Envisioning value: Certification, matchmaking, and returns to brokerage.*

Christopher I. Rider

Georgetown University

chris.rider@georgetown.edu

Sampsa Samila

National University of Singapore

sampsa.samila@nus.edu.sg

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In many markets, brokers' intermediary positions afford views of information asymmetries between buyers and sellers. Emphasizing this "vision advantage" and focusing on the returns to brokerage for buyers and sellers, we propose a general approach to identify two mechanisms by which brokers can create and capture value in mediated exchange: (1) certification and (2) matchmaking. Analyses of U.S. venture capital fundraising transactions demonstrate our approach. Venture capital funds represented by brokers (i.e., placement agents) attract more investors than unrepresented funds but do not generally outperform them; only within investors' portfolios do represented funds exhibit better investment returns than unrepresented ones. Results are generally stronger for more reputable brokers. We, therefore, infer that in this market brokers facilitate mutually-beneficial exchanges between specific buyers and sellers (i.e., matchmaking) and not by screening offerings for value (i.e., certification). Because the dominant mechanism likely differs across empirical settings, we discuss how our approach might apply in other contexts.

Keywords: brokerage, intermediation, matchmaking, certification, venture capital

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1. INTRODUCTION

Information asymmetry is a pervasive feature of markets, as many offerings are difficult and costly to value prior to exchange (e.g., Akerlof, 1970; Spence, 1973; Geertz, 1978; Stiglitz and Greenwald, 1986). Despite various remedies for asymmetry (e.g., incentives, norms, laws), buyer and seller often refrain from exchange, resulting in market failure. Parties who lack trust in each other can, alternatively, rely upon intermediaries – "brokers" – to evaluate offerings and exchange terms prior to transacting. Extensive finance and sociology research accordingly establishes that brokers play a vital – and well-compensated – role in market exchange (e.g., Leland and Pyle, 1977; Campbell and Kracaw, 1980; Baker, 1984; Booth and Smith, 1986; Eccles and Crane, 1988; Abolafia, 1996; Zuckerman, 1999; Khurana, 2002; Fernandez-Mateo, 2007). Yet, these literatures evoke different theoretical mechanisms to explain how brokers facilitate exchange, so the mechanisms generating returns to brokerage are unclear (Burt, 2004: 354-356).

With an eye toward explicating brokerage mechanisms, we note that research in finance and in sociology highlights information asymmetry as a precondition for brokerage and also casts a broker's reputation as critical to facilitating exchange (e.g., Booth and Smith, 1986; Chemmanur and Fulghieri, 1994; Bielby and Bielby, 1999; Rider, 2009; Stovel, et al., 2011; Stovel and Shaw, 2012; Nee and Opper, 2012; Burt and Merluzzi, 2014). But, importantly, these perspectives differ in terms of how brokers earn good reputations. We, therefore, develop an approach to distinguish two plausible intermediation mechanisms by focusing, analytically, on the returns to brokerage for the *brokered* (i.e., buyer and seller) instead of the *broker* (i.e., the intermediary).

Financial theories emphasize how intermediaries, like underwriters or investment managers, incur costs to screen offerings and then certify some offerings as acceptable for exchange (e.g., Booth and Smith, 1986). In contrast, sociological theories emphasize matchmaking: headhunters (e.g., Khurana, 2002) and staffing agencies (e.g., Fernandez-Mateo, 2007) facilitate transactions between those who might not otherwise engage in mutually beneficial exchange (e.g., Marsden, 1983; Burt, 1992) by tending to specific buyer and seller concerns. Thus, certification and matchmaking accounts differ in the extent to which brokers alleviate asymmetry for (a) *all* buyers and sellers versus (b) *specific* buyers and sellers. These two mechanisms are not mutually exclusive, so our approach enables brokerage to be attributed to either, neither, or both.

When brokers facilitate market exchange, they presumably create value for buyer and seller in the form of economic surplus (Brandenberger and Stuart, 1996). From a buyer's perspective, brokers create value by facilitating exchanges that, relative to the buyer's next-best alternative, deliver either offerings of higher quality at a given price or equivalent quality at a lower price. For a seller, value entails greater demand for a focal offering, which can yield either price or quantity benefits. By creating value in an exchange, brokers position themselves to appropriate some of the value created (i.e., returns to brokerage). This value creation perspective informs our approach to understanding how brokers facilitate market exchange.

Both certification and matchmaking mechanisms imply that brokers lend credibility to a seller's offering and, therefore, enhance its expected value to prospective buyers (i.e., brokers generate demand). But, financial theory implies that credibility is lent because certified offerings offer greater expected value than uncertified offerings (e.g., higher quality at a given price). Failure to certify high value offerings compromises a broker's reputation and threatens their

ongoing business. Certification theory, therefore, implies that market intermediary positions enable brokers to assess an offering's value more credibly than sellers and at costs lower than buyers.

In contrast, matchmaking theory implies that brokers earn and maintain a good reputation by, more modestly, facilitating exchanges that make buyer and seller better off than they would be otherwise (Burt, 1992, 2005). Importantly, matchmaking implies that brokers need not deal exclusively in high value or even high quality offerings to achieve this "better off" objective.[1] Whereas certification suggests that offerings marketed by a broker deliver, on average, greater value than those not marketed by one, the matchmaking mechanism motivates a more nuanced prediction: marketed offerings will deliver greater value than non-marketed offerings *for a given buyer*. Put simply, certification implies that brokers sustain their positions by trading primarily in the market's best offerings while matchmaking does not; matchmaking implies only that buyers and sellers are better off participating in a brokered exchange than a non-brokered one. We, consequently, motivate both *across*-buyer and *within*-buyer comparisons of exchange outcomes.

Motivated by this theoretical tension, we build upon Burt's notion of a "vision advantage" – the idea that brokers create and claim value by detecting and exploiting informational asymmetries between otherwise disconnected actors (2004; 2010). Although the returns associated with this vision advantage are extensively established by prior research (see Burt 2000, 2005, 2010), Burt (2004: 354) notes that evidence of the underlying mechanism is "not abundant." Our approach thus enables identification of the responsible mechanism(s) for the returns to brokerage in any market setting in which brokers play a prominent exchange role.

[1] Because we conceive of "value" as quality given price, a value condition is necessarily more restrictive than a quality condition.

We demonstrate our approach by analyzing the role of fundraising intermediaries called "placement agents" in U.S. venture capital fundraising between 2001 and 2012. Although most venture capital funds are not represented by placement agents, the rate of representation has increased dramatically since 2000 (Rider, 2009; Cain, McKeon, and Solomon, 2015). To evaluate seller and buyer outcomes, respectively, we analyze the number of institutional investors that invest in a given venture capital firm's fund (i.e., seller value) as well as the returns realized by each fund (i.e., buyer value). To assess the vision advantage, we use coarsened exact matching and propensity score weighting to compare outcomes for funds represented by placement agents to observationally-equivalent funds that are not – both across investors and within investor portfolios. In this way, we differentiate funds based on factors that are difficult or costly to observe but are presumably more "visible" to brokers than others.

We treat venture capital partnerships as sellers of equity stakes in funds and institutional investors as buyers of fund equity. The key analytical issue is whether brokers generally create value or, alternatively, create value for specific funds or investors. Two institutional features lead us to demonstrate our approach in this setting. First, standard measures of fees incurred (i.e., 2 percent management fees plus 20 percent carried interest) and returns realized (i.e., net internal rates of return) by investors enable us to characterize buyer value (i.e., quality given price) as the percentage return, net of fees, on invested capital. We treat seller value as the number of investors who commit capital to a focal fund. Holding price constant across funds and investors effectively reduces value to the quality dimension (i.e., returns). Second, because most investors diversify their investment portfolios both within and across fund type categories, we can estimate clear counterfactuals across funds, across investors, and within investor portfolios – all necessary conditions of our approach.

