Online Appendix
Gender Homophily in Referral Networks: Consequences for the Medicare Physician Earnings Gap

By Dan Zeltzer*

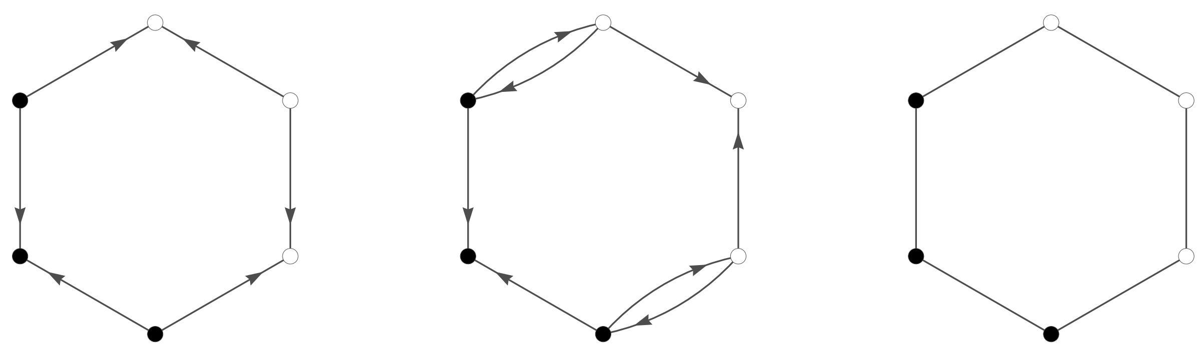
A. Mathematical Appendix

1. *Defining Relative Homophily with Weighted Links*

Relative homophily can be easily adapted to accommodate weighted links. First, define n_{gG} using weighted degrees, as follows: Let n_{jk} be the weight of the link from j to k (e.g. number of patients referred). The weighted out-degree of j is $d(j) = \sum_k n_{jk}$. The weighted out-degree to females is $d^F(j) = \sum_k \mathbb{1}_{g_k=F} n_{jk}$. Now n_{mF} is the average of d^F/d over all male j, and so on for n_{gG}. The rest of the definition is as previously indicated in Section III.A.

2. *The Importance of Link Direction in Defining Homophily*

Considering a directed network as if it is undirected is undesirable when studying homophily. Figure A1 illustrates the sensitivity of relative homophily to link direction.



(a) Relative Homophily

(b) No Relative Homophily

(c) Common Undirected Representation

Figure A1. Homophily and Link Direction

Notes: Because referrals are asymmetric, link direction is important for defining relative homophily: the network (a) exhibits relative homophily while (b) does not, a difference concealed in their undirected counterpart (c). More generally, this example speaks against treating asymmetric relationships as if they were symmetric when studying homophily.
Source: Author's calculations

Neglecting link directions may also give rise to spurious inbreeding homophily. Consider the directed network of referrals among $2N$ physicians, exactly half of which are doctors. Denote as

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before by m and M the fractions of male doctors and male specialists. Assume no gender bias: all doctors make the same average number of total referrals and send a fraction M of their referrals to male specialists. Suppose that we ignore directions, and consider the undirected version of this network. Formally, let the degree of each node in the undirected representation be the sum of out-degree and in-degree in the directed networks. In such case, although there is no gender bias in referrals, the undirected representation would exhibit inbreeding homophily, unless the gender mix of doctors and specialists happens to be equal. To see this, without loss of generality normalize the overall number of referrals (links) to one. Assuming referrals are gender-neutral, the gender composition of referrals is simply a function of the physician population gender shares (Table A1). In contrast to the directed version of the referral network (Case B), in the undirected version (Case A) there is no distinction between male-to-female and female-to-male referrals, of which there are in total $m(1-M)+(1-m)M$. Hence, in the undirected network there are only three possible gender compositions of physicians involved in a referral: both male, both female, and mixed gender. inbreeding homophily is zero when the fraction of ingroup referrals by men equals their population fraction. In this example, the population fraction of male physicians is $(m+M)/2$. Therefore, inbreeding homophily is zero when

$$\frac{mM}{mM+\frac{1}{2}(m(1-M)+(1-m)M)}=\frac{m+M}{2},$$

which holds if and only if $m=M$. In all other cases, inbreeding homophily is nonzero, despite the fact that, by construction, referrals are unbiased.

Table A1—Directed and Undirected Representations of Unbiased Referrals

Referral Gender Composition		
A. Undirected Network	B. Directed Network	Fraction of Referrals
both male	male to male	mM
mixed gender {	male to female	$m(1-M)$
	female to male	$(1-m)M$
both female	female to female	$(1-m)(1-M)$

Notes: m and M are the shares of doctors and specialists who are male.
Source: Author's calculations

3. *Interpreting The Common Tendency to Refer to Male Specialists as Bias*

The analysis in Section III.C maintained that the tendency common to both genders to refer more to males reflects unobserved heterogeneity in specialist characteristics that makes male specialists more *appropriate* referral targets. This section considers the other extreme interpretation, and considers all such common tendencies to refer to men as a bias in favor of men (and against women) that is common to both genders. Table A7 shows that under this assumption, at the current estimated gender-specific bias β and gender shares, the gender bias in referrals contributes 20.1 percentage points to the physician gender earnings gap.

Formally, Table A7 shows estimates obtained from rederiving (10) with a common term $e^{\delta \mathbb{1}_{g_k=m}}$, viz., including the estimated $\hat{\delta}=0.165$ in the bias. Linearly approximating the gap around $\beta \approx$

$0, \delta \approx 0$ provides some intuition about the first-order effect of a common bias δ:

$$Gap \approx \delta + (1 - (M - \frac{1}{2})2\delta)(m - \frac{1}{2})2\beta + O(\beta^2) + O(\delta^2).$$

With $M = 0.5$, (1) boils down to $\delta + \kappa$, where $\kappa = (m - \frac{1}{2})2\beta$ is the first-order gap as it appears in (10). With $M = 1$, it boils down to $\delta + (1 - \delta)\kappa$. Namely, for the estimated levels of bias, the first-order effect of a common bias is approximately an additive shift in demand toward male and away from female specialists. Table A7 does not rely on this approximation and shows the exact calculations, which include small nonlinear effects.

4. Proofs

Proof of Proposition 1.

PROOF:

First consider the homogeneous case: $\delta = 0$, and note that the conditional probabilities of referrals to a male specialist are:

$$P(M_m) = \frac{M}{M + \omega(1 - M)} \geq M \geq \frac{\omega M}{\omega M + (1 - M)} = P(M_f) \tag{1}$$

where $P(G_g) := P(g_k = G|g_j = g)$ denotes the probability that the chosen specialist's gender is G conditional on doctors' gender being g, and $\omega = e^{-\beta} \in (0, 1]$.

Where $P(M_m)$ and $P(M_f)$ are derived by summing up probabilities of referrals to all available specialists. E.g., for $g_j = m$:

$$\begin{aligned} P(M_m) &= \sum_{k:g_k=M} P(Y_{jk} = 1) = \frac{\sum_{k:g_k=M} e^{\beta \mathbb{1}_{g_j=g_k}}}{\sum_k e^{\beta \mathbb{1}_{g_j=g_k}}} \\ &= \frac{\sum_{k:g_k=M} e^{\beta}}{\sum_{k:g_k=M} e^{\beta} + \sum_{k:g_k\neq M} e^{0}} = \frac{Me^{\beta}}{Me^{\beta} + 1 - M}. \end{aligned}$$

For all $M \in (0, 1)$, biased preferences result in relative homophily, $P(M_m) > P(M_f)$: doctors of each gender slightly discount the other (by a factor ω).[1] Conversely, with unbiased preferences ($\beta = 0$), relative homophily is zero, as $P(M_m) = M = P(M_f)$.

