Online Appendix to

Gender Differences in Medical Evaluations: Evidence from Randomly Assigned Doctors

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APPENDIX

A Additional Details on Setting and Data

Prevalence of Independent Medical Evaluations Note that while 6.7% of claims for injuries occurring from 2013 to 2017 had an independent medical exam by the end of 2017, a higher share of these claims will have an exam at some point, since claims are more likely to have an independent medical exam the longer they are open. For example, for claims for 2013 injuries, 9% have had an independent medical exam by the end of the sample period. Because independent medical exams typically settle disputes about the worker's continued inability to work, they predominately occur for claims with cash disability benefits, which have higher stakes for both employers and injured workers than claims involving only medical benefits. Among claims for 2013 injuries, the 22% of claims receiving any cash benefits accounted for 86% of total medical and cash benefits paid out through the end of the sample period and 39% of these claims had an independent medical exam by the end of the sample period.

Information for Insurer, Diagnosis, and Injury Day of Week Fixed Effects In some specifications, we control for insurer fixed effects. There are 466 distinct insurers represented in the disputed claims sample. Because certified self-insured employers have their own insurer codes, insurer fixed effects are equivalent to controlling for an employer fixed effect among claimants working for some large employers.

We classify claims as sprains, fractures, muscle issues, or contusions using ICD-9 diagnosis codes from medical care received on the first day of injuries. For bills that identify ICD-10 codes, we convert ICD-10 codes to ICD-9 codes using a crosswalk from the Centers for Medicare & Medicaid Services so that we have consistent definitions of injuries over time. We classify claims based on their most frequently listed ICD-9 codes from among the above injury types with ties broken randomly. The 11% of claims without an ICD-9 code on the first day for sprains, fractures, muscle issues, or contusions are classified as claims for Other Injuries. We use this classification when testing for heterogeneity by injury type and for the descriptive statistics shown in Table 1. In addition, we also control for fixed effects for initial diagnoses in certain specifications. These fixed effects are based on the first three digits of the ICD-9 code used to classify the injury type for claims classified as sprains, fractures, muscle issues, or contusions and for the most frequently listed ICD-9 code for Other Injuries. We also use the first treatment to determine the day of the week that injuries occurred.

Identifying Gender of Designated Doctors We identify the gender of approximately 94% of doctors performing designated doctor exams in the sample using information from the CMS NPI registry. For doctors with missing NPI information in the workers' compensation insurance data, we classify their gender based on their first name if at least 99% of the providers in Texas in the CMS registry with that first name have the same gender.

Isolating Conditional Random Assignment As we describe in Section II, our estimation approach controls for the credential of the assigned designated doctor (known ex post) by claimant county fixed effects, as the assignment process means the designated doctor assigned to a claimant is random among designated doctors with that credential in the claimant's county. An alternative approach to isolate conditional random assignment would be to instead control for each injury type by county combination—the ex ante information the regulator uses to decide which subset of designated doctors within a county are eligible to evaluate a claimant. A potential concern with basing the estimation on a control for injury type is that we can only imperfectly observe the injury type information used by the regulator in selecting which doctor credentials are required to evaluate a claimant. Our measure of injury type, which is based on the claimant's diagnosis on the first day of treatment for that injury, is imperfect as it could in principle miss aspects of a claimant's injury that the regulator considers when deciding which types of doctors are eligible to evaluate the claimant (MDs, DOs, and/or DCs). For example, while it is straightforward to identify musculoskeletal injuries, our measure of injury type may miss secondary non-musculoskeletal conditions (e.g., subsequent secondary diagnoses of mental health conditions, secondarily affected body systems) that may lead the regulator to require an evaluation by an MD or DO, rather than a DC. Thus, to be conservative, our baseline approach is to control for credential of the assigned doctor by county, as the assignment mechanism means that it is as good as random which doctor was assigned to the claimant among designated doctors in that

county with that credential. In practice, we obtain very similar estimates if we control for injury type by county fixed effects instead of credential by county fixed effects in our analysis. See Appendix Tables A4 and A5 for estimates from this alternative specification. It is not surprising that we obtain similar results using either approach. The measurement error in our injury type variable may be limited in practice, and the vast majority of exams are for claimants with musculoskeletal injuries, whose exams can be performed by any designated doctor regardless of credential.

Construction of Normalized Additional Benefits Measure To assess the value of benefits received after the exam, we create a second variable—"normalized additional cash benefits"—to reflect the total cash benefits received in the year after the exam 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 benefit rate for each benefit type—the population-wide mean inflation-adjusted benefits paid per week receiving benefits based on all claims with nonzero benefits.[1] We then calculate the normalized additional benefits received as the sum of the post-evaluation temporary income benefits and permanent impairment benefits valued at the mean benefit rate for that benefit type. Specifically, we multiply the mean benefit rate for each type of benefit by the number of weeks the claimant received benefits and then add these two amounts to calculate the normalized additional cash benefits. A feature of this measure is that it depends on only the claimant's evaluated degree of disability rather than the claimant's pre-injury wages.

Identifying Treating Doctors We identify a claimant's treating doctor as the doctor who submits a workers' compensation report describing a claimant's ability to work. If a claimant does not have a bill that explicitly states that a work status exam was performed, we identify the claimant's treating doctor as the doctor who bills for case management services. If multiple doctors bill for case management services for a claim, we identify the treating doctor as the first doctor to bill for case management services. We can identify the treating doctor and the treating doctor's gender for about half of claims in our sample using this approach. For the other half of claims, either no case management services were billed, which often happens for medical-only claims (i.e., claims without cash benefits), or the case management services were billed to a health care organization rather than to a specific provider (in which case, we cannot determine the gender of the treating doctor). We obtain similar results if we instead adopt a treating doctor definition based on first office visit, which likely misidentifies treating doctors more often than our baseline approach does but leads to fewer claimants having missing treating doctor gender.

Predicting Cash Benefits with Lasso Model To create the measure of predicted cash benefits, we first fit a lasso model of normalized cash benefits where benefits are measured through one year after the designated doctor exam. We then predict claimants' cash benefits based on this lasso model. For the lasso model, we include indicator variables for ten-year age bins, wage deciles, day of the week of first medical treatment, industry, and injury type. We also include the cost of first-day medical treatment and indicator variables for first treatment occurring in the emergency department and for marital status.

B Additional Results

Robustness to Included Controls Appendix Tables A4 and A5 further probe the robustness of our findings to the inclusion of different combinations of fixed effects. The estimates from these alternative specifications are similar to our baseline estimates. For instance, we obtain similar estimates when excluding injury year and exam year fixed effects. We also obtain similar estimates when replacing separate county-credential and exam year fixed effects with county-credential-year fixed effects or county-credential-quarter fixed effects. This rules out alternative explanations related to the pool of designated doctors changing over time. We also obtain similar estimates in a specification including county-doctor-year fixed effects, in which the coefficient on the female doctor and female claimant interaction term is identified using differences in outcomes between male and female claimants who are assigned the same doctor from the same pool of

[1] As described in the text, temporary income benefits are paid for the weeks that individuals miss work while healing from temporary impairments. Permanent impairment severity—as rated by a claimant's treating doctor or designated doctor—determines the number of weeks permanent impairment benefits are paid, though these benefits are paid regardless of whether a claimant remains out of work or returns to work. Among individuals who receive non-zero benefits for a particular benefit type, we calculate an individual's inflation-adjusted benefit rate for that benefit type as the ratio of the inflation-adjusted dollars of benefits received to the weeks receiving benefits. We then calculate the population-wide mean weekly rate for a particular benefit type by taking the mean weekly rate among individuals who receive non-zero benefits for that benefit type.

potential designated doctors. Further, the estimates are similar in specifications with interactions between claimant gender and time, which validates that the documented differences are not driven by unobserved factors related to female claimant evaluations that vary across time or space. We also obtain similar estimates when we replace the county-by-credential fixed effects with county-by-diagnosis fixed effects, an alternative approach to isolating conditional random assignment.[2] We obtain similar estimates if we supplement the baseline specification with insurer-by-year fixed effects, which rules out changes in insurer practices across time as an explanation of the results. Further, we obtain similar estimates when we include fixed effects for insurer-county-credential-year or insurer-county-credential-quarter, providing reassurance that exclusions due to conflicts of interest with insurers do not impact the estimates. Finally, we obtain similar estimates in specifications where we interact all our baseline controls with claimant gender. Overall, the results are very similar regardless of the combination of fixed effects included.

