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

Dan Zeltzer*

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Abstract

Female physicians—now a quarter of active U.S. doctors—still work puzzlingly less than their male counterparts. This paper suggests an explanation: gender homophily in physician referrals (more same-gender referrals). I model how referral networks form when doctors decide which specialists to refer to. The model highlights that homophily can arise from either gender-biased preferences or physician sorting by gender into market segments like hospitals. I suggest how to separately identify and quantify gender bias in directed networks empirically and propose a homophily measure robust to differences in physician availability. Analyzing administrative data on 100 million Medicare physician referrals from 2008–2012 I find reduced-form evidence for gender homophily in referrals and estimate it is predominantly due to biased preferences, not sorting. As most referrals are still made by men, biased referrals lower demand for female specialists. Homophily explains 14% of the average within-specialty workload gap. Evidence suggests it further contributes to the absence of women from specialties relying on referrals from men. In the healthcare environment, my results imply that increased participation of female physicians generates positive externalities for related specialties. More generally, my findings suggest that homophily contributes to the persistence of occupational inequalities.

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

*Princeton University, Department of Economics, Princeton, NJ 08544 (dzeltzer@princeton.edu). I especially thank Janet Currie, Ilyana Kuziemko, Bo Honore, and Sylvain Chassang for invaluable advice throughout the research process. I thank Matt Jackson, Lisa Kahn, Alexandre Mas, Jessica Pan, Aureo de Paula, Tom Vogl, Juan Pablo Xandri, and seminar participants at UPenn, UT Austin, University of Maryland, EIEF, The Hebrew University and Tel Aviv University for helpful comments and discussions. I am also grateful to Jean Roth and Mohan Ramanujan for their assistance in obtaining and managing the data. Drs. David Krol, Bon Ku, Maria Maguire, and Steven Vogl provided helpful practitioners' perspectives. Financial support for this research was provided by the Program for U.S. Healthcare Policy Research of the Center For Health and Wellbeing at Princeton University.

1 Introduction

Despite the extensive entry of women into medicine, female physicians, like women in other occupations, still have substantially lower earnings: women work less than male physicians, and practice lower-paying specialties. Why would they make such choices, after long and costly investment in education and training as doctors? This question reflects a broader concern that despite the great convergence in education, female earnings still fall behind, for reasons not well understood (Blau and Kahn, 2000; Goldin, 2014). Supply-side factors are clearly important. For example, maternity-related career interruptions have lasting consequences (Bertrand et al., 2010).[1] But it is also acknowledged that some differences may not be voluntary, as confirmed by quasi-experimental evidence for gender discrimination (e.g. Goldin and Rouse, 2000). Yet, despite the importance of understanding the causes of earnings inequality, little work empirically addresses the demand side. Even with detailed data on individuals, testing for differences in opportunities due to gender is difficult: data typically record individuals in isolation, whereas opportunities intrinsically depend on interactions.

This paper proposes a new demand-side channel that contributes to the gender earnings gap: physicians prefer to work with others of their same gender. A key empirical prediction of such gender-biased preferences is that the network of referrals displays *gender homophily*: disproportionately more referrals within gender. I demonstrate this using data on 100 million referrals among half a million physicians from Medicare.[2] This web of micro-level interactions exhibits significant gender homophily and reveals how biased connections generate disparities.

This paper makes three main contributions. First, it studies homophily in an important setting where reimbursement rates are fixed, so pay gaps are not due to differences in compensation. Second, it defines a new measure of homophily that is robust to unobserved heterogeneity in the propensity to send or receive referrals. Third, it shows, for the first time, that a substantial part of the persistent gap in earnings of female relative to male physicians is due to gender bias in referrals. Significantly, this paper explains a part of the gap that 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. When facing otherwise similar specialists, doctors are 10% more likely to refer to those of their own gender. This

[1] Other works highlight gender differences in norms (Bertrand et al., 2013, 2014) and in preferences and attitudes towards competitions and negotiations (e.g. Croson and Gneezy, 2009). In contrast, educational gaps have closed and even reversed (Goldin et al., 2006).

[2] Medicare is the U.S. federal health insurance program for elderly patients, patients with certain disabilities, and patients with kidney failure. The use of administrative Medicare data to study referral networks has been validated by Barnett et al. (2011) who compared them against self-reported relationships.

bias contributes to the gender earnings gap by reducing demand for female specialists. It further discourages their entry to lucrative specialties relying on referrals from men. The insight that homophily contributes to the persistence of earning inequality extends to other occupations and to dimensions other than gender. It could apply to any domain where referrals, or more generally networking, are important—from hiring through employee referrals to venture capital funding.[3]

Identifying gender bias from observed homophily is challenging. Although homophily may reflect preferences for working with others of the same gender, it could also be due to differences in the gender mix of available specialists. There are two main concerns. First, *sorting*: the situation where physicians are unevenly distributed by gender across market segments (e.g. hospitals, or medical specialties). Sorting makes doctors more exposed to specialists of their own gender. Second, *heterogeneity*: systematic differences between the genders in the propensity to send or receive referrals (as highlighted by Graham, 2014). For example, if women chose to work less than men, their effective availability would be lower than is suggested by their fraction of the physician population.[4]

To identify the part of gender homophily in referrals that is due to gender-biased preferences, I begin by defining a new measure for homophily in directed networks, *directed homophily*, that fully accommodates unobserved heterogeneity in the propensity to refer or receive referrals. This measure compares the fraction of referrals made to male specialists between male and female doctors. Unlike previous measures, it not only allows for there to be fewer female specialists, but also "differences out" any other systematic differences between the genders. The assumption is that if male specialists have characteristics (observed or not) that inherently attract more referrals, then both male and female doctors are expected to refer more to them. But in the absence of gender bias, both genders should be referring the same fractions of their total volume to male specialists.

Reduced-form estimates show significant directed homophily in Medicare referrals. 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). This accounts for specialty and experience differences, and for the gender mix of patients. Most of the observed homophily (3 percentage points) still exists even when fixed-effects are used to narrow the comparison to that between doctors of the same specialty within the same hospital. To the extent such doctors face similar pools of specialists, directed homophily identifies gender bias in preferences. I also find homophily is somewhat

[3] For example, see Fernandez and Campero (2012); Burks et al. (2014); Rubineau and Fernandez (2015).

[4] It could also be, for example, that one gender is more inclined to refer patients rather than treat them. There could also be unobserved differences in quality between specialists of different genders. There are also observed differences between the genders in experience and specialization.

stronger among older doctors.

However, reduced form estimates of directed homophily identify only the presence of a gender bias in referrals, but not its size. For a given gender bias, homophily varies nonlinearly with the fraction of available male specialists. It mechanically approaches zero as this fraction approaches zero or one. Naive extrapolations from these estimates to other settings where this fraction is different are false. I therefore model link formation to explicitly account for this nonlinearity and separately estimate the parameter of interest: gender bias in preferences, which is used for counterfactuals.

To estimate gender bias in preferences, I model local referral networks as forming when *doctors* choose *specialists* to refer to.[5] 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 explicitly influence outcomes. The model makes explicit 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. In addition, the model yields two testable predictions. First, with gender bias, the minority receives fewer referrals. Second, with gender bias, homophily is greater in larger markets. Importantly, gender bias is also necessary for both predictions, so they provide an additional way to separate such bias from sorting empirically.

The model further illuminates the impact of homophily on specialist earnings. The relationship seems intuitive: with men handling most outgoing referrals, homophily implies more patients are referred to male specialists and fewer to female specialists. The model helps refine this intuition, and shows it holds only if observed homophily is due to gender-biased preferences. Sorting only affects the gender composition of referrals to female specialists, not their overall volume. Moreover, with gender-biased preferences the demand for female specialists depends on the gender composition of both doctor and specialist populations. Female specialists' demand suffers twice. First, there are fewer female doctors, resulting in fewer referrals to female specialists, and second, there are more male specialists, raising the opportunity cost of choosing a female specialist.

I estimate this model using Medicare data. The determinants of link formation are identified from the distribution of characteristics between chosen and unchosen specialists. The main concern is to identify the gender bias in preferences separately from sorting and heterogeneity. Heterogeneity is addressed by using a conditional logit specification akin to including doctor fixed-effects and by allowing for more referrals to male specialists. Tight control for sorting is facilitated by comprehensive and standardized reporting of physician

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

and pairwise characteristics, including: specialties and experience of both the doctor and the specialist, distance, shared hospital and practice group affiliations, and shared medical school. A more technical challenge is that the estimation of the model is computationally difficult: since referral networks are very large, there are many potential alternatives to each chosen specialist. I overcome this difficulty using sampling.[6]

Estimates show doctors' preferences exhibit significant gender bias: all else equal, doctors are 10% more likely to refer to a specialist of their own gender. I also find age-homophily: physicians are 9% 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. Gender-bias estimates are robust to multiple controls for sorting. They are also uniform across different markets. In contrast, directed homophily is increasing in the size of the market, conforming with the prediction of the model when homophily is due to gender biased preferences.

Next, I turn to study the consequences of homophily for the earnings gap. Physician Medicare payments exhibit a large gender disparity: on average, a female physician receives half the annual payments male physicians do. Since the Medicare payment schedule is common to all physicians, the setting is well suited for studying the impact of referrals on earnings, because this gap is exclusively due to differences in specialization and workload. Such differences also account for most of the earnings gap for physicians in other settings[7] and for other highly skilled professionals.[8] Decomposing the Medicare pay gap confirms earlier findings, showing that a third of it is due to specialty differences, and another significant part is due to women having more no-work spells. I focus on the half of the gap that remains unexplained.

Evidence suggests a significant and substantial contribution of biased referrals to gender earnings disparity. I test directly the model prediction that the gender composition of doctors should impact demand for specialists of different genders differentially. Using a monthly panel of individual payments for 2008–2012 I estimate whether specialists pay depends on the gender of primary care doctors near them. I find that, as predicted, more claims handled by male primary-care physicians in a market leads to higher pay for male specialists and lower pay for female specialists. Using specialist fixed-effects, this result is robust to both unobserved heterogeneity in specialists' labor supply and sorting into markets. It further

[6] I compare each chosen specialist to two others of the same market and medical specialty, while controlling for other characteristics. This design is known as *choice-based*, *endogenous stratified*, or *case-control* sampling (see McFadden, 1984; Manski and Lerman, 1977; King and Zeng, 2001). Directed homophily is estimated from the gender distribution of chosen specialists and thus does not require sampling.

[7] See Weeks et al. (2009); Lo Sasso et al. (2011); Esteves-Sorenson et al. (2012); Seabury et al. (2013).

[8] For example, Bertrand et al. (2010) show large gender workload gaps exist for MBA graduates, and Azmat and Ferrer (2013) show they exist for lawyers.

confirms that referrals are gender biased. Counterfactuals 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. This amounts to thousands of dollars a year, comparable to the gap due to gender differences in no-work spells. The overall impact of homophily on the pay gap could be even larger, as demand disparities appear to discourage female entry to higher-paying specialties, which rely more heavily on referrals from men—a "boys' club" effect. I test for this effect by leveraging observed differences in clinical dependency between different medical specialties. Using retrospective cohort data on physician specialty choices between 1965–2005, I find evidence consistent with female choice of specialties being affected by the paucity of female referrals from related specialties.

Data on physician first names provide an opportunity to test for prejudice, using a quasi-audit strategy. I check whether homophily is weaker when specialists' names are gender ambiguous (e.g., Alex or Robin) compared with names that reveal gender (e.g., Robert or Jennifer). I find homophily is unchanged, regardless of how revealing names are. This result rules out strong-form prejudice, one based on names alone. Doctors appear to know the specialists they work with and prefer them to be of their own gender. A separate analysis of link dynamics reveals that same-gender referral relationships are also relatively more persistent (i.e., less likely to dissolve over time) than between-gender ones.

The emerging picture is one of a widespread tendency to prefer working with similar others, which leads to an overall unfavorable environment for the female minority. The finding that women in upstream specialties induce positive externalities for women in downstream specialties has two implications. First, helping female doctors further integrate into primary care specialties would facilitate, through referrals, female integration into higher-paying specialties. In particular, it would promote female entry to 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. Second, although in the long run the part of the pay 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. More broadly, this paper demonstrates how homophily due to biases in professional interactions between individuals provides a key to understanding propagation and perpetuation of inequalities.

This paper proceeds as follows: Section 1.1 discusses related literature and background. Section 2 discusses the data. Section 3 discusses the gender pay-gap in Medicare. Section 4 defines, models, and estimates gender homophily and gender bias in Medicare referrals. Section 5 estimates the impacts this gender bias has on pay disparities. Section 6 considers prejudice and patient outcomes. Section 7 concludes.

1.1 Related Literature and Background

This paper is part of a nascent economic literature studying homophily, its causes and implications, and the challenges to identifying it. Homophily, the tendency of individuals to connect with similar others, is a robust phenomena, which has been documented by numerous studies in sociology, in many different contexts: friendship networks, organizations, weaker acquaintances, and online networks; it has been documented on different dimensions including: gender, age, race, religion, and educational level (for a comprehensive survey see McPherson et al., 2001). Most related to the current study, Currarini et al. (2009), show both homophily and degree disparity between types can be explained by an interplay of preferences and sorting, an insight used as a basis for my model; Graham (2014) shows homophily could be an artifact of heterogeneity and develops a method to account for it, which motivates the use of directed homophily to deal with heterogeneity. Another related work by Leung (2014) shows that inference about link formation is possible using a single network observation, based on the presence of effectively isolated parts in the network. Leung illustrates his method using public data on Medicare referrals, and shows that referrals between primary care doctors exhibit homophily on distance and institutional affiliation, and partly reflect reciprocity. He does not consider gender. Few papers study the consequences of homophily. One is Golub and Jackson (2012), which shows that clustering due to homophily slows down information dissemination and learning. The current study adds to that literature the idea that homophily leads to propagation of inequality in networks, and documents it for a large professional network.

Central to this paper are interactions between physicians through referrals. Referrals are ubiquitous in medicine, and are commonly used to resolve diagnostic or therapeutic dilemmas and to manage conditions that fall outside a physician's scope of practice (Forrest et al., 2002). For patients, referrals provide information about available providers: Although in Medicare it is not obligatory to obtain a referral to see a specialist, a third of all physician encounters are referred. Referrals are most central to the practice of primary care physicians, but are also a routine part of specialized care (Barnett et al., 2012a). Furthermore, referral use is increasing: Barnett et al. (2012b) show the fraction of ambulatory visits resulting in referrals has almost doubled between 1999–2009. Economists have mostly studied referrals in the context of their impact on care value and cost, in light of conflicting incentives of patients, doctors, and insurers.[9] In contrast, the current focus is on the impact on referrals on physician labor demand. Doctors are well aware of the importance of referral relationships for clinical and financial outcomes. There is plenty of on-line advice for physicians regarding

[9]For example, Ho and Pakes (2014) show that capitated insurance plans influence physicians referral decisions towards sending patients to cheaper, more distant, hospitals for childbirth.

how to establish and develop such relationships[10]. As per the reasons for choosing specific physicians to refer to, surveys show physicians consider the main factor after clinical appropriateness to be between-physician communication (Barnett et al., 2012a). Communication is also an oft mentioned process-measure for referral quality (Choudhry et al., 2014; Gandhi et al., 2000; Song et al., 2014; Mehrotra et al., 2011). The importance of communication for referrals hints as to why physicians may pick others of similar gender, age, or other attributes, since communication could be facilitated by such similarity.

In data and methods, this paper is part of a fast growing literature that uses large administrative data to solve nested prediction or classification problems, as a strategy for identification. For example, Currie et al. (2015); Currie and MacLeod (2013) demonstrate how large administrative databases of medical records can be used to benchmark the appropriate course of medical treatment (essentially a classification problem), a against which diagnostic skills can then be evaluated. In a similar spirit, I use extensive data on Medicare patients to find how medical specialties are related by referrals, and use this information to construct demand shifters for identifying the impact of homophily on specialty choice. And I use the names of nearly all U.S. physician to classify how informative first-names are about gender, to test for prejudice. Before analyzing the pay gap and homophily in physician referrals, I begin by describing the data.

