Referral Triads

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Abstract

Third parties that refer clients to providers help clients navigate market uncertainty by: (i.) curating well-tailored matches between clients and experts, and (ii.) facilitating post-match trust. We argue that these two roles often conflict with one another because they require referrers to activate network relationships with *different* experts. While strong ties between referrers and experts promote trust between clients and experts, such ties reduce the likelihood that intermediaries consider referrals to more distal experts that are be better suited to serve a client's needs. We examine this unexplored tension using full population medical claims data for the state of Massachusetts. We find that when primary care physicians (PCPs) refer patients to specialists with whom the PCP has a strong tie, patients demonstrate more confidence in the recommendations of the specialist. However, a strong tie between the PCP and specialist also reduces the expertise match between a patient's diagnosis and a specialist's clinical experience. These findings suggest that the two central means by which referrers add value may be at odds with one another because they are maximized by activation of different network relationships.

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Introduction

Referrals take center stage in the dynamics of many different economic markets. As intermediaries that assist in matching prospective exchange partners and building trust between them, referrers are vital in settings in which inherent transactional risks are part and parcel of exchange relations. The latter is true of dealings in which there is latitude for opportunistic behavior and those in which market participants lack the ability to assess a partner's competence or integrity. In these settings, ego will be reluctant to enter an exchange with alter absent some mechanism to increase the odds of dependable behavior.

The markets for credence goods meet these conditions. These are goods or services in which product quality is difficult for consumers to evaluate *even after consumers have experienced or purchased a good.* Many professional services, in which expert providers generally know far more about client needs than do clients themselves, are of this ilk (Dulleck and Kerschbamer, 2006; Heinz et al., 2001). A particularly salient example of credence goods is the enormous market for medical care, the focus of our work, along with those for legal counsel, financial advice, and many other services. These markets share a few common features. First, experts in these sectors advise on some of life's most complex and consequential decisions. Second, the potential for abuse of client interest is notorious, especially because diagnosis and treatment are often performed by the same expert provider (Afendulis and Kessler, 2007).

Given the difficulty consumers face in appraising the quality and reliability of providers of professional services, a set of intermediaries have arisen to facilitate exchange. These include institutions that disseminate the reputations of service providers, such as certification bodies or repositories of online reviews (Sharkey et al., 2022; Fleischer, 2009). They also include brokers that match buyers with sellers. For example, in creative industries, talent and literary agents serve as matchmakers (Bielby and Bielby, 1999), along with the gallerists and dealers that enable the art market (Aerne, 2021); in financial services, venture capital firms and investment banks match providers and users of financial capital (Jääskeläinen and Maula, 2014; Rider, 2009).

In addition, a large fraction of consumption decisions in the service sector are routed through personal or interorganizational referrals from non-compensated or informal intermediaries (Garicano and Santos, 2004). We refer to these social structures as "referral triads". They include three, distinct roles: a recommender/referrer, a client/referee, and an expert/referred-to provider. Referral triads are omnipresent in the market for professional services and may account for the majority of the flow of first-time client work.[1]

Referrers perform two, vital functions. First, they act as matchmakers (Marsden, 1982). Through their past investments in knowing the players in a market, referrers acquire the purview to tailor introductions between clients and experts (Burt, 1992; Burt et al., 2005). Thus, intermediaries in referral triads are the structural clearinghouse that determines which client-expert dyads come to be (Gulati and Gargiulo, 1999). Once a triad has formed, the referrer often plays a second role: to foster the trust necessary for successful transactions to ensue (Coleman, 1994). A referrer's willingness to endorse an expert often hinges on his or her history of interaction with that provider. Specifically, referrers that have prior, close relationships with experts are more able and (often) more willing to vouch for those providers, and possibly to monitor a client engagement to provide assurances to the risk-exposed party. In doing so, referrers mitigate the perceived risk that clients take when they place critical decisions regarding their health, finances and other important matters in the hands of experts.

Our argument is that these two functions of the intermediary in referral triads – optimizing match quality and cultivating trust between clients and experts – both rely on a referrer's relationships but because they often depend on the activation of *different* ties, they frequently stand at odds with one another. In particular, our core assertion is that the

[1] Wilson (1994) estimates that across markets, service providers acquire 80% of their clients from interpersonal referrals. He writes (p. 13), "The prospect that referrals are the most important source of obtaining new clients can be tested with reference to the reader's own experience obtaining professional advisors. It will be found that most of our links with our accountants, solicitors, architects, surveyors, dentists, and private health-care practitioners have come through an introduction or recommendation from a third party."

specific experts that referrers know well enough to foster trust in referral triads frequently will differ from the providers that have the deepest experience in a client's specific issue. This means that the very same referrals that create high trust client-expert dyads may in fact also result in pairings with a lower degree of expert-client expertise concordance. We refer to the latter as lower match quality.

The logic is as follows. To obtain the knowledge to recommend quality matches, referrers first establish ongoing relationships with experts and other market participants. Once in place, the existence of these relationships bolsters the intermediary's ability to create trust between a client and an expert, but these ties also naturally influence the referrers' choice of which expert to recommend to a client. In particular, as referrers develop stronger ties with a handful of "go to" experts, whether based on habit, preference, convenience, or reciprocity, they tilt toward matching clients to experts with whom they are closely connected (Sorenson and Waguespack, 2006). This proclivity to concentrate referrals among a few strong-tie, go-to associates, while arguably maximizing the intermediary's ability to promote trust, likely comes at the expense of optimizing the quality of expertise-based matches. In effect, the social connections that evolve alongside the market's transactional structure gently promote inertial referral behaviors, which then undermines optimal matching (Martin and Yeung, 2006; Dahlander and McFarland, 2013). Because of this, *referrers that are embedded in strong tie networks may facilitate expert-client relationships that develop more trust, while simultaneously embodying lower-quality matches.*

To examine this argument, we study the structure of referral triads that impacts consumption choices in the largest of the professional service markets: healthcare. In this setting, the referrer is typically a primary care physician (PCP), the referee is a patient, and the referred to is a specialist provider. We ask two main questions: (i.) does tie strength between the *PCP and the referred-to medical specialist* affect the confidence that the *patient* places in the specialist's care? And (ii.) does the tie strength between the PCP and referred-to medical specialist affect the quality of the match between the patient's health condition and the specialist's expertise?

In regressions that include PCP-by-specialty fixed effects and in 2SLS models that instrument for tie strength between PCPs and specialists, we show that patients referred to their PCPs' strong-tied specialists demonstrate two behaviors that signal the presence of trust. They are: (i.) less likely to seek a second opinion (SO) from a different expert after consulting the specialist they were first referred to, and (ii.) they consume more medical services provided by the referred-to specialist. However, we then show that, (iii.) a strong tie between PCP and referred-to specialist diminishes the quality of the match between the patient's health needs and the specialist's clinical focus, as evidenced by the specialist's own history of practice.

Theory: Referral Triads in Professional Services

Information problems

In the professions, clients seek counsel from experts that diagnose problems and recommend solutions. A core feature of this context is that clients often have an imperfect understanding of their problems and of the services they require (Freidson, 1988). As a result of this information asymmetry, clients may incur high search costs to identify a reliable and well-matched expert and are often left with questions about whether they were attended to with aptitude and best efforts, even after services have been rendered and outcomes are witnessed (Sharma, 1997).

Prior work has documented how these features of the market for expert services may result in abuse of clients' interests (Ackerloff, 1970; Kollock, 1994). When a consumer takes a car to a repair shop, for example, she hopes that the mechanic is knowledgeable enough to diagnose the issue and scrupulous enough not to overcharge for the repair. Wolinsky (1995), however, reported that almost half of auto repairs performed at the time were unnecessary. Likewise, studies have shown that physicians and their relatives receive fewer or less costly medical services than do non-expert patients with similar health states, and that patients sometimes endure shifts in treatment protocols that maximize provider billings rather than their welfare (e.g. Emons, 1997; Schwartz et al., 2011; Gruber et al., 1999; La Forgia, 2020). In historical contexts, many scholars have documented dubious conduct among professionals (Carlin, 1966; Peterson, 1978). In sum, the predicaments of suboptimal matching, mediocre or worse service, outright incompetence, specious advice, and overallocation of time to generate excess billings, are looming issues across these markets.

What solutions have arisen to ameliorate these market frictions? Briefly, the professions are home to myriad certification bodies that specify (and verify) the competencies required of providers (Muzio et al., 2011). There is also compulsory licensure, which restricts professional practice to individuals that have been deemed to exceed a threshold level of competence (Zhou, 1993; Kleiner, 2000). Sociological work, notably Parsons (1942; 1975), has considered socialization and the ethical obligations of professionals rather than externally imposed constraints. To Parsons, the information gap between client and provider necessitates social controls to stem the rampant potential for abuse. Parsons focused on internalized, normative forms of control, which are often outwardly instantiated in a code of professional ethics.