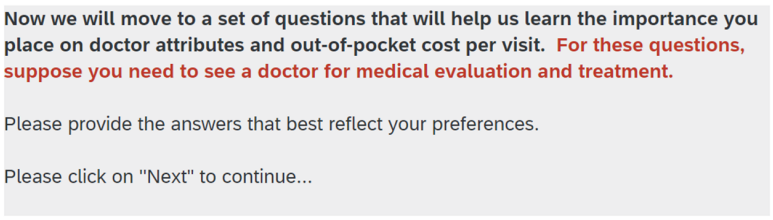
C Survey Questions: Full Text

A Experiences with Health Care System (summarized in Appendix Table A9)

- Thinking about your experiences with health care visits in the past, have you ever felt that a doctor did any of the following? *Answer options: Yes, has happened; No, has not happened.*
  - Talked down to you or didn't treat you with dignity or respect
  - Didn't understand or relate to your experiences and concerns
  - Didn't believe you were telling the truth about your symptoms or concerns
  - Refused to order a test or treatment you thought you needed
  - Made you feel uncomfortable discussing your concerns
  - Assumed something about you without asking
  - Refused to prescribe pain medication you thought you needed
- Thinking about your experiences getting health care for yourself, which doctor—male or female—would be more likely to *Answer options: Male doctor; Female doctor; Male and Female doctors are equally likely.*[3]
  - treat you with dignity and respect?
  - understand or relate to your experiences and concerns?
  - believe you are telling the truth about your symptoms or concerns?
  - provide needed testing and treatments?
  - make you feel comfortable with discussing your concerns?
  - ask appropriate questions instead of making assumptions?
  - be the most qualified?
  - be available near you?

B Preferences and Homophily (summarized in Appendix Table A10)

Hypothetical Choice Questions The hypothetical choice questions are designed to measure willingness to pay to see an own-gender provider. Before this set of questions, we provided the following framing:



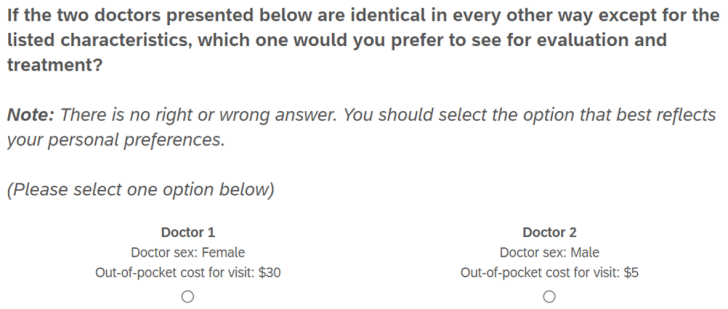
[2] See Section I and Appendix Section A for a detailed description of the designated doctor assignment mechanism and alternative approaches to empirically isolate conditional random assignment.

[3] To ensure primacy bias did not impact our results, we randomized which option—Male doctor or Female doctor—appeared first for this set of questions.

Respondents were then presented with a hypothetical choice question. Specifically, the respondents were presented with one of four choice sets:

- Female doctor, $30 out-of-pocket cost or Male doctor, $5 out-of-pocket cost
- Female doctor, $10 out-of-pocket cost or Male doctor, $5 out-of-pocket cost
- Female doctor, $5 out-of-pocket cost or Male doctor, $10 out-of-pocket cost
- Female doctor, $5 out-of-pocket cost or Male doctor, $30 out-of-pocket cost.

The choice set presented to each respondent was randomly assigned among those above. An example of the presentation of this hypothetical choice question is copied below:



For completeness, we asked sequential follow-up questions—moving either upward or downward from the initial randomly assigned choice set among the choice sets listed above—based on the respondent's answer to prior questions to discern the maximum the respondent is willing to pay for a doctor of a particular gender in terms of out-of-pocket cost differentials. Thus, each respondent is asked at most four hypothetical choice questions, though the median respondent was only asked 2 questions (mean 2.5 questions). To ensure that primacy bias did not lead to a higher percentage of respondents choosing either the male or female doctor option, we randomly assigned which option–the male doctor or the female doctor option—appeared first in each of the four choice sets above, both in the initially assigned hypothetical choice question and all follow-up hypothetical choice questions. While the discussion in the text focuses on the results from the initial randomly assigned choice set, Appendix Figure A5 illustrates that the patterns in selecting own-gender doctors are very similar when based on estimates from the full set of hypothetical choice questions asked of respondents.

Other Questions

- Have you ever received care from a. . . .
  - Male doctor? *Answer options: Yes; No.*
  - Female doctor? *Answer options: Yes; No.*
- Given the choice, would you prefer to see a doctor who is male or female, or does it not make much difference to you? *Answer options: Prefer to see a doctor who is female; Prefer to see a doctor who is male; Doesn't make much difference.*[4]
- Please indicate how important each of the following characteristics is if you were choosing a doctor. *Answer options: Not at all important; Slightly important; Moderately important; Very important; Extremely important.*
  - Out-of-pocket cost for a visit
  - Doctor reviews (e.g., on websites like Healthgrades or Google or from friends or family)

[4]We randomized which option was presented first—Prefer to see a doctor who is female or Prefer to see a doctor who is male—to ensure primacy bias did not affect the estimates.

  - Travel time to get to doctor's office
  - Wait time at the doctor's office
  - Doctor's sex
  - Doctor's age

C Respondent Characteristics (summarized in Appendix Table A8)

- Are you male or female? *Answer options: Male; Female; Other.*
- What is your age? *Answer options: under 30 years; 30 to 39 years; 40 to 49 years; 50 to 59 years; 60 to 64 years; 65 years or over.*
- Have you worked in the last 12 months? *Answer options: Yes; No.*
- In the last year, have you ever been unemployed or out of the labor force? *Answer options: Yes; No.*
- Are you currently married, living with a partner, widowed, divorced, separated, or have you never been married? *Answer options: Married; Living with partner; Not married and not living with a partner.*
- Are you of Hispanic, Latino, or Spanish origin? *Answer options: Yes; No; Decline to state.*
- Do you or anyone in your household work in a health care delivery setting, such as a doctor's office, clinic, hospital, nursing home, or dentist's office? *Answer options: Yes, I work in health care delivery setting; Yes, both myself and someone else in household; Yes, someone else in household works in health care delivery setting; No.*
- Are you, yourself, now covered by any form of health insurance or health plan? *Answer options: Yes; No.*
- In the past five years, have you interacted with a doctor to get health care for yourself? *Answer options: Yes; No.*
- In the last five years, have you experienced chronic physical pain that has interfered with your daily activities? *Answer options: Yes; No.*
- What is your race? *Answer options: White; Black or African American; Asian; Other; Decline to state.*
- What is the highest level of school you have completed or the highest degree you have received? *Answer options: Less than High School; High School Graduate or GED; Some College; Bachelor's Degree; Postgraduate Degree.*
- About how much do you earn in a year through your job(s)? *Answer options: Less than $10,000; $10,000 to less than $20,000; $20,000 to less than $30,000; $30,000 to less than $40,000; $40,000 to less than $50,000; $50,000 to less than $75,000; $75,000 to less than $90,000; $90,000 to less than $100,000; $100,000 or more.*
- What is the industry of the main job you have held in the past year? (Please select the answer option that fits best.) *Answer options: Agriculture/Forestry/Fishing/Hunting; Arts/Entertainment/Accommodation/Food Services; Information/Finance/Real Estate/Professional Services; Health Care/Educational Services; Manufacturing; Mining/Utilities/Construction; Public Administration/Other Services; Wholesale Trade/Retail Trade/Transportation.*

D Policy Counterfactuals

Below, we outline the setup for the back-of-the-envelope policy counterfactuals. In the discussion below, references to the "gender gap" pertain to the gender gap conditional on all available observable characteristics. To conduct this analysis, we combine our estimates on the effect of gender match from the randomized evaluations with our broader evidence on the gender gap and gender homophily in patient selection of treating doctors within workers' compensation insurance more generally. We note that this broader back-of-the-envelope counterfactual analysis involves extrapolation beyond the randomized evaluations, and thus the quantitative findings from this analysis should be interpreted with the appropriate caution.