2 Data

Since payments and referrals are jointly observed, confidential administrative data on Medicare physician claims are useful for studying homophily in physician referrals and its impact on pay disparities. These data present a departure from most previously used for studying earnings disparity: not only individual characteristics, but also micro-level interactions *between* individuals are observed. With more than half a million doctors over 306 local markets, data are fairly representative of the United States. This section describes the data, and the way event-level claims are linked and aggregated to a panel of payments and referral networks.

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. Medicare is the federal health insurance program for people who are 65 or older,

[10]For example, "Three Keys to Setting Up a Referral Network for Your Practice", `www.physicianspractice.com/blog/three-keys-setting-referral-network-your-practice`. Accessed August 2015.

certain younger people with disabilities, and people with End-Stage Renal Disease. The data contain claims from traditional ("Fee-For-Service") beneficiaries, which account for two-thirds of all Medicare patients, with 35 million covered lives (the other third is covered by private carriers). It is run by a government agency, the Centers for Medicare and Medicaid (CMS) and has standardized payments and billing systems.

Referrals are not limited or driven by institutional constraints. A useful feature of traditional Medicare for the purpose of this study is that beneficiaries can see any provider that accepts them: Unlike in private managed care 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.

I use the confidential version of the data, which contains both payment and referral information for each claim[11]. Only physician providers are included, based on CMS specialty code. 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. 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]. These data are combined with beneficiary residential zip-code and sex from the Master Beneficiary Summary File, the CMS database keeping track of all Medicare beneficiaries. Data are further combined with additional data on physician gender and other characteristics from Physician Compare, a public CMS database[13]. The included characteristics are: sex, specialty, medical school attended, hospital affiliation, and year of graduation (used to calculate experience).

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

[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/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.

Table 1: Descriptive Statistics: Physicians

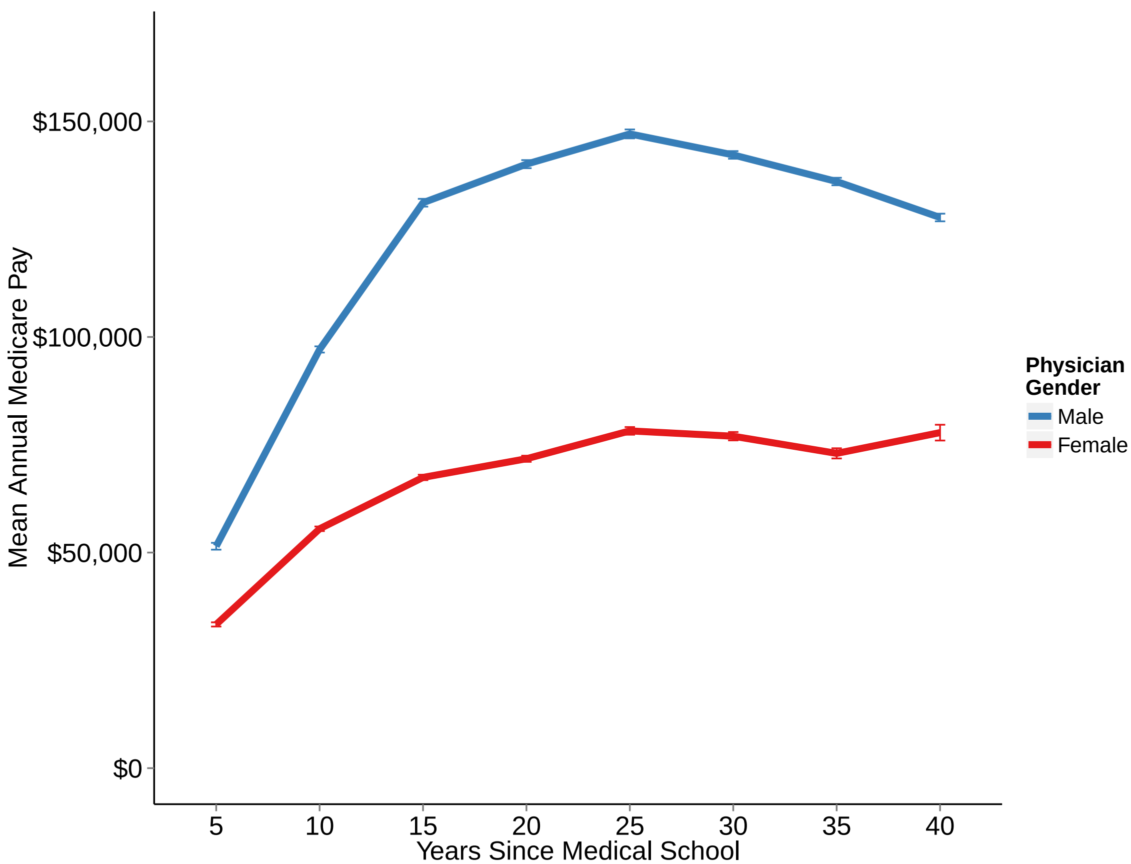
	All	Men	Women
A. All Physician			
Male Physician	0.723		
Experience (years)	22.4	24.2	17.9
Patients*	311	346	219
Claims*	755	850	515
Pay*	$106,112	$121,997	$64,620
Obs. (All Physicians)	530,357	383,525	146,832
B. Doctors (any outgoing referrals)			
Male Physician	0.734		
Avg. Outgoing Referral Volume*	$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.

dollars[14], about 3% of the U.S. GDP. 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.

Physician Payments To study the pay gap, I aggregate payments from claims to obtain annual Medicare payments for each physician, and link to physician characteristics from Physician Compare (see above). Mean pay and characteristics used for the analysis of the pay gap are shown in Table 1 and Figure A2.

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).

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

Referral Networks 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. Representing the referral relationships in Medicare over the period 2008–2012, this panel of directed and weighted networks is used for the study of homophily.

Augmenting network data with physician characteristics from Physician Compare allows me to calculate multiple dyad-specific attributes. For each dyad (pair of physicians) the following are included: practice locations (5-digit zipcode), whether physicians went to the same medical school or whether they share any hospital affiliation. To account for the impact of patient's gender preferences, the gender mix of patients referred is used. The use of physician and dyad attributes both supports the identification of homophily, and helps compare its magnitude against other determinants of referrals.

Men both send and receive more referrals on average, in part due to practicing different specialties. On average, conditional on making any referrals doctors refer to 16 specialists; and conditional on receiving any referrals specialists receive referrals from 18 doctors. But men send referrals to 5 more specialists and receive referrals from 6 more doctors. These gender differences are clearly related to occupational differences: as seen in Figure A3, the average number of working referral relationships each physician has (both incoming and outgoing) varies a lot by medical specialty: Primary care specialties, such as family medicine, mostly send referrals, whereas other specialties, such as neurology, mostly receive referrals. Surgical specialties (where men are the vast majority) both send and receive many referrals. Hence gender differences in participation in the different specialties translates to differences in both incoming and outgoing referral volume. It is therefore particularly important to control for underlying heterogeneity, specifically by specialty, when studying homophily in referrals.

Market Definition 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 are effectively isolated

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

networks: Less than 15% of referrals cross their boundaries.

To study the impact of homophily on pay, I construct, for each market (HRR), a monthly panel for 2008–2012 summarizing the fraction of primary-care claims handled by male doctors, and the fraction of services incurred by male patients (a control variable). In addition, total monthly payments are computed for each physician.

Cohort Data To study the impact of homophily on female entry to medical specialties I reconstruct a retrospective cohort panel, by calculating the number of currently-active physicians who have entered each specialty in each of the years between 1965–2005. Cohort information is obtained from medical school graduation years, recorded in Physician Compare. For each CMS specialty and each year, physician counts are calculated, for those that have graduated before and exactly at that year, and the fraction male among them. Cohort-specialty cells with fewer than 500 specialists are omitted.

3 Documenting and Decomposing The Gender Pay 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 reach its peak in mid-career. Since per service Medicare pays men and women equally, this gap only reflect disparities in work quantity and type. Only about half of the gap is explained by gender differences in characteristics and previously studied causes of gender earnings disparities.

To quantify the contribution of previously studied explanations and observable differences, 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 physician gender dummy, and X contains a constant and the following characteristics: physician specialty dummies; physician experience in years, including a quadratic terms; no-work spells, defined as the fraction of quarters without claims, a dummy for city (HRR), a dummy for the medical school attended. Results of this analysis are shown in (Table 2).

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

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
City	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. City 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.

but less than 6% of active orthopedic surgeons (Figure A2). More career interruptions for female also explain additional 10 log points (Table 2, Columns 1–3), consistent with previous works (Bertrand et al., 2010). Difference in experience, location, and medical school attended explain a little more. Yet about half of the within-specialty gap in workload remains unexplained. These results are discussed in more details in Appendix B.

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 Azmat and Ferrer (2013) 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.

4 Homophily in Referral Networks

In this section I show physician referrals exhibit gender homophily (i.e., doctors refer relatively more patients to their own gender). I define homophily and model it in directed networks to generate testable differences between its two potential mechanisms: preferences and sorting. I then estimate homophily using data on Medicare referrals, showing it is mostly driven by gender-biased preferences, not sorting.

4.1 Measuring Homophily in Directed Networks

Before examining evidence for gender homophily in Medicare referrals, I first propose a new measure of homophily for directed networks, which I term *directed homophily*. Unlike existing homophily measures, directed homophily compares referrals between the genders and not to population baseline fractions. This comparison identifies gender-bias in preferences separately from unobserved heterogeneity in the propensity to refer or receive referrals (e.g., due to differences in labor supply). This section discusses this measure.

Consider the network of physician referrals in a given market[16], where a link exists between *doctor* j and *specialist*[17] k if j referred any patients to k. There are two genders: male and female ($g \in \{m, f\}, G \in \{M, F\}$, lowercase indexes are used for doctors and uppercase for specialists). Let n_{mF} be the average number of links a male doctor sends to female specialists (likewise define n_{gG}). The average fraction of referrals male doctors send to female specialists is:

$$r_{F|m} := \frac{n_{mF}}{n_{mF} + n_{mM}} \tag{2}$$

Likewise define $r_{G|g}$. We are now ready to define directed homophily.

Table 3: Directed Homophily (DH)

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

$$DH = 85\% - 80\% = 20\% - 15\% = 5pp$$

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):

$$DH := r_{M|m} - r_{M|f} = r_{F|f} - r_{F|m}$$

Directed homophily exists ($DH > 0$) 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

[16]For concreteness I focus on gender homophily in physician referrals, but both this homophily measure and the following model are more broadly applicable to directed networks in general.

[17]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 actual 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. Medical specialties are explicitly introduced and discussed later.

[18]In general, referrals could also be biased toward the other gender as well, if $DH < 0$. In this case the network exhibits *directed heterophily.* Being the difference of referral rates denoted in percentage terms directed homophily is denoted in percentage points (or, in case referral rates are considered as fractions, as a scalar in the range $[-1, 1]$).

doctors who refer 80% of their patients to male specialists, so $DH = 5pp$ (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.

Directed homophily captures a tendency to link within gender beyond what is expected from random sorting. Particularly, 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.

Directed homophily admits the use of weighted links. Weights reveal whether same-gender referrals are not only more likely, but also more voluminous. 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.

Most previous studies of homophily have used a different homophily measure: *inbreeding homophily*.[19] inbreeding homophily uses population shares as the baseline:

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

$$r_{M|m} > M$$

Where M is the fraction of males in the specialist population. Likewise, female doctors exhibit inbreeding homophily if $r_{F|f} > F$. Where $F = 1 - M$ is the fraction of female specialists.

Note that inbreeding homophily by both genders immediately implies directed homophily, while the reverse is not true, e.g. if $r_{M|m} > r_{M|f} > M$.

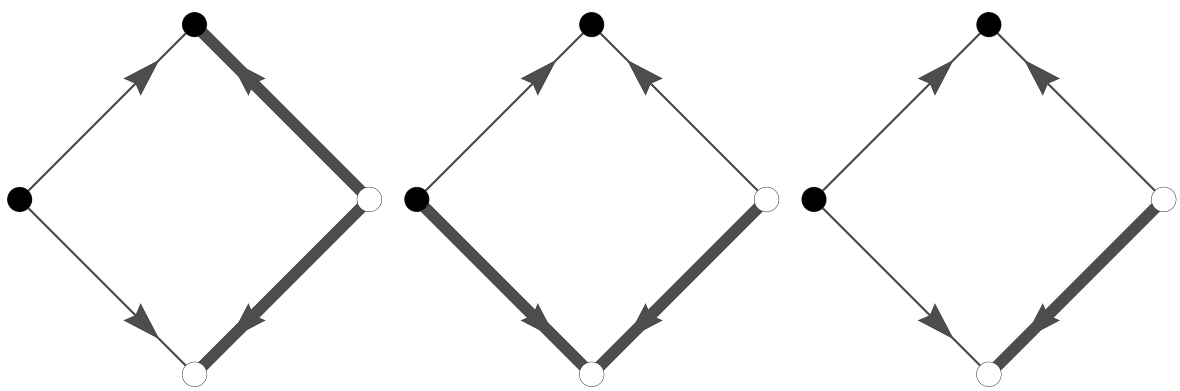
Because directed homophily is not using population gender shares as a benchmark, it is more robust than inbreeding homophily to potential heterogeneity in the propensity to send or receive referrals. For example, suppose male specialists are more likely to receive referrals

[19] 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.

(e.g., because they are more experienced or choose to work longer hours). Then there are more referrals to men than their fraction in the specialists population (as in Figure 2b), but unlike Inbreeding Homophily, directed homophily would not confound such differences with homophily (c.f. Figure 2c).

Note that the cost of directed homophily's robustness to heterogeneity is that it makes no distinction as to whether men or women are more homophilous: rates are compared against each other, and not to an external baseline. In other words, directed homophily measures relative, not absolute, gender differences in referrals. Absolute differences are generally not identified with unobserved heterogeneity. However, if heterogeneity can be ruled out or fully accounted for, inbreeding homophily is more informative.

Figure 2: Directed Homophily and Heterogeneity



(a) Men Refer More (b) Men Receive More (c) Directed Homophily

Directed Homophily (DH) is robust to systematic differences in the tendency to refer or receive referrals (e.g., due to men choosing to work longer hours): it compares referrals across genders, not to population fractions. For example, even though men (in white) are half of the specialist population, in (a) they send the majority of referrals (line thickness denotes volume) and in (b) they receive the majority of referrals. Yet in both cases $DH = 0$, since the fraction of referrals from men to men is the same as from women to men (Heterogeneity is "normalized", or "differenced out"). Only in case (c) $DH > 0$, since men refer not only refer more overall, but also refer disproportionally more to other men.

Before moving to model homophily, I show preliminary evidence for its presence in Medicare referrals.

4.2 Preliminary Evidence for Homophily in Medicare Referrals

Physicians are more likely to refer and receive referrals within their gender. Table 4 tabulates all sampled 2012 patient referrals by physician gender. Medicare referrals exhibit directed homophily: of all referrals by male doctors, only 15.23% were to female specialists. In contrast, of all referrals by female doctors 19.73% were to female specialists, so $DH =$

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.