In addition to these safeguards, however, an extremely common practice in professional services is for clients to rely on formal or informal third party referrals to identify and screen providers. These referrals come from third parties that, by dint of their position in the market, serve as intermediaries. Because they typically interact with the market more frequently than clients do, intermediaries have a much broader view of the service providers in the market (De Silva et al., 2018). When intermediaries are active in a market, they weave a social fabric of repeated exchange that is rife with concerns about reputations and norms (Granovetter, 1985; Biglaiser, 1993; Uzzi, 1996; Smith, 2005; Botelho and Abraham, 2017; Canales and Greenberg, 2016). Thus, intermediaries are key actors in the reputation system that allows these markets to function. The potential of the intermediary to improve outcomes for market participants is likely to be the reason why triadic referral structures have evolved to the point of ubiquity in medicine, law, accounting, real estate, consulting, and most other professional services (Heinz et al., 2001; Song et al., 2014; Shane and Stuart, 2002). In healthcare, market intermediaries are so important that their referrals are institutionalized and obligatory in many insurance plans.

Triads

The triadic structure is a central construct in Simmel's (1950) writing and Heider's (1958) balance theory. Triads are regarded as a constitutive form of social interaction because the properties of these tripartite systems cannot be reduced to their individual or pairwise elements. Stated in another way, the introduction of a shared third party nearly always engenders differences in the dynamics in dyadic interaction that otherwise would have occurred in the absence of an intermediary situated between two alters (Granovetter, 1985; Coleman, 1994; Burt et al., 2005). The presence of three actors in social interactions creates a new set of social mechanisms and social roles, as the third party may seek to facilitate the relationship between the others, or conversely, to seed or promote oppositional sentiments among them (Simmel, 1950; Burt et al., 2005).

The position of the intermediary between two otherwise unconnected market participants is of course a defining feature of a broker. (Throughout the paper, we interchangeably use the terms broker, intermediary, referrer and third party to refer to the person who connects a client to a referred-to service provider.) In the context of market exchange, brokers enable transactions by making introductions or reducing frictions between buyers and sellers. However, there is substantial variation in how brokers carry out their role. For instance, how a broker is embeddeded in the social structure of the market influences whether he or she will disproportionately serve the interests of the client, provider, or his or her own self-interest (Stovel and Shaw, 2012).

Given how much broker behavior varies across settings, it is important to be precise about the context in this paper. First, the intermediaries we study act as matchmakers and sometimes facilitate interactions once a match is established. This form of brokerage often is known as "tertius iungens" (Obstfeld, 2005), a term which describes a third party that unites disconnected individuals or that facilitates additional collaboration between existing contacts. The roles of matchmaker and facilitator distinguish the tertius iungens from a middleman that refrains from making introductions to preserve disunity (Stovel et al., 2011). Thus, the intermediaries we study deliberately work toward establishing matches that result in triadic closure, whereas other brokers aim to preserve structural separations. Second, we consider a context in which professional standards of conduct and regulations aim to curb extreme forms of self-interested behavior by the referrer. For example, in medicine, the Hippocratic Oath reinforces the profession's standards of conduct and regulations such as the Anti-Kickback statute and Stark Law prohibit medical specialists from compensating PCPs for referrals. These regulations are in place to ensure that the PCP acts as an intermediary serving the interests of the patient, not their interests or those of the specialist. Similar rules discourage compensation for referrals in other contexts, such as the legal profession.

Research on brokers establishes significant variation in whether, how, and for whom this structural configuration adds value. Burt's (1992; 2005) influential body of research has, across multiple contexts, developed evidence that brokers have a positional advantage that garners high returns for themselves. Comparing brokers to others, those in brokerage positions are thought to exploit an information advantage to obtain higher rates of promotion (Podolny and Baron, 1997; Burt et al., 2005), more favorable evaluations at work (Burt et al., 2005), to close deals at a higher frequency (Mizruchi and Stearns, 2001), to generate more options for strategic partnerships (Stuart et al., 2007), and so on.

Others also have examined how intermediaries capture or redistribute rents generated through exchange. For example, using stock market data, Khwaja and Mian (2005) show that brokers often exploit their information advantage when trading on their own, rather than clients', behalf. Fernandez-Mateo (2007) shows that major clients of staffing agents are able to negotiate lower prices for recruiting services, but that the agency/broker is able to pass these costs on to workers to sustain its margin. This work illustrates that intermediaries influence how resources are distributed. However, there is limited research on whom the intermediary refers to and how this choice influences the evolution of de novo exchange relationships.

This is the focus of our work. Building on the idea that the extent to which intermediaries add value is a function of the relationships in which they are embedded, we scrutinize how referrers' networks influence the outcomes of the transactions they broker.

Matching in Triads

The triads we study in this paper comprise prospective clients C, third party referrers R, and experts E. Thus, a we examine C(lient)-R(eferrer)-E(xpert) triads. In practice, the client often requests R to make an introduction to a qualified E, or E may enlist R to assist in matching her services to potential Cs. In the majority of cases, we assume that the referrer has met the client and often has direct or indirect knowledge of the referred-to expert. Therefore, two sides of a potential triad, R-C and R-E, often share some form of a connection, while we assume the third edge, C-E, to be absent prior to R's matchmaking. Because the referrer assists in the creation of a direct relationship between the heretofore disconnected actors C and E, the referrer behaves in the role of tertius iungens.

There is a (very) wide range of examples of such referral triads in professional services. For illustration, they include: a patient (C) that requests a referral from a primary care physician (R) to a specialist medical provider (E); a client (C) that requests a referral from a financial advisor (R) to an estate attorney (E); or a homeowner (C) that asks a real estate agent (R) to recommend a mortgage broker (E).

A core function of the R is to abet the formation of client-expert pairings. In fact, Marsden (1982, p. 202) defines brokerage by the act of matchmaking. Brokers enter the fray when two parties are interested in transacting but lack the ability to discover (or trust) one another (Gould and Fernandez, 1989; Burt, 1992; Bidwell and Fernandez-Mateo, 2010). By developing direct experience with some of the participants in a market, brokers position themselves to learn the competences and the reliability of sellers and/or buyers (Rider, 2009; Reagans and Zuckerman, 2008; Gargiulo et al., 2009). In many contexts, intermediaries influence which specific actors are included in any given brokered exchange (Bielby and Bielby, 1999).

One domain in which there has been significant research on third parties and brokered exchanges is the labor market. Since Granovetter's (1973) seminal arguments about the social structure of job searches, for example, much work has evaluated how network contacts influence job search and candidate recruiting behaviors. The matching argument in versions of referral triads has been developed in Fernandez and colleagues' research agenda. In a series of papers, they show that because certain intangible characteristics of both work roles and job applicants are unobservable in the absence of first-hand experience (Fernandez et al., 2000; Fernandez and Weinberg, 1997), preexisting social ties between current workers of an employer and job prospects may enhance the quality of worker-employer matches (Castilla, 2005). Comparing referred to non-referred job applicants, those that match to their positions by an employee-referrer appear to be more likely to be hired, more likely to accept job offers, less likely to quit, and to earn slightly higher wages (Burks et al., 2015).

Studies in other settings also find that intermediaries learn about specific experts and obtain better information about their qualities over time, which may improve match quality between Cs and Es. For example, in the U.S. venture capital industry, Zhelyazkov (2018) finds that when an intermediary observes a failed collaboration, it reduces future introductions to the recipient of the referral. Likewise, in health care, Sarsons (2017) finds that when a patient referred to a specialist by a primary care physician experiences an adverse health outcome, the primary care physician reduces future referrals to that specialist. Epstein et al. (2010) compares patient-specialist match quality in referrals from PCPs in group practices and solo practices. They find that the more extensive information available to better-networked PCPs in group practices leads to the formation of higher quality C-E matches. In sum, there is substantial evidence suggesting that referrers have access to and use information to curate exchange relations between clients and experts.

Trust in Triads

In addition to expediting matches, the presence of a third party referrer can engender trust in client-expert dyads (Simmel, 1950; Coleman, 1994; Obstfeld, 2005). In Simmel and Coleman, many trust relations are seen to evolve in three-actor systems. The intermediary that promotes trust in a referral triad conforms to classic roles in Simmel's (the "non-partison") and in Coleman's ("advisor") thinking. These theorists describe the third party role as having the potential to nurture a relationship by facilitating information sharing, easing tensions in negotiations between counterparts, and bolstering potential exchange partners' confidence in one another. Thus, in professional services, a client's view of an E is likely to be directly influenced by the opinion of R, who advises on the integrity, competence, professionalism or some transaction-relevant characteristic of a service provider. In short, reliance on the referrer-qua-intermediary's judgment can cement trust between the transacting parties in the triad, C-E.