A Setup

We define some notation to describe this analysis. Let r_j be the share of patients of gender j who choose a female treating doctor, and let s denote the share of patients who are female. In this notation, the share of overall treating doctors who are female can be expressed as: $r \equiv r_m(1-s) + r_f(s)$. We define relative gender homophily as the ratio of the share of female patients selecting female doctors to the share of male patients selecting female doctors, $Z \equiv \frac{r_f}{r_m}$. Let Gap_j denote the expected gender gap in benefit receipt— the percent reduction in the rate of benefit receipt for females relative to the analogous rate for males—when female claimants are evaluated by doctors of gender j. Using this notation, the overall gender gap in benefit receipt can be expressed as: $Gap \equiv Gap_m(1-r_f) + Gap_f(r_f)$. We define the gender-match effect as the ratio of the gender gap when patients are evaluated by female doctors relative to the gender gap when patients are evaluated by male doctors: $X \equiv \frac{Gap_f}{Gap_m}$.

It is straightforward to show that we can express the gender gap as a function of the overall share of treating doctors who are female (r) and the degree of homophily in the market (Z):

$$Gap(r, Z) = Gap_m \times (1 - \frac{r}{\frac{1-s}{Z} + s}) + Gap_f \times (\frac{r}{\frac{1-s}{Z} + s}), \tag{1}$$

where $Gap_f \equiv \frac{XGap^0}{r_f^0(X-1)+1}$, $Gap_m \equiv \frac{Gap^0}{r_f^0(X-1)+1}$, and Gap^0 and r_f^0 denote the overall gender gap and share of female patients selecting female doctors in the status quo, respectively. Appendix Section C below presents this derivation in more detail. In the calculations that follow, we take the share of female patients (s) as given at the observed share in the workers' compensation insurance population: 38%.

We make two simplifying assumptions. First, we assume that patient-doctor gender match causes the same percent reduction in gender gaps in the likelihood of cash benefit receipt in broader workers' compensation insurance as it does within the set of claims with randomized evaluations. In other words, we assume the gender match effect (X) we estimate among the set of randomized evaluations applies more broadly within workers' compensation insurance. Second, we assume relative gender homophily in patient selection of treating doctors (Z) is constant with respect to the overall share of female treating doctors. For instance, female patients may select female doctors at Z times the rate that male patients select female doctors, but Z is constant as the share of doctors who are female varies.[5]

B Results

Using the relationship defined in Equation (1), Figure A3 illustrates the effect of varying one dimension holding the other fixed at the observed values in the status quo. In both panels, the vertical axis displays the expected gender gap in benefit receipt—the percent reduction in the rate at which females receive cash benefits relative to analogous rate for males with the same observable characteristics, while the horizontal axis displays either the share of female treating doctors (Panel A) or the relative gender homophily in patient-doctor matches (Panel B). For reference, each figure displays an "x" representing the observed combination in the status quo: a gender gap is 15.3% (i.e., females are 15.3% less likely to receive cash benefits than males with the same observables), the share of treating doctors who are female is 27.9%, and the degree of relative gender homophily is 1.051 (i.e., female patients select female doctors at 1.051 times the rate that male patients select female doctors).

Holding fixed the observed degree of gender homophily, Figure A3 Panel A plots the relationship between the gender gap and the share of female treating doctors. This figure indicates that increasing the share of female treating doctors by 22.1 percentage points—moving from 27.9% to parity—-would lead to a 33.7% decrease in the observed gender gap. The observed degree of gender homophily in patient-doctor matches works to reinforce the effects of increasing gender diversity among doctors, with a 22.1 percentage point increase in the share of female treating doctors translating to a 22.8 percentage point increase in the share of female claimants who see female doctors. Additionally, Figure A3 Panel A can be used to determine the increase in the share of female doctors necessary to offset a given amount of the gender gap in

[5]While it would be straightforward to extend these calculations to allow gender homophily to vary with the share of doctors who are female, we avoid doing this for a few reasons. First, whether Z and r are correlated—and the direction of any correlation—is ex ante unclear. Second, we cannot credibly estimate how Z varies with r. While Section IV presents estimates of relative gender homophily across the workers' compensation insurance system in Texas, there is no plausibly exogenous variation in the availability of female doctors across geography to identify how relative gender homophily varies with the share of doctors who are female.

cash benefit receipt. To offset a quarter of the gender gap in benefit receipt observed in the status quo, it would take a 16.4 percentage point increase in the share of treating doctors who are female.

Figure A3 Panel B plots the relationship between the gender gap and the degree of gender homophily, fixing the gender composition of doctors as observed in the status quo. An increase in relative gender homophily from the observed level to two (i.e., where female patients choose female doctors at twice the rate that male patients choose female doctors), would lead to a 17.3% decrease in the observed gender gap. Holding all else equal, female patients would need to choose female doctors 2.7 times as often as male patients choose female doctors to offset a quarter of the observed gender gap.

More broadly, we can characterize the trade-offs between policies that may increase gender diversity among doctors and policies that increase sorting of patients to own-gender doctors. Figure A4 illustrates level curves of Equation (1), which characterize the combinations of gender composition in the doctor workforce and gender homophily patient-doctor matches that would result in a given value of the gender gap. The combination of conditions in the status quo is represented as "x" in this figure. There are at least two important qualitative properties worth noting. First, the level curves are negatively sloped. This indicates that a given reduction in the gender gap can be achieved by trading-off increases in the share of doctors who are female and increases in relative gender homophily. Second, the level curves are convex relative to the origin. This convexity reflects the fact that the inputs—the share of doctors who are female and relative gender homophily—are complementary in reducing the gender gap.

Suppose we are interested in understanding the change in conditions needed to reduce the gender gap from 15.2% to 12.5%. This reduction in the gender gap could be accomplished by increasing the share of doctors female to 39.8%, holding homophily fixed at 1.051. Alternatively, it could be accomplished by increasing homophily to 2.06, holding the share of female doctors fixed at 27.9%. More generally, the combinations of conditions that would lead to the same closure of the gap are depicted by the level curve corresponding to 0.125, where the difference between this curve and the observed conditions "x" indicates the changes in conditions necessary to achieve this closure. Reducing the gender gap to 12.5% could be accomplished by a convex combinations of changes in the gender composition of treating doctors and relative gender homophily—for example, by increasing gender homophily to 1.75 and the share of treating doctors who are female to 30.1%, or increasing gender homophily to 1.25 and the share of treating doctors who are female to 35.9%.

C More Detail on Policy Counterfactuals

The goal of this analysis is to understand how gender gaps conditional on observables are impacted by: (i) the share of treating doctors who are female (r) and (ii) the degree of gender homophily in patient-doctor matches (Z). In other words, we would like to express the gender gap (conditional on observables) as a function of the overall share of treating doctors who are female and the degree of homophily in the market: $Gap(r, Z)$. We derive this function in two steps. First, following directly from the definitions above, we can express the share of female claimants seeing female doctors (r_f) as a function of the share of female treating doctors overall (r) and the degree of relative gender homophily (Z):

$$r_f = \frac{r}{\frac{1-s}{Z} + s}. \tag{2}$$

Second, we can use our estimate of the gender-match effect (X) and the definitions to infer the values of Gap_m and Gap_f:

$$Gap_m \equiv \frac{Gap^0}{r_f^0(X-1)+1} \tag{3}$$

$$Gap_f \equiv \frac{XGap^0}{r_f^0(X-1)+1}, \tag{4}$$

where Gap^0 and r_f^0, respectively, represent the observed values of the gender gap and the share of female patients selecting female treating doctors in the status quo.

Putting these together, we obtain:

$$Gap(r, Z) = Gap_m \times (1 - \frac{r}{\frac{1-s}{Z} + s}) + Gap_f \times (\frac{r}{\frac{1-s}{Z} + s}), \tag{5}$$

where $Gap_f \equiv \frac{XGap^0}{r_f^0(X-1)+1}$ and $Gap_m \equiv \frac{Gap^0}{r_f^0(X-1)+1}$.

