Competitive Overlap as a Signal in Expert Partner Choice: Evidence from Patent Law Firm Selection*

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Abstract

Research Abstract In market networks, firms regularly seek partners with needed expertise, but these partners often work with the firms' competitors. How such second-order competitive overlap affects partner selection is unclear. Prior theory assumes firms view networks as "pipes" and emphasizes flows of competitor information via the shared partner as key in partner selection. We propose that firms also view networks as "prisms" and use competitive overlap as a signal of a potential partner's expertise. Hence, firms may prefer partners with competitive overlap. We find support for our claims in the patent law firm selection context. Furthermore, higher competitive overlap leads to slower patent acceptance but results in broader patents, implying that the competitive overlap expertise signal reduces search costs without significant performance loss.

Managerial Summary When selecting expert partners like law firms or consultants, some companies may consider avoiding firms that also serve their competitor. However, when little is known about potential partners, this "competitive overlap" might be a way to asses their quality. We found that firms are more likely to choose patent law firms who work with their competitors. This occurs because a competitor's choice signals that partner's expertise. Companies rely on this signal most when they lack direct experience with potential partners or when entering new technological domains. While working with partners who serve competitors might slightly increase processing times, it can increase patent protection without compromising overall performance. These findings suggest that avoiding partners based solely on competitive overlap may limit access to valuable expertise.

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Introduction

Market ties, relationships created by the exchange of goods, services, or money, represent the predominant linkages between business firms (Baker, 1990). Via these linkages, firms regularly seek partners to supply expertise critical to their operations yet not held within the firm. For example, firms engage advertising firms for their expert marketing services, consulting firms for strategic expertise, and law firms for litigation expertise. Selecting an expert partner can be difficult because ex ante, absent direct prior experience, the firm cannot be certain whether the partner can offer the needed expertise. This raises the risk of selecting a partner that lacks relevant knowledge (Akerlof, 1970; Benner and Zenger, 2016), which is discovered only ex post, when the firm's performance may have suffered. The situation is complicated by the fact that potential partners often serve a firm's competitors, as the partner's expertise is sought by firms with similar needs, creating second-order competitive overlap for the focal firm.

The majority of prior research on second-order competitive overlap in market networks (hereafter competitive overlap) (e.g., Aobdia, 2015; Pahnke et al., 2015; Kang et al., 2022) builds arguments around its role as a deterrent in partner selection. They employ a leakage logic: a focal firm will be reluctant to work with partners that also work with the focal firm's competitors because its relevant knowledge might leak to competitors. In other words, these scholars have implicitly adopted a "pipes" metaphor for network ties created by market exchange (Podolny, 2001, p.34) and focused on the negative aspects of competitive overlap for partner choice in market networks.

However, a close examination of prior studies reveals a lack of clear support for the negative competitive overlap prediction for expert partner selection in market networks. Asker and Ljungqvist (2010) observed that clients of investment banks dissolved ties to banks when competitive overlap increased, but only for overlap with the three largest rivals. In Rogan (2014)'s study of advertising firms, the effect was insignificant except for clients with embedded relationships. Furthermore, neither study examined partner selection, limiting their relevance to the question of expert partner choice. Studies by Aobdia (2015) and Chang et al. (2016) found evidence of a negative effect on partner selection but again only for the top three rivals in the industry. While consistent with a pipes logic, their findings indicate that the negative prediction does not apply to most competitors or tie formation. In contrast to these papers, studies by Bills et al. (2020) and Kang et al. (2022) observed a positive effect of competitive overlap on partner firm selection, suggesting that partner selection is informed by more than a pipes logic.[1] In summary, the inconsistency between theory and evidence suggests the need for further study of the effect of competitive overlap on partner choice.

We believe that this inconsistency reflects a failure of extant research to embrace alternative mechanisms by which second-order overlap shapes tie formation. There are potential positive effects as well. For example, if knowledge can leak *from* the focal firm, it can also leak *to* it (Lim, 2009). Firms might intentionally seek partners with competitive overlap to learn about their competitors. Still, the pipes view alone cannot explain the observed positive effect of competitive overlap on expert partner choice. If firms seek competitors' knowledge, they are likely aware that their own knowledge might leak, and most firms also weigh potential losses more strongly than gains in their decisions (Thaler et al., 1997; Pope and Schweitzer, 2011).

In this paper, we posit a new mechanism that may explain positive findings in the prior literature. We build on Podolny's (2001) observation that network ties may act not only as pipes but also as prisms, "splitting out and inducing differentiation among actors on at least one side of a market" (Podolny, 2001, p. 35). As Podolny (2001) notes, the presence or absence of a tie between two firms serves as an informational cue used by other firms to infer unobservable characteristics, such as quality. These cues affect partner choice most when alter-centric uncertainty – uncertainty confronted by a firm regarding the quality of the output that a potential partner brings to the market (Podolny, 2001, p.33) – is high.

[1]Kang et al. (2022) observed that the positive effect of competitive overlap on partner selection was lower for firms that are concerned about information leakage, but the effect remained positive.

We propose that firms also view networks as prisms when seeking expert partners. They use a potential partner's competitive overlap as an informational cue about the relevance of its expertise. Observing that similar firms have selected the partner reduces alter-centric uncertainty in expert partner choice. Hence, we propose that, on average, firms choose partners with competitive overlap. In this way, competitive overlap acts as a network signal like status but plays a different role in partner selection because it addresses a different type of alter-centric uncertainty and has effects above and beyond status on partner choice.

If firms view networks as prisms, their reliance on the competitive overlap signal should be greater especially when alter-centric uncertainty is high. Therefore, we anticipate that firms will be more likely to select partners with competitive overlap when selecting a new partner, when selecting partners in nascent industries, and when the expertise needed is distant from the focal firm's own expertise. By contrast, in situations of low alter-centric uncertainty, firms view networks primarily as pipes, and our arguments would not apply.

We test our predictions in the context of patent law firm selection by inventing firms (i.e., clients). Firms rely on patent law firms to prosecute their patents, i.e., to prepare and file patent applications. For each patent application, they select a law firm whose expertise matches the patent's technological class. Patent law firms serve multiple clients, and these clients (potential and actual) may also be competitors in product markets. From the publicly available patent application documents, clients can observe which patent law firms their competitors have engaged. Although law firms are not allowed to serve clients with directly adverse legal interests, they are not prohibited from serving clients with competing economic interests (*Maling v. Finnegan, Henderson, Farabow, Garrett & Dunner LLP,* 2015).[2] Hence, although firms may assess competitive overlap when selecting a patent law firm, there are no legal constraints prohibiting competitive overlap in patent law firms' portfolios. Partner choice in this setting is shaped by the client's search for a law firm with relevant expertise,

[2]In *Maling v. Finnegan, Henderson, Farabow, Garrett & Dunner LLP* (2015), the Court held that law firms may represent patent clients who are competitors in the marketplace and pursue related inventions.

balanced against concerns about sharing that law firm with a competitor.[3]

To analyze patent law firm choice, we use US patent data from the PatentsView Project, creating a corresponding law firm-client patent dyad for each patent and comparing the realized pair to a matched hypothetical dyad. In our main analyses, we restrict our data to public firms to match the patent data to clients' product portfolios, derived from 10-K filings, and measure competitive overlap. We estimate the likelihood of a law firm being selected by a client firm while controlling for other law firm or dyad characteristics that could affect partner choice and controlling for client and patent characteristics with patent fixed effects. Our findings support our hypotheses, indicating that client firms are more likely to select law firms high in competitive overlap. We confirm that our results hold for a larger sample that includes non-public firms. Evidence from variations in non-compete legislation helps rule out alternative explanations related to firms seeking knowledge of competitors.

Although using competitive overlap as a signal of expertise may reduce search costs, we also consider whether it benefits performance. We conduct an exploratory analysis of the performance effects of selecting partners with competitive overlap by investigating its effect on several outcomes relevant to patent prosecution: the value of the patent, forward citations, the number of claims, and days to acceptance. Taken together, our findings indicate that the competitive overlap expertise signal reduces search costs without significant performance loss.

To date, second-order competitive overlap has not been considered as a network signal. Prior arguments assuming firms view networks as pipes have proposed that competitive overlap can be both a deterrent and an attractor for partner choice in market networks. Recognizing that firms also view networks as prisms when selecting expert partners, we develop predictions about when competitors choose to share common partners. Furthermore, we pro-

[3]Despite the public availability of patent applications, typically additional private information is exchanged between clients and law firms, and the potential leakage of such information may in theory be a deterrent. As one patent attorney described, "You need to be able to trust, ... [to] have kind of honest conversations. A lot of the instructions on anything extremely sensitive would go on via phone you don't want to put it in writing." (Interview with Attorney #1, November 8th, 2021)

pose that the presence of competitors in an expert partner's network can prove beneficial by reducing search costs. Importantly, our theory of competitive overlap as an expertise signal provides a parsimonious explanation for when competitors choose to share the same partner without assuming that competitors desire to learn from or cooperate with one another.

Theory

Expert Partner Choice

Firms regularly rely on the expertise of other firms to implement their strategies effectively. The selection of expert partners is characterized by information asymmetry and, often, by alter-centric uncertainty. Although the choice of a partner in market exchange settings is influenced by several factors, we expect that firms seeking a business partner will generally weigh the relevant expertise of potential partners. However, doing so can be challenging because expertise is often difficult to observe directly.

As defined by Teece (2018, p.540), experts "offer unique knowledge and experience, supported by advanced methods and tools of the service provider." The expertise of a potential business partner is a function of its technical knowledge and contextual knowledge gained from experience (Levitt and March, 1988; Mayer et al., 2012). Partners with relevant expertise can address the specific problems and needs of client firms as well as anticipate concerns or difficulties that clients themselves did not consider, resulting in better outcomes for the client (Mayer et al., 2012). As such, the relevant expertise of potential business partners increases the quality, speed, and likelihood of success for the services they provide. Firms therefore generally seek business partners that possess relevant expertise (Aobdia et al., 2021). Given that a firm's competitors seek similar expertise, competitive overlap often accompanies the selection of expert partners.

Competitive Overlap as a Conduit of Information

Paralleling arguments regarding information leakage to competitors via direct ties (i.e., first-order competitive overlap) (Awate and Makhija, 2022; Awate et al., 2024; Dushnitsky and Shaver, 2009), most prior research into second-order competitive overlap predicts that firms will also avoid indirect ties with competitors. In market networks, firms often have divergent interests from their partners' partners due to competition for resources or market share (Shipilov and Li, 2012). They fear knowledge leaking to their competitors. Accordingly, second-order competitive overlap avoidance has been predicted in various fields including accounting (Aobdia, 2015), finance (Asker and Ljungqvist, 2010; Chang et al., 2016), strategy (Rogan, 2014) and entrepreneurship (Katila et al., 2008; Pahnke et al., 2015).

Yet, empirical evidence for competitive overlap avoidance during tie formation in market networks is limited. Prior work has frequently focused on top three industry rivals (Aobdia, 2015; Chang et al., 2016) or relationship dissolution (e.g., Asker and Ljungqvist, 2010; Rogan, 2014; Aobdia, 2015). Other studies found a negative correlation between second-order competitive overlap and innovation performance for a subset of firms (Pahnke et al., 2015), but few studies have examined partner choice. In fact, recent work studying tie formation in market networks has even found a positive effect of competitive overlap (Bills et al., 2020; Kang et al., 2022).

The inconsistency between theory and evidence suggests that prior work has failed to embrace the multiple ways in which competitive overlap can affect partner choice.

While the majority of studies adopting a pipes view of competitive overlap in market networks has predicted a negative effect on partner selection, in principle, a pipes view could also predict a positive effect. If networks act as pipes, knowledge flows should be bi-directional. Firms that are seeking knowledge of their competitors might pursue partners with ties to competitors in the hopes of benefiting from those knowledge flows. However, there are at least two reasons why a positive overall prediction based on a pipes explanation alone is unlikely. First, if firms seek partners in the hopes of gaining knowledge of competitors they are likely aware of the risk of their own knowledge leaking. Second, most actors are risk averse and weigh potential losses more strongly than gains (Kahneman and Tversky, 1979; Thaler et al., 1997). Considering that loss aversion holds for even those with the highest levels of experience (Pope and Schweitzer, 2011), it is unlikely that firms would remain unconcerned by the risk of knowledge leakage. Further, competitive overlap often creates ties to multiple competitors. This multiplies the odds of any one of these competitors having the absorptive capacity, tacit knowledge, and routines to take advantage of the focal firm's leaked knowledge (Lim, 2009). While the pipes view can explain individual instances when firms seek partners with competitive overlap, bi-directional knowledge flows and loss aversion complicate the prediction. Recognizing that firms also view networks as prisms provides the basis for a clearer prediction.

Competitive Overlap as a Signal of Expertise

Expert partner choice in market ties often involves substantial alter-centric uncertainty. The firm often cannot know with certainty how relevant the expertise of the prospective partner is, absent prior direct interaction. Although readily observable attributes such as age, size, or location influence choice, they do not resolve the uncertainty firms face when seeking a partner with relevant expertise. In this case, competitive overlap can act as a prism signaling expertise.[4] As noted by (Podolny, 2001, p.35), "the pattern of exchange relations in which a firm engages ... is not only relevant because of the resources that flow between firms but also because of how the pattern of those resource flows affect the perceptions of third parties."

[4]Unlike signals in information economics (Spence, 1973), network signals arise from bilateral tie formation decisions and often are generated as by-products of other processes (e.g., Podolny, 1993, 2001). Trapido (2013, p.503) offers a clear description of these types of signals: "As White (1981: 518) summarized, "[W]hat a firm does in a market is to watch the competition in terms of observables.".... Sociological theories of the markets imply that because information about competition may travel as a result of organizations' monitoring efforts rather than as a result of intentional signaling, signals are not necessarily actions. They may be any observable attributes of competitors that organizations' leaders monitor and that affect the leaders' behavior." Competitive overlap is generated when ties form between competing firms and the same partner. Other firms infer that the shared partner possesses relevant expertise when they observe that their competitors with the same expertise have ties with the partner. In this way, firms use competitive overlap as a signal when attempting to distinguish between partners with relevant expertise and those without.

Whereas a pipes view of competitive overlap sees ties as conduits for information flows, a prismatic view considers how the presence (or absence) of the ties affects the perceptions of others. Seeing one's competitors served by a particular partner may indicate that the partner's expertise is relevant to the focal firm, reducing alter-centric uncertainty. In contrast, the absence of relationships with one's competitors could cast doubt on the supplier's relevant expertise. Qualitative evidence from Bills et al. (2020, p.5) on clients seeking audit firms supports this idea. An audit firm partner in their study commented:

> Given that experience of the team is valuable, this often leads to situations where performing audits for direct competitors increases the chances of being engaged as the auditor. In fact, in nearly all proposals, the prospective client will want to know which companies you serve in the local market and will often contact those companies to obtain references.

Expert partner choice decisions exhibit high alter-centric uncertainty because information about expertise is often unavailable, costly to access, or difficult to interpret. Therefore, we propose that firms use second-order competitive overlap as a signal to reduce uncertainty when selecting expert partners.

Competitive overlap as a signal is similar to status in that it is observable via the network of relationships among firms and reduces alter-centric uncertainty. A partner who has relationships to the focal firm's competitors has competitive overlap, just as a partner who has relationships with other well-connected firms has status. Yet competitive overlap differs from status in the unobservable characteristic proxied by the network of relationships and the type of alter-centric uncertainty resolved. Status signals proxy for quality and indicate that the firm will have more reliable access to resources and information than other partners (Pfeffer and Salancik, 1978; Podolny, 1993). They resolve alter-centric uncertainty about the general quality of the partner and the likelihood that the partner will survive over the long term. Status signals, however, do not resolve uncertainty about the specific expertise of the partner firm.

