Gender Homophily in Referral Networks: Consequences for the Medicare Physician Pay Gap

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Abstract

This paper documents a new demand-side channel for the gender gap in earnings: a preference for working with others of the same gender. Analyzing administrative data on 100 million Medicare patient referrals, I document significant gender homophily among U.S. physicians—doctors refer more to specialists of their same gender. Homophily is predominantly due to physicians' gender biased preferences, not sorting. As most referrals are still made by men, biased referrals lower demand for female relative to male specialists, significantly contributing to the average earnings gap among physician specialists. In medicine, results imply that increased participation of female physicians generates positive externalities for females in related specialties. More generally, my findings suggest that homophily contributes to the persistence of gender inequality in context where networking is important.

Keywords: gender inequality, homophily, referrals, networks, physician markets

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1 Introduction

Why women are still underrepresented in top career position and earn less than their male counterparts remains unclear. Existing work documents several contributing channels that are rooted in differences between male and female workers such as in time devoted to childrearing, in education, in performance, or in preferences. But except for a handful of studies, researchers have been generally unable to address the concern that women are also treated differently.[1] Proving differential treatment is difficult. Most studies infer it only indirectly, when observed differences between the genders fail to fully account for differences in outcomes.[2]

In this paper, I study a demand-side channel that contributes to gender disparity: a preference for working with others of the same gender. Such gender-biased preference leads to professional networks that exhibit *gender homophily*: disproportionately more same-gender connections. When connections are important for outcomes, homophily is disadvantageous to the minority. I demonstrate this channel empirically by analyzing data on 100 million patient referrals among half a million physicians from Medicare. Medicare payments to physicians exhibit a large gender disparity. Since reimbursement rates are fixed, earnings gaps are not due to differences in compensation. Like in other high skilled occupations, this gap mostly reflects gender differences in workload.[3] However, unlike in other settings, referrals and payments are jointly observed, clearly revealing how gender biased professional connections translate into gender disparity in earnings.

The main contribution of this paper is documenting the contribution of homophily to earnings disparity in an important setting where connections and earnings are directly and observably related. I define a new homophily measure that is robust to unobserved heterogeneity in the propensity to refer or to receive referrals. I show, for the first time, that a substantial part of the persistent gap in earnings of female relative to male physicians is due to gender homophily in referrals. I argue that these results cannot be explained by differences between the genders and, instead, are consistent with gender-biased referrals putting women—who are still the minority of active physicians—in disadvantage relative to otherwise similar men. These results suggest that homophily may contribute to the persistence of earning inequality in many other domains where networking is important for outcomes.

[1] Exceptions include Neumark et al. (1996), Goldin and Rouse (2000), and Bertrand and Mullainathan (2004), and more recently Kuhn and Shen (2013). For a review of the strengths and limitations of audits and for recent lab experiments, see Azmat and Petrongolo (2014).

[2] For surveys of recent advances see Croson and Gneezy (2009); Bertrand (2011).

[3] The gender gap for physicians has been documented by Weeks et al. (2009); Lo Sasso et al. (2011); Esteves-Sorenson et al. (2012); Seabury et al. (2013). Bertrand et al. (2010) show large gender workload gaps exist for MBA graduates, and Azmat and Ferrer (2016) show they exist for lawyers.

The main identification challenge is to separate gender-biased preferences from other differences between the genders that could lead men to work more or attract more referrals than women, such as differences in labor supply or experience.[4] Data on referrals allow me to do so, as I can match the gender of the referring doctor and the receiving specialist. I am therefore able to test whether doctors refer to specialists of their same gender disproportionally. In particular, I show that if higher referral rates to male specialists were fully explained by gender differences, then, all else equal, referral decisions should be independent of the gender of the doctor making them. Thus, I define a new measure for homophily in directed networks, *directed homophily*, that compares the fraction of referrals made to male specialists between male and female doctors.[5] I argue that differences in the fraction of referrals made to male specialists between male and female doctors provide evidence that referrals are gender biased. A second identification concern is sorting of physicians by gender into market segments (e.g. hospitals, or medical specialties). Sorting makes doctors more exposed to specialists of their own gender, making it appear as if referrals are biased if segmentation is ignored. To account for sorting, I combine referrals with data on multiple physician characteristics and affiliations. These data allow me to compare referrals within narrowly defined market segments, while accounting for characteristics that influence referrals.

Medicare referrals exhibit significant directed homophily. Across the United States, female doctors refer to female specialists a third more than male doctors do (19% women-to-women compared with 15% men-to-women, a 4 percentage-point difference). Homophily estimates decline only modestly (to 3 percentage points) even when fixed-effects are used to narrow the comparison to that between doctors of the same specialty within the same hospital. Moreover, estimated homophily hardly changes when controls are included for the gender of patients, suggesting that results are not explained by preferences of patients to see physicians of their same gender.

However, while directed homophily identifies a gender bias in referrals, it does not identify its size. For a given gender bias, homophily varies with the fraction of available male specialists. This relationship is nonlinear, as homophily mechanically approaches zero when all available specialists are either male or female. Thus, quantifying the bias in preferences requires accounting for variation in specialist availability.

To estimate the underlying gender bias in preferences that yields the observed homophily in referrals, I model how referral networks form when *doctors* choose *specialists* to refer to.[6]

[4]This problem of identifying homophily with underlying heterogeneity is highlighted in Graham (2014).

[5]This strategy is similar to the use of two-sided data for studying racial profiling in Anwar and Fang (2006) and Antonovics and Knight (2009).

[6]Doctor and specialist are used throughout to denote the roles of sender and receiver of a referral, regardless of their medical specialties.

This discrete choice model builds on Currarini et al. (2009), but extends the analysis from social to referral networks, which are directed and where links directly influence the flow of patients that generate income to specialists. The model makes explicates the decomposition of directed homophily into sorting versus preference bias, by allowing for both biased preferences and correlation between the gender of doctors and the gender of available specialists in their market.

I estimate the model parameters using Medicare data. Unlike directed homophily, that considers the correlation between the genders of doctors and their chosen specialists, I identify biased preferences by comparing the distribution of characteristics between chosen and unchosen—but available—specialists. For each doctor, I compare each chosen specialist to two randomly samples specialists of the same market and medical specialty, using a conditional logit specification akin to including doctor fixed-effects.[7] To address sorting, I also control for individual and pairwise characteristics, including: the distance between each doctor and specialist, their common hospital and group practice affiliations, their specialties, experience, their experience, and whether they have graduated from the same medical school.

Doctors' preferences exhibit significant gender bias: all else equal, doctors are 10% more likely to refer to a specialist of their own gender. This accounts for the fact doctors refer more to specialists who are nearby, who have common institutional affiliations, and who have attended their same medical school. I also find age-homophily: physicians are 12% more likely to refer to a physician a decade closer to them in age. Hence there is a comparable effect between being of a different gender and having a ten-year age difference. The estimated gender bias in preferences is consistent with the observed homophily in referrals for the current fraction of male specialists, and is predicted to result in an even greater homophily as this fraction declines.

The model further illuminates the contribution of homophily to the earnings gap. Intuitively, with men handling most outgoing referrals homophily implies more patients are referred to male specialists and fewer to female specialists. The model refines this intuition, and shows that it holds only if observed homophily is due to gender-biased preferences: sorting only affects the gender composition of incoming referrals.[8] Therefore, the model helps quantifying the implications of biased referrals in two ways. First, it is instrumental for calculating counterfactual. Second, it suggests a direct test for both the bias in preferences and

[7] I use choice-based sampling (also known as case-control sampling) to overcomes the computational difficulty of there being many potential alternatives to each chosen specialist (see McFadden, 1984; Manski and Lerman, 1977; King and Zeng, 2001).

[8] Moreover, with gender-biased preferences the demand for female specialists depends on the gender composition of both doctor and specialist populations. The demand for female specialists suffers not only because there are fewer female doctors, resulting in fewer referrals to female specialists; but also because there are fewer female specialists, raising the opportunity cost of choosing each one of them.

its impact on earnings: with biased preferences, a correlation should exist between workload of specialist and the gender of nearby doctors.

Evidence suggests that biased referrals contribute to gap in earnings of female relative to male physicians substantially. To test directly the model prediction, that the gender composition of doctors should impact demand for specialists of different genders differentially, I construct a monthly panel of specialist payments for 2008–2012. These longitudinal data allow me to test whether each specialist's pay is correlated, over time at a rather high frequency, with the gender of nearby primary care doctors. I find that, as predicted, more claims handled by male primary-care physicians in a market is associated with higher pay for male specialists and lower pay for female specialists. Identified from within-specialist variation, this result is robust to unobserved differences between specialists in labor supply. Counterfactual calculations show that referrals originating in a gender-balanced (or equivalently, unbiased) doctor population would eliminate on average 14% of the within-specialty gender pay gap. The earnings gap due to female specialists receiving fewer referrals amounts to thousands of dollars a year, comparable to the gap due to impact of gender differences in no-work spells. The overall impact on the pay gap could be even larger, if demand disparities discouraged female entry to higher-paying specialties.

The emerging picture is one of a widespread gender homophily in referrals, rooted in a tendency to prefer working with similar others, which leads to an overall unfavorable environment for the female minority. Homophily has been documented quite broadly, across characteristics such as age, race, and political inclination, and is known to homogenize social networks, creating "echo chambers" that limit individual information exposure.[9] This paper shows that homophily also segregates professional networks, creating for minority groups a persistent disadvantage by limiting their access to work and career opportunities. The main implication for medicine is that women in specialties such as primary care, that make most referrals, induce positive externalities for women in other specialties. Thus, helping female doctors further integrate into primary care specialties would increase, through referrals, the demand for services by female specialists. This effect is particularly important in specialties where much of the work depends on referrals, such as most surgical specialties, an area in which there are currently still very few women. Furthermore, although in the long run the part of the earnings gap due to homophily is expected to vanish, or even reverse, as recent female entrants gradually transform the gender composition of the physician labor force homophily is still a hindrance to pay convergence. The results are not only applicable to the

[9]See McPherson et al. (2001) for a review. Golub and Jackson (2012) show homophily segregates networks and changes the speed of learning; Himelboim et al. (2013); Halberstam and Knight (2016) document "echo chambers" in Twitter.

medical profession, and highlight a key mechanism that holds back women from succeeding in professions and careers where networking is important.

This paper proceeds as follows: Section 2 describes the data and decomposes the gender earnings gap among physicians in Medicare. Section 3 presents a new homophily measure and documents homophily patterns in Medicare referrals. Section 4 develops a model of homophily and estimates the underlying gender bias in physician preferences. Section 5 studies the impact of this bias on earnings. Section 6 concludes.

2 Data and Background

2.1 Data Sources

The main data source for this study is the Carrier database, a panel of all physician-billed services for a random sample of 20% Medicare beneficiaries for 2008–2012.[10] Data encode the gender of doctors, specialists, and patients, as well as payments, and are linked to rich data on physician characteristics. The sample contains patients with traditional ("Fee-For-Service") Medicare, which account for two-thirds of all Medicare beneficiaries, with a total of 35 million covered lives. Covering more than half a million doctors over 306 local markets, data are fairly representative of the United States.

I use a confidential version of the data, which contains both payment and referral information for each claim, and thus allow for studying homophily and its impact on pay disparities.[11] For each encounter of a patient with a physician, the data contain the following: the date of service and its location, the type of service, patient gender, the physician specialty, and payments made to the physician by all payors; data also record the referring provider, if there was one. Non-physician providers (such as nurse practitioners) are excluded, based on CMS specialty code. A small number of services are excluded, such as lab tests, which are often ordered by physicians directly, in which case the ordering physician is reported instead of the referring physician.[12]

[10] Medicare is the federal health insurance program for people who are 65 or older, certain younger people with disabilities, and people with End-Stage Renal Disease. It is run by a government agency, the Centers for Medicare and Medicaid (CMS).

[11] For a detailed description of these data see "Carrier RIF Research Data Assistance Center (ResDAC)", `http://www.resdac.org/cms-data/files/carrier-rif`. Accessed May 2015. To protect the privacy of patients, no statistics are reported for demographic cells based on fewer than 11 individual patients. Thanks to the large sample size, such cells are rarely encountered.

[12] Claims are reported using CMS Health Insurance Claim Form 1500, which contains a fields (17, 17a) for the name and identifier of the referring or ordering provider. For details see CMS Claims Processing Manual (Rev. 3103, 11-03-14) Chapter 26, 10.4, Item 17. Services are excluded with BETOS codes for Tests, Durable Medical Equipment, Imaging, Other, and Unclassified Services. For detail description of these codes see `https://www.cms.gov/Research-Statistics-Data-and-Systems/`

Data are combined with additional data on physician gender and other characteristics from Physician Compare, a public CMS database that provides information on physicians and other health care professionals who provide Medicare services.[13] The included characteristics are: sex, specialty, hospital and group practice affiliations, medical school attended, and year of graduation (used to calculate experience). Panel A of Table 1 and Figure A6 summarize physician characteristics. These data are further combined with beneficiary sex and summary cost and utilization from the Master Beneficiary Summary File.

The sample is fairly representative of U.S. physicians, with more than 90% of U.S. physicians providing Medicare services, although specialties related to elderly patients are over-represented. By volume, Medicare billed physician services are a quarter of the market for physician services in the United States, which has an annual volume of half a trillion dollars, about 3% of the U.S. GDP.[14] Even though claims for 20% of all patients are observed, selection of physicians into the sample based on their workload is negligible: even for those with minimal workload, the probability of being sampled is close to 1. The average physician has hundreds of Medicare patients every year. Seeing 30 patients is enough to be sampled with probability 0.999. For the same reason, the probability of missing links between physicians drops sharply as long as they see more than just a few patients.

Referrals in Medicare For the study of homophily I construct the network of physician referrals from referral information recorded on claims. If one physician referred patients to another during the year, a link is recorded, with the link weight depending on the volume of the relationship, measured as either of the following: the number of patients, the number of claims, and total dollar value of services referred during the year. Table 1 (Panels B and C) shows that there are difference in the number of colleagues men and women physicians work with. Conditional on making any referrals, doctors refer to 16 specialists an average; and conditional on receiving any referrals, specialists receive referrals from 18 doctors on average. But compared with women, men send referrals to 5 more specialists and receive referrals from 6 more doctors. These differences explained in part by differences in specialization. As seen in Figure A7, the average number of working referral relationships each physician has (both incoming and outgoing) varies a lot by medical specialty. Women are more likely to practice medical specialties that mostly send referrals, such as family medicine or internal medicine, whereas men are more likely to practice specialties that receive more referrals,

`Statistics-Trends-and-Reports/MedicareFeeforSvcPartsAB/downloads/BETOSDescCodes.pdf`. Accessed May 2015. About a third of the remaining claims record a referring physician provider.