Consistent with both certification and matchmaking, our empirical analyses reveal that funds represented by placement agents attract more investors than unrepresented funds. Inconsistent with certification, represented funds do not generally outperform unrepresented ones. Consistent with matchmaking, represented funds outperform unrepresented-but-observationally-equivalent funds within investors' portfolios. In other words, brokered exchanges generate greater seller value (i.e., more fund investors) and greater value *for a focal buyer* (i.e., higher returns than similar funds within a focal investor's portfolio) but *not for all buyers*. Moreover, mediated exchange outcomes are generally more favorable when investments are brokered by relatively more reputable placement agents. We accordingly infer that brokers in venture capital fundraising create and capture value by envisioning and facilitating mutually beneficial matches between funds and investors but *not* necessarily by certifying high-value fund offerings. These findings motivate a concluding discussion of how others might utilize our approach in other settings to identify the mechanisms underlying the impressive returns to brokerage.

2. THEORETICAL DEVELOPMENT

Information Asymmetry in Markets

In most markets, information asymmetry is an obstacle to exchange between buyer and seller. For example, automobile owners acquire first-hand information on a vehicle's quality through repeated use so that, with time, asymmetry between an owner and prospective buyers increases (Akerlof, 1970). This asymmetry is an obstacle to resale because, due to potential buyers' suspicions of opportunistic sellers (i.e., moral hazard), owners of high-quality vehicles cannot credibly convey information about vehicle quality to prospective buyers any better than owners of low-quality vehicles can. Unable to differentiate the two types prior to purchase,

potential buyers are unwilling to pay more for high quality vehicles than low quality ones and, at equal prices, owners of low-quality vehicles are more likely to sell than owners of high-quality ones are. Therefore, the used car market can be considered a market for "lemons."

Seller guarantees of offering quality can alleviate moral hazard concerns in such markets, so long as guarantees are more costly for sellers of low quality offerings. For example, some automobile dealers certify used vehicle quality to assuage buyers' concerns (e.g., Sultan, 2010). But, asymmetry also presents opportunities for intermediaries to create and capture value by facilitating exchange. For example, CARFAX obtains vehicle information from government agencies, auto auctions, fire and police departments, repair facilities, rental agencies, and others to compile detailed vehicle history reports for used cars.[2] Reports may be purchased by sellers who wish to document the quality of their vehicle or by buyers who wish to verify quality prior to purchase. In this way, CARFAX alleviates asymmetry between potential buyers and sellers and allows them to negotiate a fair price given their quality beliefs. But, does CARFAX certify quality for all potential buyers? Or does CARFAX enable some buyers to obtain greater value than they would have from their next-best alternative? We develop a theory-driven, empirical approach that clarifies the asymmetry-alleviating mechanism by analyzing seller and buyer outcomes.

Labor markets are similarly plagued by information asymmetry. Employers cannot clearly ascertain an individual's capabilities prior to hiring but can learn about an employee's capabilities over time. To overcome this asymmetry, capable individuals invest in costly educational signals to differentiate themselves from less capable candidates (Spence, 1973) and employers withhold higher titles and greater responsibilities from employees until their productive capabilities are known or competitive conditions force their hand (e.g., Lazear, 1986;

[2] http://www.carfax.com/company/about

Waldman, 1990; Phillips, 2001). Although higher education institutions can certify candidate quality via credentialing and employers often alleviate information asymmetries through trial employment, many employers utilize intermediaries (e.g., Fernandez-Mateo, 2007; Bonet, Cappelli, and Hamori, 2013). Yet, like in the CARFAX example, it is unclear if intermediaries like staffing agencies or search firms serve a certification or a matchmaking function. To identify mechanisms in various contexts, we contrast financial and sociological theory to motivate testable certification and matchmaking predictions.

Theories of Market Intermediation

The finance field offers a large body of research on the role of market intermediaries in facilitating exchange. The extant literature focuses largely on how financial institutions (e.g., banks) alleviate information asymmetries between investors and companies offering securities (e.g., Leland and Pyle, 1977; Campbell and Kracaw, 1980; Diamond, 1984; Allen and Santomero, 1998). Generally, asymmetry is attributable to corporate executives possessing better information to project future corporate cash flows than potential investors do (Myers and Majluf, 1984). As in the market for lemons, over-valued companies face stronger incentives to offer equity to investors than under-valued companies do unless investors are somehow able to differentiate the two groups of companies (e.g., Allen and Faulhaber, 1989). To that end, underwriters typically evaluate companies seeking to raise capital on behalf of potential investors and bring the offering to market at a price that reflects its discerned quality (Booth and Smith, 1986). In this way, intermediaries separate good offerings from bad ones to facilitate investments that might not otherwise be made.

In this financial account, the intermediary is uncertain *ex ante* if screening will yield a marketable offering so screening is considered an investment made under conditions of

uncertainty. Fees represent returns on that investment. Although intermediation can alleviate asymmetry between buyer and seller, moral hazard concerns might simply be transferred from seller to intermediary. Intermediaries might misrepresent an offering's expected value and/or the extent of its due diligence in order to facilitate exchanges that generate fees. A reputation for credible certification and pricing is, therefore, valuable in assuaging buyers' concerns about opportunism (e.g., Chemmanur and Fulghieri, 1994). Intermediaries generally earn good reputations when *ex post* realized value is in accordance with *ex ante* expectations. In summary, certified offerings appeal more to buyers than do uncertified offerings and this incremental appeal is increasing with the intermediary's reputation.

Sociological Theories of Market Intermediation

Sociological theories of intermediation differ on the issue of how exchange is facilitated. Simmel (1955) observed that the introduction of a third party to a dyad fundamentally alters interactions by enabling the triad's third member to mediate exchanges between the other two. Noting that disagreements regularly arise between dyads, Simmel discusses how intermediaries can consider opposed parties' interests and offer mutually agreeable proposals. Others extend these insights substantially to examine social relationships in which the third member benefits by preventing relationships from forming between the other two (Burt, 1992) or, conversely, encouraging relationships to form (Obstfeld, 2005; Samila, Oettl, and Hasan, 2016).

It is unsurprising, then, that Simmelian intermediaries feature prominently in sociological accounts of markets. Blalock (1967), for example, discusses "middleman minorities" who mediate exchanges between employees and employers, producers and consumers, landlords and tenants, etc. Padgett and Ansell (1993) describe how Cosimo de Medici mediated economic exchange among Florentine families who avoided social interaction. Granovetter (1985: 490) notes that "information from a trusted informant that he has dealt with the individual" is

generally preferred to knowledge of the focal individual's general reputation. Khurana (2002: 240-241) surmises that an intermediary "initiates or strengthens the union" of two parties who "are aware of each other and could engage in direct exchange, but choose not to do so." Like finance research, this work implies a need for an intermediary when buyer and seller lack trust in each other.

Additional sociological research naturally examines the role of intermediaries in financial markets. For example, Baker (1984) examines the role of brokers in facilitating stock trades. Eccles and Crane (1988) investigate the role of investment banks in facilitating mergers and acquisitions. Abolafia (1996) identifies Wall Street banks as "market makers" in the trading of stocks, bonds, and futures. Zuckerman (1999) and Fleischer (2009) consider how analysts mediate investments in corporate equities. Rider (2009) examines the role of intermediaries in venture capital fundraising. These studies collectively advance the idea that, often, neither buyer nor seller are privy to information held by the intermediary and that the intermediary sees how that information might be used – profitably – to assuage both parties' concerns.

This informational resource is central to the brokerage phenomenon (e.g., Burt, 1992, 2005). Brokers maintain relationships with unconnected parties, a position which affords timely access to novel information and control over its use – what Burt (2010: 5) terms a "…vision advantage in detecting and developing productive opportunities." Borne primarily of structural position and not – as in financial theories of intermediation – extensive screening investments, this vision advantage enables brokers to claim returns to brokerage that can be considered "rents" or profits realized by virtue of the broker's position and not necessarily attributable to effort or ability (Sørensen, 1996).