Competitive overlap proxies for relevant expertise which may or may not be correlated with status and resolves alter-centric uncertainty about the partner firm's ability to provide knowledge to address the task at hand. For example, a firm may need to know if a prospective partner knows how to operate in a particular geography or if it has sufficient knowledge about a new technology. In this case, competitive overlap is a more useful signal than status. Observing that a firm's competitors in a particular geography or technology area are served by the same partner reduces alter-centric uncertainty about the partner's relevance to the focal firm's needs. Contrast that to the status signal of a firm that has connections to many large, well-connected clients. The firm may have status, but the status signal does not provide information about how relevant its knowledge will be for the focal firm.

Given the alter-centric uncertainty and information asymmetry in expert partner choice in market networks, firms look to signals of expertise. Competitive overlap is used as one such signal of expertise, affecting partner choice beyond the partner's status. We propose that when a client observes a prospective partner serving its competitors, the client infers that the partner has relevant expertise, and competitive overlap positively influences expert partner choice.[5] Clearly, there are instances in which the pipes view might dominate, particularly when ego-centric uncertainty is high. When decisions exhibit uncertainty surrounding the expertise of a potential partner instead, competitive overlap acts as a prism and positively affects partner choice. Formally,

> *H1: A prospective partner's competitive overlap increases the likelihood it will be chosen as a partner.*

Competitive Overlap Signals under Alter-Centric Uncertainty

The benefit of competitive overlap as an expertise signal depends on the presence of alter-centric uncertainty when choosing a partner. Therefore, the value of the competitive overlap

[5]Note that our theory about partner *selection* does not depend on the actual relationship between competitive overlap and expertise, but more so the perceived one.

signal of expertise should be greatest when uncertainty about a potential partner's actual expertise is highest, and least when it is lowest. Based on prior research into uncertainty in partner choice, we consider three conditions under which alter-centric uncertainty is lower, and therefore when competitive overlap is less likely to affect expert partner choice.

Prior interactions. Although alter-centric uncertainty can be driven by many factors, a common one is the lack of prior direct interaction with a prospective partner. As a firm gains direct experience with a partner, it obtains better information about the partner's expertise. The firm learns private information about a partner via prior interactions (Uzzi, 1997; Uzzi and Gillespie, 2002). This reduces information asymmetry regarding expertise and decreases the value of competitive overlap as a signal. When the firm has first-hand knowledge of the partner's expertise, the effect of the competitive overlap signal on partner choice decreases. Because prior ties are associated with lower alter-centric uncertainty, firms will rely less on competitive overlap as a signal of expertise when they have had prior interactions with the potential partner.[6] Formally,

> *H2: The positive effect of competitive overlap on partner choice decreases when the firm has prior ties with the potential partner.*

Industry maturity. In nascent industries, all firms, including primary producers and potential partners providing supportive services, are still accumulating knowledge and experience as well as developing their expertise in the technology area. Alter-centric uncertainty is high in nascent industries partly because the firm's ability to assess a potential partner's

[6] Rogan (2014) also predicts a negative moderating effect of prior ties on the competitive overlap effect. However, in Rogan (2014) a change in competitive overlap is predicted to have a negative effect on retention (positive effect on dissolution), and prior ties negatively moderate that effect due to greater information leakage concerns of long term clients who have divulged a lot of private information to their partners. In contrast, in this study we argue for a positive effect of competitive overlap on relationship formation and a negative moderating effect of prior ties whereby the positive competitive overlap effect weakens because prior ties provide more direct information about a partner's expertise lowering alter-centric uncertainty. Relevant to our study is the lack of a significant effect of the baseline competitive overlap on relationship dissolution in Rogan (2014) which suggests that firms do not necessarily avoid competitive overlap.

expertise is low due to its limited industry experience (Cohen and Levinthal, 1990). Judging the relevant expertise of potential partners is difficult. As an industry matures, both the expertise of potential partners and the firm's ability to judge potential partners' expertise increase, as more experience is accumulated, reducing alter-centric uncertainty. Therefore, we anticipate that if firms view networks as prisms, they will rely more on competitive overlap as an expertise signal in nascent industries with new knowledge or technology, and less so in mature industries with established knowledge or technology (cf. Ozmel et al., 2017; Ni Sullivan and Tang, 2013). Formally, we propose,

H3: The positive effect of competitive overlap on partner choice decreases with the age of the technology area.

Technology relatedness. Holding constant industry maturity, firms also vary in their abilities to assess the potential partner's expertise as a function of the relatedness of the technology or knowledge to the firm's prior tasks (Henderson and Cockburn, 1993). Even without direct experience with the potential partner, having had related experience in the same technology or knowledge area enhances the firm's ability to evaluate the potential partner's expertise claims (Teece, 1980). The more related the firm's previous projects are to its current needs, the better able it will be to assess the match on expertise of potential partners. Therefore, the level of alter-centric uncertainty overall decreases, and the value of the competitive overlap signal decreases. Formally,

H4: The positive effect of competitive overlap on partner choice decreases with the relatedness to the firm's existing technology.

Our proposed moderators capture conditions where alter-centric uncertainty is reduced, which should decrease the positive effect of competitive overlap on partner choice if firms primarily use networks as prisms. However, firms also use networks as pipes when facing high ego-centric uncertainty (Podolny, 2001). If the moderators also affect ego-centric uncertainty, abated effects could reflect firms' consideration of information flows via competitive overlap rather than reduced reliance on competitive overlap as a signal of expertise. Yet, the direction of the moderating effect suggested by the pipes view is not apparent *ceteris paribus*. For example, prior interaction increases trust, which could reduce firms' fears of information leakage and increase the likelihood of receiving information on competitors (Ried et al., 2021), but it also could imply that the focal firm has already benefited from knowledge leakage and has less to learn. Regarding industry maturity, information flows from competitors could be valuable in nascent industries as firms learn about the new technology, but they also could be very harmful, as firms' competitive positions could be less well-established and easily disrupted. Regarding technology relatedness, information flows mean that the firm is both better able to use information it gains about a competitor via a shared partner but also the consequences of information leakage could be greater, because the leaked knowledge could affect a set of related technologies held by the firm. Support across all three moderators would be more consistent with firms' views of networks as prisms when evaluating competitive overlap of prospective partners than firms' views of networks as pipes.

Scope Conditions

Our theory is intended to apply to market ties – relationships in which goods and services are exchanged, and our arguments pertain to partner choice in relationships in which expertise is sought. Extending our arguments to horizontal ties between firms or alliance networks is beyond the scope of the current theory. In contrast, our theory pertains to second order competitive overlap where the firm does not compete directly with the partner but does with the partner's partners. While prismatic views of networks do apply to alliance networks, as evidenced by studies showing status effects on alliance partner selection (Podolny, 1993; Ozmel et al., 2013), alliance partners need to learn from one another and require extensive bi-directional information flow. We would therefore expect the pipes view of competitive overlap to influence partner choice to a greater degree in alliance networks. Our arguments are also not intended to apply to board interlock networks (Hernandez et al., 2015). Among these, anti-trust laws play a larger role, and one would have to conceive of competitive overlap as executives from competing firms being board members for a shared third firm – this would not serve as the same signal of expertise as our theory proposes.

Our arguments are subject to several boundary conditions that will affect their generalizability. First, clients must require a minimal level of relevant expertise. Consequently, clients cannot easily develop the skills for which potential business partners might be solicited. This is most often the case in industries that rely on professional services, including law, auditing, advertising, and consulting. For this reason, we focused our theory and analyses on external partner choice rather than the make v. buy decision (Mayer et al., 2012; Chondrakis and Sako, 2020).

Relatedly, clients' tie formation and maintenance with partners must depend on that relevant expertise. For example, if switching costs are so high that firms do not change partners even if these are low in expertise, competitive overlap would not function as an expertise signal. Second, competitive overlap must be unevenly distributed such that only a limited set of potential partners can build portfolios of competing clients, as a function of their relevant expertise for these clients. If all partners have competitive overlap, then it is no longer useful as an expertise signal. Third, as previously noted, our theory assumes that the ties between business partners and competitors are observable. Hence, our arguments will apply most to settings where competitive overlap can be observed. In our empirical setting, patents are publicly available which allows for observation of the prior work and prior clients of a law firm that is under consideration as a partner - including competitors it may serve. This assumption is not unique to our empirical context but also applies in other settings where firms are aware of the clients of potential partners (Chen and Miller, 2012; Downing et al., 2019). In settings where firms are not aware of their competitors, neither competitive overlap avoidance nor the competitive overlap signal of expertise affects partner choice. The less observable competitive overlap becomes, the more likely firms are to rely on other signals, and the less our theory will apply. Lastly, prismatic effects of ties operate when alter-centric uncertainty exists (Podolny, 2001). We expect that when firms make partner decisions without alter-centric uncertainty, they use a pipes view of networks, and our theory would not apply.

Setting & Data

We test our theory on the selection of patent law firms who play an integral role in the patent application process. Patent applications follow a well-defined process: the patenting organization (the client) identifies an invention, searches for a patent law firm with relevant expertise, and requests its services. Most client firms engage patent law firms rather than using an in-house legal department, and they often work with multiple patent law firms.[7] When patenting in the same technology area as their prior patents, clients may choose the same patent law firm; however, this is not necessarily the case. For patents unrelated to the client's prior patents, the client is likely to search broadly to identify the patent law firm with the most relevant expertise. As described by one patent attorney, a client needs to find a patent law firm that "is able to fully understand [the] invention at the most technical level so that [they] can draft a document that fully describes it" (Schweiger, 2021).

Several publicly available databases (e.g., USPTO, WIPO) provide information about prior patents, including the client firm and the patent law firms that prosecuted the patents. Therefore, clients are able to observe the other firms that are served by a given patent law firm, including whether their competitors have engaged the patent law firm and the specific technology of the patent prosecuted.

Once the client has identified a suitable patent law firm, the law firm then meets with the client to gather information and decide whether to prepare and file the patent application with the USPTO. At this point in the process, the law firm conducts a conflict of interest check to confirm that its representation of the new client will not be directly adverse for

[7] A minority of patenting firms use in-house legal counsel to prosecute some of their patents. In-house law firms handle below one percent of the patents in our sample. Since our theoretical focus is on the selection of business partners external to the focal firm, we exclude these observations.

its current clients. Although law firms are prohibited from representing clients applying for patents of the same technology, according to our interviewees, there is a significant gray area in the definition of conflict of interest. Therefore, it is possible for patent law firms to have competitive overlap in their client portfolios, particularly as conflicts are defined narrowly at the level of the technology of the specific patent.

After the law firm and client agree to work together, they interact closely to prepare the application. The law firm, in preparing the application, decides which prior art should be cited and how broad or narrow the claims in the patent application can be with broader claims indicating stronger patents yet not so broad that the patent examiner would reject the application. Once the application is submitted, the law firm responds to requests for further information from the patent office. The average time at the USPTO from the initial patent application to patent approval is three years (Jensen et al., 2018). Hence, the choice of patent law firm represents a multi-year relationship starting before the application is submitted and continues until the patent is granted by the examiner. As one interviewee, Attorney #1, communicated on November 12, 2020: "In my view the importance of patent examination actually makes the choice of partner even more important. The client is selecting someone to work on their behalf for years in an area that requires deep engagement with the subject matter but also a great deal of independence on the attorney's part, and therefore a great deal of trust. For these reasons, the decision... is one that is quite significant for clients, and more significant than many scholars might think upon first glance."

Focusing on the patenting process offers distinct advantages to test our theory. First, it allows for the observation of interactions between organizations and third parties (i.e., partners) that are not themselves competing with each other but where third parties can serve organizations that compete with each other. Patent law firms aid multiple clients by providing essential services in the patent application process. The patenting process requires legal representation that is most frequently sought outside of one's own organization. Given the considerable variation in law firm expertise, profit maximization pressures should create a setting where multiple clients vie for the same legal representation, resulting in overlapping representation across companies.

Patent prosecution —the preparation, filing, and processing of patents— is not a simple rubber stamping exercise and requires both legal and technical expertise. Law firms, as patent prosecutors, "need to access specialized legal resources for conducting prior art searches, [draft] patent applications, and [prosecute] these applications at the patent office" (Somaya et al., 2007, p.923). At the same time, their attorneys are required to have at least "a bachelor's degree (or equivalent) in a technical field and [to have passed] the patent bar exam" with many also holding post-doctoral degrees (Somaya et al., 2007, p.935). As noted by Reitzig and Puranam (2009, p.767), a granted patent "represents the ability of an applicant to convince a patent examiner of sufficient novelty, inventive step (non-obviousness), and commercial viability when judging the applicant's technical invention."

In patent law, legal expertise can be substantive, referring to technical know-how, or relational, which involves understanding the social distribution of knowledge and discretion in the actual relationships through which professional work takes place (Barley, 1996; Sandefur, 2015; Sytch and Kim, 2020). A patent law firm having previously prosecuted a patent related to a particular technology will not only be more versed in that technology but will also know which prior patents to cite, what resources to access, or how to tailor an application to a specific patent examiner's taste such that the patent will be accepted in a timely manner. Both types of expertise are sought by clients, and clients look for cues to reduce alter-centric uncertainty regarding both types of expertise. Hence, empirically, we do not distinguish between the two types.

We collect data from the publicly accessible PatentsView Initiative, which provides access to information on all USPTO patents, including longitudinal links to patent prosecutors, assigning organizations (i.e., client firms), and inventors for the years 1987-2015. Figure A.1, in the Appendix, illustrates what the front page of a patent looks like and where our data come from. Our dataset includes the pairs of patents and law firms selected to prosecute them, which are then matched to a set of hypothetical patent-law firm pairs. We restrict our sample to publicly listed firms with 10-K filings to measure product-market competitive overlap. To identify the client firm associated with each patent, we use data from Arora et al. (2021) which identify clients at the parent-company level, minimizing concerns that we are mis-identifying competitors. Lastly, we draw on pairwise similarities of clients' product portfolios using measures of Hoberg and Phillips (2010, 2016).

Empirical Strategy

The difficulty in analyzing how clients select law firms lies in defining a plausible risk set. Ideally one could identify which patent law firms were actively considered by a firm that is looking to file a patent. Such data, however, are hard to come by without being deeply embedded into the decision-making process and, even then, might be driven by subconscious influences of which the decision-maker is unaware.

We follow prior literature and use a case-control design in which law firms observationally similar to the one used by a client firm on a particular patent are matched as counterfactual patent-law firm pairs (Rogan and Sorenson, 2014; Carnabuci et al., 2015). Each patent i appears in two observations: one paired with a hypothetical law firm and the other with the actual law firm that handled the patent (for an example of the data structure, see Table A.1 in the Appendix).[8] Case-control approaches require correcting for bias that stems from sampling on the dependent variable (Sorenson and Stuart, 2008). One approach is to weight each observation as per Manski and Lerman (1977) and estimate population-level effects. Instead, we estimate conditional probabilities to test hypotheses by relying on case-control fixed effects. This approach leverages the matched design, is less susceptible to inefficient or attenuated results, and estimates unbiased effects conditional on unobserved characteristics related to the patent and client (Sorenson and Stuart, 2008; Breslow and Day, 1980).

[8] We found equivalent results when using a 1:4 design. We chose to present the 1:1 results as at times there were not four good matches for each observed patent-law firm pair and to present more conservative specifications.

To be considered in the risk set, a law firm needed to have handled *any* patent over the past three years within the larger geographical division, such as the Pacific or West South Central (see Census, 2010). We further restrict our risk set to exact matches regarding the existence of a prior client-law firm relationship. That is, when the observed law firm had not previously worked with the client, we chose a control case with which no prior relationship existed either, and vice versa.