[13]Physician Compare Database, `https://data.medicare.gov/data/physician-compare` Accessed May 2015.

[14]2012 National Health Expenditure Accounts (NHEA).

Table 1: Descriptive Statistics: Physicians and Referrals

	All	Men	Women
A. All Physician			
Male Physician	0.723		
Experience (years)	22.4	24.2	17.9
Patients*	311	346	219
Claims*	755	850	515
Pay*	$106,112	$121,997	$64,620
Obs. (All Physicians)	530,357	383,525	146,832
B. Doctors (any outgoing referrals)			
Male Physician	0.734		
Avg. Outgoing Referral Volume*	$43,925	$48,315	$31,810
Fraction Male Patients	0.430	0.463	0.339
Links (out-degree)	16.2	17.1	13.7
Outgoing Referrals to Men:	0.834	0.848	0.795
Obs. (Doctors)	383,173	281,238	101,935
C. Specialists (any incoming referrals)			
Male Physician	0.755		
Avg. Incoming Referral Volume*	$48,730	$55,405	$28,155
Fraction Male Patients	0.412	0.433	0.348
Links (in-degree)	18.0	19.9	12.3
Incoming Referrals from Men:	0.777	0.795	0.719
Obs. (Specialist)	345,390	260,795	84,595

Notes: 20% Sample of patients; *volume variable, multiplied by 5 to adjust for sampling; Physician demographics and average work volume are for all sampled physicians (Part A). Referred work volume (Parts B, and C) are for Doctors and Specialists, namely physicians with at least one outgoing referral (Part B) or incoming referral (Part C) and complete demographic characteristics The terms *doctor* and *specialist* reflect roles in referrals, not physician specialty. Experience is years since medical school graduation. Pay is average annual Medicare payments by all payors in current dollars. Claims and Patients are average counts. Links is the number of distinct physicians with whom the physician had referral relationships. Incoming and outgoing referrals fractions are of fraction of referral dollar volume.

such as surgical specialties. It is therefore important to control for specialty when studying homophily in referrals.

A useful feature of traditional Medicare for the purpose of this study is that referrals are not limited or driven by institutional constraints, as beneficiaries can see any provider that accepts them. Unlike in some managed care private insurance plans, there is no formal requirement to obtain a referral in order to see a specialist. Thus referrals are not mechanically constraint in that way.

Referrals are a very local phenomenon, mostly targeted at nearby specialists. To study the implications of homophily on the pay gap, I therefore relate physician participation and pay at the local market level. I define local markets based on Hospital Referral Regions (HRR) from the 2012 Dartmouth Atlas of Healthcare.[15] There are in total 306 HRR, corresponding roughly to a metropolitan area. Each zip-code maps to one and only one HRR. HRR are the smallest geographical areas that represent nearly isolated networks: Less than 15% of referrals cross their boundaries.

2.2 Documenting and Decomposing The Gender Earnings Gap in Medicare

In 2012, the average female physician in the sample received a total of \$64,620 from Medicare, compared with the average male physician, who received \$121,995: that is, 48% less (66 log points). Figure 1 shows a gap in pay exists in every experience level, and reaches its peak for mid-career physicians. Medicare has standardized payments per service and pays men and women equally, hence this gap only reflect disparities in work quantity and type.

To quantify the contribution to the gap of previously studied explanations, I decompose the gross earnings gap by estimating a standard (log) annual pay equation:

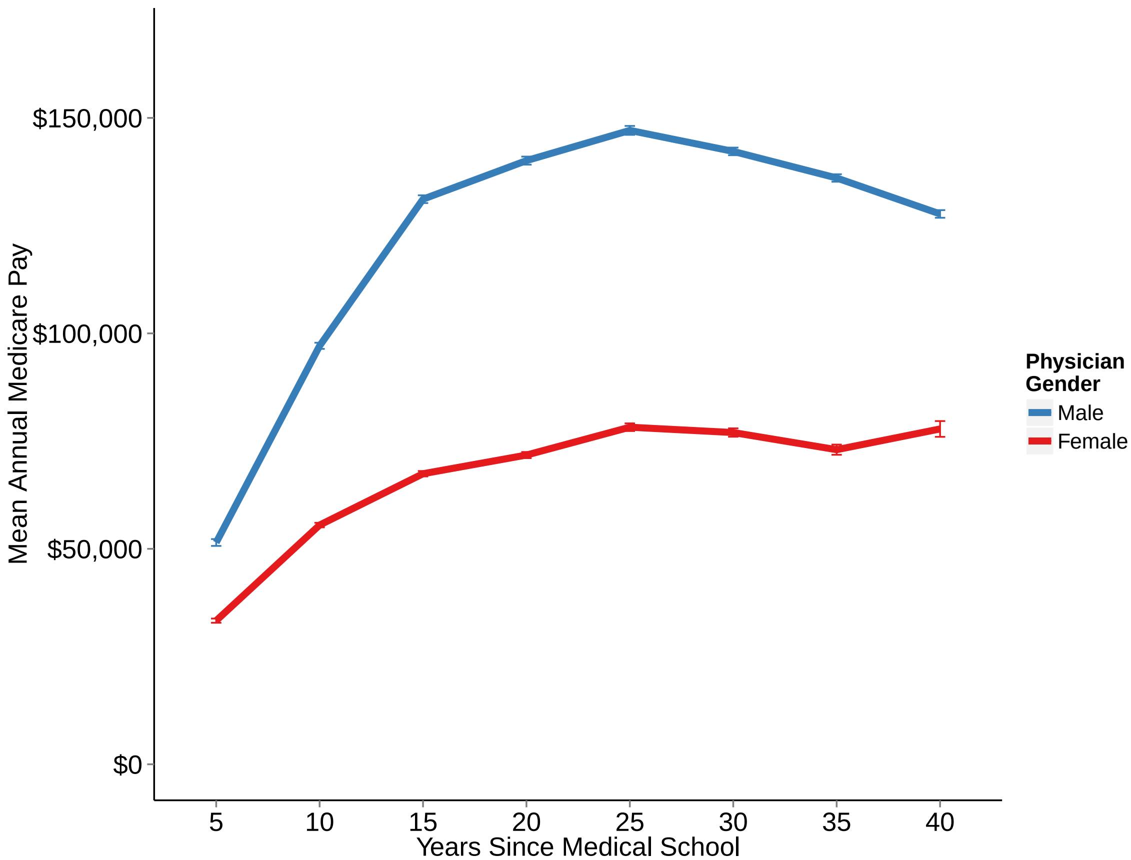
$$log(Pay_k) = \beta \mathbb{1}_{g_k=M} + \delta X_k + \varepsilon_k \tag{1}$$

Where k index physicians, $\mathbb{1}_{g_k=M}$ is a dummy for male physician, and X contains a constant and the following characteristics: physician specialty dummies; physician experience in years, including a quadratic terms; previous no-work spells, defined as the fraction of quarters with zero claims in the observed history (i.e., during all sampled years, excluding the year of graduation and the current year), a dummy for city (HRR), a dummy for the medical school attended. Results of this analysis are shown in (Table 2).

About half of the Medicare physician pay gap is accounted for by known factors. The

[15] "Dartmouth Atlas of Healthcare", `http://www.dartmouthatlas.org/tools/downloads.aspx?tab=39`. Accessed May 2015

Figure 1: The Unadjusted Gender Pay Gap, by Experience



Notes: Source: 20% 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 maximum, e.g. 10 stands for 6-10).

Table 2: The Gender Pay Gap for Medicare Physicians

	Dependent variable:					
	Log(Annual Pay)					
	(1)	(2)	(3)	(4)	(5)	(6)
Male Physician	0.668	0.654	0.468	0.361	0.337	0.340
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Experience Quadratic	No	Yes	Yes	Yes	Yes	Yes
Specialty	No	No	Yes	Yes	Yes	Yes
No-Work Spells	No	No	No	Yes	Yes	Yes
HRR	No	No	No	No	Yes	Yes
Med. School	No	No	No	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	498,580	447,863	447,863	424,361	420,319	296,199
Adjusted R^2	0.033	0.052	0.290	0.407	0.441	0.471

Notes: Estimates from an OLS regression of annual pay on physician attributes. Experience is years since graduation. Specialty is a dummy for 54 CMS specialty code. No-work spells are previous quarters with no claims. HRR is a dummy for one of 306 Dartmouth Hospital Referral Regions. Med. School is Physician Compare medical school ID. The number of observations vary due to incomplete data on some characteristics.

largest part (20 log points, or about a third of the overall gap) is due to women practicing lower paying specialties. For example, women are 51% of active obstetrician-gynecologists but less than 6% of active orthopedic surgeons (Figure A6). Consistent with previous works (e.g., Bertrand et al., 2010), female physicians also have more career interruptions, which explain additional 10 log points (Table 2, Columns 1–3). Difference in experience, location, and medical school attended explain a little more. The remaining half of the gross gap (34 log points), reflecting the within-specialty gender gap in workload, remains largely unexplained. Understanding the causes for this large difference in workload is important, as beyond its direct effect on pay, lower workload by women could feed back to their specialization and career choices (Chen and Chevalier, 2012).

The earnings gap documented here for Medicare physicians conforms with previous studies of gender earnings gaps for physicians and other high skilled professionals. Seabury et al. (2013) use Current Population Surveys (CPS), estimate a median gap ranging between 16% and 25% (18–30 log points) among U.S. physicians, and quite persistent throughout the period between 1987 to 2010. Using Physician Surveys administered between 1998 and 2005, Weeks et al. (2009) find women earn about a third less than men. My estimates of the gender pay gap in Medicare are also on par with pay gaps in other high-skilled occupations: Bertrand et al. (2010), using data from MBA graduates working in the financial and corporate sectors, found a gross gap of almost 60 log points 10 to 16 years after graduation, and **?** find large gaps in hours billed and new clients revenue between male and female lawyers.

While some of this and previously documented gaps clearly reflect voluntary differences in labor supply, there remains the question of how much of them is non-voluntary, and is due to differences in opportunities men and women face because of their gender. In the next sections, I document such a difference: homophily in referrals, and show it contributes to the Medicare physician earnings gap.

3 Homophily in Physician Referrals

In this section, I show that physician referrals exhibit gender homophily, that is, doctors refer more patients to specialists of their same gender.

3.1 Measuring Homophily with Unobserved Gender Differences

Before examining evidence for gender homophily in physician referrals, I first define a new homophily measure, *directed homophily*. Directed homophily compares the fraction of referrals to male specialists between male and female doctors. Unlike previous homophily measures, directed homophily is insensitive to unobserved differences between the genders in the propensity to refer or receive referrals, and thus better reflects underlying bias in preferences towards same-gender others.

Consider the network of physician referrals in a given market, where a link exists between *doctor* j and *specialist* k if j referred any patients to k; in such case we say j *refers* to k.[16] Let G_g be the average fraction of referrals doctors of gender $g \in \{m, f\}$ send to specialists of gender $G \in \{M, F\}$.[17] (Throughout, I use lowercase and uppercase to index doctors and specialists, respectively.) I define directed homophily as follows:

Table 3: Overall Directed Homophily (DH) in Medicare

From (Doctor) \ **To (Specialist)**	Female (F)	Male (M)
Female (f)	20%	80%
Male (m)	15%	85%

$$DH = 85\% - 80\% = 20\% - 15\% = 5p.p.$$

Definition 1 (Directed Homophily)**.** *Directed homophily* is the difference between the fraction of outgoing referrals of male and female doctors to male specialists (or equivalently, to female specialists):

$$DH := M_m - M_f = F_f - F_m$$

That is, referrals exhibit directed homophily ($DH > 0$) if male doctors refer to male specialists more than their female counterparts.[18] Table 3 illustrates this definition using Medicare data. In Medicare, male doctors refer 85% of their patients to male specialists, compared to female doctors who refer 80% of their patients to male specialists, so $DH = 5p.p.$ (figures are rounded to the nearest integer). Instead of comparing outgoing referrals, one could define homophily based on the difference in incoming referral rates. It is easy to verify such a measure has always the same sign as directed homophily. Preserving link direction

[16]Throughout this paper the terms *doctor* and *specialist* are used to denote the role of a physicians as a referral origin or target, regardless of their medical specialties, similar to how "ego" and "alter" often used in the sociology literature. Thus, the same physician can be a doctor with respect to one link and a specialist with respect to another.

[17]For example, the fraction of referrals male doctors send to female specialists is $F_m = \dfrac{n_{mF}}{n_{mF} + n_{mM}}$, where n_{gG} be the average number of referrals doctors of gender g send to specialists of gender G.

[18]Referrals exhibit *directed heterophily* if they are biased towards the other gender, that is, $DH < 0$.

is important (e.g., see Figure A2). Directed homophily can also be redefined to admits weighted links. Weights reveal whether same-gender referrals are not only more likely, but also more voluminous.[19]

Directed homophily is not driven by baseline imbalance in the gender distribution of doctors or specialists: if most specialists are men then both male and female doctors are expected to refer more to male specialists, but not differentially so.

It is useful to compare directed homophily with a different homophily measure: *inbreeding homophily*.[20] inbreeding homophily uses population shares as the baseline:

Definition 2 (Inbreeding Homophily)**.** Male doctors exhibit *inbreeding homophily* if

$$M_m > M$$

Where M is the fraction of male specialists. Likewise, female doctors exhibit inbreeding homophily if $F_f > F$, where $F = 1 - M$ is the fraction of female specialists (or equivalently, if $M_f < M$).

Note that inbreeding homophily by both genders immediately implies directed homophily, while the reverse is not true, e.g. if $M_m > M_f > M$.

Unlike inbreeding homophily, directed homophily is not using population gender shares as a benchmark. Hence, directed homophily is insensitive to difference between the genders in the propensity to send or receive referrals. For example, if both genders referred more patients to male specialists only because male specialists were more qualified or preferred to work longer hours, unlike inbreeding homophily, directed homophily would still be zero. Directed homophily is positive only if there is a correlation between the gender of the referring doctor and the receiving specialists. Put differently, directed homophily, unlike inbreeding homophily measures relative, not absolute, gender differences in referrals. With unobserved heterogeneity, absolute differences are generally not identified.

[19] To adapt directed homophily to weighted links just redefine 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 $\frac{d^F}{d}$ over all male j, and so on for n_{gG}. The rest of the definition is verbatim.