Consider next the case: $\delta \neq 0$, where a correlation exists between gender and decision-relevant specialist characteristics (e.g., men may be more experienced or women may be available for fewer hours). In this case, (1) becomes:

$$P(M_m) = \frac{M}{M + \omega\eta(1 - M)} \geq \frac{\omega M}{\omega M + \eta(1 - M)} = P(M_f), \tag{2}$$

[1] Clearly, if specialists are mostly men then men refer more to men than to women: $P(M_m) > P(F_m)$, which is not to be confused with $P(M_m) > P(M_f)$.

which holds, because:

$$P(M_m) = \frac{\sum_{k:g_k=M} e^{\beta \mathbb{1}_{g_j=g_k}+\delta X_k}}{\sum_k e^{\beta \mathbb{1}_{g_j=g_k}+\delta X_k}} = \frac{\sum_{k:g_k=M} e^{\beta+\delta X_k}}{\sum_{k:g_k=M} e^{\beta+\delta X_k} + \sum_{k:g_k\neq M} e^{\delta X_k}}$$
$$\xrightarrow{P} \frac{M\eta_M e^{\beta}}{M\eta_M e^{\beta} + (1-M)\eta_F} = \frac{Me^{\beta}}{Me^{\beta} + \eta(1-M)}$$

where $\eta_G = \mathrm{E}[e^{\delta X_k}|g_k = G]$ for $G \in \{M, F\}$, and $\eta = \frac{\eta_F}{\eta_M}$ (so $\eta \gtreqless 1$ when $\mathrm{E}[e^{\delta X_k}|g_k = F] \gtreqless \mathrm{E}[e^{\delta X_k}|g_k = M]$. The convergence is by the Law of Large Numbers, assuming characteristics are independent across specialists.

Regardless of gender-biased preferences, if $\eta < 1$ male specialists attract a disproportionally high fraction of referrals from both genders (Figure 2). Conversely, if $\eta > 1$, female specialists attract more referrals, so whether $P(M_m)$ and $P(M_f)$ are each greater or smaller than M depends on η. In (2) too, $P(M_m) = P(M_f)$ if and only if preferences are unbiased, i.e., $\beta = 0$. So, Proposition 1 also holds for the heterogeneous case.

PROPOSITION A1 (Nonidentificiation of gender-specific gender bias): *Consider the model:*

$$\underset{k\in K}{\operatorname{argmax}} U_j(k) = \beta_f \mathbb{1}_{g_j=f,g_k=F} + \beta_m \mathbb{1}_{g_j=m,g_k=M} + \delta X_{jk} + \varepsilon_{jk} \tag{3}$$

where β_f, β_m are gender-specific same-gender preferences and ε_{jk} is as before independently and GEV distributed. Then β_f, β_m and let the common tendency to refer to men, η' (defined as η before), are not separately identified.

For example, the case when $\eta = 0.2$ and $\beta_f = \beta_m = 0.1$ (namely, male specialists have a 20 percent higher baseline probability of being chosen by both genders. In addition, doctors choose specialists of their own gender with a 10 percent higher probability) is observationally equivalent to $\eta = 0.15, \beta_f = 0.05, \beta_m = 0.15$ (male specialists have a 15 percent higher baseline, and female doctors are less likely than male doctors to choose same-gender specialists—5 percent versus 15 percent).

Proof of Proposition A1.

PROOF:

Under model (3), the probabilities of referrals to a male, conditional on the doctor gender are:

$$P(M_m) = \frac{M}{M + e^{-\beta_m}\eta'(1-M)} \geq \frac{e^{-\beta_f}M}{e^{-\beta_f}M + \eta'(1-M)} = P(M_f).$$

Exactly the same probabilities (4) can be obtained by the following reparameterization: $\beta = \frac{1}{2}(\beta_f + \beta_m)$ and $\eta = e^{\beta-\beta_f}\eta' = e^{\beta_m-\beta}\eta'$. Namely, we can only identify the average of the same-gender bias across men and women, not the gender specific bias, as any bias that is common to both genders is observationally equivalent to an unobserved difference between male and female specialists.

Before considering the proof of Proposition 2, some intuition for why sorting generates homophily can be gained by considering the case of no bias.

CLAIM 1 (Sorting-Based Homophily): *Assume zero bias. With sorting, referrals exhibit homophily when pooled across all markets:*

$$P(M_m) > M > P(M_f)$$

for all $\beta \geq 0$.

PROOF:

The overall conditional probability is a weighted average of market-specific conditional probabilities (weights are proportional to both market size and the relative share of male doctors in each market). Using Bayes' rule:

$$\begin{aligned} P(M_m) &= \sum_{c\in C} P(c|m)P(M|m,c) = \sum_{c\in C} \mu^c \frac{m^c}{m} P(M|m,c) \\ &\geq \sum_{c\in C} \mu^c \frac{m^c}{m} M^c = \frac{1}{m} E[m^c M^c] \\ &> \frac{1}{m} E[m^c]\mathrm{E}[M^c] = M. \end{aligned}$$

The first inequality is due to preferences: $P(M|m,c) \geq M^c$ (equality being the case $\omega = 1$), and the second is due to segregation. By symmetry, the same proof works for females.

Note that the definition of sorting extends to the more general case where K_j is specific to each doctor as: $\mathrm{Cov}(m^j, M^{K_j}) > 0$, where $m^j = \mathbb{1}_{g_j=m}$ and M^{K_j} is the fraction of males in K_j. (This definition is indeed more general, as by covariance decomposition, $\mathrm{Cov}[m_j, M^j] = \mathrm{Cov}[m^c, M^c]$ under separate markets with common $K_j = K^c$ in each.) For this more general definition of sorting, the proof follows immediately from Proposition 1: with unbiased preferences $P(M_m) = E[M^j|g_j = m] > M$, by $\mathrm{Cov}[m_j, M^j] > 0$.

Now, for the proof of Proposition 2.

PROOF:

$$\begin{aligned} P(M_m) - M &= \sum_{c\in C} \mu^c \left(\frac{m^c}{m} P(M|m,c) - \frac{m^c}{m} M^c + \frac{m^c}{m} M^c - M^c\right) \\ &= \sum_{c\in C} \mu^c \left(\frac{m^c}{m}(P(M|m,c) - M^c) + M^c\left(\frac{m^c}{m} - 1\right)\right) \\ &= \mathrm{E}\left[\frac{m^c}{m}(P(M|m,c) - M^c)\right] + \mathrm{Cov}\left[\frac{m^c}{m}, M^c\right]. \end{aligned}$$

Where μ^c denotes market size.

Note that this proof only uses Bayes' rule to relate aggregate and market-specific referral probabilities and does not rely on a specific parameterization of these probabilities: it only requires relevant moments to exist.

Proposition A2 restates Proposition 2 using relative homophily.

