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

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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 referral networks (more same-gender referrals). I model how referral networks are formed when doctors decide which specialists to refer to. The model highlights that homophily can be explained by both biased preferences and sorting. I then suggest how to identify and quantify both types of biases in directed networks empirically. Analyzing administrative data on more than 100 million Medicare physician referrals from 2008–2012, I find that there exists significant gender homophily, and most of it is due to preferences, not sorting. As most referrals are still made by men, homophily lowers demand for female specialists, explaining 10% of the average within-specialty workload gap, and contributing to the absence of women from lucrative specialties that rely on referrals from men. In the healthcare environment, my results imply that increased participation of female physicians facilitates further integration into related specialties. More generally, my findings suggest that homophily contributes to the persistence of occupational inequalities.

JEL classification: J72; I11; L14

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

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1 Introduction

Despite the successful and rapid entry of women into medicine, female physicians, like females in other occupations, still have substantially lower earnings: women work less than male physicians, and practice lower paying specialties. Why would they so choose, after long and costly investment in education and training as doctors? This question reflects a broader concern that despite the great convergence in education and earnings females still fall behind, for reasons not well understood (Goldin, 2014). Some argue for supply side explanations: women have fundamentally different preferences (Croson and Gneezy, 2009), opt for less competitive jobs (McGee et al., 2015), and are held back by family-related career interruptions and their lasting consequences (Bertrand et al., 2010). Others contend that not all differences are voluntary, as quasi-experimental evidence exists for discrimination by gender (e.g. Goldin and Rouse, 2000). Yet it is difficult to support, let alone quantify, demand-side explanations for the earning gap because data typically reveal only individual characteristics, but not the external differences in opportunities individuals might face because of their gender.

This paper utilizes unique data on the network of referrals between over half a million U.S. Medicare¹ physicians and their payments for 2008–2012, to propose a new demandside explanation for the pay gap: female physicians receive fewer referrals due to gender homophily (i.e., physicians referring to their same gender). I find evidence for significant gender homophily in Medicare referrals, beyond what is expected from random sorting. Modeling the formation of referral networks, I show that homophily sustains inequality by reducing demand for the minority. And I find that homophily indeed contributes to the Medicare physician pay gap through two channels: first, by reducing demand for female specialists, and second, by discouraging their entry to lucrative specialties relying on referrals from men. Insights extend to disparities on dimensions other then gender, and to any domain where referrals (or connections) are important, such as hiring, where employee referrals are frequently used by firms as an informal way to screen and monitor new employees (Kugler, 2003; Antoninis, 2006; Dustmann et al., 2011; Burks et al., 2014). More broadly, this paper demonstrates how interactions between individuals in professional networks (their "networking") provide a key to the understanding of propagation and perpetuation of inequalities.

Since Medicare payment schedule is common to all physicians, Medicare data are well suited for the study of pay differences due to difference in specialization and in workload, free from the difficulties involved with wage differentials in other settings. Broadly, one can

 $^{^{1}}$ Medicare is the U.S. federal health insurance program for the elderly patient with certain disabilities, and patient with kidney failure.

decompose gender differences in pay to three components: differences in the type of work performed, differences in quantity of work, and, differences in the per-unit pay. And while the popular debate of gender pay disparities is focused on "cents per dollar", per-unit differences, much of the great convergence in earning between genders over time, as well as much of still existing gaps come from the other two factors: women working more, and women entering previously male occupations. Understanding gender workload and specialization is therefore important to understand what path forward would facilitate further pay convergence. Decomposing the Medicare physician earnings gap shows that it confirms earlier findings that female physicians earn much less than male physicians (Weeks et al., 2009; Lo Sasso et al., 2011; Esteves-Sorenson et al., 2012; Seabury et al., 2013). Unconditional on any attributes, a female physician annual payments are 48% lower than those of a male physician. Accounting for specialty differences and career interruptions (Bertrand et al., 2010) explain a significant part, but as much as half of this gap remains unexplained.

Confidential data on more than half a billion Medicare physician services reveal how gender-biases in the work flows between physicians, through referrals, contribute to earnings gaps. Data allow for scrupulous empirical analysis of homophily: a large directed and weighted network spanning many local markets is observed over time. This setup is quite exceptional in that it offers more than just detailed individual data—it records a vast web of micro-level interactions of *between* individuals, with clear economic outcomes. Such data reveal how disparities arise from biased interpersonal interactions. Such interactions may indeed be present in many other settings, but are rarely so systematically recorded².

To study homophily, I model local referral networks as forming when doctors (upstream) choose specialists (downstream) to refer to. In these networks, a link exists between a doctor and specialist if one referred patients to the other in a given year, and its weight depends on the volume of work referred. The model builds on Currarini et al. (2009), but extends the analysis from social to referral networks, which are directed. In the model homophily is a combination of both preferences and sorting: doctors may prefer to work with same-gender specialists but may also face biased opportunity pools³. It yields testable predictions that distinguish between these mechanisms, and it illuminates their implications for the pay gap. The model has two main predictions: First, the minority receives fewer referrals. Second, unlike sorting, preference biases generate stronger homophily in larger markets.