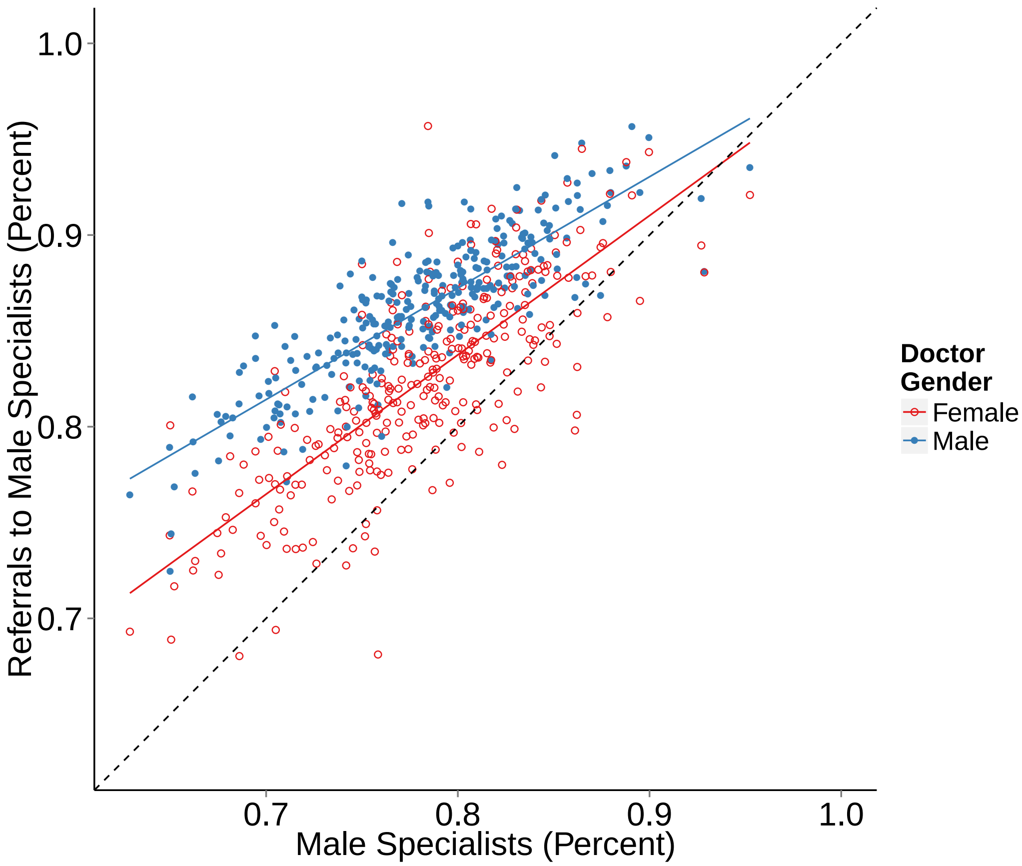
19.73% − 15.23% = 4.5% (Panel B of Table 4). (The same difference can be obtained from the difference between referral rates to male specialists: 84.77%, and 80.27%). Put differently, women refer 30% more often to other women than do men ($^{19.73\%}/_{15.23\%} - 1$). Were directed homophily zero, the rows of Panel B of Table 4 would have been equal to each other. Panel C of Table 4 shows the difference in terms of specialists' incoming work volume.

In itself, directed homophily (Table 4) does not imply physicians have gender-biased preferences, since it could reflect physician sorting by gender (e.g., into markets). It is therefore useful to consider homophily within local markets (Figure 3). Even within markets, male systematically refer more to male, suggesting gender-biased preferences might play a role. Also clear from this figure is that directed homophily is non-linear in the fraction of male specialists: it is always zero if there are only male specialists (or only female ones). A characterization of it thus requires accounting for the variation in gender composition of different choice sets faced by different doctors. To clarify this dependency, and to study homophily's consequences for the pay gap, I develop a model of referrals.

4.3 A Model of Homophily in Referrals

I model referrals to characterize homophily in directed networks, its mechanisms, and their consequences for the pay gap. Doctors choose specialists to refer to from local opportunity pools. Both gender-biased preferences (i.e., a preference for working with same-gender others), and physician sorting on gender may cause homophily, but these mechanisms have different implications. In particular, only homophily due to preferences increases with the availability of choice and with market size. And only gender-biased preferences make the demand for specialists decrease if fewer doctors share their gender (and even more if fewer fellow specialists do). I later estimate the model, and its predictions further illuminate my strategy to identify gender-biased referrals and their impact on female pay.

Figure 3: 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 fit lines.

Mechanisms: Preferences versus Sorting

To study the causes and consequences of homophily, 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:

$$\underset{k \in K_j}{\operatorname{argmax}} U_j(k) = \beta \mathbb{1}_{g_j = g_k} + \delta X_k + \varepsilon_{jk} \tag{3}$$

Where $\mathbb{1}_{g_j=g_k}$ indicates both physicians are of same gender, $(g_j, g_k) \in \{(f, F), (m, M)\}$. The choice of specialists depends on individual and specialist attributes (X_k; e.g., experience or other quality dimension), but may also depend on gender: $\beta > 0$ represents *gender-biased preferences.* For now, I abstract from the multiplicity of medical specialties (explicitly introduced later, in Section 5.2). If ε_{jk} is independently and identically distributed Gumbel-extreme-value, equation (3) yields the conditional logit probability for a referral from j to k, given gender and other characteristics:

$$p_{jk} := Pr(Y_{jk} = 1|g, X) = \frac{e^{\eta_{jk}}}{\sum_{k' \in K_j} e^{\eta_{jk'}}} \tag{4}$$

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

Homophily due to Gender-Biased Preferences Biased preferences cause 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 $j \in J$. Let $M = \frac{1}{|K|} \sum_k \mathbb{1}_{g_k = M}$ be the fraction of male specialists (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, there is 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):

$$p_{M|m} = \frac{M}{M + \omega(1 - M)} \geq M \geq \frac{\omega M}{\omega M + (1 - M)} = p_{M|f} \tag{5}$$

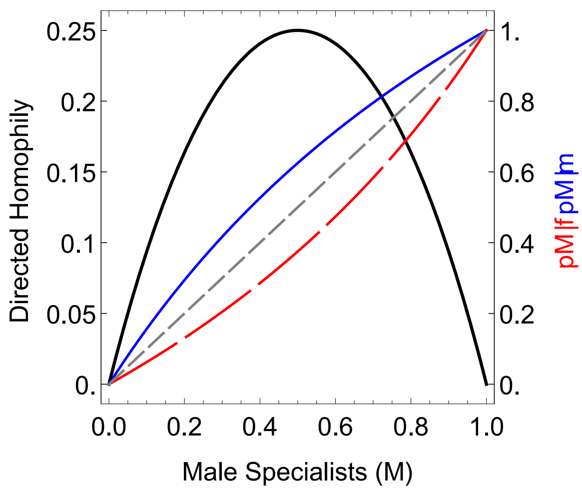
where $p_{G|g} := Pr(g_k = G|g_j = g)$ denote probabilities conditional on doctors' gender, $\omega := e^{-\beta} \in (0, 1]$. Equation (5) shows biased preferences result in directed homophily ($p_{M|m} > p_{M|f}$) for all $M \in (0, 1)$: doctors of each gender slightly discount the other (by a factor ω). Conversely, if preferences are unbiased ($\beta = 0$) referral rates to men are common to doctors of both genders:

$$p_{M|m} = M = p_{M|f} \tag{6}$$

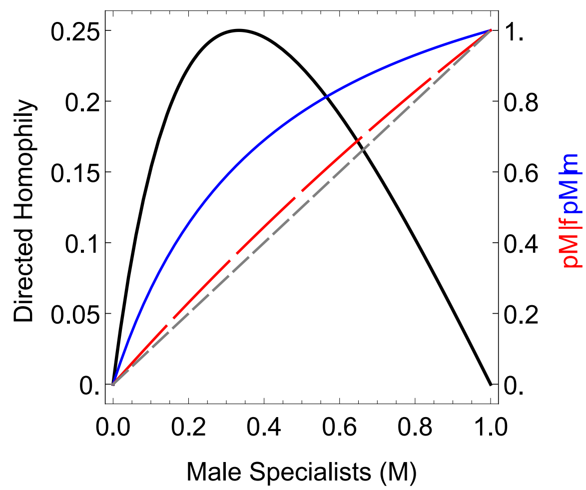
This is the baseline: directed homophily is zero. Clearly, if the most specialists are men then men refer more to men than to women: $p_{M|m} > p_{F|m}$, which is not to be confused with $p_{M|m} > p_{M|f}$.

An important implication of (5) is that observed homophily depends on the fraction of

Figure 4: 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.

male (or female) specialists in the opportunity pool: when the pool is more gender-balanced, observed homophily is greater (as illustrated in Figure 4a, and as seen before in Figure 3). 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 $M \in \{0, 1\}$, there is no homophily even if preferences are biased. Estimating preference bias is therefore more portable than estimating directed homophily, as it accounts for differences in the opportunity pool of specialists.

Considering the heterogeneous case ($\delta \neq 0$), in which there could be a correlation between gender and specialist characteristics that determine the volume of incoming-referrals (e.g. men have greater capacity to receive referrals, or women are better specialists). In this case, (5) becomes:

$$p_{M|m} = \frac{M}{M + \omega\eta(1-M)} \geq \frac{\omega M}{\omega M + \eta(1-M)} = p_{M|f} \tag{7}$$

Regardless of gender-biased preferences, if $\eta < 1$ male specialists attract a disproportionally high fraction of referrals from both genders (Figure 4b). 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 (7) too $p_{M|m} = p_{M|f}$ if and only if preferences are unbiased $\beta = 0$. So Proposition 1 holds also in 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 Markets Apart from preferences, physicians sorting by gender into markets also causes homophily, as it makes women and men more exposed to their own gender.[20] To see how suppose instead of a single market there is a set C of separate markets. Each market $c \in C$ has its own sets of doctors J^c and specialists K^c, with 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 $\mu^c = \dfrac{J^c}{J}$ (so $\sum_c \mu^c = 1$). The conditional probabilities of referrals to men now vary by market and are denoted $p^c_{M|m}$ and $p^c_{M|f}$. Define *Sorting* to be a positive correlation between the genders of doctors and specialists in a market[21]

[20] A market in the current context can refer not only for geographically-defined markets, but also for other segmentations that determine referrals (e.g., institutional affiliations).

[21] 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.

$\text{Cov}(m^c, M^c) > 0$ (equivalently, $\text{Cov}(f^c, F^c) > 0$). Homophily then arises at the aggregate, when all markets are pooled together:

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)[22].

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

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

The proof of Proposition 3 uses Bayes rule to relate aggregate and market-specific referral probabilities.

That is, the overall Inbreeding 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 while it is natural to derive the probabilities $p^c_{M|m}$ by nesting the single-market case discussed above, this decomposition does not rely on a specific parameterization of these probabilities: it only requires relevant moments to exist. Note also that sorting could also dampen homophily, rather than augments it: If $\text{Cov}[m^c, M^c] < 0$ then even if preferences are biased overall homophily could be zero.

A corollary of Proposition 3 is that when market boundaries are observed, preferences and sorting are separately identified: homophily observed within each market is due to preferences, while the rest is due to sorting. When markets boundaries are imperfectly observed,

[22]The proposition is stated here for inbreeding homophily for clarity. Its equivalent for directed homophily is in the appendix.

so multiple market *segments* (or sub-markets) are pooled together (e.g., if physician sort by gender into hospitals, but only city, not hospital boundaries are observed), Proposition 3 shows that homophily at each observed market is a combination of preferences and sorting into unobserved segments within this market.

Market Size Effects: A Marker for Preference-Based Homophily Another way to distinguish between preferences and sorting, even if market boundaries are imperfectly observed, is to consider market size $N = |K^c|$ (i.e., the total number of specialists). Consider a sequence of markets $c_1, c_2, \ldots$ of increasing sizes $N_1 < N_2 < \ldots$. Entry into markets is independent if individual specialist gender is Bernoulli distributed with mean M (the overall population mean). Alternatively, there could be unobserved sorting: Each market c may consist of unobserved and potentially sorted segments $l \in L_c$ such that referrals occur within segments: $K^c = \bigcup_{l_c \in L_c} K^{l_c}$, and $J^c = \bigcup_{l_c \in L_c} J^{l_c}$, and $K^j = K^{l_c}$ for all $j \in J^{l_c}$. Define the expected directed homophily $DH(N) = E[p_{M|m} - p_{M|f}|N]$. Define homophily as greater in large markets if for every market size N there exists $N' > N$ such that $DH(N') > DH(N)$. The next proposition shows conditions under which homophily is greater in large markets if it is due to biased-preferences, but not if it is due to sorting:

Proposition 4 (Market-Size Effects)**.** *Homophily is increasing in market size under the following conditions:*

i With gender-biased preferences, $\beta > 0$, if DH is strictly concave in M and specialists enter markets independently, then homophily is greater in large markets.

ii If preferences are unbiased, $\beta = 0$, homophily is only greater in large markets if sorting into unobserved segments $\text{Cov}[m^{l_c}, M^{l_c}]$ is greater in large markets.

Proposition 4 provides an additional test for gender-bias in referrals and an instrument for considering potential sorting threats. Intuitively, smaller markets are more likely to have extreme specialist gender-mix, which restricts choices, and prevents the gender-bias in preferences from being revealed. In contrast, if preferences are unbiased, for sorting to exhibit market size effects, it must be that (i) market boundaries are imperfectly observed, and (2) sorting into unobserved segments is itself increasing.

Homophily's Consequences for Gender-Disparities in Specialist Demand

Homophily causes disparity in demand between the genders: When preferences are gender-biased, specialist receive fewer referrals the fewer doctors share their gender. 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 5 (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 5 is by noting that demand for male specialist—the average number of referrals received (denoted by D)—is a weighted-average of doctors' respective probability of referring to male:

$$D = mp_{M|m} + (1-m)p_{M|f} \tag{8}$$

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 (5) into (8) and differentiating by m and M yields:

$$\frac{\partial D}{\partial m} = \overbrace{p_{M|m} - p_{M|f}}^{\text{directed homophily}} \tag{9}$$

$$\frac{\partial D}{\partial M} = (1-m)\overbrace{\frac{w(1-w)}{(1-M(1-w))^2}}^{\text{Complements (+)}} + m\overbrace{\frac{-(1-w)}{(M+w(1-M))^2}}^{\text{Substitutes (–)}} \tag{10}$$

Intuitively, specialists are better-off when most doctors upstream share their gender. But the magnitude of this effect is mediated by the number of downstream specialists who are of the same gender. And whether downstream specialists substitute or complement each other depends on the gender distribution upstream: with biased-preferences, a specialist of the same gender as of most doctors upstream is most popular if most other specialists downstream are of the opposite gender. But the converse is true for a specialist of the opposite gender than most upstream doctors.

To further develop this intuition, consider first the special case $m = M$: identical fractions of male doctors and specialists. With gender-biased preferences, the relationships between a population gender and the percent of referrals it receives is S-shaped[23] (Figure A4). With biased preferences the majority gender receives dis-proportionally more referrals.

The relationship in the general case where $m \neq M$ is a bit more nuanced, as demand depends on the gender of physicians both upstream and downstream. This dependency is illustrated in Figure 5, which depicts the average demand for a female specialist, as a function of the both the fraction of female doctors (upstream), and the fraction of female specialists (downstream). With gender-biased preferences, a female specialist faces higher demand the more doctors are female (9). The effect of other female specialists depends on which gender is the majority upstream: if most doctors are male, female specialists are complement, whereas if most doctors are female they are substitutes (10). As female are in fact both the minority of doctors and the minority of specialists in most markets (darker area of the surface), they suffer a lower demand due to both these effects: fewer doctors favor them, and it is easier for male doctors to choose male specialists over them.

Since specialists of the majority gender face higher demand, sorting—so far taken as exogenous—could also be endogenous. An implication of Proposition 5 is that it is better for female specialists to enter markets where a greater share of referrals is handled by female doctors. For an extreme example, if men and women were to sort into fully segregated markets, there would be no room for gender preferences to impact demand. For similar reasons, even partial sorting is beneficial. In Section 5.2 I developed and empirically test one aspect of this idea: that biased preferences may contribute to occupational segregation.