PROPOSITION A2 (Relative Homophily Decomposition): *The overall relative homophily decomposes as follows:*

$$P(M_m) - P(M_f) = \mathrm{E}\left[\frac{m^c}{m} P(M|m,c) - \frac{1-m^c}{1-m} P(M|f,c)\right] + \frac{1}{m(1-m)} \mathrm{Cov}[m^c, M^c]$$

PROOF:

Applying the proof of Proposition 2 to females (by symmetry) and substituting $P(M_f) = 1 - P(F_f)$ yields :

$$M - P(M_f) = \mathrm{E}\left[\frac{1-m^c}{1-m}(M^c - P(M|f,c))\right] + \mathrm{Cov}\left[\frac{m^c}{1-m}, M^c\right]$$

Hence

$$P(M_m) - P(M_f) = \mathrm{E}[\frac{m^c}{m}(P(M|m,c) - M^c) + \frac{1-m^c}{1-m}(M^c - P(M|f,c))] + \frac{1}{m(1-m)}\mathrm{Cov}[m^c, M^c]$$

Proof of Proposition 3.
PROOF:

Pick any male specialist k. The demand k faces in market c is obtained by aggregating over all doctors in that market (as all variables are market specific, I suppress the superscript c):

$$\begin{aligned} D_M &= \sum_{j\in J} p_{jk} = \sum_{j\in J} \frac{e^{\beta s(j,k)}}{\sum_{k'\in K} e^{\beta s(j,k')}} \\ &= \sum_{j\in J, g_j=1} \frac{e^{\beta s(j,k)}}{\sum_{k'\in K} e^{\beta s(j,k')}} + \sum_{j\in J, g_j=0} \frac{e^{\beta s(j,k)}}{\sum_{k'\in K} e^{\beta s(j,k')}} \\ &= \frac{1}{N}(\sum_{j\in J, g_j=1} \frac{1}{M+\omega(1-M)} + \sum_{j\in J, g_j=0} \frac{\omega}{\omega M + (1-M)}) \\ &= \frac{n}{N}(\frac{m}{M+\omega(1-M)} + \frac{\omega(1-m)}{\omega M + (1-M)}). \end{aligned}$$

Where $n = |J|$ and $N = |K|$. When $\omega = 1$ then $D_M = \frac{n}{N}$, which is independent of both M and m. Suppose $\omega < 1$. To see that ii(a) is true, rewrite:

$$\begin{aligned} D_M &= \frac{n}{NM}\big(mP(M_m) + (1-m)P(M_f)\big) \\ &= \frac{n}{NM}\big(P(M_f) + m(P(M_m) - P(M_f))\big) \end{aligned}$$

and note that $\partial D_M/\partial m > 0$ since $P(M_m) - P(M_f) > 0$ for every $\beta > 0$. To see that ii(b) is true take the derivative of D_M with respect to M:

$$\frac{\partial D_M}{\partial M} = \frac{n(1-w)}{N}\Big(\underbrace{\frac{(1-m)w}{(1-M(1-w))^2}}_{\text{Complements}} - \underbrace{\frac{m}{(M+w(1-M))^2}}_{\text{Substitutes}}\Big).$$

The denominators of the terms labeled "Complements" and "Substitutes" are both positive. Therefore, for m near enough zero, Complements dominates and the derivative $\partial D_M/\partial M$ is positive, whereas for m near enough one Substitutes dominates and the derivative is negative. For intermediate values of m, the sign of the derivative may depend on M.

B. Additional Tables and Figure

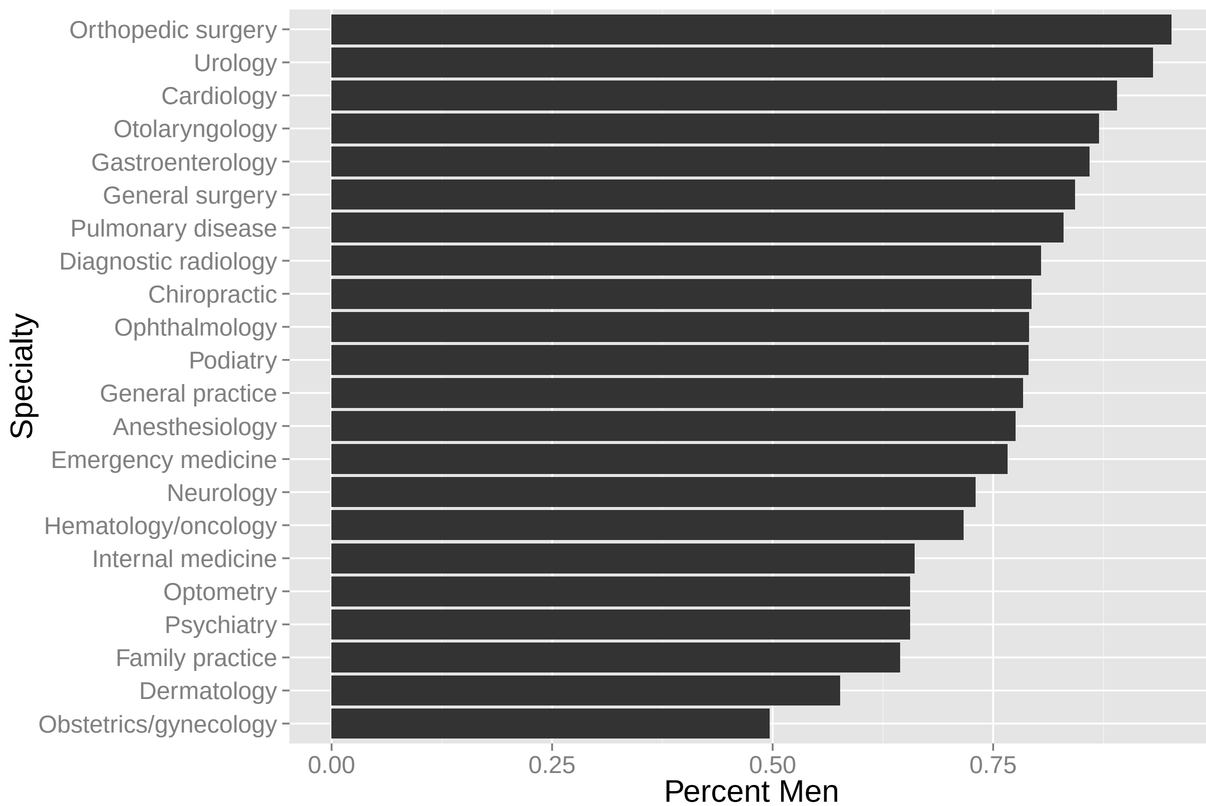


Figure A2. Male Fraction of Physicians in Common Medical Specialties

Notes: Percent of active physicians (with any claims) who are male in 2012, for the most common specialties by overall number of physicians. Columns are sorted so specialties with the greatest male shares are at the top.
Source: CMS, author's calculations

