0.78
Post-Exam Claim Outcomes (within Three Years after Exam)		
Total Additional Cash Benefits	-	8,431
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 Workers' Compensation 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, $z_{d(i)t}$		
	coefficient	std error	p-value
	(1)	(2)	(3)
Male Claimant	0.006	(0.020)	[0.786]
Age	0.345	(0.530)	[0.516]
ED Claim	-0.010	(0.023)	[0.655]
Log(First-Day Medical Spending)	0.035	(0.060)	[0.558]
Log(Med Spending Prior to Exam Request)	-0.007	(0.047)	[0.887]
Log(Weeks from Injury to Exam Request)	0.003	(0.025)	[0.899]
Claimant Contested	0.002	(0.013)	[0.858]
Injury Type:			
Contusion	-0.002	(0.014)	[0.894]
Sprain or Muscle Issue	-0.003	(0.023)	[0.907]
Other	0.005	(0.020)	[0.824]
Industry:			
Agriculture/Forestry/Fishing/Hunting	-0.001	(0.004)	[0.785]
Arts/Entertainment/Accommodation/Food Services	0.006	(0.009)	[0.541]
Information/Finance/Real Estate/Professional Services	-0.012	(0.012)	[0.308]
Health Care/Educational Services	0.014	(0.015)	[0.355]
Manufacturing	0.013	(0.014)	[0.351]
Mining/Utilities/Construction	-0.019	(0.015)	[0.220]
Public Administration/Other Services	-0.008	(0.020)	[0.709]
Wholesale Trade/Retail Trade/Transportation	0.007	(0.019)	[0.716]
F-test for All Variables in Multivariate Regression [p-value]	0.564 [0.912]		

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

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

	Dependent Variable Mean and Std Dev	Leave-Out Doctor Generosity, $z_{d(i)t}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.965	0.962
	(0.412)	(0.014)	(0.014)	(0.013)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,431	16,913	16,932	16,792
	(14,038)	(969)	(966)	(925)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.157	0.153
	(0.471)	(0.030)	(0.030)	(0.029)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	15.863	15.704
	(18.56)	(1.261)	(1.258)	(1.216)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	3,956	7,881	7,906	7,827
	(9,249)	(628)	(627)	(606)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.735	0.734
	(0.476)	(0.024)	(0.024)	(0.023)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	6.992	6.947
	(5.670)	(0.345)	(0.341)	(0.332)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,475	9,031.921	9,025.354	8,965.644
	(7,931)	(532.509)	(529.481)	(505.909)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	7,385.971	7,144.480
	(12,936)	(760.453)	(753.379)	(719.236)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,554	24,259.508	24,317.545	23,936.846
	(24,136)	(1,623.918)	(1,614.083)	(1,534.121)
		[<0.001]	[<0.001]	[<0.001]
Controls:				
Baseline		x	x	x
Claimant Demographics			x	x
Injury Diagnosis				x

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

Table 5: Variation Across Doctors

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

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

Table 6: Relationship Between Doctor Generosity and Patient Volume

	(1)	(2)	(3)	(4)	(5)
			Panel A: Static. Dep Var: ln(N)		
DD X $\tilde{\theta}$	2.759	3.384	1.923	2.366	1.301
	(0.893)	(1.158)	(1.423)	(0.848)	(1.122)
	[0.002]	[0.004]	[0.177]	[0.005]	[0.246]
			Panel B: Dynamic. Dep Var: Δ		
DD X $\tilde{\theta}$	1.982	2.820	0.627	2.169	1.606
	(0.681)	(0.872)	(1.103)	(0.694)	(0.932)
	[0.004]	[0.001]	[0.569]	[0.002]	[0.085]
Sample Restriction	None	Medical Market HHI< Median	Medical Market HHI> Median	None	None
Claims used to Construct Dependent Variable	All Claims	All Claims	All Claims	Claims with Predicted Cash Benefits> Median	Claims with Predicted Cash Benefits< Median

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

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

	Independent Medical Exam is Requested	Insurer Requests Independent Medical Exam	Claimant Requests Independent Medical Exam
	(1)	(2)	(3)
DD X $\tilde{\theta}$	0.567	0.555	0.026
	(0.162)	(0.142)	(0.037)
	[<0.001]	[<0.001]	[0.495]
Dependent Variable			
Mean	0.101	0.085	0.017
Standard Deviation	0.301	0.279	0.128

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

Table 8: Relationship Between Doctor Generosity and Observational Outcomes

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD X $\tilde{\theta}$	0.709	19,858.225	0.627	27.590	0.584	4.069	15,749.241
	(0.241)	(5,454.809)	(0.241)	(8.114)	(0.152)	(1.007)	(5,464.275)
	[0.003]	[<0.001]	[0.009]	[0.001]	[<0.001]	[<0.001]	[0.004]
Dependent Variable							
Mean	0.269	3,076	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	9,504	0.428	14.09	0.321	2.467	8,266

