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# Referral Triads

**Mathijs de Vaan[1] and Toby Stuart[1]**

## Abstract

Third parties who refer clients to expert service providers help clients navigate market uncertainty by curating well-tailored matches between clients and experts and by facilitating post-match trust. We argue that these two functions often entail trade-offs because they require referrers to activate network relationships with *different* experts. While strong ties between referrers and experts promote trust between clients and experts, the presence of such ties reduces the likelihood that intermediaries refer clients to socially distal experts who may be better suited to serve clients' needs. We examine this central and unexplored tension by 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 PCPs have strong ties, patients demonstrate more confidence in the specialists' recommendations. However, a strong tie between the PCP and specialist also reduces the expertise match between a patient's health condition 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 the activation of different network ties.

**Keywords:** social networks, trust, embeddedness, intermediation, expertise

Referrals take center stage in many economic markets. As intermediaries who 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 epitomize these conditions. These are goods or services for which consumers find it difficult to evaluate product

[1] University of California, Berkeley

**Corresponding author:**
Mathijs de Vaan, Haas School of Business, University of California Berkeley, 2220 Piedmont Ave, Berkeley, CA 94720
Email: mdevaan@berkeley.edu

quality even after having purchased or experienced them. Many professional services are of this ilk, as expert providers generally know far more about clients' needs for these services than do clients themselves (Heinz, Nelson, and Laumann, 2001; Dulleck and Kerschbamer, 2006). Salient examples of credence goods are medical care, legal counsel, and financial advice. These markets share several 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 (Afendulis and Kessler, 2007).

Given the difficulty consumers face in appraising the quality and reliability of professional service providers, 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 (Fleischer, 2009; Sharkey, Kovács, and Hsu, 2022). They also include brokers who match buyers with sellers. In creative industries, talent and literary agents serve as matchmakers (Bielby and Bielby, 1999), along with the gallerists and dealers who enable the art market (Aerne, 2021); in financial services, venture capital firms and investment banks match providers and users of financial capital (Rider, 2009; Jääskeläinen and Maula, 2014). In the service sector, many consumption decisions are routed through referrals from non-compensated or informal intermediaries (Garicano and Santos, 2004). We label this social structure a "referral triad." It encompasses three distinct roles: a recommender/referrer, a client/referee, and an expert/referred-to provider. Referral triads are omnipresent in professional services markets and may account for most of the flow of first-time work with clients.[1]

Referrers perform two vital functions. First, they act as matchmakers (Marsden, 1982). Through their past investments in knowing the participants in a market, referrers acquire the purview to tailor introductions between clients and experts (Burt, 1992). Thus, intermediaries in referral triads are the structural clearinghouse that determines which client–expert dyads come to be. Once a triad has formed, the referrer often plays a second role: to build trust necessary for ensuing interactions (Coleman, 1994). A referrer's willingness to endorse an expert often hinges on the referrer's history of interaction with that provider (Smith, 2005). Specifically, referrers who have prior close relationships with experts are more able and (often) more willing to vouch for those providers, and possibly to monitor client engagements 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 with experts. But because performing these functions well often depends on the referrer activating ties to *different* experts, the two frequently stand at odds with each other. Our core

[1] Wilson (1994: 13) estimated that across markets, service providers acquire 80 percent of their clients from interpersonal referrals, and wrote, "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."

assertion is that the experts who intermediaries know well enough to foster trust in referral triads—their strong ties—will often differ from the providers who have the deepest experience in a client's specific issue or need. Therefore, it is generally the case that only one of the two functions of a referrer—to cultivate trust or to curate high-quality matches—is optimized. This means that the same referrals that create high-trust client–expert dyads may also result in pairings with a lower degree of concordance between client needs and expert expertise, compared to matches that are optimized on the latter dimension. We refer to these as cases of 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 these relationships are in place, their existence bolsters the intermediary's ability to create trust between a client and an expert, but these ties also naturally influence the referrer's choice of which expert to recommend to a client. As referrers develop stronger ties with a handful of go-to experts, referrers tilt toward matching clients to experts with whom they are closely connected, whether their decisions are based on habit, preference, or convenience (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 the presence of variation in specialization among experts, leaning on a small number of strong ties prevents referrers from using the full range of the expertise landscape. In effect, the social connections that evolve alongside the market's transactional structure gently promote inertial referral behaviors, which then undermine optimal matching. Because of this, referrers embedded in strong-tie networks may facilitate high trust in expert–client relationships while simultaneously recommending lower-quality matches.

To examine this argument, we study the structure of referral triads in the largest of the professional service markets: health care. In this setting, the referrer is often a primary care physician (PCP), the referee is a patient, and the referred-to expert is a specialist provider. We ask two main questions. First, does tie strength between the PCP and the referred-to medical specialist affect the trust that the patient places in the specialist's care? Second, does the tie strength between the PCP and referred-to medical specialist affect the quality of the match between the patient's 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 who are referred to their PCPs' strong-tie specialists demonstrate two behaviors that signal trust: They are less likely to seek a second opinion from a different expert after consulting the specialist they were first referred to, and they consume more medical services from the referred-to specialist. However, we then show that a strong tie between the PCP and the referred-to specialist diminishes at least one dimension of the quality of patient–specialist matches: the fit between a patient's health needs and the specialist's clinical focus, as evidenced by the specialist's own history of practice. In a pair of post-hoc analyses, we establish two related results: PCPs are more likely to refer to strong-tie specialists on their busy days, which is consistent with the idea that reliance on default experts is most pronounced when search costs are high, and lower match quality is associated with adverse health outcomes.

Collectively, these results highlight trade-offs between two of the functions performed by market intermediaries.

## THEORY: REFERRAL TRIADS IN PROFESSIONAL SERVICES

### Information Problems

In the professions, clients seek counsel from experts who 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 research has shown that these features of the market for expert services often result in abuse of clients' interests (Ackerloff, 1970; Kollock, 1994). When a consumer takes a car to a repair shop, they hope 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 receive fewer or less costly medical services than do non-expert patients with similar states of health and that patients sometimes endure shifts in treatment protocols that maximize provider billings rather than their welfare (e.g., Emons, 1997; Gruber, Kim, and Mayzlin, 1999; Schwartz, Luce, and Ariely, 2011; La Forgia, 2023). The predicaments of suboptimal matching, mediocre or worse service, outright incompetence, specious advice, and excess billings loom across these markets.

What solutions ameliorate these market frictions? Briefly, the professions are home to myriad certification bodies that specify (and verify) the competencies required of providers (Muzio, Kirkpatrick, and Kipping, 2011). There is also compulsory licensure, which restricts practice to individuals who have been deemed to exceed a threshold level of competence (Zhou, 1993; Kleiner, 2000). Sociological research, notably by Parsons (1942, 1975), has considered socialization and the ethical obligations of professionals as guardrails. To Parsons, the information gap between client and provider necessitates social controls to stem the 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, a very 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 actors that, by dint of their position in the market, serve as intermediaries. Because they interact with the market more frequently than clients do and often have pertinent expertise, intermediaries have more understanding of the landscape of service providers than clients do (De Silva, Howells, and Meyer, 2018). Moreover, when intermediaries are active in a market, they weave a social fabric of repeated exchange that is rife with concerns about reputations and adherence to market norms (Granovetter, 1985; Biglaiser, 1993; Uzzi, 1996; Smith, 2005; Canales and Greenberg, 2016; Botelho and Abraham, 2017).

Thus, intermediaries are key actors in the reputation system that allows markets to function. The potential of triadic referral structures to improve market outcomes is the reason they are ubiquitous in medicine, law, accounting, real estate, consulting, and other professional services (Heinz, Nelson, and Laumann, 2001; Shane and Stuart, 2002; Song, Sequist, and Barnett, 2014). In health care, intermediaries are so important that their referrals are obligatory in many insurance plans.

## Triads

Triads are 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. A shared third party nearly always engenders differences in the dynamics in the dyadic interactions that would have occurred in the absence of an intermediary situated between two alters (Granovetter, 1985; Coleman, 1994; Burt, 2005). The presence of three actors creates a new set of social mechanisms and social roles, as the third party may seek to facilitate a relationship between the others or, conversely, to promote oppositional sentiments among them (Simmel, 1950; Burt, 2005).

The position of the intermediary between two otherwise unconnected market participants is, of course, a defining feature of a broker. (Throughout the article, we interchangeably use the terms broker, intermediary, referrer, and third party for the person who connects a client to a referred-to service provider.) In market exchanges, brokers enable transactions by relaying information, making introductions, or promoting trust between buyers and sellers, but they vary in how they perform their role. For instance, the specific incentive and social structures under which brokers operate may influence whether they disproportionately serve the interests of the client, the expert, or their own self-interest (Stovel and Shaw, 2012). Given this variation, prior research has examined whether, how, and for whom triadic exchange structures add value.

Burt's (1992, 2005) research, for example, shows many contexts in which brokers have a positional advantage that garners high returns for themselves. By keeping the other two members of a triad separated, brokers exercise control over the flow of information. Compared to others, those in brokerage positions enjoy higher promotion rates (Podolny and Baron, 1997; Burt, 2005), receive more-favorable evaluations at work (Burt, 2005), close deals more frequently (Mizruchi and Stearns, 2001), generate more options for strategic partnerships (Stuart, Ozdemir, and Ding, 2007), and so on. Scholars also have examined how intermediaries capture or redistribute rents generated through exchange; Fernandez-Mateo (2007) showed that major clients of staffing agents are able to negotiate lower prices for recruiting services but that to sustain their margins, brokers transfer these costs to workers.

Given how much brokers' behavior varies across settings, it is important to be precise about the context in this article. 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 describing 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 an intermediary who refrains from making introductions to preserve disunity (Stovel, Golub, and Meyersson Milgrom, 2011). Whereas some other brokers aim to preserve structural separations, the intermediaries we study deliberately establish matches that result in triadic closure. Second, we consider a context in which professional standards of conduct and regulations aim to curb most 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 the Stark Law prohibit medical specialists from compensating PCPs for referrals.

The rich literature on brokers and intermediaries has generated important insights into how resources are distributed among exchange partners, but little research has studied to whom intermediaries refer and how this choice influences the quality and the evolution of *de novo* relationships. This is our focus.