Table A1: Effect on Indicator for Receiving Additional Benefits, Sensitivity to Clustering Level

Dependent Variable: I(Additional Cash Benefits > 0)						
	(1)	(2)	(3)	(4)	(5)	(6)
Female Doctor X Female Claimant	0.031	0.031	0.031	0.031	0.031	0.031
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
	[0.002]	[0.002]	[0.001]	[0.001]	[<0.001]	[0.001]
Female Doctor	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
	[0.964]	[0.952]	[0.954]	[0.951]	[0.964]	[0.963]
Female Claimant	-0.032	-0.032	-0.032	-0.032	-0.032	-0.032
	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Level of Clustering						
Doctor	x				x	x
None		x				
County			x		x	
County by Quarter				x		x
Mean of Dep. Var.	0.619	0.619	0.619	0.619	0.619	0.619
N	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables. Each column represents a separate regression with the dependent variable being I(Additional Cash Benefits > 0). The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the indicated level are reported in parentheses, and p-values are reported in brackets.

Table A2: Effect on Amount of Additional Benefits, Sensitivity to Clustering Level

	Dependent Variable: Additional Cash Benefits					
	(1)	(2)	(3)	(4)	(5)	(6)
Female Doctor X Female Claimant	0.086	0.086	0.086	0.086	0.086	0.086
	(0.030)	(0.029)	(0.026)	(0.029)	(0.027)	(0.031)
	[0.004]	[0.003]	[0.001]	[0.003]	[0.002]	[0.005]
Female Doctor	0.032	0.032	0.032	0.032	0.032	0.032
	(0.026)	(0.016)	(0.015)	(0.016)	(0.024)	(0.025)
	[0.208]	[0.050]	[0.031]	[0.046]	[0.178]	[0.202]
Female Claimant	-0.140	-0.140	-0.140	-0.140	-0.140	-0.140
	(0.013)	(0.013)	(0.016)	(0.014)	(0.017)	(0.014)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Level of Clustering						
Doctor	x				x	x
None		x				
County			x		x	
County by Quarter				x		x
Mean of Dep. Var.	6,281	6,281	6,281	6,281	6,281	6,281
N	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables. Each column represents a separate Poisson regression with the dependent variable being the amount of additional normalized benefits received after the exam. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the indicated level are reported in parentheses, and p-values are reported in brackets.

Table A3: Effect on Amount of Additional Benefits, Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Female Doctor X Female Claimant	0.086	498.237	0.109	494.014	0.101	513.389
	(0.030)	(189.407)	(0.033)	(184.872)	(0.034)	(189.974)
	[0.004]	[0.009]	[0.001]	[0.008]	[0.003]	[0.007]
Female Doctor	0.032	206.351	0.027	174.474	0.020	143.214
	(0.026)	(170.932)	(0.027)	(184.661)	(0.026)	(187.043)
	[0.208]	[0.228]	[0.308]	[0.345]	[0.441]	[0.444]
Female Claimant	-0.140	-844.925	-0.405	-2,245.698	-0.233	-1,261.951
	(0.013)	(79.111)	(0.015)	(80.123)	(0.015)	(82.918)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Estimation						
Poisson	x		x		x	
OLS		x		x		x
Dependent Variable						
Additional Cash Benefits	x	x				
Additional Cash Benefits, without Normalization			x	x	x	x
Control for log(wage)					x	x
Mean of Dep. Var. for Females Evaluated by Male Doctors	5,622	5,622	4,478	4,478	4,752	4,752
N	70,748	70,748	70,748	70,748	67,233	67,233
Implied % Effect of Coefficient on Female Doctor X Female Claimant		0.089		0.110		0.108
Implied $ Effect of Coefficient on Female Doctor X Female Claimant	483.731		487.017		478.240	

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables. The estimation and dependent variables are indicated in the table. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A4: Effect on Indicator for Receiving Additional Benefits, Robustness to Varying Fixed Effects

	Dependent Variable: I(Additional Cash Benefits > 0)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female Doctor X Female Claimant	0.031	0.031	0.033	0.037	0.040	0.030	0.030	0.030	0.028	0.026	0.033	0.030
	(0.010)	(0.010)	(0.010)	(0.011)	(0.014)	(0.010)	(0.010)	(0.011)	(0.010)	(0.013)	(0.016)	(0.011)
	[0.002]	[0.002]	[0.002]	[0.001]	[0.005]	[0.004]	[0.004]	[0.006]	[0.006]	[0.050]	[0.036]	[0.004]
Female Doctor	-0.000	-0.002	-0.001	-0.002		0.000	-0.000	0.000	-0.000	0.004	-0.009	0.000
	(0.008)	(0.008)	(0.008)	(0.008)		(0.008)	(0.008)	(0.009)	(0.008)	(0.010)	(0.010)	(0.008)
	[0.964]	[0.822]	[0.917]	[0.849]		[0.972]	[0.967]	[0.956]	[1.000]	[0.656]	[0.407]	[0.980]
Female Claimant	-0.032	-0.031	-0.031	-0.031	-0.020			-0.032	-0.021	-0.017	-0.019	
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)			(0.005)	(0.005)	(0.006)	(0.007)	
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.001]			[<0.001]	[<0.001]	[0.006]	[0.007]	
Additional Controls												
County by Credential Fixed Effects	x	x				x	x		x			x
Exam Year Fixed Effects	x							x				x
Injury Year Fixed Effects	x		x	x	x	x	x	x	x	x	x	x
County by Credential by Exam Year Fixed Effects			x									
County by Credential by Exam Quarter Fixed Effects				x								
County by Provider by Exam Year Fixed Effects					x							
Gender by County and Gender by Exam Year Fixed Effects						x						
Gender by County by Exam Year Fixed Effects							x					
County by Diagnosis Fixed Effects								x				
Insurer by Exam Year Fixed Effects									x			
Insurer by County by Credential by Exam Year Fixed Effects										x		
Insurer by County by Credential by Exam Quarter Fixed Effects											x	
Baseline Controls by Gender												x
Mean of Dep. Var.	0.619	0.619	0.619	0.619	0.619	0.619	0.619	0.619	0.619	0.619	0.619	0.619
N	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables. Each column represents a separate regression with the dependent variable being I(Additional Cash Benefits > 0). The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A5: Effect on Amount of Additional Benefits, Robustness to Varying Fixed Effects

	Dependent Variable: Additional Cash Benefits											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female Doctor X Female Claimant	0.086	0.084	0.087	0.096	0.103	0.082	0.079	0.090	0.081	0.059	0.065	0.084
	(0.030)	(0.031)	(0.031)	(0.031)	(0.038)	(0.031)	(0.031)	(0.031)	(0.030)	(0.033)	(0.036)	(0.031)
	[0.004]	[0.006]	[0.005]	[0.002]	[0.007]	[0.007]	[0.010]	[0.004]	[0.007]	[0.074]	[0.072]	[0.006]
Female Doctor	0.032	0.025	0.040	0.038		0.033	0.036	0.035	0.032	0.058	0.030	0.033
	(0.026)	(0.026)	(0.025)	(0.024)		(0.026)	(0.025)	(0.026)	(0.026)	(0.025)	(0.026)	(0.026)
	[0.208]	[0.332]	[0.105]	[0.123]		[0.200]	[0.150]	[0.176]	[0.217]	[0.021]	[0.251]	[0.194]
Female Claimant	-0.140	-0.141	-0.137	-0.138	-0.111			-0.140	-0.091	-0.082	-0.085	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)			(0.014)	(0.014)	(0.016)	(0.018)	
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]			[<0.001]	[<0.001]	[<0.001]	[<0.001]	
Additional Controls												
County by Credential Fixed Effects	x	x				x	x		x			x
Exam Year Fixed Effects	x							x				x
Injury Year Fixed Effects	x		x	x	x	x	x	x	x	x	x	x
County by Credential by Exam Year Fixed Effects			x									
County by Credential by Exam Quarter Fixed Effects				x								
County by Provider by Exam Year Fixed Effects					x							
Gender by County and Gender by Exam Year Fixed Effects						x						
Gender by County by Exam Year Fixed Effects							x					
County by Diagnosis Fixed Effects								x				
Insurer by Exam Year Fixed Effects									x			
Insurer by County by Credential by Exam Year Fixed Effects										x		
Insurer by County by Credential by Exam Quarter Year Fixed Effects											x	
Baseline Controls by Gender												x
Mean of Dep. Var.	6,281	6,281	6,281	6,281	6,281	6,281	6,281	6,281	6,281	6,281	6,281	6,281
N	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables. Each column represents a separate Poisson regression with the dependent variable being the amount of additional normalized benefits received after the exam. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A6: Effect on Indicator for Receiving Additional Benefits, Controlling for Additional Claimant and Injury Characteristics