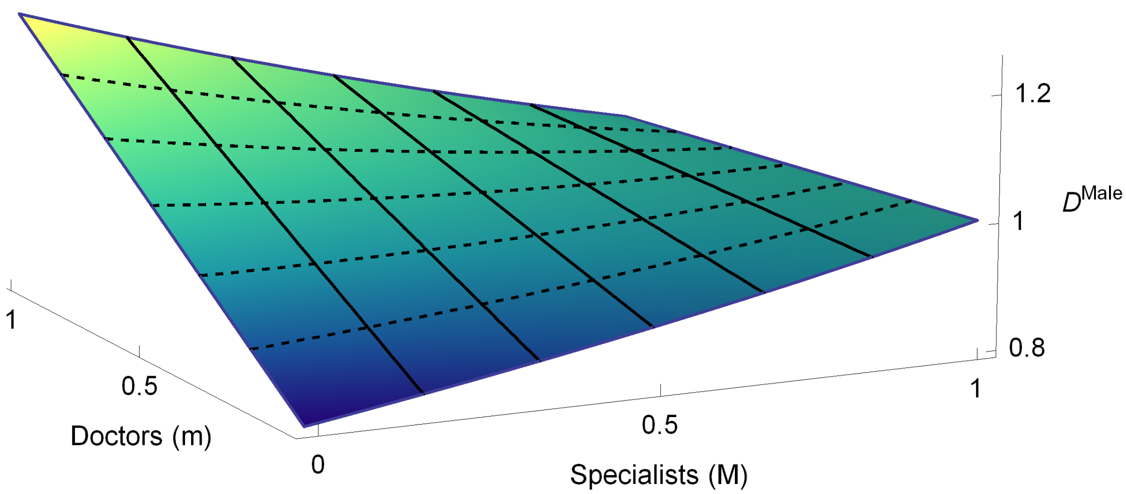
To conclude, this model of referrals shows homophily is a composition of gender-biased preferences and sorting. When driven by gender-biased preferences, homophily is stronger in larger markets and it results in fewer referrals to the minority gender. Induced demand disparities create incentives for specialists to segregate (i.e., join market segments where more referrals are handled by their own gender). I now turn to estimating homophily.

4.4 Empirical Strategy: Estimating Homophily and Gender-Biased Preferences

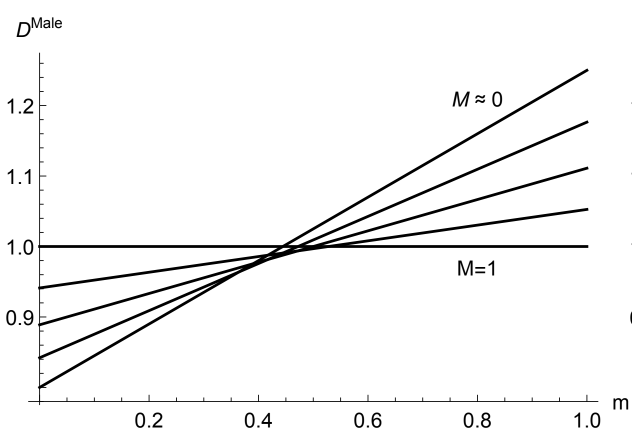
The above model shows directed homophily in referrals is a combination of biased preferences and sorting. In this section, homophily and its part due to preference bias are separately estimated. First, I estimate my proposed homophily measure, directed homophily (defined in Section 4.1) using reduced form specifications, by comparing outgoing referral rates of doctors of opposite genders. Second, I estimate preference bias using a discrete-choice model

[23]This case is similar to previous results of (Currarini et al., 2009, Section 4.5) for undirected networks. There too the basic mechanism underlying the S-shaped curve is preferences, albeit the setting is different.

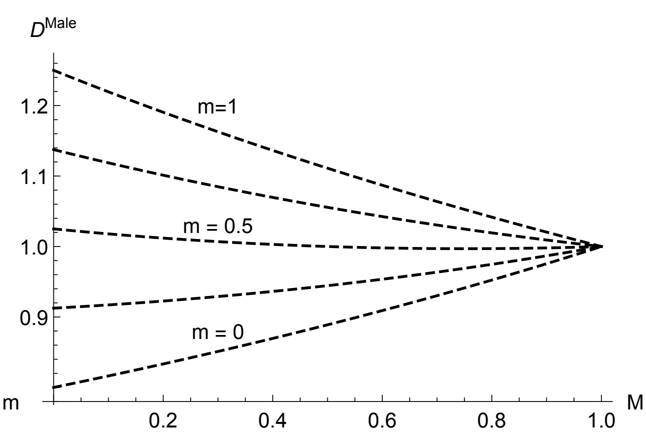
Figure 5: Average Specialist Demand with Gender-Biased Preferences



(a) Male Demand and Gender



(b) Male Demand and Male Doctors



(c) Male Demand 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 $\omega = 0.8, \eta = 1$). Panel (a) shows the average demand $D^{\text{Male}}(m, M)$, a function of the fractions of both male doctors (m) and male specialists (M). Panel (b) shows the cross sections $D^{\text{Male}}(m)$ for different levels of M. Panel (c) shows the cross sections $D^{\text{Male}}(M)$ 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.

of link formation (developed in Section 4.3), by comparing doctors' chosen specialists to those not chosen. Directed homophily is an easy-to-estimate measure that identifies the presence of gender-bias in preferences. But it does not identify the size of such bias, since it implicitly depends on the male specialist fractions in different markets (See Equation 7). It is thus natural in this context to use the model to account for the variation in specialist gender composition and estimate preference bias. This more fundamental parameter is then used for calculating out-of-sample counterfactuals.

Identification of homophily and preference-bias involves two main concerns. First, heterogeneity: if men systematically make and receive more referrals it could appear as if they tend to refer more among themselves. Second, sorting by gender could make male doctors more exposed to male specialists. I "difference out" unobserved heterogeneity by comparing referrals between genders, and by using within-physician variation. To address possible sorting, three completing approaches are taken: comparing physicians who face similar opportunity pools when estimating homophily, controlling for rich individual and pairwise characteristics when estimating the link formation model, and directly testing theoretical predictions that distinguish preference-driven homophily from sorting. Since referral networks are large, estimation also involves a technical challenge: it is difficult to compute statistics depending on the immense number of possible physician pairs. I therefore use reduced form estimates that rely on realized links (of which there are many fewer because networks are sparse). And I use choice-based sampling to estimate the model.

Reduced Form Estimation of Homophily and Preference Bias Directed homophily can be estimated by regressing the fraction of patients each doctor j referred to male specialists[24], r_{jM}, on the doctor gender g_j and other characteristics X_j:

$$r_{jM} = \alpha_1 + \beta_1 g_j + \delta_1 X_j + \varepsilon_j, \tag{11}$$

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.

To further estimate how much of homophily is due to sorting I use a variant of (11):

$$r_{jM} = \beta_2 g_j + \delta_2 X_j + \gamma_{h(j)} + \varepsilon_{jh} \tag{12}$$

Where now $\gamma_{h(j)}$ is a fixed-effect for the hospital with which doctor j is affiliated (for robust-

[24]That is, $r_{jM} = \frac{\sum_{k:g_k=M} n_{jk}}{\sum_k n_{jk}}$, where $n_{jk} \geq 0$ is the volume of referrals from j to k. The unweighted specification uses (with slight abuse of notation): $n_{jk} = \mathbb{1}_{\{n_{jk}>0\}}$.

ness, hospital interacted with medical specialty are also considered). As shown in Proposition 3, if doctors affiliated with the same hospital face approximately the same opportunity pool of specialists, K, then β_2 estimates average preference-based homophily.

Note that these estimates possess some desirable properties: They do not rely on assumptions regarding the opportunity pool faced by each doctor (they depend only on realized—not potential—links); they can easily incorporate link weights, capturing potential homophily through same-gender links being more voluminous; and they are computationally easy.

Yet directed homophily estimates are only useful for identifying the presence of biased-preferences, but not its size. Estimating the size of the bias requires accounting more structurally for the variation in male fractions across different choice sets, to which I turn next.

Estimation of Preference Bias I estimate gender-bias in preferences using a conditional logit model in (4) 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:

$$log\frac{p_{jk}}{p_{jk'}} = \beta(\mathbb{1}_{g_j=g_k} - \mathbb{1}_{g_j=g_{k'}}) + \delta(X_{jk} - X_{jk'}) \tag{13}$$

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: gender-bias in preferences. Directed homophily is a function of β and specialist availability (See Equation 5 above).

Identification: Homophily and Preference Bias The primary concern is to identify the part of homophily due to gender-biased preferences separately from homophily due to sorting and individual heterogeneity in the propensity to refer or receive referrals. To address it, I use reduced form estimates shown above to be robust to heterogeneity, and use hospital fixed effect to restrict comparison to doctors who face similar opportunity pools. Structural estimates accommodate heterogeneity by using within-doctor variation, and mitigate potential sorting 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 hospital affiliation. The residual threat is from factors correlated with the gender of both physicians and that determine referrals, or put differently, by sorting on unobserved attributes. 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 hospitals are also gender-sorted. Furthermore, 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.

I further validate the findings of gender-bias in preferences by directly testing two predictions of the model, which are derived in Section 4.3 above and shown to be unique to biased-preferences: First, an increase in homophily with market size (Proposition 4). Second, a correlation of doctors' gender distribution with specialist demand (Proposition 5).

Estimation: Homophily and Preference Bias Since the opportunity pools of specialists are very large (the number of possible links is square the number of physicians), considering all possible dyads is computationally difficult. I therefore estimate the model using choice-based sampling (also known as case-control sampling). That is, instead of considering all possible dyads, each *case*: linked dyad (j, k), 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. Controls for the other observed attributes are included[25]. Estimates are consistent under this sampling scheme (Manski and Lerman, 1977). Sampling is not required for the estimation of (11) and (12), as they rely solely on realized links.

4.5 Results: Homophily and Gender-Biased Preferences

Table 5 shows reduced-form estimates for directed homophily obtained from individual-physician data. Controlling for specialty, Medicare male doctors refer on average 4.3% more to male (Column 2), compared with female doctors of similar specialty and experience (Column 3). One concern is that patient preferences could lead to apparent physician homophily, if patients choose doctors of their own gender and request to see such specialists.[26] I address

[25]Sampling by the rather broad HRR and specialty cells implies a weak assumption about substitutability: it does not assume all specialists in a cell substitute for each other. Rather, it assumes that specialists outsize the cell do not (Thus, radiologists are assumed not to substitute for dermatologists, and physicians in Boston not to substitute for those in Chicago). The parameters, estimated using variation within those cells, capture the actual substitutability.

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

Table 5: Reduced Form 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

Derived from sample of 20pct of patients. (t-statistics in parentheses.)

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; t statistics in parentheses. Estimates of (11) and (12) are for the sample of doctors with any referrals. Percent of referral to male specialists is the fraction of each doctor's referrals-relationships who are with male specialists. Percent male patients is each doctor's fraction of referred patients who are male. Column 4 estimates the same specification of Column 3 using the sub-sample used in Columns 5 and 6, namely the sub-sample of doctors with at least one hospital affiliation. For further details regarding sample and variable definitions, see Section 2.

it by controlling for the gender-mix of patients (Column 4). Doctors with more male patients are more likely to refer to male specialists, suggesting patients too exhibit some homophily. But rather than explain physician homophily, patient homophily coexists with it. About a quarter of overall homophily can be attributed to systematic differences in the opportunity pool of specialists, as seen by the reduction in the magnitude of the estimate by 25% when fixed-effect are included for the doctors' hospital affiliation interacted with their medical specialty (Column 6). That is, male doctors affiliated with the same hospital, and of the same medical specialty (Column 7), refer 3% more to male specialists (i.e., the fraction of their working relationship which are with other men is 3% higher). As such doctors likely face similar opportunity pools of specialists, this suggests most homophily is driven not by sorting, but by preference for same-gender specialists.

Older doctors (with above-median experience) exhibit greater directed homophily than younger ones (Table A5). Older doctors could be more homophilous because they have more biased preferences. But this age-pattern of gender homophily could be the consequences of a longer accumulation process, in light of later findings that same-gender links are more persistent.

Homophily estimates are virtually unchanged when links are weighted. Appendix Table A6 shows estimation results for different measures of referral volume: number of patients, number of claims, or overall dollar value of services.

That homophily is mostly due to preference is further supported by the fact it is stronger in larger markets (Figure 6). The greater variance in smaller markets is due to the greater variability in the gender composition of smaller pools, and is expected regardless of the cause of homophily. But the increase in homophily with size is a marker of homophily being driven by gender biased preferences (Proposition 4).

Table 6 shows estimates of the link formation model. All else equal, doctors are 10% more likely to refer to specialists of the same gender. Estimates represent odds ratios, but due to sparsity they approximately equal the increase in link probability with an increase in the attributes[27]. 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 they are included as controls.

The estimated gender-bias is comparable with the reduced-form homophily estimates from Table 5, as seen by substituting $\hat{\beta} = 0.1$ in (5): facing an opportunity pool with 80% male specialists (roughly the U.S. average), the estimated gender bias of 10% implies directed

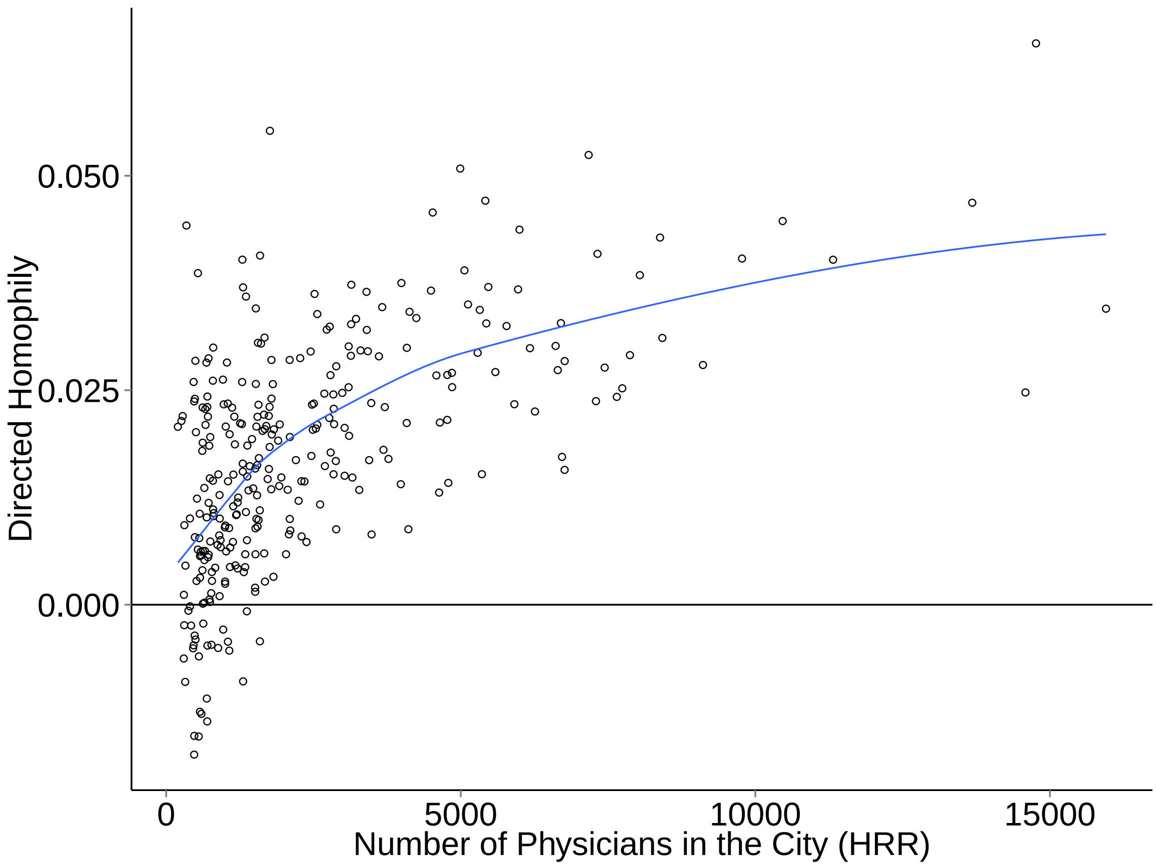
[27]Estimates close to zero approximately equal the percentage increase in probability. That is, using the notation of (3), around zero $\beta \approx \dfrac{p_{jk}|g_j = g_k}{p_{jk'}|g_j \neq g_{k'}} - 1$.