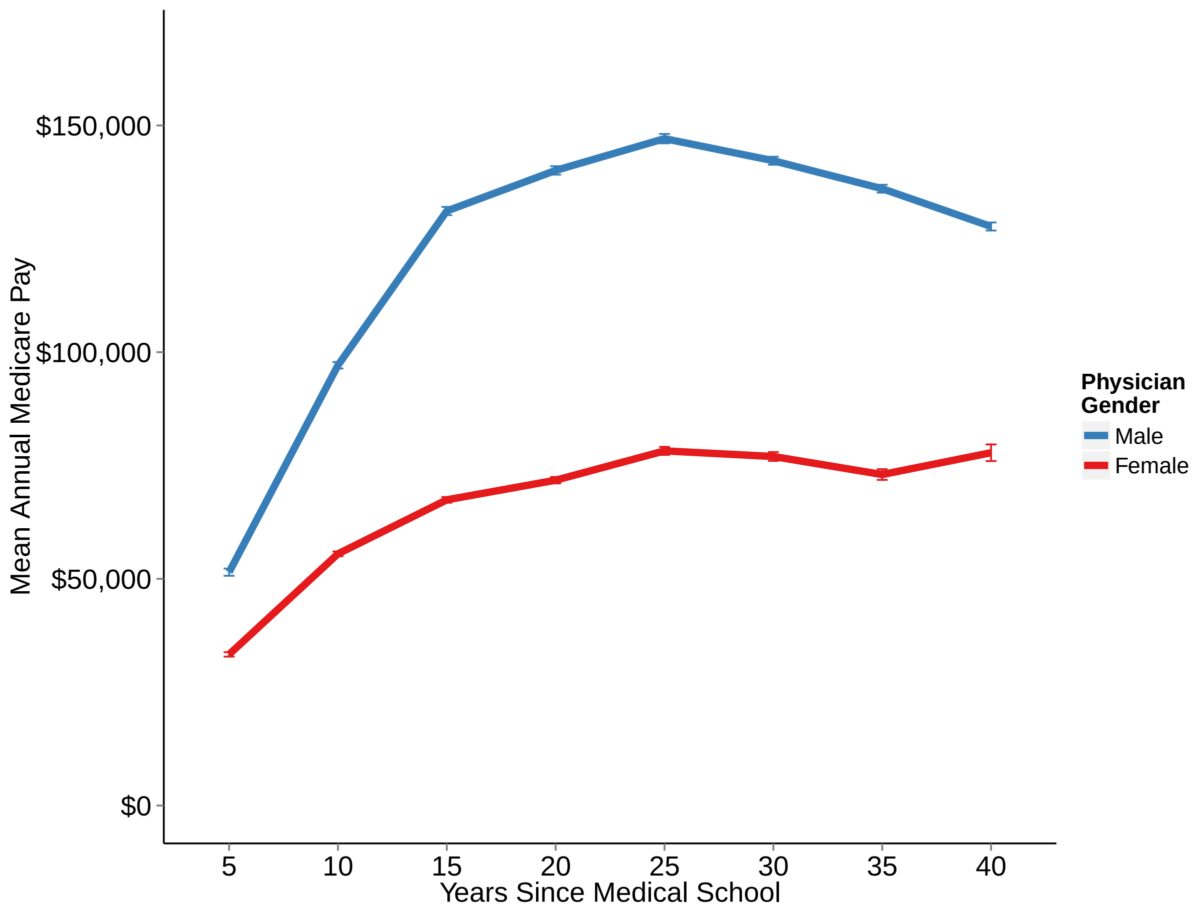


Figure A3. The Unadjusted Gender Pay Gap, by Experience Level

Notes: Source: 20 percent sample of Medicare physician claims for 2012. Mean Annual Medicare Pay is total annual payments (by all payers) to physicians for Medicare services, multiplied by 5 to adjust for sampling. Years are since medical school graduation (bin labels are the range maximum, e.g. 10 stands for 6–10).
Source: CMS, author's calculations

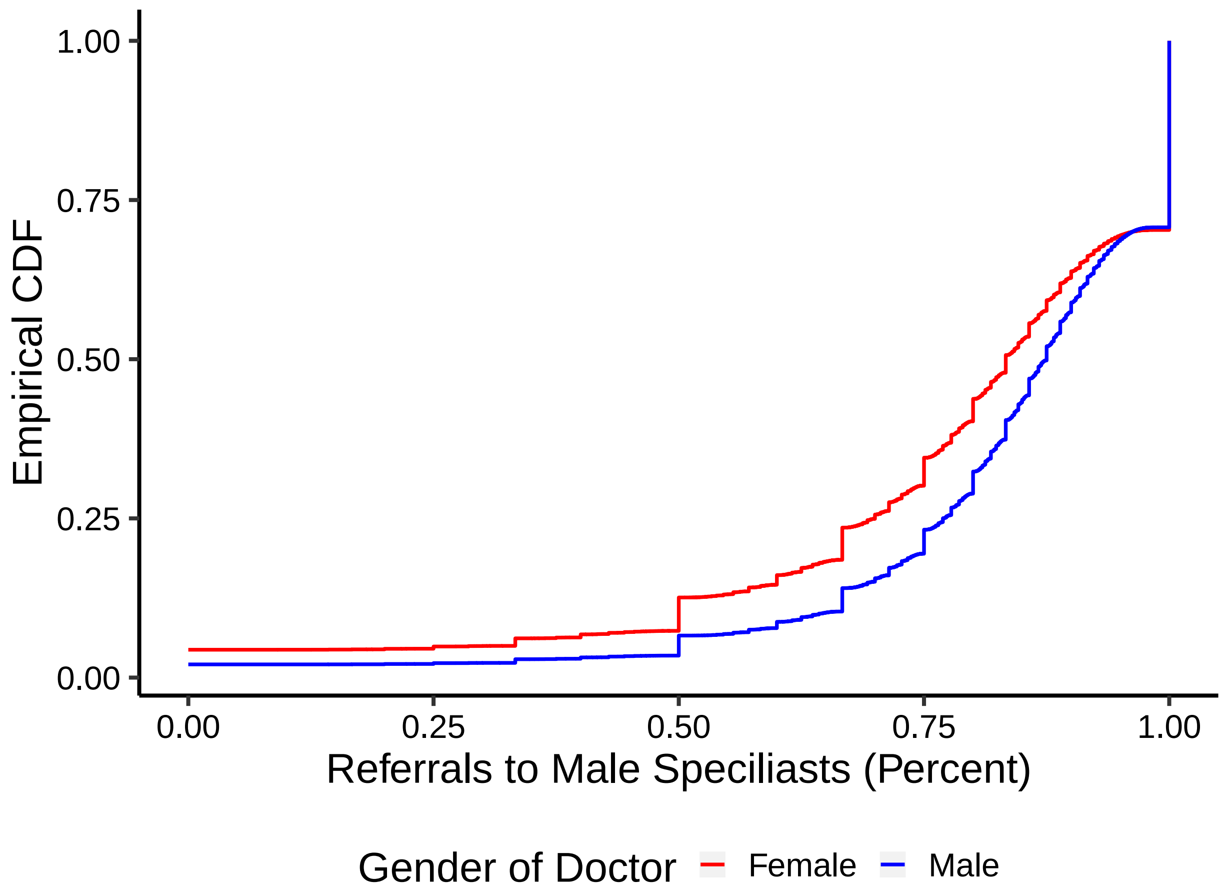
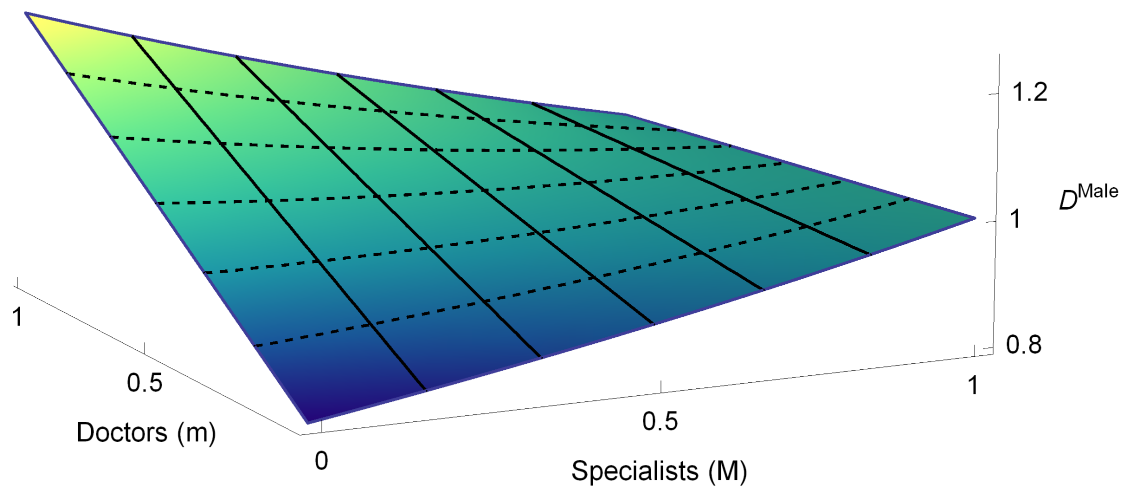
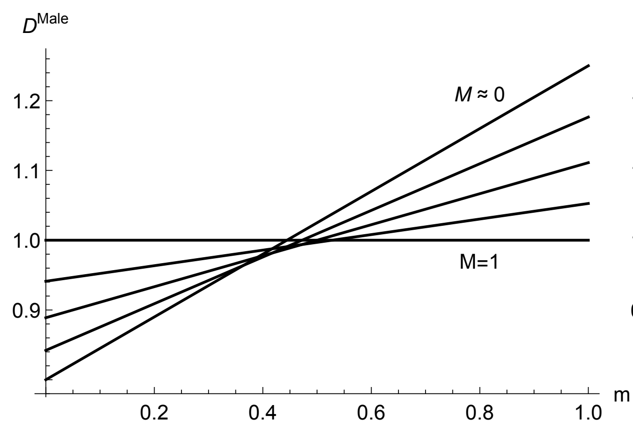