We then use propensity score matching (Rosenbaum, 1983) to identify potential patent law firms the focal client did not choose.[9] Patent-law firm pairs were matched based on the squared law firm size (measured as the logged number of patent applications filed over the past three years), the age of the law firm (founding year quintile), as well as whether the law firm has handled a patent from the same NBER category over the past three years. By matching on the first digit NBER classes, such as "Chemical" or "Electrical & Electronics", we can identify plausible controls (i.e., law firms that were at reasonable risk of being selected) while avoiding matching so stringently that controls could not be identified. We estimated propensity scores using a logit model and kept the control case for which the p-score is closest to the observed pair. Alternative matching methods, such as coarsened exact matching (CEM) and other binning methods, lead to worse balance in our matches because of skewed distributions within each bin and the propensity score method identifies more similar control cases. The resulting dataset contains 553,663 patents, assigned by 3,470 clients, and handled by 3,744 law firms.

Table 1 shows summary statistics of our matching variables by group. While results from t-tests indicate statistically significant differences between our treated and control units, the Cohen's d normalized difference measures indicate that these differences are small. We see that the matched controls differ by between 1 and 7 percent of a standard deviation from the observed law firms. To assure that any issues which could stem from the matching procedure are minimized, we control for our matching variables in all models.

[9]Note that in our setting propensity score matching is not used to claim causality, or even approximate a causal X-Y relationship. Rather, we use the method to identify a subset of broadly similar control cases.

—— INSERT TABLE 1 HERE ——

We estimate law firm selection using linear probability models with patent fixed effects. Most prior work has modelled choice using conditional logit models (Alcácer and Chung, 2007; Sorenson and Stuart, 2008; Rogan and Sorenson, 2014; Carnabuci et al., 2015). However, many of our hypotheses rely on interaction terms which require strong assumptions to interpret in logit models (e.g., Ai and Norton, 2003; Mood, 2010). Fixed effects are also critical to our estimation strategy and can lead to incidental parameter bias in logit models (cf. Clough and Piezunka, 2020). Therefore, we follow recent recommendations to rely on linear probability models, whose coefficients, particularly for interaction terms, are subject to fewer biases and easier to interpret and compare across models (Gomila, 2021). The models report standard errors clustered at the level of the client–law firm–year.[10]

Fixed effects at the patent level control for all idiosyncratic characteristics of either the patent or patenting firm. Therefore, we look to characteristics varying across law firms, or the patenting firm-law firm dyad, as potential confounders explaining the choice of law firm.[11] Our modeling strategy assumes that clients set the relationship and choose a law firm. We recognize that forming a tie requires the law firm to agree to enter a relationship, resembling more a two-sided, sequential matching process. We considered estimating our partner choice models using a two-sided matching approach, but were limited by available software and approaches.[12] Nonetheless, modeling partner choice as a one-sided approach is supported by qualitative evidence. First, our interviews with patent attorneys point to client size and prior

[10]Our "treatment" variable depends not only on the client-law firm dyad but also on the law firm's ties to competitors. Given significant variation in law firms' client portfolios, this clustering approach follows the rule of thumb for clustering errors at the treatment level. Alternatively, our empirical strategy could be viewed as revealed preferences without a single treatment. In this case, our standard errors similarly adjust for dependence in the sets of features of client–law firm dyads which vary over time. In an alternative specification in the robustness tests section, we employ law firm-year fixed effects and client- and law firm two-way clustered standard errors.

[11]Price differences across law firms could also influence partner choice. While we do not observe the prices, existing research (AIPLA, 2009) indicates that patent prosecution pricing is mainly determined by firm size, location, and patent type and complexity. We control for these factors either via patent fixed effects or via the matching and control variables.

[12]We are unaware of any statistical package available to estimate two-sided matching models. Existing methods model simultaneous matching, whereas in our setting the decision is sequential. Advances in methods for two-sided sequential choice are needed to better model the choices observed in our data.

interaction as two key factors that affect a law firm's likelihood of accepting the tie. Both are characteristics of the law firm or dyad which are part of our matching strategy. Second, law firms are unlikely to turn down work if it matches their expertise. For example, one attorney commented, "...Often there is a huge ramp up to learning a technology and patent prosecutors can only be expert in so many areas. So, it is hard to turn down work in an area where there are already experts at the law firm.... Their business models depend on getting lots of work that is similar." (Writer, 2015)

Variables

Dependent Variable: Law Firm Choice

The dependent variable, *law firm choice*, is binary, denoting whether or not the client patent-law firm pair has been observed, thereby indicating a realized choice. For each patent, this variable takes on the value one when the law firm was chosen to work on the patent. It takes on the value zero for the matched law firm that was not chosen.

Independent Variable: Competitive Overlap

We measure *competitive overlap* by constructing the product market space using Hoberg and Phillip's (2010; 2016) measure of firm-to-firm product portfolio similarities derived from textual product descriptions in 10-K filings. Publicly listed firms are legally required to accurately describe the products they offer in this form annually, and Hoberg and Phillips (2010)'s measure is updated yearly to reflect the changes in the 10-K filings. The resulting measure is the pairwise cosine similarity of the texts, ranging from 0 to 1, with higher values indicating more similar product portfolios.

We start by identifying all clients of a law firm during the three years prior to the application of the focal patent. Then, we merge on the firm-to-firm product similarities for each focal firm-client pair. We give more weight to firms that are similar to the focal patent's assigning firm by using the Shepard transformation (Shepard, 1987), which has similar properties to an exponential decay curve and is calculated as follows:

$$sim(i,j) = exp(-\gamma\ d(i,j)), \quad \gamma > 0$$

Very close distances result in similarity values close to one. Depending on γ, farther distances will approach zero values more quickly. Since Hoberg and Phillip's (2010) product market overlap measure is a similarity measure, we apply the Shepard transformation to the absolute value of its inverse. The γ parameter regulates whether the measure captures proximity or depth. High γ captures proximity, discounting distant products; low γ captures depth, discounting fewer distant products. We set $\gamma = 7$ in our preferred operationalization but describe our calibration process and the sensitivity of results to this choice in detail in the robustness test section. Finally, we sum each of these transformed similarities and take the natural log before dividing the measure by its standard deviation. As such, law firms that have worked with many of the focal patenting firm's (product market) competitors, as well as those who have worked with their closest competitors, exhibit high values on our measure.

To illustrate our measure, consider the following example. First, for patent #6534535, an invention related to novel chemical compounds, Millenium Pharmaceuticals worked with the prominent law firm Townsend and Townsend. For this patent-law firm pair, our measures indicates very high levels of competitive overlap (99th percentile of the distribution). A look into the underlying data illustrates why: Townsend and Townsend worked with Millenium Pharmaceutical's top two (and four of the top ten) competitors in the previous years. The top two competitors are Oscient Pharmaceuticals and Myriad Genetics, whose product portfolios are highly similar to Millenium Pharmaceuticals' portfolio. Townsend and Townsend has also worked with Millenium Pharmaceuticals' fifth and ninth closest competitors, Onyx Pharmaceuticals and Sirna Therapeutics. Further, Townsend and Townsend has also worked with additional firms with some overlap to Millenium Pharmaceuticals in their product portfolio, combining elements of breadth and depth that add up to a high competitive overlap score. For a moderate example, consider Patent #6112868, a shock absorber for engines by Meritor that was prosecuted by McAndrews, Held, and Malloy, which ranks just above the median on our competitive overlap measure. McAndrews, Held, and Malloy have only worked with one of Meritor's ten closest product market competitors, Arvin Industries, the tenth closest, as well as a few distant ones.

Moderating Variables

In various specifications, we include moderators that vary at the level of the patent. First, to test how prior interactions moderate the effect of competitive overlap on law firm choice, we identify whether a prior relationship exists between the patenting firm and the law firm. This variable helps distinguish initial interactions from those in which the client has first-hand, prior experience with the law firm. The variable *prior tie* takes the value one if a client's prior patent was handled by the law firm.[13] Second, to test the effect of industry maturity, we interact our main predictors with *technology age*, measured as the average age of patents in the same two-digit USPC category. Third, to test the effect of the relatedness of the patenting firm's prior technology, we interact our main predictors with *technology similarity*, a measure of a patent's proximity to a client's prior work. To construct the measure, we calculate the Jensen-Shannon distance to the ten closest patent applications of the same client over the past three years, accounting for large clients' diverse expertise, and normalize this measure (0-1) within each client. Values closer to 0 represent distant technologies, while values closer to 1 represent similar patents.

Control Variables

Related experience. An important control variable for our estimations of competitive overlap effects on partner choice is the *related experience* of the law firm. A law firm's ability

[13] In robustness checks not shown here, we exclude patents of a client-law firm pair from our sample for which applications were filed within the first 3 (or 12) months after the initial shared patent application. This is done to ensure that we are correctly identifying the first interaction between a client and law firm. Given that we do not observe the process leading up to the filing of the first patent application we might incorrectly be identifying the original patent of collaboration as one for which a prior tie exists if a later patent was less complicated to file. These patents make up fewer than 1% of our sample and our results remain unchanged.

to perform certain tasks increases with its accumulated experience (Levitt and March, 1988) which affects the baseline likelihood that a firm will be selected by a client. For example, Li and Rowley (2002) find that a partner's experience makes them more likely to be selected in the investment banking context (bank to bank relationships). In the setting of our study, clients can observe the prior patent applications prosecuted by patent law firms to judge a law firm's related experience. Related experience also likely attracts similar client firms, potentially increasing competitive overlap.

To measure *related experience*, we first map the technology space and locate the patents within it to measure patent-to-patent similarity. Prior research has typically used patent classification codes (Le Mens et al., 2015) or citation overlap (Podolny et al., 1996) to map patent similarity and construct patent and firm locations in the technological space. While meaningful, these measures are less than ideal because they do not capture fine-grained, unbiased differences between patents: patent classes typically contain thousands of patents, and classification-based measures assume those within the same class are identical. Patent-citations-based measures are also suboptimal due to human and institutional biases in the citation process (Kuhn et al., 2020; Kovács et al., 2021). In line with research showing that patent text provides a more precise, less biased measure of technological content (Younge and Kuhn, 2016), we construct the technological space using patent text.

We analyze the patents' abstracts to locate each patent in a 412-dimensional technology space. We use 412 dimensions, corresponding to the 412 USPC categories. While USPTO categorization is binary (assigned or not), our deep learning method provides a continuous measure (0-1) for each category. The model is trained on the data to learn parameter values for optimal categorization performance. This occurs via an updating algorithm that proceeds by trial-and-error to maximize the out-of-sample categorization accuracy. Specifically, we use the model Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018), developed by Google. BERT has been shown across multiple data sets to significantly outperform previous text analysis and machine learning methods. For example, Le Mens et al. (2023) show that BERT substantially outperforms commonly used NLP techniques such Bag-of-words and GLOVE embeddings in predicting a book's genre.[14]

Patent-to-patent similarity serves as the fundamental building block for our measure of related experience. We start by calculating the Jensen-Shannon distance between any two patents in the technology space, formally:

$$d(i,j) = \sqrt{\sum_{k=1..412} (dim_{i,k} * ln((dim_{i,k} + dim_{j,k})/2) + (dim_{j,k} * ln((dim_{j,k} + dim_{i,k})/2)},$$

where i and j denote the patent identifiers and $dim_{i,k}$ denotes patent i's location in the kth dimension of the technological space. The resulting distance is bound by 0 and 1, where a distance of 0 implies that two patents share the exact same location and larger numbers denote farther distances in the technology space.

Second, because our measure relies on similarities rather than distances, we, again, transform the patent-to-patent distance measure by applying the negative exponential transformation based on Shepard's formula (Shepard, 1987).

We operationalize the *related experience* variable as the logarithm of the aggregated similarity of patents that the law firm has worked on during the three years prior to the application date of the focal patent. Lastly, we divide the resulting measure by its standard deviation to increase ease of comparison of effect sizes with our main predictor, competitive overlap.

Like the competitive overlap measure, our *related experience* measure combines two dimensions of experience that are relevant to patent prosecution: proximity and depth. By transforming distances using something akin to an exponential decay curve we give much more weight to patents that are more similar to the technology that is to be patented. A law firm previously having handled a patent that is close to the focal patent indicates experience specific to the focal technology (given that we are only able to include successful patent ap-

[14]We use the BERT-base-cased representation, which itself consists of 12-layers, 768-hidden dimensions, 12-heads, and 110M parameters (see https://github.com/google-research/bert). The deep learning algorithm was programmed in Python using the Pytorch package and trained using Google's Colab cloud services. The code is available from the authors.

plications, this also indicates having succeeded with said prior patent application). Summing over all recently handled patents adds the element of depth to our measure. A law firm that has prosecuted ten very similar patents in the past is likely better suited than another one which has only worked on two related patents.

Other Controls

Our empirical approach keeps the patenting firm (i.e., client) constant, controlling for client-side characteristics. To control for other partner characteristics, we include multiple law firm controls that could affect both competitive overlap and law firm choice. We start by controlling for the measures used in our matching procedure. We control for the *size* of the law firm measured as the logged count of patents handled by the law firm over the past three years, the *founding year* quintile of the law firm, and whether the law firm has previously handled a patent in the same two-digit NBER technology category (*Any prior NBER class* to ensure that any remaining differences between the observed and control cases on our matching dimensions are minimized.

To ensure that the effect of competitive overlap is not confounded by differences along the generalist-specialist spectrum, we capture *Law firm generalization*, which we calculate as the average pairwise distance between all patents handled by a law firm. This is a time-varying measure, calculated for each year in our data based on the three previous years' patents. Lower average distances indicate that most patents handled by the law firm are close to one another in the technology space, indicating higher levels of specialization.

We also include measures of the law firm's past performance which could predict selection, both by the focal client as well as competitors. We include control variables for the average time it takes a law firm to get a patent accepted, the average number of citations their patents receive, and the average number of claims that their accepted patents get granted (all calculated based on the three years prior to the application of the focal patent). Further, to ensure that our competitive overlap measure is not picking inventor mobility events, i.e.

inventors bringing law firms from one competitor to another, we include an indicator variable that captures whether the inventor has previously worked with the law firm while working for a different employer, *prior inventor tie at competitor.*

Our theory underlines the importance of distinguishing between competitive overlap and status signaling effects. To measure law firm status, we use data from the Am Law 100 reports for each of the years in our sample (American Lawyer, 2013). The Am Law 100 lists the 100 most successful US law firms in terms of annual revenue, "a common measure by which law firms are evaluated and ranked within the industry" (Somaya et al., 2008, p.942). We create a binary indicator, *Am Law 100*, set to one if a law firm was in the Am Law 100 list for that year. This status measure helps control for a potential confounding effect which would be characterized by clients being more likely to choose law firms with lower levels of expertise because these are higher in status. We also control for the *Law firm average client size* using the number of patent applications of its clients and the law firm's *Proportion of Fortune 500* clients, both calculated over the past three years, to proxy for status a law firm might receive from its client portfolio.

Law Firm Choice Results

Table 2 provides summary statistics of the main variables, and Appendix Table A.2 shows within-fixed effect pairwise correlations. The competitive overlap variable (mean = 0.76) is heavily right-skewed, consistent with the assumption that this signal is difficult for law firms to obtain.