[20] This measure, originally due to Coleman (1958), has long been long used in sociology (see McPherson et al., 2001; Thelwall, 2009), and more recently in economics, by Currarini et al. (2009); Bramoullé et al. (2012); Currarini and Vega-Redondo (2013) (normalized or approximated variants are often used). Golub and Jackson (2012) define a different measure, *spectral homophily*: the second-largest eigenvalue of a matrix that captures relative densities of links between various pairs of groups; this measure captures a notion of segregation of the network: how “breakable” it is to two groups with more links within them and less between them. Spectral homophily, or its simpler estimate, *degree-weighted homophily*, neither imply directed homophily nor they are implied by it.

Table 4: Medicare Referrals by Gender

		A. Referrals			B. Percent of Outgoing				C. Percent of Incoming	
		To			To				To	
		F	M		F	M	Total		F	M
From	f	420,976	1,712,510	f	19.73	80.27	100	f	24.74	19.36
	m	1,280,691	7,130,872	m	15.23	84.77	100	m	75.26	80.64
								Total	100	100

Notes: Referral counts and percentages, by gender of referring and receiving physician. Since services are sometimes billed on several separate claims, multiple referrals of the same patient from a doctor to a specialist are counted as one. Source: 20% sample of Medicare physician claims for 2012.

The rest of this section estimates directed homophily in physician referrals. Section 4 below links directed homophily and underlying gender bias in preferences, and estimates the latter.

3.2 Patterns of Homophily in Physician Referrals

Overall, Medicare referrals exhibit directed homophily (Table 4). Physician referrals also exhibit directed homophily within geographic segments. Figure 2 plots the average fraction of referrals to male specialists over the fraction of male specialists in 306 local U.S. markets. Each market is represented by two vertically-aligned points, capturing referral rates to male specialists by male and female doctors in the market. Unsurprisingly, the overall relationship between the fraction of male specialists and the fraction of referrals they receive is positive. However, two additional facts are apparent. First, the fraction of referrals going to male specialists is greater than the fraction of male specialists in the population (most points are above the 45-degree line). Second, even within local markets referrals exhibit directed homophily (the vertical difference between the fitted curves).

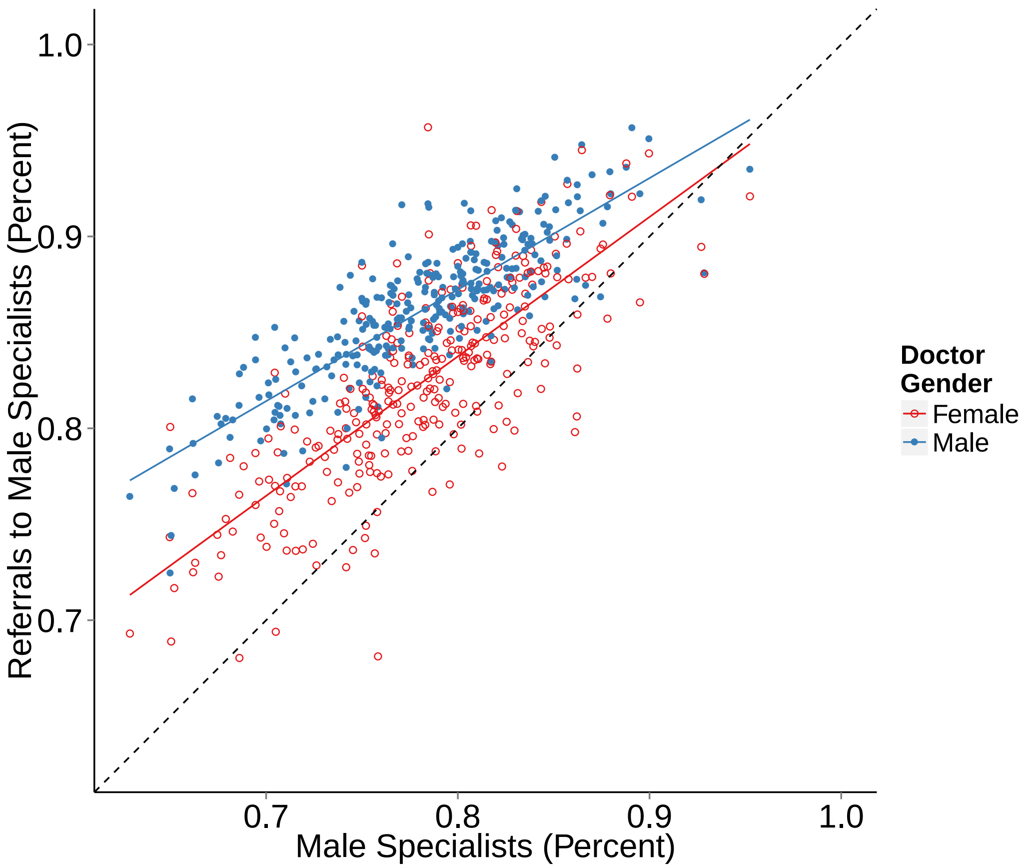
Directed homophily can be estimated separately for different bins by regressing the fraction of patients each doctor j referred to male specialists, M_j, on the doctor's gender g_j and other characteristics X_j:

$$M_j = \alpha_1 + \beta_1 g_j + \delta_1 X_j + \varepsilon_j, \tag{2}$$

for doctors with any referrals. The ordinary least squares estimate of β_1 measures average directed homophily: how much more men refer to men on average across markets.

A potential explanation for observed homophily, rather than bias in physian's preferences, is that physicians sort into market segment by gender, which makes the pool of

Figure 2: Referrals to Male Specialists Over Their Population Fraction, by Doctor Gender



Notes: For each local physician market (Dartmouth Hospital Referral Region), average fractions of referrals from male and from female doctors to male specialists are plotted over the fraction of male specialists in the market. Each of these 306 local U.S. markets is thus represented by two vertically-aligned data points. On average, men refer more to men than women do, even after accounting for the variation between markets in the availability of male specialists. The proposed measure, *directed homophily* represents the vertical difference between the fitted curves.

specialists doctors face biased towards their own gender. Some control for sorting can be obtained from a variant of (2):

$$M_j = \beta_2 g_j + \delta_2 X_j + \gamma_{h(j)} + \varepsilon_{jh} \tag{3}$$

where $\gamma_{h(j)}$ is a fixed-effect for the hospital with which doctor j is affiliated (for robustness, hospital interacted with medical specialty are also considered). The estimate β_2 measures the average directed homophily within market segments defined by hospital and specialty bins. It captures the differences in referral rates to men between male and female doctors of the same medical specialty that are affiliated with the same hospitals. To the extent such doctors face similar pools of specialists, β_2 indicates a bias in preferences.

Anotehr potential explanation for homophily is that patients may prefer seeing physicians of their same gender.[21] If such preferences affect both patient's choice of doctors and their choice of specialists, they may yield directed homophily among physicians, even absent any gender preferences among physicians. One way to account for patient preferences is to control for each doctor's gender mix of patients in (2) or (3); another is to estimate similar specifications with disaggregate data, where each observation represents one referral of a patient by a doctor to a specialist, and directly include all their genders (See Appendix).

Accounting for each doctor's gender mix of patients hardly changes estimated directed homophily, suggesting homophily in physician referrals is not driven by homophily on behalf of patients. Table 5 shows estimates for directed homophily obtained from individual-physician data. There is a 4.3 percentage points difference between their referral rate and that of female doctors of similar specialty and experience (Column 2). Estimated homophily is 4.0 percentage points when the gender-mix of patients of each doctor is controlled for (Column 3). Physicians with more male patients do refer to male specialists more patients, on average. But doctors with similar fractions of male patients still referr more to specialists of their same gender. Note that controlling for the gender of patients accounts for patients' gender-preferences that are correlated with their gender, but not for residual gender-preferences that are uncorrelated with patient gender. In light of how little of homophily is explained by the former, it would be surprising were much of it explained by the latter.[22]

Doctors refer more to specialists of their same gender even when comparison is re-

[21] For example, Reyes (2006) shows that female patients are more likely to visit female obstetrician-gynecologists.

[22] The use of patient fixed-effects analogous to the hospital fixed-effects in (3) is limited by the fact that patients seldom obtain referrals from different doctors of the same specialty. Restricting attention to patients who have been referred by two such doctors of opposite genders yields a small sample, and one possibly selected on patient preferences.

Table 5: Estimates of Directed Homophily

	Percent of Referrals to Male Specialists					
	OLS				FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Male Doctor	0.053	0.043	0.040	0.040	0.029	0.030
	(62.7)	(49.1)	(44.8)	(44.0)	(30.5)	(32.6)
Male Patients (pct.)			0.029	0.028	0.031	0.043
			(16.5)	(14.7)	(16.1)	(23.4)
Cons.	0.79	0.81	0.80	0.81	0.82	0.78
	(1027.6)	(263.8)	(254.3)	(256.9)	(249.4)	(589.1)
Specialty (Doctor)	No	Yes	Yes	Yes	Yes	No
Experience (Doctor)	No	Yes	Yes	Yes	Yes	Yes
Obs. (Doctors)	385,104	384,985	384,985	347,534	347,534	347,534
Groups (Hospital/Specialty)					4,819	66,563
Rank	2	56	57	57	57	4
Mean Dep. Var.	0.82	0.82	0.82	0.83	0.83	0.83
R^2	0.012	0.038	0.039	0.041		
R^2 Within					0.034	0.0079

Notes: t statistics in parentheses. Estimates of equations (2) and (3) for the sample of doctors with any referrals. The dependent variable, percent of referral to male specialists, is the fraction of referrals that are made to male specialists. Percent male patients the fraction of referred patients who are male. Column 4 shows estimates of the same specification as Column 3 using the sub-sample of doctors with at least one hospital affiliation, used also in Columns 5 and 6. For sample and variable definitions, see Section 2.

stricted to market segments defined by doctors' hospital affiliation and their medical specialty (Columns 5 and 6). That is, male doctors affiliated with the same hospital, and of the same medical specialty, and with the same gender mix of patients still refer more to male specialists (a 3 percentage points difference). These estimates rule out the possibility that homophily only reflects homophily on behalf of patients or sorting of physicians by gender into hospitals.

Homophily estimates are virtually unchanged when links are weighted. Appendix Table A3 shows estimation results for different measures of referral volume: number of patients, number of claims, or overall dollar value of services. I also find that older doctors (with above-median experience) exhibit greater directed homophily than younger ones (Table A2).

To conclude, directed homophily estimates reveals a correlation between the gender of doctors and specialists they refer patients to, even within different market segments defined by locations, hospitals, and specialties, and even when the patient gender mix is accounted for. Such correlation is hard to explain in terms of unobserved differences between specialists of opposite genders, as any such difference should affect all referring doctors similarly, independently of their gender. Directed homophily thus suggests doctors may be preferring to work with specialists of their same gender. However, directed homophily varies with the fraction of male specialists available (n.b., the fitted curves in Figure 2 are not parallel). It does not directly reflect the magnitude of an underlying preference bias. For example, in markets where nearly all specialists are male doctors' choices are constraint and reveal little about their preferences. In such case, directed homophily would be close to zero even if preferences are biased. Therefore, identifying and quantifying the underlying bias in preferences requires accounting for differences between doctors in the fraction of available specialists, to which I turn next.

4 The Link Between Homophily in Referrals and Gender Biases in Physician Preferences

This section examines the relationship between the observed homophily in referrals and the underlying gender bias in doctors' preferences and estimates the latter directly. Analyzing a discrete choice model where doctors choose specialists, I show that homophily decomposes to gender-biased preferences within market segments and sorting across such segments. I then use this model to estimate the gender bias in doctor's preferences. The bias in preferences is identified by comparing the average characteristics between chosen and unchosen specialists. I find that faced with a choice between otherwise similar male and female specialists, doctors are 10% more likely to prefer to the specialist of their same gender.

4.1 A Model: Gender-Biased Referrals versus Sorting

Consider a model where doctors $j \in J$ choose specialists to refer patients to, from an opportunity pool $k \in K_j$. Denote the gender of doctors and specialists by $g_j \in \{f, m\}$, and $g_k \in \{F, M\}$. Doctors maximize a gender-sensitive utility function, and choose a specialist:

$$\underset{k \in K_j}{\text{argmax}} U_j(k) = \beta \mathbb{1}_{g_j = g_k} + \delta X_{jk} + \varepsilon_{jk} \tag{4}$$

Where $\mathbb{1}_{g_j=g_k}$ indicates both physicians are of the same gender, i.e., $(g_j, g_k) \in \{(f, F), (m, M)\}$. The choice of specialists depends on individual and specialist attributes (X_{jk}; e.g., specialist experience, or distance between clinics), but may also depend on gender, if $\beta > 0$. This case represents *gender-biased preferences.* If ε_{jk} is independently and identically distributed Gumbel-extreme-value, equation (4) yields the conditional logit probability for a referral from j to k, given gender and other characteristics:

$$p_{jk} := P(Y_{jk} = 1 | g_j, g_k, X) = \frac{e^{\eta_{jk}}}{\sum_{k' \in K_j} e^{\eta_{jk'}}} \tag{5}$$

Where $Y_{jk} = 1$ if j refers to k and $Y_{jk} = 0$ otherwise, and $\eta_{jk} := \beta \mathbb{1}_{g_j=g_k} + \delta X_{jk}$. That is, referral relationships are determined by pairwise characteristics. This excludes more strategic setups where links are formed in response to other links or in anticipation of such links.

Homophily due to Gender-Biased Preferences Biased preferences lead to homophily. To see how, consider first the case where there is one market with one common pool of specialists $K_j = K$, for all doctors $j \in J$, and where $X_{jk} = X_k$, namely, it includes only specialist characteristics but not pairwise ones, so all doctors face essentially the same choice set. Let $M = \frac{1}{|K|} \sum_k \mathbb{1}_{g_k=M}$ be the fraction of male specialists in this set (with slight abuse of notation: M is also used throughout to label male specialists). The first proposition shows that gender-biased preferences lead to homophily.