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

Table 9: Policy Counterfactuals: Alternative Pool of Doctors

	Doctors eligible to perform exams							
	All Observed Doctors (Baseline)		Doctors with MD or DO credentials		Doctors specializing in orthopedic surgery		Doctors with at least three years experience	
	(1)		(2)		(3)		(4)	
Panel A. Mean and Standard Deviation of Outcomes	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Rated as Having Continued Impairment	0.757	0.108	0.700	0.094	0.732	0.076	0.739	0.105
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Total Additional Cash Benefits	7,963	1,897	6,966	1,641	7,528	1,332	7,639	1,833
	(19.3)	(11.7)	(26.7)	(20.4)	(47.3)	(34.1)	(28.9)	(19.1)
Total Additional Workers' Compensation Costs	13,883	2,721	12,451	2,354	13,259	1,911	13,417	2,629
	(27.7)	(16.8)	(38.3)	(29.2)	(67.8)	(49.0)	(41.4)	(27.3)
Panel B. Mean Difference in Outcomes Relative to Baseline								
Rated as Having Continued Impairment	-		-0.057		-0.025		-0.019	
	-		(0.00006)		(0.00009)		(0.00006)	
Total Additional Cash Benefits	-		-998		-435		-324	
	-		(1.0)		(1.6)		(1.1)	
Total Additional Workers' Compensation Benefits	-		-1,431		-624		-465	
	-		(1.5)		(2.3)		(1.6)	

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

Table 10: Policy Counterfactuals: Alternative Assignment Process

	Regulator Selects… one random doctor and assigns this doctor (Baseline)		Insurer Selects		Claimant Selects		one random doctor from specialty indicated by insurer and assigns this doctor		Regulator Selects… random panel of three doctors from which claimant chooses doctor		random panel of three doctors from which each party strikes one and remaining is assigned	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A. Mean and Standard Deviation of Outcomes	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Rated as Having Continued Impairment	0.757	0.108	0.477	0.054	0.990	0.015	0.696	0.096	0.851	0.085	0.754	0.075
	(0.0011)	(0.0007)	(0.0098)	(0.0102)	(0.0003)	(0.0011)	(0.0022)	(0.0017)	(0.0013)	(0.0006)	(0.0011)	(0.0006)
Total Additional Cash Benefits	7,963	1,897	3,051	946	12,039	255	6,893	1,690	9,603	1,481	7,912	1,322
	(19.3)	(11.7)	(171.6)	(179.3)	(5.6)	(19.9)	(38.6)	(29.9)	(22.5)	(10.1)	(19.5)	(10.3)
Total Additional Workers' Compensation Costs	13,883	2,721	6,836	1,357	19,728	365	12,347	2,425	16,234	2,124	13,809	1,896
	(27.7)	(16.8)	(246.2)	(257.2)	(8.0)	(28.5)	(55.3)	(42.9)	(32.3)	(14.4)	(28.0)	(14.8)
Panel B. Mean Difference in Outcomes Relative to Baseline												
Rated as Having Continued Impairment	-		-0.280		0.233		-0.061		0.094		-0.003	
	-		(0.00031)		(0.00004)		(0.00008)		(0.00005)		(0.00005)	
Total Additional Cash Benefits	-		-4,913		4,075		-1,071		1,639		-51	
	-		(5.5)		(0.6)		(1.4)		(0.9)		(0.9)	
Total Additional Workers' Compensation Benefits	-		-7,047		5,846		-1,536		2,351		-73	
	-		(7.8)		(0.9)		(2.0)		(1.3)		(1.2)	

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

FOR ONLINE PUBLICATION

APPENDIX

A Additional Details on Setting and Data

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

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

When a designated doctor decides a claimant has a continued impairment, the designated doctor influences the amount of future benefits at the initial exam by assigning a permanent impairment rating or by assigning a future date at which maximum medical improvement will be reached. If designated doctors determine the claimant is still healing from the injury and declines to provide a future date at which maximum medical improvement will be reached, future benefit decisions revert to the claimant's treating doctor, unless and until the insurer or claimant requests another designated doctor evaluation. Typically, future decisions are governed by the workers' normal treating doctor. In our data, only 12% of claims with independent medical exams have a subsequent independent medical exam requested in the six months after the initial exam. Though designated doctors control 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 total benefits claimants assessed as having a continued disability eventually receive. Because any subsequent decisions by treating doctors, workers, insurers, and employers 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.

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

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

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

For the analysis of treating doctors, we identify a claimant's treating doctor as the doctor who bills the most case management services for the claimant. As with the designated doctor analysis, we focus on

treating doctors with MD, DO, or DC credentials and with non-missing NPI information, and we focus on doctors in Texas who treat claimants residing in Texas.