Our review of the financial and sociological literatures on intermediation implies two contrasting mechanisms by which brokers might plausibly realize the returns to brokerage: (1) certification and (2) matchmaking. Finance and sociological theories are distinguished by how general the asymmetry-alleviating, intermediation mechanism is. Certification necessitates that a broker distinguish high value offerings from low value ones for many buyers; matchmaking implies that brokers identify specific buyers and sellers who would benefit from exchange in offerings of varying value. Below, we motivate signature predictions for each account.

Certification versus Matchmaking

Certification and matchmaking mechanisms imply different constraints on the exchanges that a broker can facilitate. In the financial account, the extent of the market is limited by the supply of offerings above the intermediary's certification threshold. But, in the sociological account the extent of the market is limited only by buyers' and sellers' next-best options to mediated exchange.

Figures 1 and 2 depict the tension between certification and matchmaking mechanisms in market intermediation. Both figures depict a market in which the value v of prospective offerings is quasi-normally distributed according to f(v) and defined as price at a given level of quality. When fulfilling a certification role, a broker screens offerings and certifies those above a single threshold level v_c as acceptable for exchange for all buyers who will be satisfied with an expected offering value no lower than v_c. In this scenario, certified offerings are of average higher expected value than offerings not certified by the intermediary.

[INSERT FIGURE 1 ABOUT HERE]

In contrast, the matchmaking mechanism depicted in Figure 2 implies that buyers differ in terms of the minimum expected value required to enter exchange. For any buyer i who would

otherwise purchase an offering of value v_i the broker need only produce an offering positioned to the right of v_i in the value distribution to satisfy the buyer. Buyer *j*, who would otherwise purchase an offering of value v_j, requires an offering of greater value than that required by buyer *i*. Because matchmaking requires only that the matched offering be positioned to the right of the buyer's next-best alternative, the average value of mediated offerings relative to unmediated ones is ambiguous. Here, the relative value of mediated and unmediated exchanges depends on the balance of buyer value expectations (i.e., the offering each matched buyer would purchase absent the broker's involvement).

[INSERT FIGURE 2 ABOUT HERE]

Certification and matchmaking mechanisms imply similar predictions on the seller side of the market but differ in terms of the buyers' outcomes. If an offering's appeal is increasing with its expected value then certified offerings will be in greater demand than uncertified offerings. Matchmaking also implies that, all else equal, offerings marketed by brokers will be on average more appealing than offerings not marketed by brokers. Both mechanisms, therefore, motivate the prediction that mediated offerings will be more appealing to buyers, on average, than unmediated ones. This "seller value" logic motivates our first testable hypothesis, which represents a scope condition on subsequent hypothesis tests – we must observe exchange benefits for sellers that participate in mediated exchange.

> Hypothesis 1 (*seller value*): Mediated offerings are in greater demand than observationally-equivalent unmediated offerings.

A buyer's *ex post* satisfaction with an offering should be increasing with an offering's revealed value. We now consider how the two accounts of market intermediation differ. As Figure 1 illustrates, certification implies that mediated offerings are on average higher value than unmediated offerings. Therefore, certification implies that mediated offerings will, on average,

produce better buyers' outcomes than unmediated ones. This logic motivates our second testable hypothesis.

> Hypothesis 2a (*certification*): Mediated offerings deliver greater buyer value than observationally-equivalent unmediated offerings.

The certification account necessitates support for Hypothesis 2a. Failure to support Hypothesis 2a is consistent with matchmaking but not necessarily supportive. As Figure 2 illustrates, matchmaking implies that value expectations vary by buyer so that, consequently, mediated offerings need not produce better buyer outcomes than unmediated offerings – brokers can facilitate exchange at many levels of expected value. Only under the narrow condition that all buyers hold identical value expectations does the matchmaking account imply that the expected value of mediated offerings will exceed the expected value of unmediated offerings.

Matchmaking consequently motivates a more specific testable prediction. Figure 2 implies that brokers match buyers with offerings of higher expected value than the offerings they would otherwise purchase. If so, then mediated offerings purchased by a specific buyer should deliver greater *ex post* value than unmediated offerings purchased by the same buyer. A key difference between our second and third prediction is that Hypothesis 2a implies a comparison *across buyers* while Hypothesis 2b implies a *within-buyer* comparison. Figures 1 and 2 illustrate this intuition. Figure 1 implies that all buyers will obtain greater value, on average, with a mediated offering but Figure 2 implies, less restrictively, that a given buyer will find the mediated offerings it purchases more valuable than the unmediated ones.

> Hypothesis 2b (*matchmaking*): A mediated offering purchased by a focal buyer delivers greater value than an observationally-equivalent unmediated offering purchased by the same buyer.

Implications for Intermediary Reputation

Certification and matchmaking imply different role expectations for the intermediary. Merton's (1957) seminal role theory implies that an actor's role is a set of normative expectations about how the actor should behave, given their position. In an integration of role theory and reputation research, Jensen, Kim, and Kim (2012) develop a role-theoretic perspective on reputation. Drawing on economics research (e.g., Shapiro, 1983; Bar-Isaac and Tadelis, 2008), they propose that actors reduce uncertainty and earn positive reputations by consistently meeting or exceeding role expectations over time.

Applying this role-theoretic perspective on reputation to market intermediaries, we expect that the effects hypothesized above will differ for intermediaries of varying repute. The certification role implies that a reputable broker screens offerings and identifies those of high average value whereas the matchmaking role implies, less restrictively, that a reputable broker identifies offerings that are of higher value than those a buyer would otherwise purchase. Therefore, relatively more reputable brokers who provide certification services should, on average, identify higher value offerings than less reputable ones. In contrast, more reputable brokers who provide matchmaking services will not necessarily identify higher value offerings but will deliver greater value to buyers than less reputable ones do. Several moderating effects are implied.

> Hypothesis 3 (*reputational contingency*): The greater the broker's reputation, the more incremental demand a mediated offering generates than an observationally-equivalent unmediated offering.

> Hypothesis 4a (*certification*): The greater the broker's reputation, the greater the value ***buyers*** obtain from a mediated offering than from an observationally-equivalent unmediated one.

> Hypothesis 4b (*matchmaking*): The greater the broker's reputation, the greater the value ***a focal buyer*** obtains from a mediated offering than from an observationally-equivalent unmediated one.

Implications of Hypotheses

To aid interpretation of results and also applications of our approach to other market settings, we consider the various results that might be obtained from empirical analysis. First, Hypothesis 1 represents a scope condition on subsequent hypothesis tests. A broker with a vision advantage must "make a market" among buyers if our arguments are to provide insight into the mechanisms underlying the returns to brokerage. Hypothesis 1, therefore, constitutes a test of seller value: brokers generate additional demand for a seller's offering. Assuming that this scope condition is satisfied, we then consider returns to brokerage for the buyer (H2a/H2b) to ascertain support for the certification and matchmaking predictions.

Support for Hypothesis 2a constitutes evidence of certification but does not rule out the matchmaking mechanism; it is logically possible for brokers to both certify offerings and to facilitate mutually beneficial matches. Failure to support Hypothesis 2a implies that brokers do not certify offerings but Hypothesis 2b must be supported to infer that matchmaking is at least partially responsible for the returns to brokerage. Failure to support both Hypothesis 2a and 2b implies that another (untheorized) mechanism is responsible for the returns to brokerage in the focal setting, such as a pure marketing advantage (e.g., excess demand is generated independent of offering value) or, if tests for H2a/b yield negative results, even malfeasance (e.g., excess demand is decreasing with offering value). Figure 3 summarizes the most plausible outcomes of empirical analysis and their implications for our approach. Hypothesis 3 similarly represents a scope condition for testing Hypotheses 4a and 4b: reputational differences in buyers' outcomes must be observed for reputation to moderate certification and/or matchmaking main effects.

[INSERT FIGURE 3 ABOUT HERE]

3. EMPIRICAL CONTEXT & ANALYSIS

Our general approach is designed to apply across numerous contexts but we demonstrate its applicability in a single empirical setting. Subject to the condition that a broker plays a prominent role in mediating market exchange, many settings are suitable for applying our approach. Of course, several additional considerations influence strategic research site selection (Merton, 1987). First, because a key construct in our approach is "value" empirical contexts in which value is readily measured will be most suitable. We define value as price at a given quality level or, alternatively, quality at a given price. In other contexts, researchers might measure both price and quality or otherwise hold one dimension constant across offerings to apply our approach.