	Dependent Variable: I(Additional Cash Benefits > 0)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female Doctor X Female Claimant	0.031	0.027	0.027	0.028	0.027	0.028	0.027
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
	[0.002]	[0.008]	[0.008]	[0.006]	[0.008]	[0.007]	[0.008]
Female Doctor	-0.000	0.001	0.001	0.000	0.002	0.002	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
	[0.964]	[0.903]	[0.900]	[0.961]	[0.825]	[0.842]	[0.835]
Female Claimant	-0.032	-0.020	-0.020	-0.026	-0.026	-0.026	-0.026
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Additional Controls							
Insurer Fixed Effects		x	x	x	x	x	x
Injury Day-of-the-Week Fixed Effects			x	x	x	x	x
Age Fixed Effects				x	x	x	x
Diagnosis Code Fixed Effects					x	x	x
Indicator for First Medical Treatment at ED						x	x
Medical Spending on First Treatment Date							x
Mean of Dep. Var.	0.619	0.619	0.619	0.619	0.619	0.619	0.619
N	70,748	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables from OLS regressions of Equation (1) that control for credential-by-county fixed effects, exam year fixed effects, and injury year fixed effects. Each column represents a separate regression with the dependent variable being I(Additional Cash Benefits $>$ 0). The specifications include additional controls as noted in the table. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A7: Effect on Amount of Additional Benefits, Controlling for Additional Claimant and Injury Characteristics

	Dependent Variable: Additional Cash Benefits						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female Doctor X Female Claimant	0.086	0.078	0.078	0.080	0.076	0.076	0.076
	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)
	[0.004]	[0.012]	[0.012]	[0.009]	[0.013]	[0.012]	[0.012]
Female Doctor	0.032	0.033	0.033	0.031	0.035	0.035	0.035
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
	[0.208]	[0.199]	[0.200]	[0.227]	[0.169]	[0.179]	[0.178]
Female Claimant	-0.140	-0.087	-0.087	-0.103	-0.106	-0.105	-0.104
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Additional Controls							
Insurer Fixed Effects		x	x	x	x	x	x
Injury Day-of-the-Week Fixed Effects			x	x	x	x	x
Age Fixed Effects				x	x	x	x
Diagnosis Code Fixed Effects					x	x	x
Indicator for First Medical Treatment at ED						x	x
Medical Spending on First Treatment Date							x
Mean of Dep. Var.	6,281	6,281	6,281	6,281	6,281	6,281	6,281
N	70,748	70,748	70,748	70,748	70,748	70,748	70,748

Notes: This table displays estimates of the coefficients on the female doctor indicator variable, the female claimant indicator variable, and the interaction of the female doctor and female claimant indicator variables from Poisson regressions of Equation (1) that control for credential-by-county fixed effects, exam year fixed effects, and injury year fixed effects. Each column represents a separate regression with the dependent variable being the amount of additional normalized benefits received after the exam. The specifications include additional controls as noted in the table. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017. Standard errors clustered at the doctor level are reported in parentheses, and p-values are reported in brackets.

Table A8: Survey: Respondent Characteristics

	Survey Respondents				Workers in ACS		Workers' Comp Claimants	
	Female	Male	Difference	p-value	Female	Male	Female	Male
	(1)	(2)			(3)	(4)	(5)	(6)
Ever unemployed in last 12 months	0.270	0.225	0.044	[0.045]	-	-	-	-
Married	0.516	0.640	-0.124	[<0.001]	0.590	0.639	0.454	0.558
Hispanic	0.093	0.074	0.019	[0.187]	0.158	0.184	-	-
Works in healthcare	0.179	0.117	0.063	[0.001]	0.193	0.052	-	-
Has health insurance	0.878	0.891	-0.013	[0.424]	0.908	0.867	-	-
Interacted with a doctor to get health care in last five years	0.932	0.918	0.014	[0.299]	-	-	-	-
Experienced chronic physical pain that interfered with daily activities in last five years	0.442	0.491	-0.049	[0.056]	-	-	-	-
Age:								
30-39 years	0.355	0.270	0.085	[<0.001]	0.314	0.322	0.262	0.339
40-49 years	0.260	0.351	-0.091	[<0.001]	0.292	0.292	0.315	0.311
50-55 years	0.296	0.309	-0.013	[0.587]	0.282	0.276	0.296	0.244
60-64 years	0.089	0.070	0.019	[0.176]	0.112	0.110	0.092	0.076
Race:								
White	0.822	0.837	-0.015	[0.434]	0.721	0.744	-	-
Black or African American	0.085	0.073	0.012	[0.377]	0.135	0.106	-	-
Asian	0.043	0.036	0.007	[0.457]	0.069	0.066	-	-
Other	0.038	0.045	-0.007	[0.490]	0.074	0.085	-	-
Decline to State	0.012	0.009	0.003	[0.632]	-	-	-	-
Highest Level of Education:								
< High School	0.009	0.011	-0.001	[0.778]	0.068	0.103	-	-
High School Graduate or GED	0.181	0.146	0.035	[0.065]	0.208	0.266	-	-
Some College	0.344	0.225	0.119	[<0.001]	0.309	0.277	-	-
Bachelor's Degree	0.291	0.350	-0.059	[0.014]	0.245	0.218	-	-
Postgraduate Degree	0.175	0.269	-0.093	[<0.001]	0.171	0.136	-	-
Annual Earnings:								
<10K	0.064	0.029	0.035	[0.001]	0.103	0.054	0.030	0.010
10-20K	0.084	0.034	0.049	[<0.001]	0.129	0.071	0.168	0.054
20-30K	0.134	0.056	0.078	[<0.001]	0.146	0.103	0.292	0.155
30-40K	0.140	0.090	0.050	[0.002]	0.139	0.119	0.166	0.180
40-50K	0.115	0.095	0.020	[0.208]	0.109	0.109	0.104	0.162
50-75K	0.208	0.179	0.029	[0.148]	0.186	0.215	0.140	0.263
75-100K	0.135	0.225	-0.090	[<0.001]	0.086	0.117	0.073	0.117
>100K	0.120	0.291	-0.171	[<0.001]	0.102	0.213	0.028	0.059
Industry:								
Agriculture/Forestry/Fishing/Hunting	0.014	0.026	-0.012	[0.096]	0.007	0.018	0.006	0.014
Arts/Entertainment/Accommodation/Food Services	0.064	0.061	0.003	[0.796]	0.075	0.065	0.065	0.033
Information/Finance/Real Estate/Professional Services	0.170	0.274	-0.104	[<0.001]	0.208	0.217	0.071	0.065
Health Care/Educational Services	0.297	0.131	0.166	[<0.001]	0.376	0.113	0.432	0.086
Manufacturing	0.063	0.136	-0.074	[<0.001]	0.068	0.145	0.069	0.147
Mining/Utilities/Construction	0.037	0.077	-0.040	[0.001]	0.023	0.153	0.018	0.198
Public Administration/Other Services	0.190	0.142	0.048	[0.012]	0.103	0.094	0.193	0.259
Wholesale Trade/Retail Trade/Transportation	0.165	0.152	0.013	[0.502]	0.140	0.196	0.146	0.199
Region:								
West	0.174	0.208	-0.034	[0.093]	0.232	0.246	-	-
Midwest	0.246	0.197	0.049	[0.022]	0.212	0.210	-	-
Northeast	0.212	0.217	-0.005	[0.806]	0.181	0.176	-	-
South	0.368	0.377	-0.010	[0.697]	0.375	0.369	-	-

Notes: Columns 1 and 2 of this table display respondent characteristics from the survey described in Section V. The survey was conducted by Qualtrics and included 1,519 adults ages 30 to 64. Eligibility was restricted to individuals who reported working at some point in the last 12 months and individuals who self-identified as either male (755 respondents) or female (764 respondents). For comparison, columns 3 through 6 of the table also display characteristics of workers ages 30 to 64 from the 2019 American Community Survey and characteristics of workers' compensation claimants in Texas ages 30 to 64 injured between 2013 and 2017. As described in Section I, the presence of wage and industry information is related to the receipt of cash benefits in the workers' compensation data. All wages are in 2020 dollars, and the American Community Survey numbers are weighted using IPUMS weights.