In addition to the trust that may arise from enhanced information exchange, the third actor also may be able to enforce trustworthiness because he or she can sanction malfeasance (Granovetter, 1985; Raub and Weesie, 1990). Rational choice scholars observe that local reputations function best in continuing (as opposed to one-shot) systems of relations, especially if information about an actor's conduct in one relationship spreads to other, current or would-be partners via an information network. Thus, the reputation risk of deceitful conduct is greater in the presence of a third party that is an active participant in a market's social structure. Not only is the intermediary prone to withdraw from any potential, future engagement with an untrustworthy party, but the referrer also is likely to share information about any questionable behavior with others. Therefore, the risk of reputation damage cascades in the presence of additional parties to a transaction, especially if they are well-networked (Robinson and Stuart, 2007). This heightens the incentives for trustworthy conduct in referral triads.[2]

Hypotheses: A Collision of Mechanisms?

To summarize, referrers may: (i.) abet client-expert matching so that clients incur fewer search costs to match to suitable experts, and (ii.) cultivate clients' confidence in an experts' competence and integrity.

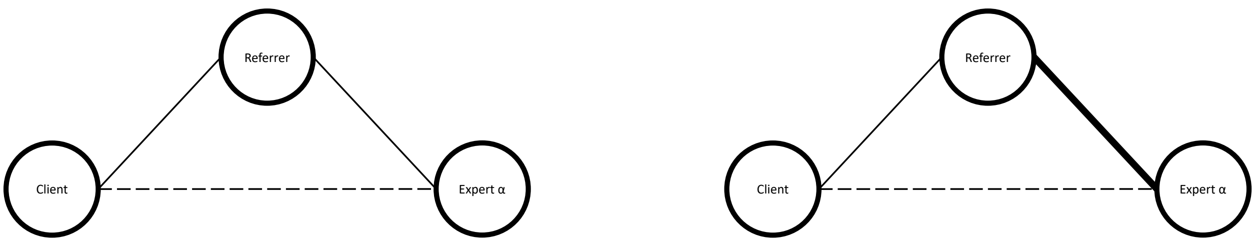
But these outcomes occur to variable extents. In formulating our hypotheses, we zero in on how variation within the preexisting social structure of triads shifts how referrers balance optimal matching and trust-building, which leads to different outcomes in client-expert dyads. In particular, we posit that tie strength between a referrer and the referred-to expert acts as a dial that shifts the emphasis across these two mechanisms to the point that it renders them in opposition of one another.

The two panels in Figure 1 crystallize the variation we explore. We focus on tie strength along the referrer-expert edge, and for ease of exposition, we collapse a continuum of strength to consider ties to be either strong or weak. In figure 1 in Panel A, the thin line between R and Expert α represents a weak (or even non-existent) tie. In Panel B, the bold line between R and Expert α indicates a strong tie. We examine differences in *client-expert* (C-E) interactions when clients consult a referrer R's weak tie (left image in figure 1) versus when they consult one of R's strong tie (right image in figure 1). Again, note the critical distinction is that in the left panel, there is a weak preexisting tie between R and E, and in the right panel, the tie is strong. We are unaware of past work that delves into this critical

[2]These relational dynamics then subtly bridge to the endorsements literature, which further strengthens the potential impact of intermediaries in referral triads. As Podolny (2001) observes, the same relationships that convey information about actors – the 'pipes' of the market – also function as 'prisms' that implicitly transfer status between the parties to an association. If a referrer that is admired or trusted by a C has a strong tie with an E, the mere existence of this association can function as an endorsement that influences C's perception of E's value (Stuart et al., 1999). Therefore, referral triads are fertile structures for information exchange, sanctions, and endorsements.

R-E relationship in the context of brokerage or referral triads or work that examines the question in a manner either that addresses the endogeneity of the relationship strength in triadic social structures or that contemplates the influence of tie strength on the relative weight that referrers place on the social roles that they perform.[3]

Figure 1: Variation in R-E tie strength



An intuitive literature establishes that strong ties imply relationships of greater texture and affect (Krackhardt et al., 2003, chap. 8). Demonstrating this in market contexts, both quantitative and ethnographic studies often show the evolution of personal friendships alongside the economic exchanges in the market, or inversely, the development of economic ties that follow the rails of preexisting ethnic or social relationships (e.g. Macaulay, 1963; Uzzi, 1996; Waldinger, 1995; Gulati and Sytch, 2007). This is, of course, a central claim in the embeddedness literature: the economic and social structure of the market co-evolve, and the social relationships among market participants always influences how economic ties are formed, managed, and progress over time.

Assuming greater personal attachment as tie strength increases, Rs are likely to invest in bolstering clients' confidence in experts' abilities when a strong R-E tie predates a referral. Although relationships act as transmission pipes, network researchers note that information exchange is a discretionary activity (Reagans and McEvily, 2003). A connection to an

[3]With respect to the first assertion, a very large literature, which is inspired by Granovetter's work, considers the effect of weak ties between the client and the referrer, or the C-E edge in Figure 1. Note that our theory pertains to the R-E edge. With regard to the second point, at this stage, we simply acknowledge that much about the actors and relationships in referral triads, including referrer-expert tie strength in any given triad, may be endogenously related to outcomes of interest to researchers.

actor establishes the possibility of information sharing but not a guarantee of it. Both the likelihood of information exchange and its throughput increase in the strength of ties (Granovetter, 1973; Aral and Van Alstyne, 2011), which influences actors' understandings of each other's knowledge, expertise, and interests. In particular, strong R-E ties enable the referrer to vouch for the expert with greater credibility because the R has greater knowledge of an E's prior work with clients. Also and perhaps of even greater importance, referrers are more likely to have a socio-emotional interest in taking the time to endorse an expert that is at least an acquaintance, if not a friend. In a healthcare context, for example, a well-informed physician referrer might attest to a strong-tied specialist's knowledge of state-of-the-art procedures in the area of a patient's condition, or in the expert's responsiveness to patient concerns. The central point is that the referrer with a strong tie to an expert understands how to best assure a client of an E's skill, and likely has a stronger personal interest in doing so. Therefore:

Hypothesis 1. Relative to referral triads in which there is no tie or a weak tie between referrers and experts, in those in which the referrer and expert have a strong tie, the <u>*client*</u> *is more likely to develop trust in the expert's opinion.*

Perhaps it occurs unintentionally, but we argue that strong ties also introduce blind habit, relational inertia, the availability heuristic, and in many cases, an emotional draw into the dynamics of referral triads (Dahlander and McFarland, 2013). In particular, as referrers establish stronger ties with certain experts, they cultivate a set of defaults – go to experts to whom they direct clients without much thought (Sorenson and Waguespack, 2006). We argue that given a history of past exchanges, referrers and experts are more likely to develop a close relationship, and by dint of this, the referrer is more likely to possess confidence in a given, strong-tied expert. The upshot is that for the very same reason that R is more likely to take the time to reinforce the C-E relationship if she has a strong tie to an expert, R is also more likely to refer a client to a strong-tied E.

Whether for relational, cognitive or emotional factors, if a referrer habitually relies on a limited set of strongly tied experts, what will this proclivity do to the quality of the expert-client matches that are cemented by recommendations from R? Subject to a boundary condition of a broad range of sub–specializations of expertise in a focal market, reliance on a handful of experts is likely to result in sub-optimal C-E matches, at least if match quality is defined on the basis of the alignment between a client's problem and an expert's specific professional experience. This is simply a distributional assertion. If there are multiple sub-types of expertise in a market but it becomes second nature for any specific referrer to match clients to a small number of providers relative to the number of sub-specializations, the resultant C-E match quality may suffer relative to some other decision rule for assigning clients to experts. For example, if there are 100 areas of legal sub-specialties and a referrer has strong ties to five attorneys, the legal problems of referred-out clients are not likely to always fall within the practice areas of the subset of strong ties. In short, a habitual use of strong-tie referrals is more likely to result in an expertise mismatch than would be true of a broader search over the expertise distribution. This leads to our second proposition:

Hypothesis 2. Relative to referral triads in which there is no tie or a weak tie between referrers and experts, in those in which the referrer and expert have a strong tie, the <u>*client*</u> *problems are likely to be less-well matched to providers' expertise.*

Setting: Referrals in Medicine

To examine how referral triads shape outcomes in a market for credence goods, we study behavior in physician referrals of patients to specialist providers in US healthcare.[4] Healthcare is an ideal setting to examine referral triads. First, it is an enormous market representing close to 20% of U.S. GDP, and its importance for the public welfare obviously extends

[4]Throughout the remainder of the paper, we will typically use the terms, patient, Primary Care Physician (PCP), and specialist, for the three actors in a referral triad. Respectively, these map to client, referrer, and expert, in a more general characterization of referral triads.

beyond its immense economic significance. Second, healthcare is rife with the information problems that hamper exchange in professional services, including that patients are generally non-experts in their health states and that specialists provide both diagnosis and treatment. Likewise, the decisions patients must make in this context can be among life's most important which elevates the need for trust in expert guidance to a critical level (de Vaan and Stuart, 2022). Finally, PCPs are vital intermediaries in health care, as they have knowledge of and preexisting relationships with many specialist providers, whereas patients with first-time health conditions often have limited knowledge of their own condition, and almost none of the landscape of potential specialist providers.