— INSERT TABLES 2 AND 3 HERE —

Table 3 shows results for our main specifications. Before introducing the control variables, we find that a one standard deviation increase in competitive overlap is associated with an 11 percentage point increase in the probability that a law firm is selected. After including control variables, we continue to find an effect of competitive overlap on partner choice whereby a one standard deviation increase is associated with a 6.5 percentage point increase in the probability that a law firm is selected, supporting Hypothesis 1.[15]

Next, we investigate the effect of competitive overlap under varying alter-centric uncertainty. Notably, the coefficient decreases in magnitude for dyads with prior ties, supporting our prediction in Hypothesis 2. Figure 1 plots the marginal effects (see also Appendix Table A.4). While a one-standard deviation increase in competitive overlap is associated with a 27 percentage point increase in the probability of initial tie formation, this drops to 7 percentage points when the choice is between two firms with which a prior relationship exists. Figure 2 shows that the effect of competitive overlap also decreases when the technology area of the patent is more mature, supporting Hypothesis 3, and when the patent is more similar to prior technology of the client, supporting Hypothesis 4. It graphs the estimated effect of competitive overlap at the 10^{th} and 90^{th} percentiles of the moderators.

— INSERT FIGURES 1 AND 2 HERE —

Alternative Explanation: Seeking Information Leakage

An alternative explanation for the positive effect of competitive overlap on partner choice is that clients intentionally seek law firms with ties to competitors to access their competitors' knowledge. This argument follows from a pipes view of networks in contrast to the prisms view we propose. We offer a test to assess the likelihood of this alternative explanation.

If clients' preference for law firms with competitive overlap is driven by a desire for competitor knowledge, they should rely more on competitive overlap when alternative means of accessing such information are unavailable. We assess whether changes in alternative means of accessing competitors' knowledge change clients' reliance on competitive overlap when selecting law firms, consistent with a pipes rather than prisms explanation. First, we investigate whether clients' abilities to hire employees from their competitors change their

[15] Appendix Table A.3 shows results before standardizing competitive overlap by dividing it by its standard deviation.

reliance on law firm competitive overlap. When non-compete laws are strictly enforced, this alternative pathway is closed, and clients might rely *more* on accessing information on competitors via law firms. Second, we explore whether the American Inventors Protection Act (AIPA), which made patent applications publicly available earlier, made clients less reliant on competitive overlap to select law firms. Our findings suggest that a pipes explanation alone does not fully explain the observed patterns.

First, we interact competitive overlap with state-level measures of the intensity of (enforced) non-compete laws Starr (2019). If our effect were driven by firms seeking competitor information through law firms, we would expect the effect of competitive overlap to be stronger when non-competes are enforced more strongly, i.e., when other means of acquiring information are less available. Columns 1 and 2 of Table 4 show the opposite pattern.

Second, for a more rigorous test of the same phenomenon, we examine states that experienced changes in non-compete laws during the sample period, using data from Ewens and Marx (2017). We interact the competitive overlap coefficient with separate pre- and post- indicators for states that either experience an increase or decrease in the intensity of non-compete law enforcement. Figure 3 plots marginal effects for the competitive overlap coefficient. An increase in non-compete enforcement is not associated with any meaningful increase in reliance on competitive overlap, but a decrease is. This pattern is inconsistent with a pipes view, which predicts an increase in reliance on competitive overlap when non-competes are enforced.

Third, in column 3 of Table 4 we examined whether the reliance on competitive overlap changed with the introduction of the AIPA act. A pipes explanation would predict that with the law's introduction, firms gain faster access to information and therefore rely less on leakage through law firms. We find no meaningful change in the effect of competitive overlap before or after this decision, increasing our confidence that the positive effect is not driven by clients seeking competitor knowledge via law firms. We conclude that although firms may view networks as pipes and realize the information flows enabled by competitive overlap, they also view them as prisms, whereby competitive overlap's positive effect on partner choice remains robust to changes in other sources of information flows.

—– INSERT TABLE 4 AND FIGURE 3 HERE —–

We also ensure that our main regressions are robust to the inclusion of two additional control variables aimed at alleviating concerns of a pipes explanation in Table A.5 in the Appendix. First, we control for the count of patents in the same USPC three digit category as the focal patent to hold constant the potential pool of knowledge to which the law firm might provide access.[16] We also control for client churn (stability), measured as the share of clients in a given year that the law firm already worked with in the previous two years, to account for potential variation in law firms' access to new knowledge. The inclusion of these variables, if anything, increases the magnitude of the competitive overlap coefficient.

Additional Analyses and Robustness Checks

Repeated interactions between competitors and law firms. Our theory posits that a focal firm selects a law firm based on the belief that competitors work with the law firm because of its expertise. We can assess the extent to which a focal firm feels more secure in that belief. We propose that repeat interactions between competitors and law firms are stronger signals than first-time interactions. If a competitor repeatedly works with a law firm, the competitor develops private information about the law firm's expertise, even if the initial collaboration was random. A continued relationship then strengthens the focal firm's belief that the law firm is high in expertise. A negative initial experience may lead the competitor to avoid further collaboration. Thus, competitive overlap based on repeated interactions is likely a clearer signal than competitive overlap based on one-off interactions between competitors and law firms. To investigate, we create two new versions of our competitive overlap variable. The first counts competitors who worked with the law firm at least

[16] We further confirmed results using the six digit category. We show results with- and without the related experience control in columns 2 and 3 as the two variables are highly correlated.

twice in the prior three years, while the second is based exclusively on one-off relationships over the same period. Findings in Table A.6 indicate that repeated interactions between law firms and competitors largely drive the observed competitive overlap effect. The estimate based on repeated interactions in column 2 is nearly four times as large as the estimate based on one-off interactions in column 3.[17]

Parameters in Shepard transformation. We conduct several robustness checks to ensure that our results are not sensitive to analytical decisions related to the operationalization of our variables. First, we explore the sensitivity of our findings to our choice of γ in the Shepard transformation. When choosing γ for the Shepard transformation of both competitive overlap and related experience, there is a trade-off between retaining important information and ensuring that our variables do not simply proxy for law firm size. Appendix Tables A.7 and A.8 explore this variation. Table A.7 shows how mean and median values of both measures drop rapidly with more extreme values of γ. However, Table A.8 highlights necessary balance. At $\gamma = 2$, related experience and competitive overlap are correlated at $r = 0.52$, and both are strongly correlated with law firm size. At $\gamma = 15$, much variation in our predictors disappears and many law firms display values close to zero. For our preferred specifications, we use $\gamma = 10$ for related experience and $\gamma = 7$ for competitive overlap, as these are the lowest thresholds for which our variables correlate at or below $r = 0.3$ with each other and law firm size.

Figure A.2 explores the sensitivity of our results to γ. We plot the marginal effects for our competitive overlap coefficient for initial and repeated ties in panel (a) by estimating the same specification as in column 1 of Table A.4. We select five γ for both competitive overlap and related experience, estimating all pairwise combinations. The graph plots marginal effect size coefficients for all possible combinations. Estimates are sorted by increasing γ values

[17]When adding both covariates to the same equation the coefficient based on one-off relationship becomes statistically and substantively insignificant, whereas the one based on repeat interactions changes little. We choose not to present this results since very high levels of correlation ($r > 0.6$) make meaningful interpretation difficult.

on the x-axis. For each γ value of competitive overlap, there are five sets of coefficients corresponding with models in which we use increasing values of γ for related experience. While the magnitude of our coefficients varies with γ, the overarching relationship remains the same across all specifications. Competitive overlap positively predicts selection, with stronger effects for initial relationships than for prior ties.

Alternative specifications of closest competitors and competitive overlap. We confirm our results by considering only a client's closest competitors, regardless of our measure creation method. First, we check for possible nonlinearities that could mask diminishing or disappearing effects at peak competitive overlap. Figure A.3 shows marginal effects of our competitive overlap measure across 50 quantiles, each representing roughly 2 percentiles, graphed for initial and repeated ties. Point estimates for the lowest levels of competitive overlap are imprecise for initial tie formation, but overall Figure A.3 supports a linear, positive relationship. The likelihood of selecting a law firm increases even at high levels of competitive overlap, further supporting a prismatic view. For repeated ties, we observe a drastic decline from no overlap to low competitive overlap. Still, the remaining distribution shows a monotonic positive effect on law firm selection, strengthening at maximum overlap.[18]

Second, we identify each client's closest competitors using Hoberg and Phillip's (2010; 2016) product portfolio similarities. We then replace our prior competitive overlap measure with a dummy variable indicating whether the law firm has worked with the client's closest, three closest, or closest competitor with a product portfolio similarity above 0.4. For brevity, we focus on hypotheses 1 and 2 here. Table A.9 shows that even with only the closest competitors, competitive overlap powerfully predicts law firm selection, especially for initial ties.

[18] We replicate this by creating a *technological overlap* measure, summing the Shepard-transformed distances of each competitor's closest patent to the law firm. This measure is similar to our measure of competitive overlap but constructed using the knowledge space. We show results in Figure A.4, which look qualitatively similar to our market-space-based measure of competition.

Alternative specifications of technological overlap and including private firms. We confirm that our findings are not limited to publicly traded firms and remain robust to a technological operationalization of competitive overlap. By constructing our main competitive overlap variable using Hoberg and Phillips (2010)'s measure, we make assumptions that limit generalizability in two ways: First, we follow an assumption from the prior literature that competition in the product- and technology space closely map onto another (Podolny et al., 1996; Pontikes and Barnett, 2017). Should these two diverge, however, clients would neither be able to rely on product market overlap as a signal of expertise nor would it indicate a potential pipe for knowledge flows. Second, we restrict our sample to public firms, which tend to be larger and have more extensive patent portfolios. Their incentives and competitive concerns might differ from those of smaller firms.

Table A.10 address these concerns by i) creating a measure of technological overlap, ii) adding a secondary sample of patents that includes private firms, and iii) investigating whether patterns change for younger (vs. older) clients. We create a *technological overlap* measure by summing the Shepard-transformed distances of each competitor's closest patent to the focal patent and dividing the measure by its standard deviation. These regressions exclude our related experience control because it is highly correlated (r=0.6) with technological overlap and not independently interpretable in the same regression. Therefore, we use the product market-based measure as our main operationalization of competitive overlap in the rest of the paper as it allows us to more closely estimate its effect on law firm selection *net of* (observable) technical expertise. In columns 1-3 of Table A.10, we find that the technological overlap measure positively predicts law firm selection and varies little for older vs. younger clients.[19] In columns 4-6, we switch to a sample of patent applications from 2003 to 2013 that includes patents of private firms.[20] Technological overlap continues to positively predict law

[19]We also estimated regressions in which we split the sample by client age using our main, product market based, operationalization of competitive overlap in Appendix Table A.11 and similarly find little variation by age.

[20]Computational limitations force us to restrict the sample to the shorter time window as well as clients that ever (including before 2003) patented at least 50 technologies and law firms which worked on at least 20 patents. The network of pairwise distances increases exponentially when lowering this threshold and slows

firm selection in this sample as well and, if anything, appears to be more positively predictive for younger clients.

Alternative sampling and analytical choices. We estimate other models in the Appendix to verify our results' robustness. In Table A.12 we employ law firm-year fixed effects. While we believe that our control variables address most of the relevant confounders, there could always be unobservable characteristics of the law firm, e.g., differential investment in informational barriers, that remain unaddressed. High-dimensional fixed effects control for all firm-specific characteristics, including yearly variation. We usually omit these as our controls capture most law firm features, and cross-nested fixed effects are difficult to interpret. We present results with conservative standard errors, two-way clustered at the client and law firm level. Table A.12 shows that while overall effect sizes decrease in these specifications, most of our predicted patterns continue to hold: competitive overlap positively predicts law firm selection with stronger effects for new clients. We also continue to find that the maturity of the technology area decreases the strength of the positive competitive overlap effect. While the estimate for the interaction with the patent's similarity to the client's prior work becomes noisier, it continues to point in the hypothesized direction and is only slightly weaker in magnitude.

We address additional concerns regarding our sample and strategy in Tables A.13 and A.14. In Table A.13, column 1, we use client number, not average size, as an alternative measure for law firm size. In column 2, we interact all control variables with the prior-tie indicator, allowing their effects to differ across initial and repeated ties. The rest of the table accounts for potential batch assignments of patents to law firms. Based on our conversations with patent prosecutors and IP managers or legal officers, this seems most likely to occur for related patents. Hence, we exclude "child" patents (columns 3, 5, 7) and only keep the first patent from families identified by Younge and Kuhn (2016) (columns 4, 6, 8).[21]

down calculations immensely.

[21] Younge and Kuhn (2016) identify patent families based on technical similarities, priority dates, and shared inventors. Their data includes patents issued from 2005 onward only. Our sample, restricted to the

In Table A.14, we employ different sampling strategies for control cases to ensure that our results are not unique to the closest cases identified by our propensity score method. First, we use a different random draw in cases in which two law firms had the same propensity score in columns 1 and 2. Then, we show results when using the two closest propensity score matches in columns 3 and 4. Lastly, we use two control cases, one with a higher and one with a lower propensity score. Overall, we find that the effect of competitive overlap continues to positively predict law firm selection. The effect decreases slightly in magnitude when including control cases with less similar propensity scores, but always remains positive and stronger for initial ties.

Finally, we conduct several permutation tests to ensure that our results are not driven by random patterns of competitive overlap. We start by randomizing the dependent variable within each cluster, randomly assigning which law firm is coded as the realized tie. Next, we randomize assignment of competitive overlap values across law firms. We reshuffle them a) completely at random, b) within the patent fixed effect, c) across client–law firm–year observations, and d) across client–law firm dyads within each year. The last two approaches, in particular, represent random assignments of network structures across clients. We estimate 1000 permutations for each approach. Not a single one produces a competitive overlap estimate exceeding our original estimate. To illustrate, panels (a) and (b) of Figure A.6 graph the distribution of simulated estimates for the first (randomizing the dependent variable) and last approach (randomizing across client–law firm dyads within each year), respectively. Collectively, these permutation tests provide reassurance that our results are not driven by any specific network constellation.

post-2004 patent applications in their data, is not sensitive to yearly cutoff alterations.

Consequences of Choosing Partners based on Competitive Overlap

As we have shown, clients choose patent law firms based on competitive overlap, which serves as a signal of expertise. Whether these choices translate into desirable outcomes for clients remains an open question. We explore the performance consequences of selection based on competitive overlap in a set of additional analyses. We use a set of indicators to explore the influence of a selected law firm's characteristics on patent performance: forward citations, the number of granted claims, the value of a patent, and time to acceptance. First, forward citations are an important performance indicator, because patent use by other firms provides direct financial benefits (e.g., licensing royalties) and indirect benefits (e.g., increased status). Second, patent claims define the protected technological area of the invention. A larger number of these is correlated with broader protections and serves as a proxy for more valuable patents (Moore, 2004; Lemley and Shapiro, 2005) Third, we use Kogan et al. (2017)'s measure to capture a patent's economic importance. They capture stock market returns following patent news, confirming their measures reflect the private valuation of these innovations. Finally, as faster times to acceptance and being first to patent are associated with higher growth and follow-on innovation (Farre-Mensa et al., 2020; Hegde et al., 2022), we examine a patent's time to acceptance. Illustrating this point, an executive from Nokia was quoted by Reitzig and Puranam (2009, 784): "In this domain, obtaining a fast grant is absolutely crucial, as you want to use the patent to add an additional protective edge to your existing product, and for that you'd rather have the patent today than tomorrow."

Consider the ideal experiment to estimate a law firm characteristic's effect on patent outcomes: One might randomly assign law firms, similar on all characteristics except the focal one, to a set of patents. Due to random assignment, all "cells" (i.e., the different treatment groups defined by levels of the characteristic in question) should be balanced in terms of client- and patent-characteristics, leaving only the focal characteristic of the law firm to drive any observed differences between groups.