## Matching in Triads

The triads we study in this article comprise prospective clients (C), third-party referrers (R), and experts (E). Clients require the services provided by experts, and the referrer matches the client to the expert and facilitates their exchange. Thus, we examine C(lient)–R(eferrer)–E(xpert) triads. In practice, the client often requests that the referrer make an introduction to a qualified expert, or the expert may enlist the referrer to assist in matching their services to potential clients. In most cases, the referrer has met the client and often has knowledge of the referred-to expert. Therefore, two sides of a potential triad, C–R and R–E, often share some form of a connection. We assume the third edge, C–E, to be absent prior to the referrer'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 tertius iungens role.

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

The role of a referrer in this triadic structure is pivotal: R abets the formation of C–E pairings. In fact, Marsden (1982: 202) defined brokerage by the act of matchmaking. Brokers enter the fray when two parties are interested in transacting but have difficulty discovering or trusting each other (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 competencies and the reliability of sellers and/or buyers (Reagans and Zuckerman, 2008; Gargiulo, Ertug, and Galunic, 2009; Rider, 2009) and use this knowledge to match needs to expertise (Bielby and Bielby, 1999).

One domain in which there has been significant research on third parties and brokered exchanges is the labor market. Scholars have shown that because certain intangible characteristics of both work roles and job applicants are hard to observe in the absence of firsthand experience, preexisting social ties between an employer and job prospects may enhance the quality of worker–employer matches (Fernandez and Weinberg, 1997; Fernandez, Castilla, and

Moore, 2000; Castilla, 2005). Compared to non-referred job applicants, referred applicants earn slightly higher wages and are more likely to be hired, more likely to accept job offers, and less likely to quit (Burks et al., 2015). Studies in other settings have also found that intermediaries learn about specific experts over time, which in theory improves referrals' match quality between clients and experts (Sarsons, 2017; Zhelyazkov, 2018).

### Trust in Triads

In addition to expediting matches, referrers can engender trust in C–E dyads (Simmel, 1950; Coleman, 1994; Obstfeld, 2005). In Simmel and in Coleman, the third party in three-actor systems has 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 referrer can influence a client's view of an expert by endorsing the integrity, competence, professionalism, or some transaction-relevant characteristic of the provider. In short, reliance on the referrer-qua-intermediary's judgment can cement trust between the transacting parties in the triad C–E.[2]

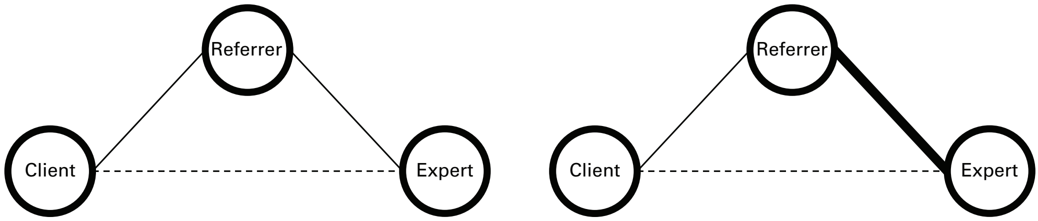
In addition to the trust that may arise from enhanced information exchange, a third actor also may promote trustworthiness because they can sanction malfeasance (Granovetter, 1985; Raub and Weesie, 1990). Rational choice scholars observe that local reputations function best in continuing (as opposed to one-shot) systems of relations, especially if information about an actor's conduct in one relationship might spread to other current or would-be partners. Thus, there is a reputation risk of deceitful conduct 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 may choose to share information about 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.

### Hypotheses: Incompatible Considerations?

Referrers use their experience in brokering market exchanges to match clients to suitable experts and to cultivate clients' confidence in experts' competence and integrity, but these two relational outcomes occur to variable extents. In formulating two hypotheses, we zero in on how variation within the preexisting social structure of referral triads alters how referrers balance optimal matching

[2] These relational dynamics are similar to endorsements, which further strengthen the potential impact of intermediaries in referral triads. As Podolny (2001: 33) observed, 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 who is admired or trusted by a client has a strong tie with an expert, the mere existence of this association can function as an endorsement that influences the client's perception of the expert (Stuart, Hoang, and Hybels, 1999). Therefore, referral triads are fertile structures for information exchange, sanctions, and endorsements.

**Figure 1. Variation in R–E Tie Strength**




and trust-building, which leads to different outcomes in C–E dyads. In particular, we posit that the strength of the relationship between a referrer and the referred-to expert acts as a dial that shifts the emphasis across these two tasks to the point that it renders them in partial opposition of one another. Our argument is that while a strong R–E relationship increases the likelihood that R will endorse E (thereby promoting trust), it simultaneously creates default referral patterns—reliance on a handful of favored experts—that potentially jeopardize the quality of the C–E match.

Figure 1 crystallizes the variation we explore. We focus on tie strength along the R–E edge. For ease of exposition, we collapse tie strength to strong or weak. On the left side of Figure 1, the thin line between R and E represents a weak tie. On the right side, the bold line between R and E indicates a strong tie. We examine differences in C–E interactions—the dashed line in the figure—when clients consult a referrer's weak tie (left image in Figure 1) versus when they consult one of R's strong ties (right image in Figure 1). Again, 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 much prior research that has explored this critical R–E relationship in the context of brokerage or referral triads. Likewise, very little prior research has addressed the endogeneity of tie strength.[3]

Before deriving our hypotheses, we specify four boundary conditions for the theory to hold. First, information asymmetries and opaque evaluative criteria mean that the typical client cannot easily evaluate an expert's quality. This condition implies that clients face significant uncertainty adjudicating among potential service providers. Second, a typical client trusts the referrer. This trust enables the referrer to sway the client's behavior, although the influence may be subtle. Trust may arise because clients and referrers have a relationship that predates a referral or because the referrer has a reputation as an honest broker. Third, search to optimize client–expert matches entails costs to referrers. These search costs may arise because of the complexity of the expertise landscape, the sheer number of experts, or the difficulty of observing service providers' specific expertise (Boudreau et al., 2017). The existence of search costs implies that satisficing behavior may emerge when referrers recommend

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

experts. Fourth, experts must offer a variety of services, and there must be variance in the quality of the services they provide. For example, one family attorney may specialize in complex custody cases, while another is a specialist in estate planning. One gastroenterologist may be an expert in treating diseases of the liver, while another specializes in bowel problems. Variation in quality and specialization implies an expertise distribution that referrers must uncover to match clients and experts.

### Tie Strength and Trust

An intuitive literature has established that strong ties imply relationships of greater texture and affect (Krackhardt, 1992). Demonstrating this in market contexts, both quantitative and ethnographic studies have shown the evolution of personal friendships alongside market exchanges or, inversely, economic ties that form along the rails of preexisting ethnic or social relationships (e.g., Macaulay, 1963; Waldinger, 1995; Uzzi, 1996). This is, of course, the central assertion in the embeddedness literature: The economic and social structure of the market are joined at the hip, and the social relationships among market participants influence how economic ties are established, managed, and evolve.

If we assume that personal attachment is greater as tie strength increases, referrers are more likely to invest in building clients' confidence in experts' abilities when a strong R–E tie predates a referral. Researchers note that information exchange in a network is discretionary (Reagans and McEvily, 2003; Aral and Van Alstyne, 2011), which means that simply because a tie is present does not mean that it is activated. The stronger the tie, the more likely it is to be a live pathway for information exchange and socio-emotional investment.

Strong R–E ties enable the referrer to credibly vouch for the expert because the referrer has greater knowledge of an expert's prior work with clients. Also, and perhaps of greater importance, referrers are more likely to have a socio-emotional interest in making the effort to endorse an expert who is at least an acquaintance, if not a friend. In the health care context, for example, a well-informed physician referrer might attest to a strong-tie specialist's knowledge, thoughtfulness, or responsiveness to patient concerns. Subject to the first two boundary conditions (C–E information asymmetries exist, and clients trust the intermediaries from whom they seek referrals), such endorsements should impact the confidence a client places in an expert. The central point is that the referrer with a strong tie to an expert understands how to best assure a client of the expert's skill and likely has a personal interest in doing so, which leads to the following hypothesis:

**Hypothesis 1 (H1):** In referral triads, as tie strength between a referrer and an expert increases, the client is more likely to develop trust in the expert's opinion.

### Tie Strength and Match Quality

Compared to the impact of R–E tie strength on a client's trust of the expert's opinion, the impact of tie strength on the referrer's ability to create a high-quality match between a client's needs and a provider's expertise is more ambiguous. On one hand, Biglaiser (1993) showed that in markets for heterogeneous services, referrers are able to add more value if they are knowledgeable about the offerings of specific experts. Naturally, referrers learn about the expertise of providers they frequently recommend, and this may contribute to curating high-quality matches. On the other hand, increases in tie strength may bring diminishing returns on this front. If reliance on strong-tie referrals comes at the expense of learning about other providers with different expertise (McFadyen and Cannella, Jr., 2004), referrers who heavily use strongly tied experts do so at the expense of breadth of coverage of the expertise landscape (Dodds, Muhamad, and Watts, 2003; Bhargava and Choudhary, 2004).

Subject to the third and fourth boundary conditions (i.e., there are costs to optimally matching clients and experts, and the market is characterized by expert sub-specialization), reliance on a small number of experts is likely to result in some suboptimal C–E matches, at least if match quality is defined on the basis of alignment between a client's problem and an expert's experience. If expertise is broadly distributed and it is also customary for any given referrer to match clients to a small number of providers relative to the variation in sub-specializations, C–E match quality will suffer relative to other decision rules for assigning clients to experts.

Assuming this to be true, why would referrers rely on strong ties with experts rather than cast a wider net composed of weaker professional ties? One explanation is that referrers and experts may share a non-market tie that establishes a bond. For instance, they may have matriculated from the same graduate program, work in the same office complex, live in the same neighborhood, or have children attending the same school. Not only are these social ties associated with more emotional attachment (Oelberger, 2019), but they also reduce search costs. Regardless of whether the origin of a tie is social or professional, as R–E dyads develop a history of working together and their relationship strengthens, the referrer likely acquires a preference for the strong-tie expert.