Table A9: Survey: Experiences with the Health Care System

					Regression - Female Coefficient		
	Female	Male	Difference	p-value	Est	Std Error	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Thinking about your experiences with health care visits in the past, have you ever felt that a doctor did any of the following? - Share answered yes							
Talked down to you or didn't treat you with dignity or respect	0.393	0.340	0.052	[0.035]	0.087	(0.026)	[0.001]
Didn't understand or relate to your experiences and concerns	0.450	0.356	0.094	[<0.001]	0.104	(0.027)	[<0.001]
Didn't believe you were telling the truth about your symptoms or concerns	0.317	0.286	0.031	[0.193]	0.045	(0.025)	[0.068]
Refused to order a test or treatment you thought you needed	0.223	0.232	-0.009	[0.666]	0.022	(0.022)	[0.310]
Made you feel uncomfortable discussing your concerns	0.292	0.250	0.042	[0.069]	0.059	(0.024)	[0.014]
Assumed something about you without asking	0.357	0.328	0.029	[0.236]	0.050	(0.026)	[0.054]
Refused to prescribe pain medication you thought you needed	0.175	0.249	-0.074	[<0.001]	-0.055	(0.021)	[0.008]
Share answered yes to any of the above	0.596	0.538	0.058	[0.023]	0.103	(0.026)	[<0.001]
Thinking about your experiences getting health care for yourself, which doctor---male or female---would be more likely to [Answer options: male doctor, female doctor, male and female doctors are equally likely]							
Share selected doctor of own-gender							
treat you with dignity and respect?	0.343	0.193	0.150	[<0.001]	0.178	(0.024)	[<0.001]
understand or relate to your experiences and concerns?	0.517	0.295	0.222	[<0.001]	0.232	(0.027)	[<0.001]
believe you are telling the truth about your symptoms or concerns?	0.304	0.175	0.129	[<0.001]	0.159	(0.023)	[<0.001]
provide needed testing and treatments?	0.249	0.176	0.073	[0.001]	0.103	(0.022)	[<0.001]
make you feel comfortable with discussing your concerns?	0.416	0.240	0.176	[<0.001]	0.179	(0.026)	[<0.001]
ask appropriate questions instead of making assumptions?	0.326	0.177	0.148	[<0.001]	0.177	(0.023)	[<0.001]
be the most qualified?	0.161	0.160	0.001	[0.969]	0.016	(0.020)	[0.406]
be available near you?	0.154	0.184	-0.030	[0.124]	-0.007	(0.020)	[0.733]
Share did not select doctor of opposite gender							
treat you with dignity and respect?	0.931	0.820	0.111	[<0.001]	0.108	(0.018)	[<0.001]
understand or relate to your experiences and concerns?	0.932	0.826	0.105	[<0.001]	0.088	(0.018)	[<0.001]
believe you are telling the truth about your symptoms or concerns?	0.928	0.816	0.112	[<0.001]	0.114	(0.018)	[<0.001]
provide needed testing and treatments?	0.932	0.853	0.079	[<0.001]	0.079	(0.017)	[<0.001]
make you feel comfortable with discussing your concerns?	0.932	0.837	0.095	[<0.001]	0.090	(0.017)	[<0.001]
ask appropriate questions instead of making assumptions?	0.933	0.813	0.120	[<0.001]	0.120	(0.018)	[<0.001]
be the most qualified?	0.958	0.890	0.068	[<0.001]	0.053	(0.014)	[<0.001]
be available near you?	0.914	0.898	0.016	[0.298]	0.011	(0.016)	[0.501]

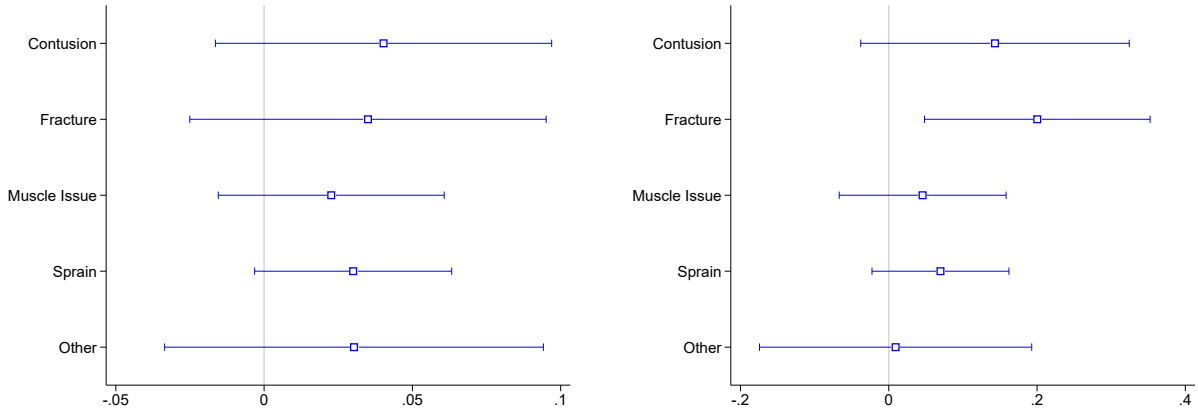
Notes: This table summarizes responses from several questions from the survey described in Section V. The table above reports the raw means for each of the indicated variables, along with the difference by respondent gender and the associated p-value testing whether the difference is zero. The table also includes the estimated coefficient on female (and associated standard error and p-value) from a regression of the indicated response on a female indicator and all the respondent characteristics reported in Appendix Table A8. The survey was conducted by Qualtrics and included 1,519 adults ages 30 to 64. Eligibility was restricted to individuals who reported working at some point in the last 12 months and individuals who self-identified as either male (755 respondents) or female (764 respondents).

Table A10: Survey: Preferences over Providers and Homophily

					Regression - Female Coefficient		
	Female	Male	Difference	p-value	Est	Std Error	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Have you ever received care from a…. - Share answered yes							
Male doctor?	0.901	0.968	-0.068	[<0.001]	-0.062	(0.013)	[<0.001]
Female doctor?	0.941	0.767	0.174	[<0.001]	0.162	(0.019)	[<0.001]
Given the choice, would you prefer to see a doctor who is male or female, or does it not make much difference to you? - Share select each option below							
Prefer to see a doctor who is female	0.463	0.136	0.327	[<0.001]	0.315	(0.024)	[<0.001]
Prefer to see a doctor who is male	0.058	0.290	-0.232	[<0.001]	-0.207	(0.020)	[<0.001]
Doesn't make much difference	0.479	0.574	-0.094	[<0.001]	-0.108	(0.028)	[<0.001]
Choices based on initial hypothetical choice question: doctor gender and out-of-pocket cost - Share select own-gender doctor							
Own Gender $30 vs. Opp Gender $5	0.254	0.240	0.014	[0.748]	0.029	(0.048)	[0.544]
Own Gender $10 vs. Opp Gender $5	0.485	0.293	0.192	[<0.001]	0.200	(0.054)	[<0.001]
Own Gender $5 vs. Opp Gender $10	0.929	0.833	0.095	[0.005]	0.067	(0.036)	[0.064]
Own Gender $5 vs. Opp Gender $30	0.988	0.854	0.134	[<0.001]	0.129	(0.031)	[<0.001]
Choices based on full set of hypothetical choice questions: doctor gender and out-of-pocket cost - Share select own-gender doctor							
Own Gender $30 vs. Opp Gender $5	0.229	0.147	0.082	[<0.001]	0.091	(0.021)	[<0.001]
Own Gender $10 vs. Opp Gender $5	0.427	0.273	0.154	[<0.001]	0.159	(0.026)	[<0.001]
Own Gender $5 vs. Opp Gender $10	0.929	0.828	0.102	[<0.001]	0.088	(0.018)	[<0.001]
Own Gender $5 vs. Opp Gender $30	0.970	0.910	0.060	[<0.001]	0.050	(0.014)	[<0.001]
Please indicate how important each of the following characteristics is if you were choosing a doctor - Share indicating at least moderately important							
Out-of-pocket cost for a visit	0.829	0.824	0.005	[0.809]	0.005	(0.022)	[0.807]
Doctor reviews (e.g., on websites like Healthgrades or Google or from friends or family)	0.847	0.807	0.040	[0.038]	0.048	(0.022)	[0.027]
Travel time to get to doctor's office	0.831	0.834	-0.003	[0.864]	0.002	(0.021)	[0.914]
Wait time at the doctor's office	0.863	0.848	0.015	[0.410]	0.018	(0.020)	[0.361]
Doctor's sex	0.414	0.336	0.077	[0.002]	0.112	(0.026)	[<0.001]
Doctor's age	0.349	0.370	-0.020	[0.416]	0.021	(0.026)	[0.415]