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

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

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 benefit rate separately for temporary income-replacement benefits (in benefits per week) and permanent impairment benefits (in benefits per percentage impaired) using the populations of claimants receiving each type of benefit injured from 2013 to 2019. We then multiply the mean benefit rate for temporary income-replacement benefits by the number of weeks claimants received benefits and multiply the mean benefit rate for permanent impairment benefits by the permanent impairment rating. Finally, we add these two amounts to calculate the total normalized additional cash benefits.

B Distribution of Doctor Effects

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

B.1 Estimating Doctor Effects

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

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

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

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

B.2 Estimating Variance of Doctor Effects

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

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

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

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

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

B.3 Estimating the Distribution of Doctor Effects

To characterize the population distribution of doctor effects, we apply an approach following Walters (2024) and Kline, Rose, and Walters (2024) based on Efron (2016). This approach produces a flexible empirical Bayes prior distribution of the population of doctor effects, taking as inputs the estimated doctor effects and associated standard errors. As in many settings, the estimates of interest are correlated with the associated standard errors in our setting. Specifically, following tests recommended in Walters (2024), we empirically assess potential dependence by regressing $\hat{\theta}_d$ on $log\ s_d$, which yields a coefficient of -0.113 with a robust standard error of 0.007.

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

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

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

We then estimate G_r using a log-spline deconvolution estimator described in Walters (2024) based on Efron (2016) applied to these residuals, assuming $\hat{r}_d | r_d, s_d \sim \mathcal{N}\left(r_d, \frac{s_d^2}{(\phi_2\ log\ s_d)^2}\right)$. This procedure approximates G_r with a smooth log density parameterized by a natural cubic spline, where the parameters of this spline are estimated via penalized maximum likelihood. As in Walters (2024), we calibrate penalty parameter in the maximum likelihood estimation so that the implied variance from the deconvoluted distribution matches an unbiased variance estimate of r_d.[1] In practice, we select the other log-spline tuning parameters

[1] Note that we estimate the unbiased variance of r_d following the same split-sample approach described above in Appendix Section

by setting the number of spline knots to five and using 1,000 equally spaced support points over the range of r considered, where we constrain this range to span from the minimum to the maximum implied value of r evaluated at the empirical minimum and maximum of θ, respectively.[2]

Using this distribution, we recover the marginal distribution of θ_d by applying a change in variables to the distribution of the residuals combined with the empirical distribution of the standard errors, where we constrain the range of this distribution to the empirical range of $\hat{\theta}_d$. Figure 2 Panel A in the text displays the deconvoluted distribution of the residuals, and Panel B displays the implied distribution of doctor effects. Figure 2 Panel C plots an associated curve summarizing the concentration of denials in impairment assessments. As reported in the text, the estimates imply the least generous 25% of doctors are responsible for 39.5% of the denials of continued impairment, while the most generous 25% of doctors are only responsible for 9.5% of continued impairment denials.

B.4 Empirical Bayes Posteriors of Doctor Effects

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

C Policy Counterfactuals: Additional Details

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

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

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

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

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

B.2 for estimating the unbiased variance of θ_d.

[2]Specifically, the range of r considered is $[min_d(\frac{min_d(\hat{\theta}_d)-\hat{\phi}_1}{\hat{\phi}_2\ log\ s_d}), max_d(\frac{max_d(\hat{\theta}_d)-\hat{\phi}_1}{\hat{\phi}_2\ log\ s_d})]$.

- **Baseline.** For each claim, randomly assign one doctor from the constructed pool of doctors available in the claim's county (as described above).
- **Insurer selects a doctor.** For each claim, assign the doctor who is the least generous from the pool of doctors available in the claim's county (as described above).
- **Claimant selects a doctor.** For each claim, assign the doctor who is the most generous from the pool of doctors available in the claim's county (as described above).
- **Regulator selects a randomly assigned doctor with specialty chosen by insurer.** For each claim, randomly assign one doctor from the constructed pool of doctors available in the claim's county who specialize in primary care/internal medicine (as described above). (Note: Analysis reported in the paper indicates primary care/internal medicine is the least generous specialty on average.)
- **Regulator randomly selects a panel of three doctors from which claimant chooses a doctor.** For each claim, randomly select three distinct doctors from the constructed pool of available doctors in the claim's county (as described above), and assign the most generous among these three doctors.
- **Regulator randomly selects a panel of three doctors from which each party strikes one and the remaining doctor assigned.** For each claim, randomly select three distinct doctors from the constructed pool of available doctors in claim's county (as described above), and assign the median generosity doctor among these three doctors.