Prior research has suggested that convenience, relational inertia, and (in many cases) an emotional draw endogenously shape interactions in embedded relationships (Dahlander and McFarland, 2013). As referrers build 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). The existence of the prior relationship becomes a prime criterion for future match formation, especially in the presence of search costs that interfere with the assessment of other dimensions of a match (Azoulay, Liu, and Stuart, 2017). The upshot is that for the same reason that R is more willing to invest to reinforce the C–E relationship if R has a strong tie to a particular expert, R is also more inclined to refer a client to the strongly tied E in the first instance.

Habitual reliance on strongly tied experts, whether for relational, cognitive, or emotional reasons, may jeopardize the quality of the expertise match compared to broader searches over the expertise distribution. This leads to our second proposition:

**Hypothesis 2 (H2):** In referral triads, as tie strength between a referrer and an expert increases, clients' problems are likely to be less well matched to providers' expertise.

## Setting: Referrals in Medicine

To test the hypotheses, we study physician referrals of patients to specialist providers in U.S. health care.[4] This is an ideal setting to examine referral triads. Health care is an enormous market, representing close to 20 percent of U.S. GDP, and its importance for the public welfare extends beyond its immense economic significance. The market also is rife with information and incentive problems, including patient–specialist information asymmetries and the fact that medical specialists provide both diagnosis and treatment. Moreover, the decisions patients must make in this context can be among life's most consequential, which elevates the need for high trust in expert guidance (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. Conversely, patients with a first-time health issue often have limited knowledge of their own condition and almost no knowledge of the landscape of potential specialist providers.

The referral process begins when a patient consults with their PCP about a health condition. The PCP determines whether the problem merits further medical attention and, if so, whether to refer the patient to a specialist for care. Although the number of specialists varies by field (e.g., there are more dermatologists than neurosurgeons), there are usually multiple providers to treat the patient's condition. When a PCP refers a patient to a particular specialist, the PCP weighs their own preferences, their knowledge of or prior experiences with a provider, and the patient's needs and preferences. A PCP generally recommends a specific provider in a time-constrained context, as they attempt to avoid schedule slippage and high wait times for subsequent patients.

In making a referral, a PCP may prioritize a specialist with whom they have an established relationship (Zuchowski et al., 2015). Patients often value other factors, such as the specialist's location, gender, or age (Yahanda et al., 2016; Blödt et al., 2021). Subject to insurance plan restrictions, the patient generally has discretion in the choice of a provider. Although a patient may deviate from a PCP's recommendation, the literature indicates that a PCP's guidance is the most important factor determining the specific physician with whom the patient consults (Forrest et al., 2002). This raises the question of how PCPs weigh patient preferences, non-medical factors that may lead a PCP to favor a given specialist, and the PCP's knowledge of which specialists are best equipped to treat a patient's health condition. The latter aspect of the referral process—specialist expertise in treating the patient's diagnosed condition—is an important dimension of patient–specialist match quality and one of the key outcome variables in this study.

After receiving a referral, the patient schedules a consultation with the specialist. For benign conditions, the specialist's recommendation may be that no follow-up is required. However, if the diagnosis and treatment options are new to the patient and are consequential, the patient faces uncertainty regarding both.[5] If the patient experiences significant doubt about the specialist's

[4] We typically use the terms patient, primary care physician (PCP), and specialist provider for the three actors in a referral triad, and these map to client, referrer, and expert, respectively, in a more general characterization of referral triads.

[5] As we explain below, we limit the sample to the first visit of a patient to a provider in a given specialty. This increases the likelihood that the diagnosis and treatment options are new to the patient.

recommendations, the patient may seek a second opinion from another expert or may opt not to return for follow-up care. These two outcomes, second opinions and follow-up visits, are measures of the confidence that the patient places in the specialist consulted: Patients who trust the advice they receive are less likely to request a second opinion and more likely to return to the specialist for follow-up care.

We study 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, our analyses explore two questions: (1) does a strong-tie history in a PCP–specialist dyad increase the level of trust that a current, referred patient places in the specialist provider, and (2) does a strong-tie history in a PCP–specialist dyad decrease the quality of the match between a current patient's medical condition and the referred-to specialist's prior expertise?

We posit that a PCP is more likely to endorse a specialist's qualifications to a patient if the PCP shares an extensive referral history with the focal specialist. In the presence of a strong tie history, we surmise that PCPs convey positive signals to the patient about the specialist, such as ''you'll love this doctor,'' or ''she's an excellent cardiologist,'' or ''she'll take great care of you.''[6] Therefore, a strong PCP–specialist tie should promote a patient's trust in the specialist's clinical guidance.

While an extensive referral history is likely to promote trust, we also predict that strong ties in PCP–specialist dyads often lead to habit-driven referrals, which under the boundary conditions specified earlier may undermine the quality of the patient–provider expertise match relative to other approaches to matching patients and specialists.

## DATA AND SAMPLE

We used the Massachusetts All Payers Claims Database. The data are collected by the Center for Health Information and Analysis (CHIA) and contain remarkably comprehensive information derived from the medical and pharmacy claims of virtually every resident in Massachusetts. We used 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 who change insurance plans over time. The database contains multiple files, but we mainly drew from the 650-million-record medical claims file. These data include physician and patient identifiers, complete diagnosis codes, dates and locations of provider visits, any medical procedures performed, charges, and referral information. The latter includes an indicator for whether the patient was referred to a given specialist and a unique identifier of the referring physician. Although we had data on all medical claims and all insurance plans, to ensure data accuracy we

[6] There are two points in time at which such affirmations may promote trust between the patient and the specialist: during the initial patient–PCP consultation when the referral is made and after the visit with the specialist, when the patient may consult with the PCP in a follow-up visit or phone call to discuss any ongoing health issues.

limited the analysis to patients covered by insurance plans that required a referral to reimburse a claim. Effectively, this limited the sample to health maintenance organization (HMO) and point of service plans.

We began by extracting all 12.8 million medical claims for adult patients (18+) referred by their PCPs to specialists for consultations. We then eliminated a number of specialties from this sample. First, we removed small specialties with fewer than 50,000 medical claims for referred services, because PCPs have insufficient opportunities to build strong ties with providers in those fields. Second, we removed non-patient-facing specialties and those in which the patient cannot select their provider, such as pathology, radiology, and anesthesiology. These two sampling steps reduced our sample to 11 million referrals spread across 45 specialties. (See Figure 2, panel C for a list of specialties included.)

Next, we limited the sample to first-time office visits.[7] Specifically, for any provider in specialty *s*, we conditioned on the patient having not previously seen a provider in specialty $s, t < T$. Limiting the data to patients' first-time consultations within specialty *s* makes it unlikely that the patient is familiar with providers in the focal specialty. This is the first assumption of our theory and 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. This step reduced the number of observations to 1.9 million cases.[8]

## Measures

**Dependent variables.** The first hypothesis is that a patient's confidence in a specialist's care will be greater in the presence of a strong PCP–specialist tie. We derived two outcome variables to capture patient trust. Does the patient seek a *Second opinion* after a first consultation with a specialist? And does the patient return to the first specialist for a *Follow-up visit*? We set both variables equal to one if there was a second opinion or if there was a follow-up visit and to zero otherwise. We viewed both outcomes as measures of patient confidence in a specialist: A patient who trusts the specialist will be less likely to obtain a second opinion and more likely to return for follow-up care.[9]

Follow-up visits were straightforward to identify in the data: We simply evaluated whether the patient returned to the referred-to specialist for follow-up care within 365 days following the first visit. Pinpointing second opinions was more complex. To identify second opinion consultations, we followed the method outlined and validated in de Vaan and Stuart (2022). In a nutshell, we identified all instances in which a patient saw a second specialist in the same specialty following a first-time consultation in that specialty. We required the

[7] Office visits were identified by relying on Current Procedural Terminology code 992. The first visit with a specialist is typically an office consultation.

[8] While the drop from 11 million to 1.9 million observations may seem large, it is unsurprising. Health care utilization is very skewed such that most people consume relatively little health care, while a relatively small group of patients (most with chronic conditions) use the majority of care. Our sampling strategy means we focused on the former group of relatively healthy patients.

[9] Of course, the decisions to seek a second opinion and return for a follow-up visit also are driven by other factors like the complexity and severity of the health issue and the patient's cost of care. The empirical analysis conditions on these factors.

second opinion visit to occur within 180 days of the first consultation, and both appointments must have originated from a PCP's referral. Under this definition, 4 percent of all first-time specialist referrals were followed by a second opinion consultation.

In a second set of regressions, we analyzed the level of the expertise match between the patient's health condition and the specialist's clinical expertise. Prior research has highlighted the importance of this dimension of match quality (Epstein, Ketcham, and Nicholson, 2010; Sahni et al., 2016). The literature clearly establishes both that physicians specialize in treating certain conditions and that more specialization leads to higher quality of care. In obstetrics, Epstein, Ketcham, and Nicholson (2010) found that a one-standard-deviation increase in a provider's cesarean section specialization results in a 60 percent reduction in the number of hospital days due to complications from the procedure. Likewise, Sahni et al. (2016) found that patients of cardiologists with top-quartile specialization in coronary artery bypass grafting have a 15 percent lower operative mortality than do those of providers in the bottom quartile. Chan, Gentzkow, and Yu (2022) reported similar findings in radiology. Coupled with the fact that there is tremendous variation in the conditions that providers in each specialty treat (Molitor, 2018; Cutler et al., 2019; Chown, 2020), there are compelling reasons to believe that physician specialization in the patient's health condition may influence health outcomes.

Informed by this work, we constructed a measure of patient–specialist match quality that we labeled *Diagnostic specialization.* It captures the extent to which a provider specializes in treating the patient's diagnosis. To compute the measure, we counted the number of patients the specialist saw in the prior 12 months with the same diagnosis as the focal patient and divided this number by the total number of patients the specialist treated in that time window. We constructed this variable as a fraction rather than a count, to be consistent with most prior research on physician specialization and health outcomes. Online Appendix A provides more measurement details and full regression results for three alternative measures of diagnostic specialization.

While prior research and a validation exercise discussed later in this article suggest that condition-specific physician specialization is an important dimension of patient–specialist match quality, it is far from the only dimension of match quality. For instance, prior research has found considerable variation in communication quality in clinical contexts, which is sometimes ameliorated in gender-concordant patient–physician pairs. Other factors, such as geographic proximity, also may be significant to patient care. In short, specialization captures an important component of match quality, but it certainly does not encapsulate every relevant dimension.