The referral process is initiated when a patient consults with their PCP for a health condition. The PCP determines whether the problem merits further attention and if so, whether to refer the patient to a specialist for diagnosis and care. Although the number of specialists varies by field (e.g., there are more dermatologists than neurosurgeons), typically there are multiple physicians available to treat the patient. When selecting a specialist for a referral, PCPs weigh their knowledge of and prior experiences with providers as well as patient preferences. A PCP may prioritize minimizing frictions in interacting with the specialist and may be inclined to suggest a specialist with whom she has an established a relationship (Zuchowski et al., 2015). Patients, however, may introduce other considerations, such as the specialist's location, gender, or age (Blödt et al., 2021; Yahanda et al., 2016). In general, a PCP's personal knowledge of a specialist is the most important predictor of the specific physician with whom the patient consults (Forrest et al., 2002). It is important to note, however, that the patient often has significant discretion to choose the specialist in the specialty that she consults. This means that she may end up deviating from the recommendation by the PCP.

After receiving the referral to seek specialty care, the patient schedules a consultation in which the specialist will attempt to diagnose any underlying medical condition and discuss a treatment plan. If the patient's condition is benign, the recommendation may be that no follow-up or treatment is required. If the information about the diagnosis and treatment options are new to the patient, she may face uncertainty regarding both. If the patient experiences significant doubt about the specialist's recommendations, she may decide to seek a second opinion (SO) from another specialist or she may decline to return for a followup visit[5]. These two outcomes, SOs and followup visits, can be thought of as measures of the confidence that the patient places in the provider she consulted. Patients that trust the advice they receive are *less likely* to request an SO and *more likely* to return for followup care.

We delve into the social dynamics in the referral network that is created through the aforementioned steps in the diagnosis-treatment process. Translating the hypotheses to this setting, the analyses explore two questions: (i.) does the history of the PCP-Specialist referral relationship influence the level of confidence that current, referred patients have in their specialist? and (ii.) Does the history of the PCP-Specialist referral relationship affect the quality of the match between a current patient's medical needs and her referred-to specialist's expertise?

Because a PCP is likely to be more invested in promoting and endorsing a specialist's qualifications to a patient if the PCP and specialist share an extensive relational history, a strong tie between PCP and specialist should amplify the trust that the patient places in the specialist's clinical guidance. Conversely, we also posit that strong ties in PCP-specialist dyads often lead to habit-driven referrals, which undermine the quality of the expertise match relative to other approaches to pairing patients and specialists.

Note that null or even opposite effects for this prediction are plausible. For example, strong ties are thought to enable greater channel "bandwidth" (Aral and Van Alstyne, 2011). In contrast, weak ties offer less communication and fewer opportunities for granular information flow between actors (Granovetter, 1973; Uzzi, 1997; Hansen, 1999). Thus, if a strong tie

[5] Patients routinely choose not to adopt medical recommendations. For example, prior work has found that patients frequently opt not to take prescribed medication (Fischer et al., 2010; Koenig, 2011) and that many choose not to return for followup visits after a hospitalization (Gavish et al., 2015).

between a PCP and a specialist causes the PCP to have greater knowledge of the specialist's expertise, this information may facilitate superior matching. Alternatively, no relationship between tie strength and match quality may simply reflect the opacity of evaluating expertise in this setting, even for PCPs that regularly refer patients.

Data and Sample

We examine these research questions using the Massachusetts All Payers Claims Database (MA APCD). The MA APCD is collected and maintained by the Center for Health Information and Analysis (CHIA) and contains remarkably comprehensive information derived from the medical and pharmacy claims of virtually every resident in Massachusetts. We use data from January 1, 2010 to December 31, 2014.

Massachusetts requires all health insurers in the state to report detailed information on every medical claim they receive. CHIA collects these data and prepares them for use in research. For instance, CHIA processes the data to create a hashed identifier to link records of individuals that change insurance plans over time. The MA APCD contains multiple data files, but we mainly draw from the medical claims file, which contains about 650 million distinct medical claims. Data in the medical claims file include a physician identifier, a patient identifier, diagnosis codes, dates and locations of provider visits, identification of medical procedures performed, charged dollar amounts, and, importantly, referral information. The latter includes an indicator for whether the patient was referred to a given specialist and an identifier for the specific, referring physician.

We start by extracting all 4.6 million office visits to specialists that resulted from a referral from a PCP.[6] We next limit this sample to all *first-time* office visits to a physician in specialty k by conditioning on the patient having not previously seen a provider in speciality k, $t < T$. Doing so reduces the sample to slightly more than 1.8 million observations. Limiting

[6] The referral indicator in the data is used in both HMO and POS insurance plans as well as a few PPO plans. Each referral also lists the PCP that provided the referral. Office visits are identified by relying on Current Procedural Terminology codes (CPT) 992**.

the data to patients' first-time consultations within speciality k serves a few purposes. Most importantly, focusing on a diagnosis that is new to the patient makes it likely that the patient has limited knowledge of the providers in the pertinent field of expertise. This is the base condition in which a third party referrer (the PCP) is likely to be influential in curating a match and shaping the client-expert relational dynamic.

Measures

Dependent Variables. The first hypothesis is that patient confidence in a specialist's expertise will be greater in the presence of a strong PCP-specialist tie, relative to a weak or non-existent prior PCP-specialist relationship. We develop two outcome variables to capture this form of patient trust in a specialist. First, we assess the probability of a *patient-initiated* second opinion (SO) after a first consultation with a physician in that speciality. Second, we observe whether a patient returns to the specialist she was first referred to for a followup appointment. We view both outcomes as measures of the confidence that the patient places in the recommendation of the specialist. Specifically, a patient that fully trusts the assessment of the specialist will be less likely to seek an SO and more likely to return for followup care.

The number of followup visits is relatively straightforward to identify in our data, but identifying patient-initiated SOs is more complex. To do so, we follow the method outlined and validated in de Vaan and Stuart (2022). In a nutshell, we identify all instances in which a patient sees a second specialist in the same specialty following a first-time consultation in that speciality, but then limit these to cases in which the PCP supplied both the original and the second referral. We further require the SO visit to occur within 180 days of the first referral. Under this definition, 4% of all specialist referrals result in a patient-initiated SO.

In a second set of regressions, we analyze the quality of the expertise match between the patient's health condition and her specialist's expertise. In building this measure we rely on prior work (Epstein et al., 2010; Sahni et al., 2016) that highlights two key facts about medical specialists. First, within specialties there is considerable variation in the extent to which a physician specializes in diagnosing and treating specific conditions (Chown, 2020). For example, while one orthopedist may be very experienced in spinal surgery, another orthopedist may may focus on joint replacements. Second, the literature establishes that experience in treating a medical condition typically is associated with better health outcomes. For example, in obstetrics, Epstein et al. (2010) finds that in pregnancies that require a c-section, a one-standard-deviation increase in a provider's c-section specialization results in a 60% reduction in the number of hospital days due to complications. Likewise, Sahni et al. (2016) finds that the patients of cardiologists with top-quartile experience in coronary artery bypass grafting had a 15% lower operative mortality than those of providers in the bottom quartile.

Informed by this work, we construct a measure of match quality by first identifying the diagnosis that the specialist assigns to the patient in the first visit. In the next step, we evaluate the specialist's prior experience in treating that medical condition by counting the number of patients the specialist saw in the prior year with the same diagnosis. We then divide this count by the total number of patients the specialist saw in the prior year to create a measure of a clinician's diagnosis-specific focus.

PCP-Specialist Tie Strength. Across analyses, the central explanatory variable is the strength of the relationship between the PCP and specialist in each referral triad. Specifically, we use the referral history between two physicians to construct a simple measure of tie strength. Assessing the strength of a relationship is not straightforward (Marsden and Campbell, 1984). Prior work has relied on a variety of measures including the duration of a relationship, frequency of contact, and reported affect. That said, research that focuses on professional relationships rather than personal friendships has generally relied on straightforward measures of interaction frequency to assess tie strength. For example, also in healthcare, Landon et al. (2012) shows that there is a high correlation between a physician's referral frequency and the peers that she/he rates as most influential to their professional practice. Likewise, Everson et al. (2018) finds that repeated interactions between physicians are associated with perceptions of better teamwork.

One complication with using the frequency of referrals to measure tie strength is that frequency varies by specialization. How should we think about the tie strength between a PCP and a dermatologist and the tie strength between a PCP and a thoracic surgeon? The average PCP refers much more often to dermatologists than to heart surgeons. It is therefore important to make comparisons within specialties rather than between them. Likewise, the formation of ties between PCPs and specialists also is constrained by patient health status. For example, PCPs with relatively healthy patients will refer less to specialists than will PCPs with a less healthy patient mix. For this reason, we condition on the PCP's referral frequency *to a specialty*. As we describe later, we accomplish this by including PCP-by-specialty fixed effects and a count of PCPs' total number of referrals to a specialty in the prior year.