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

Table A1: Balance for Exams All Doctors Can Perform

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

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

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

	Dependent Variable Mean and Std Dev	Leave-Out Doctor Generosity, $z_{d(i)t}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.979	0.985
	(0.412)	(0.014)	(0.013)	(0.024)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,431	16,913	17,034	18,583
	(14,038)	(969)	(981)	(1,029)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.163	0.209
	(0.471)	(0.030)	(0.029)	(0.036)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	15.792	17.234
	(18.56)	(1.261)	(1.279)	(1.447)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	3,956	7,881	7,871	8,589
	(9,249)	(628)	(637)	(721)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.747	0.766
	(0.476)	(0.024)	(0.024)	(0.031)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	7.150	7.641
	(5.670)	(0.345)	(0.340)	(0.386)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,475	9,031.921	9,163.714	9,994.188
	(7,931)	(532.509)	(522.202)	(543.749)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	7,297.685	7,686.307
	(12,936)	(760.453)	(747.443)	(830.975)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,554	24,259.508	24,331.969	26,269.779
	(24,136)	(1,623.918)	(1,623.914)	(1,718.925)
		[<0.001]	[<0.001]	[<0.001]
Controls:				
Baseline: Required credential X county X exam year-quarter		x		
Required credential X county X exam year			x	
Required credential X county X exam year-quarter X insurer				x

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

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

	Dependent Variable Mean and Std Dev	Doctor Generosity, $z_{d(i)t}$		
	(1)	(2)	(3)	(4)
Panel A. Continued Impairment				
Rated as Having Continued Impairment on Exam Date	0.784	0.965	0.889	1.000
	(0.412)	(0.014)	(0.016)	(0.005)
		[<0.001]	[<0.001]	[<0.001]
Panel B. Other Subsequent (Post-Exam) Claim Outcomes				
Total Additional Cash Benefits	8,431	16,912.871	15,383.415	15,341.515
	(14,038)	(969.116)	(902.701)	(766.475)
		[<0.001]	[<0.001]	[<0.001]
Any Income-Replacement Benefits	0.332	0.156	0.134	0.175
	(0.471)	(0.030)	(0.028)	(0.024)
		[<0.001]	[<0.001]	[<0.001]
Weeks Receiving Income-Replacement Benefits	7.938	15.813	14.322	14.578
	(18.56)	(1.261)	(1.191)	(0.991)
		[<0.001]	[<0.001]	[<0.001]
Amount of Income-Replacement Benefits	3,956	7,880.951	7,138.188	7,265.590
	(9,249)	(628.386)	(593.836)	(493.818)
		[<0.001]	[<0.001]	[<0.001]
Any Permanent Impairment Benefits	0.654	0.736	0.684	0.733
	(0.476)	(0.024)	(0.024)	(0.018)
		[<0.001]	[<0.001]	[<0.001]
Permanent Impairment Rating	4.052	7.005	6.421	6.342
	(5.670)	(0.345)	(0.321)	(0.274)
		[<0.001]	[<0.001]	[<0.001]
Amount of Permanent Impairment Benefits	4,475	9,031.921	8,245.227	8,075.925
	(7,931)	(532.509)	(490.442)	(421.024)
		[<0.001]	[<0.001]	[<0.001]
Medical Spending	6,122	7,346.636	6,419.347	6,993.067
	(12,936)	(760.453)	(710.785)	(605.576)
		[<0.001]	[<0.001]	[<0.001]
Total Additional Workers' Compensation Benefits	14,554	24,259.508	21,802.762	22,334.582
	(24,136)	(1,623.918)	(1,512.721)	(1,283.458)
		[<0.001]	[<0.001]	[<0.001]
Doctor Generosity Measure				
Baseline		x		
Alternative: Leave-Out Mean Shrunk Using Deconvoluted Distribution			x	
Alternative: Doctor Effects Estimated in Section 3				x

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

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

	Panel A: Weeks Receiving Income Benefits					
	0-6 months	7-12 months	13-18 months	19-24 months	25-30 months	31-36 months
	(1)	(2)	(3)	(4)	(5)	(6)
Doctor Generosity, $Z_{d(i)i}$	7.959	5.344	2.064	0.394	0.048	0.005
	(0.619)	(0.423)	(0.251)	(0.077)	(0.025)	(0.016)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.062]	[0.741]
Dependent Variable						
Mean	4.447	2.292	0.985	0.184	0.020	0.009
Standard Deviation	8.778	6.872	4.455	1.627	0.641	0.451
Implied % Impact for One Std. Dev.	18%	24%	21%	22%	24%	6%
	Panel B: Medical Spending					
	0-6 months	7-12 months	13-18 months	19-24 months	25-30 months	31-36 months
	(1)	(2)	(3)	(4)	(5)	(6)
Doctor Generosity, $Z_{d(i)i}$	2,582.034	2,128.169	1,373.600	817.342	307.590	293.362
	(303.263)	(258.018)	(186.709)	(152.252)	(110.127)	(80.220)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.005]	[<0.001]
Dependent Variable						
Mean	2,760	1,613	909	557	310	199
Standard Deviation	5,887	5,074	3,946	3,190	2,897	1,990
Implied % Impact for One Std. Dev.	10%	13%	15%	15%	10%	15%