Second, ideal settings enable researchers to characterize offering appeal or demand. Third, our test of certification versus matchmaking requires comparisons to be made both across and within-buyers. Specifying the across-buyer counterfactual is fairly straightforward but the within-buyer counterfactual is more restrictive. To conduct within-buyer tests, one must be able to specify the offering a buyer would have purchased had the buyer not purchased the one it did. Alternatively, as in our setting, buyers might purchase multiple offerings to structure a diversified portfolio. As discussed below, venture capital fundraising is an excellent context for applying our approach to distinguishing certification and matchmaking mechanisms in mediated markets.

Placement Agents in Venture Capital Fundraising

Venture capital funds are raised by general partnerships (GPs) that market fund offerings to limited partners (LPs) in the hopes of securing a targeted amount of capital from many LPs;

GPs constitute the market's supply side (i.e., sellers of investments) and LPs the demand side (i.e., buyers). Funds are structured as limited partnerships with a finite lifespan, typically ten years with options to extend by a year or two. LPs commit at fundraising time to a maximum investment in the fund, but transfer capital to the GPs as the GPs identify investment opportunities and call on the LPs to provide committed capital. LPs generally invest in a portfolio of venture capital and other private equity funds, in addition to their other investments (e.g., bonds, equities, real estate). Although expectations vary based on a fund's investment focus, LPs generally expect to earn greater returns on venture capital investments than other assets because venture capital returns are highly variable (i.e., risky).

By the nature of the limited partnership, LPs do not tell GPs how to invest committed capital. If and when target companies are successful at attaining an initial public offering, merger, or acquisition, GPs typically sell their stake in the company and the proceeds are distributed immediately to the LPs rather than used for new investments. The compensation for the GPs has converged to an industry standard "2-20" arrangement whereby GPs annually collect two percent of the total committed capital, including capital not yet invested in startup companies, as a management fee and twenty percent of profits on each managed investment.

While high-net-worth individual investors may invest in these funds, the majority of committed capital comes from institutional investors. It is possible – and not uncommon -- for only individuals to invest in a general partnership's first fund. The proportion of a fund's capital committed by institutions varies over the course of a GP's life cycle and also across GPs. Initial funds tend to be smaller and often have a greater proportion of individuals than later funds. If the fund is successful, then subsequent funds tend to be larger and disproportionately funded by institutional investors.

The biggest sources of institutional commitments are pension funds, insurance companies, foundations, banks, and endowments. Although LPs are, as noted above, not involved in investment decisions, there are clear status distinctions between individual and institutional LPs. Generally, institutional LPs are considered higher status investors by GPs. Even within institutional LPs, university endowments and in particular the endowments of top-tier universities are generally seen as the highest status LPs (Lerner, Schoar and Wang, 2008).

The role of placement agents of varying repute in venture capital fundraising is documented in Rider's (2009) study. Basically, placement agents are brokers who make a market in a given fund. GPs retain placement agents to market their fund to LPs, generally paying one percent of total capital raised as well as a negotiated percentage of profits for the placement agent's services. As Rider (2009) theorizes and demonstrates empirically, there is generally positive assortative matching of a fund's perceived quality and a placement agent's reputation. Due to the intersection of fund needs and agents' reputational concerns, placement agents tend to represent funds of moderate quality and more reputable placement agents tend to represent higher quality funds. Figure 4 depicts trends in placement agent representation since 2000, when representation became relatively more common.

[INSERT FIGURE 4 ABOUT HERE]

As others document (e.g., Cain, et al., 2015), whether or not placement agents provide valuable services is a matter of substantial debate because agent reputations vary widely. GPs and LPs generally agree on the market's most reputable agents, as indicated by survey results used in Rider's (2009) study, which investigates tendencies of funds to be represented by placement agents and the matching of funds and agents but does not examine the outcomes for GPs and LPs (i.e., the returns to brokerage for the brokered), as we do here.

Returning to our discussion of applicability above, the U.S. venture capital fundraising market is – for several reasons – an excellent setting for applying our approach. First, placement agents charge standard fees to GPs for representing their funds. So, we can hold fees charged to sellers constant in our analyses and interpretation. Second, the matching process theorized by Rider (2009) provides clear insights on GP selection into representation as a fundraising strategy. Our analyses of fund and investor outcomes can, therefore, account for observable determinants of representation in structuring comparisons among observationally-equivalent funds.

Third, the market offers clear measures of our key theoretical constructs: seller and buyer value. More appealing funds typically attract more institutional investors than less appealing funds (i.e., seller value) and investor satisfaction is increasing with a fund's return on invested capital (i.e., buyer value). Moreover, because LPs pay standard 2-20 fees to GPs for their investments, we can hold price constant across buyers, which effectively reduces buyer value to offering quality, which is readily measured on a per-dollar-invested basis as returns on invested capital. Last, LPs maintain diversified investment portfolios that often include multiple funds of similar type (e.g., multiple early-stage funds managed by California-based GPs). Therefore, we can construct clear comparisons between observationally-equivalent venture capital funds at the level of the market and at the level of the investor portfolio – the across-buyer versus within-buyer comparison that is critical to testing Hypotheses 2a and 2b.

Data and Sample

Our data comes from two main sources. Our primary source of data is the Private Equity Intelligence database ("Preqin"), which contains data on the fundraising side of the private equity and venture capital industries. It is the most comprehensive source of data on LP investments in

venture capital and private equity funds as well as on returns for those funds. Second, we obtain information on the investments side of the industry from the VentureXpert database of ThomsonReuters. We focus on venture capital funds raised between 2000 and 2012, as the coverage of funds raised prior to 2000 is not nearly as complete, and we focus on GPs located in the United States, where placement agents focus their venture capital fundraising services. This sampling frame yields 2,072 venture capital funds that attracted a total of 8,758 investments from LPs. Our main unit of analysis is the venture capital fund, but in some regressions we analyze fund-LP pairs as the basic unit (i.e., an investment). We construct the variables below and summarize them in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Dependent Variables

Fund Number of LPs: Our primary measure of seller value is the count of institutional investors that commit capital to a fund. We assume that more appealing funds attract more institutional investors (i.e., greater demand) and that, all else equal, GPs prefer more institutional investors to fewer such investors because dependence on any one investor generally decreases with the number of investors. Hypothesis 1 predicts that this count is higher for funds represented by placement agents than funds not represented by placement agents.

Fund Net IRR: Our measure of buyer value is the internal rate of return (IRR) of the fund as of 2012. The IRR is the most commonly used metric of fund performance and is calculated based on the cash flows into and out of the fund. The IRR represents the discount rate necessary to make the net present value of LPs' investments in the fund equal to zero. All else equal, LPs

prefer higher IRRs to lower IRRs. This variable is an excellent measure of buyer value because LPs in a fund typically pay the industry standard of two percent of committed capital and twenty percent of carried interest to the GPs. Holding price constant in this way arithmetically collapses value from quality at a given price to a straightforward value measure: IRR. Hypotheses 2a and 2b predict a positive partial correlation between this variable and placement agent representation in comparisons across (2a) or within (2b) LP portfolios.

Independent Variables

Fund Used PA: Our key market intermediation measure is a dichotomous variable that indicates whether or not the fund was represented by a placement agent, according to Preqin. Approximately 11 percent of all funds in our data are represented by placement agents.