As one doctor's referrals are another's income, the link between gender homophily in

 $^{^{2}}$ The use of administrative Medicare data to study referral networks has been validated by Barnett et al. (2011), who showed that recorded referrals coincides well with self-reported relationships.

³Sorting is causing systematic differences in the opportunity pools to which men and women are exposed. Sorting may be reflecting segregation, or clustering of physicians by gender (see Massey and Denton, 1988; Echenique and Fryer, 2007).

referrals and the gender pay gap seems intuitive: with men handling most of outgoing referrals, homophily implies more patients are referred to male specialists and fewer to female specialists. The model helps refine this intuition: it holds only if observed homophily is due to gender-biased preferences, but not if it is due to sorting, as sorting only affects which referrals women get, not how many. Moreover, with gender-biased preference the demand for female specialists depends on the gender composition of both upstream and downstream markets. Female specialists' demand suffers twice: first, there are fewer female doctors, resulting in fewer referrals to females, and second, there are more male specialists, raising the opportunity cost of choosing a female specialist.

To identify homophily and gender-bias in referrals one needs to account for heterogeneity in the propensity to refer or receive referrals, as discussed by Graham $(2014)^4$. I propose a new measure of homophily that compares the fractions of referrals male and female doctors made to males. Unlike previous measures that compared referral rates with the fraction of male specialists, this measure (*Directed Homophily*) is robust to heterogeneity in individual physicians' propensity to refer or receive referrals. Tight control for heterogeneity is further facilitate by comprehensive and standardized reporting of physician characteristics.

A second identification concern when estimating homophily is to distinguish the role of gender-biased preferences from homophily driven by sorting, namely from physicians being over-exposed to their same gender. To rule out sorting I take three complementary approaches: I estimate homophily by comparing referrals of physicians who face similar opportunity pools, estimate link formation with controls for rich pairwise characteristics, and directly test theoretical predictions that are unique to preference-driven homophily. Comparison of referral rates by doctors affiliated with the same hospital provides one way to estimate the presence of gender bias in referrals, as such doctors face similar opportunity pools. Another way is to structurally estimate the impact of gender on referral probability by comparing realized and unrealized links, while controlling for pairwise characteristics, including: distance, shared hospital affiliation, similar experience, and shared medical school⁵. Finally, two of the model's predictions: that homophily increases with market size and that it generates demand effects, are shown to be driven by biased-preferences, not sorting, and thus provide another way to test for their existence.

I find significant gender homophily in referrals, mostly due to preferences: All else equal,

 $^{^{4}}$ Graham (2014) also suggests a method to account for heterogeneity, yet his method is restricted to dense networks (where node degree is proportional to network size), while physician referral networks are sparse

⁵To deal with the technical challenge that referral networks are large and sparse, I sample and match realized and unrealized links. This design is known as *choice-based*, *endogenous stratified*, or *case-control* sampling (Manski and Lerman, 1977; King and Zeng, 2001). Sampling is not required for the estimation of homophily, as it only considers gender correlation within realized links.

doctors are 10% more likely to refer within- rather than between-gender. Across all markets, female doctors refer to female specialists a third more than males do (19% women-to-women compared with 15% men-to-women), i.e. the average difference between the genders is 4p.p. This average masks heterogeneity between markets in the availability of female specialists: as predicted by the model, homophily is greater in larger markets. Gender-homophily is stronger among older doctors, and same-gender relationships are also relatively more persistent than between-gender ones. Some sorting does exist, but it only explains a quarter of the overall gender homophily. I also find age-homophily: physicians are 1% more likely to refer to a physician one year closer to them in age. Hence there is a comparable effect between being of a different gender and having a ten-year age difference.

Data on physician first names provide an opportunity to test for prejudice, using a quasiaudit 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 are names. This rules out strong-form prejudice, one based on names alone. The emerging picture is not one of illdisposed individual biases, but rather one in which a widespread tendency to prefer similar others leads to an overall unfavorable environment for the female minority.

Next, I turn to directly testing the predicted effects of homophily, using reduced form specifications with longitudinal data. I find homophily has significant impact on physician pay: more male primary care physicians in a market lead to higher pay for male specialists and lower pay for female specialists. This result is obtained using a monthly panel of individual payments for 2008–2012, with specialist fixed-effects, so it is robust to unobserved heterogeneity in specialists' labor supply, in particular due to other known differences between the genders. The impact of homophily on the workload gap is fairly large, and comparable to that of gender differences in career interruptions.

The overall impact of homophily on the pay gap could be 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. To test it, I leverage observed differences in clinical dependency between different medical specialties. Using retrospective cohort data on physician specialty choices between 1965–2005, I find evidence for female choice of specialties being affected by the paucity of female referrals from related specialties. Notwithstanding its adverse effects on the physician gender pay-gap, I find no effects of homophily on patient mortality or cost, suggesting the clinical appropriateness of referrals is not compromised by homophily.