**Independent variables: PCP–specialist tie strength.** Across analyses, the central explanatory variable is the *Tie strength* between the PCP and specialist in each referral triad. To assess tie strength, prior research has considered the duration of a relationship, frequency of contact, and reported affect (Marsden and Campbell, 1984). That said, research on professional relationships has generally relied on straightforward measures of interaction frequency to assess tie strength. For example, in health care, Landon et al. (2012) demonstrated a high correlation between physician referral frequency and the peers that the referrer rates as most influential to their professional practice. Likewise, Everson et al. (2018) found that repeated interactions between physicians are associated with self-perceptions of better teamwork. In light of this, we defined PCP–specialist tie strength as a count of the number of referrals from the former to the latter in the year preceding the first opinion consultation between patient and specialist, which we refer to as the ''index'' visit.[10]

One challenge with using referral frequency to measure tie strength is that it significantly varies by both PCP and specialty. First, the average PCP refers more frequently to (say) dermatologists than to hematologists. Second, a PCP's patient mix directly influences the ties that the PCP forms. PCPs in practices with a young patient mix will refer less often to oncologists and cardiologists than will PCPs with an older patient mix. To address this issue, we included PCP-by-specialty fixed effects and included *Referrals to specialty* frequency, which is a count of the total number of referrals a PCP made to a specific specialty in the prior year.

To illustrate the variance that informs the estimations with the inclusion of PCP–specialty fixed effects, consider a PCP $j$ providing referrals to orthopedics for two patients, $\alpha$ and $\beta$, each of whom consults a different provider $k$. In the majority of cases, there will be variance in tie strength between PCP $j$ and the orthopedists $k$ seen by patients $\alpha$ and $\beta$. This is the variation we exploit in the regression analysis.

For the cleanest test of our theory, it is also necessary that PCP $j$ has a strong tie to at least one specialist in specialty $s$ at the time these referrals are made. In the absence of a strong tie to any specialist in specialty $s$, the regressions would in part estimate off the presence versus absence of a single past referral. For instance, suppose PCP $j$ had referred only one patient to an orthopedist $k$ in the previous year and patient $\alpha$ sees that orthopedist while patient $\beta$ visits any other provider. This creates variation in PCP–specialist tie strength between the $\alpha$ and $\beta$ referral triads, but the results do not directly address the impact of strong ties about which we hypothesize. To limit the analysis to the variation that is pertinent to the theory, we therefore sampled only PCP $j$–specialty $s$ combinations in which the focal PCP had established at least one strong tie with a provider in the specialty.[11]

**Control variables.** We included *Patient age* at the time of a consultation. To allow for nonlinearity in the effect of patient age, we specified a four-piece spline: 18–44, 45–54, 55–64, and 65+. *Female patient* is assigned one if the patient was female and zero otherwise. We constructed the *Charlson score* for each patient based on their prior-year medical history. This comorbidity score is commonly used in medical research to predict one-year mortality rates. It is based on the presence of 22 serious health conditions, such as heart disease.

[10] Online Appendices D and E provide more measurement details and regression results for alternative measures of *Tie strength*.

[11] We provide descriptive statistics on the full sample and the analytic sample below and show that the samples are remarkably similar except for the distribution of tie strength. Also, in Online Appendix D we show full sample results that are similar to those in the analytic sample.

To directly account for all diagnosed current health conditions, we also included the full suite of diagnostic code fixed effects, using ICD-9 three-digit codes.[12]

We were able to identify and control for all insurance plans in the data. In total, 208 distinct insurance plans were in operation in the Massachusetts health care market during the observation window. Our analytical sample includes the 48 plans that require patients to obtain a referral for reimbursement, all of which are either HMO or point of service plans. Jointly, these plans cover 71 percent of the medical claims in the state. The regressions include a fixed effect for every operative plan.

Next, we included a set of PCP controls. We included a *Female PCP* dummy. As mentioned, we included *Referrals to specialty* frequency, which is a count of the total number of referrals a PCP made to a specific specialty in the prior year. Finally, we included year-by-month fixed effects.[13]

Including these controls and fixed effects in the regressions adjusted for selection processes in patient–specialist relationships, which may lead to a spurious association between *Tie strength* and the three outcome measures. However, because these controls may not account for all confounding factors, we also implemented an instrumental variable strategy.

## Empirical Strategy

The analyses evaluate whether a strong PCP–specialist tie is associated with an increase in the referred patient's confidence in the specialist's recommendations and also whether a strong tie leads to a lower-quality match between patient diagnosis and physician specialization. We estimated the following equation to evaluate the effect of tie strength on the likelihoods of either a second opinion (SO) or a follow-up visit:

$$\mathrm{P(SO=1)/P(Follow\text{-}up\ visit=1)} = \beta_1 \times \mathrm{Tie\ strength}_{jk} + \beta_2 \times X_i + \gamma_{j(s)} + \epsilon, \tag{1}$$

where $i$ 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. We then estimated a second equation to evaluate the effect of *Tie strength* on *Diagnostic specialization*:

$$\mathrm{Y} = \beta_1 \times \mathrm{Tie\ strength}_{jk} + \beta_2 \times X_i + \gamma_{j(s)} + \epsilon, \tag{2}$$

The $\gamma_{j(s)}$ term represents PCP-by-specialty fixed effects. As noted, the primary variation in this setup is across patients but within PCP $j$ referring to specialists $k$ within specialty $s$ with whom the referring PCP has different tie strengths.

[12] ICD-9-CM is a widely adopted system for coding for disease diagnoses and procedures. The system is modeled after the World Health Organization (WHO) International Classification of Diseases (Ninth Revision) (ICD-9). It is the basis for medical billing in the U.S.

[13] The regressions omit variables that represent attributes of the specialist provider. Elwert and Winship (2014) cautioned against including variables that are realized only after treatment. Since treatment (patient assignment to a specialist with a particular PCP–specialist tie strength) is "realized" once the decision to consult a specific specialist is made, we omitted specialist controls. We did, however, evaluate whether including specialist attributes alters the estimates; we found that it does not.

Endogeneity concerns stem from the fact that both the PCP and the patient have discretion in choosing a specialist. Suppose that patients with health anxieties, which we do not observe, are more likely to choose a provider who differs from a PCP's referral and that these patients also are more likely to seek a second opinion. This would create a spurious relationship between PCP–specialist tie strength and second opinions. Another confounding factor might be differences in patients' levels of medical literacy, which could affect both their selection of specialists and proclivity to seek a second opinion.

The relationship between *Tie strength* and *Diagnostic specialization* also may be confounded. For example, consider patients with severe medical conditions. We included several controls to adjust for patient health, but it is unlikely that we captured all variation on this dimension. This is problematic because condition severity may cause a PCP to increase the search for a high-quality diagnostic match.

In an ideal scenario, we would randomly assign patients to referral triads with varying levels of PCP–specialist tie strength. In the absence of an experimental design, we leveraged quasi-random variation in the likelihood that a focal patient will visit the specialist with the PCP's strongest tie.

We used an instrumental variable (IV) that is based on variation in patients' insurance plan coverage for specific specialists. Insurance plans often only cover treatment by providers who have a negotiated contract with the plan. Specialists who are covered by an insurer are considered to be in network for that plan. The IV relies on the fact that a PCP's strongest-tied specialist may or may not be in network in any given patient's insurance plan. Ideally, we would have data on all insurance contracts in place. Unfortunately, our data do not map plans to coverage, but they do include, for every medical claim, an indicator for whether that claim is considered by the insurer to be out of network. While these data include patients who were seen by out-of-network physicians, they do not include information about patients being referred to an out-of-network physician but choosing not to visit that physician. Given that out-of-network providers are costly, this latter scenario is very common. To circumvent this issue, we computed the fraction of in-network claims from the focal patient's insurance plan for each PCP $j$'s strongest-tied provider $k$ in specialty $s$.

The logic of the IV is that if the specialist with the strongest tie to a PCP is out of network for a particular patient's insurance, that patient is likely to choose a different, in-network provider. This means that the patient is less likely to consult a specialist with whom their PCP has a strong tie. Intuitively, the IV quasi-randomly shifts a PCP's patients from seeing the PCP's stronger-tied specialists to consulting weaker- or non-tied specialists. For the instrument to be relevant, it is only necessary that the in-network status of a PCP's strongest-tied specialist influence whether the patient sees that clinician. Prior research has shown this to be the case (Ziemba, Allaf, and Haldeman, 2017), and results from our first-stage regressions decisively confirm it.

For the exclusion restriction to hold, the IV also must be uncorrelated with the error term. We believe this to be the case but only in a model that fully adjusts for heterogeneity in insurance plan quality. Better insurance plans may offer broader coverage networks and may affect a patient's propensity to pursue a second opinion or to seek follow-up care. For this reason, the IV will meet the exclusion restriction only after conditioning on insurance plan–specific fixed effects.[14] In Online Appendix B, we describe the instrument in more detail and provide a balance check that shows results that are consistent with the validity of the exclusion restriction.

## Descriptive Statistics

Table 1 presents summary statistics for both the full and analytical samples. The distinction between the two is that the analytical sample limits the data to PCP *j*-specialty *s* pairings in which a PCP *j* has at least one strong tie to a provider *k* in that specialty. Comparing the two samples, we find that the descriptive statistics—with the exception of *Tie strength* and *Referrals to specialty*—are very similar. It is mechanical that *Tie strength* and *Referrals to specialty* are higher in the analytical sample because to construct it, we omitted PCP *j*-specialty *s* dyads in which PCPs made few referrals and therefore had no strong-tie specialist relationships.[15]

Next, we took a close look at variation in the primary independent variable, *Tie strength*. Figure 2, panel A plots the distribution of tie strength for the analytical sample of 890,121 referrals from PCPs to specialists. In one-third of the observations, the PCP has no prior referral relationship with the specialist the patient consulted, while the right tail of the distribution represents PCPs who referred to a single specialist at least twice a week. Panel B of Figure 2 shows the variation in tie strength within every PCP–specialty combination. Because the regression analyses incorporate PCP-by-specialty fixed effects, we estimated off of variance within these groups. For every PCP–specialty pair (n=46,446), we computed the standard deviation in tie strength and plotted the distribution of these values. The graph shows that within these strata there remains significant variation in PCP–specialist tie strength for the specialists that patients consult.