Table 6: Conditional Logit Estimates: Link Probability

	Link Exists (Doctor j Refers to Specialist k)				
	(1)	(2)	(3)	(4)	(5)
Same Gender	0.11***	0.10***	0.10***	0.096***	0.11***
	(56.5)	(51.3)	(51.2)	(46.7)	(37.4)
Male Specialist	-0.029***	-0.024***	-0.024***	-0.00034	-0.016***
	(-14.9)	(-12.3)	(-12.4)	(-0.16)	(-5.22)
Similar Experience		0.0091***	0.0091***	0.0088***	0.0090***
		(111.1)	(110.3)	(102.9)	(73.1)
Same Hospital			1.16***	1.02***	0.95***
			(261.1)	(224.7)	(158.5)
Same Zipcode				2.28***	2.22***
				(487.4)	(373.6)
Same School					0.27***
					(72.8)
Obs. (Dyads)	14,222,742	14,217,381	14,217,381	13,991,067	6,607,612
Clusters (Doctors)	375,032	374,908	374,908	366,968	242,352
Pseudo R Sqr.	0.000	0.001	0.013	0.105	0.106

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; t statistics in parentheses. Results of conditional logit estimates of (4) 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 was a link between the doctor j and the specialist k during the year. Same gender is a dummy for the specialist and doctors being of the same gender. Male specialists is a dummy for the specialist being male. Similar Experience is the negative of the absolute difference in physicians' year of graduation. Schooling information is only partly available.

Figure 6: Homophily and Market Size



Notes: Homophily estimates of (11), 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.

homophily of 3.2 percentage points, net of sorting (the implied directed homophily at the maximally-diverse pool, with the same number of men and women, is 5 percentage points).

In addition to gender homophily, referrals also exhibit homophily on other dimensions: doctors refer disproportionally to specialists of similar experience, and to specialists that previously went to the same medical school. A doctor and a specialist one year closer in age (approximated by graduation year) have 0.9% 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 30% 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 effect of gender against the effects 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 a ten years age difference. And the effect on referrals of being of the same gender is about a third of that of having graduated from the same medical school. Note however, that as long as no age group or medical school dominates the upstream gender population these dimensions of homophily do not create real disadvantage.

In Appendix D I further study the dynamics of homophily, and find same-gender physicians are more likely to maintain referral relationships over time. I find 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 are more common partly as a consequence of a dynamic process in which same-gender relationships are more likely to survive over time.

In sum, both reduced-form estimates of homophily and structural estimates of link formation point to a significant gender homophily in referrals, mostly due to gender-bias in referral choices. That is, men still refer to men more than their female counterparts facing a similar set of specialists. That observed homophily is not due to residual sorting on unobserved factors is further supported by the findings that homophily is stronger in larger markets, as predicted from the model only for gender-biased preferences. 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 is that homophily should divert demand away from female (the gender minority), and generate a gap in pay. I next turn to test this implication directly.

5 Homophily's Consequences for the Pay Gap

The previous section has shown homophily in referrals is ubiquitous and is largely due to gender-biased preferences. In this section I directly test the model prediction that gender-biased referrals should divert work away from women, the minority, towards men, the majority. Such an effect could work on both the intensive and the extensive margins: female specialist may be working less, or they may be discouraged from choosing specialties relying on referrals from male. I find evidence for both.

5.1 Homophily's Impact on The Gender Workload Gap

The model above predicts women should receive fewer referrals because they are the minority of doctors and specialists (Proposition 5). Because female specialist pay is predicted to be negatively correlated with to the fraction of male doctors in their market, inter-temporal variations in this fraction identify the link between homophily and pay, and reveal its strength.

I find that a higher monthly fraction of claims handled by primary care doctors (who make most referrals) is associated with greater pay for male and lower pay for female non-primary-care specialists. The effect is large: were half of all primary-care referrals handled by women (as opposed to the current 30%), demand shifted to female specialists would reduce the average gender-pay gap for specialists by between 10–16%.

Strategy

To directly estimate the effect biased referrals has on the pay gap, I use the model prediction that with homophily female specialists have less work the more referrals are handled by men (Proposition 5). I focus on primary-care physicians, who handle the majority of outgoing referrals. Using a monthly panel of physician payments I estimate:

$$log(Pay_{k,t}) = (\beta_M \mathbb{1}_{g_k=M} + \beta_F \mathbb{1}_{g_k=F}) m_{c(k,t),t} + \gamma_t + \alpha_k + \varepsilon_{k,t} \quad (14)$$

For all non-primary care physicians 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 percent of claims handled by male primary-care doctors at specialist k's market at month t; 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.

The inclusion of specialist fixed effects means the identifying variation is within individual physicians, over time. This specification therefore allows for systematic differences between male and female specialists, differences we know exist (e.g., due to maternity-related no-work spells), and does not confound them with homophily. It 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 physicians and decrease the monthly workload of female physicians in non-primary care specialties. To rule out the possibility that patient homophily may confound the results, controls are included for the monthly fraction of services incurred by male patients.[28]

Since upstream demand is correlated with the gender composition of doctors only if preferences are biased, testing for such correlation, apart from quantifying the impact of homophily on the gap, further supports the presence of preference bias.

The empirical model (14) is estimated using a monthly panel of individual-physician pay

[28]By including a term $(\delta_M \mathbb{1}_{g_k=M} + \delta_F \mathbb{1}_{g_k=F})\mu_{c(k,t),t}$ 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.

for the period 2008–2012. The data are described in Section 2 above.

Results: Homophily's Impact on The Gender Workload Gap

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-specialists variation in workload, so they are not an artifact of systematic differences in between male and female specialists labor supply.

Table 7: Male Fraction of Primary Care and Specialist Workload

	(1) Log monthly pay	(2) Log monthly pay
Female Specialist X Pct male PCP (city)	-0.26***	-0.27***
	(0.054)	(0.054)
Male Specialist X Pct male PCP (city)	0.49***	0.47***
	(0.029)	(0.029)
Month Dummies	Yes	Yes
M,F x Pct Male patients (city)	No	Yes
Obs. (Phys x Month)	18087629	18087629
Clusters (Phys)	418939	418939
R Sqr.	0.0323	0.0322

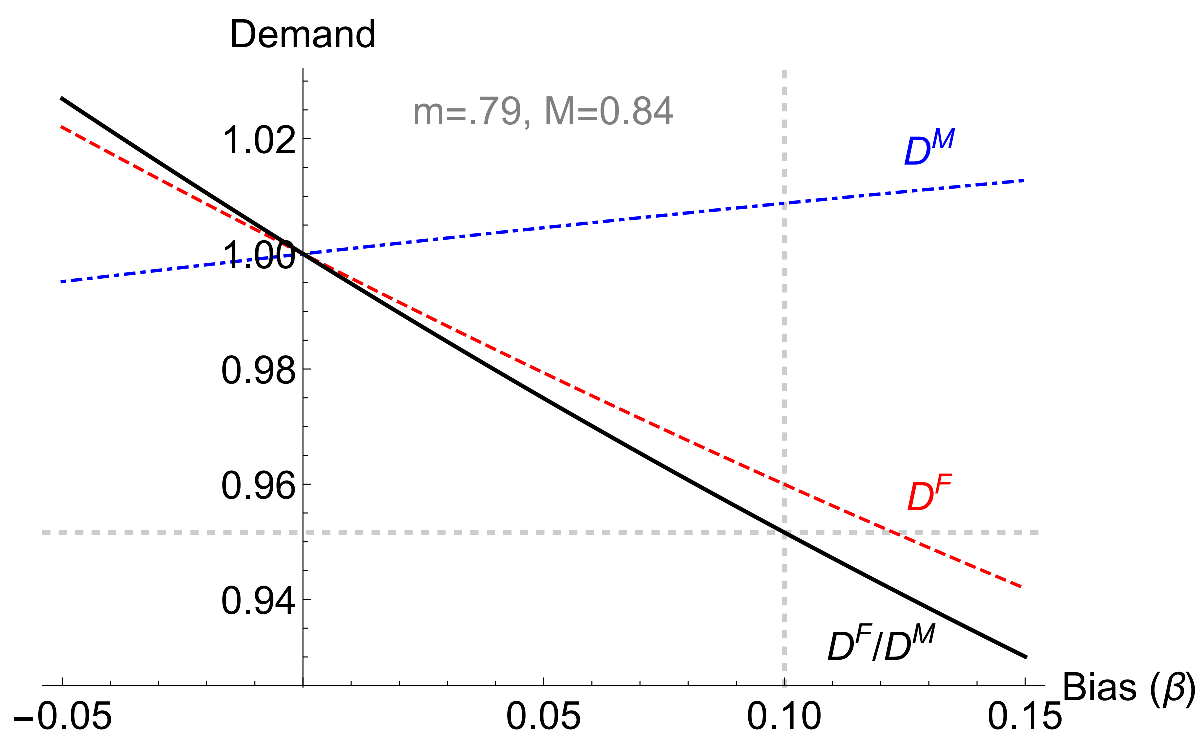
Notes: Fixed-effect estimates of (14) with and without controls for patient gender. For each specialists (non-primary-care physician), monthly pay is the the total monthly pay for Medicare services billed. Specialist gender is interacted with the fraction of claims handled by male primary-care physicians 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.

This relationship supports my previous results, showing homophily is indeed due mostly to gender-bias in referrals. As shown above (Proposition 5), demand for specialists varies with their gender and upstream gender fractions only when homophily is caused by gender-biased preferences, not sorting.

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 (about 35%). 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. These estimates do not account for indirect benefits from referred patients, such as returning patients (in specialties where patients are monitored repeatedly), or from additional patient obtained through word of mouth. However, neither they hold constant that overall volume of patients, and therefore should be taken as suggestive, rather than conclusive.

A more appealing method to quantify the counterfactual impact on the gender pay gap is to use the model estimated in Section 4 (Figure 7). I calculate the counterfactual demand for the average upstream and downstream gender fraction in the United States. Overall, biased-preferences of the level estimated from Medicare referrals result in 5% lower demand for female, relative to male. This is in addition to any other factors that may contribute to the gap, such as differences in labor supply. Note the asymmetric effect of preference-bias on demand by gender: it increases the demand for men while decreasing the demand for women. This is because men are the majority upstream.

Figure 7: 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.

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 current referral being handled by men.

These estimates of the short-run, intensive impact of biased-referrals on the gender pay gap could be further augmented by long-run, extensive effects on specialty choice, discussed next.

5.2 Homophily's Impact on The Gender Specialization Gap

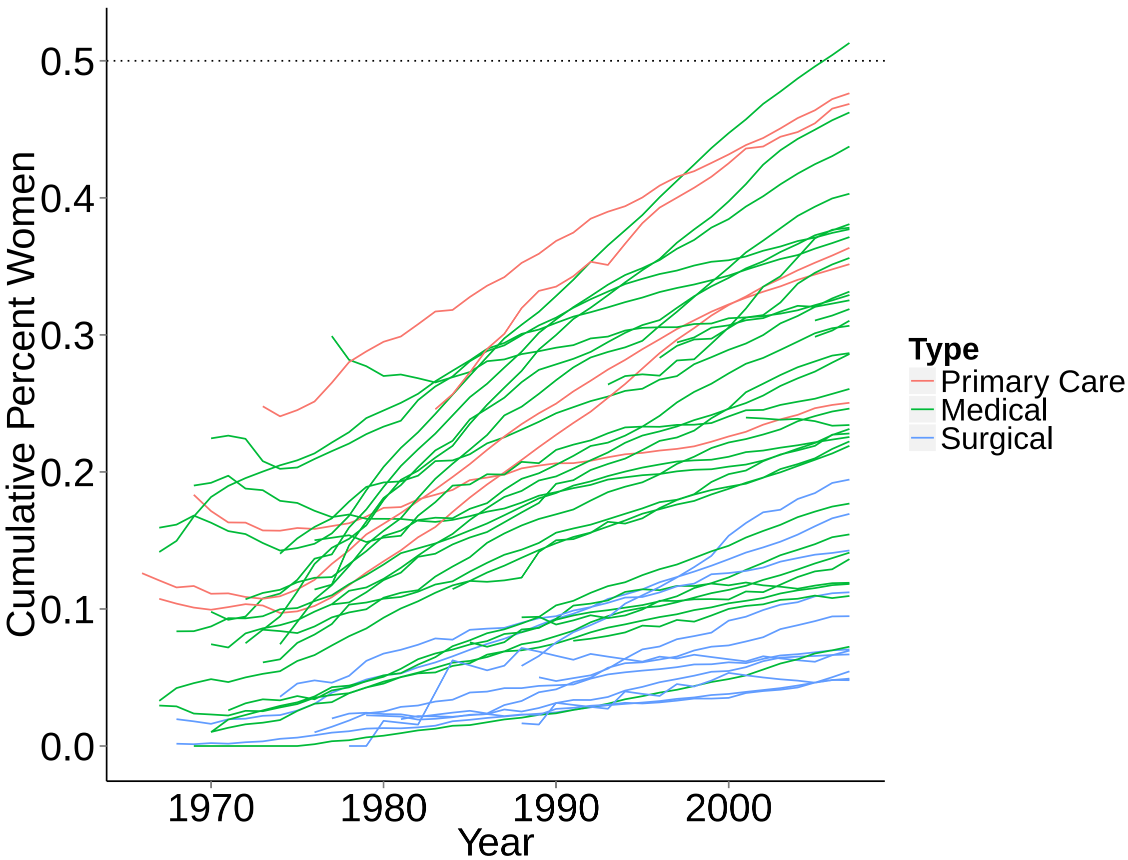
Women choose lower paying specialties. As shown in Section 3, close to 20% of the unconditional pay gap are due to differences in specialty choice. Although recent decades are marked by great equalization in entry into medicine (from 10% female graduates in the 1970s to a half today), still many fewer women enter high-paying, surgical and medical specialties (Figure 8). Differences in specialty choice may exist because women, balancing career and family, put a premium on flexibility or prefer shorter training (for example, surgical specialties require more years of residency, fellowships, and later permit less flexibility in schedule). The great changes in entry of the last decades are due, according to such explanations, to shifting family roles, attitudes and preferences of women.

Yet occupational differences may be further driven by homophily: when a substantial fraction of work in a specialty relies on referrals from men, which advantages men, women may be less inclined to join. In this section I present cross-sectional and longitudinal evidence showing such "Boys' Club" effect is empirically plausible. Currently, there are more women in specialties where more referrals come from women. And analysis of cohort data for 1965–2005 shows female entry to specialties was higher when a greater fraction of their referrals came from female. To identify the impact of homophily on entry, I first use data on patient flows to estimate how medical specialties are interconnected by referrals, then use these estimates to approximate the share of referrals made by female to each medical specialty at each past period.

Strategy: Identifying Homophily's Impact on Medical Specialty Choice

My empirical strategy to identify the link between homophily and specialization relies on testing whether over time, women enter specialties where a larger share of referrals comes from women. The main concern is to separately identify the effect of homophily in referrals from unobserved specialty characteristics that may attract women. To address it, I use variation between cohorts in the fraction of referrals each specialty received from females at the time of specialty choice, variation induced by differential female entry to *related* specialties over time. For example, cardiac surgeons often receive referrals from cardiologists, but rarely if ever from dermatologists. So because of homophily female entry to cardiac surgery should have responded to the fraction of female cardiologists, but not to the fraction of dermatol-

Figure 8: Female Participation Rates by Medical Specialty, 1965–2005



Notes: Percent of active female physicians by medical specialty, for different specialty categories. Source: Cohort data reconstructed from current data on graduation years. Specialty-year cells with fewer than 500 physicians were omitted.

ogists. To extend this idea to all medical specialties, I leverage the fact clinical relations between specialties, which are essentially a technology parameter unrelated to gender, and are revealed from extensive data on patient flows.

To provide theoretical basis for the following test, I being by formalizing the interconnectedness of specialties used for identification, by extending the model from Section 4.3 to multiple specialties.