Given that we cannot perform this ideal experiment because only one law firm can prosecute a patent, we choose an empirical case-control approach that approximates to this setup. We draw on patent-to-patent similarity measures from Arts et al. (2018) to construct a case-control sample for which we identify the most similar patent application filed in the same year and by the same client (but with a different law firm) as the focal patent application.[22] We restrict our sample to patents in the same two-digit NBER category and to those that are not classified as children of other patents. We also match cases and controls based on whether a prior tie with the law firm exists. The similarity measure by Arts et al. (2018) is bound between 0 and 1 and we drop cases whose similarity levels exceed 0.9 as these are frequently clones or duplicates. Our approach, therefore, holds constant all characteristics of the focal firm and minimizes all differences related to the patent or technology.

The remaining sample consists of 44,794 patent pairs from 518 clients and 1,462 law firms. The sample is skewed towards larger client firms than our prior analyses and includes fewer than 50 initial ties. This illustrates the difficulty in navigating the generalizability-bias tradeoff: broadening our inclusion criteria (e.g., including pairs from other clients) would yield a more representative sample, but would increase endogeneity concerns. We focus on minimizing endogeneity concerns while retaining a sample that detects small effect sizes compared to patent characteristics, acknowledging we cannot eliminate all technology-related variation or address unobservable factors in law firm choice.

The average similarity between each focal patent and its control patent is 0.18. As an example of two patents of average similarity, consider patents #8402739 and #7927067 from Raytheon. Both concern gas turbine engine assembly parts: the former, a variable inlet for the outer casing; the latter, blades controlling gas flow. The least similar pair (similarity = .05) includes patents #6816483 and #6460084 from Cisco (filed in 1999), handled by

[22]This approach is similar to research designs based on simultaneous discoveries (e.g., Bikard, 2020). However, we cannot exactly replicate Bikard's setup as there are very few exact "idea twins" and since these would not occur within the same client, but we are concerned about holding client-characteristics constant.

different law firms. Both are about communications network systems: the former is about virtual call routing and the latter is about identifying underlying session states to manage communications. At the high end of the similarity distribution, the patents are extremely similar. For example, Patents #7670368 and #8012198 from Boston Scientific Scimed are both valves with a frame and cover controlling liquid flows.

Table 5 shows results from ordinary least squares estimations with patent-pair fixed effects for the performance variables. We add patent-examiner fixed effects in the even columns (Models 2, 4, 6 and 8) and cluster our standard errors at the patent-pair level. Collectively, our results indicate a nuanced relationship between competitive overlap and performance outcomes. We find that competitive overlap positively predicts the number of claims on a patent. A standard deviation increase is associated with a 1% to 1.4% increase in the number of claims. At the same time, higher levels of competitive overlap are associated with slightly longer times to acceptance, such that a standard deviation increase corresponds to about 0.5% slower acceptance times. However, there is no effect on forward citations or Kogan and colleague's (2017) patent value measure.

—– INSERT TABLE 5 HERE —–

Overall, we find that the effect of competitive overlap on performance outcomes is substantively small and associated with both desirable and less desirable outcomes. Taken together, the performance results suggest competitive overlap may improve the entire search and patenting process: as a faster search heuristic, it could save enough initial costs and time to offset slower patent acceptance. Second, if competitive overlap serves as a proxy for expertise, it could quickly identify law firms higher in related experience, generally associated with more desirable outcomes (more forward citations and faster patenting times; see Table 5). In fact, we find that competitive overlap and related experience are positively correlated in the performance sample. Predicting relevant experience of selected law firms using a nonlinear operationalization of competitive overlap indicates that it spikes at the highest levels (see Appendix Figure A.5). Thus, negative effects of competitive overlap on time to acceptance might be offset because competitive overlap acts as a proxy for relevant experience reducing initial search costs.

Lastly, our methodological approach provides a robust test of the relationship between competitive overlap and patent performance, and thereby restricts the analyses to a substantially smaller sub-sample compared to our selection models. Although our initial results largely hold when re-estimating our law firm selection models on the performance analysis sample (see Appendix Table A.15), we lack sufficient power to test the prior tie interaction. To the extent that performance results differ for initial ties, we cannot capture these differences. It remains possible that a performance analysis using a sample with the same proportion of initial ties as the choice analysis sample would generate more positive performance effects of competitive overlap.

Discussion

Firms regularly turn to other firms to supply expertise critical to their operations yet not held within the firm. In this paper, we asked: do firms use second-order competitive overlap to select expert partners? Prior work has largely approached this question viewing networks as pipes of information flows and predicted both avoiding or seeking partners with competitive overlap. We forward an alternative conceptualization of networks as prisms and argue that under conditions of alter-centric uncertainty, firms rely on competitive overlap when choosing expert partners, preferring those who also work with their competitors. This is because competitive overlap serves as a signal of expertise when direct information about a potential partner's expertise is not available. When alter-centric uncertainty is low, the positive signaling effect of second-order competitive overlap is mitigated. Finally, we investigated the effect of choosing a partner with competitive overlap on performance.

We investigated the effect of competitive overlap on expert partner choice and performance in the context of patent law firm selection by inventing firms. We found robust evidence of a positive effect of competitive overlap on partner choice in analyses of client firms selecting patent law firms across approximately 500,000 patents. We also found that this signaling effect of second-order competitive overlap weakens when alter-centric uncertainty is lower; when the client firm and the law firm have a prior relationship, when the technology area is mature, and when the new technology is related to the firm's existing technology.

Finally, in additional analyses we explored the performance implications of relying on second-order competitive overlap as a signal. In a patent-pair analysis, we found significant effects of competitive overlap on performance outcomes. Patents handled by law firms with higher levels of competitive overlap took longer to get accepted, but they resulted in broader patents, which may result in higher patent value in the long term (Lemley and Shapiro, 2005). The pattern of performance effects suggests that firms may rely on competitive overlap as an expertise signal because it reduces search costs without a net loss in performance.

Limitations and Future Research

Our study has limitations. First, the risk set of law firms considered by the patenting firms during the selection phase is not observable, nor can we make causal claims. Our matching approach and use of fixed effects estimations help alleviate these concerns. However, it remains possible that unobserved characteristics of firms or dyads influence expertise or competitive overlap and the likelihood of selection. Future research should seek settings in which the risk set during selection is known. Nevertheless, to the extent that unobservable characteristics are correlated with observable ones, our approach combining matching and regression adjustment provides confidence in the findings. Second, like much prior research, we analyze only granted patent applications, but not rejected ones. Although data on unsuccessful patent applications are available from the USPTO's Public Pair system, these do not include the original law firms that handled the applications. Observing only granted patents could bias our results if the success rate is related to law firm competitive overlap. Yet, this is likely not a major problem, as over 75 percent of the patent applications submitted to the USPTO are eventually granted, and many rejections occur due to applicants either not submitting revised applications on time or abandoning them (Carley et al., 2015). The USPTO is more likely to err on the side of granting patents than rejecting them. Lastly, we cannot account for two processes that may influence law firm selection: referral networks and employee mobility. Two interviewees mentioned that social networks and referrals play an important role in choosing potential law firms. Likewise, mobility of inventors and patent attorneys could also influence law firm selection. As one interviewee, Attorney #1, put it (interview on August 14th, 2019): "you connect with a person and then that person goes from one company to another company and then the third company and you kind of stay with him." Our fixed effects and control variables account for inventor mobility events, but our data do not cover attorney movements. These are theoretically available from the USPTO, but only exist episodically and in unstructured formats. We leave this for future research.

Implications

Our findings fly in the face of the generally accepted belief that firms should avoid working with law firms that represent their competitors. This belief is often held in academic research as well as in the practice of lawyers who should avoid conflicts of interest. Yet, our results consistently show that second-order competitive overlap increases the likelihood of law firm choice, even at very high levels of competitive overlap. What should we make of these findings?

First, although the literature has generally argued for a negative effect of second-order overlap on partner choice, prior studies show mixed support for competitive overlap avoidance. Some studies focus only on top three industry rivals (Aobdia, 2015; Chang et al., 2016) or the context of relationship dissolution (Asker and Ljungqvist, 2010; Rogan, 2014; Aobdia, 2015). When studying relationship formation more recent studies have observed positive effects (Bills et al., 2020; Kang et al., 2022).

Second, even though law firms are, per bar regulation, required to check for conflicts of interest and decline cases with substantial conflicts, the patent attorneys we interviewed repeatedly pointed out that "conflicts management is a gray area" (Interview with Attorney #1, June 26th, 2019), that "it's how you slice that pie (...) again, it's not like black and white" (Interview with Attorney #2, August 14th, 2019). Patenting firms may waive a conflict (Interview with Attorney #1, August 11th, 2021), and often firms, especially small firms, may not even care about or consider conflicts (Interview with Attorney #2, August 14th, 2019). Given the practice of conflict of interest checks, it is less surprising to see many cases in which inventor firms choose law firms with high competitive overlap. Our findings may also appear less surprising given anecdotal evidence regarding the role of competitive overlap in law firm selection. As one attorney explained: "It's not unusual for potential competitors to choose the same law firm to do their patent work — clients typically want patent lawyers who have scientific and legal expertise in a particular field" (Simon, 2002).

Another explanation could be that inventors and patent attorneys hold a narrow view of who their competitors are and believe they are avoiding competitors, when in fact they choose law firms with competitive overlap. Illustrating this point, Porac et al. (1989), in a study of Scottish knitwear manufacturers, found that most managers thought only of other Scottish knitwear manufacturers as their competition. Firms from other parts of the UK and other countries were seen as only 'somewhat' competitors (Porac et al., 1989, pp. 407–8). Instead of doing systematic market research, managers tended to consult existing agents, design consultants, and buyers, and their own network acted "as an information filter by narrowing the range of market data to that which is of immediate concern" (Porac et al., 1989, p. 409). Starting from March and Simon (1958), researchers have argued that organizational responses are mediated by the interpretations by managers, who when faced with an environment high in uncertainty, use simplifying heuristics. Inventor firms may not explicitly use competitive overlap to select partners, but rather use it as a heuristic to find experts.[23] Our findings support this interpretation, as firms are more likely to rely on second-order

[23] And they are not mistaken in doing so – our results on Figure A.5 shows a strong positive correlation between second-order competitive overlap and related experience.

competitive signals in uncertain environments. Even if managers' perception of competitors are inaccurate, they still may select partners who also serve their competitors, either because they use competitive overlap explicitly as an expertise signal, they use it as a heuristic to find experts while underestimating competition, or because their existing networks constrain their attention to prospective partners serving competitors. Regardless, we view all three processes as consistent with a prismatic view of competitive overlap.

It is worth noting that in robustness checks defining competitive overlap narrowly, both in terms of market and technology space, we continued to observe a positive effect of competitive overlap on partner choice. Nevertheless, while the evidence we present is consistent with a prisms view of competitive overlap, we do not have direct evidence for it. As a next step in the research program, it would be imperative to collect direct data on perceptions of the competitive space for patenting firms and attorneys. This could be achieved, for example, by surveying patent attorneys and inventor firms, as Baum and Lant (2003) did when mapping out competition among hotels. We leave this for future research.

The prisms argument may provide a better explanation for partner choice in our setting, but the pipes argument may help explain variance in performance after partners have been selected. The ties formed after partner choice provides the network architecture ('pipework') for positive and negative information flows which can affect performance such as innovation output of firms (Pahnke et al., 2015). That is, pipes may work better to explain performance within networks with competitive overlap and prisms may work better to explain choice of partners with competitive overlap. This investigation is beyond the scope of the present study but we note this as an area for further research.

Contributions

Our study joins a stream of recent research bringing a network perspective to partner choice in interorganizational relationships (Rogan, 2014; Hernandez et al., 2015; Pahnke et al., 2015; Zhelyazkov, 2018). Extending earlier work that emphasized dyadic characteristics as drivers of partner choice, this research has advanced arguments for when network level competitive dynamics affect partner selection. We contribute to this literature by developing competitive overlap as a signal affecting partner choice. Rather than viewing competition among firms as a friction on tie formation or continuity (Rogan, 2014; Pahnke et al., 2015), we highlight instances where the presence of competitors might provide beneficial information to firms (cf. Clough and Piezunka, 2020; Katila and Chen, 2008), by reducing search costs when seeking expert partners.

Our findings regarding the prismatic effects of competitive overlap on tie formation suggest that the pipes function of networks is not the sole lens through which actors view competitive overlap.

As our empirical analysis demonstrates, firms do select partners with second-order competitive overlap. This finding is inconsistent with the competitive overlap avoidance prediction that much of the literature in the pipes view posits. This prompts the question of when the pipes view or prisms view best predict network behaviors.

While not definitive, our theory provides some insight into the conditions when the pipes or prisms view might apply. We show a pattern of evidence indicating that alter-centric uncertainty drives the positive effect of overlap on selection. Alter-centric uncertainty is often high in expert-partner search, such as when firms evaluate potential partners, e.g., lawyers, advertising agencies, or specialized consultants. The competitive overlap *preference* prediction should thus be more likely to hold when competitive overlap serves as a signal of expertise, or some otherwise limited resource, which is hard to identify in potential partners ex ante. When there is little uncertainty surrounding the potential partner's quality, we would expect the pipes view to dominate. Similarly, when the cost or benefit of knowledge flows is large, such as under weak intellectual property protection regimes, the pipes explanation would gain significance (Dushnitsky and Shaver, 2009). Under which conditions the pipes view would predict competitive overlap preference or avoidance lies largely outside the scope of this paper but warrants further investigation.

Our main contribution is introducing competitive overlap as a signal of expertise. The prismatic view of competitive overlap represents a different way to view the behaviors of competitors, not as a deterrent or barrier, but as a prism that provides information regarding expertise, an otherwise unobservable characteristic of prospective partners.

Conclusion

Our study of the prismatic effects of competitive overlap highlights the signaling properties of ties and networks, an area largely overlooked by prior network research (Zaheer et al., 2010, p. 71). As noted by Podolny (1994, p. 458), "in order to avoid the problems posed by market uncertainty and forestall market failure, organizations adopt a more social orientation, taking the social structural position of potential exchange partners as cues..." Despite the broader implications of Podolny's theory for the signaling effects of social structure, subsequent research focused nearly exclusively on status signals. Consequently, scholars have overlooked other signaling effects of social structure. In this study, we have begun to rectify this oversight by forwarding a view of second-order competitive overlap as a signal of expertise.