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

Table A5: Variation Across Doctors Across Different Outcome Measures

	F-test for Heterogeneity	Standard Deviation Based on Split-Sample Variance Estimator	Standard Deviation Based on Variance Estimated Using Approach as in KRW (2022)
	(1)	(2)	(3)
Rated as Having Continued Impairment on Exam Date	4.835	0.102	0.105
	[<0.001]	(0.007)	(0.003)
Total Additional Cash Benefits	2.537	2,045	2,078
	[<0.001]	(179)	(107)
Any Income-Replacement Benefits	1.658	0.044	0.050
	[<0.001]	(0.010)	(0.004)
Weeks Receiving Income-Replacement Benefits	2.289	2.675	2.596
	[<0.001]	(0.235)	(0.138)
Amount of Income-Replacement Benefits	2.289	1,234.624	1,293.741
	[<0.001]	(122.424)	(72.830)
Any Permanent Impairment Benefits	2.892	0.084	0.086
	[<0.001]	(0.007)	(0.003)
Permanent Impairment Rating	2.372	0.754	0.804
	[<0.001]	(0.087)	(0.041)
Amount of Permanent Impairment Benefits	2.221	1,024.149	1,074.492
	[<0.001]	(136.365)	(56.358)
Medical Spending	1.638	1,076	1,190
	[<0.001]	(246)	(78)
Total Additional Workers' Compensation Benefits	2.232	2,974	3,172
	[<0.001]	(339)	(162)

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

Table A6: Relationship Between Doctor Generosity and Patient Volume—Alternate Specifications

	Static			Dynamic		
	Dep Var: ln(N)			Dep Var: Δ		
	(1)	(2)	(3)	(4)	(5)	(6)
DD X $\tilde{\theta}$	2.759	2.630	2.621	1.982	1.867	1.981
	(0.893)	(0.857)	(0.883)	(0.681)	(0.660)	(0.674)
	[0.002]	[0.002]	[0.003]	[0.004]	[0.005]	[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 (4), where the measure of doctor generosity is calculated using empirical Bayes shrinkage with the deconvoluted distribution estimated in Section 3 on the coefficients from Equation (2). The coefficient reported in the table is the coefficient on the interaction of the doctor generosity measure and an indicator for the doctor having a generosity measure (being a designated doctor with at least five exams during the analysis period). The coefficient in each column is from a separate regression that includes an indicator for the doctor having a generosity measure and the controls indicated in the table. The dependent variable for columns 1 through 3 is the natural log of the total number of claimants for whom the doctor serves as the treating doctor during the analysis period, while the dependent variable in columns 4 through 6 is the mean annual growth rate from the first half of the analysis period to the second half of the analysis period in the number of claimants for whom the doctor is the treating doctor as defined in Section 5. The sample contains 5,821 doctors identified as being treating doctors for workers injured from 2013 to 2019. Robust standard errors are reported in parentheses, and p-values are reported in brackets.

Table A7: Relationship Between Doctor Generosity and Patient Volume—Unadjusted Doctor Effects

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

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

Table A8: Relationship Between Doctor Generosity and Likelihood Claim is Contested—Alternate Specifications

	Independent Medical Exam is Requested			Insurer Requests Independent Medical Exam			Claimant Requests Independent Medical Exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DD X $\tilde{\theta}$	0.567	0.528	0.557	0.555	0.521	0.551	0.026	0.020	0.019
	(0.162)	(0.148)	(0.156)	(0.142)	(0.130)	(0.137)	(0.037)	(0.036)	(0.035)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.495]	[0.580]	[0.575]
Controls									
Injury Year-Month, Claimant Sex and Age	x	x	x	x	x	x	x	x	x
Specialty X HSA	x	x		x	x		x	x	
Specialty X HRR			x			x			x
Additional Claimant Characteristics		x			x			x	

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

Table A9: Relationship Between Doctor Generosity and Likelihood Claim is Contested—Unadjusted Doctor Effects

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

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

Table A10: Relationship Between Doctor Generosity and Observational Outcomes—Alternate Specifications

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline Specification							
DD X $\tilde{\theta}$	0.709	19,858.225	0.627	27.590	0.584	4.069	15,749.241
	(0.241)	(5,454.809)	(0.241)	(8.114)	(0.152)	(1.007)	(5,464.275)
	[0.003]	[<0.001]	[0.009]	[0.001]	[<0.001]	[<0.001]	[0.004]
Panel B: Including Basic Claimant Controls							
DD X $\tilde{\theta}$	0.707	19,776.064	0.625	27.447	0.583	4.062	15,684.315
	(0.233)	(5,291.062)	(0.233)	(7.889)	(0.147)	(0.974)	(5,316.067)
	[0.002]	[<0.001]	[0.007]	[0.001]	[<0.001]	[<0.001]	[0.003]
Panel C: Including Expanded Claimant Controls							
DD X $\tilde{\theta}$	0.604	18,376.826	0.526	25.484	0.547	3.781	13,970.107
	(0.197)	(4,817.199)	(0.199)	(7.238)	(0.132)	(0.873)	(4,797.411)
	[0.002]	[<0.001]	[0.008]	[<0.001]	[<0.001]	[<0.001]	[0.004]
Dependent Variable							
Mean	0.269	3,076	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	9,504	0.428	14.09	0.321	2.467	8,266