Notes: This table summarizes responses from several questions from the survey described in Section V. The table above reports the raw means for each of the indicated variables, along with the difference by respondent gender and the associated p-value testing whether the difference is zero. The table also includes the estimated coefficient on female (and associated standard error and p-value) from a regression of the indicated response on a female indicator and all the respondent characteristics reported in Appendix Table A8. The survey was conducted by Qualtrics and included 1,519 adults ages 30 to 64. Eligibility was restricted to individuals who reported working at some point in the last 12 months and individuals who self-identified as either male (755 respondents) or female (764 respondents).

Figure A1: Heterogeneity: Estimate on Interaction of Female Doctor and Female Claimant by Injury Type

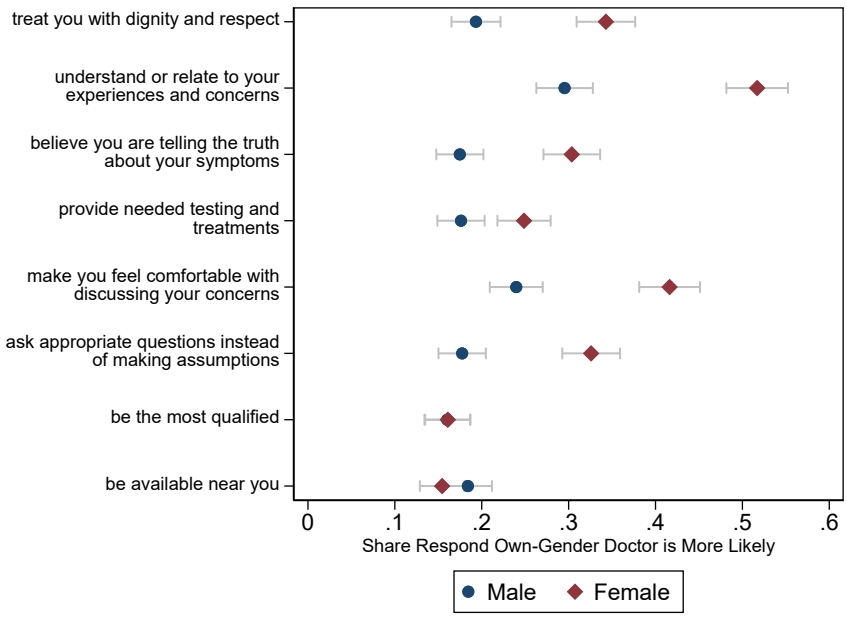


(a) OLS: I(Additional Cash Benefits>0)

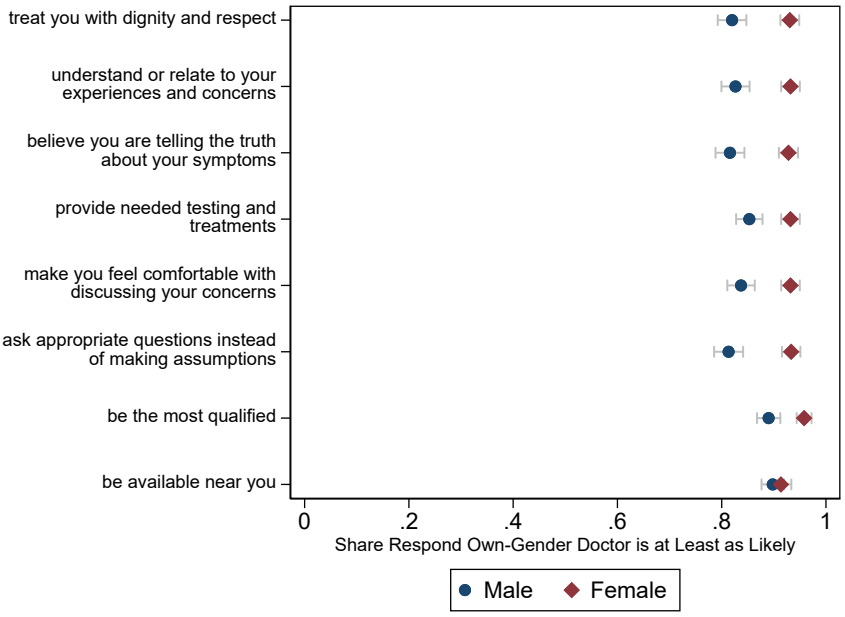
(b) Poisson Regression: Additional Cash Benefits

Notes: Each marker is the coefficient on the interaction of the female doctor and female claimant indicator variables from separate regressions of Equation (1) for the specified sample of claimants. All regressions control for a female doctor indicator variable, a female claimant indicator variable, credential-by-county fixed effects, exam year fixed effects, and injury year fixed effects. The dependent variables are as indicated in the figure: an indicator for receiving any additional cash benefits (Panel A) and (normalized) additional cash benefits received (Panel B). The 95% confidence intervals displayed along with the coefficient estimates are calculated using standard errors clustered at the doctor level. The sample includes claims occurring from 2013 to 2017 that had an independent medical exam by the end of 2017 and that have non-missing values for the specified characteristic.

Figure A2: Additional Results from Survey: "Thinking about your experiences getting health care for yourself, which doctor—male or female—would be more likely to..." [answer options: male doctor, female doctor, male and female doctors are equally likely]



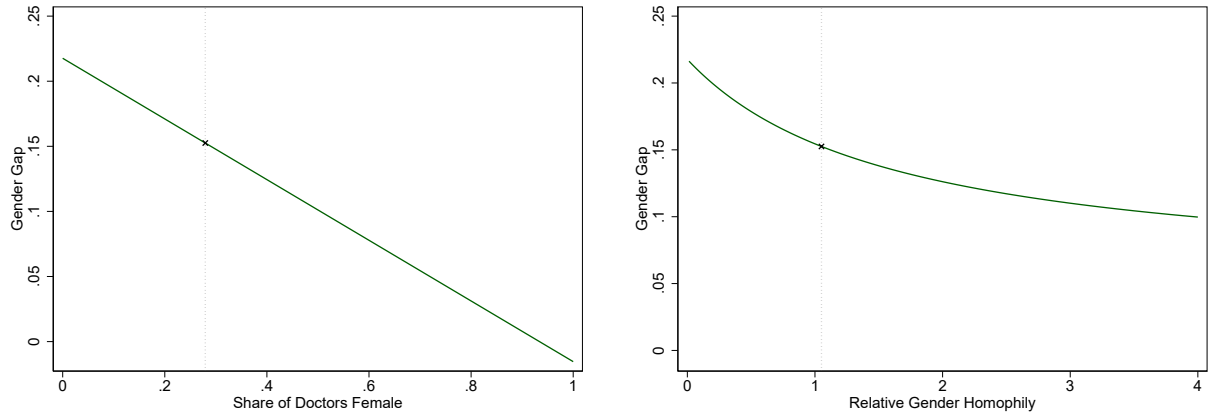
(a) Share that Select Own-Gender Doctor



(b) Share that Do Not Select Opposite-Gender Doctor

Notes: The figure above shows the means and associated 95% confidence intervals for survey responses to the indicated question by respondent gender. The survey was conducted by Qualtrics and included 1,519 adults ages 30 to 64. Eligibility was restricted to individuals who reported working at some point in the last 12 months and individuals who self-identified as either male (755 respondents) or female (764 respondents). See Section V for more detail on the survey. Table A9 reports raw and regression-adjusted differences in means for these survey questions and the associated p-values.