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Tables and Figures

Table 1: Balance Table

Variable	Mean/(SE)	Mean/(SE)	Normalized difference
Ln law firm size	6.36	6.46	-0.07
	(0.00)	(0.00)	
Law firm founding year	1984.18	1985.00	-0.05
	(0.02)	(0.02)	
Any prior NBER class	1.00	1.00	-0.01
	(0.00)	(0.00)	
Prior tie	0.98	0.98	0.00
	(0.00)	(0.00)	
Number of observations	542,729	542,729	1,085,458

Table 2: Summary Statistics

	Mean	Std Dev	Min	Median	p75	Max
Competitive overlap	0.77	0.97	0	0.4	1.0	21.0
Prior tie	0.98	0.14	0	1	1	1
Technology area age	9.42	3.04	2.2	9.0	11.4	26.0
Technology relatedness	0.53	0.29	0.010	0.5	0.8	1
Related experience	0.95	1.00	0.0002	0.6	1.4	7.2
Ln law firm size	6.41	1.49	0.7	6.6	7.5	9.6
Law firm founding year	1984.6	16.6	1901	1989	1995	2012
Any prior NBER class	1.00	0.055	0	1	1	1
Law firm generalization	0.77	0.057	0.0010	0.8	0.8	0.8
Ln avg past acceptance time	7.05	0.33	5.0	7.1	7.3	8.9
Ln avg past citations	2.92	0.62	0	2.9	3.3	7.4
Ln avg past claims	3.04	0.26	0.7	3.0	3.2	5.5
Prior inventor tie at competitor	0.035	0.18	0	0	0	1
AmLaw 100	0.14	0.35	0	0	0	1
Law firm avg client size	7.69	1.44	0	7.9	8.3	10.6
Prop. Fortune 500 clients	0.45	0.24	0	0.4	0.6	1
N	1,085,458					

Table 3: Linear probability models of law firm choice in case-control dyads

	(1)	(2)	(3)	(4)	(5)
Competitive overlap	0.111	0.062	0.042	0.038	0.065
	(0.012)	(0.008)	(0.008)	(0.008)	(0.008)
Related experience		0.454	0.446	0.424	0.414
		(0.010)	(0.009)	(0.009)	(0.009)
Law firm founding year		0.003	0.003	0.003	0.003
		(0.000)	(0.000)	(0.000)	(0.000)
Ln law firm size		-0.060	-0.038	-0.036	-0.063
		(0.006)	(0.006)	(0.006)	(0.006)
Any prior NBER class		0.139	0.133	0.117	0.021
		(0.070)	(0.075)	(0.075)	(0.068)
Law firm generalization			-0.152	-0.137	-0.102
			(0.104)	(0.101)	(0.098)
Ln avg past acceptance time			0.409	0.412	0.299
			(0.016)	(0.016)	(0.017)
Ln avg past citations			0.038	0.033	0.053
			(0.010)	(0.010)	(0.009)
Ln avg past claims			0.044	0.043	0.058
			(0.021)	(0.020)	(0.020)
Prior inventor tie at competitor				0.459	0.451
				(0.012)	(0.012)
AmLaw 100					-0.096
					(0.014)
Law firm avg client size					0.063
					(0.003)
Prop. Fortune 500 clients					0.135
					(0.021)
Obs	1,085,458	1,085,458	1,085,458	1,085,458	1,085,458
R2	0.01	0.30	0.32	0.34	0.35

Standard errors clustered by client–law firm–year

All models include patent fixed effects.

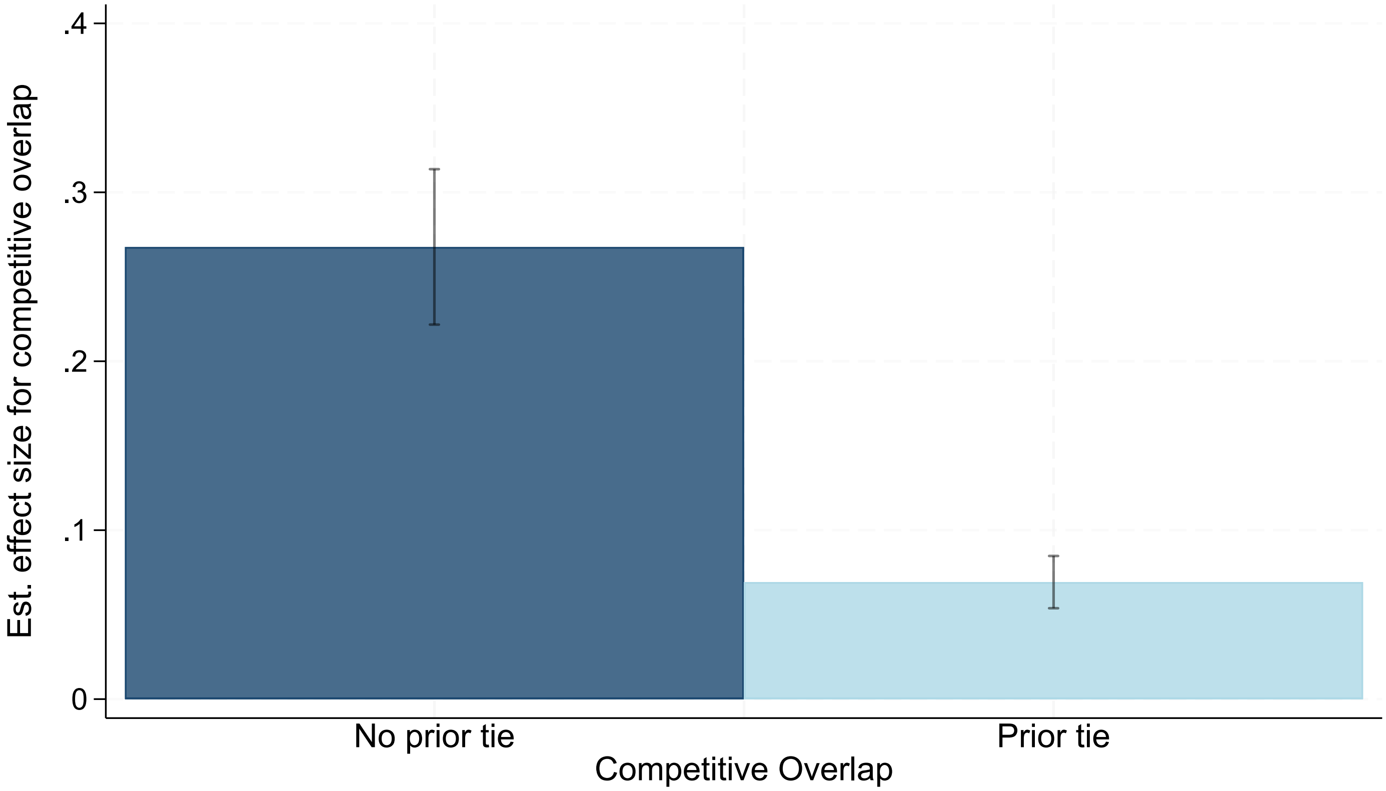

Figure 1: Marginal effects of competitive overlap on law firm choice by prior relationship

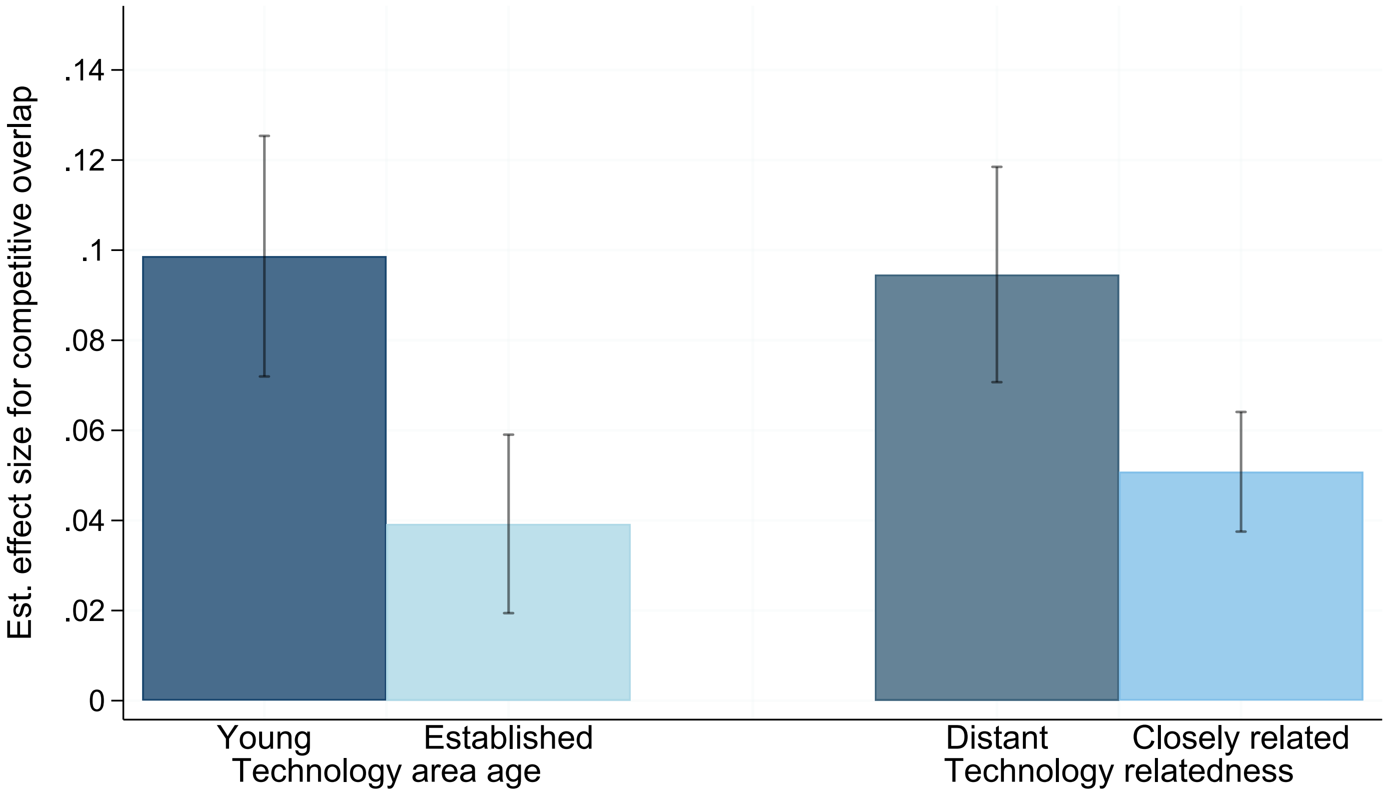

Figure 2: Marginal effects of competitive overlap on law firm choice by technology area age and technology relatedness

Table 4: Law firm choice: Interactions with pipes conditions

	(1)	(2)	(3)
Competitive overlap	0.052	0.092	0.066
	(0.008)	(0.008)	(0.009)
Comp olap X Non-compete intensity (Starr, 2019)	-0.018		
	(0.002)		
Comp olap X Non-compete above median		-0.035	
		(0.009)	
Comp olap X pre-AIPA enactment			-0.000
			(0.017)
Obs	947,668	947,668	1,085,458
R2	0.36	0.36	0.35

Standard errors clustered by client–law firm–year.
Main effects of the moderating variables are subsumed by the patent fixed effect.
All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.

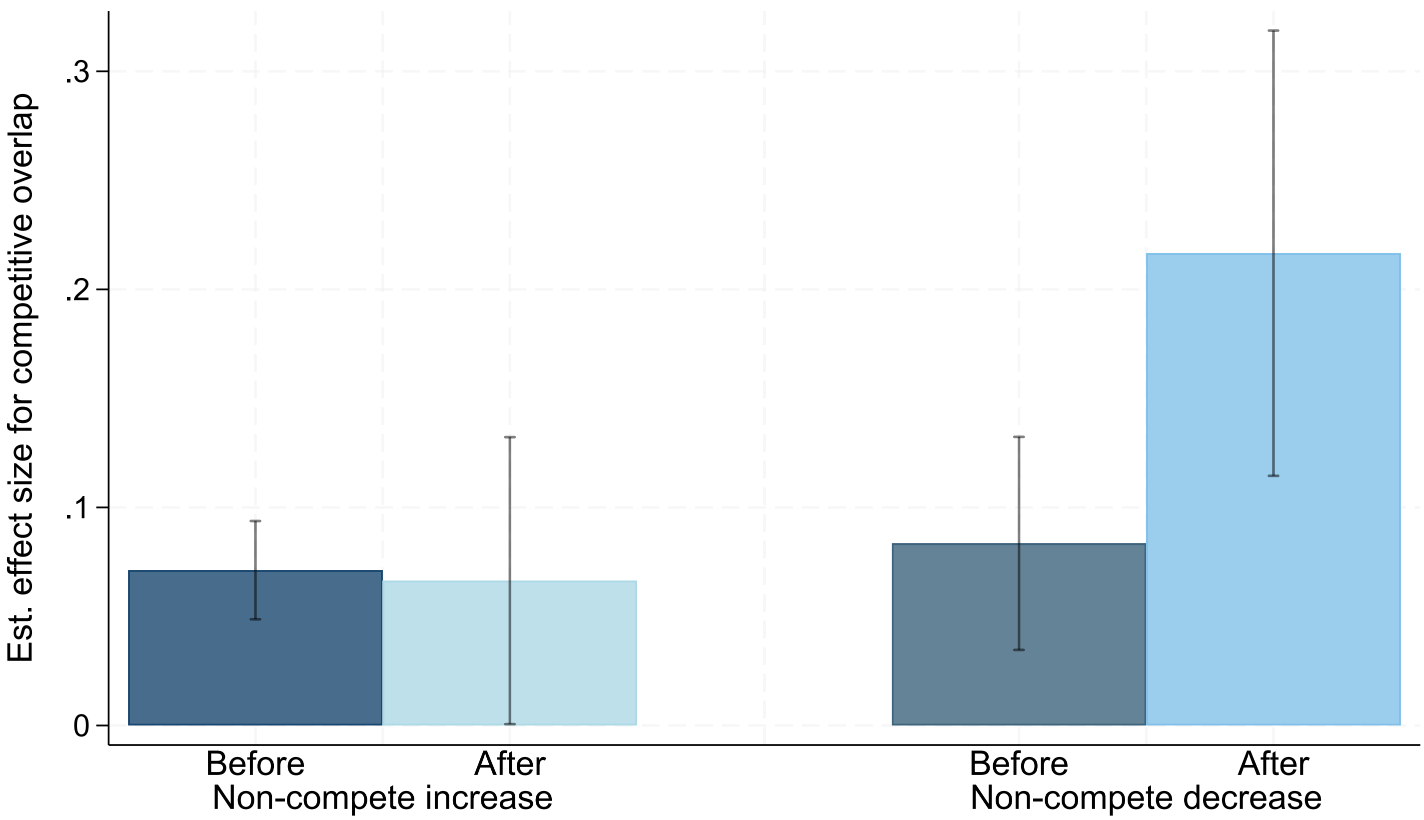

Figure 3: Marginal effects of competitive overlap on law firm choice by non-compete law changes

Table 5: Performance effects: OLS regressions of patent pairs

	Ln 5yr cites		Ln claims		Ln patent value		Ln days to accept	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competitive overlap	-0.009	-0.009	0.010	0.014	-0.007	-0.001	0.006	0.005
	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)
Related experience	0.023	0.027	0.001	0.007	-0.011	-0.005	-0.009	-0.007
	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
Law firm founding year	-0.001	-0.002	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln law firm size	-0.034	-0.034	-0.004	-0.012	0.003	0.000	0.015	0.009
	(0.005)	(0.007)	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Any prior NBER class	0.130	0.199	0.006	-0.009	-0.081	-0.005	-0.119	-0.172
	(0.066)	(0.085)	(0.046)	(0.051)	(0.048)	(0.057)	(0.028)	(0.032)
Law firm generalization	0.746	0.309	0.047	0.095	0.353	0.183	-0.004	0.049
	(0.074)	(0.089)	(0.033)	(0.043)	(0.051)	(0.066)	(0.022)	(0.025)
Ln avg past acceptance time	-0.139	-0.129	0.001	0.012	-0.164	-0.140	0.412	0.300
	(0.019)	(0.024)	(0.011)	(0.014)	(0.013)	(0.016)	(0.007)	(0.008)
Ln avg past citations	0.064	0.071	-0.015	-0.008	-0.025	-0.017	0.025	0.020
	(0.011)	(0.013)	(0.006)	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)
Ln avg past claims	0.232	0.291	0.443	0.480	0.070	0.065	-0.053	-0.021
	(0.024)	(0.029)	(0.015)	(0.017)	(0.017)	(0.020)	(0.009)	(0.009)
Prior inventor tie at competitor	0.062	0.068	0.036	0.056	0.015	0.004	0.014	0.018
	(0.025)	(0.029)	(0.014)	(0.016)	(0.016)	(0.019)	(0.008)	(0.009)
AmLaw 100	-0.012	0.010	-0.037	-0.038	0.027	0.007	-0.018	-0.014
	(0.015)	(0.018)	(0.008)	(0.009)	(0.010)	(0.011)	(0.005)	(0.005)
Law firm avg client size	-0.004	0.003	0.013	0.010	0.007	0.009	-0.005	-0.002
	(0.007)	(0.008)	(0.004)	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)
Prop. Fortune 500 clients	-0.015	0.048	0.052	0.062	-0.001	0.002	-0.031	-0.034
	(0.022)	(0.026)	(0.012)	(0.015)	(0.013)	(0.016)	(0.008)	(0.008)
Ln prior interactions	0.009	0.009	0.004	0.007	0.000	-0.001	-0.009	-0.006
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
Constant	2.762	3.914	0.533	0.563	2.918	3.025	5.159	5.434
	(0.559)	(0.658)	(0.346)	(0.391)	(0.307)	(0.361)	(0.198)	(0.206)
Obs	89,588	81,820	89,588	81,820	73,810	66,440	89,588	81,820
R2	0.64	0.73	0.62	0.73	0.89	0.93	0.79	0.88
Patent-pair FEs	yes	yes	yes	yes	yes	yes	yes	yes
Examiner FEs		yes		yes		yes		yes

Standard Errors clustered by patent-pair.