FIGURE A4. THE DISTRIBUTION OF RATES OF REFERRAL TO MALE SPECIALISTS

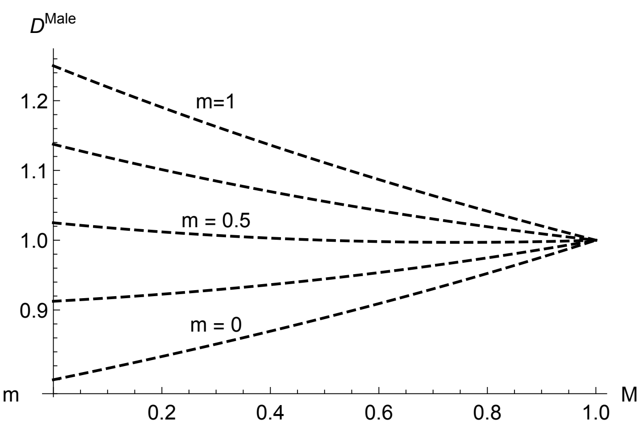
Notes: Empirical cumulative distribution function of M_j, the fraction of doctor j referrals that are made to male specialists.
Source: CMS, author's calculations



(a) Demand for male specialists over the shares of male doctors and male specialists



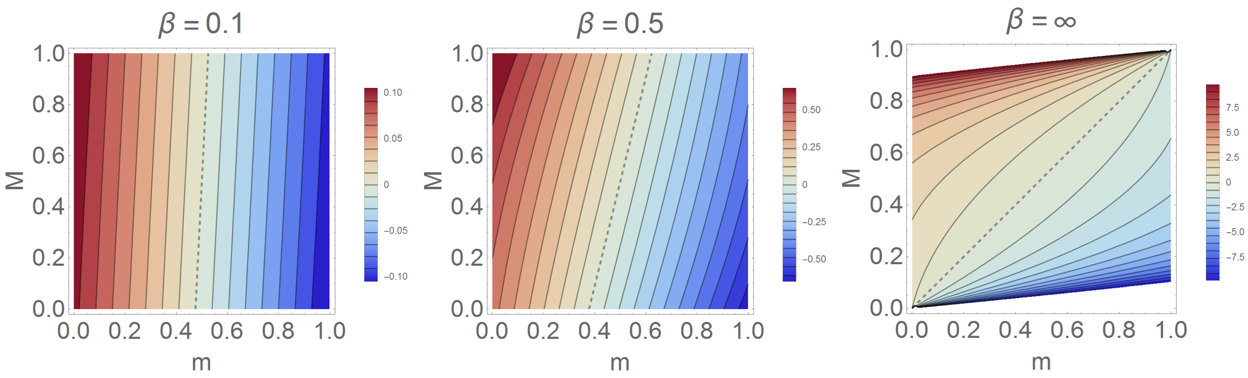
(b) Demand and the share of male doctors, m



(c) Demand and the share of male specialists, M

Figure A5. Average Specialist Demand with Gender-Biased Preferences

Notes: Average male specialist demand as a function of the fractions of male doctors and male specialists, with gender-biased preferences, i.e. $\beta > 0$ (calculated from the model with $\omega = 0.8, \eta = 1$). The surface in Panel (a) depicts the average demand D^{M}, a function of the fractions of both male doctors, m, and male specialists, M. Panel (b) shows different cross sections of D^{M} for different levels of M. Panel (c) shows different cross sections D^{M} for different levels of m. Demand for male specialists is increasing in the share of doctors who are male. Male specialists are complements when only few doctors are men and become stronger substitutes the greater the share of doctors who are are male.
Source: Author's calculations



(a) (b) (c)

Figure A6. Counterfactual Gender Earnings Gap with Different Levels of Bias

Notes: Colored contour plots of the gender earnings gap, $D^F - D^M$, for different fractions of males upstream m and downstream M, each for a different level of bias β. Blue (right) and red (left) darker shades reflect greater demand for male and female specialists, respectively. The zero-gap contours are dashed. For (a) the estimated level of bias for U.S. physicians ($\beta = \hat{\beta} = 0.10$), and even for (b) much higher levels of bias ($\beta = 0.50$), the sign and size of the gender earnings gap mostly depend on the fraction of males upstream. In contrast, for (c) extreme bias ($\beta = \infty$), a bias that reflects lexicographic preferences, the gap depends on the relative fractions of male doctors and male specialists.
Source: Author's calculations

Table A2—Homophily Estimates with Weighted Links

	Dependent variable:			
	Percent Referrals to Male Specialists, by:			
	Links	Patients	Claims	Dollars
	(1)	(2)	(3)	(4)
Male Doctor	0.038	0.040	0.040	0.040
	(0.001)	(0.001)	(0.001)	(0.001)
Percent Male Patients	0.029	0.029	0.029	0.029
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.80	0.80	0.80	0.81
	(0.003)	(0.003)	(0.003)	(0.003)
Specialty (Doctor)	Yes	Yes	Yes	Yes
Experience (Doctor)	Yes	Yes	Yes	Yes
Obs. (Doctors)	384,985	384,985	384,985	383,054
R^2	0.0384	0.0394	0.0360	0.0368

Notes: Standard errors in parentheses. OLS estimates of (5) using different definitions of link weights. The first column shows results for unweighted links. Columns 2–4 show results for different weights: number of patients, number of claims, and dollar value of services.
Source: CMS, author's calculations