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

Table A11: Relationship Between Doctor Generosity and and Observational Outcomes—Unadjusted Doctor Effects

	Any Cash Benefits	Total Cash Benefits	Any Temporary Income-Replacement Benefits	Temporary Income-Replacement Benefit Duration	Any Permanent Impairment Benefits	Permanent Impairment Rating	Medical Spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DD X $\tilde{\theta}$	0.382	10,517.037	0.330	14.569	0.310	2.169	8,830.071
	(0.155)	(3,415.169)	(0.151)	(4.947)	(0.096)	(0.655)	(3,229.179)
	[0.014]	[0.002]	[0.029]	[0.003]	[0.001]	[0.001]	[0.006]
Dependent Variable							
Mean	0.269	3,076	0.241	4.276	0.117	0.630	3,969
Standard Deviation	0.443	9,504	0.428	14.09	0.321	2.467	8,266

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

Table A12: 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 $\tilde{\theta}$	0.011	-0.203	0.360	0.123	0.226	1,516.858	0.173
	(0.184)	(2.488)	(0.210)	(0.172)	(0.157)	(856.523)	(0.200)
	[0.953]	[0.935]	[0.087]	[0.476]	[0.150]	[0.077]	[0.388]
Dependent Variable							
Mean	0.605	41.98	0.501	0.501	0.487	3,076	5.867
Standard Deviation	0.489	13.31	0.500	0.500	0.500	2,733	0.816

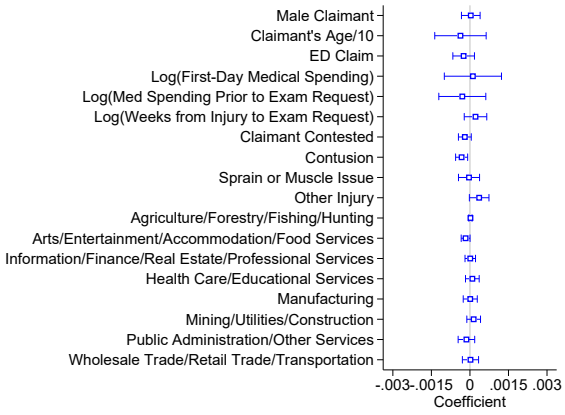
Notes: This table displays estimates of the coefficients from separate regressions of the dependent variable indicated in the column on doctor generosity from OLS regressions of Equation (5), where the measure of doctor generosity is calculated using empirical Bayes shrinkage on the coefficients from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

Table A13: Relationship Between Doctor Generosity and Observational Outcomes—Robustness to Selection

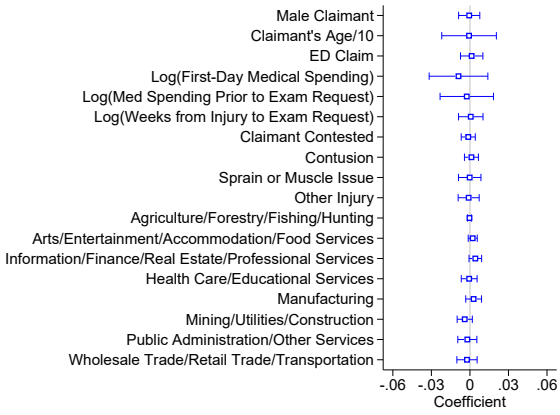
	Dependent Variable		Baseline Effect (Std. Error) [R^2]			Controlled Effect (Std. Error) [R^2]			Bias-Adjusted β [if equal selection on unobservables and observables, δ=1]	Selection (δ) on unobservables relative to observables needed to make β=0
	mean	std dev	coef	std err	R^2	coef	std err	R^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Any Cash Benefits	0.269	0.443	0.709	(0.027)	[0.002]	0.604	(0.026)	[0.114]	0.572	18.232
Total Cash Benefits	3,076.347	9,504.098	19,841.811	(592.281)	[0.003]	18,376.826	(572.520)	[0.071]	17,918.935	37.418
Any Temporary Income-Replacement Benefits	0.241	0.428	0.628	(0.027)	[0.002]	0.526	(0.025)	[0.103]	0.494	16.415
Temporary Income-Replacement Benefit Duration	4.276	14.087	27.594	(0.885)	[0.002]	25.484	(0.863)	[0.054]	24.822	35.710
Any Permanent Impairment Benefits	0.117	0.321	0.583	(0.020)	[0.003]	0.547	(0.019)	[0.074]	0.536	46.473
Permanent Impairment Rating	0.630	2.467	4.057	(0.157)	[0.002]	3.781	(0.153)	[0.064]	3.696	41.845
Medical Spending	3,969.038	8,265.971	15,710.688	(499.904)	[0.002]	13,970.108	(465.353)	[0.138]	13,437.675	25.375