Finally, panel C shows the distribution of mean PCP–specialist tie strength between PCP–specialist pairs across all the specialties in the data. The distributions reveal considerable variation both within and between specialties. This graph illustrates how important it is to condition on PCP-by-specialty fixed effects. Given the wide variation we observed in referrer–expert tie strength across specialties, it would not make sense to base inference on variation in relationship strength by comparing across, for example, PCP–nephrologist and PCP–allergist referral dyads.

Next, we looked at whether our data show patterns consistent with the assumptions laid out earlier in this article. The third assumption for our theory requires the presence of search costs in client–expert matching, and the fourth assumption states that there is variation in providers' expertise. Are these

[14] Specifically, in the first stage of the 2SLS we regressed the endogenous variable, PCP–specialist tie strength, on the instrument Z, other control variables, and insurance plan fixed effects. If Z is conditionally exogenous, it becomes valid only after we control for the confounding covariate (insurance plan quality, in our case) in the first stage of the 2SLS estimations. Controlling for insurance plan quality adjusts for the component of Z that might be correlated with the error term in the main equation. In the second stage, one then regresses Y on the predicted values of X from the first stage and other control variables. Since X-hat is constructed using a valid instrument (because the researcher has conditioned on the key covariate[s] in the first stage), it is uncorrelated with the error term in the second stage.

[15] Recall that the reason for this step is to ensure informative variation in tie strength within each PCP–specialty combination.

**Table 1. Sampling Statistics***

Panel A. Full Sample (N = 1,887,253)

| | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| Second opinion | 0.03 | 0.00 | 0.18 | 0.00 | 1.00 |
| Follow-up visit | 0.53 | 1.00 | 0.50 | 0.00 | 1.00 |
| Diagnostic specialization | 0.15 | 0.09 | 0.17 | 0.00 | 1.00 |
| Tie strength | 7.84 | 2.00 | 16.87 | 0.00 | 455.00 |
| Referrals to specialty | 47.57 | 25.00 | 64.01 | 0.00 | 1070.00 |
| Strongest tie | 0.36 | 0.00 | 0.48 | 0.00 | 1.00 |
| Patient age | 48.08 | 50.00 | 13.94 | 18.00 | 75.00 |
| Female patient | 0.59 | 1.00 | 0.49 | 0.00 | 1.00 |
| Charlson score | 0.59 | 0.00 | 1.06 | 0.00 | 16.00 |
| Female PCP | 0.43 | 0.00 | 0.50 | 0.00 | 1.00 |

Panel B. Analytic Sample (N = 890,121)

| | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| Second opinion | 0.03 | 0.00 | 0.18 | 0.00 | 1.00 |
| Follow-up visit | 0.52 | 1.00 | 0.50 | 0.00 | 1.00 |
| Diagnostic specialization | 0.14 | 0.09 | 0.15 | 0.00 | 1.00 |
| Tie strength | 14.95 | 9.00 | 22.41 | 0.00 | 455.00 |
| Referrals to specialty | 87.45 | 65.00 | 73.83 | 10.00 | 1070.00 |
| Strongest tie | 0.31 | 0.00 | 0.46 | 0.00 | 1.00 |
| Patient age | 48.30 | 50.00 | 13.65 | 18.00 | 75.00 |
| Female patient | 0.58 | 1.00 | 0.49 | 0.00 | 1.00 |
| Charlson score | 0.57 | 0.00 | 1.03 | 0.00 | 15.00 |
| Female PCP | 0.39 | 0.00 | 0.49 | 0.00 | 1.00 |

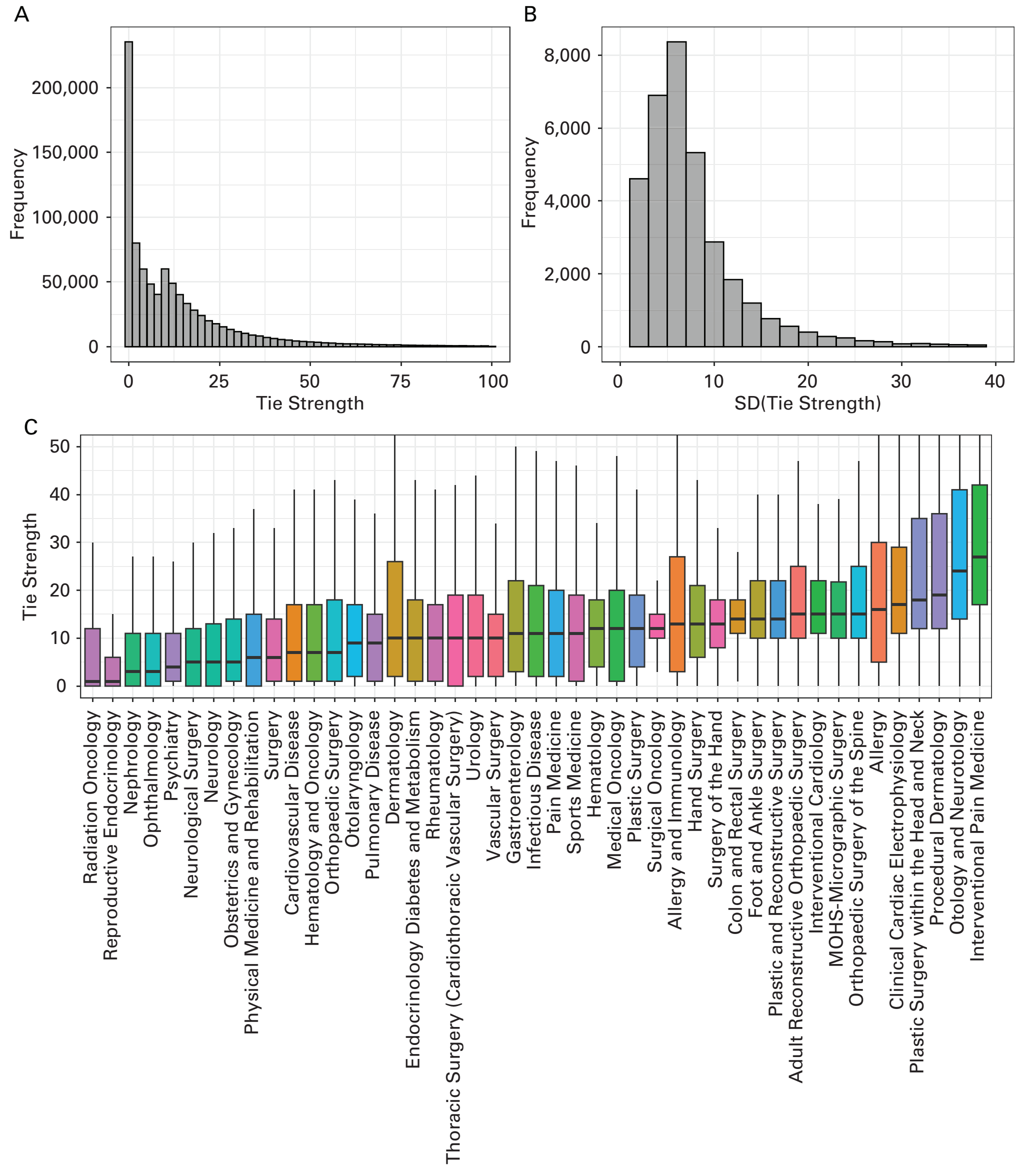
Panel C. Correlation Table Analytic Sample

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| (1) Second opinion | | | | | | | | | |
| (2) Follow-up visit | –0.075 | | | | | | | | |
| (3) Diagnostic specialization | –0.014 | 0.059 | | | | | | | |
| (4) Tie strength | –0.034 | 0.009 | –0.025 | | | | | | |
| (5) Referrals to specialty | 0.023 | –0.062 | –0.018 | 0.411 | | | | | |
| (6) Strongest tie | –0.053 | 0.034 | –0.018 | 0.530 | –0.100 | | | | |
| (7) Patient age | –0.004 | 0.070 | 0.054 | 0.015 | –0.006 | 0.025 | | | |
| (8) Female patient | 0.005 | –0.031 | 0.005 | –0.022 | 0.010 | –0.026 | –0.066 | | |
| (9) Charlson score | 0.017 | 0.070 | 0.016 | –0.036 | –0.078 | –0.003 | 0.293 | –0.052 | |
| (10) Female PCP | 0.005 | –0.043 | 0.006 | –0.068 | –0.023 | –0.038 | –0.110 | 0.379 | –0.064 |

* The full sample is filtered on PCP–specialty *s* pairs in which the PCP has more than nine referrals (the overall median in the data) to their strongest tie in the specialty to create the analytic sample.

assumptions warranted in health care? To address this question for the third assumption, we identified the number of specialists to whom PCPs counterfactually could have referred the patients they treat, as well as the PCP's tie strength with each of those alternative options. Our main analyses exploit variation in tie strength among actual referrals, but it was also possible to create all counterfactual referral choices for every patient. In other words, every observation in the analytical sample is an actual patient–specialist dyad, but we could

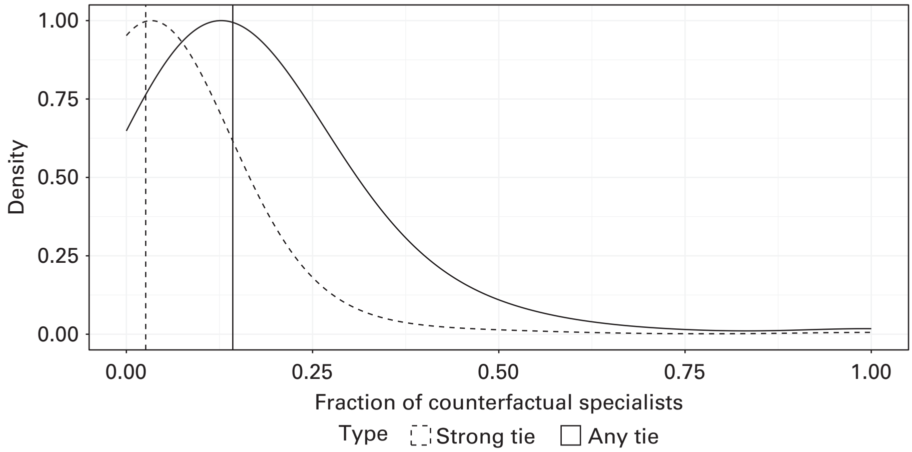
**Figure 2. Distribution of Tie Strength Between Referral Partners***