Control Variables. We include *patient age* at the time of a consultation. The association between age and the probability of an SO or followup visits is unlikely to be linear, so we include age as a set of dummy variables: 18 to 44, 45 to 54, 55 to 64 and 65+. *Patient gender* is defined to be one if the patient is female. We also construct the *Charlson comorbidity score* for each patient based on their past-year medical history. This co-morbidity score is commonly used in medical research to predict one-year mortality rates. It is based on the presence of 22 conditions including heart disease, AIDS, and cancer. Each condition is assigned a score of 1, 2, 3, or 6, depending on the associated risk of mortality. These scores are summed to create the aggregate co-morbidity index.

We also control for a patient's *Insurance type* and *Insurance provider*. We incorporate indicators for: Health Maintainance Organization (HMO), Point of Service (POS), Preferred Provider Organization (PPO), Medicaid, Exclusive Provider Organization (EPO) and Other insurance type. And because coverage within insurance types varies between insurance providers, we include indicator variables for all insurers in the data. In total, there are about 200 different insurance plans in the Massachusetts market during our observational window. To approximate patients' socioeconomic status, we include residential zip code fixed effects. Finally, to directly account for a patient's current medical condition, we include the full suite of *diagnosis code fixed effects*.[7]

Next we include a set of physician controls. We include a *Female PCP* dummy. We also include *specialty referral frequency*, which is a count of the total number of referrals a PCP made to a specific specialty in the prior year. Finally, we include *year fixed effects* and *PCP-by-specialty fixed effects*.[8]

Including these control variables in the regressions adjusts for selection effects in patient-specialist relationships. For example, the *Charlson comorbidity score* accounts for the potential selection of less healthy patients into specialists with whom the PCP has a weaker tie. Suppose that PCPs refer their most severely ill patients only to weakly tied specialists. In that case, patients of weakly tied specialists may initiate SOs more frequently, but on account of their health status rather than the social structure of the market. Including controls that adjust for the severity or complexity of health states reduces the likelihood that we spuriously interpret the link between tie strength and our three outcome measures. However, because these controls may not account for all confounding factors, we also develop an instrumental variables strategy that we describe below.

Empirical strategy

The primary analyses evaluate whether a strong PCP-specialist tie is associated with an increase in referred patient's confidence in the specialist's recommendations and also whether

[7]For each visit, the physician provides a diagnosis and reports this using ICD-9 codes. ICD-9 is a hierarchical system of codes that comprise up to 5 digits. Because of the nesting of codes, we use ICD-9 3 digit codes. For example, ICD-9 code 550 refers to inguinal hernia, a hernia of abdominal-cavity contents through the inguinal canal.

[8]Note that none of the regressions include variables that represent attributes of the specialist provider. Elwert and Winship (2014) caution against including variables in a model that are realized only after treatment. Since our treatment is "realized" once the decision to see a specific specialist is made, no specialist controls are included. We did, however, evaluate whether the inclusion of such variables (*Graduation year* and *medical school ranking*) alter the estimates – we found that they do not.

a strong tie leads to a lower quality match between patient needs and specialist expertise. We estimate the following equation to evaluate the effect of tie strength on the probability of the patient seeking an SO:

$$\text{P(SO=1)} = \beta_1 * \text{Tie Strength}_{jk} + \beta_2 * X_i + \gamma_{j(s)} + \epsilon, \tag{1}$$

We then estimate a second equation to evaluate the effect of Tie Strength on the i.) number of followup visits[9] and ii.) the patient diagnosis-specialist experience match quality:

$$\text{Y} = \beta_1 * \text{Tie Strength}_{jk} + \beta_2 * X_i + \gamma_{j(s)} + \epsilon, \tag{2}$$

In these models, i refers to the patient, j refers to the PCP, k refers to the specialist, s refers to the specialty, and X_i is a vector of controls. The $\gamma_{j(s)}$ term represents the PCP-by-specialty fixed effects. These ensure that we make comparisons within the set of patients of PCP j that require care from a physician in specialty s.[10] The primary variation we exploit in this setup is across patients of PCP j consulting specialists k within a given specialty s but with different tie strengths with PCP j. In 28% of cases, the patient consults the specialist with whom the PCP has his or her strongest tie in that specialty (we provide further descriptives below). This means that while a patient often sees a PCP's preferred specialist, there is considerable variation in whether this happens or not.

In terms of the identification problem, the fact that both the PCP and the patient have discretion in choosing a specialist does create endogeneity concerns. For example, if patients

[9]We use OLS but Poisson regressions yield similar results.

[10]Note that the variation in *tie strength* between these cases has a temporal dimension (i.e. tie strength between j and k varies across time), although temporal variation is mostly absorbed by the inclusion of year dummies.

with health anxieties are more likely to make an independent choice that deviates from a PCP's suggested provider and also are more likely to seek an SO, a relationship between tie strength and seeking an SO should not be attributed to variations in trust created by PCP-specialist tie strength. In an ideal scenario, we would randomly assign patients to specialists with varying levels of tie strength with the PCP. In the absence of an experimental design, we leverage quasi-random variation in the probability that a focal patient will visit the strongest tie of the PCP.

Specifically, we use an instrumental variable (IV) that is based on differences in referral behavior driven by variation in insurance plan coverage. Most insurance plans only cover treatment by providers that have a negotiated contract with the plan. Covered specialists with an insurer i are considered "in-network" for that plan, while those without a contract are "out-of-network". To construct the IV we leverage the fact that a PCP's strongest tied specialist may or may not be in-network for a given patient. Ideally, we would have data on all contracts in place and we would simply construct a binary indicator that captures whether a specialist is in-network for a focal patient's plan. While our data do not map plans to coverage, they do include, for every medical claim, an indicator for whether that claim is considered to be in-network by the insurer. We exploit this indicator to compute the percentage of a specialist's insurance claims in the year prior to the index visit that were in-network for each patient's insurance plan. In other words, the IV captures the fraction of all claims filed by each PCP's strong tie provider in specialty s in the prior 365 days that were labeled "in-network" for the insurance plan of the focal patient.

A key feature of the IV is that if the strongest tie of a PCP is out-of-network, the patient is responsible for all charges for that visit. This substantially reduces the likelihood that the patient opts to consult that particular specialist. Intuitively, the IV will quasi-randomly shift patients of PCPs between stronger- and weaker-tied specialists. For the instrument to be relevant, it is only necessary that the in-network status of a PCP's strongest tie specialist influences whether the patient sees that clinician. Prior research and common sense suggest that this is the case (Ziemba et al., 2017) and results from first-stage regressions will confirm it. For the exclusion restriction to hold, however, the IV also must be uncorrelated with the error term. We believe this to be the case in a model that adjusts for insurance plan-specific features. Better insurance plans may include broader coverage networks and they also may provide better coverage for SOs. For this reason, including plan-specific fixed effects is necessary for the exclusion restriction to hold. In appendix A, we describe the instrument in more detail and we provide a balance check that shows results that are consistent with the validity of the exclusion restriction.

Descriptive statistics

In figure 2, panels A and B, we plot the distribution of tie strength for the sample of 1.8 million referrals from PCPs to specialists. The dark grey bars show the distribution of tie strength between a patient's PCP and the specialist that the patient actually visited for all consultations in the sample.