Extension of the Model to Multiple Specialties Let (with the usual abuse of notation) $S = \{1, \ldots, S\}$ be the set of medical specialties, and suppose doctors choose specialists as in (3), separately for each specialty. The relative volume of referrals between specialties depends on medical practice and can be summarized in a transition matrix:

$$\mathbf{R} = \left[r_{s|s'} \right]_{S \times S} \tag{15}$$

Where $r_{s|s'}$ is the average fraction of specialty s referrals coming from specialty s', so $\sum_{s' \in S} r_{s|s'} = 1$. The fraction of referrals made by men to each specialty depends on exactly which other specialties refer to it. To see how, for each specialty $s \in S$ denote by M_s be the fraction of men practicing it, and by m_s the fraction of referrals to it made by men. In vector notation: $\mathbf{M} = (M_1, \ldots, M_S)'$, and $\mathbf{m} = (m_1, \ldots, m_S)'$. Then:

$$\mathbf{m} = \mathbf{R}'\mathbf{M} \tag{16}$$

Namely, for each specialty, the fraction of referrals coming from male is the weighted average of the fractions of men in clinically related specialties[29]. For example, if referrals occur only within-specialty, $\mathbf{R}$ is the identity matrix and $\mathbf{m} = \mathbf{M}$. The matrix $\mathbf{R}$ is generally asymmetric.

The demand for specialists of each medical specialty now depends on the fractions of men in all related specialties, in proportion to how related they are. Formally, the demand for male specialists in specialty s varies with the fraction of males in another specialty s' as follows:

$$\frac{\partial D_s}{\partial M_{s'}} = \frac{\partial D_s}{\partial m_s} \frac{\partial m_s}{\partial M_{s'}} = (p_{M|m} - p_{M|f}) r_{s|s'} \tag{17}$$

for all pairs of specialties $s \neq s' \in S$. This is an extension of (9) to multiple specialties.

Identification and Estimation: Homophily and Medical Specialty Choice by Gender Variation in the fraction of female in related specialties is used to identify the impact of homophily on entry, based on the relationships given in (17): Observing the changes in $\mathbf{M}$ over time weighted by $\mathbf{R}$ gives a set of demand shifters that vary between specialties and over time. I proceeds in two step. First, estimate $\mathbf{R}$ from current observed referrals flows across all specialties. Second, using a panel of gender fractions in all specialties M_{st} and rates of entry, $\Delta M_{st} = M_{s,t} - M_{s,t-1}$, I estimate how has entry responded to contemporaneous gender mixes of doctors in related specialties[30]:

$$\Delta M_{st} = \beta_4 \hat{m}_{st} + \eta_s + \gamma_t + \varepsilon_{st} \tag{18}$$

Where the scalar $\hat{m}_{st} = (\hat{\mathbf{m}}_t)_s = (\hat{\mathbf{R}}'\mathbf{M}_t)_s$ is the estimated fraction of referrals to specialty s made by male at period t (to avoid endogeneity same-specialty referrals are omitted, by zeroing the diagonal of $\hat{\mathbf{R}}$). Fixed effects η_s and γ_t for specialty and year capture potential specialty-specific attributes that impact referrals and a flexible time-trend in entry. The

[29] That is, $m_s = \sum_{s' \in S} r_{s|s'} M_{s'}$

[30] To keep previous notation, the following is articulated in terms of male, rather than female fractions, but by symmetry the same holds verbatim for female

parameter β_4 captures the response of male entry to male participation in related upstream specialties (likewise for female), where relatedness is estimates in the first stage. The identification assumptions are thus (a) the clinical-relatedness of specialties has not changed (absent historical data, I estimate it from current data), and (b) there are no unobserved time-varying factors beyond referrals that cause male entry to be correlated with the stock of male in clinically-related specialties (that is, beyond time trends in entry that impacts all specialties together and time-invariant differences in entry rates to the different specialties).

Since data only cover 2008–2012, the model (18) is estimated using retrospective cohort data covering a longer period of time: 1965–2005. This period saw substantial variation in entry, and is more suitable for studying long-term effects. Clearly, a limitation of retrospective cohort data is that exits are not observed, so results should be interpreted in light of the possibility that they reflect gender differences in exit rates. The panel is truncated at 2005, to permit medical school graduates several years to appear on claims.

Results: Homophily and Medical Specialty Choice by Gender The first-stage estimates, $\hat{\mathbf{R}}$ are visualized in Figure A7. Clearly, primary care is the main source of referrals, and there are some within-specialty referrals as well. There is, however, considerable variation across specialties, which is used for identification in the second stage.

Table 8: Female Entry and Specialty Fraction of Referrals from Female

	Percent Female Entrants			
	(1)	(2)	(3)	(4)
Percent Referrals from Female	1.255***	1.167***	1.372***	1.198***
	(27.17)	(15.23)	(35.00)	(7.65)
Year Fixed-Effects	No	Yes	No	Yes
Specialty Fixed-Effect	No	No	Yes	Yes
Obs. (Specialty-Year)	1501	1501	1501	1501
R-sqr.	0.296	0.306	0.842	0.851
Clusters	41	41	41	41

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results of fixed-effect estimates of (18) using cohort data. Observation represent specialty-year pairs (s, t), for specialty-years with at least 500 physicians. Percent Referrals from Female is the fraction of active female in all other specialties $s' \in S \setminus \{s\}$ at year t, weighted by the estimated dependency of s on each of s' for referrals from the first stage, depicted in appendix Figure A7. Standard errors are clustered by year.

I find that over 1965–2005 more women entered specialties with a greater fraction of referrals from women, beyond specialty-specific entry rates and a common flexible time-trend

(Table 8). Bearing the limitation of reconstructed cohort panel in mind, these results still suggest homophily had an impact on female specialization: it affects the pay gap also through this extensive margin. Results mean some of the occupational segregation in medicine is due not to supply side differences, but rather to demand effects of gender-biased referrals. Results also suggest further female entry to upstream specialties like primary care would facilitate entry of female to more lucrative specialties by increasing the demand to their services. Quantifying how much of the gap is explained by entry differences requires more assumptions

6 Extensions

Before concluding, I perform two additional analyses that further explore the causes and consequences of homophily. The first uses data on physician first names to test the hypothesis that homophily is driven by outright discrimination. The second uses detailed data on patients to check whether homophily has impact on their care. I find no evidence of prejudice based on first names, and no evidence for impact on patient outcomes. Combined with earlier findings on the presence of preference-bias and adverse effects on female workload and specialty choice, these results propose a more nuanced picture of gender homophily: while it may neither be ill-disposed, nor harmful to patients, it is still detrimental for female physicians.

6.1 Testing for Prejudice Using Specialist Names

"What's in a name?"

In this section I further leverage data on physician first names to test for prejudice. I perform a quasi-audit study, comparing whether specialists with gender-ambiguous names (e.g. Alex, or Robin) are treated differently than specialists with generized names (e.g. David, or Jennifer). If prejudiced doctors choose referrals based on a specialist names alone, without even knowing them, specialists whose names are uninformative of gender show experience milder homophily. I find no evidence for that: doctors choices discriminate even between ambiguously named specialists, suggesting they know the specialists they work with, at least enough to know their gender not just based on their name.

Identifying prejudice is challenging because it involved elicitation of beliefs, and is often reserved for audit studies. The problem is separating the impact beliefs have on choices from the impact of other privately observed information. Audit studies elicit beliefs by manipulating signals while holding constant the information available to subjects. For example, Bertrand and Mullainathan (2004) elicit racial discrimination by sending fictitious resumes with names sounding either very African American or very White. Since names convey little information other than on individual race, a differential response indicates the presence of discriminatory beliefs regarding racial groups[31].

With observational data one cannot control for private information, so I use a different design: instead of considering responses to very genderized names, I consider responses to gender-ambiguous names. By definition, such names are uninformative of the gender of the specialists, so doctors who discriminate based on names alone could not discriminate against such individuals. Therefore, responses to ambiguous names identify whether choices respond to perceived and not actual gender of individuals. This is tested against the null that referrals to ambiguously names individuals are still homophilous, which means doctor prefer same-gender specialists based on more than just their name.

This strategy is implemented in two steps. First, I classify the names of all specialists by their *name masculinity* $\gamma \in [0,1]$, defined as the fraction of name-bearers who are male[32]. Higher name masculinity corresponds to a higher probability that the name-holder is male. Names with masculinity $\gamma = 0$ are only given to female (e.g., Jennifer), conversely, names with masculinity $\gamma = 1$ are only given to men (e.g., David). Names with index between 0 and 1 are sometimes given to both genders (e.g., Alex or Robin). The most ambiguous names have $\gamma = 0.5$: they are as likely to be male as they are to be female (neglecting the prior).

In the second stage, I then test whether directed homophily is lower for specialist with ambiguous names, against the null that homophily is unrelated to name-masculinity. The point is that knowing the names of specialists with ambiguous names do not reveal their gender, so discrimination against them suggests doctors base referral decisions on more than just names[33]. The identifying variation is in the informativeness of name as a signal for

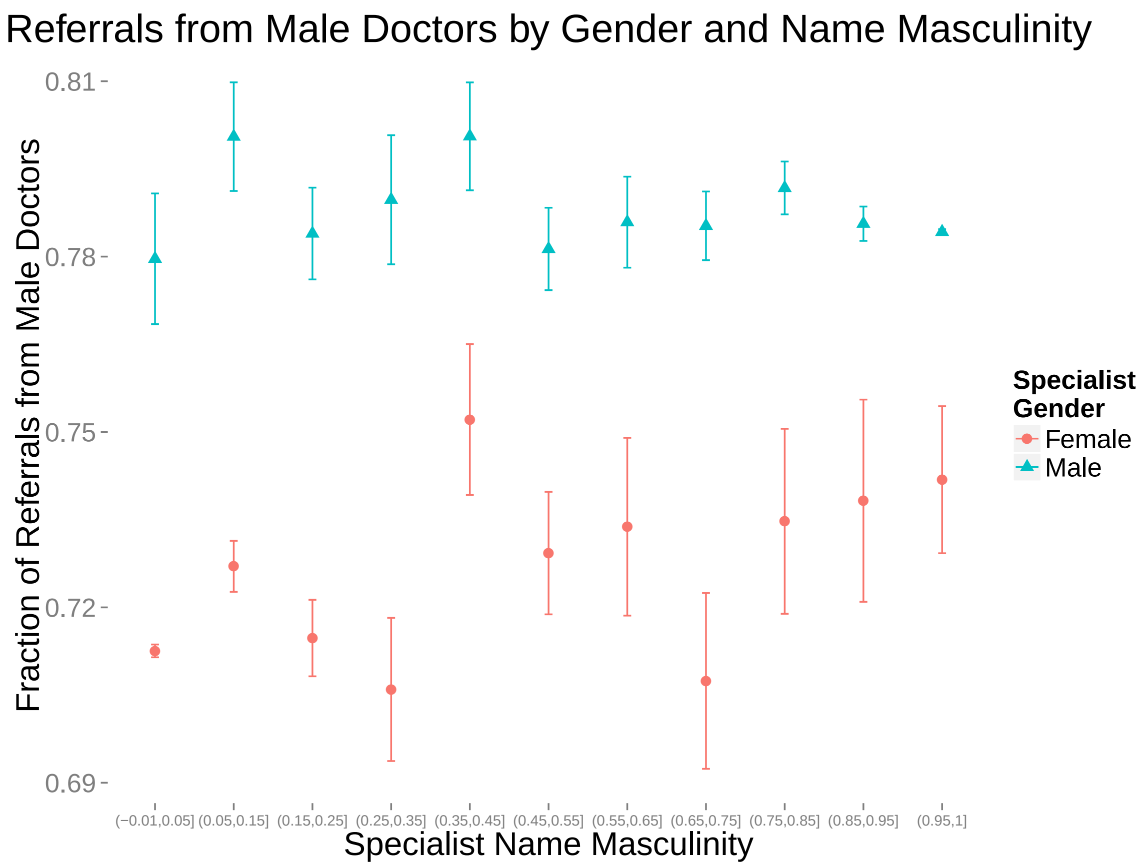
[31]Note that whether discriminatory beliefs exist, and whether such beliefs are rationalized by group differences in productivity are separate questions.

[32]Formally, denote the gender of specialist k by $g_k \in \{M,F\}$ and the first name of an individual k by $m_k \in M = \{m_1, m_2, \dots, m_M\}$ I assign an index $\gamma : M \mapsto [0,1]$ measuring *name masculinity*:

$$\gamma(m) = \frac{|\{k \in K : m_k = m, g_k = M\}|}{|\{k \in K : m_k = m\}|}$$

[33]More formally, let Γ denote a level of name-masculinity (an element of a partition of $[0,1]$ to bins, e.g.,$\{[0,.1),[.1,.2),\dots,[.8,.9),[.9,1]\}$). Define $r^{\Gamma}_{g|M}$ to be the average fraction of referrals to male specialists received from doctors of gender g (for $g = m, f$), calculated over the set of specialists $k \in K$ with name-masculinity $\gamma(m_k) \in \Gamma$. I then test for discriminatory beliefs by considering the relationship between ambiguity and homophily. That is, if homophily is driven by discriminatory beliefs then one should expect (H_1) $DH(\Gamma) = r^{\Gamma}_{m|M} - r^{\Gamma}_{f|M}$ to be lower for ambiguous names ($\Gamma \ni \frac{1}{2}$ or close to that), than it is for unambiguous names (Γ close to 0 or 1). (I use the version of DH defined by comparing incoming referrals

Figure 9: Homophily and First-Name Masculinity



Notes: The figure shows the fraction of referrals specialists of different name-masculinity received from male doctors. Name-masculinity is defined as the share of name-holders who are male. The two extreme bins contain all unambiguous names (about 93% of specialists): left-most bin contain all specialists with feminine names (e.g. Jennifer), the right-most bin contains all specialists with masculine names (e.g., David). The middle bins contain more ambiguous names (e.g., Alex or Robin). That male doctors treat male and female with ambiguous names differently suggest that they do not base their referral decisions on name alone.

gender, across different levels of name masculinity.

Figure 9 shows the results of the first-name analysis, plotting rates of referrals from males and females to male specialists with different levels of name-masculinity[34]. Male and female referrals to ambiguously-named specialists (mid-range masculinity) still shows significant homophily: men refer more and women refer less even to ambiguously named specialists. Thus the null hypothesis is not rejected: referrals seems not to be prejudiced, at least not

across specialists, not outgoing referrals across doctors. The two measures always have the same sign.) The null (H_0) that there is no difference in DH between more and less ambiguous names.

[34]The standard errors for the estimates of referral rates to men are decreasing in the specialist name masculinity because of sample size: by construction, there are many more men with higher name-masculinity than there are men with lower name-masculinity. Conversely for women.

based on names alone.

6.2 Homophily and Patient Outcomes

I find no significant impact of homophily on patient mortality or cost.

The above analysis has shown that doctors are more inclined to refer to specialists of their own gender, which hurts female physicians, the minority gender. Next, its effects on patients are studied. Gender-homophily in referrals could harm patients, if patient care is compromised by preferring inappropriate specialists over appropriate ones of the opposite gender. On the contrary, homophily could have no effect on outcomes if gender differences in specialist quality are insubstantial, or if gender-preferences only break ties between otherwise-equally appropriate specialties. Homophily could even have a positive effect, for example if physicians of the same gender communicate better.

To test whether homophily has consequences for patients, I compare outcomes of patients who have been referred and treated by same-gender and mix-gender providers, using the following specification:

$$Y_{ijk}^{t+1} = \beta_5 \mathbb{1}_{g_j=g_k} + \delta_5 X_i^{t-1} + \alpha_j + \alpha_k + \varepsilon_{ijk} \tag{19}$$

where each observation is a triple (i, j, k) of patient i referred to specialist k by doctor j at period t, for a single base year t. The dependent variable Y is subsequent patient outcomes: period $t+1$ overall cost of Medicare services, a proxy for sickness severity. The parameter of interest β_5 captures the impact of same-gender dyads.