The findings that women in upstream specialties induce positive externalities for women in downstream specialties have 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, where there are currently still very few women. Second, in the longer run, as recent female entrants gradually transform the gender composition of the physician labor force, the part of the pay gap due to homophily is expected to vanish, or even reverse. Referrals originating in a gender-balanced doctor population would eliminate on average 10% of the within-specialty gender pay-gap.

This paper proceeds as follows: I discuss related literature and background (Section 1.1), the data (Section 2), and the gender pay-gap in Medicare (Section 3); define, model, and estimate gender homophily in Medicare referrals (Section 4); estimate homophily's impacts on pay disparities (Section 5); consider prejudice and patient outcomes (Section 6); and conclude (Section 7).

1.1 Related Literature and Background

Homophily, the tendency of individuals to connect more 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 on-line 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). This paper is part of a nascent economic literature studying homophily, its causes and implications, and the challenges to identifying it. 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 in dense graphs, 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 also uses a public version of the Medicare referrals data for illustration of his method, 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 impact of homophily. One is Golub and Jackson (2012), which shows that clustering due to homophily slows down information dissemination and learning. The current paper 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. 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. In contrast, the current focus is on the impact on referrals on physician labor demand. In its focus it is close to Johnson (2011) who showed the career path of cardiac surgeons in Medicare is affected by learning about their quality by doctors. 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 how to establish and develop such relationships⁶. 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 address questions that previously seemed beyond reach. Extensive data support identification not just in revealing variables of interest, directly or through linkages across databases, it also opens new avenues for identification by allowing researchers to solve nested prediction or classification problems. For example, Currie et al. (2015); Currie and MacLeod (2013) demonstrate how large administrative databases of medical records can be used to predict the appropriate course of medical treatment (essentially a classification problem), a benchmark 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

⁶For 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.

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 Medicare physician-billed services for a random sample of 20% Medicare beneficiaries. Medicare is the federal health insurance program for people who are 65 or older, certain younger people with disabilities, and people with End-Stage Renal Disease. The data contain the complete record of claims for physician-billed services for the period 2008–2012. It is run by a government agency, the Centers for Medicare and Medicaid (CMS) and has standardized payments and billing systems. The data studied here are for traditional ("Fee-For-Service") Medicare, which covers two-thirds of all Medicare patients (the other third is covered by private carriers).

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 claim⁷. 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,

⁷For 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.

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 physician⁸. 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 database⁹. 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 dollars¹⁰, about 3% of the U.S. GDP. The data I use are from traditional "Fee-For-Service" Medicare, which is responsible for two-thirds of all Medicare beneficiaries, with 35 million covered lives. 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 very 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 A1.

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

⁸Claims 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 BE-TOS 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.

⁹Physician Compare Database, https://data.medicare.gov/data/physician-compare Accessed May 2015.

¹⁰2012 National Health Expenditure Accounts (NHEA).

	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 referra	ls)		
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 refe	rrals)		
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

Table 1: Descriptive Statistics: Physicians

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.



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. Experience is years since medical school graduation.

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 A2, 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 Healthcare¹¹. 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 networks: Less than 10% 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.

¹¹"Dartmouth Atlas of Healthcare", http://www.dartmouthatlas.org/tools/downloads.aspx?tab=39. Accessed May 2015

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.

		Dependen	t variable:		
		Log(Anr	nual Pay)		
(1)	(2)	(3)	(4)	(5)	(6)
$\begin{array}{c} 0.668^{***} \\ (0.005) \end{array}$	$\begin{array}{c} 0.654^{***} \\ (0.005) \end{array}$	$\begin{array}{c} 0.468^{***} \\ (0.005) \end{array}$	$\begin{array}{c} 0.361^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.337^{***} \\ (0.004) \end{array}$	$\begin{array}{c} 0.340^{***} \\ (0.005) \end{array}$
No	Yes	Yes	Yes	Yes	Yes
No	No	Yes	Yes	Yes	Yes
No	No	No	Yes	Yes	Yes
No	No	No	No	Yes	Yes
No	No	No	No	No	Yes
Yes	Yes	Yes	Yes	Yes	Yes
498,580 0.033	447,863 0.052	447,863 0.290	$424,361 \\ 0.407$	420,319 0.441	296,199 0.471
	(1) 0.668*** (0.005) No No No No Yes 498,580 0.033	(1) (2) 0.668*** 0.654*** (0.005) (0.005) No Yes No No Yes Yes 498,580 447,863 0.033 0.052	Dependent (1) (2) (3) 0.668*** 0.654*** 0.468*** (0.005) (0.005) (0.005) No Yes Yes No No Yes No No No Yes Yes Yes 498,580 447,863 447,863 0.033 0.052 0.290	Dependent variable: Log(Annual Pay) (1) (2) (3) (4) 0.668*** 0.654*** 0.468*** 0.361*** (0.005) (0.005) (0.005) (0.004) No Yes Yes Yes No No Yes Yes No No Yes Yes No No No Yes No No No No Yes Yes Yes Yes 498,580 447,863 447,863 424,361 0.033 0.052 0.290 0.407	$\begin{tabular}{ c c c c } \hline $Dependent variable:$ $Log(Annual Pay)$ \\ \hline (1) (2) (3) (4) (5) \\ \hline (0.668^{***} & 0.654^{***} & 0.468^{***} & 0.361^{***} & 0.337^{***} \\ \hline (0.005) (0.005) (0.005) (0.004) (0.004) \\ \hline Ves & Yes$ & Yes$ \\ \hline Vo & No$ & Yes$ & Yes$ & Yes$ \\ \hline No & No$ & Yes$ & Yes$ & Yes$ \\ \hline No & No$ & No$ & Yes$ & Yes$ \\ \hline No & No$ & No$ & Yes$ & Yes$ \\ \hline No & No$ & No$ & Yes$ & Yes$ \\ \hline No & No$ & No$ & Yes$ & Yes$ \\ \hline No & No$ & No$ & No$ & Yes$ \\ \hline No & No$ & No$ & No$ & Yes$ \\ \hline No & No$ & No$ & No$ & No$ \\ \hline Yes & Yes$ & Yes$ & Yes$ & Yes$ \\ \hline $498,580$ & 447,863$ & 447,863$ & 424,361$ & 420,319$ \\ \hline 0.033 & 0.052$ & 0.290$ & 0.407$ & 0.441$ \\ \hline \end{tabular}$