Proposition 1 (Preference-Based Homophily)**.** *Within a market, referrals exhibit directed homophily iff preferences are gender-biased. Namely, for $M \in (0, 1)$, $DH > 0$ if and only if $\beta > 0$.*

To see why Proposition 1 is true, first consider the homogeneous case: $\delta = 0$, and note that the conditional probabilities of referrals to a male specialist are (see appendix for derivation of this and other results):

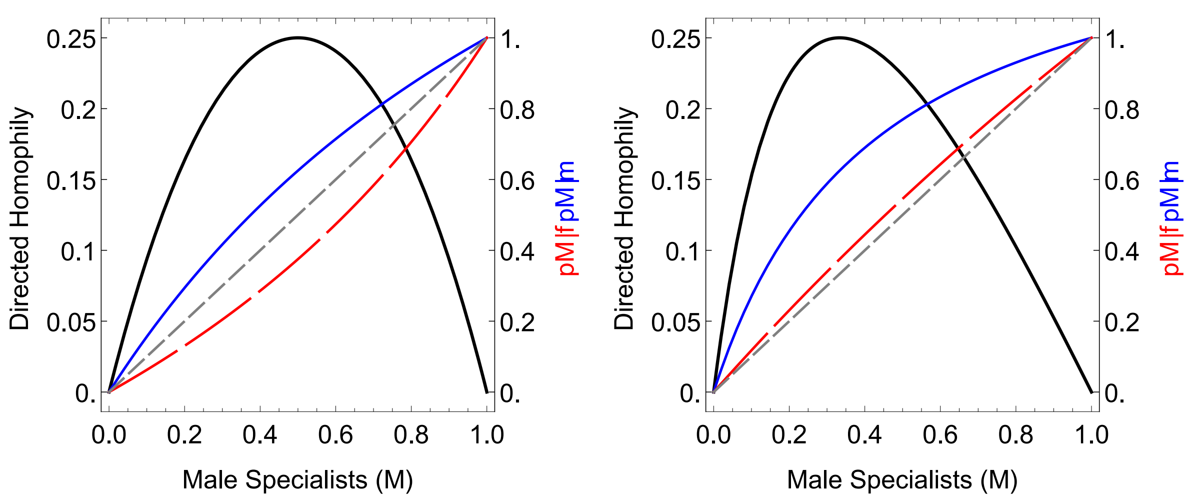
$$P(M_m) = \frac{M}{M + \omega(1-M)} \geq M \geq \frac{\omega M}{\omega M + (1-M)} = P(M_f) \tag{6}$$

where $P(G_g) := P(g_k = G | g_j = g)$ denote the probability that the chosen specialist's gender is G conditional on doctors' gender being g, and $\omega = e^{-\beta} \in (0, 1]$. Equation (6) shows that for all $M \in (0, 1)$, biased preferences result in directed homophily, $P(M_m) > P(M_f)$: doctors of each gender slightly discount the other (by a factor ω). Conversely, with unbiased preferences ($\beta = 0$) directed homophily is zero, as referral rates to men are common to doctors of both genders:

$$P(M_m) = M = P(M_f) \tag{7}$$

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

Figure 3: Preference-Based Homophily, With and Without Heterogeneity



(a) Homogeneous Case ($\omega = 0.6, \eta = 1$)

(b) Heterogeneous Case ($\omega = 0.6, \eta = 0.5$)

Notes: Probability of referrals to male specialists by male and female doctors, and the difference: Directed Homophily for different fractions of male specialists, M, with gender-biased preferences ($\omega = e^{-\beta} = 0.6$). Case (a) shows gender-biased preferences in a homogeneous specialist population ($\eta = 1$): Male specialists receive more referrals than their fraction in the population from males, and less than this fraction from females. Case (b) combines gender-biased preferences with heterogeneity ($\eta = .5$): male specialists receive more referrals than their fraction in the population from both male and female doctors, but more from male than from female doctors.

An important implication of (6) is that observed homophily varies with the gender composition of the pool of available specialists: when the pool is more gender-balanced, observed homophily is greater (as illustrated in Figure 3a, and as seen before in Figure 2). With balanced pools doctors' choices more strongly reflect their preferences. Conversely, when most specialists are of one gender there is less room for choice and thus homophily is weaker. In the extreme cases where $M \in \{0, 1\}$, there is no homophily even if preferences are biased. The preference bias β is therefore a more portable parameter than directed homophily, which in part reflects differences among doctors in the mix of available specialists.

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, (6) becomes:

$$P(M_m) = \frac{M}{M + \omega\eta(1-M)} \geq \frac{\omega M}{\omega M + \eta(1-M)} = P(M_f) \tag{8}$$

Regardless of gender-biased preferences, if $\eta < 1$ male specialists attract a disproportionally high fraction of referrals from both genders (Figure 3b). 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 (8) 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.

With heterogeneity ($\eta \neq 1$), directed homophily is a better measure of homophily than inbreeding homophily because it is not using M as the benchmark, but rather compares referrals of both genders against each other. For simplicity, for the rest of this section again assume homogeneity.

Homophily due to Sorting by Gender into Market Segments Apart from preferences, physicians sorting by gender into local markets also leads to homophily.[23] Sorting generates homophily by making doctors more exposed to specialists of their same gender. Formally, suppose that instead of a single market there is a set of separate markets indexed by $c \in C$, each with its own sets of doctors J^c and specialists K^c, and the corresponding fractions of male doctors, m^c, and male specialists, M^c, assumed throughout to be in $(0, 1)$. Referrals only occur within markets. That is, $K_j = K$ for all $j \in J^c$. Markets may also vary in size $\mu^c = \frac{J^c}{J}$ (so $\sum_c \mu^c = 1$). The conditional probabilities of referrals to men now vary by market and are denoted $P(M_m|c)$ and $P(M_f|c)$. One way to define *sorting* is as a positive correlation between the genders of doctors and specialists across markets $\mathrm{Cov}(m^c, M^c) > 0$.[24]

[23]Sorting could also be into market segments, like institutional affiliations, that determine the scope for referrals

[24]This definition 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 male in K_j.

Proposition 2 (Sorting-Based Homophily)**.** *With sorting, referrals exhibit homophily when pooled together across all markets:*

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

for all $\beta \geq 0$.

Intuitively, if fractions of male doctors and specialists are correlated then referrals coming from male doctors are more likely to occur in markets with more male specialists. Homophily then appears at the aggregate level, even when preferences are unbiased ($\beta = 0$) so there is no homophily within each market.

Sorting and preferences are in fact exhaustive: combined together, they fully account for the overall homophily observed. The following proposition decomposes homophily into these two causes: preferences (within market) and sorting (across markets). For clarity, the proposition is stated here for inbreeding homophily. Its equivalent for directed homophily is in the appendix.

Proposition 3 (Homophily Decomposition)**.** *Homophily observed across all markets decomposes to preferences and sorting as follows:*

$$\overbrace{P(M_m) - M}^{\textit{Overall Homophily}} = \frac{1}{m}\left(\overbrace{\mathrm{E}[m^c(P(M_m|c) - M^c)]}^{\textit{Biased Preferences}} + \overbrace{\mathrm{Cov}[m^c, M^c]}^{\textit{Sorting}}\right)$$

That is, the homophily observed when all markets are pooled together is the sum of two terms: (a) the average market-specific (preference-based) homophily, weighted by market size μ^c and share of doctors, $\frac{m^c}{m}$, and (b) sorting into markets. Note that sorting could also dampen homophily, rather than augments it: If $\mathrm{Cov}[m^c, M^c] < 0$ then even if preferences are biased overall homophily could be zero.

The proof of Proposition 3 only uses Bayes rule to relate aggregate and market-specific referral probabilities. So, while it is natural to specify the probabilities $P(M_m|c)$ as done in the case of a single market discussed above, the proof of Proposition 5 does not rely on a specific parameterization of these probabilities: it only requires relevant moments to exist.

A corollary of Proposition 3 is that when market boundaries are observed, homophily observed within each market identifies the presence of a bias in preferences. When market boundaries are imperfectly observed (e.g., if physician sort by gender into hospitals, but hospital affiliation is not observed), Proposition 3 shows that observed homophily in each market is a combination of preferences and sorting into unobserved market segments. Accounting for sorting is therefore required to identify preference bias. Inasmuch as sorting is accounted for, the directed homophily estimated in Section 3 provide suggestive evidence for the presence of gender bias in preferences. I now turn to estimate this bias.

4.2 Identification and Estimation of Preference Bias

My primary concern is to identify the gender-bias in doctor's preferences separately from sorting and from individual differences between the genders in the propensity to refer or receive referrals. In Section 3, I defined a homophily measure that identifies gender bias by comparing referrals between genders (thus "differencing out" unobserved differences between the genders), and by narrowing this comparison to within smaller market segments (thus accounted for sorting). In this section, I take a more direct approach, and estimate the parameters of the specialist choice model specified in equation (5). The main parameter of interest, the gender-bias in preferences, quantifies how much doctors are more likely to refer to specialists of their own gender, all else equal.

Identification is based on comparing gender and other characteristics between the set of specialists that were chosen by each doctor and the set of specialists that were available but not chosen. The model allows different doctors to face different pools of specialists. In fact, such variation in choice sets is exactly what identifies the parameters. Potential sorting is mitigated by including controls for multiple factors that are expected to impact the likelihood of referrals between pairs of physicians, including: location (distance), specialty, experience, patient gender, shared medical school, and shared affiliations. The residual threat is from sorting on unobserved attributes. Namely, from factors correlated with the gender of both doctors and specialists, and that are relevant for the choice of referrals. Note that for an omitted factor to confound the estimates, it must not only be related to referrals, but also correlated with the genders of both doctors and specialists. For example, if doctors mostly refer within-hospitals, omitting hospital-affiliation is only a problem if both doctors and specialists sort by gender into hospitals, i.e., if there is a correlation across hospitals between the gender mix of affiliated doctors and specialists. Furthermore, I argue that characteristics unrelated to referral appropriateness that might be shaping preferences are not confounders, but rather underlying mechanisms (e.g., if men refer to men because they golf together, golf-club affiliation explains homophily, but does not explain it away). The identification assumption is therefore that no clinically-related factors correlated with both the probability of a referral and with the gender of both physicians are omitted. In Section 5 below I further mitigate concerns for residual sorting, by directly testing for a correlation between the gender mix of doctors and specialist demand, a correlation that is expected to exist if and only if preferences are gender biased.

I estimate gender bias in preferences using a conditional logit model in (5) for the probability of referrals from doctor j to specialist k, conditional on gender g and other specialist and pairwise characteristics X. The identifying variation comes from differences within each doctor's choice set, thus any doctor-level attributes are differenced-out, as is clear from comparing the log of the ratio of probabilities:

$$log\frac{p_{jk}}{p_{jk'}} = \beta(\mathbb{1}_{g_j=g_k} - \mathbb{1}_{g_j=g_{k'}}) + \delta(X_{jk} - X_{jk'}) \tag{9}$$

The data consist of an observation for each dyad (j, k), with associated physician and dyad (pairwise) characteristics X_{jk}, and a binary outcome standing for whether the dyad is linked. To account for differences between opportunity pools, X_{jk} includes specialist gender. The main parameter of interest is β, the average gender-bias in preferences.

Since the opportunity pools of specialists is very large, considering all possible dyads is computationally unfeasible. I therefore use choice-based sampling (also known as case-control sampling). That is, instead of considering all possible pairs of doctors and specialists in the United States, each connected doctor-specialist dyad (i.e. (j, k) such that $Y_{jk} = 1$), is matched with two *controls*: unlinked dyads (j, k') and (j, k'') with k', k'' sampled at random from K_j, defined as all k within the same referral region (HRR) and of the same specialty of k, the specialist to which j actually referred. This choice makes a conservative (weak) assumption about substitutability. Specifically, because controls for multiple other characteristics are included (e.g., distance), it does not imply that all specialists in the same city and medical substitute are perfect substitutes. Rather, it only assumes that specialists from different markets or from different medical specialties are not substitutes. The model parameters, estimated using variation within city and specialty, capture the actual substitutability within those cells. Estimates are consistent under this sampling scheme (see McFadden, 1984).

4.3 Estimation Results: Homophily and Gender-Biased Preferences

On average, doctors choose specialists that are similar to themselves on gender and other observed characteristics. Table 6 compares the average characteristics of specialists that are chosen with randomly samples specialists that were not chosen, from the same market (HRR) and medical specialty, the sample used for estimating preference bias. Chosen specialists are much more likely to have common institutional affiliations with the referring doctor, to be located nearby, to be of similar age and to have went to the same medical school.

Table 6: Average Characteristics of Chosen versus Unchosen Specialists

	Doctor Referred to Specialist	
Doctor and Specialist:	Yes	No†
Same Gender	0.712	0.678
Same Zipcode	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: † Two specialists not chosen for referrals were randomly sampled from the set of specialists with the same HRR and medical specialty as those of each chosen specialist by each doctor. + for the sample with non-missing school data. All differences are significant ($p < 0.001$).

All else equal, doctors are 10% more likely to refer to specialists of the same gender, as seen in Table 7, which shows estimates of the specialist choice model (5).[25] Distance (proximity) and hospital affiliation are the strongest determinants of referrals, with referrals far more likely between providers sharing an affiliation and within the same zip-code. Modest sorting on location and hospital affiliated is confirmed by the slight decrease in same-gender estimates when these characteristics are included as controls. Estimated separately by specialty, preference bias is stronger in all large enough specialties (Figure A5). The estimated bias is not positive only for small specialties, where doctors are likely too restricted in their choices to be able to express any gender preference. Results from including interaction terms in the estimated model suggest that the preference bias is somewhat stronger within hospitals, and somewhat weaker within groups, albeit only slightly (Table A4). There is no additional increase in the probability of referral between doctors and specialists that graduated from the same medical school and are of the same gender.

The estimated gender-bias is comparable with the previously estimated homophily (Table 5). Substituting $\hat{\beta} = 0.1$ in equation (6) shows that facing an opportunity pool with 80% male specialists (roughly the U.S. average), the estimated gender bias of 10% implies directed homophily of 3.2 percentage points, net of sorting. In comparison, the counterfactual

[25]Estimates represent odds ratios, but due to sparsity, estimates close to zero approximately equal the percentage increase in probability. That is, using the notation of (4), around zero $\beta \approx \dfrac{p_{jk}|g_j = g_k}{p_{jk'}|g_j \neq g_{k'}} - 1$.