To control for doctor and specialist differences, fixed effects for both are included. Accounting for such differences is important because otherwise physicians treating more complex patients, who are of higher risk, would appear to have worse outcomes, a typical selection problem. To control for patient heterogeneity, X includes detailed patient characteristics, including demographics, utilization, and cost for $t-1$. Cost and utilization for t are excluded, to avoid endogeneity: they may be outcomes of the physicians encounters of interest. As the same patient could encounter multiple dyads, standard errors are clustered by patient.

Patients referred and treated by providers of the same gender fare similarly as those who saw providers of opposite gender, as seen in Tables A7 and A8. These table shows the estimates of (19) for two different outcomes: patient log annualized cost and mortality. Patient referred and treated by physicians of the same gender have slightly lower subsequent cost and mortality rates, but these differences all but vanish when physician fixed-effects are included, suggesting male physicians treat sicker patients. There seems to be no impact of the provider gender mix on patient.

Evidence is far from conclusive, but it suggests homophily has on average no effect on patient outcomes: gender biased referrals do not appear to compromise patients. Further research is required to evaluate the impact of homophily, as zero averages effect may conceal heterogeneity in effects. Overall, widespread homophily impacts physicians but not patients.

7 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. I extend existing models of homophily to directed referral networks. This model illuminates how homophily, particularly its part due to gender-biased preferences, impacts the pay gap. I then estimate the model and directly test its implications using confidential administrative data on payments and referrals between half a million U.S. physicians across all medical specialties during the period 2008–2012. Data are from Medicare, where there are no gender differences in compensation for services.

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.

This paper also proposes a new measure of homophily in directed networks. This measure identifies the presence of gender bias in referrals separately from potentially unobserved differences between the genders in individual propensity to send or receive links (e.g., due to differences in labor supply). This measure can be used to study homophily in any other contexts where unobserved heterogeneity in the propensity to form links is a concern.

The empirical evidence suggests the observed homophily in physician referrals is mostly due to gender-biased physician preferences. On the intensive margin, homophily is currently diverting away from female thousands of dollars worth of work each year. Moreover, evidence exists that women enter less specialties to which more referrals come from men. Evidence for this "Boys' Club" effect is admittedly weaker, as it is based on retrospective cohort data. But if it indeed exists, it will further contribute to pay disparity. Although homophily makes the closing of the earnings gap slower, results also suggest that current entry trends will have favorable impact on the earnings of female physicians eventually. Particularly favorable effect would result from the equalization of female participation in primary care, a main source of referrals for many other specialties.

Even among the highly-educated, preference biases in favor of same-gender, and more broadly in favor of similar others are ubiquitous. Such biases, while slight and innocuous from an individual perspective, translate to systematic disadvantage to minority groups, especially when resources are made available through connections. Data on such connections and the social interactions facilitating their formation can be elicited from transaction-level data of the kind that is increasingly becoming available, and its analysis could therefore shed light on the propagation of inequality, on dimensions beyond gender and in domains beyond medicine.

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Appendices

A Proofs

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

$$
\begin{aligned}
p_{M|m} &= \sum_{k:g_k=M} p_{jk} \\
&= \frac{\sum_{k:g_k=M} e^{\beta \mathbb{1}_{g_j=g_k}}}{\sum_k e^{\beta \mathbb{1}_{g_j=g_k}}} \\
&= \frac{\sum_{k:g_k=M} e^{\beta}}{\sum_{k:g_k=M} e^{\beta} + \sum_{k:g_k\neq M} e^{0}} \\
&= \frac{Me^{\beta}}{Me^{\beta} + 1 - M}
\end{aligned}
$$

The probability $p_{M|f}$ is similarly derived. For (7):

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

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:

$$\begin{aligned}
p_{M|m} &= \sum_{c\in C} p_{c|m} p_{M|m,c} = \sum_{c\in C} \mu^c \frac{m^c}{m} p^c_{M|m} \\
&\geq \sum_{c\in C} \mu^c \frac{m^c}{m} M^c = \frac{1}{m} E[m^c M^c] \\
&> \frac{1}{m} E[m^c]\mathrm{E}[M^c] = M
\end{aligned}$$

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

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 4) To prove 1., Let $h(M) = p_{M|m} - p_{M|f}$, so $DH(N) = \mathrm{E}[h(M)|N]$. Recall that: $h(M)$, given in Proposition 1, is concave in M (strictly for $\beta > 0$) and satisfies $h(0) = h(1) = 0$. Since entry is independent, the fraction of male specialists in a given market c, denoted M^c, is a random variable distributed $F(N) := \mathit{Binomial}(N^c, M)/N^c$, with mean M. By the Law of Large Numbers, for every $\varepsilon > 0$ there exists N' such that for $N'' > N'$ the probability of $|F(N'') - M| > \varepsilon$ is arbitrarily small, so $h(F(N''))$ is arbitrarily close to $h(M)$. the result then follows from the concavity of h by Jensen's inequality. To prove 2., note that if $\beta = 0$, then by Proposition 3 within each market homophily equals $\mathrm{Cov}[m^{l_c}, M^{l_c}]$. □

Proof. (Proposition 3)

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

□

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

Proof. (Proposition 5) 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 5 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 6 (Directed Homophily Decomposition)**.** *The overall directed homophily decomposes as follows:*

$$p_{M|m} - p_{M|f} = \mathrm{E}\Big[\frac{m^c}{m} p^c_{M|m} - \frac{1-m^c}{1-m} p^c_{M|f}\Big] + \frac{1}{m(1-m)}\mathrm{Cov}[m^c, M^c] \tag{20}$$

Proof. (Proposition 6) Applying the proof of Proposition 3 to female (by symmetry) and substituting $p_{M|f} = 1 - p_{F|f}$ yields :

$$M - p_{M|f} = \text{E}[\frac{1-m^c}{1-m}(M^c - p^c_{M|f})] + \text{Cov}[\frac{m^c}{1-m}, M^c]$$

Hence

$$\begin{aligned} p_{M|m} - p_{M|f} =& \text{E}[\frac{m^c}{m}(p^c_{M|m} - M^c) + \frac{1-m^c}{1-m}(M^c - p^c_{M|f})] \\ &+ \frac{1}{m(1-m)}\text{Cov}[m^c, M^c] \end{aligned}$$

rearranging yields the result. □

B Documenting and Decomposing the Pay Gap for Medicare Physicians

This section discusses the details of the decomposition of current Medicare physician pay gap. I find large differences in pay between male and female Medicare physicians, consistent with previous findings of large gender pay gaps both in medicine and in other occupations. However, existing explanations account for only half of this gap.

About a third of the gender pay gap in Medicare is due to differences in specialization: women participate much more in lower paying specialties (Figure A2). While men are the majority of active physicians in almost all specialties, the fraction of women varies greatly. Accounting for specialty in the gender pay gap specification (1) reduces the coefficient on gender from 65.4 to 46.8 log points (Table 2). That is, between-specialty gaps explain a third of the gap, while the remaining two thirds are difference in workload within specialty. These findings again resonate with previous works (e.g., Weeks et al., 2009).

Gender differences in career interruptions also explain part of the pay gap in Medicare. As previously shown by Bertrand et al. (2010) such differences also explain a large part of the gap among highly skilled professional in the financial and corporate sectors: More interruptions were reported by female MBA alumni on surveys, and those interruptions have had persistent, and sizable effect on their subsequent earnings. Career interruptions may be related to existing (if shifting) differences in family roles: women taking time off for having children and later taking care of them may explain both the initial interruption and the subsequent persistent change in work hours.

Inactive quarters are indeed more common for women physicians in Medicare, and account for additional 10 log points of the Medicare pay gap (Column 4). The number of leaves each physician had is approximated by calculating, for each physician, the share of inactive quarters—with no claims—in the sampled history. Quarters are used, and not shorter time intervals, to limit confounding of low workload with periods of inactivity due to sampling errors. The active history includes all sampled years, excluding the year of graduation and the current year, to avoid confounding changes in exact time of graduation with career interruptions.

Experience differences, while substantial, explain little of the gap. Because women have been entering the profession in equal numbers only recently, female physicians are on average 7 years less experienced than male physicians. Experience is also a strong determinant of Medicare work volume: Experienced physicians work more, with the peak volume reached towards mid-career. Yet experience differences explain very little of the gender gap in pay (Column 2 of Table 2).

Neither the medical school physicians attended, nor where they are located explain much of the gap (Columns 5 and 6). Location differences could in principle contribute to the gap due to the geographic adjustment of the Medicare fee schedule, but they in fact do not contribute much.

About half of the gender pay gap in Medicare remains unexplained even after known explanations are accounted for: differences in specialty, career interruptions, experience, location, and education. The question therefore remains: why do female Medicare physicians work fewer hours than their male counterparts? 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 choices, and impact their wage. For example, Chen and Chevalier (2012) show that lower expected workload alters the net-present-value of alternative career choices, possibly making it rational for women to invest less in specialization.

C Counterfactuals

In Section 5.1 I have estimated the impact of homophily on the pay gap directly, as well as provided counterfactual estimates of the impact of estimated bias on demand. In this section, I provide model counterfactual for how much would have the gap been reduced had there been no bias in preferences, for different upstream and downstream gender fraction.

Table A1 shows estimation of the impact on the pay gap contributed by the estimated preference-bias $\hat{\beta} = 0.1$ (i.e., doctors are 10% more likely to work with same-gender oth-

Table A1: Homophily Pay-Gap Counterfactuals (Female Cent per Male Dollar)

	Fraction Males Downstream (M)						
Upstream (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 upstream and downstream. The formula is given below. The row and column in bold are the current U.S. averages across all specialties. At $M = m = 0.75$ the gender-bias in referrals alone is contributing 4.75 percentage points (or "cents-per-dollar") to the physician gender earnings gap.

ers), buy calculating the demand disparity with different male fractions upstream (m) and downstream (M):

$$Gap(m, M; \beta) = D^F - D^M = \frac{1}{1-M}(mp_{F|m} + (1-m)p_{F|f}) \\ - \frac{1}{M}(mp_{M|m} + (1-m)p_{M|f}) \tag{21}$$

Substituting $p_{G|g} = p_{G|g}(G; \beta)$ for $g \in \{m, f\}$ and $G \in \{M, F\}$ given in (5) above and simplifying yields:

$$Gap(m, M; \beta) = -\frac{(1-w)((M-m) + w(1-(M+m)))}{(1-M(1-w))(w+M(1-w))} \tag{22}$$

Where $w = \exp^{-\beta}$. Note that with balanced gender ($M = m = 0.5$) there is no gap, even when preferences are biased. In this case homophily only affects the composition of demand, not its level.

The Earnings Gap with Extreme Levels of Bias 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 A1 the gender gap in earnings for the actual level of bias (10%) depends mostly on the fraction of males upstream (m) and varies only little with the fraction of males downstream (M). This fact is more generally true for small levels of bias, as can be seen by linearly approximating the gap around $\beta = 0$:

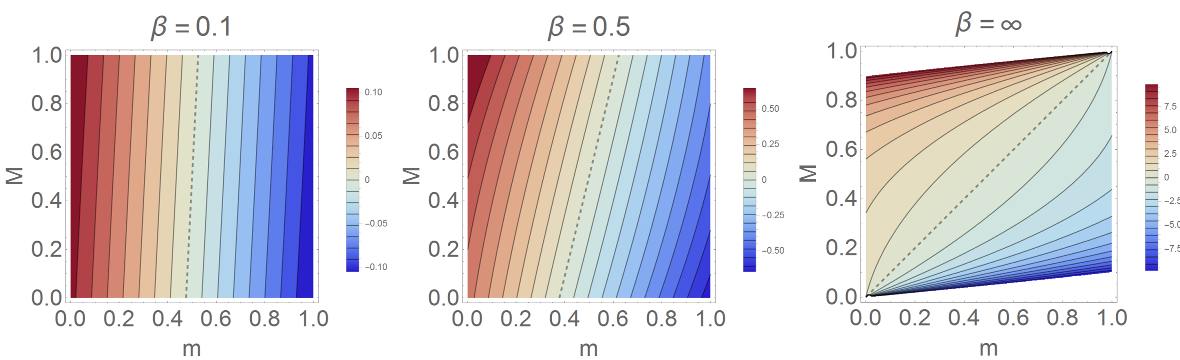
$$Gap \approx (2m - 1)\beta + O(\beta^2) \tag{23}$$

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:

$$\lim_{\beta \to \infty} Gap = \frac{m - M}{M(1 - M)} \tag{24}$$

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.[35]

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 22) 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.

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

D 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:

$$p^{persist}_{jk,t+1|jk,t} := Pr(Y_{jk,t+1} = 1 | Y_{jk,t} = 1, g, X) = \frac{e^{\eta_{jkt}}}{1 + e^{\eta_{jk't}}} \tag{25}$$

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, (25) 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 A2 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.

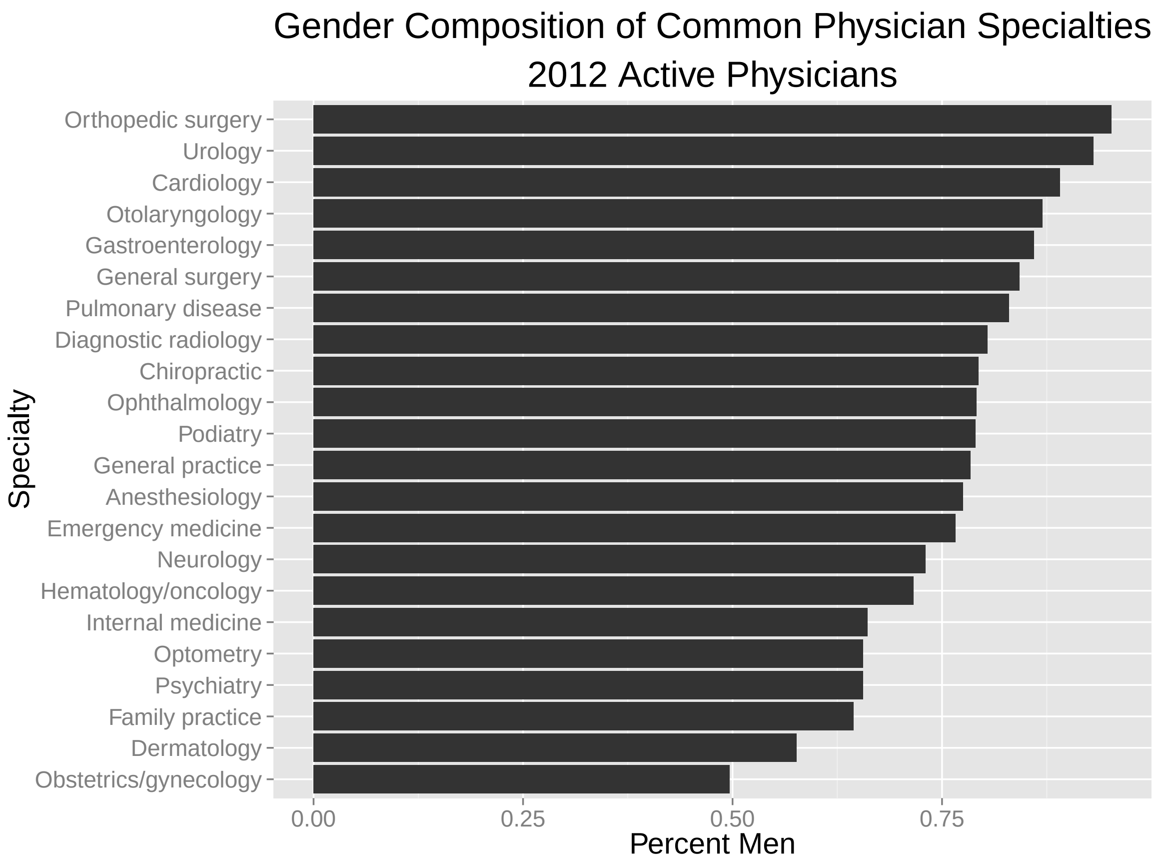
Table A2: Estimates: Link Persistence

	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)	7255778	7204471	5734596	1496658
Rank	8	5	58	58
R^2		0.20	0.10	0.11
N. Cluster	280750	255507	191647	64579
FE1 (Doctors)		255507	191647	64579
FE2 (Specialists)		237363		

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; t statistics in parentheses. Results of link persistence estimates. Column (1) shows estimates (4) 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.