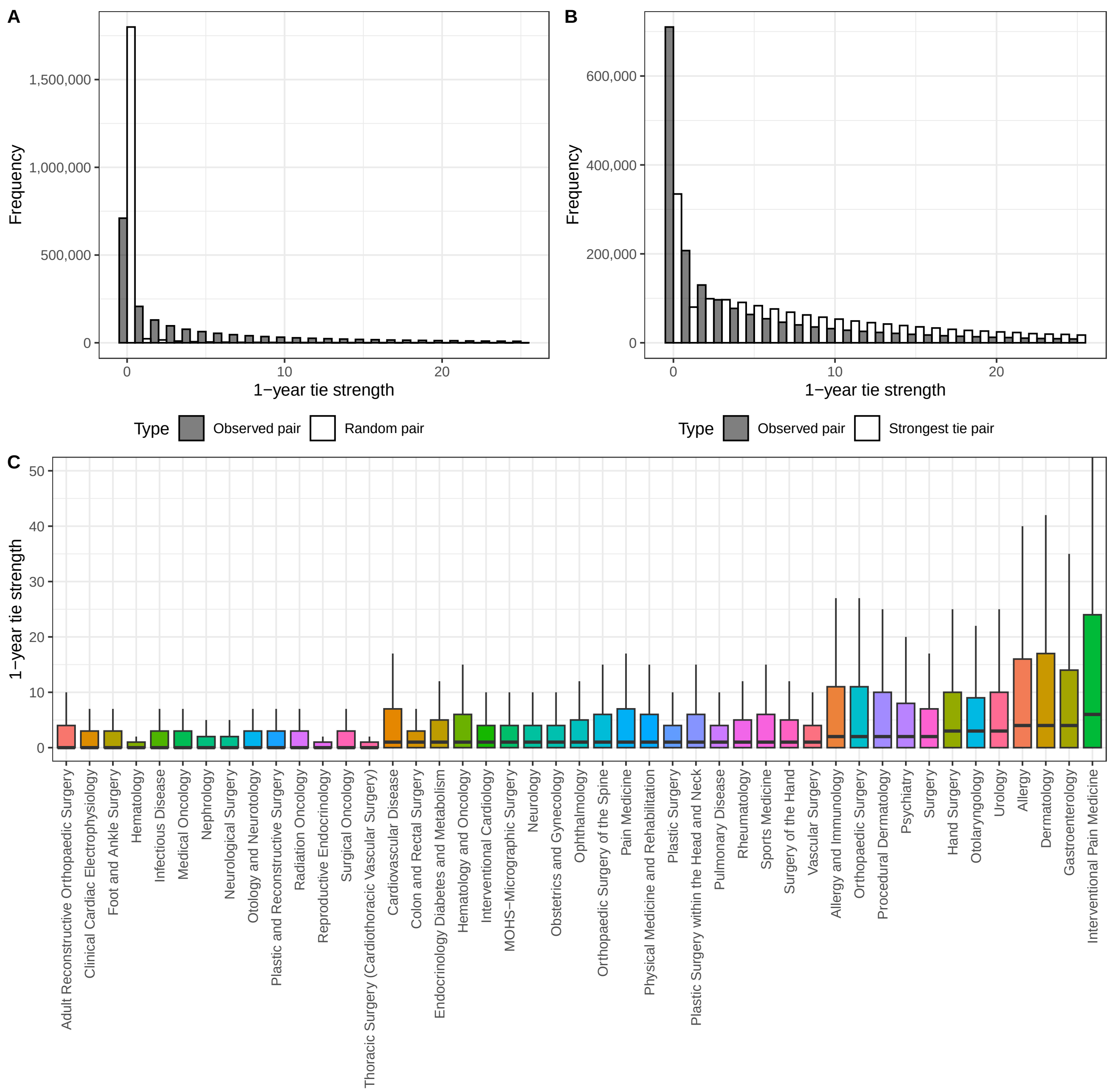
We then benchmark this distribution by creating two counterfactual comparisons. The goal of examining these counterfactual benchmarks is to evaluate how much PCP-expert tie strength appears to affect the choice of specialist that a patient consults. First, we generate a randomized set of counterfactual PCP-specialist pairings from all feasible referrals. To construct the random counterfactual, we create a pool of all possible specialists that the patient could have been referred to based on (i.) the specialty k the patient was actually referred to, and (ii.) the hospital referral region (HRR) of the patient's PCP.[11] From this pool of feasible options, we then randomly select a specialist in k and compute the tie strength between that specialist and the PCP based on the actual past referral history in that pair. The resulting distribution is displayed in the white bars in Panel A. The graph clearly shows that the distribution for the counterfactual pairs with randomly selected specialists (white

[11] The HRR is a geographically delineated area based on referral patterns for tertiary medical care. HRRs are created and published by the Dartmouth Atlas of Health Care.

bars) is much more left-skewed than the realized distribution of tie strengths (gray bars). This demonstrates that relative to a random benchmark, PCPs favor referring patients to specialists with whom they have prior, strong ties. In Panel B we show a second benchmark to demonstrate that while PCPs frequently refer to a set of go-to specialists in most specialties, patients still oftentimes visit physicians with whom their PCP has a weak tie or no tie at all. Specifically, for each actual referral of a patient to specialty k, we identify the referring PCP's strongest tie to any physician in specialty k in the patient's HRR, and plot its distribution alongside the distribution of realized ties. The resulting distribution in Panel B (in white) represents the upper limit on the possible tie strength between a PCP and the pool of available specialists, given the actual history of prior referrals. (Note that the gray distribution of realized ties is identical in Panels A and B, but appears to be different because of the scaling of the y-axis.) Importantly, in comparing the two upper panels in figure 2, the mean absolute difference between the actual tie strength distribution and the two counterfactual distributions is smaller for the "strongest tie" benchmark in Panel B. This tells us that patients more frequently consult specialists with whom their PCPs have past relational histories rather than specialists that are arms length from their primary care providers.

Panel C shows the distribution of average, observed PCP-specialist tie strength between PCP-specialist pairs across each of the broad categories of specialties in the data. The distribution shows that there is considerable variation both within and between specialties. This graph illustrates how important it is to condition on PCP-by-specialty fixed effects. For example, given the wide variation we observe in referrer-expert tie strength across specialties, it would not make sense to base inference on variation in relationship strength comparing across (say) a PCP and hematologist and a PCP and a dermatologist.

Figure 2: Distribution of tie strength between referral partners



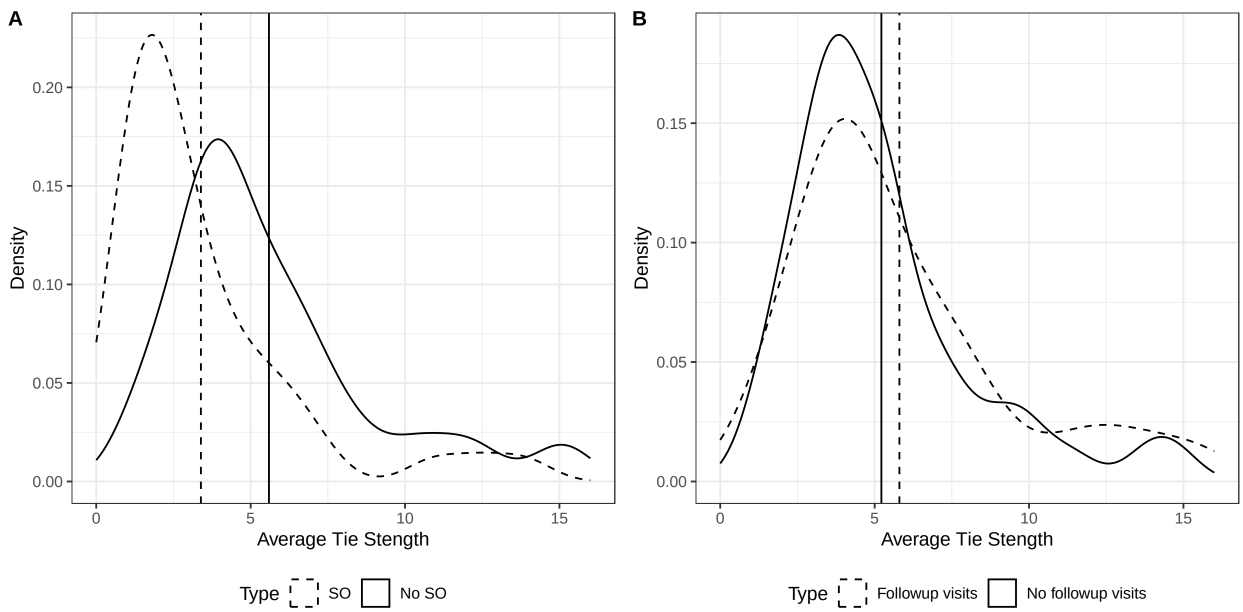
Note: Panel A and B show the distribution of tie strength between all observed pairs of PCPs and specialists (dark grey bars). In Panel A we benchmark this against a distribution of the same PCPs and randomly chosen specialists. This random distribution is highly left-skewed and most observations fall in the "no tie" bin. This suggests that for each referral by a PCP, there are typically several alternative specialists with whom the PCP does not have a prior relationship. In Panel B we benchmark the observed tie strengths against a distribution of the strongest possible ties. The gap between these two distributions suggests that while there is a tendency to refer to specialists with whom the PCP has a strong relationship, there are frequent instances in which that this does not occur. Panel C shows the distribution of tie strength between the observed PCP-specialist pair by medical specialization. It shows significant variation in tie strength both between and within specialties.

Results

Main analyses

In figure 3, Panel A and B, we show the relationships in the raw data between the first two outcome variables and PCP-specialist tie strength. Specifically, *within* medical specialties, we compute the average tie strength between the PCP and the specialist each patient consults. We then plot separate distributions of this variable, which are split by the first two dependent variables: the patient subsequently sought a second opinion (0—1), and the patient returned to the referred-to specialist for one or more followup visits (0—1). The vertical lines represent the means of the distributions. In line with hypothesis 1, the left-side panel of the figure shows that PCP-specialist tie strength is significantly lower in the SO sample, and it is significantly higher in the followup visits sample. *This tells us that in the bivariate distributions, patients that consult their PCPs' stronger-tied specialists are less likely to question providers' expertise and more likely to return for followup treatment.*

Figure 3: Distribution of relationship between outcomes and tie strength by specialty



Note: For each specialty, we computed the average tie strength between PCP and specialist for SOs (Yes = 1, No = 0) and followup visits (One or more = 1, None = 0) and then plot these distributions. The means of the distributions are shown by the vertical lines.