PA Reputation: We distinguish placement agents based on their reputation by constructing two indicator variables based on the type of placement agent that represented the fund: (1) *Fund Used Top PA* and (2) *Fund Used Non-Top PA*. This scheme establishes funds not represented by a PA as the baseline comparison in all regressions. We identified top and non-top placement agents based on the results of GP and LP surveys conducted by *Private Equity International* (PEI) in 2005 and 2009. Each respondent nominated three placement agents they deemed to be highly reputable. PEI tallied these responses to construct a full ranking of nominated placement agents in 2005 and a top ten ranking of nominated placement agents in 2009. Unable to construct a time-varying, continuous measure of reputation using this data, we simply dichotomized our reputational measure to distinguish the most reputable placement agents from all others based on whether or not the agent was ranked in either 2005 or 2009. This is consistent with our

interviews of industry insiders, who implied such a dichotomy is generally acknowledged. Top placement agents and other placement agents in our data are listed in Appendix A.

Control Variables

We include several control variables so that we may compare observationally-equivalent funds that are and are not represented by a placement agent. Acknowledging that selection into using a placement agent is not random (e.g., Rider, 2009), we rely upon these control variables to characterize the placement agent's key task: to alleviate information asymmetry between GPs and LPs by selecting funds for representation that are comparable to alternative investment vehicles on easily-observed dimensions but superior on dimensions that are relatively more difficult or costly to observe. In essence, a vision advantage implies that investors select funds based on observed variables, including the placement agent's endorsement or lack thereof, while placement agents select funds for representation based on observed *and* unobserved variables.

To characterize a broker's vision advantage, it is necessary for our specification to omit some important variables. We wish to include those variables most likely to influence LP investment decisions independent of placement agent representation (e.g., fund characteristics that are easily and/or cheaply observed by potential investors). The control variables below proxy for easily observed indicators of fund quality, which shapes each fund's underlying appeal to investors as well as its eventual returns on invested capital. We include squared terms of most control variables to account for non-linear relationships between fund quality and outcomes of interest (e.g., Rider, 2009). We assume that PAs identify funds for representation based on variables that influence fundraising outcomes and investment performance but also that these variables are observed more readily by PAs than LPs.

GP Invs Prior 5 yrs: The number of distinct companies in which the GP invested in the prior five years through earlier funds. This measure serves as a proxy for a GP's recent capital management experience.

GP IPOs Prior 5 yrs: The count of companies among the GP's investments that had an IPO in the last five years. The investments were often made more than five years prior. This measure indexes a GP's prior investment success as a proxy for GP investment skill.

GP M&As Prior 5 yrs: The count of companies among the GP's investments that were sold to larger entities in the prior five years. As for IPOs, the investments could have been made several years prior and this measure also proxies for investment skill.

GP Prior LPs: The count of institutional LPs that committed capital to the GP's other funds prior to raising the focal fund. This variable controls for the fact that LPs often invest in multiple funds managed by the same GP over time. So, prior LP relationships inform our expectations of the LP investor count for subsequent funds. We control for such relationships using a full set of dummy variables, each indicating a distinct value of this count variable. Coefficients for these variables are not reported but their presence is indicated in rows at the bottom of the regression output tables.

GP Fund Count: The count of funds the GP had raised prior to the focal fund. This variable also proxies for experience and is accounted for by using a full set of dummy variables, each indicating a distinct value of this count variable. Coefficients are unreported but variable inclusion is noted at the bottom of each table.

GP Centrality: To control for the status of the GP, we calculate the Bonacich centrality of the GP in the syndication network of GPs using the same formula used in Rider's (2009) study.

Year, State & Fund Type Fixed Effects: We also include a series of indicator variables to control for unobserved heterogeneity across time, geography, and fund type. First, we specify indicator variables for each fund's vintage year to control for market conditions at time of fundraising. Second, we add more indicator variables for the state in which the GP is located to control for stable differences in access to capital and deals across geographic locations. Third, we further add indicator variables for the type of fund in Preqin's classification: "Early Stage, "Early Stage: Seed", "Early Stage: Start-up", "Expansion", "Expansion / Late Stage", "Growth", "Late Stage", "Venture (General)", and "Balanced". The analytical upshot of this approach is that our specification enables us to compare the market outcomes for funds that are observationally equivalent in terms of GP track records as well as very specific fund types.

Empirical Methods

Attributing the returns to brokerage to either certification or matchmaking is not straightforward. A conventional fund-level regression with *Fund Number of LPs* on the left-hand side and *Fund Used PA* on the right-hand side could produce a positive coefficient for *Fund Used PA* in two ways. First, there could be a "selection-on-observables" effect: PAs select good funds to represent based on characteristics observable to LPs and these funds appeal more to LPs than unrepresented funds. Second, there could be a "treatment" effect: PAs effectively market funds and, therefore, more LPs invest in represented funds than unrepresented funds.

Somewhat counter-intuitively, we aim to identify neither a "selection-on-observables" nor a "treatment" effect. Rather, a broker's vision advantage implies a third "selection-on-unobservables" effect that is not clearly identified by a conventional fund-level regression of *Fund Number of LPs* on *Fund Used PA*. An ideal test for a vision advantage would directly rule

out selection-on-observables and also treatment effects, leaving only a selection-on-unobservables effect. Our general approach aims to achieve this through a multi-step analysis.

We associate a vision advantage with evidence of both buyer *and* seller value created in an exchange. Our hypotheses establish two basic empirical expectations. First, selection on unobservable quality (i.e., vision) is associated with greater seller value – more LPs investing in a focal fund in this context. Second, vision is also associated with greater buyer value – higher IRR in this context. In other words, vision enables brokers to generate demand for offerings because offering quality is greater, in expectation, than observable characteristics suggest.

Although greater seller value can be associated with a treatment effect (i.e., PAs are effective fund marketers) as well as a selection-on-unobservables effect, we assume that brokers do not influence buyer value post-exchange. In this context, for example, it is inconceivable that PAs influence a fund's investment performance. So a vision advantage is most closely associated with evidence of brokers producing greater buyer *and* seller value – in this context, more LPs and higher IRR for represented funds than for observationally-equivalent, unrepresented funds. Again, our identifying assumption is that PAs can distinguish quality differences between funds better and/or more cheaply than LPs can.

Our approach is admittedly second-best. Ideally, one would observe all fund characteristics that are observable to PAs but not LPs and vice versa (although PAs can likely observe all characteristics that LPs can). One could then estimate regressions that separately account for these two sets of characteristics. This is, however, implausible because characteristics observable to researchers are also likely observable to LPs and we cannot observe what PAs observe.[3] That said, our approach is superior to a design based one exogenously-determined representation status. Random assignment of PAs to funds effectively eliminates a

[3] If we could credibly do so, then we would enter the placement agent business.

broker's vision advantage by preventing selection-on-unobservables so that fund outcomes vary only with representation status. Although random assignment would facilitate identification of a broker's treatment effect, the theoretically-important vision advantage could not be identified.

This understanding informs our general approach. We first include observable fund characteristics in the specification either as sets of dummy variables (e.g., one for each fund vintage year), as linear terms (e.g., the centrality of the GP), or as non-linear terms (e.g., the square of the centrality of the GP). Our objective is to characterize the focal fund's appeal to LPs, conditional on observables. This method is, admittedly, still limited by the ways in which we choose to express these variables. We then improve upon this method by controlling for fund characteristics non-parametrically through matching, as this is the most flexible way to diminish the influence that our measurement choices exert on the outcomes. To do so, we utilize two matching methods: coarsened exact matching, or CEM (Iacus, King, and Porro, 2012), and propensity-score matching, or PSM. These techniques reduce the sensitivity of our analyses to outlier observations and also reduce fund-level differences to PA representation, which is conditioned on characteristics that are not readily observed by LPs (or researchers).

In our view, these matching techniques are as much art as science. There is a trade-off between the precision of a match and the resulting sample size: the closer the match between the treated group (represented funds) and the control group (unrepresented funds), the more observations from both groups are dropped. While a closer match is better, all else equal, if the matched sub-sample is a small fraction of the original sample then the representativeness of the findings is compromised. We, therefore, try to match funds closely but also try to retain a significant proportion of our observations. To allow readers to evaluate our choices, our appendices present balance tests for the full sample and the matched sub-samples as well as

kernel density plots depicting the estimated probabilities of using a PA for funds that are and are not represented by a PA. We also present regression results that are both favorable and unfavorable to our preferred interpretation. Our comfort in our inferences is based on the fairly consistent pattern of results across specifications and matching approaches but readers should, of course, judge based on their consistency standards.