* Panel A shows the distribution of tie strength. Panel B reports the distribution of variation in tie strength within each PCP-by-specialty combination. Panel C shows the distribution of tie strength by specialization. It shows significant variation in tie strength both between and within specialties.

also identify all specialists the patient could have seen but did not. To do so, we selected the patient's residential zip code and then identified all instances in which other patients hailing from that zip code were referred to a specialist in *s*. We then calculated the fraction of those specialists to whom the patient's PCP had (1) any past referral tie and (2) a strong referral tie. The two distributions are shown in Figure 3. The takeaway is that the median PCP had any tie

**Figure 3. Distribution of Ties (Any and Strong) to Counterfactual Specialists***



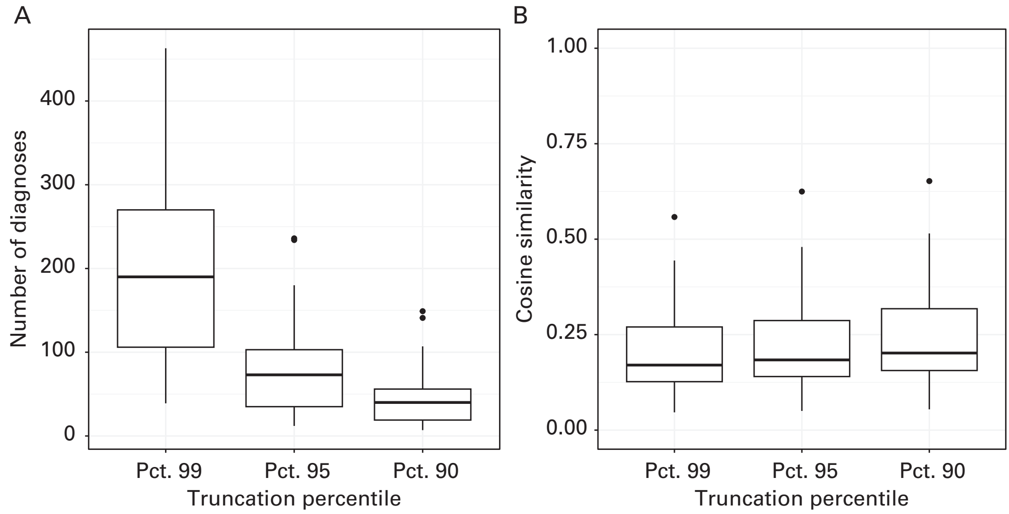

* Using each patient's zip code and the specialty they were referred to, we identified all "convenient" counterfactual specialists the patient could have consulted. We then calculated the fraction of these specialists to whom the patient's PCP had referred patients in the past year (*Any tie*) and the fraction of specialists with whom the focal PCP had an above-median referral history (*Strong tie*). Vertical lines represent the medians of both distributions, which are low.

to only 15 percent of the counterfactual specialists and strong ties with only 3 percent of these potential providers. These statistics illustrate that referrers in health care generally have strong ties (or, for that matter, any prior tie) with a small fraction of expert providers. This pattern suggests search costs because referrers lack firsthand experience with the majority of experts.

We then examined whether our fourth theoretical assumption (there is variation in providers' expertise) holds in the health care setting. To examine this, we sampled all medical claims for specialists for one year of the data and calculated the number of patients a specialist saw with a given diagnosis. We then computed the number of diagnoses collectively treated by all specialists in a specialty and truncated the tail of the distribution to remove rare conditions. In Figure 4, panel A, we show that in a typical specialty, providers treated a large number of diagnoses. This is true even when we remove the long tail of the 10 percent rarest diagnoses. In Figure 4, panel B, we directly evaluate whether providers sub-specialize in certain diagnoses. For every specialist *k*, we created a vector of diagnosis frequencies based on their own prior 12-month treatment histories. Within each specialty *s*, we then computed the cosine similarity between all pairs of specialists' treatment histories.[16] Panel B shows the resulting distribution. What jumps out in the figure is that the commonality in treatment vectors among providers *within specialties* is quite low, with a median below 0.2 across all specialties. In fact, even when we restricted the sample to the most common diagnoses (the far-right box and whisker), there is still very little overlap in treatment histories among providers within specialties. Jointly, these patterns suggest that, as laid out in the fourth boundary condition, PCPs

[16] Cosine similarity ranges between zero and one, where zero indicates maximum distance and one indicates maximum similarity between two treatment vectors.

**Figure 4. Provider Specialization***




* Graphs are based on 2012 treatment data. Other years show similar patterns. Panel A is the distribution of the number of diagnoses treated by providers in all specialties. Panel B shows the distribution of cosine similarities of the treatment vectors of all providers within each specialty. The x-axes show truncation levels on diagnostic rarity: removing the 1%, 5%, or 10% of observations with the least common diagnoses.

face a complex expertise landscape and considerable sub-specialization among specialists.

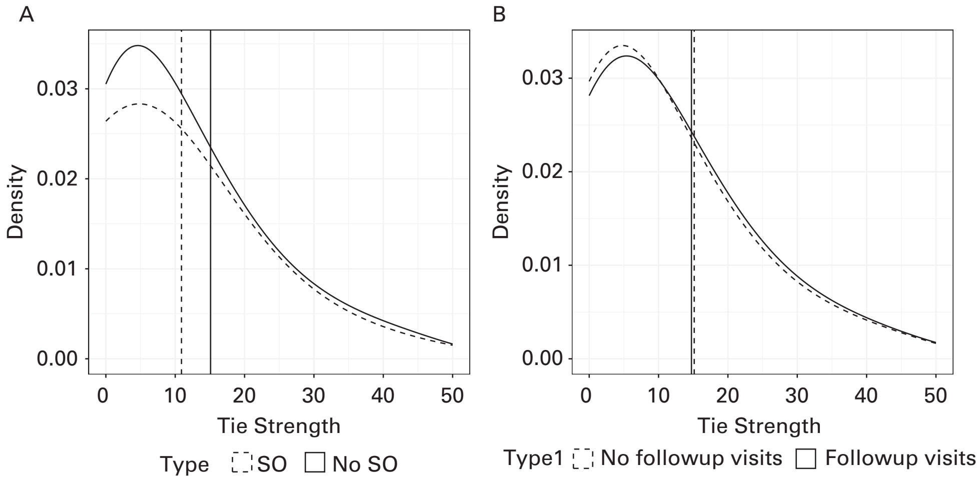
## RESULTS

### Primary Analyses

We begin by illustrating relationships in the raw data between the first two outcome variables and PCP–specialist tie strength. Figure 5 panels A and B show the distribution of PCP–specialist tie strength broken out by whether the original consultation was followed by (1) a second opinion and (2) a follow-up visit. The vertical lines represent the means of the distributions. In line with Hypothesis 1, panel A of the figure shows that PCP–specialist tie strength is significantly lower for referral dyads in which the patient obtains a second opinion, and panel B shows that tie strength is higher for patients returning for follow-up care. The bivariate distributions are consistent with the premise that patients who consult their PCPs' stronger-tied referrals place greater trust in specialists' expertise.

Table 2 shows the results of a formal test of H1. The regressions in the table include PCP-by-specialty fixed effects and report clustered standard errors at this level. Coefficients for controls are displayed in Online Appendix C. Model 1 of panel A includes tie strength as a continuous measure. We find a strong, negative correlation between tie strength and the probability that a patient later seeks a second opinion: A one-standard-deviation increase in tie strength reduces the probability of a second opinion by about 17 percent. In model 2, tie strength is specified as a median split (a dummy variable takes the value of one if there have been nine or more referrals between the PCP and

**Figure 5. Distribution of Relationship Between Outcomes and Tie Strength by Specialty***




* The means of the distributions are shown by the vertical lines. For second opinions, the difference in means (10.9 versus 15.1) is 4.19 (t = 40.62); for follow-up visits, the difference in means (15.15 versus 14.74) is 0.41 (t = 8.54). The medians are different as well: 5 versus 9 for second opinions and 9 versus 8 for follow-up visits.

specialist in the past year). The dichotomous specification also shows that in strong PCP–specialist referral triads, the patient is less likely to seek a second opinion: Above-median tie strength is associated with about a 34 percent reduction in the probability of a second opinion. Model 3 includes a binary indicator equal to one 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, too, negatively affects the probability of the patient seeking a second opinion. The effect size is substantial: Patients who consult a PCP's strongest tie in a specialty are 37 percent less likely to seek a second opinion. Columns 4 to 6 of panel A in Table 2 present the same set of regressions for the second dependent variable: whether the patient returns to the referred-to specialist for follow-up care within 365 days of the initial visit. Supporting H1, patients referred to a PCP's strongly tied specialist are more likely to return for a follow-up consultation. Similar to the findings on the probability of a second opinion, the results suggest that the association is nonlinear and that the effect of tie strength is driven by the upper range of the tie strength distribution. The effect sizes across the three models range between 3 and 4 percent. In model 4, a one-standard-deviation increase in tie strength is associated with a 3 percent increase in the probability of a return visit, while models 5 and 6 suggest an increase of about 4 percent.