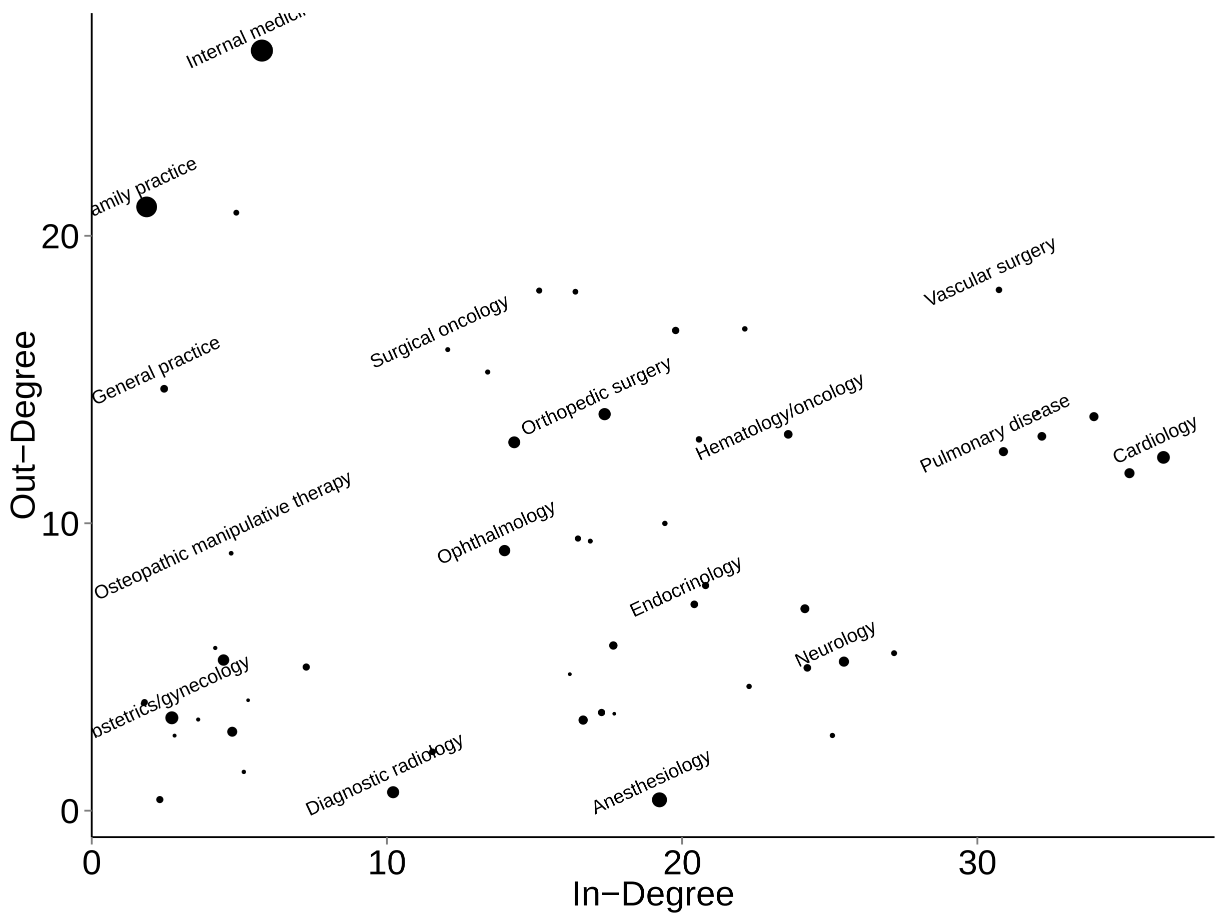


Figure A7. Average Number of Referral Relationships by Medical Specialty

Notes: Degree-heterogeneity is to be expected because doctors in different specialties play different roles in routing patients: some mostly diagnose and refer out, others mostly receive referrals and treat. The figure shows degree distribution by specialty for 2012 referrals: Out-degree is the average number of physicians to whom a physician referred patients during the year. In-degree is the average number of physicians from whom a physician received referrals. Physicians with neither incoming nor outgoing referrals during the year were excluded. Point diameter is proportional to the square root of the number of practitioners in a specialty. Common specialties are labeled. See Table A9 for the data used to generate this figure.
Source: CMS, author's calculations

Table A3—Estimates of Relative Homophily Using Disaggregated Data

	Dependent Variable: Male Specialist				
	(1)	(2)	(3)	(4)	(5)
Male Doctor	0.045***	0.039***	0.038***	0.035***	0.042***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Male Patient				0.021***	0.037***
				(0.0003)	(0.0006)
Male Doctor x Male Patient					-0.019***
					(0.0007)
Specialty (both)	No	Yes	Yes	Yes	Yes
Experience (both)	No	No	Yes	Yes	Yes
Obs. (Triples)	10,545,049	10,545,049	10,127,806	10,127,806	10,127,806
Clusters (Doctors)	385,104	385,104	382,924	382,924	382,924
R Sqr.	0.00242	0.0689	0.0989	0.0997	0.0998

Notes: Standard errors in parentheses. Estimates of relative homophily using one observation for each unique triple of a doctor, a specialist and a referred patient. The sample consists of all such triples for 2012, for a sample of 20 percent of Medicare patients. Standard errors are clustered by doctor.
Source: CMS, author's calculations

Table A4—Residualized Referral Rates to Male Specialists, by Gender of Doctor and Patient

Mean Residual (Male Specialist)	Patient Gender			
Doctor Gender	Female	Male	All	Difference (M–F)
Female	−0.0705	0.0205	−0.0397	0.0910
Male	0.0329	0.0949	0.0623	0.0620
All	0.0078	0.0835	0.0416	0.0757
Difference (M–F)	0.1034	0.0744	0.1021	

Notes: Average Pearson residuals of logistic regression of a dummy for the specialist being male on doctor and specialist experience and medical specialty. Each cell shows the mean residual among doctors and patients of a given gender. For convenience, the differences between male and female averages are shown in the margins. The sample includes 10,127,806 patient-doctor-specialist triples in 2012.
Source: CMS, author's calculations