Second, propensity score matching produces a sub-sample that is well matched on the treatment likelihood but matching is an incidental result of a tedious and iterative specification process that might not balance treated and untreated observations on key control variables. Conversely, through a similarly tedious and iterative process, CEM produces sub-samples that are balanced, by design, on key control variables but that balance is highly sensitive to the ways in which the analyst coarsens those variables. Given these trade-offs, some statisticians recommend using CEM to create sub-samples that balance observations on controls and then to weight observations based on the treatment propensity (Blackwell et al., 2009). We adopt this hybrid method, although we report regression results obtained through no matching (i.e., full sample), coarsened exact matching (CEM), propensity-score matching (PSM), and CEM with propensity-score weighting (CEM-PSW).

Seller Value Analyses

We begin by assessing the evidence for a vision advantage with descriptive statistics. A straightforward comparison of funds represented by placement agents and unrepresented funds reveals that, on average, 6.61 LPs invest in represented funds and 3.96 LPs invest in unrepresented ones. This difference is statistically significant ($p < 0.01$) but does not account for the possibility that represented and unrepresented funds differ on key observable dimensions like

location, investment focus, GP experience, etc. Similar concerns are raised in comparisons of net IRRs. On average, represented funds produce an IRR of 4.89 percent versus 2.79 percent for unrepresented funds.[4] In addition, this comparison obscures the important distinction between across-LP and within-LP comparisons. We, therefore, turn to the multivariate regression results.

Our tests of Hypothesis 1 are presented in Table 2, where *Fund Number of LPs* is the dependent variable. We use OLS as our estimation method and cluster standard errors by the intersection of year and fund type to allow for interdependency within vintage-type groups of funds (e.g., 2010 early stage funds), as venture capital performance differentials are in a large part driven by times, locations, and stages of investments (Nanda, Samila, and Sorenson, 2016).[5] Comparing Models 1 and 2, we infer that using a PA is correlated strongly with the number of LPs that a fund attracts. Represented funds attract 2.58 more LPs than observationally-equivalent, unrepresented funds – a 61 percent increase over the mean value of 4.24 LPs (see Table 1).

[INSERT TABLE 2 ABOUT HERE]

In Model 3 ("PS 0"), we use propensity score matching on our full set of control variables to obtain a balanced sample of funds that are and are not represented by PAs. For this matching and those that follow, Appendix B reports the resulting covariate balance, comparing both the means and the ratios of variances orthogonal to the propensity score (Rubin, 2001), and also plots the likelihood of using a PA for both those that did in fact use a PA and those that did not. In this matched sub-sample, variables for funds that used a PA and those that did not are similar in means and variances for continuous controls as well as fund type and the three most

[4] This difference is not statistically significant, largely because of the large variance of the net IRR figure.
[5] In unreported analyses, we obtained similar results with a negative binomial model estimator. These results are available upon request.

prominent states.[6] By dropping 248 funds from our analysis (2,072 - 1,824), we remove outlier funds from our sample to produce appropriate comparisons. As Model 3 indicates, estimates from this matched sample are very similar to those obtained from a straightforward OLS regression of all funds (i.e., 2.3 versus 2.6 additional LPs).

In Model 4 ("CEM 1"), we match funds coarsely using a three-group classification of fund types (i.e., "Early", "Late", and "General") and exactly by the fundraising year (e.g., 2002). We only include fundraising year and fund type combinations where we can find at least two funds, one of which used a PA and one of which did not use a PA. For an LP making an investment choice in a particular year, a primary criterion is the fund type and hence, by matching on it, we ensure that the LP choice set includes similar funds that used PA and those that did not. This exercise eliminates 27 funds from our unmatched sample that do not have a suitable counterfactual observation in our data (2,072 – 2,045). Model 4 then uses this sample with the CEM weights to perform the same regression as in Models 2 and 3; the results in Model 4 are statistically indistinguishable from prior estimates. In Model 5 ("CEM + PS 1"), we combine coarsened exact matching with propensity score matching by performing propensity score matching on the coarsely matched sample used in Model 4. As Appendix B reports, this improves the covariate balance. Model 5 results are almost identical to those reported in Model 3.

In Model 6 ("CEM 2"), we use CEM with even more restrictive matching to reduce our sample to 1,254 funds. In addition to fundraising year and fund type, we further match on the sequence number of this fund for the general partner, on the number of LPs that the prior funds of this GP have attracted, on the IPOs that this GP has had in the prior 5 years, on the

[6] We test here the location of the fund in reference to three states, California, Massachusetts, and New York, only, but the full set of states was used in the matching.

investments that this GP has done in the prior 5 years, and on the centrality of the general partner in the syndication network of general partners. Specifically, we match first funds, second or third funds, fourth or fifth funds, sixth through fifteenth funds, and all later funds. The later the fund, the more information exists about the ability of a GP to deliver returns, which are considerably persistent (Nanda, Samila, and Sorenson, 2016). Hence, by matching on fund number, we are matching on the amount of information that the LPs would have about the GP. We similarly match on GPs who have not had institutional LPs in past funds, those who have had 1 or 2 LPs, those who have had 3 or 4 LPs, and those who have had 5 or more LPs. We also using matching to exclude outliers in the number of IPOs (>200), number of investments (>200), centrality (>6). Appendix B again reports the balance tests. Model 6 results again suggest an effect that is very similar in magnitude to previous estimates (i.e., 2.7 additional LPs). In Model 7 ("CEM + PS 2"), we again combine coarsened exact matching and propensity score matching by performing propensity score matching on the sample used in Model 6.

As the kernel density plots and balance tables in Appendix B indicate, the treatment and control groups again are well balanced. Matching brings the distribution of the probability of placement agent representation for represented and unrepresented funds into tighter alignment – an indication that matching and weighting observations produces more appropriate counterfactuals than those provided by our full data set. Most importantly, the key results are consistent across a wide variety of estimation approaches.

It is plausible that the greater demand implied by Hypothesis 1 does not manifest as more investors but, rather, investments by more discerning investors like university endowments (Lerner, et al., 2008). Therefore, we also coded an indicator dependent variable *Fund Has Endowment as LP* as an alternative measure of seller value. As a robustness check, we re-

estimated Models 1 through 7 but with this dependent variable (0/1), both with linear probability model and logit, and obtained similar results. We do not report these results (available upon request) but believe that this analysis alleviates concerns that the LP quantity results obscure LP quality differences. We found that represented funds are more likely to secure a university endowment LP than observationally-equivalent, unrepresented funds. Again, the CEM and propensity score results are very similar to the OLS estimates obtained from the full sample.

Using a variety of estimators, specifications, and matching approaches, our analyses imply that funds represented by placement agents secure approximately 2.1 to 2.6 more LPs than do observationally-equivalent, unrepresented funds. The evidence, therefore, strongly supports Hypothesis 1: mediated offerings appeal more than observationally-equivalent, unmediated offerings. Referring back to Figure 3, the scope condition for our analysis is, therefore, satisfied.

We turn to testing Hypothesis 3 by examining the potential of a broker's reputation to moderate this main effect. In Model 8 ("CEM + PS 2"), we use the matching from Model 7 to investigate whether using a top PA enhances an offering's appeal. Funds represented by the most reputable PAs secured more LPs than either funds represented by more typical PAs or unrepresented funds. Consistent with Hypothesis 3, funds represented by top placement agents attracted approximately three times as many incremental LPs as those represented by typical placement agents (e.g., 4.07 versus 1.26 in Model 8). We infer seller value from these results: brokers generate additional demand for offerings by mediating information asymmetry between buyers and sellers.

Buyer Value Analyses

We then consider buyer value in analyses of fund-level investment performance, with an eye towards inferring evidence of certification and matchmaking mechanisms and thus testing Hypotheses 2a and 2b. Fund returns data is not always available both because it is difficult for Preqin to obtain this information for many funds and because not enough time has elapsed for recent funds to have accumulated meaningful investment returns. Hence, the sample size for this analysis is smaller (n=637 unmatched funds). See Table 3 for summary statistics.