Table 2: The Gender Pay Gap for Medicare Physicians

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.

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 but less than 6% of active orthopedic surgeons (Figure A1). 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.

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. Such 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 market¹², where a link exists between "doctor" j and "specialist"¹³ 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)



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):

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

 $^{^{12}}$ 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.

¹³Throughout 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.

Directed Homophily exists (DH > 0) if male doctors refer to male specialists more than their female counterparts¹⁴. Table 3 illustrates this definition using Medicare data. In Medicare, male doctors refer 85% of their patients to male specialists, compared to female doctors who refer 80% of their patients to male specialists, so DH = 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 samegender 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.

To see what makes Directed Homophily a useful measure, contrast it with the commonly used measure of homophily: Inbreeding Homophily (see McPherson et al., 2001; Currarini et al., 2009; Bramoullé et al., 2012). Instead of comparing referral rates across genders, 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

¹⁴In 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]).

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 (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

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

		A. Referrals		В.	B. Percent of Outgoing			C. Percent of Incoming			
		Г	0		То		То			То	
		F	М		F	М	Total		F	М	
From	f	420,976	1,712,510	f	19.73	80.27	100	f	24.74	19.36	
FIOIII	m	$1,\!280,\!691$	$7,\!130,\!872$	m	15.23	84.77	100	m	75.26	80.64	
								Total	100	100	

Table 4: Medicare Referrals by Gender

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.

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 = 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



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.

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.

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 gendersensitive utility function, and choose a specialist:

$$\underset{k \in K_j}{\operatorname{argmax}} U_j(k) = \beta \mathbb{1}_{g_j = g_k} + \delta X_k + \varepsilon_{jk}$$
(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 $(X_k; \text{ e.g., experience}$ or other quality dimension), but may also depend on gender: $\beta > 0$ represents genderbiased 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 Gumbelextreme-value, equation (3) yields the conditional logit probability for a referral from j to k, given gender and other characteristics:

$$p_{jk} := Pr(Y_{jk} = 1 | g, X) = \frac{e^{\eta_{jk}}}{\sum_{k' \in K_j} e^{\eta_{jk'}}}$$
(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 following claim shows that gender-biased preferences lead to homophily.

Claim 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 Claim 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):

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

$$\tag{5}$$

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 $p_{M|m} > p_{M|f}.$





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

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

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

$$\tag{7}$$

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 Mdepends on η . In (7) too $p_{M|m} = p_{M|f}$ if and only if preferences are unbiased $\beta = 0$. That is, Claim 1 holds for the heterogeneous case as well.

With heterogeneity $(\eta \neq 1)$, Directed Homophily is 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 Apart from preferences, sorting also causes homophily, as it makes women and men more exposed to their own gender. 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 $j \in J^c$. The definition of a market is abstract, and can stand not only for geographically-defined markets, but also for other segmentations (e.g., institutional affiliations). Markets may also vary in size $\mu^c = \frac{J^c}{J}$ (so $\sum_c \mu^c = 1$). The conditional probabilities of referrals to men now vary by market and are denoted $p_{M|m}^c$ and $p_{M|f}^c$. Define *Sorting* to be a positive correlation between the genders of doctors and specialists in a market¹⁵ Cov $(m^c, M^c) > 0$ (equivalently, Cov $(f^c, F^c) > 0$). Homophily then arises at the aggregate, when all markets are pooled together:

Claim 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

¹⁵This definition extends to the more general case where K_j is specific to each doctor as: $\operatorname{Cov}(m^j, M^{K_j}) > 0$, where $m^j = \mathbb{1}_{g_j=m}$ and M^{K_j} is the fraction of male in K_j .

these two causes: preferences (within market) and sorting $(across markets)^{16}$.