We report the IV regressions, estimated using 2SLS, in panel B of Table 2. We use the continuous measure of tie strength to construct the instrument, but other operationalizations produce consistent results. In column 1, the first-stage regression, a one-standard-deviation increase in the instrumental variable is associated with about one additional referral between the PCP and specialist. The F-statistic of 809 is large and far above the level at which a standard error adjustment is needed (Lee et al., 2022). Columns 2 and 3 report the IV

**Table 2. Strong Ties and Trust***

Panel A. OLS Estimates

| | Probability of Second Opinion after First Consult | | | Probability of Follow-up Visit after First Consult | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Tie strength | –0.0003••• | | | 0.0006••• | | |
| | (0.0000) | | | (0.0001) | | |
| Tie strength ($\geq$ 9) | | –0.0119••• | | | 0.0228••• | |
| | | (0.0005) | | | (0.0014) | |
| Strongest tie | | | –0.0128••• | | | 0.0224••• |
| | | | (0.0005) | | | (0.0015) |
| Controls included | Yes | Yes | Yes | Yes | Yes | Yes |
| PCP $\times$ Specialty FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 890,121 | 890,121 | 890,121 | 890,121 | 890,121 | 890,121 |

Panel B. IV Estimates

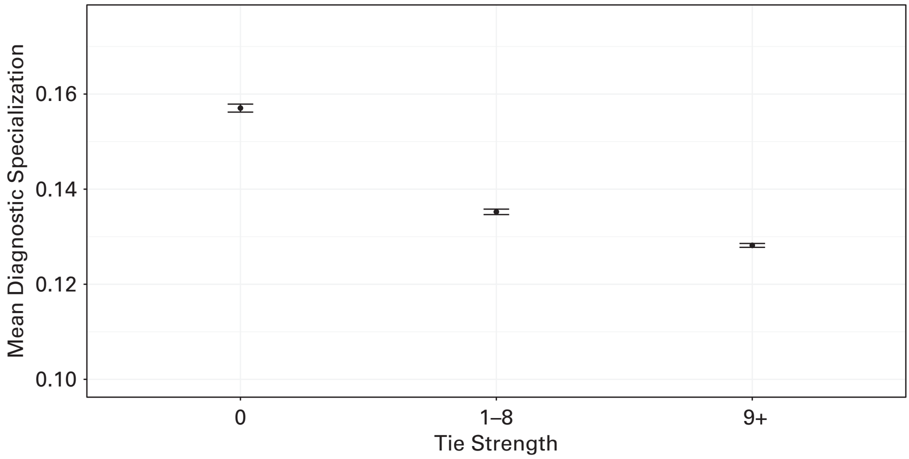
| | First Stage | P(SO=1) 2SLS | P(Follow-up Visit=1) 2SLS |
|---|---|---|---|
| Fraction of patients with same plan → Strong tie | 12.5300••• | | |
| | (0.8568) | | |
| Tie strength (IV) | | –0.0010• | 0.0063••• |
| | | (0.0004) | (0.0012) |
| Controls included | Yes | Yes | Yes |
| PCP $\times$ Specialty FEs | Yes | Yes | Yes |
| F-statistic | – | 809 | 809 |
| N | 890,121 | 890,121 | 890,121 |

• $p < .05$; •• $p < .01$; ••• $p < .001$; two-tailed tests.
* Panel A shows second opinions and follow-up visits regressed on PCP–specialist tie strength. Columns 1–3 report estimates for the probability of a second opinion after an initial consultation. Columns 4–6 show estimates for whether a follow-up consultation occurred. Three measures of tie strength are shown: (1) continuous, (2) a spline, and (3) binary. Panel B shows the IV estimates. Column 1 contains the estimate for the first stage. Columns 2 and 3 report results for the second stage of the IV regressions.

estimates. The instrumented regressions show that the effects of PCP–specialist tie strength on the probability that the referred patient seeks a second opinion or returns for follow-up visits may be interpreted as causal. The effect of tie strength in both columns is significant, substantial, and consistent with H1.

The effect sizes estimated using the 2SLS model are larger than the effect sizes estimated using OLS (a one-standard-deviation increase in tie strength causes a 61 percent decrease in the second opinion probability and a 27 percent increase in the probability of a follow-up visit). This is fairly common in the literature and likely stems from the fact that 2SLS estimates the local average treatment effect, while OLS estimates the average treatment effect. The local average treatment effect is the effect in the subset of the data for which the IV drives variation in treatment (i.e., the compliers). For example, if low socioeconomic status (SES) patients are more likely to respond to the out-of-network status of a strong tie because of financial constraints, we may have a group of compliers (low SES patients) and a group of non-compliers (high SES people). If

**Figure 6. Diagnostic Specialization by Tie Strength***




* The graph shows the mean of diagnostic specialization across three bins of tie strength: no tie (0), weak tie (1–8), and strong tie (9+).

low SES patients are also more responsive to endorsements by a PCP, the local average treatment effect obtained through 2SLS would exceed the average treatment effect obtained through OLS. In sum, both OLS and IV estimates suggest that patients place greater confidence in specialists with whom their referring PCP has a strong relationship.

The next set of analyses evaluate whether, in referral triads, the strength of the PCP–specialist tie influences the quality of the patient–specialist diagnostic match. Recall that *Diagnostic specialization* is a provider's prior history of treating a patient's diagnosed medical condition. Figure 6 plots the bivariate relationship between patient–specialist diagnostic specialization and PCP–specialist tie strength. For illustration, we bin tie strength into three groups. The graph clearly shows that strong PCP–specialist ties are associated with lower levels of diagnostic specialization for the patient's health condition. The raw means of the data therefore are in line with H2.

We formally tested the relationship between diagnostic specialization and tie strength by estimating the model defined in equation 2: We regressed diagnostic specialization on PCP–specialist tie strength. As with the previous regression analyses, we included PCP-by-specialty fixed effects, effectively comparing a patient who sees a PCP's strong- versus weak-tied provider within a given specialty. The results of this regression are shown in Table 3.

Model 1 of panel A includes tie strength as a continuous measure and shows a negative association with the diagnostic specialization of the specialist. Model 2 incorporates tie strength as a spline. Like the result from model 1, this regression shows that the stronger the PCP–specialist tie, the less specialized the physician is in treating the patient's diagnosed medical condition. In model 3, we included a binary indicator equal to one if a patient consults the provider with whom their PCP has the strongest tie in specialty s. This alternative measure is also negatively associated with the diagnostic specialization of the

**Table 3. Strong Ties and Diagnostic Specialization***

Panel A. OLS Estimates

| | Diagnostic Specialization | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Tie strength | –0.0002••• | | |
| | (0.0000) | | |
| Tie strength ($\geq$ 9) | | –0.0139••• | |
| | | (0.0004) | |
| Strongest tie | | | –0.0103••• |
| | | | (0.0005) |
| Controls included | Yes | Yes | Yes |
| PCP × Specialty FEs | Yes | Yes | Yes |
| N | 890,121 | 890,121 | 890,121 |

Panel B. IV Estimates

| | First Stage | Diagnostic Specialization 2SLS |
|---|---|---|
| Fraction of patients with same plan → Strong tie | 12.5300••• | |
| | (0.8568) | |
| Tie strength (IV) | | –0.0011••• |
| | | (0.0003) |
| Controls included | Yes | Yes |
| PCP × Specialty FEs | Yes | Yes |
| F-statistic | – | 809 |
| N | 890,121 | 890,121 |

• $p < .05$; •• $p < .01$; ••• $p < .001$; two-tailed tests.
* Panel A shows diagnostic specialization regressed on PCP–specialist tie strength. Three different measures of tie strength are reported: (1) continuous, (2) a spline, and (3) a binary measure. Panel B shows the IV estimates. Column 1 contains the estimate for the first stage. Column 2 reports the IV results.

specialist. The effect sizes across the three models are substantial: In model 1, a one-standard-deviation increase in tie strength is associated with a 3.7 percent decrease in diagnostic specialization. Models 2 and 3 suggest that a patient seeing an above-median or strongest tie is associated with decreases of 10 and 8 percent, respectively, in the diagnostic specialization of the specialist.

We report the IV regressions in panel B of Table 3. Model 2 shows the second stage of the 2SLS regressions. Like the results for our two other outcomes, the estimate in this model suggests a large effect size: A one-standard-deviation increase in tie strength is associated with an 18 percent reduction in diagnostic specialization. To put this number in context, this is equivalent to going from a specialist at the median of the diagnostic specialization distribution to a specialist at the 40th percentile. This finding suggests a causal effect of tie strength on diagnostic specialization. Thus, while a strong tie between a PCP and specialist enhances patient–specialist trust, it also reduces the likelihood that patients are matched to providers with the deepest expertise in their medical conditions.

## Post-Hoc Analyses

We conducted two post-hoc analyses, both of which establish fact patterns that further illustrate two key arguments developed in this article. First, we have argued that one reason certain providers become default options for a PCP is that referrers face search costs and that when these costs are salient, patients may be matched for reasons other than a provider's condition-specific expertise. If search costs partly drive default referrals, one would expect these types of referrals to be most common when referrers have limited time for search.

To determine whether there is evidence of this behavior in the data, we investigated whether PCPs are more likely to refer patients to their strong-tie specialists on the days in which they see more patients. Our reasoning is that if PCPs in part default to strong ties to economize on search, we should observe a heavier reliance on strong-tie referrals on busy days. Table 4 shows this to be the case. For the majority of the index visits in the analytical sample, we were able to count the number of patient consultations each PCP had on the corresponding day. We found that when a PCP's patient count is high, either in the cross section (comparing across PCPs) or when computed as a Z-score based on the PCP's own level of busyness (comparing within PCP) during the prior month, a PCP is more likely to refer patients to their strong-tie specialists. This is consistent with the view that strong-tie specialists become mental defaults for PCPs, and time pressure causes PCPs to favor these options relative to a search for an alternative provider.

**Table 4. Busyness and Default Referrals***

| | Tie Strength | |
|---|---|---|
| | (1) | (2) |
| # of patients | 0.0005••• | |
| | (0.0001) | |
| # of patients (z-score) | | 0.0050•• |
| | | (0.0018) |
| Controls included | Yes | Yes |
| Insurance plan FEs | Yes | Yes |
| 3-digit zip code FEs | Yes | Yes |
| Diagnosis FEs | Yes | Yes |
| Year × Month FEs | Yes | Yes |
| PCP × Specialty FEs | Yes | Yes |
| N | 627,089 | 627,089 |

• $p < .05$; •• $p < .01$; ••• $p < .001$; two-tailed tests.

* The sample used for these analyses is smaller than the one for the main regressions. The reason is that we cannot link every index visit to the specific PCP–patient interaction that resulted in the referral. This is likely because some referrals arise from telephone or email requests that do not result in a medical claim. Both regressions include the same control variables used in the prior regressions. Model 1 shows the number of patients the PCP treated on the day of the referral. Because the model includes PCP-by-specialty fixed effects, it compares PCP referrals to the same specialty on busy versus less busy days. In the second regression, we measured busyness as the number of patients the PCP saw on the day of the referral relative to their patient volume on other days in the month of the referral.