[INSERT TABLE 3 ABOUT HERE]

In Table 4, we report the results using the same pattern of matching methods as in Table 2 with the balance tests and distribution plots reported in Appendix C. It is striking that each propensity score match produces nicely balanced covariates, but the results differ. As we move toward more restrictive matches and consequently smaller sample sizes, the estimated magnitude of the PA coefficient first increases and eventually becomes statistically significant, only to later reverse and become again insignificant in the most-closely-matched, but also smallest sample. Given that the balance appears satisfactory across all matches, there is no reason in principle to prefer one matched set to the others. While tighter matches might be preferred, all else equal, tighter matches cause us to lose a considerable number of observations. There is no widely-accepted rule for making such compromises. Hence, these results offer ambiguous support for the certification Hypothesis 2a, which predicted that mediated offerings deliver greater buyer value than unmediated ones. Furthermore, Model 8 tests Hypothesis 4a. Funds represented by PAs may or may not outperform unrepresented funds but it does not appear that the most reputable PAs represent funds deliver greater value to buyers than typical PAs do.

[INSERT TABLE 4 ABOUT HERE]

To test Hypothesis 2b, we shift from using the fund as the unit of analysis to the fund-LP pair. For this analysis, we have 5,900 LP-fund relationships to analyze in the full, unmatched sample. The descriptive statistics are presented in Table 5 and the regression results in Table 6.

[INSERT TABLES 5 & 6 ABOUT HERE]

Table 6 presents the regression results. Unlike the prior buyer value analysis, the specification for this analysis includes a fixed effect for each LP in our data so that we compare the returns of funds *within* each LP's portfolio. This approach also enables us to compare the performance of the same fund within two LP portfolios that differ in terms of the two LPs' other investments. The key comparison is the performance of represented funds versus unrepresented ones of the same type within the same LP's investment portfolio. The models in this Table replicate the same matching methods as the corresponding models in Tables 2 and 4. *Appendix D* presents the balance tests and distribution plots.

It becomes clear in Table 6 that support for Hypothesis 2b is stronger than the support for Hypothesis 2a. The effects of using a PA are now larger in magnitude and statistically significant in every model, regardless of the matching technique used. Again, tighter matches produce larger estimates for the PA variable, but the change across samples is much smaller than that observed in Table 4. Furthermore, in each model except Model 7, the coefficient estimate is larger in Table 6 than in Table 4. Funds represented by PAs do in fact perform better when compared to other funds in which the LP has invested. The effect sizes appear considerable: funds represented by PAs have returns 70 percent to 115 percent higher than average funds. These results are more consistent with the matchmaking mechanism implied by Hypothesis 2b than the certification mechanism implied by Hypothesis 2a. Model 8 indicates that funds represented by top PAs

outperform funds represented by typical PAs. These results are more supportive of Hypothesis 4b than 4a.

Given that the results thus far seem more consistent with the matchmaking account of intermediation, we test the matchmaking hypothesis even more stringently. By focusing only on observations in which the same LP in the same year invested in at least two funds of the same type (early, late, or general), one of which was represented by a PA and one of which was not, we force a very, very specific comparison. Naturally, this comes at a cost of a much smaller sample size, as these funds are a fraction of all the observations.

In Model 9 ("CEM 3") of Table 6, we then use CEM to perform this tight matching and find a strong and significant coefficient for the PA variable even though the sample size is reduced to about a quarter of the full sample. Balance tests and distribution plots are reported in Appendix D. In Model 10, we then perform propensity score matching on this narrow sample. The sample size drops further but the magnitude and significance of the coefficient is fairly robust and consistent. Funds represented by PAs have returns roughly double the average funds. We, therefore, infer that funds represented by PAs perform better than observationally-equivalent funds for LPs with portfolios that provide precisely the counterfactual estimate we would like to have for all LPs. In Model 11, we assess whether top PAs perform better than others. The evidence now clearly favors Hypotheses 2b and 4b: PAs appear to perform a matchmaking function in the venture capital fundraising market.

4. DISCUSSION

The hypotheses tested in this study constitute a framework for understanding brokers' vision advantages and, consequently, the returns to brokerage. Although vision advantages are

well-established by prior research, the underlying mechanism by which brokers convert advantage to returns is not well understood (Burt, 2004: 354). Our approach to disentangling the certification and matchmaking mechanisms implied by financial and sociological theories, respectively, can be applied in various market settings. The necessary precondition for doing so is that a broker plays an important role in mediating information asymmetry for a substantial volume of exchanges between buyers and sellers.

Researchers who wish to apply our approach elsewhere should consider several analytical requirements. First, our approach identifies certification and matchmaking mechanisms based on the value of mediated exchange for buyers and sellers, where value is a ratio of price to quality. Settings in which one or the other is fixed (e.g., venture capital) are particularly well-suited for applying our approach, but researchers can also use a price-quality ratio (or its inverse) as a value measure in other settings. Second, it is necessary to compare market appeal for mediated and unmediated offerings to measure seller value. So, an appropriate empirical setting enables researchers to gauge an offering's demand. Third, most settings provide suitable data for comparing exchange outcomes across buyers but few provide the clear within-buyer counterfactuals that LP portfolios provide in our setting. Elsewhere, researchers will need to obtain buyers' consideration sets prior to purchasing an offering or, alternatively, assume which offering a focal buyer would have bought absent intermediation (i.e., their next-best alternative).

In our view, several settings seem good candidates for applying our approach – in addition to the used car and search firm examples mentioned earlier. For example, wine brokers facilitate exchanges between wineries and customers (e.g., importers, wholesalers, distributors, retailers, restaurants). Measures of wine price and quality are readily available from various sources (e.g., Roberts, Khaire, and Rider, 2011). Identifying the involvement of wine brokers in

transactions and obtaining sales data from both wineries and customers would enable researchers to apply our approach. Similarly, large companies hire many employees and some but not all of these employees with the assistance of staffing intermediaries (e.g., Fernandez-Mateo, 2007). Data on hiring, salary, and performance evaluations for mediated and unmediated hires would also enable our approach to disentangling certification and matchmaking mechanisms in labor markets.

We chose to demonstrate our approach in the venture capital fundraising market for several reasons. First, standard prices enable us to reduce value to a singular quality dimension. We characterize buyer value (i.e., quality given price) as a fund's internal rate of return, net of fees, on invested capital and seller value as the number of investors who commit capital to a focal fund. Second, LP portfolio diversification both within and across fund type categories enables us to estimate clear counterfactuals across funds, across investors, and within investor portfolios – all necessary conditions of our approach.

Our empirical analyses indicate that brokers generate seller value and buyer value in the venture capital fundraising market by mediating some market exchanges. On the seller side, funds represented by placement agents attract more investors than unrepresented funds. On the buyer side, although represented funds do not generally outperform unrepresented ones, represented funds within individual investors' portfolios do generate better investment returns than observationally-equivalent unrepresented ones. Moreover, these results are generally stronger for more reputable brokers. We, therefore, infer that in this market brokers benefit by facilitating mutually-beneficial exchanges (i.e., matchmaking) and not necessarily by identifying offerings of superior value (i.e., certification). Below, we walk through Figure 3's logic to

demonstrate how others might infer mechanisms by ruling out alternative explanations with each hypothesis test.

Consistent with Hypothesis 1, we found that represented funds attracted more LPs than unrepresented ones. Because a broker with a vision advantage must "make a market" among buyers if our arguments are to provide insight into the mechanisms underlying the returns to brokerage, satisfying this scope condition enables us to consider the mechanism underlying the returns to brokerage. In other words, our approach is applicable here.