E Additional Tables and Figures

Figure A2: 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.

Table A3: 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.

Table A4: Percent Men and Percent of Referrals from Men, by Medical Specialty

	Dependent variable:		
	Percent Men		
	(1)	(2)	(3)
Pct Ref From Male	1.260***	1.210***	1.220***
	(0.160)	(0.149)	(0.150)
Training Duration		0.066***	0.064***
		(0.013)	(0.013)
Pct Work in Weekend			−0.137
			(0.151)
Constant	−0.237*	−0.486***	−0.474***
	(0.123)	(0.124)	(0.125)
Observations	172	172	172
Adjusted R^2	0.264	0.361	0.361
Note:	*p<0.1; **p<0.05; ***p<0.01		

Notes: Percent Men is the fraction of male specialists. Percent Referrals from Male is the fraction of referrals from male doctors in all other specialties. Training Duration is residency and fellowship duration in years. Percent Work in Weekend is the fraction of claims for the specialty that record services incurred in weekends.

Table A5: 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)	200670	184315	384985
Rank	57	57	57
Mean Dep. Var.	0.82	0.83	0.82
R^2	0.035	0.041	0.039

Notes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; standard errors in parentheses. OLS estimates of (11) 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.

Table A6: 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)	384985	384985	384985	383054
R^2	0.0384	0.0394	0.0360	0.0368

Derived from sample of 20pct of patients. (t-statistics in parentheses.)

Notes: OLS estimates of (11) 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 A7: Physician Dyad Gender Mix and Subsequent Patient Spending

	(1) 2012 Cost	(2) 2012 Cost
Same Phys Gender	-0.0165***	-0.00554**
	(-8.28)	(-2.77)
Male Patient	0.0421***	0.0316***
	(22.89)	(16.94)
Male Doctor	0.0354***	
	(17.14)	
Male Specialist	0.0149***	
	(7.19)	
2010 Cost	0.126***	0.127***
	(159.97)	(164.23)
2010 Drugs	0.0345***	0.0333***
	(138.58)	(126.94)
Patient Demographics, Chronic Cond., Utilization	Yes	Yes
Experience	Yes	No
Specialty	Yes	No
Obs. (Patient, Doctor, Specialists)	7120083	7424095
Rank	169	58
R^2	0.240	0.349
Clusters	dyad	dyad
No. Cluster	4444359	4581862
FE1 (Doctors)		302997
FE2 (Specialists)		276488

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

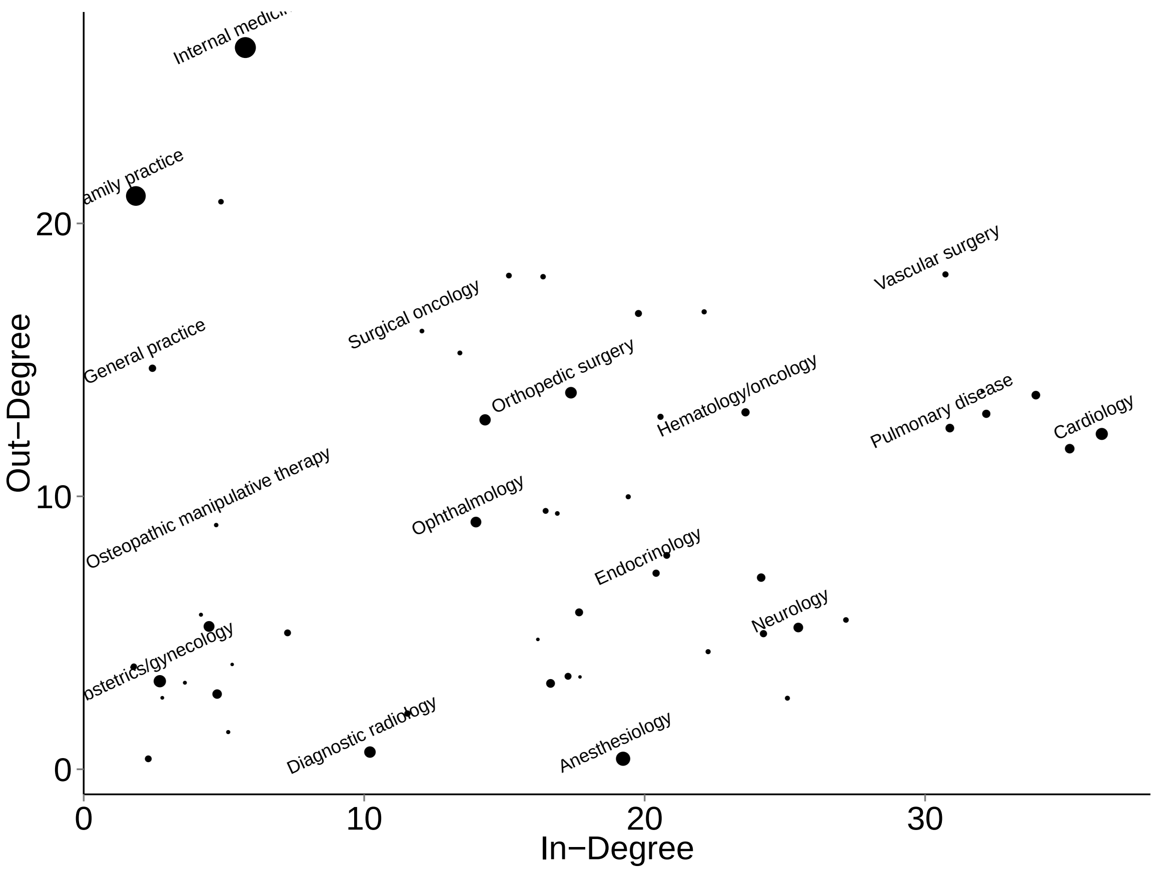
Table A8: Physician Dyad Gender Mix and Patient Mortality

	(1) Mortality (1 Year)	(2) Mortality (1 Year)
Same Phys Gender	-0.00303***	-0.00169***
	(-8.43)	(-4.52)
Male Patient	0.0270***	0.0245***
	(85.46)	(76.33)
Male Doctor	0.00759***	
	(20.24)	
Male Specialist	0.00459***	
	(12.17)	
2010 Cost	-0.000100	0.000253**
	(-1.12)	(2.78)
2010 Drugs	-0.000642***	-0.000577***
	(-12.11)	(-10.63)
Patient Demographics, Chronic Cond., Utilization	Yes	Yes
Experience	Yes	No
Specialty	Yes	No
Obs. (Patient, Doctor, Specialists)	7120083	7424095
Rank	169	58
R^2	0.104	0.236
Clusters	dyad	dyad
No. Cluster	4444359	4581862
FE1 (Doctors)		302997
FE2 (Specialists)		276488

t statistics in parentheses

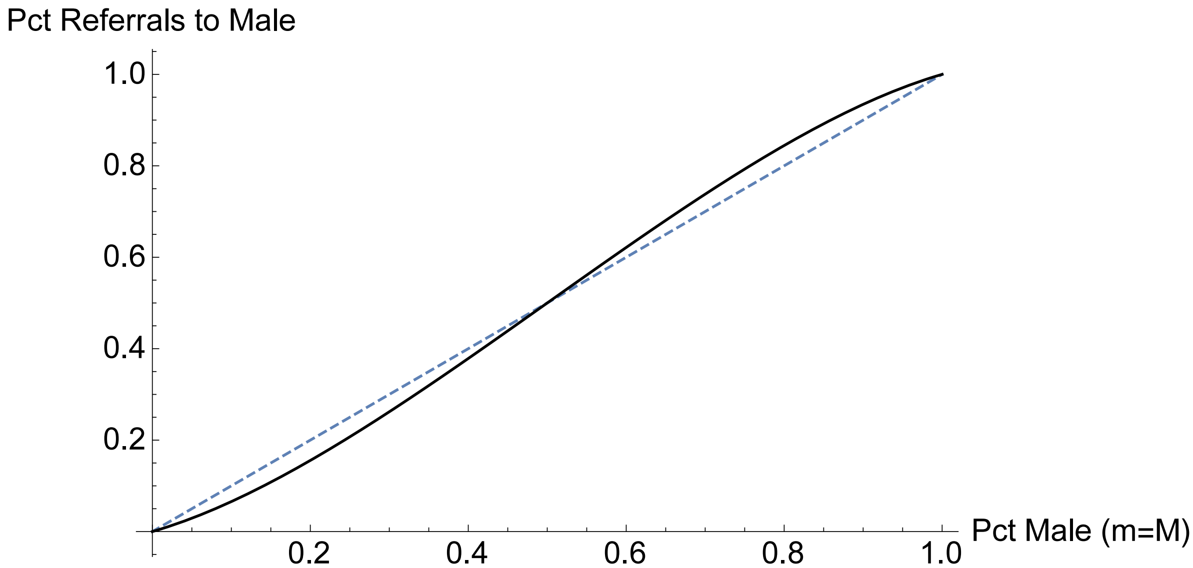
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A3: Average Number of Referral Relationships by Medical Specialty



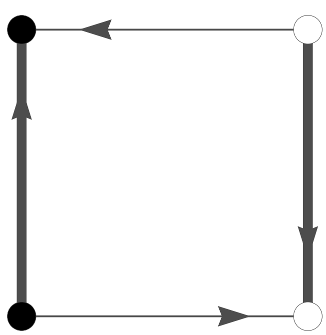
Notes: Degree-heterogeneity is to be expected since doctors in different specialties play different roles in routing patients: some mostly diagnose and refer out, others mostly receive referrals and treat. The figure shows degree distribution by specialty for 2012 referrals: Out-degree is the average 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 A3 for the data.

Figure A4: Overall Demand as a Function of Gender ($m = M$)

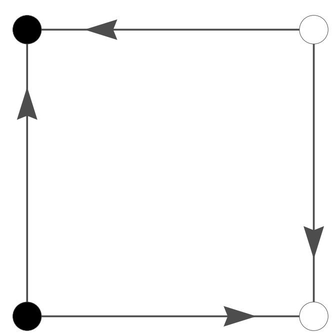


Notes: The figure plots the overall share of referrals going to male, as a function of the male population fractions, in the special case where $m = M$, for gender biased preferences ($\beta > 0$). The majority gender receives more than its share; the minority gender receives less than its share.

Figure A5: Homophily Through Link Weights



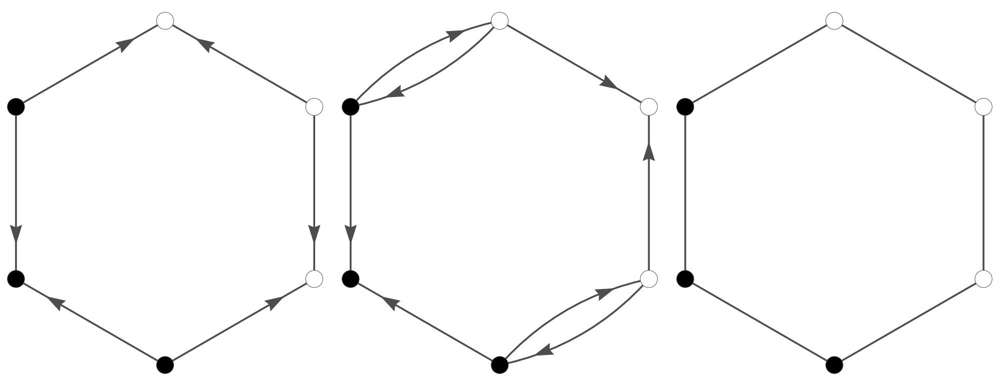
(a) Homophily via Weights



(b) Unweighted

Ignoring referral volume (link weights) may yields wrong measures of homophily: network (a) exhibits homophily: more patients are referred within-gender (higher weights between same-color nodes); this homophily is concealed if link weights are ignored (b).

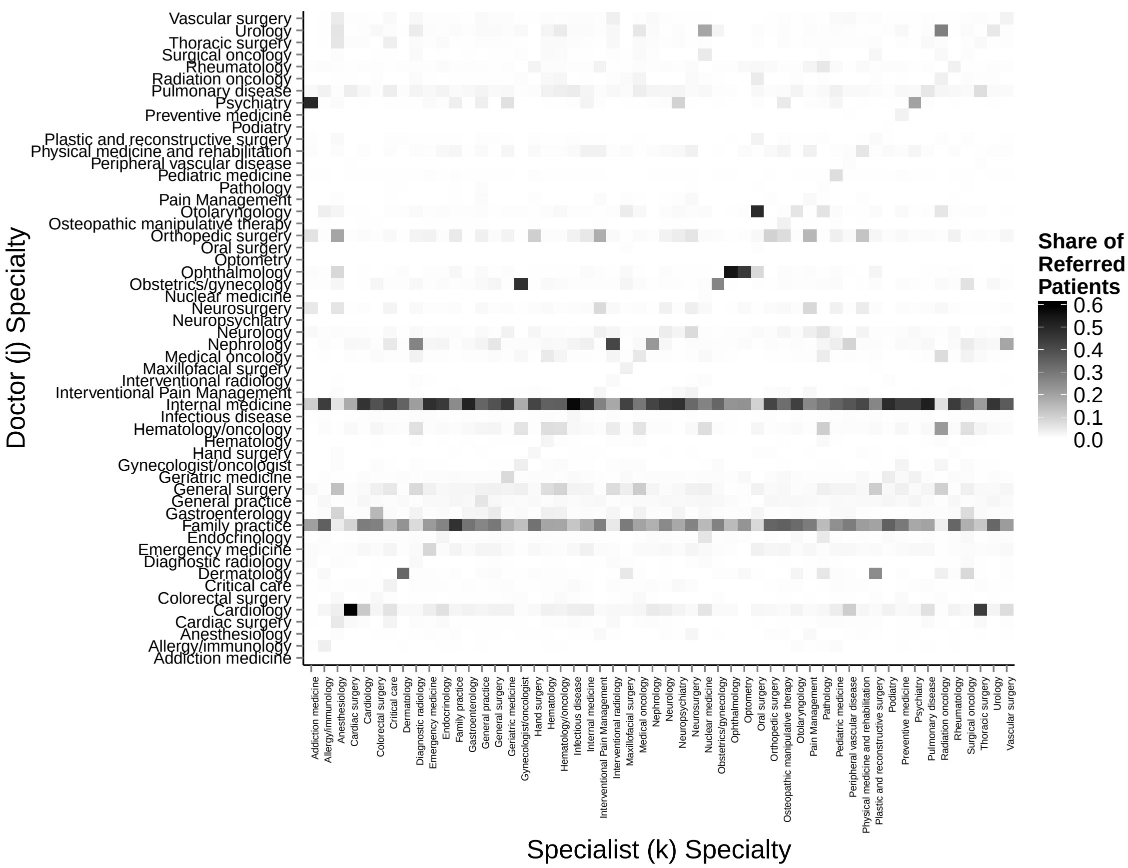
Figure A6: Homophily Through Link Direction



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

Looking at directed networks as if they are undirected yields wrong measures of homophily: the network (a) exhibits homophily while (b) does not, a difference concealed in their undirected counterpart (c). Also concealed is the asymmetry in gender shares: e.g., in (a) most most senders are black, but most receivers are white; that is, most doctors are of one gender but most specialists are of the other.

Figure A7: Estimates of **R**, Medical Specialties Dependency Matrix



Notes: Estimated transition probabilities between different specialties (numbers denote CMS specialty codes). Cell (j, k) represents the fraction of referrals to specialty k coming from specialty j, with darker colors represent higher fraction. Columns each sum to one. The dark horizontal lines are the two main primary care specialties: family medicine (8) and internal medicine (11).