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

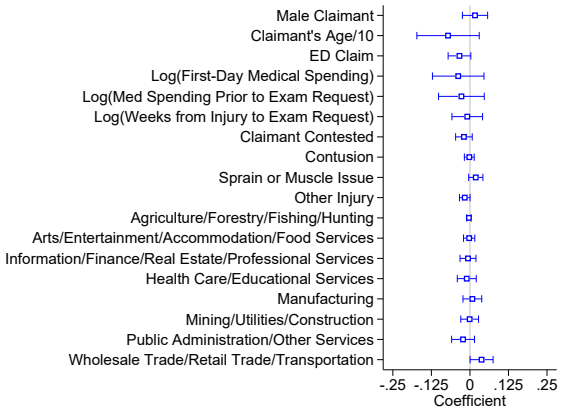
Figure A1: Balance of Claimant Characteristics across Designated Doctor Characteristics



(a) Doctor Age



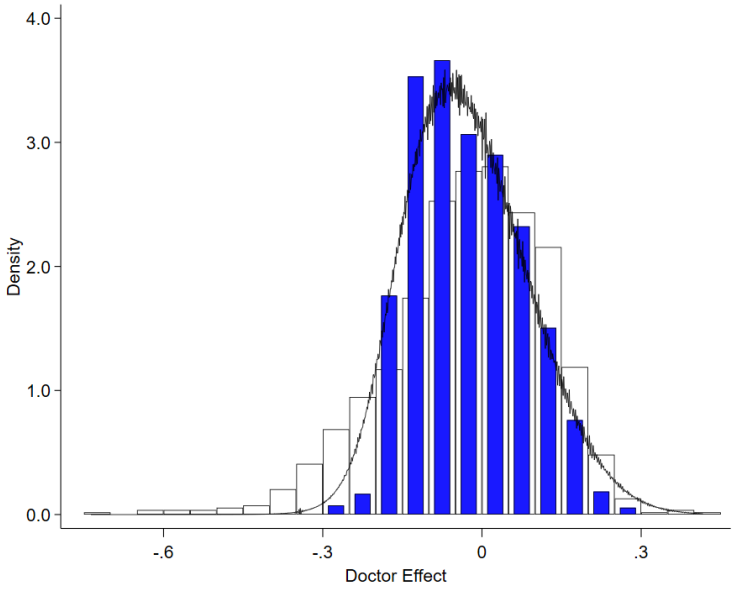
(b) Doctor Female



(c) Doctor DC credential

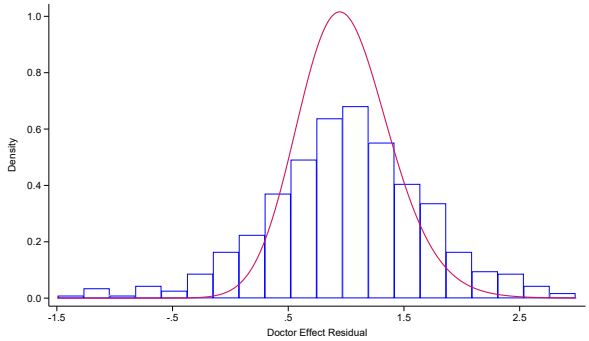
Notes: This figure displays coefficients and estimated 95% confidence intervals from separate regressions of each claimant characteristic listed on the vertical axis on the provider characteristic indicated in the panel: doctor age (Panel A), an indicator variable for the doctor being female (Panel B),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

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

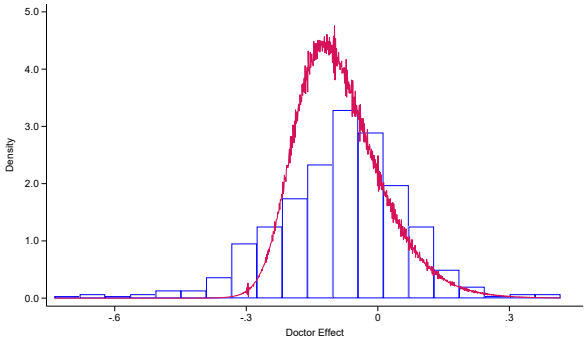


Notes: This figure displays the implied distribution of doctor effects (solid line) based on a change in variables applied to the deconvoluted distribution of residuals, overlaid on a histogram of the estimated doctor effects (hollow bars) and a histogram of the doctor effects after applying empirical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