A Appendix

US006542353B2

(12) **United States Patent**
Ardrey et al.

(10) **Patent No.: US 6,542,353 B2**
(45) **Date of Patent: Apr. 1, 2003**

(54) **CONTROL PANEL ASSEMBLY AND METHOD OF MAKING SAME**

(75) Inventors: **Kenneth J. Ardrey**, Canton, MI (US); **Mark R. Weston**, Brighton, MI (US)

(73) Assignee: **Key Plastics, LLC**, Northville, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **09/972,335**

(22) Filed: **Oct. 5, 2001**

(65) **Prior Publication Data**

US 2002/0066660 A1 Jun. 6, 2002

Related U.S. Application Data

(62) Division of application No. 09/281,155, filed on Mar. 30, 1999, now Pat. No. 6,326,569.
(60) Provisional application No. 60/080,173, filed on Mar. 31, 1998.

(51) **Int. Cl.**[7] **H02B 1/015**; H01H 9/00
(52) **U.S. Cl.** **361/660**; 200/310; 200/317; 361/622
(58) **Field of Search** 200/308–317, 200/329–345; 361/622, 600, 680

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* cited by examiner

Primary Examiner—J. R. Scott
(74) *Attorney, Agent, or Firm*—Rader, Fishman & Grauer PLLC

(57) **ABSTRACT**

A control panel assembly having a plurality of buttons located in a bezel and supported by a switch mat. A bezel and/or button is formed using a vacuum forming technique and has a transparent inner surface layer and a middle translucent color layer and an opaque outer surface layer. A portion of the opaque outer surface layer is removed to define a desired indicia on an outer surface of the bezel or button. In addition, the bezel or button can be backlit to allow visibility in low light conditions. A method of making a control panel component, such as a bezel or button, is also disclosed.

13 Claims, 3 Drawing Sheets

Figure A.1: Title page of a granted U.S. patent

Table A.1: Data structure illustration

Patent	Year	Patenting firm	Law Firm	Realized patent-law firm dyad
1	2005	Microsoft	Foley and Lardner LLP	1
1	2005	Microsoft	Buchanan and Ingersoll PC	0
2	2006	Sony Corporation	Senniger Powers LLP	1
2	2006	Sony Corporation	Merchant and Gould PA	0
3	2006	IBM	White and Case LLP	1
3	2006	IBM	Buchanan and Ingersoll PC	0
4	2006	Microsoft	Foley and Lardner LLP	1
4	2006	Microsoft	Senniger Powers LLP	0
5	2007	Apple	Foley and Lardner LLP	1
5	2007	Apple	White and Case LLP	0

Table A.2: Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Competitive overlap	1.00												
(2) Related experience	0.15	1.00											
(4) Law firm founding year	-0.15	-0.09	1.00										
(5) Any prior NBER class	0.03	0.04	-0.08	1.00									
(3) Ln law firm size	0.28	0.29	-0.40	0.14	1.00								
(6) Law firm generalization	0.11	-0.20	-0.19	0.05	0.29	1.00							
(12) Ln law firm avg client size	-0.01	0.13	-0.06	0.05	0.23	0.03	1.00						
(11) AmLaw 100	0.18	-0.04	0.06	0.00	0.07	0.12	-0.04	1.00					
(7) Ln avg past acceptance time	0.02	-0.01	0.12	-0.03	-0.17	-0.13	0.24	0.06	1.00				
(8) Ln avg past citations	0.27	0.05	-0.05	0.02	0.12	0.11	0.02	0.17	0.15	1.00			
(9) Ln avg past claims	0.20	0.08	0.02	0.01	0.04	-0.05	0.03	0.10	0.20	0.38	1.00		
(10) Prior inventor tie at competitor	0.07	0.22	-0.01	0.01	0.05	-0.05	0.03	-0.02	0.00	0.05	0.04	1.00	
(13) Prop. Fortune 500 clients	-0.27	0.00	0.01	0.01	-0.07	-0.05	0.09	-0.16	0.03	-0.23	-0.14	-0.02	1.00
Observations	1,085,458												

Table A.3: Law firm choice: non-standardized coefficients. Robustness checks for Table 3.

	(1)	(2)	(3)	(4)	(5)
Competitive overlap (unstandardized)	3.838	2.133	1.443	1.308	2.259
	(0.404)	(0.269)	(0.261)	(0.259)	(0.266)
Related experience (unstandardized)		0.500	0.491	0.467	0.456
		(0.011)	(0.010)	(0.010)	(0.010)
Law firm founding year		0.003	0.003	0.003	0.003
		(0.000)	(0.000)	(0.000)	(0.000)
Ln law firm size		-0.060	-0.038	-0.036	-0.063
		(0.006)	(0.006)	(0.006)	(0.006)
Any prior NBER class		0.139	0.133	0.117	0.021
		(0.070)	(0.075)	(0.075)	(0.068)
Law firm generalization			-0.152	-0.137	-0.102
			(0.104)	(0.101)	(0.098)
Ln avg past acceptance time			0.409	0.412	0.299
			(0.016)	(0.016)	(0.017)
Ln avg past citations			0.038	0.033	0.053
			(0.010)	(0.010)	(0.009)
Ln avg past claims			0.044	0.043	0.058
			(0.021)	(0.020)	(0.020)
Prior inventor tie at competitor				0.459	0.451
				(0.012)	(0.012)
AmLaw 100					-0.096
					(0.014)
Law firm avg client size					0.063
					(0.003)
Prop. Fortune 500 clients					0.135
					(0.021)
Obs	1,085,458	1,085,458	1,085,458	1,085,458	1,085,458
R2	0.01	0.30	0.32	0.34	0.35

Standard errors clustered by client–law firm–year

All models include patent fixed effects.

Table A.4: Law firm choice: Interactions with uncertainty proxies

	(1)	(2)	(3)
Competitive overlap	0.268	0.122	0.096
	(0.024)	(0.020)	(0.013)
Comp. olap X prior tie	-0.199		
	(0.025)		
Comp. olap X technology area age		-0.006	
		(0.002)	
Comp. olap X technology relatedness			-0.046
			(0.012)
Obs	983,940	1,085,458	1,085,458
R2	0.37	0.36	0.36

Standard errors clustered by client–law firm–year.
Main effects of the moderating variables are subsumed by the patent fixed effect.
All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.

Table A.5: Law firm choice: Additional controls – churn (/client stability) and count of prior patents in the same technology class

	(1)	(2)	(3)	(4)	(5)
Competitive overlap	0.065	0.074	0.093	0.065	0.073
	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)
Law firm client churn				0.199	0.197
				(0.024)	(0.024)
Ln same tech class count		-0.065	0.068		-0.068
		(0.004)	(0.005)		(0.004)
Related experience	0.414	0.443		0.427	0.456
	(0.009)	(0.010)		(0.009)	(0.010)
Obs	1,085,458	1,076,738	1,076,738	1,004,586	999,942
R2	0.35	0.36	0.16	0.35	0.36

Standard errors clustered by client–law firm–year.
Main effects of the moderating variables are subsumed by the patent fixed effect.
All models include patent fixed effects and control for
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.

Table A.6: Law firm choice: competitive overlap measures based on repeated interactions

	(1)	(2)	(3)
Competitive overlap (original)	0.065		
	(0.008)		
Comp olap (2+ shared patents btw lawyer-competitor)		0.069	
		(0.007)	
Comp olap (1 shared patent)			0.021
			(0.007)
Obs	1,085,458	1,021,040	1,021,040
R2	0.35	0.36	0.35

Standard errors clustered by client–law firm–year

Main effects of the moderating variables are subsumed by the patent fixed effect.

All models include patent fixed effects and control for
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.

Table A.7: Summary statistics for various gamma values

	Mean	Std Dev	Min	Median	p75	Max
Rel. exp. ($\gamma = 2$)	3.07	(0.92)	0.03	3.2	3.7	5.2
Rel. exp. ($\gamma = 5$)	2.15	(0.94)	0.007	2.2	2.9	5.1
Rel. exp. ($\gamma = 7$)	1.59	(0.97)	0.002	1.5	2.3	6.0
Rel. exp. ($\gamma = 10$)	0.95	(1.00)	0.0002	0.6	1.4	7.2
Rel. exp. ($\gamma = 15$)	0.57	(1.01)	0.000005	0.1	0.7	8.9
Comp. olap. ($\gamma = 2$)	1.43	(0.95)	0	1.3	2.1	4.3
Comp. olap. ($\gamma = 5$)	0.92	(0.96)	0	0.6	1.3	7.3
Comp. olap. ($\gamma = 7$)	0.77	(0.97)	0	0.4	1.0	21.0
Comp. olap. ($\gamma = 10$)	0.19	(1.08)	0	0.09	0.2	66.8
Comp. olap. ($\gamma = 15$)	0.025	(1.10)	0	0.001	0.003	81.1
N	1,085,458					

Table A.8: Correlation table of main predictors for various gamma values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Rel. exp. ($\gamma = 2$)	1.00										
(2) Rel. exp. ($\gamma = 5$)	0.91	1.00									
(3) Rel. exp. ($\gamma = 7$)	0.70	0.93	1.00								
(4) Rel. exp. ($\gamma = 10$)	0.42	0.74	0.92	1.00							
(5) Rel. exp. ($\gamma = 15$)	0.29	0.61	0.82	0.96	1.00						
(6) Comp. olap. ($\gamma = 2$)	0.53	0.43	0.30	0.15	0.07	1.00					
(7) Comp. olap. ($\gamma = 5$)	0.37	0.32	0.25	0.16	0.10	0.91	1.00				
(8) Comp. olap. ($\gamma = 7$)	0.28	0.26	0.22	0.15	0.10	0.77	0.92	1.00			
(9) Comp. olap. ($\gamma = 10$)	0.04	0.05	0.04	0.04	0.03	0.14	0.25	0.59	1.00		
(10) Comp. olap. ($\gamma = 15$)	-0.00	0.00	0.00	0.01	0.01	0.02	0.11	0.45	0.98	1.00	
(11) Ln law firm size	0.98	0.82	0.58	0.29	0.16	0.55	0.37	0.28	0.04	-0.00	1.00
Observations	1,085,458										

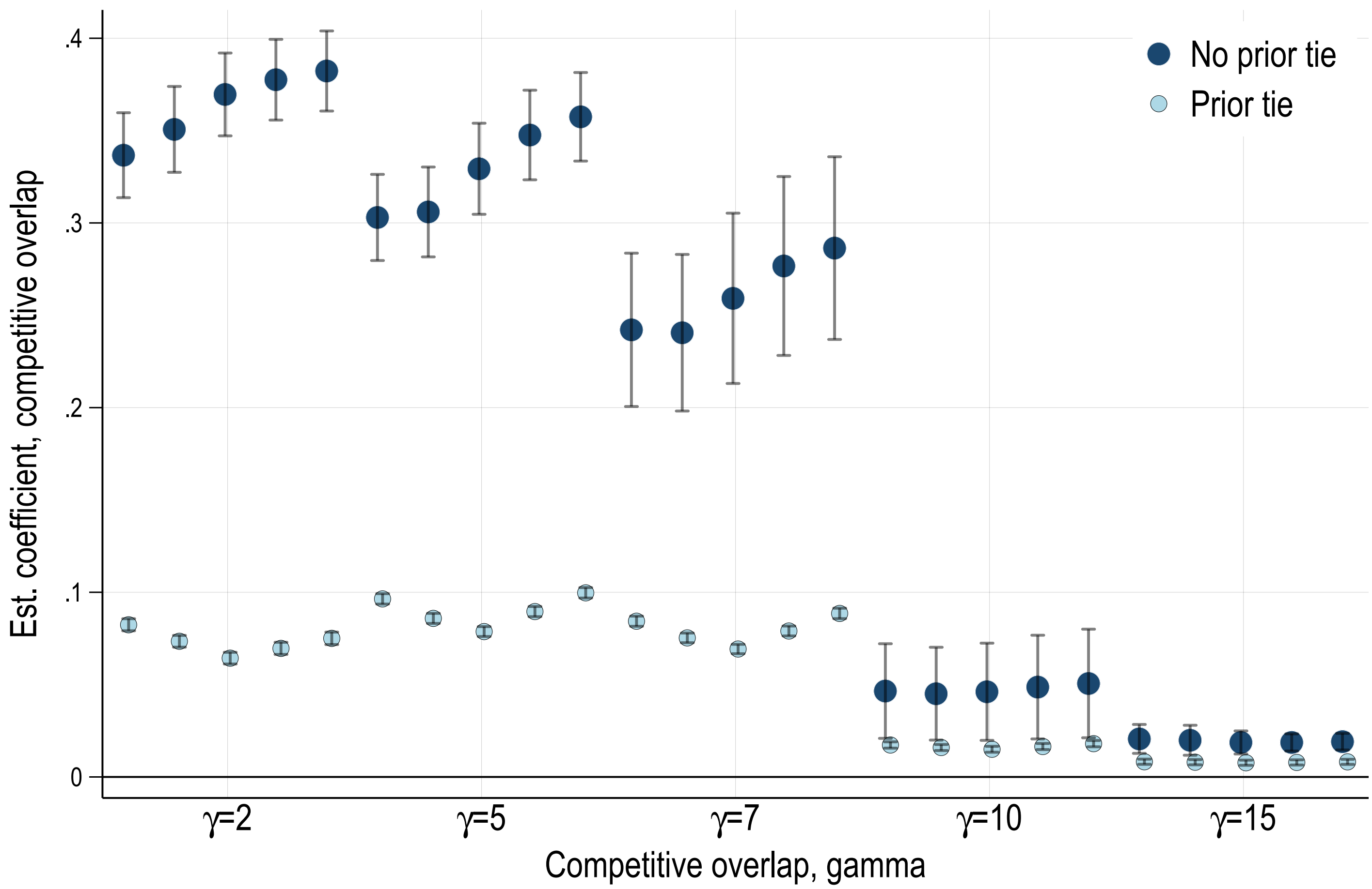
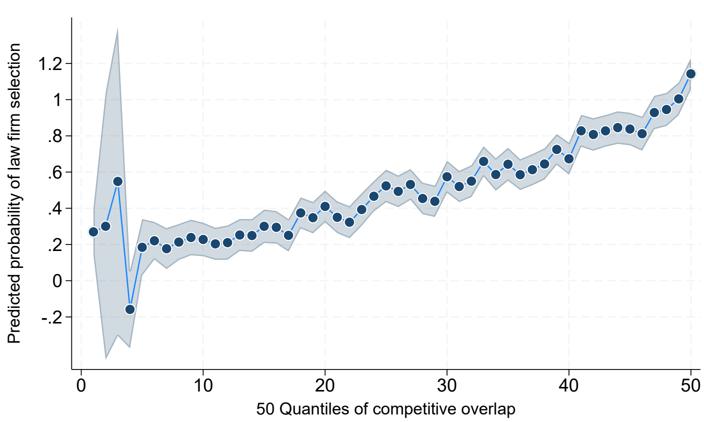
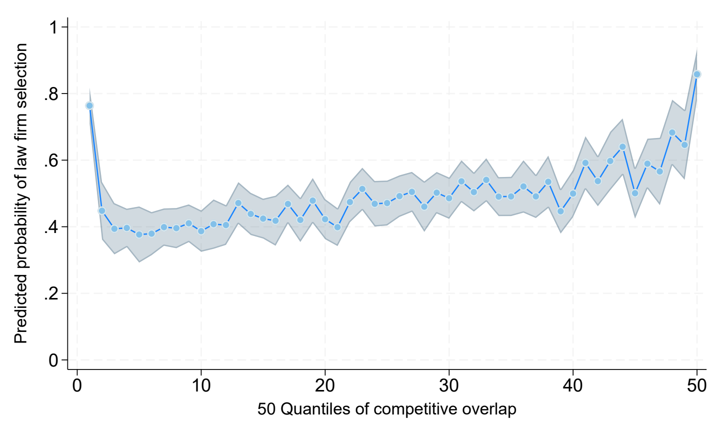


Figure A.2: Coefficient plot showing effect sizes of competitive overlap on the likelihood of selection using various values for γ for both competitive overlap and related experience.