Table 7: Conditional-Logit Estimates: Referral Probability

	Doctor Referred to Specialist					
Doctor and Specialist:	(1)	(2)	(3)	(4)	(5)	(6)
Same Gender	0.104	0.0983	0.0841	0.105	0.104	0.0844
	(55.27)	(41.96)	(35.81)	(29.79)	(29.65)	(27.71)
Male Specialist	0.197	0.169	0.175	0.165	0.165	0.194
	(103.46)	(71.43)	(73.70)	(46.09)	(46.03)	(63.15)
Same Hospital		3.116	3.114	2.945	2.941	2.803
		(721.31)	(720.15)	(541.87)	(540.97)	(568.47)
Same Practice Group		1.346	1.346	1.320	1.320	1.652
		(178.27)	(178.27)	(135.27)	(135.26)	(142.36)
Similar Experience			0.128	0.132	0.131	0.136
			(131.66)	(93.47)	(92.95)	(110.80)
Same Med. School					0.209	
					(49.96)	
Specialist Experience	Yes	Yes	Yes	Yes	Yes	Yes
Same Zipcode	No	Yes	Yes	Yes	Yes	No
Zipcode Distance	No	No	No	No	No	Yes
Obs. (Dyads)	14,793,483	14,559,311	14,555,821	6,712,241	6,712,241	8,915,969
Clusters (Doctors)	375,440	367,479	367,370	242,579	242,579	285,448
Pseudo R Sqr.	0.002	0.360	0.361	0.346	0.347	0.331

Notes: t statistics in parentheses. Results of conditional logit estimates of (5) for 2012. Data consists of all linked dyads and a matched sample of unlinked dyads, by location and specialty (see text for details). The dependent binary variable is 1 if there were any referrals between the doctor and the specialist during the year. Same Gender is a dummy for the specialist and doctors being of the same gender. Male Specialist is a dummy for the specialist being male. Same hospital and practice groups means the doctor and the specialist has at least one common affiliation of either type. Similar Experience is the negative of the absolute difference in physicians' year of graduation. Zipcode Distance is a quadratic polynomial in the distance between zipcode centroids for zipcodes with a distance of 50 or fewer miles between them. Schooling information is only partly available, thus Column (4) estimates the same specification as (3) with non-missing school data.

directed homophily with equal fractions of male and female specialists is 5 percentage points. That is, holding the underlying gender bias constant, homophily increases when choice sets are more gender balanced.

In addition to gender homophily, referrals also exhibit homophily on other dimensions: doctors prefer specialists of similar experience and specialists that attended the same medical school. A doctor and a specialist a decade closer in age have 13% greater probability of referrals between them. The other dimension of affinity: having went to the same medical school is also a strong determinant of referrals, with doctors being 20% more likely to refer to same-school graduates. Since medical-school data are partial, estimates with and without inclusion of same-school dummies are presented; they do not differ much.

Measuring the estimated role of gender in choices against the role of other attributes implies a social-distance between the genders. There is a comparable effect on the likelihood of referrals for being of different gender and for having an age difference of ten years. Note however, that unlike gender which shows imbalance with more male than female doctors, as long as no age group dominates the market by making most referrals, homophily on age do not create real disadvantage for any age group. It rather implies that work for specialists is more likely to be coming from doctors of similar age.

In Appendix C, I further study the dynamics of referral relationships. I find that same-gender physicians are also more likely to maintain referral relationships over time. Same-gender links are between 1.5–4.5% relatively more likely to persist (i.e., stay active the year after). This suggests same-gender referrals may be more common as a consequence of a dynamic process in which same-gender relationships are more likely to survive over time.

In sum, estimates point to a significant gender bias in referral choices even when multiple and detailed characteristics are included that account for possible sorting on multiple dimensions. Combined with earlier findings of robust directed homophily, evidence suggests that homophily is predominantly driven by preferences, rather than sorting. Results imply that increasing the diversity of the opportunity pools would increase homophily, rather than decrease it: gender-biased individual preferences are more manifest in diverse pools, which permit choice. Another implication—one that is central to this paper—is that homophily should divert demand away from female (the gender minority), and generate a gap in earnings. I next turn to formalize and test this implication directly.

5 The Contribution of Gender-Biased Preferences to the Gender Earnings Gap

In this section, I study the impact of homophily on the gender earnings gap. Further developing the model in Section 4, I show that when homophily is driven by gender-biased preferences, it leads to disparity in demand between the genders. Specifically, the more referrals are made by male doctors, the lower female specialists' demand. I directly test this predicted relationship using longitudinal data on Medicare payments for each specialist over 2008–2012. I find that female specialists indeed earn less—and male specialists earn more—when a greater fraction of primary care claims in their market is handled by male doctors. This contribution of biased referrals to the earnings gap is separate from possible difference between the genders in labor supply. Counterfactual calculations show that biased referrals explain 14% of the current gender gap in physician specialist earnings. Counterfactual also highlight that the resulting gap depends on the gender distribution of doctors and specialists. One way to eliminate the contribution of biased referrals on earnings is to balance the gender of referring doctors.

5.1 Homophily's Consequences for Gender-Disparities in Specialist Demand: Theory

Intuitively, when preferences are gender-biased, specialist receive fewer referrals the fewer doctors share their gender. The following proposition shows that the gender of fellow specialists matters too, in a more nuanced way. Whether same-gender specialists substitute or complement each other depends on the gender distribution of doctors.

Proposition 4 (Demand for Specialists by Gender)**.** *Average specialist demand depends on gender as follows:*

i With gender-neutral preference ($\beta = 0$) specialist demand is invariant to gender.

ii With gender-biased preference ($\beta > 0$)

(a) Average demand for specialists is higher the more doctors share their gender.

(b) Same-gender specialists are substitutes when most doctors share their gender, and complements when most doctors are of the opposite gender.

The proof of Proposition 4 is by noting that demand for male specialist—the average number of referrals received (denoted by D^M)—is a weighted-average of doctors' respective probability of referring to male:

$$D^M = mP(M_m) + (1-m)P(M_f) \tag{10}$$

where m is the fraction of male doctors in the market (superscript c is omitted for clarity as all magnitudes are within markets), and where for tractability assume $|J| = |K|$ (see appendix for general results). Substituting (6) into (10) and differentiating by m and M yields:

$$\frac{\partial D^M}{\partial m} = \overbrace{P(M_m) - P(M_f)}^{\text{directed homophily}} \tag{11}$$

$$\frac{\partial D^M}{\partial M} = (1-m)\overbrace{\frac{w(1-w)}{(1-M(1-w))^2}}^{\text{Complements }(+)} + m\overbrace{\frac{-(1-w)}{(M+w(1-M))^2}}^{\text{Substitutes }(-)} \tag{12}$$

Intuitively, equation (11) shows that when doctors are gender-biased, the demand for male specialists increases in the fraction of male doctors. This demand also depends on the gender mix of specialists. Male specialists are substitutes if most doctors are male and complements if most doctors are female, as seen by observing the terms of (12). This relationship is illustrated in Figure 4, which depicts the average demand for a male specialist, as a function of the gender compositions of doctors, for the current gender bias and for a typical specialist gender mix. As female are still the minority of both doctors and specialists in most markets (corresponding to the darker area of the surface), they suffer a lower demand due to both these effects: fewer doctors favor them, and male substitute are easily found. Figure A3 depicts the relationship for different values of M and m.

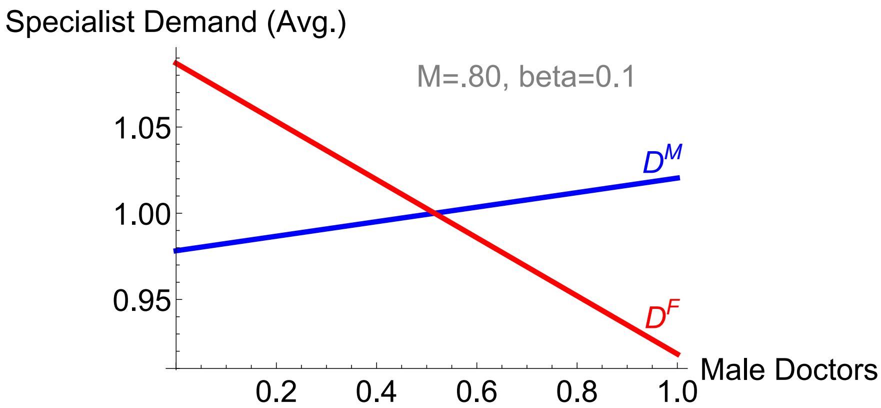
5.2 Testing for Homophily's Impact: Empirical Strategy

Proposition 4 provides a testable prediction: if referrals are gender-biased, the fraction of male doctors should be positively correlated with the earnings of male specialists and negatively correlated with the earnings of female specialists. Such correlation is expected only if preferences are gender-biased, and therefore doubles as a test for both a presence of gender bias in referrals and for the link between such bias and the gender gap in earnings.

I test this prediction using a monthly panel of physician payments. I split all physicians into two mutually exclusive groups, by their medical: primary-care physicians, who handle most outgoing referrals, and all other medical specialists. I estimate:

$$log(Pay_{k,t}) = (\beta_M \mathbb{1}_{g_k=M} + \beta_F \mathbb{1}_{g_k=F}) m_{c(k,t),t} + \gamma_t + \alpha_k + \varepsilon_{k,t} \tag{13}$$

Figure 4: Demand for Specialists and the Gender Mix of Doctors



Notes: Counterfactual demand levels, by specialist gender, as a function of m, the fraction of male doctors in the market, for the estimated gender bias $\beta = 0.1$ in a market with $M = 80\%$ male specialists.

For all non-primary-care specialists k, and months t. The dependent variable $Pay_{k,t}$ is the specialist total monthly Medicare payments; The variable $m_{c(k,t),t}$ is the fraction of claims at specialist k's market at month t handled by male primary-care doctors; Specialist and time fixed effects, α_k and γ_t, are included. Of interest is the difference $\beta_M - \beta_F$: the differential impact a higher fraction of male doctors has on male and female specialists' pay, tested against the null of unbiased-referrals, where this difference is zero.

Including specialist fixed effects allows for unobserved differences that likely exist between male and female specialists. This includes possible differences in labor supply (e.g., due to maternity-related leaves). This specification also allows for workload to be correlated across specialties. Indeed, it is likely that when primary care doctors see more patients, so do specialists, for example because of seasonality. The identifying assumption is that no omitted factors simultaneously boost the monthly workload of male primary-care physici1ans and decrease the workload of female non-primary-care specialists. Controls are also included for the monthly fraction of services incurred by male patients, to rule out patient homophily as an explanation.[26]

I estimate (13) using a monthly panel of individual-physician pay for the period 2008–2012. That is, I calculate for each market and month the fraction of primary-care claims handled by male doctors and, separately, the fraction of services incurred by male patients. Claim payments are aggregated to obtain total monthly payments for each physician specialist and each month.

[26]To control for patient homophily, a term $(\delta_M \mathbb{1}_{g_k=M} + \delta_F \mathbb{1}_{g_k=F})\mu_{c(k,t),t}$ is included, where μ is the is the percent of services incurred by male patients at k's market at t. Here too the effect is allowed to differ by specialist gender.

5.3 Results: Homophily's Impact on Specialists' Earnings by Gender

When more referrals are handled by male primary-care physicians, demand for male-specialists increases, while demand for female-specialists decreases. Specifically, each 1.0% monthly increase in the fraction of referrals handled by male doctors is associated with 0.47% increase in male workload and a 0.27% decrease in female workload. Results hardly change when controls for patient gender are included, suggesting the effect is not due to homophily on behalf of patients. These results are all identified from within-specialist variation in workload, so they are not an artifact of systematic differences in between male and female specialists labor supply. Results support the presence of a direct link between gender bias in referrals and a disparity in demand between the genders that contributes to the gender earnings gap. Such correlation between the monthly workloads of specialists of opposite genders and the gender of nearby doctors is hard to explain in terms of gender differences in labor supply.

Table 8: Male Fraction of Primary Care and Specialist Workload

	(1) log(Monthly Pay)	(2) log(Monthly Pay)
Female specialist x pct. male PCP (HRR)	-0.26***	-0.27***
	(0.054)	(0.054)
Male specialist x pct. male PCP (HRR)	0.49***	0.47***
	(0.029)	(0.029)
Month Dummies	Yes	Yes
M,F x Pct Male patients (HRR)	No	Yes
Obs. (Physician x Month)	18,087,629	18,087,629
Clusters (Physician)	418,939	418,939
R Sqr.	0.0323	0.0322

Notes: Fixed-effect estimates of (13) with and without controls for patient gender. For each non-primary-care physician specialist, monthly pay is the the total monthly pay for Medicare services billed. Specialist gender is interacted with the fraction of claims handled by male primary-care physicians in the same market during the month. In Column 2 it is also interacted, separately, with the percent of services incurred by male patients in the market (as controls). Standard errors are clustered by specialist.

As Proposition 4 shows, were homophily solely due to sorting, a correlation like the one documented, between specialist workload, their gender, and the gender of nearby doctors is not to be expected. Thus, results suggest that the observed homophily estimated in Section 3 is at least in part due to biased preferences, and further support the identification of the preference bias in Section 4.

This evidence for the impact of biased referrals on the earnings gap do not account for indirect benefits specialists might accrue from having more referred patients, such as having more returning patients (in specialties where patients are repeatedly seen), or having additional patient through word of mouth. Therefore, the overall impact of gender biased referrals could be greater.

This analysis also does not cover the potential long-term effects biased referrals may have on female entry into medicine and into specific medical specialties. Women were historically significantly underrepresented in medicine, and there remains the question of whether historically, homophily slowed down their entry. The absence of women from medicine has since dramatically changed: slightly more than half of current medical school graduates are female, and medicine is increasingly a feminine profession. But women are still grossly underrepresented in many lucrative specialties many of which, such as surgical specialties, rely much on referrals. The short time span of the data, and the presence of other differences between specialties, such as training duration and schedule flexibility, make it hard to identify these effects homophily may have on the extensive margins of female participation and specialization. But results hint to the possibility that homophily is an impedance to female entry, both in general and into particular specialties. It true, it would imply an even greater contribution of biased referrals to the gender gap.

One potential caveat is that specialist workload outside Medicare is unobserved here. However, even if women were to perfectly make up for their missing referrals by working more elsewhere, which is doubtful given that earnings gaps have been documented among physicians in other settings, results still imply that female specialists encounter a restricted demand in Medicare solely because of their gender.

The magnitude of the effect of referrals on gender pay disparities is fairly large: considering the counterfactual scenario where female handle exactly half of outgoing primary-care referrals, instead of their current share. In such case, the pay gap would decrease by an estimated $(.50 - .35) \times (0.47 + 0.27) = 11\%$, for specialties other than primary care. However, such back-of-the-envelope calculation does not hold constant the overall volume of patients, and therefore should be taken as suggestive, the next section presents more disciplined counterfactuals.

5.4 Counterfactuals

An alternative method to quantify the impact of biased referrals on the earnings gap is to calculate counterfactuals based on the model estimates from Section 3. I calculate two such counterfactual. First, I calculate the impact of reducing the bias on the average demand by specialists of each gender, using the current male fraction of doctors and specialists in the United States. Second, I calculate the impact of balancing the gender of doctors, keeping the current bias. Even by conservative estimates, each year female specialists forego to their male colleagues thousands of dollars' worth of work, due to a combination of biased preferences and most referral being made by men.