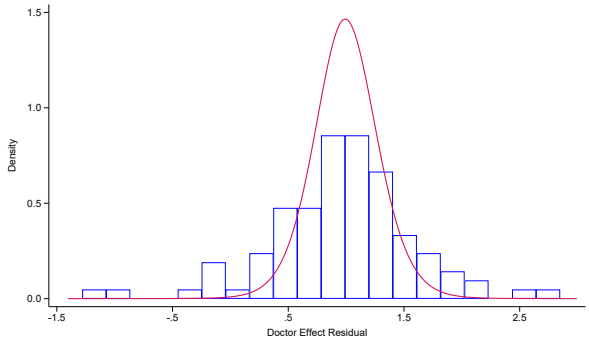
Figure A3: Distribution of Doctor Effects by Subgroup



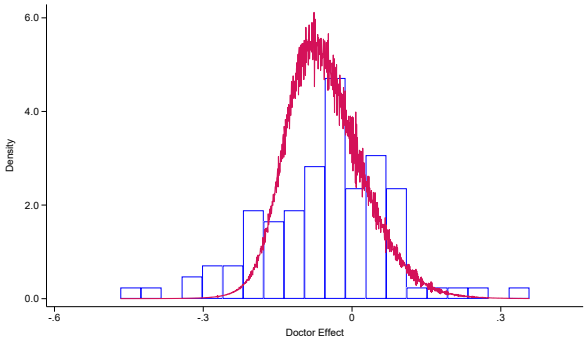
(a) Doctor Effect Residual: MD/DO Credential



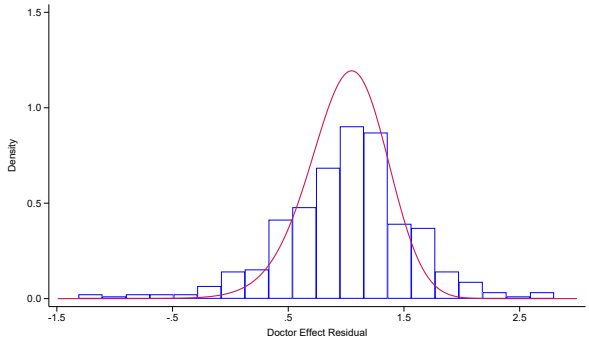
(b) Doctor Effect: MD/DO Credential



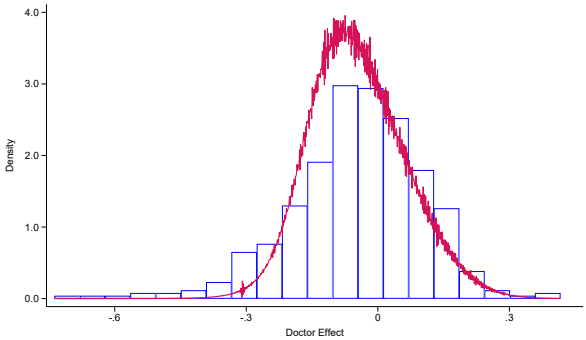
(c) Doctor Effect Residual: Orthopedic Surgery



(d) Doctor Effect: Orthopedic Surgery

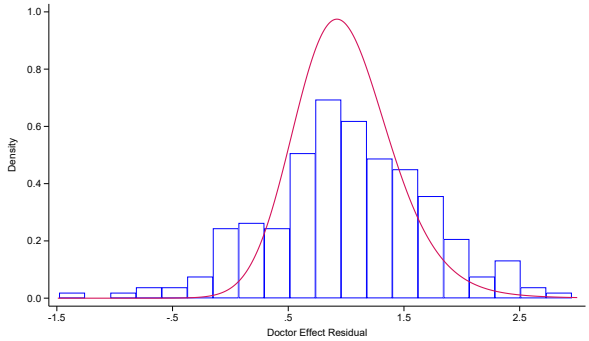


(e) Doctor Effect Residual: More Than Three Years Experience

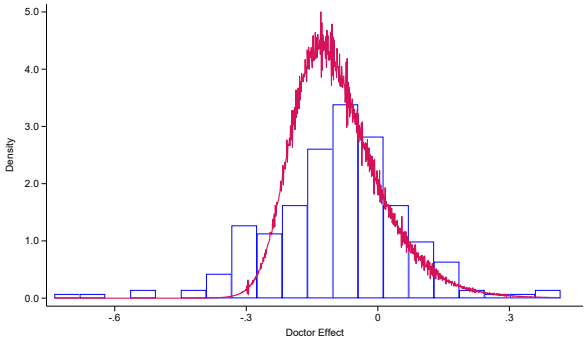


(f) Doctor Effect: More Than Three Years Experience

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



(g) Doctor Effect Residual: Primary Care



(h) Doctor Effect: Primary Care

Notes: For the indicated subgroups of doctors, this figure displays sets of panels depicting the deconvoluted distribution of doctor effect residuals (left panel) and the associated implied distribution of doctor effects (right panel) based on a change in variables applied to the distribution of residuals. These distributions overlay the associated histogram of the underlying empirical residuals and estimated doctor effects, respectively. See Appendix Section B.3 for more details on this estimation.