Proposition 1 (Homophily Decomposition). *Homophily observed across all markets decomposes to preferences and sorting as follows:*

$$\underbrace{p_{M|m} - M}_{p_{M|m} - M} = \frac{1}{m} \left(\underbrace{\mathbb{E}[m^c(p_{M|m}^c - M^c)]}_{\text{E}[m^c(p_{M|m}^c - M^c)]} + \underbrace{\mathbb{Cov}[m^c, M^c]}_{\text{Cov}[m^c, M^c]} \right)$$

The proof of Proposition 1 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 $p_{M|m}^c$ 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 $\operatorname{Cov}[m^c, M^c] < 0$ then even if preferences are biased overall homophily could be zero.

A corollary of Proposition 1 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, 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 1 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 Bernoully 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 $DH(N) = E[p_{M|m} - p_{M|f}|N]$. We say homophily is greater in large markets if for every market size N there exists N' > N such that DH(N') > DH(N).

 $^{^{16}{\}rm The}$ proposition is stated here for Inbreeding Homophily for clarity. Its equivalent for Directed Homophily is in the appendix.

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

- 1. 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.
- 2. If preferences are unbiased, $\beta = 0$, homophily is only greater in large markets if sorting into unobserved segments $\operatorname{Cov}[m^{l_c}, M^{l_c}]$ is greater in large markets.

Proposition 2 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 genderbiased, 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 3 (Demand for Specialists by Gender). Average specialist demand depends on gender as follows:

- 1. With gender-neutral preference ($\beta = 0$) specialist demand is invariant to gender.
- 2. With gender-biased preference ($\beta > 0$) average demand for specialists is higher the more doctors share their gender.
- 3. 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 3 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:

$$D = mp_{M|m} + (1 - m)p_{M|f}$$
(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 Myields:

$$\frac{\partial D}{\partial m} = \underbrace{p_{M|m} - p_{M|f}}_{p_{M|m} - p_{M|f}} \tag{9}$$

$$\frac{\partial D}{\partial M} = (1-m) \underbrace{\frac{w(1-w)}{(1-M(1-w))^2}}_{(1-M(1-w))^2} + m \underbrace{\frac{-(1-w)}{(M+w(1-M))^2}}_{(M+w(1-M))^2}$$
(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-shaped¹⁷ (Figure A3). 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 areas 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 3 is that it is better

¹⁷This case is similar to previous results for undirected homophily of (Currarini et al., 2009, Section 4.5). There too the basic mechanism underlying the S-shaped curve is preferences, albeit the setting is different.





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.

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 Directed Homophily (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 of link formation (developed in Section 4.3), by comparing doctors' chosen specialists to those not chosen. Directed Homophily is an easy-to-estimate statistic 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 specialists¹⁸, 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 robustness, hospital interacted with medical specialty are also considered). As shown in Proposition 1, 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 biasedpreferences, 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

¹⁸That is, $r_{jM} = \frac{\sum_{k:g_k=M} n_{jk}}{\sum_k n_{jk}}$, where $n_{jk} \ge 0$ is the volume of referrals from j to k. The unweighted specification uses (with slight abuse of notation): $n_{jk} = \mathbb{1}_{\{n_{jk} > 0\}}$.

differenced-out, as is clear from comparing the log of the ratio of probabilities:

$$\log \frac{p_{jk}}{p_{jk'}} = \beta(\mathbb{1}_{g_j = g_k} - \mathbb{1}_{g_j = g_{k'}}) + \delta(X_{jk} - X_{jk'})$$
(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 2). Second, a correlation of doctors' gender distribution with specialist demand (Proposition 3). 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 kwithin the same referral region (HRR) and of the same speciality of k, the specialist to which j actually referred. Controls for the other observed attributes are included¹⁹. 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 individualphysician 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 specialists²⁰. I address 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 confound 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

¹⁹Sampling 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.

²⁰For example, Reyes (2006) shows female patients are more likely to visit female obstetrician-gynecologists.

	Percent of Referrals to Male Specialists						
		O	LS		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)	385104	384985	384985	347534	347534	347534	
Groups (Hospital/Spcl)					4819	66563	
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	

Table 5: Reduced Form Estimates of Directed Homophily

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.

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.





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 an women). Lined are fitted linear and quadratic fitted to the data shown.

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 2).

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

			Link(j,k)		
	(1)	(2)	(3)	(4)	(5)
Link					
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

Table 6: Conditional Logit Estimates: Link Probability

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.

the attributes²¹. 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 homophily of 3.2%, net of sorting (the implied directed homophily at the maximally-diverse pool, with the same number of men and women, is 5%).

In addition to gender homophily, referrals also show 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 is 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.