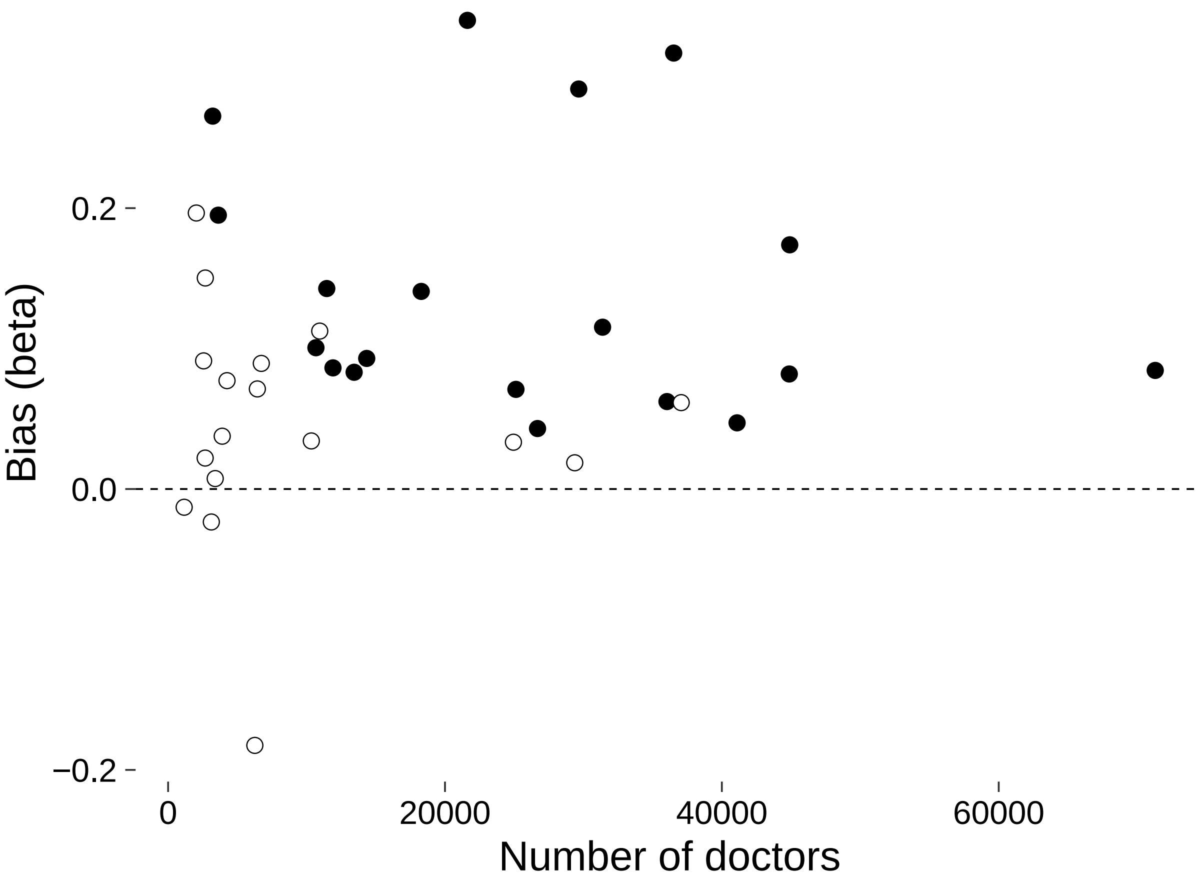


Figure A8. Conditional-Logit Estimates of Gender Bias, by Specialty

Notes: Estimates of β, the gender bias, from equation (3) with the sample in Table A5, separately for each medical specialty of the receiving physician. Black circles denote estimates that are significantly different from zero ($p < 0.05$).
Source: CMS, author's calculations

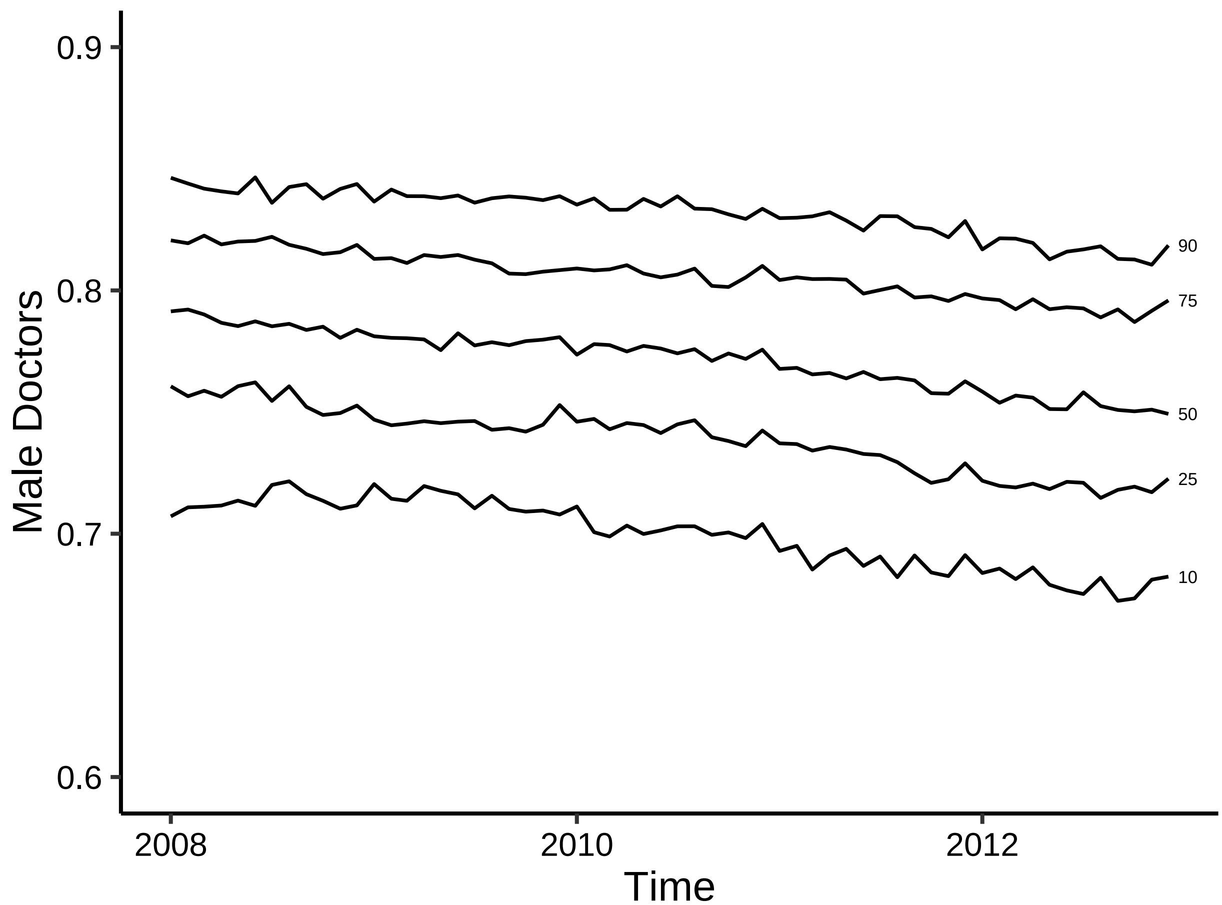


Figure A9. The Fraction of Primary Care Claims Handled by Male Doctors

Notes: Line plots show the 10th, 25th, 50th, 75th and 90th quantiles of the fraction of primary care claims handled by male doctors in each month, calculated across all hospital referral regiosns (HRR). The underlying data are used in the estimation of (13)
Source: CMS, author's calculations

Table A5—Average Characteristics of Chosen versus Unchosen Specialists

	Doctor Referred to Specialist	
Doctor and Specialist:	Yes	No
Same Gender	0.712	0.678
Same Zip Code	0.280	0.0824
Same Hospital	0.778	0.298
Same Group	0.191	0.052
Same Med. School*	0.107	0.0817
Experience Difference (years)	11.25	12.16
Observations (Dyads)	5,632,166	9,635,750
	2,852,950*	4,685,218*
Clusters (Doctors)	375,440	
	242,579*	

Notes: The table describes the sample used for estimating preference bias (as discussed in Sections III.A and IV.B). It shows average characteristics of doctor-specialist pairs. The left, "Yes" column shows data for all specialists chosen by each doctor. For each chosen specialist, the right, "No" column shows data for two randomly sampled specialists not chosen for referrals from the same market (HRR) and medical specialty as the chosen specialist. $*$ denotes the subsample with nonmissing school data. All differences are significant ($p < 0.001$).
Source: CMS, author's calculations

TABLE A6—CONDITIONAL-LOGIT ESTIMATES: REFERRAL PROBABILITY, WITH INTERACTION TERMS

	Dependent variable: Doctor Referred to Specialist			
Doctor and Specialist:	(1)	(2)	(3)	(4)
Same Gender	0.084	0.066	0.104	0.076
	(0.002)	(0.004)	(0.004)	(0.006)
Male Specialist	0.175	0.175	0.165	0.164
	(0.002)	(0.002)	(0.004)	(0.004)
Same Hospital	3.114	3.072	2.941	2.887
	(0.004)	(0.005)	(0.005)	(0.007)
Same Hospital x Same Gender		0.0598		0.0770
		(0.004)		(0.006)
Same Group	1.346	1.372	1.320	1.344
	(0.008)	(0.009)	(0.010)	(0.010)
Same Group x Same Gender		-0.039		-0.035
		(0.007)		(0.010)
Same Zip Code	1.074	1.065	1.054	1.047
	(0.005)	(0.007)	(0.006)	(0.009)
Same Zip Code x Same Gender		0.013		0.010
		(0.006)		(0.009)
Similar Experience	0.128	0.120	0.131	0.123
	(0.001)	(0.002)	(0.001)	(0.002)
Similar Experience x Same Gender		0.012		0.011
		(0.002)		(0.003)
Same Med. School			0.209	0.206
			(0.004)	(0.007)
Same Med. School x Same Gender				0.004
				(0.008)
Specialist Experience	Yes	Yes	Yes	Yes
Obs. (Dyads)	14,555,821	14,555,821	6,712,241	6,712,241
Clusters (Doctors)	367,370	367,370	242,579	242,579
Pseudo R Square	0.361	0.361	0.347	0.347