Figure A3: Counterfactual Policy Analysis: Partial Effects of Varying Share Doctors Female or Gender Homophily on Gender Gaps

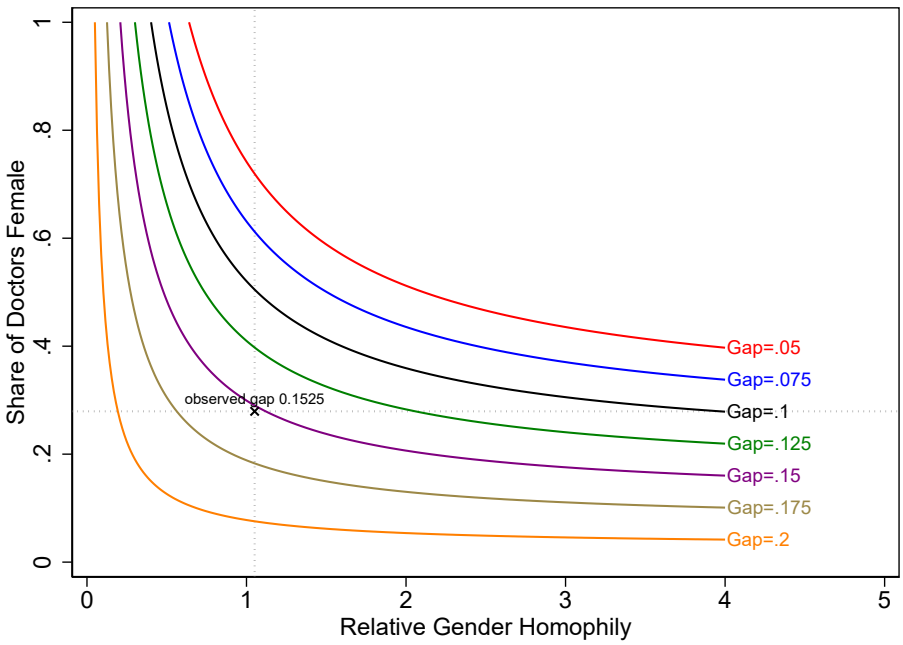


(a) Share of Doctors who are Female

(b) Relative Gender Homophily

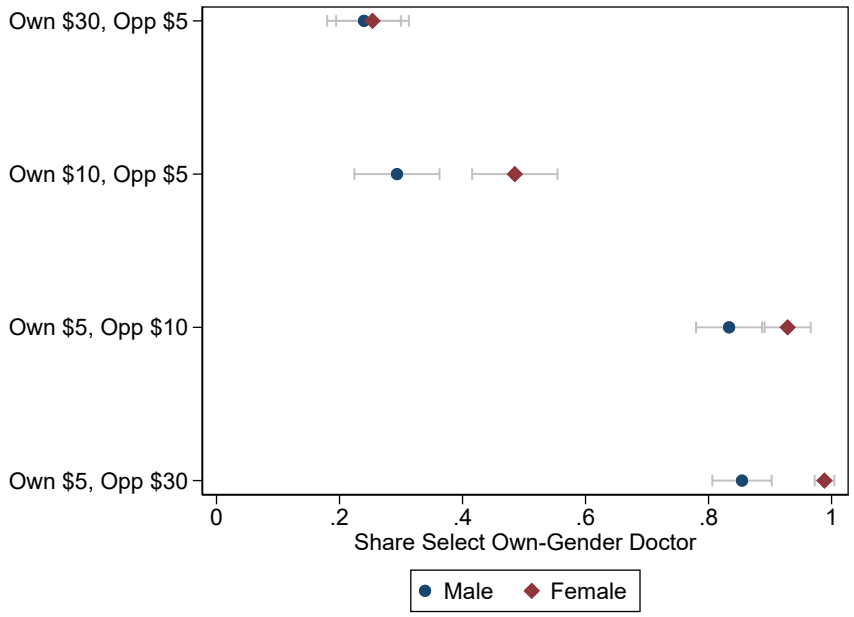
Notes: This figure displays the results from policy counterfactual analysis described in Section VI and Appendix Section D. This analysis combines the broader findings regarding the gender gap and relative gender homophily in workers' compensation more generally, with the estimated effects of gender match among claims with randomized evaluations. This analysis draws on Equation (1), which relates the gender gap (conditional on observable characteristics) to the share of doctors who are female and relative gender homophily in patient-doctor matches. For the purposes of this figure, the gender gap represents the percent reduction in the likelihood of cash benefits for female patients relative to male patients with the same observable characteristics. The point indicating the observed values in the status quo is indicated with an "x" in each panel, where the gender gap is 15.3% (i.e., females are 15.3% less likely to receive benefits than males with the same observables), the share of treating doctors who are female is 0.279, and the degree of relative gender homophily is 1.051 (i.e., female patients select female doctors at 1.051 times the rate that male patients select female doctors). Panel A displays the partial effects of varying the share of doctors who are female, holding relative gender homophily fixed. Panel B displays the partial effects of varying the degree of relative gender homophily, holding the share of doctors who are female fixed.

Figure A4: Counterfactual Policy Analysis: Effect of Share Doctors Female and Gender Homophily on Gender Gaps

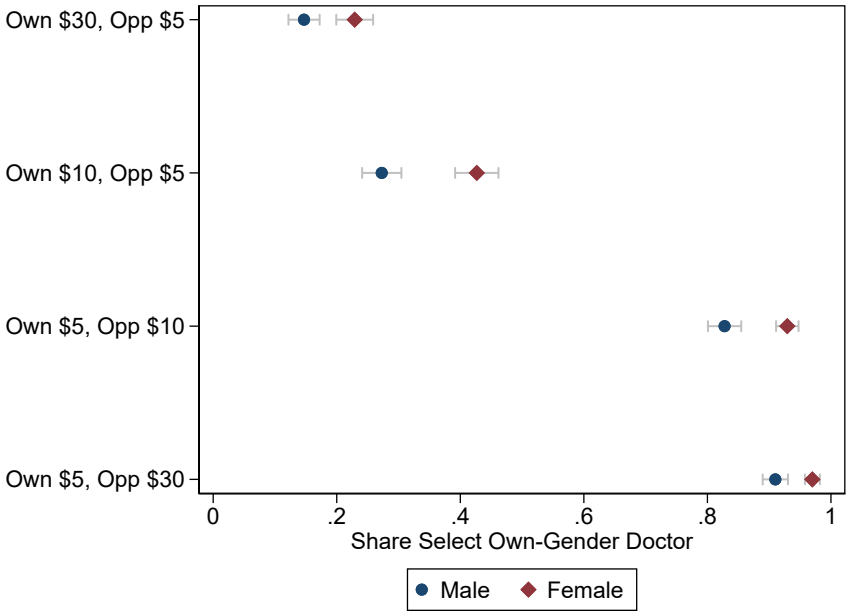


Notes: This figure displays the results from policy counterfactual analysis described in Section VI and Appendix Section D. This analysis combines the broader findings regarding the gender gap and relative gender homophily in workers' compensation more generally, with the estimated effects of gender match among claims with randomized evaluations. This figure shows the level curves of Equation (1), which relates the gender gap (conditional on observables) to the share of doctors who are female and relative gender homophily in patient-doctor matches. For the purposes of this figure, the gender gap represents the percent reduction in the likelihood of cash benefits for female patients relative to male patients with the same observable characteristics. The point indicating the observed values in the status quo is indicated with an "x", where the gender gap is 15.3% (i.e., females are 15.3% less likely to receive benefits than males with the same observables), the share of treating doctors who are female is 0.279, and the degree of relative gender homophily is 1.051 (i.e., female patients select female doctors at 1.051 times the rate that male patients select female doctors).

Figure A5: Additional Results from Survey: Share Selecting an Own-Gender Doctor in Hypothetical Choice Questions When Varying Co-Pay Differential



(a) Based on Initial Hypothetical Choice Question



(b) Based on Full Set of Hypothetical Choice Questions

Notes: The figure above shows the share selecting an own-gender doctor for each co-pay differential in hypothetical choice questions and the 95% confidence intervals by respondent gender. The survey was conducted by Qualtrics and included 1,519 adults ages 30 to 64. Eligibility was restricted to individuals who reported working at some point in the last 12 months and individuals who self-identified as either male (755 respondents) or female (764 respondents). See Section V for more detail on the survey. Table A10 reports raw and regression-adjusted differences in means for these survey questions and the associated p-values.