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

²¹Estimates close to zero approximately equal the percentage increase in probability. That is, using the notation of (3), around zero $\beta \approx \frac{p_{jk}|g_j = g_k}{p_{jk'}|g_j \neq g_{k'}} - 1.$

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's 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 3). 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 homophily 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 3). I focus on primary-care physicians, who handle the majority of outgoing referrals. Using a monthly panel of physician payments I estimate:

$$log(Pay_{k,t}) = (\beta_M \mathbb{1}_{g_k=M} + \beta_F \mathbb{1}_{g_k=F})m_{c(k,t),t} + \gamma_t + \alpha_k + \varepsilon_{k,t}$$
(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 patient²².

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 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 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.

This relationship supports my previous results, showing homophily is indeed due mostly to gender-bias in referrals. As shown above (Proposition 3), demand for specialists varies with their gender and upstream gender fractions only when homophily is caused by genderbiased preferences, not sorting.

²²By 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.

	(1) Log monthly pay	(2) Log monthly pay
Female Specialist X Pct male PCP (city)	-0.26^{***}	-0.27^{***}
Male Specialist X Pct male PCP (city)	(0.004) 0.49^{***} (0.020)	(0.004) 0.47^{***} (0.020)
Month Dummies	(0.029) Yes	(0.029) Yes
M,F x Pct Male patients (city) Obs. (Phys x Month)	No 18087629	Yes 18087629
Clusters (Phys) R Sqr.	418939 0.0323	418939 0.0322

Table 7: Male Fraction of Primary Care and Specialist Workload

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.

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 accounted 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). We 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.

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.

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.

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 advantage 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.





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.

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 dermatologists. 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) $S = \{1, ..., S\}$ 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 specialties²³. 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

²³That is, $m_s = \sum_{s' \in S} r_{s|s'} M_{s'}$

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 specialties²⁴:

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

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 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

 $^{^{24}}$ 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

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 A6. 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.

	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	

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

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 A6. 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 groups²⁵.

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

 $^{^{25}}$ Note that whether discriminatory beliefs exist, and whether such beliefs are rationalized by group differences in productivity are separate questions.

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 male²⁶. 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 names²⁷. The identifying variation is in the informativeness of name as a signal for 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-masculinity²⁸. 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.

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

²⁷More 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), ..., [.8,.9), [.9, 1]}). Define $r_{g|M}^{\Gamma}$ 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 namemasculinity $\gamma(m_k) \in \Gamma$. 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 $(H_1) DH(\Gamma) = r_{m|M}^{\Gamma} - r_{f|M}^{\Gamma}$ 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 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.

²⁸The 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.

²⁶Formally, denote the gender of specialist k by $g_k \in \{M, F\}$ and the first name of an individual k by $m_k \in M = \{m_1, m_2, \ldots, m_M\}$ I assign an index $\gamma : M \mapsto [0, 1]$ measuring name masculinity:



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.

Thus the null hypothesis is not rejected: referrals seems not to be prejudiced, at least not 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 otherwiseequally 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 have examined a demand-side explanation for the physician gender pay gap: gender-homophily in referrals (physicians refer to their same gender). Existing supply-side explanations explain only part of the gender pay gap in Medicare, which is a combination of women choosing lower-paying specialties and working fewer hours. A model of referral choices extends existing theory of homophily to directed networks, and shows that it implies a relationship between gender of physicians and demand for their services. The model also yields testable differences between two mechanisms causing homophily: preferences and sorting, and clarifies how homophily contributes to the pay gap.

The model raises two conceptual points. First, referral networks (more broadly, directed networks) provide an opportunity to measure homophily in a way robust to underlying heterogeneity, by comparing the gender-distribution of referrals not to baseline gender fractions but between genders. Second, in directed networks, both upstream and downstream gender distributions matter for how homophily impacts downstream demand. Being the minority of both, female specialists face a lower demand for their services because they receive fewer referrals than men.

Estimates of the model and its predictions using Medicare data on physician referrals and reimbursement, spanning all specialties and local U.S. markets for 2008–2012, show physician referrals exhibit significant gender homophily, partly due to sorting, bust mostly due to gender-biased preferences. All else equal, physicians are less likely to refer to the other gender, and more likely to refer to their own gender. As long as men are the majority of referring physicians, homophily in referrals diverts demand away from female. On the intensive margin homophily is currently causing female to forgo to their male colleagues thousands of dollars worth of work each year. Moreover, evidence exists for effects on the extensive margin, namely on entry: women stay away from specialties to which more referrals come from men, both historically and currently. 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. On a brighter note, results suggest that current entry trends will have favorable impact on female physicians in the future, particularly the equalization of female participation in primary care which is 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, particularly 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. (Claim 1) Pick any j such that $g_j = m$. Summing up probabilities of referrals to all available specialists gives:

$$p_{M|m} = \sum_{k:g_k=M} p_{jk}$$

$$= \frac{\sum_{k:g_k=M} e^{\beta \mathbb{1}_{g_j=g_k}}}{\sum_k e^{\beta \mathbb{1}_{g_j=g_k}}}$$

$$= \frac{\sum_{k:g_k=M} e^{\beta}}{\sum_{k:g_k=M} e^{\beta} + \sum_{k:g_k\neq M} e^{0}}$$

$$= \frac{Me^{\beta}}{Me^{\beta} + 1 - M}$$

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

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

where $\eta_G = \mathbb{E}[\delta X_k | g_k = G]$ for $G \in \{M, F\}$, and $\eta = e^{\eta_F - \eta_M}$.