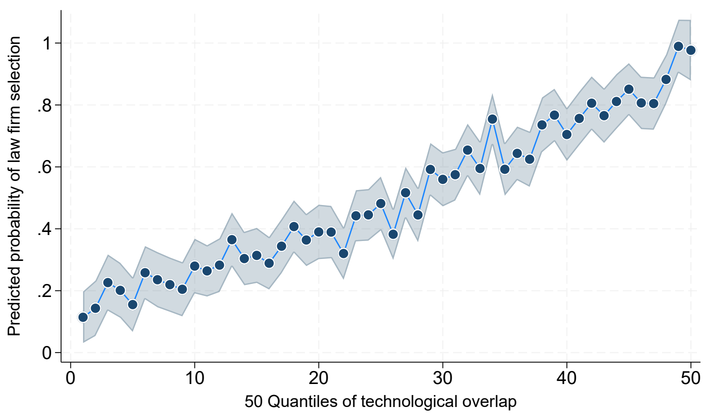


(a) Initial ties

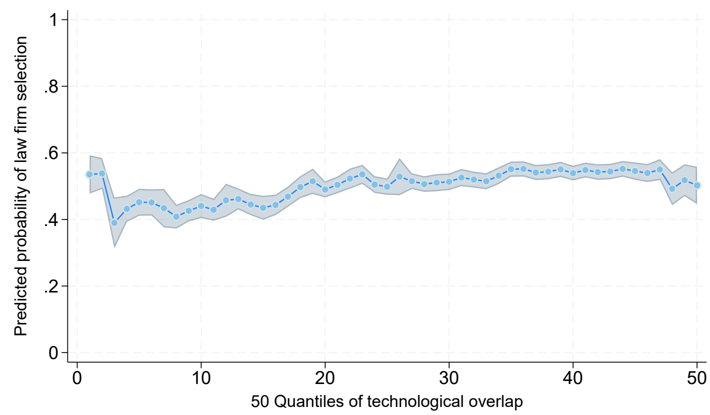


(b) Repeat ties

Figure A.3: Nonlinear effects of competitive overlap on law firm selection



(a) Initial ties



(b) Repeat ties

Figure A.4: Nonlinear effects of technological overlap on law firm selection

Table A.9: Law firm choice: alternative competitive overlap measure. Robustness checks for Table 3.

	(1)	(2)	(3)	(4)	(5)	(6)
Closest competitor	0.173	0.369				
	(0.030)	(0.058)				
Closest comp X prior tie		-0.197				
		(0.065)				
Top 1-3 competitor			0.106	0.272		
			(0.020)	(0.036)		
Top 1-3 comp X prior tie				-0.167		
				(0.041)		
Closest comp (simil. > 0.4)					0.482	0.862
					(0.089)	(0.088)
Closest comp (> 0.4) X prior						-0.382
						(0.126)
Obs	1,085,458	1,085,458	1,085,458	1,085,458	1,085,458	1,085,458
R2	0.35	0.35	0.35	0.35	0.35	0.35

Standard errors clustered by client–law firm–year.
All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents

Table A.10: Law firm choice: Technological overlap robustness check

	(1)	(2)	(3)	(4)	(5)	(6)
Tech overlap	0.150	0.147	0.149	0.279	0.332	0.209
	(0.007)	(0.012)	(0.011)	(0.010)	(0.020)	(0.019)
Obs	1,044,368	41,708	649,068	1,926,178	157,580	711,630
R2	0.17	0.21	0.18	0.14	0.19	0.18
Sample	Public only	Public only	Public only	Incl. non-public	Incl. non-public	Incl. non-public
Org age group		Youngest quintile	Oldest quintile		Young	Old

Standard errors clustered by client–law firm–year.
Models 1 thru 3 are based on our main sample of public firms.
The rest is based on a supplementary sample also including
patents between 2003 and 2013 by private firms that have more than 50 patents (ever).
All models include patent fixed effects and control for
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.
Models 1 thru 3 also control for prior inventor-law firm ties.

Table A.11: Law firm choice: Split sample by patenting firm age

	(1)	(2)	(3)	(4)
Competitive overlap	0.071	0.059	0.060	0.067
	(0.016)	(0.011)	(0.009)	(0.010)
Obs	43,986	673,924	247,344	838,114
R2	0.29	0.37	0.33	0.37
Sample age group	Youngest quintile	Oldest quintile	Below median age	Above median age

Standard errors clustered by client–law firm–year.
Main effects of the moderating variables are subsumed by the patent fixed effect.
All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents.

Table A.12: Law firm choice: saturated fixed effects. Robustness checks for Table 3.

	(1)	(2)	(3)	(4)
Competitive overlap	0.031	0.171	0.120	0.050
	(0.015)	(0.024)	(0.045)	(0.019)
Comp. olap X prior tie		-0.141		
		(0.023)		
Comp. olap X technology area age			-0.009	
			(0.004)	
Comp. olap X technology relatedness				-0.032
				(0.018)
Obs	1,078,488	1,078,488	1,078,488	1,078,488
R2	0.65	0.65	0.65	0.65

Standard errors two-way clustered by law firm and client
All models include patent- as well as law firm X year fixed effects
and control for related experience, NBER category experience,
and prior inventor-law firm ties

Table A.13: Law firm choice: interacted controls and after removing child-patents. Robustness checks for Table 3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competitive overlap	0.268	0.187	0.270	0.405	0.161	0.215	0.091	0.114
	(0.023)	(.)	(0.034)	(0.033)	(0.028)	(0.034)	(0.018)	(0.021)
Comp. olap X prior tie	-0.198	-0.116	-0.198	-0.315				
	(0.024)	(.)	(0.035)	(0.035)				
Comp. olap X tech. age					-0.010	-0.012		
					(0.002)	(0.003)		
Comp. olap X tech. simil.							-0.031	-0.044
							(0.017)	(0.018)
Obs	1,085,458	1,085,458	635,512	463,822	635,512	463,822	635,512	463,822
R2	0.36	0.36	0.32	0.35	0.32	0.35	0.32	0.35
Number of clients control	yes							
Interacted controls		yes						
Removed USPTO children			yes		yes		yes	
Removed Younge-Kuhn children				yes		yes		yes

Standard errors clustered by client–law firm–year.

Main effects of the moderating variables are subsumed by the patent fixed effect.

All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents

Table A.14: Law firm choice: alternative case-control samples. Robustness checks for Table 3.

	(1)	(2)	(3)	(4)	(5)	(6)
Competitive overlap	0.071	0.268	0.050	0.227	0.032	0.226
	(0.008)	(0.023)	(0.006)	(0.014)	(0.006)	(0.015)
Comp. olap X prior tie		-0.199		-0.179		-0.195
		(0.024)		(0.015)		(0.016)
Obs	1,107,324	1,107,324	1,646,807	1,646,807	1,591,889	1,591,889
R2	0.36	0.36	0.33	0.33	0.32	0.32
Control cases	diff. seed	diff. seed	1:2	1:2	1 high, 1 low	1 high, 1 low

Standard errors clustered by client–law firm–year.
All models include patent fixed effects and control for related experience, law firm age, NBER category experience (dummy), law firm size, law firm generalization, prior inventor-law firm ties,
law firm avg speed to patent acceptance, avg citations, and avg number of claims on past patents

Table A.15: Law firm choice: estimated on the performance sample

	(1)	(2)	(3)	(4)
Competitive overlap	0.085	-0.020	0.168	0.128
	(0.017)	(0.190)	(0.038)	(0.026)
Comp. olap X prior tie		0.105		
		(0.191)		
Comp. olap X tech. age			-0.010	
			(0.004)	
Comp. olap X tech. simil.				-0.069
				(0.025)
Obs	131,986	131,986	131,986	131,986
R2	0.39	0.39	0.39	0.39

Standard errors clustered by client–law firm–year.
All models include patent fixed effects and control for related experience,
AmLaw 100, avg client size, prop F500 clients, law firm age,
law firm size, law firm generalization, prior inventor-law firm ties,
NBER category experience (dummy), law firm avg speed to patent acceptance,
avg citations, and avg number of claims on past patents

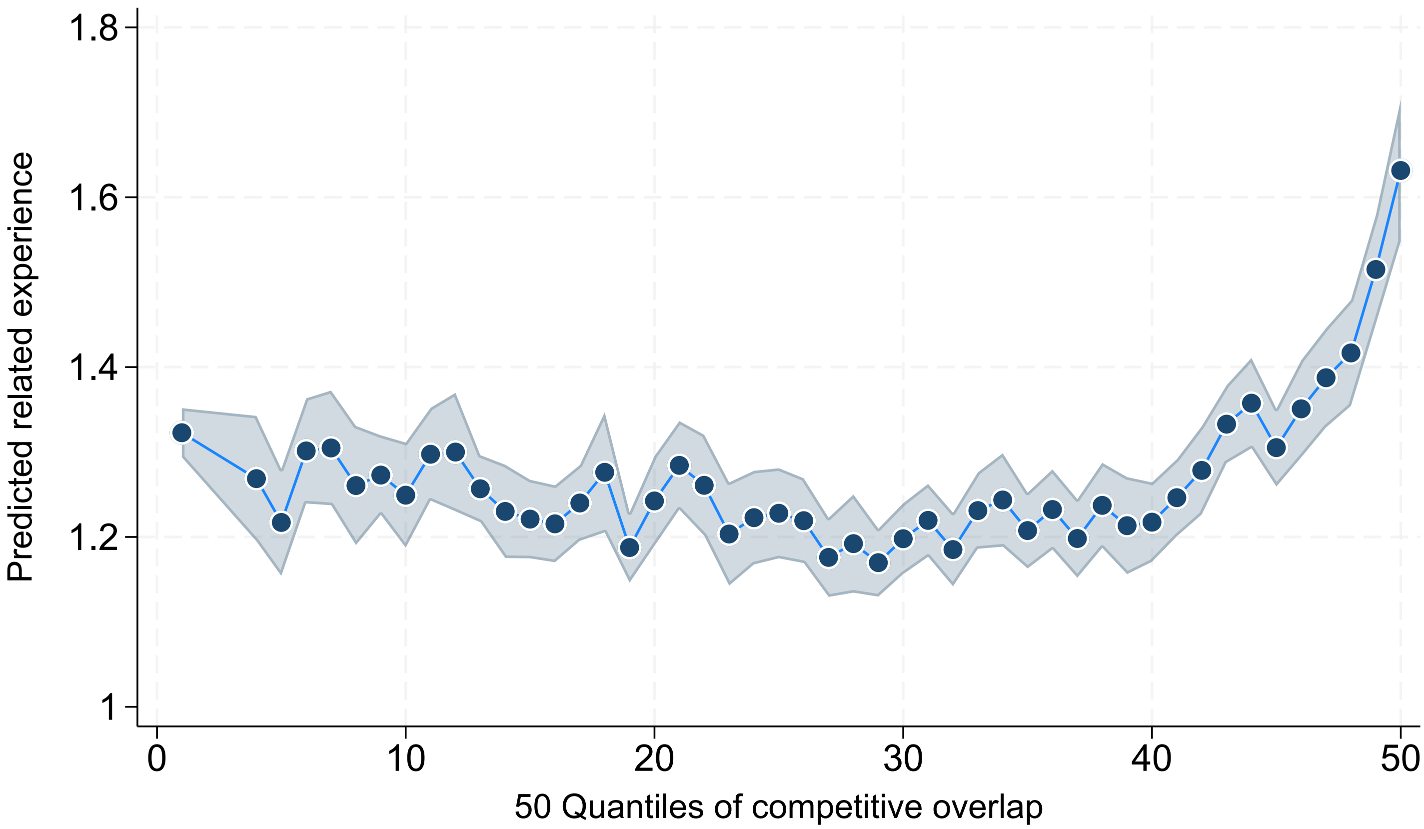
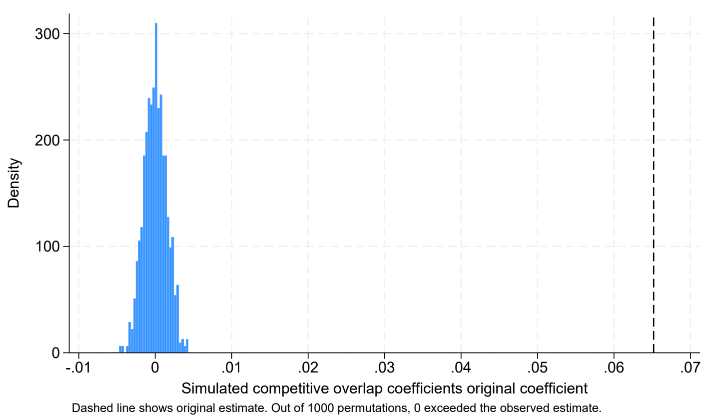
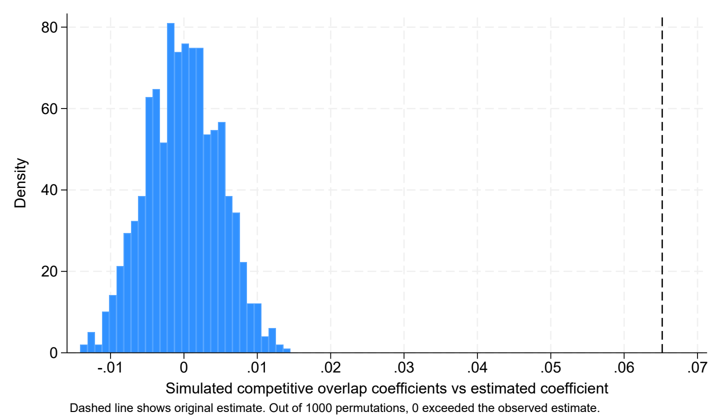


Figure A.5: Nonlinear effects of competitive overlap on related experience



(a) Randomly assigned dependent variable (within patent fixed effect)



(b) Randomly reallocated competitive overlap (across client–law firm dyads within the same year)

Figure A.6: Permutation tests