Figure 5 captures the expected average demand for male and female specialists for different levels of bias, β, for average fractions of male doctors and specialists in current U.S. physician markets. In this figure, average demand is normalized to one. Overall, biased-preferences of the level estimated from Medicare referrals, $\hat{\beta} = 0.1$, result in 5% lower demand for female specialists, relative to male ones. This bias amounts to 14% of the existing gap in workload of 36%. Eliminating the bias results in a 1% decrease in male specialist earnings and a 4% increase in female specialist earnings. Note the asymmetry, which is due to the fact female are the minority of specialists. These differences currently amount to thousands of dollars a year in missing referrals to women. The contribution of biased referrals on the earnings gap through limiting female demand is comparable in magnitude to the contribution to the gap of gender differences no-work spells (cf., Table 2).

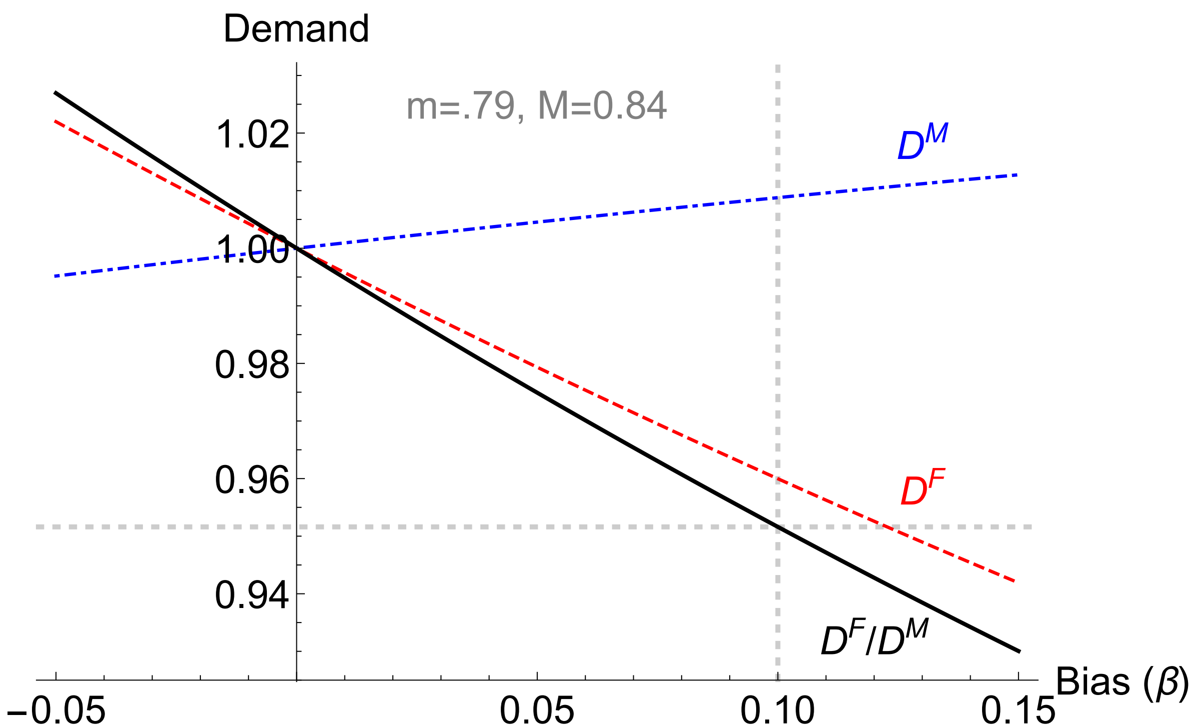
Table 9: Counterfactual Earnings Gap (Female-to-Male Difference) with Current Bias and Different Gender Mixes

Male	Males Specialists (M)						
Doctors (m)	0.4	0.5	0.6	0.7	0.8	0.9	1
0.4	0.0190	0.0200	0.0210	0.0220	0.0230	0.0240	0.0250
0.5	-0.0010	0	0.0010	0.0020	0.0030	0.0040	0.0050
0.6	-0.0210	-0.0200	-0.0190	-0.0180	-0.0170	-0.0160	-0.0150
0.7	-0.0410	-0.0400	-0.0390	-0.0380	-0.0370	-0.0360	-0.0351
0.8	-0.0610	-0.0600	-0.0590	-0.0580	-0.0570	-0.0560	-0.0551
0.9	-0.0809	-0.0799	-0.0789	-0.0780	-0.0770	-0.0761	-0.0751
1	-0.1009	-0.0999	-0.0989	-0.0980	-0.0970	-0.0961	-0.0952

Notes: Using estimated bias $\hat{\beta} = 0.1$, the table shows calculated earnings gaps: $D^F - D^M$, a function of m, M, and β, due to homophily related workload differences, for different gender distributions of doctors and specialists. The formula is given below. At $M = m = 0.75$ the gender bias in referrals is contributing 4.75 percentage points (or "cents-per-dollar") to the physician gender earnings gap.

The impact of a given bias in preferences on the earnings gap depends on the gender composition of doctor and specialist populations. Therefore, a second way to assess the impact of such bias on gender earnings disparity is to hold the bias constant at its estimated level and use the model to predict counterfactual average demand with different fractions of male doctors and specialists. Table 9 shows such counterfactual earnings gaps associated with different fractions of male doctors (m) and specialists (M). At a gender composition

Figure 5: Counterfactual Workload Gap for Different Levels of Preference-Bias



Notes: Average demand for female and male specialists are predicted using the model, given current upstream and downstream male fractions (m, and M). The thick line gives the fraction of the gap contributed solely due to homophily. Eliminating the bias would reduce the gap by about 5% (in popular terms, restoring 5 "cents-per-dollar" to women). See appendix for the same calculation with different values of m and M.

similar to the current one, $M = m = 0.8$, the estimated bias of $\hat{\beta} = 0.1$ is associated with a 5.7% lower demand for female, relative to male specialists. With equal gender fractions ($M = m = 0.5$) there is no gap, even when preferences are biased. In this case homophily only affects the composition of demand, not its level.[27]

The estimated bias in referrals explains a substantial fraction of the current gap in workload between male and female specialists. This gap is not due to difference between the genders, but rather due to differences in the demand specialists of opposite genders face, due to how doctors refer to them. Particularly, while it is conceivable that differences still gender between male and female physician specialists in their preferences for flexibility or in their overall desired workload, such difference fail to explain the documented bias in choices and the dependency of actual workload on the gender of nearby primary care doctors. The totality of evidence therefore suggests that a significant portion of the current gap is due to differences in demand, not just supply.

6 Conclusion

This paper shows that a substantial part of the physician gender earnings gap in Medicare is due to physicians tendency to refer more to their same gender. It documents homophily in referrals, and develops and estimate a model of network formation, allowing for variation between doctors in specialist availability, and using this variation to identify biases in their choices. It estimates this model using confidential administrative data on payments and referrals between half a million U.S. physicians across all medical specialties and U.S. local markets during the period 2008–2012. The empirical evidence suggests that the observed homophily in physician referrals is mostly due to gender-biased physician preferences. Further testing and quantifying the impact of biased referrals on physician earnings, biased referrals

[27] Table 9 is based on the following calculation:

$$
\begin{aligned}
Gap(m, M; \beta) = D^F / D^M \approx D^F - D^M = & \frac{1}{1-M}(mP(F_m) + (1-m)P(F_f)) \\
& - \frac{1}{M}(mP(M_m) + (1-m)P(M_f))
\end{aligned}
\tag{14}
$$

Substituting $P(Gg)$ for $g \in \{m, f\}$ and $G \in \{M, F\}$, given in (6), and simplifying yields:

$$
Gap(m, M; \beta) = -\frac{(1-w)((M-m) + w(1-(M+m)))}{(1-M(1-w))(w+M(1-w))} \tag{15}
$$

where $w = e^{-\beta}$. Note that this assumes no additional systematic bias against female specialists on behalf of doctors of both genders, a bias that is not separately identified from differences in labor supply. However, even if such bias exists, it is still true that increasing the fraction of female doctors would improve the lot of female specialists relative to their male counterparts.

are shown to divert away from the average female specialist thousands of dollars' worth of work each year in Medicare payments alone.

This paper defines a new homophily measure for directed networks, that focuses on the correlation between the gender of doctors and specialists and thus identifies a bias in referrals even with potentially unobserved differences in the propensity to send or receive referrals (e.g., due to gender differences in labor supply). This measure can be used to study homophily in any other contexts where unobserved heterogeneity is a concern.

The part of the earnings gap that this paper shows is due to gender homophily was inexplicable by previous studies that used only individual data, since it reflects not gender differences in choices or attributes of individuals, but rather differences in the way individuals of different genders are considered by others.

An important implication of these findings is that homophily slows down pay convergence. At the current estimated bias, a shift to a gender-balanced labor force that takes many years to materialize is required in order for the part of the gap due to disappear. With regard to specific policy implications, two points are worth making. First, while the tendency of women to chose primary care specialties increases pay disparity, as such specialties are among the lower paying ones, this paper shows that it has a silver lining. Female entry into primary care contributes, because of homophily, to creating more favorable terms for future women going other specialties. The faster female become the majority of referring doctors, the part of the earnings gap documented here will vanish, and even reverse. Second, notwithstanding the documented bias in preference, more evidence is required to warrant direct interference with physician choices. In particular, further research is required to find out how the gender composition of professional connections influence work productivity. In any case, intervening in specialist choices, by any Batson-like rule, is probably impractical.

Homophily, the tendency to favor similar others, is known to be ubiquitous. While slight and innocuous from an individual perspective, this paper shows that homophily presents systematic disadvantage to minority groups. Further studies of social and professional networks are due, as they can shed light on the propagation of inequality, on dimensions beyond gender and in domains beyond medicine.

Appendices

A Proofs

Proof. (Proposition 1) Pick any j such that $g_j = m$. Summing up probabilities of referrals to all available specialists gives:

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

The probability $P(M_f)$ is similarly derived. For (8):

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

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. ☐

Proof. (Proposition 2) 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. ☐

Alternatively, for the more general definition, segregation* ($\mathrm{Cov}[m_j, M^j] > 0$), the proof follows immediately from Proposition1: with unbiased preferences $P(M_m) = E[M^j|g_j = m] > M$, by segregation*. QED. Note that segregation* 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.

Proof. (Proposition 3)

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

□

See below for a statement and proof of this proposition for directed homophily.

Proof. (Proposition 4) 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):

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

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 4 is true rewrite:

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

and note that $\partial D_M / \partial m > 0$ since $P(M_m) - P(M_f) > 0$ for every $\beta > 0$. To see 0b 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. □

Proposition 5 (Directed Homophily Decomposition)**.** *The overall directed homophily decomposes as follows:*

$$P(M_m) - P(M_f) = \mathrm{E}[\frac{m^c}{m}P(M|m,c) - \frac{1-m^c}{1-m}P(M|f,c)] + \frac{1}{m(1-m)}\mathrm{Cov}[m^c, M^c] \quad (16)$$

Proof. (Proposition 5) Applying the proof of Proposition 3 to female (by symmetry) and substituting $P(M_f) = 1 - P(F_f)$ yields :

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

Hence

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

rearranging yields the result. □

B The Earnings Gap with Extreme Levels of Bias in Referrals

In this section, I study the relationship between the earnings gap and the gender mix of physicians for different levels of gender bias in referrals. For small to moderate levels of gender bias, what determines the sign and size of the gender gap in earnings is mostly the gender distribution of doctors: the more of them are male, the greater the gap in favor of male specialists. As seen in Table 9 the gender gap in earnings for the estimated bias of 10% depends mostly on m, the fraction of males upstream, and varies only little with M, the fraction of males downstream. This fact is more generally true for small levels of bias, as can be seen by linearly approximating the gap, i.e., the difference in average demand between the genders, around $\beta = 0$:

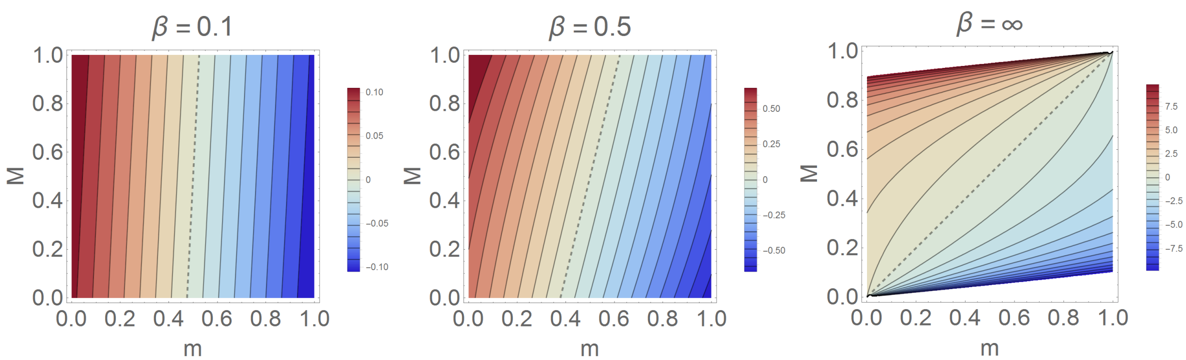
$$Gap = D^F - D^M \approx (2m-1)\beta + O(\beta^2) \tag{17}$$

That is, what matters for the size (and the sign) of the earnings gap is the fraction of males upstream: when they are the majority, men get more work downstream, and vice verse. In fact, the gap mostly depends on the gender distribution upstream even for relatively high levels of bias (Figure A1). However, for extremely high levels of gender bias, both upstream and downstream majorities matter:

$$\lim_{\beta \to \infty} Gap = \frac{m - M}{M(1-M)} \tag{18}$$

Specifically, when doctors refer *only* to specialists of their own gender, then the gender whose upstream fraction is greater than its downstream fraction gets more referrals.[28]

Figure A1: The Gender Earnings Gap With Different Levels of Bias



(a) (b) (c)

Colored contour plots of the gender earnings gap, $D^F - D^M$ (Equation 15) with different levels of bias β, for different fractions of males upstream m and downstream M. Blue (right) and red (left) darker shades reflect higher demand for male and female specialists, respectively. The zero-gap contours are dashed. For (a) the estimated level of bias for US 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 depends 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 males (females) upstream and downstream.

[28] I thank Alexander Frankel for bringing this case to my attention.

C Homophily Dynamics

The above analysis relied on a cross-section data. Here longitudinal data on the evolution of the network of referrals over several years is used to estimate the dynamics in referral relationships. I find same-gender links persist longer in time, suggesting a dynamic foundation for the static excess of same-gender links.