In table 1 we formally test hypothesis one. The regressions in the table include PCP-by-specialty fixed effects and report clustered standard errors at this level. In model 1 of panel A, we include tie strength as a continuous measure. It shows a strong, negative correlation between tie strength and the probability that a patient later seeks an SO. In model 2, we bin observations into two groups of tie strength (8 or less and greater than 8, which defines the upper quartile). Like the result from model 1, the stronger the tie between the PCP and specialist, the less likely the patient is to seek an SO. In model 3, we include a binary indicator equal to 1 if the specialist seen by the patient is the provider with whom PCP j has the strongest tie in that specialty. Consistent with the findings for the other measures of tie strength, this negatively affects the probability of an SO.

In columns 4 to 6 of Panel A Table 1 we present the same set of regressions for the second dependent variable: the number of followup visits with a referred-to specialist in the 365 days following the initial, "first opinion" visit. Also consistent with H1, patients referred to a PCP's strongly tied specialist are more likely to return for a followup visit than patients that consult a specialist with weak or no ties to patients' PCPs. Similar to the findings on the probability of an SO, the results suggest that the association is nonlinear and that much of the effect of tie strength is driven by the upper range of the tie strength distribution.

Table 1: Strong ties and trust

Panel A: OLS estimates

	Probability of second opinion after first consult			Number of followup visits after first consult		
	(1)	(2)	(3)	(4)	(5)	(6)
Tie Strength	-0.0003***			0.0043***		
	(0.0000)			(0.0003)		
Tie Strength (>8)		-0.0103***			0.1121***	
		(0.0004)			(0.0079)	
Strongest Tie			-0.0083***			0.2386***
			(0.0003)			(0.0060)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
PCP * Specialty FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	1,887,253	1,887,253	1,887,253	1,887,253	1,887,253	1,887,253

Panel B: IV estimates

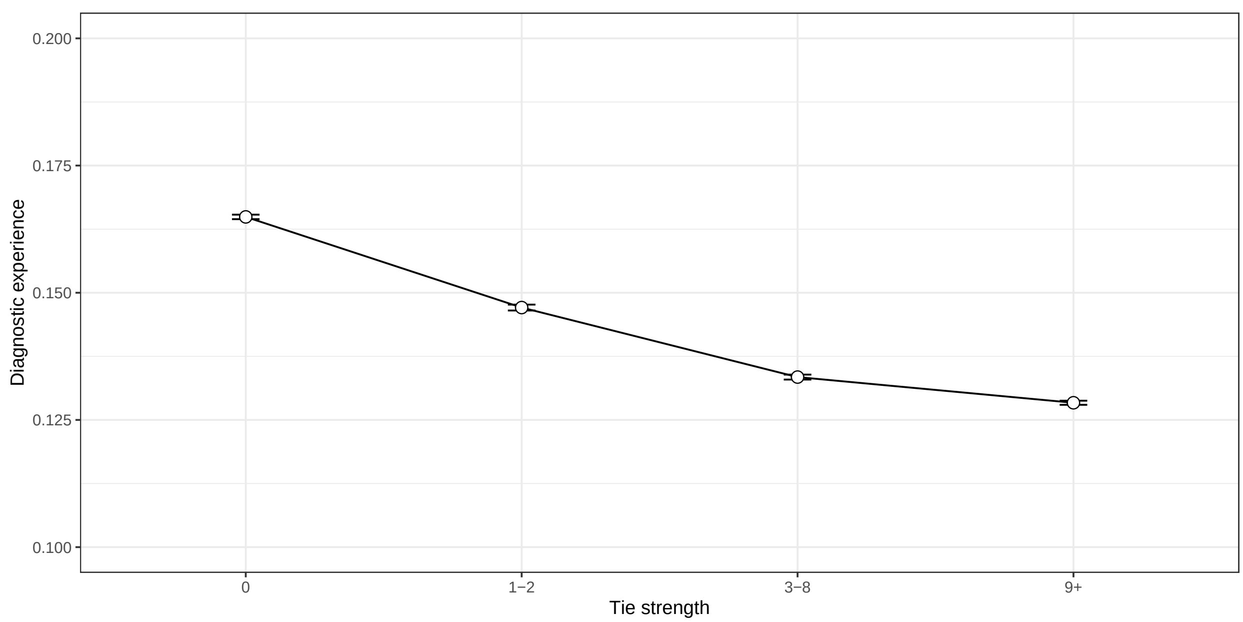
	First stage	P(SO=1)	Number of Followup visits
		2SLS	2SLS
Fraction of patients with same plan (Strong tie)	8.2388***		
	(0.6498)		
Tie strength (IV)		-0.0020***	0.0382***
		(0.0005)	(0.0110)
Controls included	Yes	Yes	Yes
PCP * Specialty FEs	Yes	Yes	Yes
F-statistic	-	1,059	1,059
N	1,887,253	1,887,253	1,887,253

Notes: Panel A shows the results of regression models that estimate the relationship between PCP-specialist tie strength and two measures of confidence, SOs and followup visits. The first three columns show the estimates for the probability of an SO after the first consult, while columns 4-6 show the estimates for the number of followup visits after the first consult. Three different measures of tie strength are used: 1) a continuous variable, 2) a spline, and 3) a binary measure. Panel B shows the results for the IV estimates. Column 1 contains the estimate for the first stage. Columns 2 and 3 show the results for the second stage of the IV regressions.
*p<0.05; **p<0.01; ***p<0.001 (Two-tailed tests).

The IV regressions, estimated using 2SLS, are shown in Panel B of table 1. The first stage of the model, shown in column 1, suggests that a one standard deviation increase in the instrument increases the likelihood the patient sees a specialist with an above median tie strength by about 43%. Models 2 and 3 report the second stages of the 2SLS regressions. The second stage results show that the effects of PCP-specialist tie strength on the probability that the referred patient seeks a SO or returns for followup visits may be interpreted as causal. The effects are significant, substantial, and consistent with proposition predictions. In sum, these analyses suggest that a patient places greater confidence in the medical services received from a specialist with whom the patient's referring PCP has a strong relationship.

The next set of analyses evaluate whether the strenght of the relationship between a PCP and a referred-to specialist influences the quality of the patient-specialist match. As described above, we define "diagnostic experience" as a specialist's prior experience in treating a patient's diagnosed medical condition. In Figure 4 we show the bivariate relationship between diagnostic experience and tie strength. Binning tie strength into 4 groups, the graph indded shows that stronger ties between PCP and specialist are associated with *lower* levels of diagnostic experience. The raw means of the data therefore are in line with H2.

Figure 4: Diagnostic experience by tie strength



Note: This graph shows how the mean of diagnostic experience varies with each quartile of tie strength.

We formally test this relationship by estimating the model defined in equation 2: we regress diagnostic match on the strength of the prior tie between PCP and specialist. Like the previous table, we include PCP-by-speciality FEs, effectively comparing a patient that sees a PCP's strong- versus weak-tied provider within a given speciality. The results of this regression are shown in table 3.

Table 3: Strong ties and diagnostic experience

Panel A: OLS estimates

	Diagnostic Experience		
	(1)	(2)	(3)
Tie Strength	-0.0002***		
	(0.0000)		
Tie Strength (>8)		-0.0119***	
		(0.0004)	
Strongest Tie			-0.0070***
			(0.0003)
Controls included	Yes	Yes	Yes
PCP * Specialty FEs	Yes	Yes	Yes
N	1,887,253	1,887,253	1,887,253

Panel B: IV estimates

	First stage	Diagnostic Experience
		2SLS
Fraction of patients with same plan (Strong tie)	8.2388***	
	(0.6498)	
Tie strength (IV)		-0.0022***
		(0.0004)
Controls included	Yes	Yes
PCP * Specialty FEs	Yes	Yes
F-statistic	-	1,059
N	1,887,253	1,887,253

Notes: Panel A shows the results of regression models that estimate the relationship between PCP-specialist tie strength and diagnostic experience, the specialist's relative frequency of treating the patient's diagnosis in the prior year. Like the models in table 1, three different measures of tie strength are used: 1) a continuous measure, 2) a spline, and 3) a binary measure. Panel B shows the results for the IV estimates. Column 1 contains the estimate for the first stage, while column 2 reports results for the second stage of the IV regressions.
*p<0.05; **p<0.01; ***p<0.001 (Two-tailed tests).

In model 1 of panel A, we include tie strength as a continuous measure and find a negative association between it and the diagnostic experience of the specialist. In model 2, we incorporate tie strength as a spline. Like the result from model 1, this regression suggests that the stronger the tie between the PCP and specialist, the less the experience the specialist has in treating the patient's diagnosed medical condition. In model 3, we include a binary indicator equal to 1 if patients consult the provider with whom their PCP has the strongest tie in specialty s. This alternative measure is also negatively associated with the diagnostic experience of the specialist.