**Table 5. Diagnostic Specialization Validation***

| | Probability of Hospitalization (1 year) (1) | Probability of Death (1 year) (2) |
|---|---|---|
| Diagnostic specialization | –0.0310••• | –0.0018••• |
| | (0.0032) | (0.0005) |
| Female patient | 0.0055••• | –0.0020••• |
| | (0.0003) | (0.0001) |
| Age 18–44 | 0.0463••• | –0.0013••• |
| | (0.0011) | (0.0001) |
| Age 45–54 | 0.0334••• | –0.0010••• |
| | (0.0012) | (0.0001) |
| Age 55–64 | 0.0511••• | 0.0005••• |
| | (0.0012) | (0.0001) |
| Age 65+ | 0.0890••• | 0.0120••• |
| | (0.0013) | (0.0003) |
| Charlson score | 0.0791••• | 0.0153••• |
| | (0.0002) | (0.0002) |
| Insurance plan FEs | Yes | Yes |
| Specialty FEs | Yes | Yes |
| Year × month FEs | Yes | Yes |
| Zip code FEs | Yes | Yes |
| Diagnosis FEs | Yes | Yes |
| N | 23,055,775 | 23,055,775 |

• $p < .05$; •• $p < .01$; ••• $p < .001$; two-tailed tests.
* The sample used in these regressions includes all office visits to a specialist for patients diagnosed with a specific condition for the first time. We used the complete dataset for these analyses for two reasons. First, measuring diagnostic specialization of specialists is not limited to cases that resulted from a referral (e.g., it can be computed for visits of PPO-insured patients). Second, because our analytic sample is designed to include relatively healthy patients, one-year hospitalization and one-year death are very rare outcomes (3% and 0.1%, respectively). Both regression models above are estimated using OLS. Model 1 shows the association of diagnostic specialization and the probability of being hospitalized in the following year. Model 2 reports the association between diagnostic specialization and the one-year probability of death.

Second, the trade-off at the center of our argument may have important health consequences: If diagnostic specialization is an important dimension of patient–specialist match quality, a less-good match should have negative implications for patient health outcomes. We provide suggestive evidence that this is the case. We examined whether there is an association between diagnostic specialization and two adverse health outcomes: hospitalization within one year and death within one year. These two health outcomes are standard in the literature on quality of care (Tsugawa et al., 2017; Kvasnicka, Siedler, and Ziebarth, 2018; Case and Deaton, 2020; Brown et al., 2022).

We compiled a large sample of patients who visited a specialist for an office consultation and were diagnosed with a specific condition for the first time. Because we could measure diagnostic specialization for all specialist patient visits, there was no reason to limit the data by type of insurance plan. The full sample includes 23,055,775 observations. In this sample, 18.4 percent of patients experienced a hospital admission in the year following the index visit, while 1.1 percent of all patients died in the year following the index visit.[17] The bivariate correlations between one-year hospitalization, one-year death, and diagnostic specialization are $-0.09$ and $-0.03$, respectively.

The regressions include all control variables used in the main models presented in the article.[18] Estimates are shown in Table 5. We find that an increase in diagnostic specialization—a higher-quality specialist–patient match—is associated with a decrease in adverse health outcomes. A one-standard-deviation increase in diagnostic specialization is associated with a 2.3 percent decrease in hospitalizations and a 2.2 percent decrease in death. Although these estimates should not be interpreted as causal, they suggest that diagnostic specialization might capture an important dimension of the quality of care.

## DISCUSSION AND CONCLUSION

Referrals are the source of many client–expert relationships in professional services. In addition to referrals 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 preexisting tie strength between the referrer and the expert, shape how individual clients become matched to specific experts and how new exchange relationships evolve.

In addition to demonstrating the importance of referral triads in health care, we also showcase a theoretical tension in the core mechanisms through which referral triads potentially remedy endemic information asymmetries in expert markets. On one hand, we find that the presence of a third-party referrer with a strong preexisting tie to a referred-to expert engenders trust in the client–expert dyad. Translating this to our empirical setting, we find that patients demonstrate greater confidence in a specialist if their referring PCP has a strong tie with that provider.

On the other hand, we posit that referrers operating in embedded exchange networks develop professional, economic, socio-emotional, or routine-based tendencies when they choose to whom to refer patients. If strong ties between referrers and experts create social preferences or even just elevate an option to be top-of-mind for referrers, the existence of such ties will have the effect of shifting which client–expert relationships are formed. Through this mechanism, strong ties anchor new relationships on past referral partners.

Conditional on a differentiated landscape of expert services—one of the boundary conditions of our theory—we show that the downside of habitual referral behavior is that it reduces patient–specialist match quality. Is there evidence that this compromise in match quality affects clients' (patients') welfare? In a post-hoc analysis, we show that, consistent with prior research, there is a cost to a lower-quality provider–patient expertise match: Patients who consult

[17] Our data include all hospitalizations for patients in Massachusetts but not other states. This is a limitation of the outcome measure. Likewise, we observed death only if it occurred in a hospital, ambulance, hospice care, or another medical facility. When we benchmarked the death rate in our sample to the Massachusetts death rate, our rough estimate is that we observed about 50 percent of all deaths in our sample.

[18] Note that we cannot include PCP $\times$ specialty fixed effects in the health outcomes regressions because the PPO patients in the data do not generally list a PCP referrer.

providers who lack a sub-specialization in treating their diagnosed health issue experience worse health outcomes.

These ideas point to a broad issue, which is that it has been difficult or impossible for scholars to observe the quality of brokered matches in most empirical settings. This is a major issue for researchers, but it is also a reality of the marketplace in any context in which the boundary conditions of our theory hold. That is, in markets with many providers and in which it is difficult for individual participants to observe the full landscape of expertise, even insiders often lack knowledge about which expert would best address a client's needs. A consequence of this measurement challenge for researchers is that, rather than observe match quality directly, they have typically inferred 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 care provided by all physicians, along with how many times a doctor has treated patients with any given diagnosis, we can directly assess the match between patient health conditions and physician experience. These data provide a unique window into matching, which is not confounded with subsequent outcomes that may or may not reveal actual match quality.

Theoretically, our core ideas marry central premises in the brokerage and embeddedness literatures. A cornerstone of the former is that many brokers enable or facilitate certain market exchanges, and a hallmark of the latter is that social relationships and social obligations underlie or emerge alongside market exchanges. Because of these socio-emotional factors, the simple presence of strong ties alters the behavior of those embedded in them. In this way, strong ties in a market structure are a partial encumbrance on future behavior, and we find this to be true of the behavior of intermediates in referral triads.

In light of our results, we posit that the stability of referrals regarding specific exchange partners is a micro-level process that may lead to one of the frequently cited 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 observation that many network structures are prone to reproduce themselves over time, we argue that the embeddedness of referrers in an incumbent exchange network—itself a precursor to a third party's ability to play the role of an intermediary in trust—quietly nudges the network toward suboptimal client–expert matches relative to those that might arise if the referrer used a broader search over the roster of possible providers. This occurs for 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 in a match. Likely, this reliance on past recipients of referrals contributes to holding the network in place.

Our research has limitations. First, a challenge for any study aiming to understand how third parties shape outcomes in markets for credence goods is that each market has its own set of institutional features. For example, referrals are often required in health care and optional in most other markets. Because of this and other institutional differences, external validity is an open question. We hope that the four boundary conditions we laid out will spark future research on this issue.

Second, in our empirical setting we observed only realized referrals, not the instances in which a patient was referred but decided not to consult a specialist. While this is common in most other empirical settings, it raises questions.

For example, does the width of a PCP's referral network or the distribution of referral tie strengths influence whether patients seek specialist care? How do patients' socio-demographic backgrounds and health statuses influence their decision to follow through with a referral? These and many other questions can be posed if rejected referrals can be observed. One idea in the context of health care may be to collaborate with a provider organization that maintains a record of all instances of referrals.

Finally, we point to a few avenues for future research. First, how might our findings vary over referrer characteristics? We absorbed relatively stationary attributes of referrers in the fixed effects in the regressions, but we speculate that older physicians and those who have been stationary in a geographic location are likely to be integrated in different relational structures that may afford them a different map of the expertise distribution. How will individual differences of this sort alter intermediaries' behavior in referral triads?

Generalizing this idea, we are very interested in how our findings might vary when we bump up to the organizational level of analysis to consider the nesting of referrers and experts inside of organizations. In the professional services sector, many physicians practice alone or in small group practices, but others work in large practices, hospitals, or integrated health systems. In law, attorneys work in settings that range from self-employment to American Bar Association top-20 firms with thousands of lawyers who span most legal specializations. Given the extent of asymmetric information in these markets, it is possible that professional service firms exist in part to facilitate matching and perhaps even influence the degree of specialization itself (Epstein, Ketcham, and Nicholson, 2010). Investigating questions about the role of referrers, the degree to which experts specialize in narrow areas, and the quality of client–expert matching across organizational settings is essential to better understand the social structure of expert markets.

At the early stage of large language models, it is time to speculate about the role that large-scale data and intelligent systems might play in the future of client–expert matching. In health care, electronic medical records with detailed patient health histories increasingly reside in a handful of software systems such as Epic System's MyChart, which currently covers about 160 million patients. Likewise, many insurers have detailed data on patients' health and providers' experience. With the availability of more and larger data sets, will the future hold a mix of algorithmic and social matching? We can envision the process of algorithmic matching beginning in large hospitals or integrated health systems and diffusing from there.

This would be a change of epic proportions. For all of industrial history, we have relied on the social fabric of the market to overcome information asymmetries and the risk of opportunistic conduct. Internalizing market transactions within complex organizations shifted social structures from outside to inside the boundaries of the firm and mitigated certain information problems, but are we on the doorstep of a fundamental change in which algorithms stand in for referrers in matchmaking? If this occurs, how will market exchange evolve when intelligent systems replace referral triads as engines of tie formation?

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## ORCID iDs

Mathijs de Vaan https://orcid.org/0000-0003-1971-7290
Toby Stuart https://orcid.org/0000-0002-3858-1360

## Supplementary Material

Find the Online Appendix at https://journals.sagepub.com/doi/10.1177/00018392241296140#supplementary-materials

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**Authors' Biographies**

Mathijs de Vaan is an associate professor at the Haas School of Business, University of California Berkeley (mdevaan@berkeley.edu). He earned his Ph.D. in sociology from Columbia University. In recent and ongoing research, he builds on rich medical claims data and Dutch registry data to examine how social networks shape labor market outcomes.

Toby Stuart is the Helzel Distinguished Professor of Entrepreneurship and Innovation at the Haas School of Business, University of California Berkeley. His recent projects examine large medical claims and résumé datasets, and he has a forthcoming general-audience book on status dynamics in social and economic life.