Proof. (Claim 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:

$$p_{M|m} = \sum_{c \in C} p_{c|m} p_{M|m,c} = \sum_{c \in C} \mu^c \frac{m^c}{m} p_{M|m}^c$$
$$\geq \sum_{c \in C} \mu^c \frac{m^c}{m} M^c = \frac{1}{m} E[m^c M^c]$$
$$> \frac{1}{m} E[m^c] E[M^c] = M$$

The first inequality is due to preferences: $p_{M|m}^c \ge M^c$ (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^{*} ($\operatorname{Cov}[m_j, M^j] > 0$), the proof follows immediately from Claim 1: 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, $\operatorname{Cov}[m_j, M^j] = \operatorname{Cov}[m^c, M^c]$ under separate markets with common $K_j = K^c$ in each.

Proposition 4 (Directed Homophily Decomposition). *The overall Directed Homophily decomposes as follows:*

$$p_{M|m} - p_{M|f} = \mathbf{E}\left[\frac{m^c}{m}p_{M|m}^c - \frac{1 - m^c}{1 - m}p_{M|f}^c\right] + \frac{1}{m(1 - m)}\mathbf{Cov}[m^c, M^c]$$
(20)

Proof. (Proposition 1)

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

Proof. (Proposition 4) Applying the proof of Proposition 1 to female (by symmetry) and substituting $p_{M|f} = 1 - p_{F|f}$ yields :

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

Hence

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

rearranging yields the result.

Proof. (Proposition 2) To prove 1., Let $h(M) = p_{M|m} - p_{M|f}$, so DH(N) = E[h(M)|N]. Recall that: h(M), given in Claim 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 $F(N) := Binomial(N^c, M)/N^c$, 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 1 within each market homophily equals $Cov[m^{l_c}, M^{l_c}]$.

Proof. (Proposition 3) 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):

$$D_{M} = \sum_{j \in J} p_{jk} = \sum_{j \in J} \frac{e^{\beta s(j,k)}}{\sum_{k' \in K} e^{\beta s(j,k')}}$$

= $\sum_{j \in J, g_{j}=1} \frac{e^{\beta s(j,k)}}{\sum_{k' \in K} e^{\beta s(j,k')}} + \sum_{j \in J, g_{j}=0} \frac{e^{\beta s(j,k)}}{\sum_{k' \in K} e^{\beta s(j,k')}}$
= $\frac{1}{N} (\sum_{j \in J, g_{j}=1} \frac{1}{M + \omega(1 - M)} + \sum_{j \in J, g_{j}=0} \frac{\omega}{\omega M + (1 - M)})$
= $\frac{n}{N} (\frac{m}{M + \omega(1 - M)} + \frac{\omega(1 - m)}{\omega M + (1 - M)})$

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 2 is true rewrite:

$$D_{M} = \frac{n}{NM} \left(mp_{M|m} + (1-m)p_{M|f} \right) \\ = \frac{n}{NM} \left(p_{M|f} + m(p_{M|m} - p_{M|f}) \right)$$

and note that $\partial D_M / \partial m > 0$ since $p_{M|m} - p_{M|f} > 0$ for every $\beta > 0$. To see 3 is true take the derivative of D_M with respect to M:

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

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

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 A1). 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 ??).

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 others), buy calculating the demand disparity with different populations upstream and downstream:

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

Where $p_{G|g} = p_{G|g}(G;\beta)$ for $g \in \{m, f\}$ and $G \in \{M, F\}$, are given in (5) above. 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.

		Fraction Males Downstream (M)							
Upstream (m)	0.4	0.5	0.6	0.7	0.8	0.9	1		
0.4	1.019	1.020	1.021	1.022	1.023	1.024	1.025		
0.5	0.999	1	1.001	1.002	1.003	1.004	1.005		
0.6	0.979	0.980	0.981	0.982	0.983	0.984	0.985		
0.7	0.960	0.961	0.962	0.962	0.963	0.964	0.965		
0.8	0.941	0.942	0.942	0.943	0.944	0.944	0.945		
0.9	0.923	0.923	0.923	0.924	0.924	0.925	0.925		
1	0.905	0.905	0.905	0.905	0.905	0.905	0.905		

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

Notes: Using estimated bias $\hat{\beta} = 0.1$, the table shows calculated earnings gaps: $\frac{D^F}{D^M}(m, M; \beta)$, 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 current rates the gender-bias in referrals alone is contributing 1-.963=3.7% to the physician earnings gap.

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:

$$p_{jk,t+1|jk,t}^{persist} := Pr(Y_{jk,t+1} = 1 | Y_{jk,t} = 1, g, X) = \frac{e^{\eta_{jkt}}}{1 + e^{\eta_{jk't}}}$$
(22)

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, (22) 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

	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			

Table A2: Estimates: Link Persistence

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. 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.