Notes: Standard errors in parentheses. Results of conditional logit estimates of (3) for 2012, including interaction terms (denoted by ×). See Table 5 notes for variable definitions and details.
Source: CMS, author's calculations

TABLE A7—COUNTERFACTUAL EARNINGS GAPS, COUNTING AS BIAS THE COMMON TENDENCY TO REFER TO MEN

A. Varying m and M ($\beta = 0.1$)

	Male Specialists (M)						
Male Doctors (m)	0.4	0.5	0.6	0.7	0.75	0.8	0.9
0.4	14.7	14.4	14.1	13.9	13.7	13.6	13.3
0.5	16.8	16.4	16.1	15.7	15.6	15.4	15.1
0.6	18.9	18.4	18.0	17.6	17.4	17.2	16.8
0.7	20.9	20.4	19.9	19.4	19.2	19.0	18.6
0.75	21.9	21.4	20.9	20.4	20.1	19.9	19.5
0.8	23.0	22.4	21.8	21.3	21.1	20.8	20.3
0.9	25.0	24.4	23.7	23.2	22.9	22.6	22.1

B. Varying β and m ($M = 0.75$)

	Male Doctors (m)						
Gender Bias (β)	0.4	0.5	0.6	0.7	0.75	0.8	0.9
-0.05	16.7	15.7	14.8	13.9	13.5	13.0	12.1
0	15.8	15.8	15.8	15.8	15.8	15.8	15.8
0.05	14.8	15.7	16.7	17.6	18.0	18.5	19.4
0.1	13.7	15.6	17.4	19.2	20.1	21.1	22.9
0.15	12.5	15.2	18.0	20.7	22.1	23.5	26.2
0.2	11.1	14.8	18.5	22.1	24.0	25.8	29.4
0.25	9.6	14.2	18.8	23.4	25.7	28.0	32.5

C. Varying β and M ($m = 0.75$)

	Male Specialists (M)						
Gender Bias (β)	0.4	0.5	0.6	0.7	0.75	0.8	0.9
-0.05	14.2	14.0	13.8	13.6	13.5	13.4	13.2
0	16.7	16.5	16.2	15.9	15.8	15.7	15.4
0.05	19.3	18.9	18.6	18.2	18.0	17.9	17.5
0.1	21.9	21.4	20.9	20.4	20.1	19.9	19.5
0.15	24.6	23.8	23.1	22.4	22.1	21.8	21.2
0.2	27.2	26.2	25.3	24.4	24.0	23.5	22.8
0.25	29.9	28.6	27.3	26.2	25.7	25.2	24.2

Notes: A variant of Table 6 that includes the estimated tendency common to both male and female doctors to refer to male specialists as bias. That is, in addition to same-gender bias, estimated common bias of 0.165 (from the most saturated model in Table 5) is also included, which further shifts demand toward male and away from female specialists.
Source: Author's calculations

Table A8—Estimates: Link Persistence

	Dependent variable: Any Referrals Next Year			
	Logit	OLS (with Fixed-Effects)		
	(1)	(2)	(3)	(4)
Same Gender	0.044	0.014		
	(0.003)	(0.001)		
Male Doctor	0.069			
	(0.004)			
Male Specialist	0.157		0.029	0.006
	(0.003)		(0.001)	(0.001)
Similar Experience	0.005	0.001	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Same Hospital	0.118	0.027	0.030	0.027
	(0.004)	(0.001)	(0.001)	(0.002)
Same Zipcode	0.159	0.097	0.092	0.076
	(0.003)	(0.001)	(0.001)	(0.001)
Same School	0.088	0.013	0.015	0.014
	(0.003)	(0.001)	(0.001)	(0.002)
Constant	-0.814			
	(0.004)			
Specialty (Specialist)	No	No	Yes	Yes
Obs. (j,k)	7,255,778	7,204,471	5,734,596	1496658
Rank	8	5	58	58
R^2		0.20	0.10	0.11
N. Cluster	280,750	255,507	191,647	64,579
FE1 (Doctors)		255,507	191,647	64,579
FE2 (Specialists)		237,363		

Notes: Standard errors in parentheses. Estimates of the persistence of referral relationships using data from 2008–2012. The sample consists of an observation for each doctor-specialist pair, for the first year a referral is observed in the data. The dependent binary variable is 1 if the doctor also referred to the specialist during the subsequent year. Same gender is a dummy for the specialist and doctor being the same gender. Male specialist/doctor is a dummy for the specialist/doctor being male. Similar Experience is the negative absolute difference in physicians' year of graduation. Column (1) shows estimates of the logit model specified in equation (11). Column (2) shows linear probability model with two-way fixed effects (for doctor and for specialist) in equation (12). Columns (3) and (4) show linear estimates with doctor fixed-effects only, estimated separately for female (3) and male (4) doctors. Sample size is restricted by the availability of medical school data. Results excluding school affiliation are very similar. All standard errors are clustered by doctor.
Source: CMS, author's calculations

Table A9—2012 Average Degree by Specialty

	Specialty	In-Degree	Out-Degree	Physicians
1	Internal medicine	5.8	26.4	86,220
2	Family practice	1.9	21.0	74,638
3	Anesthesiology	19.2	0.4	33,434
4	Obstetrics/gynecology	2.7	3.2	22,871
5	Cardiology	36.3	12.3	21,714
6	Orthopedic surgery	17.4	13.8	19,411
7	Diagnostic radiology	10.2	0.6	18,768
8	General surgery	14.3	12.8	18,011
9	Emergency medicine	4.5	5.2	16,065
10	Ophthalmology	14.0	9.1	15,702
11	Neurology	25.5	5.2	11,469
12	Gastroenterology	35.2	11.7	11,178
13	Psychiatry	4.8	2.7	10,861
14	Dermatology	16.6	3.1	8,624
15	Pulmonary disease	30.9	12.5	8,272
16	Urology	33.9	13.7	8,234
17	Otolaryngology	24.2	7.0	7,666
18	Nephrology	32.2	13.0	7,105
19	Hematology/oncology	23.6	13.1	7,019
20	Physical medicine and rehabilitation	17.7	5.7	6,224
21	General practice	2.5	14.7	4,853
22	Endocrinology	20.4	7.2	4,534
23	Infectious disease	24.2	5.0	4,492
24	Neurosurgery	19.8	16.7	4,010
25	Radiation oncology	17.3	3.4	3,933
26	Rheumatology	20.8	7.8	3,765
27	Plastic and reconstructive surgery	7.3	5.0	3,759
28	Pathology	2.3	0.4	3,627
29	Allergy/immunology	11.5	2.0	2,768
30	Pediatric medicine	1.8	3.8	2,695
31	Medical oncology	20.6	12.9	2,507
32	Vascular surgery	30.7	18.1	2,486
33	Critical care	16.5	9.5	2,046
34	Thoracic surgery	15.2	18.1	1,886
35	Interventional pain management	27.2	5.5	1,655
36	Geriatric medicine	4.9	20.8	1,597
37	Cardiac surgery	16.4	18.0	1,526
38	Colorectal surgery	22.1	16.8	1,161
39	Pain Management	22.3	4.3	1,055
40	Hand surgery	19.4	10.0	1,047

Notes: A link represents referral relationships with another physician from any specialty; specialties with less than 1,000 doctors are included but not shown due to space constraints.
Source: CMS, author's calculations