For the study of link persistence, I estimate the following specification:

$$P(Y_{jk,t+1} = 1 | Y_{jk,t} = 1, g, X) = \frac{e^{\eta_{jkt}}}{1 + e^{\eta_{jk't}}} \tag{19}$$

using data on all dyads (j, k) such that $Y_{jk,t} = 1$, where $Y_{jk,t} = 1$ if j referred to k at period t and $Y_{jk,t} = 0$ otherwise, and $\eta_{jkt} := \alpha_j + \beta \mathbb{1}_{g_j = g_k} + \delta X_{jkt}$. That is, (19) estimates the probability of links (referral relationships) existing at t would still exist at $t + 1$. Each dyad is included only once: for the first year it is observed. Since this specification is restricted to existing links, no sampling is necessary: all observed dyads are used.

Results: Link Persistence and Homophily Dynamics

Existing link are relatively more likely to persists between same-gender providers. Table A1 shows different estimates of link persistence, obtained from the sample of all initially connected dyads (physicians with referral relationships at the base year, defined as the first year they were observed in the data). Both logit and linear estimates with two-way fixed effects (for doctors and for specialists) show that same-gender links are more likely than cross-gender links to carry on to the following year (Columns 1–2). Columns (3) and (4) estimate separately for male and female doctors the probability of links persisting, again using physician fixed-effects to account for individual heterogeneity in the persistence of relationships. Consistent with the findings above, that male are much more likely to receive referrals, both male and female doctors' relationships with male specialists are more persistent, but persistence is significantly higher for male doctors than it is for female doctors ($p < 0.001$). That is, same-gender relationships persist relatively longer in time.

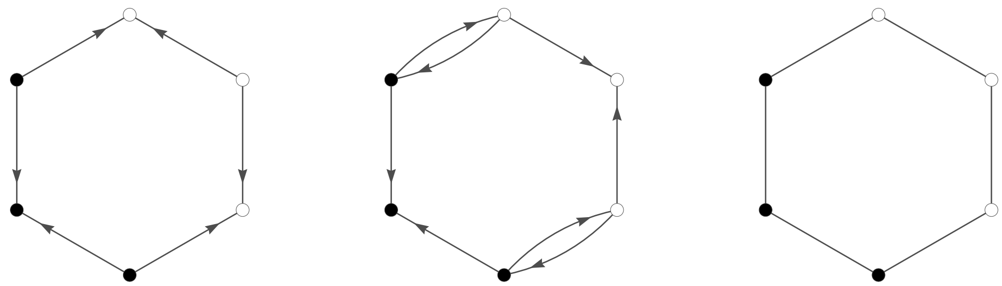
Table A1: Estimates: Link Persistence

	Link Persists Next Year			
	(1)	(2)	(3)	(4)
	Logit	FE	FE	FE
Same Gender	0.044	0.014		
	(16.2)	(24.0)		
Male Doctor	0.069			
	(16.3)			
Male Specialist	0.16		0.029	0.0062
	(57.4)		(50.4)	(5.89)
Similar Experience	0.0046	0.0011	0.0016	0.00085
	(38.1)	(39.5)	(55.3)	(15.8)
Same Hospital	0.12	0.027	0.030	0.027
	(28.5)	(29.5)	(31.6)	(14.3)
Same Zipcode	0.16	0.097	0.092	0.076
	(55.1)	(145.1)	(129.9)	(56.3)
Same School	0.088	0.013	0.015	0.014
	(26.9)	(17.1)	(20.0)	(9.09)
Constant	-0.81			
	(-193.7)			
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: t statistics in parentheses. Results of link persistence estimates. Column (1) shows estimates (5) for 2008–2012. Data consists of an observation for each linked dyad (j, k), for the first year it was observed in the data. The dependent binary variable is 1 if the link between the doctor j and the specialist k continued during the subsequent year. Same gender is a dummy for the specialist and doctors being of the same gender. Male specialists/doctor is a dummy for the specialist/doctor being male. Similar Experience is negative the absolute difference in physicians' year of graduation. Column (2) shows linear estimates with two-way fixed effect (for doctor and for specialist) using the same data. Columns (3) and (4) show linear estimates with one fixed-effects (for doctor), 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.

D Additional Tables and Figures

Figure A2: Homophily and Link Direction



(a) Homophily (b) No Homophily (c) Undirected

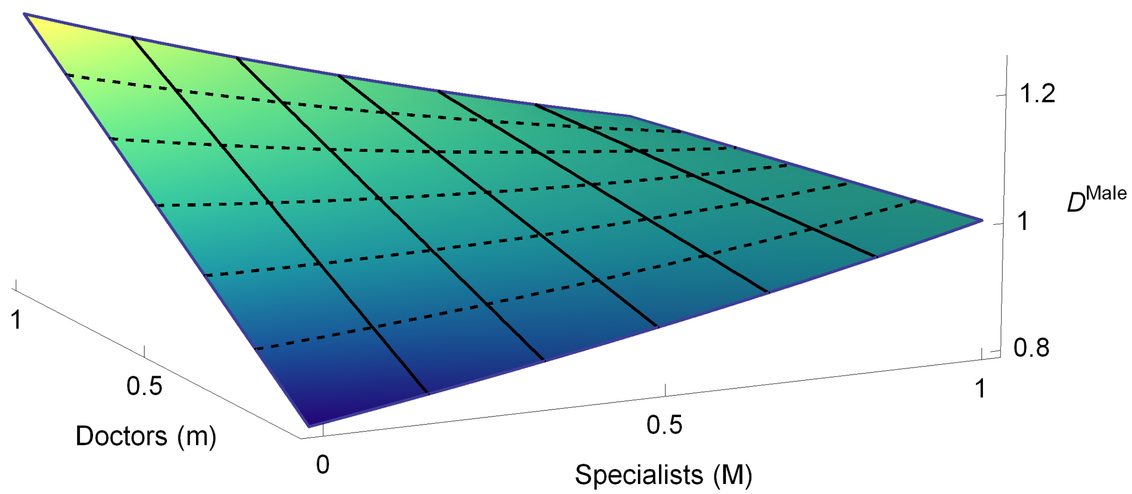
Link direction is important in defining homophily: the network (a) exhibits homophily while (b) does not, a difference concealed in their undirected counterpart (c).

Table A2: Homophily Estimates for Different Age Groups

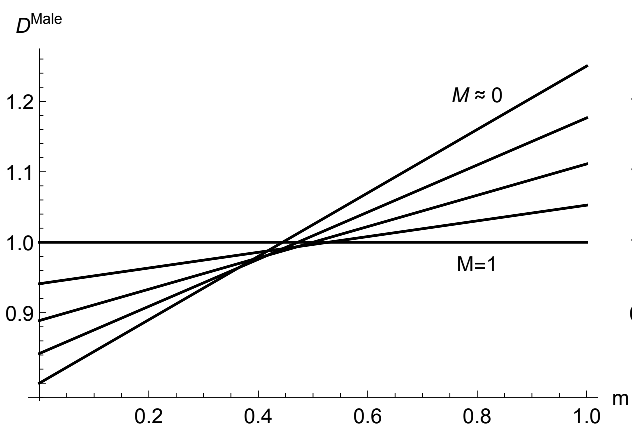
	Percent of Referrals to Male Specialists		
	Young	Old	All
Male Doctor	0.038	0.044	0.040
	(0.0011)	(0.0015)	(0.00090)
Male Patients (pct)	0.028	0.031	0.029
	(0.0024)	(0.0026)	(0.0018)
Constant	0.79	0.81	0.80
	(0.0078)	(0.0040)	(0.0032)
Specialty (Doctor)	Yes	Yes	Yes
Experience (Doctor)	Yes	Yes	Yes
Obs. (Doctors)	200,670	184,315	384,985
Rank	57	57	57
Mean Dep. Var.	0.82	0.83	0.82
R^2	0.035	0.041	0.039

Notes: standard errors in parentheses. OLS estimates of (2) are shown for three subgroups: young doctors (below median experience of 24 years, Column 1); old doctors (above median experience, Column 2); and all doctors together (Column 3). Despite the similar opportunity pools they face, older doctors exhibit stronger average directed homophily than younger ones.

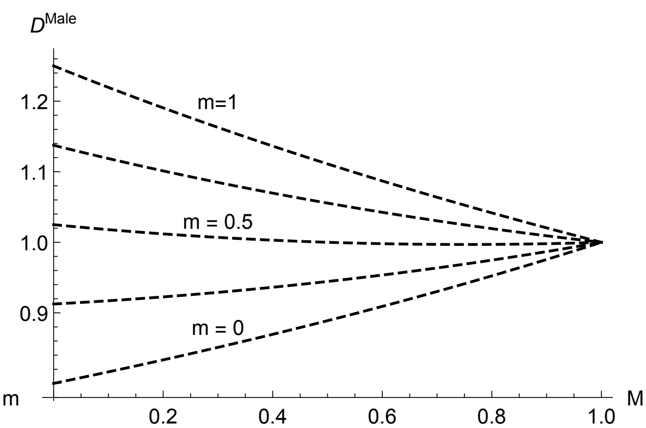
Figure A3: Average Specialist Demand with Gender-Biased Preferences



(a) Demand for Male Specialists over the Fractions of Male Doctors and Male Specialists



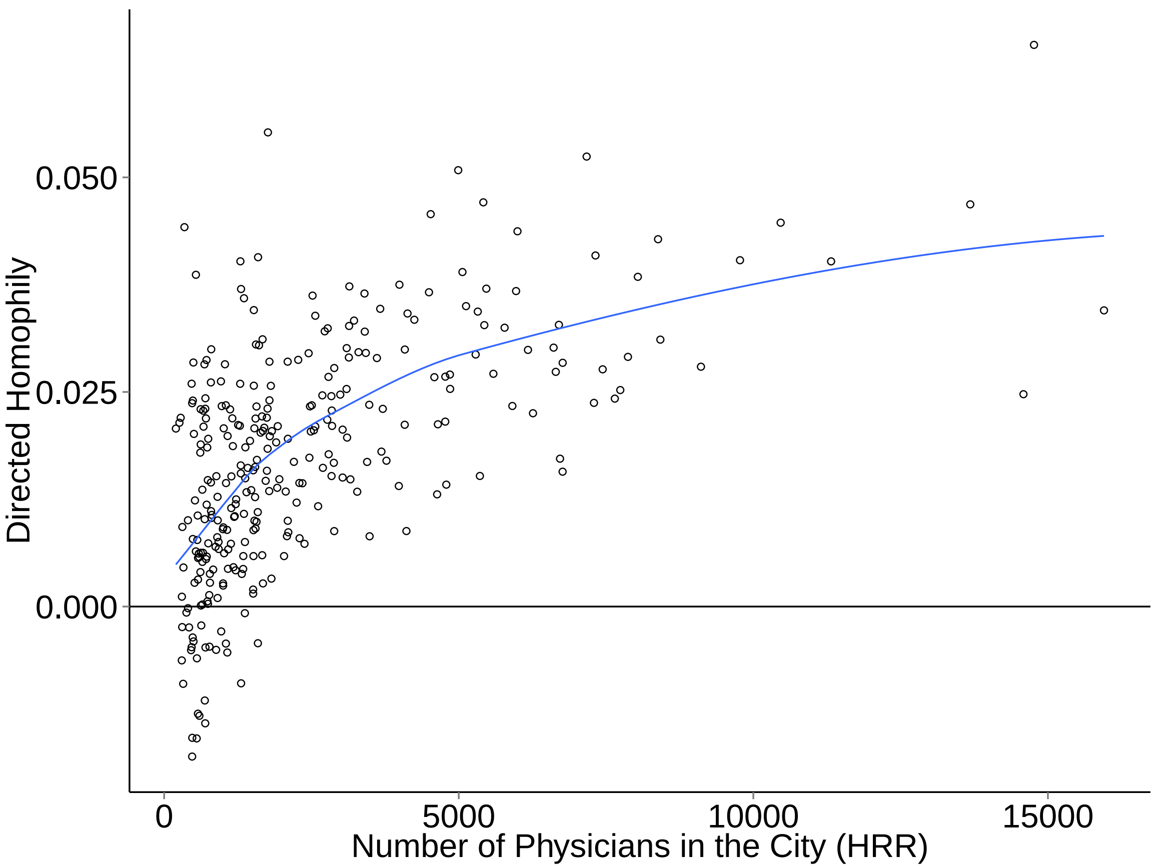
(b) Demand for Male Specialists and Male Doctors



(c) Demand for Male Specialists and Male Specialists

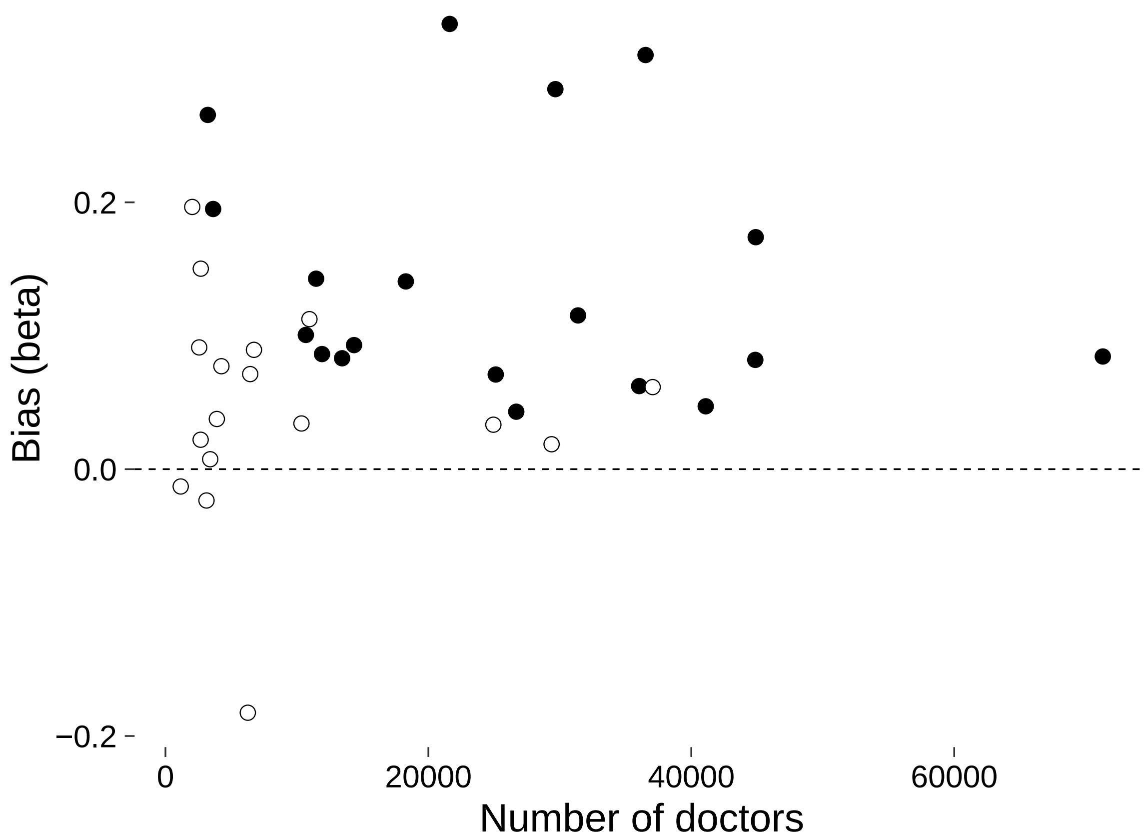
Notes: Average male specialist demand as a function of the fractions of male doctors and male specialists, with gender-biased preferences, i.e. $\beta > 0$ (calculated from the model with $\omega = 0.8, \eta = 1$). The surface in Panel (a) depicts the average demand D^{Male}, a function of the fractions of both male doctors, m, and male specialists, M. Panel (b) shows different cross sections of D^{Male} for different levels of M. Panel (c) shows different cross sections D^{Male} for different levels of m. Demand for male specialists is increasing the more doctors upstream are male. Whether specialists of the same gender substitute or complement each other depends on whether or not they are of the same gender as the upstream majority.