E Additional Tables and Figures

Figure A1: Male Fraction of Physicians in Common Medical Specialties



Gender Composition of Common Physician Specialties 2012 Active Physicians

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.

	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	Otolarvngology	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	57	6 224
21	General practice	2.5	14.7	4,853
21	Endocrinology	20.4	7 2	4 534
22	Infectious disease	20.4	5.0	4,004
20	Neurosurgery	19.8	16.7	4,402
24	Radiation oncology	17.3	3.4	3 933
26	Bheumatology	20.8	7.8	3,505 3,765
20	Plastic and reconstructive surgery	73	5.0	3 759
21	Pathology	7.5 2.3	0.4	3,627
20	Allergy/immunology	11.5	2.0	2,021 2,768
30	Pediatric medicine	1.0	2.0	2,100
31	Medical oncology	20.6	12.0	2,035 2,507
30	Vascular surgery	20.0	18.1	2,007
32	Critical care	16.5	9.5	2,400 2.046
34	Thoracic surgery	15.2	18.1	1 886
35	Interventional Pain Management	10.2 97.2	55	1,655
36	Coristria modicino	4.0	20.8	1,000 1,507
37	Cardiac surgery	4.3	20.8	1,597
38	Coloroctal surgery	22.1	16.8	1,520 1 161
20	Doin Management	22.1	10.8	1,101
39 40	Fam Management	22.3	4.5	1,035 1.047
40	Interventional radiology	19.4	10.0	1,047
41	Currence legist / encologist	20.1	2.0	930
42	Gynecologist/oncologist	10.4	10.0	604
43	Jurgical offcology	12.1	10.0	084
44	Octoopathia manipulativa therapy	10.9	9.4	462
40	Nuclear manipulative therapy	4.7	9.0	405
40	Nuclear medicine	0.2	1.4	209
41	Preventive medicine	4.2	0. <i>1</i>	217
4ð 40	Maxillolacial surgery	3.0	3.2	104
49 50	Oral surgery	2.8	2.0	108
00 F 1	Addiction medicine	1.7	3.7	(1
51 50	Peripheral vascular disease	32.0	13.9	62
52 59	Neuropsychiatry	16.2	4.8	61
53	Podiatry	17.7	3.4	40

Table A3: 2012 Average Degree by Specialty

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

	De	Dependent variable:				
		Percent Mer	n			
	(1)	(2)	(3)			
Pct Ref From Male	$\frac{1.260^{***}}{(0.160)}$	$\frac{1.210^{***}}{(0.149)}$	$\frac{1.220^{***}}{(0.150)}$			
Training Duration		0.066^{***} (0.013)	$\begin{array}{c} 0.064^{***} \\ (0.013) \end{array}$			
Pct Work in Weekend			-0.137 (0.151)			
Constant	-0.237^{*} (0.123)	-0.486^{***} (0.124)	-0.474^{***} (0.125)			
Observations Adjusted R ²	$\begin{array}{c} 172 \\ 0.264 \end{array}$	$\begin{array}{c} 172 \\ 0.361 \end{array}$	$\begin{array}{c} 172 \\ 0.361 \end{array}$			
Note:	*p<	0.1; **p<0.05	5; ***p<0.01			

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

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.

	Percent c	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

Table A5: Homophily Estimates for Different Age Groups

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.

	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

Table A6: Homophily Estimates with Weighted Links

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.

	(1)	(2)
	2012 Cost	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
\mathbb{R}^2	0.240	0.349
Clusters	dyad	dyad
No. Cluster	4444359	4581862
FE1 (Doctors)		302997
FE2 (Specialists)		276488

Table A7: Physician Dyad Gender Mix and Subsequent Patient Spending

t statistics in parentheses

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

(1)	(2)
Mortality (1 Year)	Mortality (1 Year)
-0.00303***	-0.00169***
(-8.43)	(-4.52)
0.0270^{***}	0.0245^{***}
(85.46)	(76.33)
0.00759^{***}	
(20.24)	
0.00459^{***}	
(12.17)	
-0.000100	0.000253^{**}
(-1.12)	(2.78)
-0.000642***	-0.000577***
(-12.11)	(-10.63)
Yes	Yes
Yes	No
Yes	No
7120083	7424095
169	58
0.104	0.236
dyad	dyad
4444359	4581862
	302997
	276488
	(1) Mortality (1 Year) -0.00303^{***} (-8.43) 0.0270^{***} (85.46) 0.00759^{***} (20.24) 0.00459^{***} (12.17) -0.000100 (-1.12) -0.000642^{***} (-12.11) Yes Yes Yes Yes Yes 7120083 169 0.104 dyad 4444359

Table A8: Physician Dyad Gender Mix and Patient Mortality

t statistics in parentheses

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





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 A3: 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 A4: Homophily Through Link Weights



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).



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 A6: Estimates of \mathbf{R}

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).