We report the IV regressions, estimated using 2SLS, in Panel B of table 3. Model 2 shows the second stage of the 2SLS regressions. These findings suggest a causal effect of tie strength on diagnostic experience. The effects are substantial and consistent with proposition two. In sum, while strong ties between a PCP and specialist may induce patient-specialist trust, they may also interfere with patients being matched to providers that have the deepest expertise in patients' medical conditions.

Discussion and Conclusion

Referrals are how many client-expert relationships form in professional services. In addition to playing a critical role in determining who transacts with whom, once a referral is made, an immediate byproduct is the establishment of a client-referrer-expert "referral triad." We find that the relational dynamics of this triad, and in particular the pre-existing tie strength between the referrer and expert, shape both how individual clients become matched to specific experts, and the nature of the relationship that evolves between the newly introduced exchange partners.

In addition to demonstrating the importance of referral triads in health care, the largest of the professional services markets, we also showcase empirical evidence for a theoretical tension in the core mechanisms through which referral triads potentially remedy the endemic information asymmetries in credence goods markets. On one hand, we find that the presence of a third-party referrer (PCP) with a strong preexisting tie to a referred-to expert (medical specialist) engenders trust in the client-expert (patient-specialist) dyad. Specifically, the strength of the referrer's tie to the expert influences the level of confidence the client develops in the provider. Likely, this occurs because when one professional has a strong relationship with another, a referral within that pair tends to be associated with a strong endorsement of the expert's quality and integrity. In other ways as well, the third party referrer may subtly or directly intervene to promote a positive outcome in the client-expert exchange relationship. In health care, we find that patients demonstrate greater confidence in a specialist if their referring PCP has a strong tie with that provider.

Conversely, we also posit that it generally will be the case that actors that operate in embedded exchange networks have professional, economic, social, psychological and routine-based tendencies that focus their attention on prior exchange partners when they choose who to recommend in new referrals. Indeed, the stability of referrals with respect to specific exchange partners is one micro-level process that may lead to one of the most well-established empirical facts in the networks literature: there tends to be macro-level stability of network structures across time periods (Canales and Greenberg, 2016). Consistent with the fact that over time, many network structures tend to reproduce themselves, we argue that the embeddedness of referrers in an incumbent exchange networks – itself a precursor to a third party's ability to play the role of an intermediary in trust – quietly nudges the network toward sub-optimal client-expert matches relative to those that might arise if the referrer utilized a broader search over the roster of possible providers. This occurs for exactly the same reason that embedded ties matter: actors often prefer to rely on their tried-and-true exchange partners, weighting the value or convenience of the relationship above other factors such as the optimality of a match.

(Rubineau and Fernandez, 2015) echo this line of reasoning. They argue that a reductionist leaning in many accounts of brokerage misses too much of the nuance of what transpires in a fundamentally relational, triadic process. These authors argue that referrals cannot be fully understood simply as a standard two-way matching problem with a dollop of third-party mediation on top, but rather a referral triad is a quintessentially three-way matching problem with three agentic decision makers. In short, Rubineau and Fernandez (2015) also points to the critical importance of digging into the behavior of the intermediary in referral triads.

Our findings about match quality do, however, raise a question based on a surface contradiction with empirical results in prior literature. In particular, a number of terrific studies have evaluated employee referral programs, which of course constitute a form of a referral triad in which an organization's existing workers refer members of their social network to open positions at their employer. While this context obviously differs in important ways from the market for professional services, it does represent an important form of a referral triad and one in which a third party may both promote trust and optimize the quality of matches. Research in this area often finds that referred employees turnover less frequently and perform *better* relative to non-referred workers, which generally is interpreted as evidence that in the information-asymmetric context of employer-employee matching, referrers curate better matches than the employer is able to establish based on its own, non-network-based mechanisms for identifying and screening candidates.

We believe that our finding that client-expert matching is sub-optimal in strong-tie referrals may in fact not be at odds with this work. As Castilla (2005) observed, the findings of positive labor market referral outcomes may be better evidence of a network-based bias in performance rewards, in which employees with prior network ties to their employers receive preferential treatment relative to non-tied workers for the same average level of performance, rather than a reflection of higher quality employee-employer matching. In other words, when we observe different employment outcomes for employees who entered the organization through a referral and those who did not, there may be a Hawthorne-like effect of treatment ("employee was referred").

More broadly, it tends to be very difficult or impossible to observe the quality of matches in empirical settings. In consequence, rather than observe this directly, researchers often infer it based on outcomes of the exchange relationships that are formed. The uniqueness and granularity of population medical claims data provide an exception: because the researcher can observe nearly the full history of medical procedures performed by all physicians along with the frequency with which they have treated patients with any given diagnosis, we can directly assess the match between patient needs and physician experience. In short, these data give us a unique ability to observe a critical dimension of matching, which is not confounded with outcomes that may decouple from match quality in terms of their causal underpinning. In the healthcare context, this manifests in strong evidence that when PCPs refer patients to experts with whom they have a strong-tie, the match between the patient's condition and the specialist's expertise declines. Pulling the results together, we find that the in referral triads with a strong expert-referrer tie, more trusting but lower quality matches occur between the client and the expert.

What are the welfare implications of these findings? Here, we must leave the question to future research. First, any study that establishes the existence of sub-optimal match quality begs the question of, compared to what? The comparison in this article is between patient-specialist matches that are created via strong versus weak or no ties in an existing, well-articulated referral network. But of course, there are other mechanisms for matching clients and experts, such as machine-generated referrals, that do not rely on the current social structure of a market. Second, unfortunately, assuming a trade-off between the two, there is no compelling evidence we can bring to bear on the question of whether a client/patient is better off with greater trust in a specialist provider or in the closest possible match between diagnosis and expertise. There are plenty of reasons to believe that both features are of value, and that their relative importance will be contextually variable.

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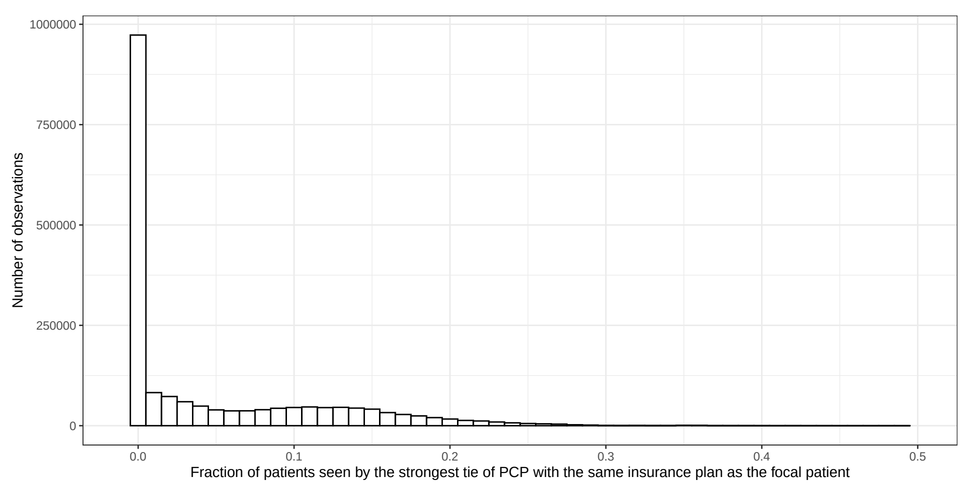
A Appendix

Figure A1 presents the distribution of the IV. It shows substantial variation in the fraction of medical claims for the insurance plan of the focal patient. In about half of the 1.8 million office visits, the strongest tied specialist of a patient's PCP is not covered by the focal patient's insurance plan. For the other half of index visits, the focal patient's insurance plan accounts for about 10% of all claims of his or her insurance plan. To evaluate whether the exclusion restriction is likely to be met, we create a binary indicator equal to one if the IV is above median and use this variable to predict *patient age*, *patient gender*, *PCP gender*, the *Charlson Score* and *tie strength*.[12]. Supporting the validity of the exclusion restriction, all variables except for *tie strength* are well balanced.

Figure A1: Distribution of instrumental variable



Note: This graph shows the distribution of the IV: the fraction of patients seen by the strongest tie of the PCP with the same insurance plan as the focal patient. The mean equals 0.05 while the third quartile equals 0.09.

[12]Estimates are adjusted for insurance plan, zip code, year and patient by specialty FEs.

Table A1: Balance statistics

	Estimate of difference	t-Statistic
Patient age	-0.14	-0.97
Patient gender	-0.00	-1.46
PCP gender	-0.00	-0.00
Charlson score	0.00	0.01
Tie Strength	1.24	4.36

Notes: This table reports results from regressing the variables in the first column on an indicator variable that equals 1 if the value of the instrument is larger than its median. The regression also includes insurance plan, time, zip code and physician by specialty fixed effects.

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$ (Two-tailed tests).