Figure A4: Homophily and Market Size



Notes: Homophily estimates of (2), estimated separately for each local physician market (Dartmouth Hospital Referral Region), over the overall number of physician in the market (men and women). The line is local regression (LOESS) fit. Beyond the mechanical effect of a reduction in variance of the estimates with sample size, estimated homophily is also greater for larger markets.

Figure A5: Conditional-Logit Estimates of Gender Bias, by Specialty



Notes: Estimates of β, the gender bias, from equation (5) with the sample in Table 6, separately for each medical specialty of the receiving physician. Black circles denote estimates that are significantly different than zero ($p < 0.05$).

Table A3: Homophily Estimates with Weighted Links

	Percent … to Male Specialists:			
	(1)	(2)	(3)	(4)
	Links	Patients	Claims	Dollars
Male Doctor	0.038	0.040	0.040	0.040
	(43.2)	(44.8)	(42.7)	(41.4)
Percent Male Patients	0.029	0.029	0.029	0.029
	(16.6)	(16.5)	(16.1)	(15.4)
Cons.	0.80	0.80	0.80	0.81
	(262.2)	(254.3)	(243.8)	(243.9)
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: t statistics in parentheses. OLS estimates of (2) using different definitions of link weights: The first column show results for unweighted links. Columns 2–4 shows results for different weights: number of patients, number of claims, and Dollar value of services.

Table A4: Conditional-Logit Estimates: Referral Probability, with Interaction Terms

	Doctor Referred to Specialist			
Doctor and Specialist:	(1)	(2)	(3)	(4)
Same Gender	0.0841	0.0662	0.104	0.0758
	(35.81)	(16.49)	(29.65)	(12.88)
Male Specialist	0.175	0.175	0.165	0.164
	(73.70)	(73.26)	(46.03)	(45.69)
Same Hospital	3.114	3.072	2.941	2.887
	(720.15)	(579.18)	(540.97)	(414.00)
Same Hospital x Same Gender		0.0598		0.0770
		(13.65)		(12.49)
Same Group	1.346	1.372	1.320	1.344
	(178.27)	(151.85)	(135.26)	(111.58)
Same Group x Same Gender		-0.0386		-0.0354
		(-5.24)		(-3.43)
Same Zipcode	1.074	1.065	1.054	1.047
	(219.53)	(163.68)	(164.04)	(118.78)
Same Zipcode x Same Gender		0.0130		0.0104
		(2.08)		(1.20)
Similar Experience	0.128	0.120	0.131	0.123
	(131.66)	(75.64)	(92.95)	(52.37)
Similar Experience x Same Gender		0.0117		0.0110
		(6.28)		(3.99)
Same Med. School			0.209	0.206
			(49.96)	(28.35)
Same Med. School x Same Gender				0.00447
				(0.54)
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 Sqr.	0.361	0.361	0.347	0.347

Notes: Results of conditional logit estimates of (5) for 2012, including interaction terms. See Table 7 notes for variable definitions and details.

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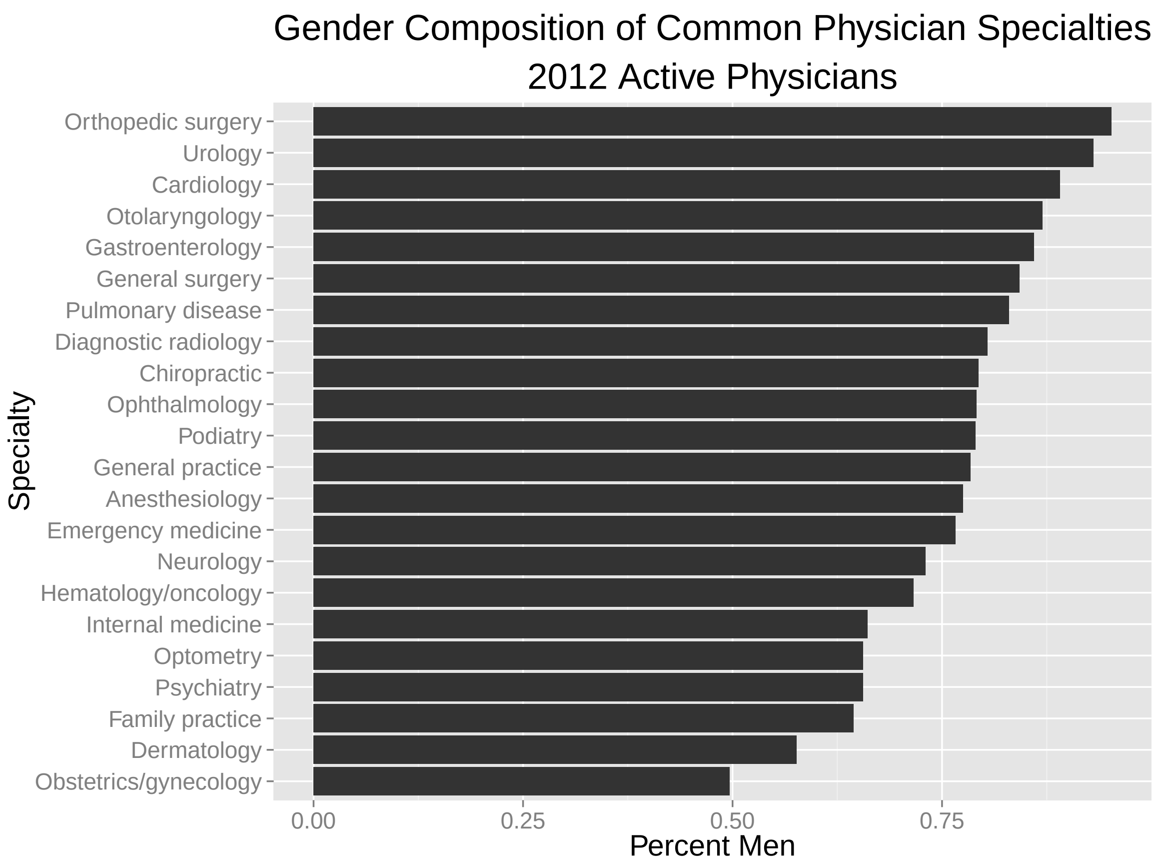
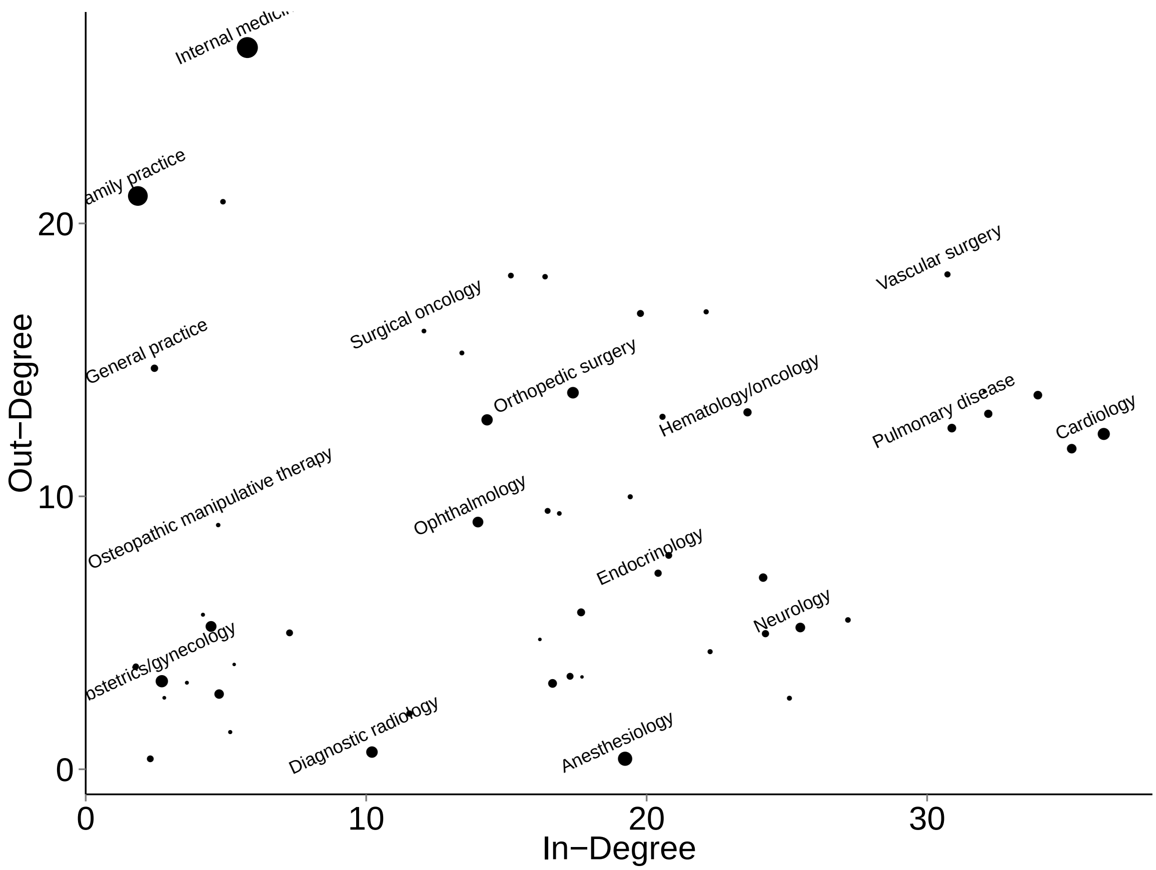
E Online Appendix Material

Figure A6: Male Fraction of Physicians in Common Medical Specialties



Notes: Percent of active physicians (with any claims) who are male, for the most common specialties by overall number of physicians. Columns are sorted so specialties with the greatest male shares are at the top.

Figure A7: Average Number of Referral Relationships by Medical Specialty



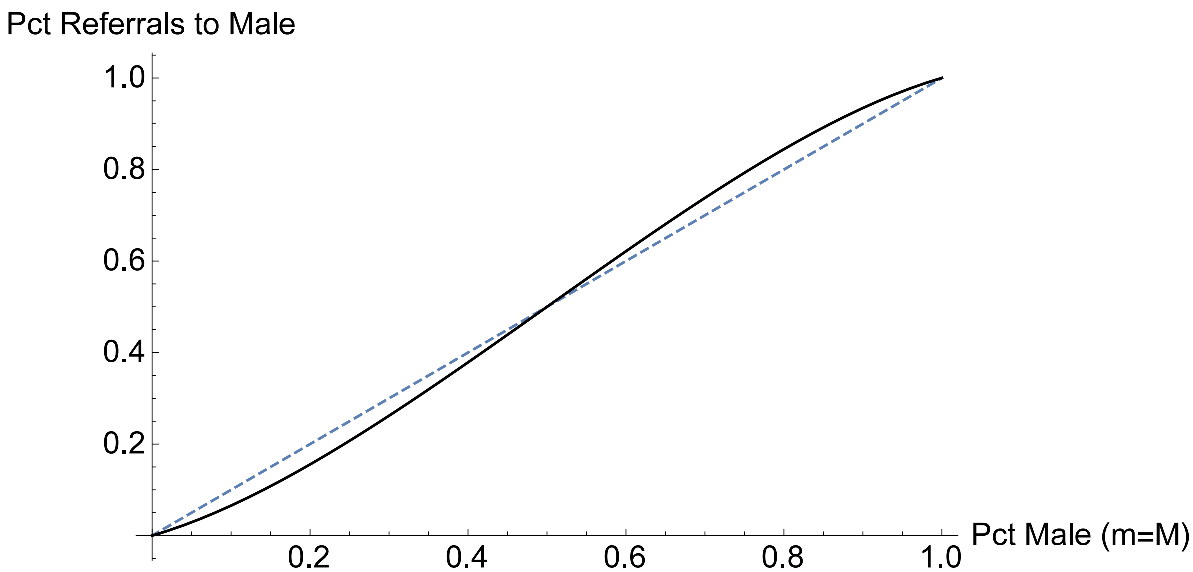
Notes: Degree-heterogeneity is to be expected since doctors in different specialties play different roles in routing patients: some mostly diagnose and refer out, others mostly receive referrals and treat. The figure shows degree distribution by specialty for 2012 referrals: Out-degree is the average 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 A5 for the data.

Table A5: 2012 Average Degree by Specialty

	Specialty	Indegree	Outdegree	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
41	Interventional radiology	25.1	2.6	938
42	Gynecologist/oncologist	13.4	15.3	834
43	Surgical oncology	12.1	16.0	684
44	Hematology	16.9	9.4	667
45	Osteopathic manipulative therapy	4.7	9.0	463
46	Nuclear medicine	5.2	1.4	289
47	Preventive medicine	4.2	5.7	217
48	Maxillofacial surgery	3.6	3.2	164
49	Oral surgery	2.8	2.6	108
50	Addiction medicine	1.7	3.7	77
51	Peripheral vascular disease	32.0	13.9	62
52	Neuropsychiatry	16.2	4.8	61
53	Podiatry	17.7	3.4	40

Notes: A link represents referral relationships with another physician from any specialty.

Figure A8: Overall Demand as a Function of Gender ($m = M$)



Notes: The figure plots the overall share of referrals going to male, as a function of the male population fractions, in the special case where $m = M$, for gender biased preferences ($\beta > 0$). The majority gender receives more than its share; the minority gender receives less than its share.