We did not find clear support for Hypothesis 2a: represented funds do not generate better investment returns, on average, than unrepresented funds. Support would have been considered evidence of the certification mechanism. But, acknowledging that ruling out the certification mechanism is not equivalent to supporting the matchmaking mechanisms, we tested Hypothesis 2b by examining investment returns to observationally-equivalent represented and unrepresented funds within the same LP portfolio. In that analysis, we found strong support for Hypothesis 2b.

Consistent with the reputational contingency implied by Hypothesis 3 we found evidence that more reputable brokers deliver greater seller value than typical brokers do. We did not find that more reputable brokers deliver greater value to all buyers (i.e., Hypothesis 4a was not supported) but we did find that more reputable brokers deliver greater value when we focus more narrowly at specific buyers (i.e., Hypothesis 4b was supported). Based on these analyses, we infer that placement agents do indeed have a vision advantage over GPs and LPs in the venture capital fundraising market and that, furthermore, placement agents convert that advantage to returns by making matches between buyers and sellers, as opposed to identifying the market's highest quality offerings. Our approach leads us to conclude that the matchmaking account of brokerage provides a more complete understanding of intermediation in the venture capital

fundraising market than does the certification account. We look forward to others producing similar and different insights by applying our approach to other empirical settings so that evidence of the mechanism underlying the returns to brokerage becomes “abundant” (Burt, 2004).

5. REFERENCES

Abolafia, M. Y.
1996. *Making Markets: Opportunism and Restraint on Wall Street*. Cambridge, MA: Harvard University Press.

Akerlof, G. A.
1970. "The market for 'Lemons': Quality uncertainty and the market mechanism." *Quarterly Journal of Economics*, 84: 488-500.

Allen, F., and G. Faulhaber.
1989. "Signaling by Underpricing in the IPO Market," *Journal of Financial Economics*, 23: 303-323.

Allen, F. and A. M. Santomero.
1998. "The theory of financial intermediation." *Journal of Banking & Finance*, 21: 1461-1485.

Bar-Isaac, H. and S. Tadelis.
2008. "Seller reputation." *Foundations and Trends in Microeconomics*, 4: 273-251.

Baker, W.
1984. "The social structure of a national securities market." *American Journal of Sociology*, 89: 775-811.

Blackwell, M., S. M. Iacus, G. King, and G. Porro.
2009. "cem: Coarsened exact matching in Stata." *Stata Journal*, *9*(4), 524–546.

Blalock, H.
1967. *Toward a Theory of Minority-Group Relations*. New York: Capricorn Books.

Bielby, W. T., and D. D. Bielby.
1999. "Organizational mediation of project-based labor markets: Talent agencies and the careers of screenwriters." *American Sociological Review*, 64: 64–85.

Brandenberger, A. M. and H. Stuart.
1996. "Value-based business strategy." *Journal of Economics and Management Strategy*, 5: 5-25.

Bonet, R., P. Cappelli, and M. Hamori.
2013. "Labor market intermediaries and the new paradigm for human resources." *Academy of Management Annals*, 7: 339-390.

Booth, J. R. and R. L. Smith.
1986. "Capital raising, underwriting and the certification hypothesis." Journal of Financial Economics, 15: 262-281

Burt, R. S.
1992. *Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, R. S.
2000. "The network structure of social capital." Pp. 345-423 in B. M. Staw and R. I. Sutton, *Research in Organizational Behavior*, 345-423.

Burt, R. S.
2004. "Structural holes and good ideas." *American Journal of Sociology*, 110: 349-399.

Burt, R. S.
2005. *Brokerage and Closure*. Oxford, UK: Oxford University Press.

Burt, R. S.
2010. "Network duality of social capital." In V. O. Bartkus and J. H. Davis (Eds.), *Social Capital: Reaching Out, Reaching In*. Edward Elgar.

Burt, R. S. and J. Merluzzi.
2014. "Embedded brokerage." In D. J. Brass, G. Labianca, A. Mehra, D. S. Halgin, and S. P. Borgatti (Eds.) *Research in the Sociology of Organizations*, 40. Bradford, UK: Emerald Publishing.

Cain, M. D., S. B. McKeon, and S. D. Solomon.
2015. "Private equity fundraising and the use of placement agents: Information production or influence peddling?" Working paper. U.S. Securities and Exchange Commission.

Campbell, T.S. and W.A. Kracaw.
1980. "Information production, market signaling, and the theory of financial intermediation." *Journal of Finance*, 35: 863-882.

Chemmanur, T. J. and P. Fulghieri.
1994. "Investment bank reputation, information production, and financial intermediation." *Journal of Finance*, 49: 57-79.

Diamond, D. W.
1984. "Financial intermediation and delegated monitoring." Review of Economic Studies, 51: 393-414.

Eccles, R. G. and D. B. Crane.
1988. *Investment Banks at Work*. Boston, MA: Harvard Univ. Press.

Fernandez-Mateo, I.
2007. "Who pays the price of brokerage? Transferring constraint through price-setting in the staffing sector." *American Sociological Review*, 72: 291-317.

Fleischer, A.
2009. “Ambiguity and the equity of rating systems: United States brokerage firms, 1995-2000” Administrative Science Quarterly, 54: 555-574.

Geertz, C.
1978. “The Bazaar Economy: Information and search in peasant marketing.” *American Economic Review*, 68(2) 28-32.

Granovetter, M.
1985. “Economic action and social structure: The problem of embeddedness.” *American Journal of Sociology*, 91: 481–510.

Iacus, S. M., G. King, and G. Porro.
2011. “Causal inference without balance checking: Coarsened exact matching.” *Political Analysis*, 20: 1-24.

Jensen, M., B. K. Kim, and H. Kim.
2012. “The importance of status in markets: A market identity perspective.” Pp. 87-118 in J. L. Pearce, *Oxford Handbook of Corporate Reputation*. Cambridge, UK: Cambridge Univ. Press.

Khurana, R.
2002 “Market triads: A theoretical and empirical analysis of market intermediation.” *Journal for the Theory of Social Behavior*, 32: 239–262.

Lazear, E. P.
1986. "Salaries and piece rates." *Journal of Business*, 59: 405-431.

Leland, H.E. and D.H. Pyle.
1977. “Informational asymmetries, financial structure, and financial intermediation.” *Journal of Finance*, 32: 371-387

Lerner, J., A. Schoar, and J. Wang.
2008. “Secrets of the academy: The drivers of university endowment success.” *Journal of Economic Perspectives*, 22: 207-222.

Marsden, P. V.
1983. “Restricted access in networks and models of power.” *American Journal of Sociology*, 88: 686-717.

Merton, R. K.
1957. *Social Theory and Social Structure*. New York: The Free Press.

Merton, R. K.
1987. “Three fragments from a sociologist's notebooks: Establishing the phenomenon, specified ignorance, and strategic research materials.” *Annual Review of Sociology*, 13: 1-29.

Myers. S. C. and N. S. Majluf.
1984. "Corporate financing and investment decisions when firms have information that investors do not have." *Journal of Financial Economics*, 13: 187-221.

Nanda, R., S. Samila, and O. Sorenson.
2016. "The Persistent Effect of Initial Success: Evidence from Venture Capital." Working Paper

Nee, V. and S. Opper.
2012. *Capitalism from Below: Markets and Institutional Change in China.* Cambridge, MA: Harvard Univ. Press

Obstfeld, D.
2005. "Social networks, the tertius iungens orientation, and involvement in innovation." *Administrative Science Quarterly*, 50: 100–130.

Padgett, J. F., and C. K. Ansell.
1993. "Robust action and the rise of the Medici, 1400–1434." *American Journal of Sociology*, 98: 1259–1319.

Phillips, D. J.
2001. "The promotion paradox: The relationship between organizational mortality and employee promotion chances in Silicon Valley Law firms, 1946-1996." *American Journal of Sociology*, 106: 1058-98.

Private Equity International.
2006. "The surveys." A Guide to Private Equity Fund Placement Specialists: 75–96. London: Private Equity International.

Rider, C. I.
2009. "Constraint on the control benefits of brokerage: A study of placement agents in U.S. venture capital fundraising." *Administrative Science Quarterly*, 54: 575-601.

Roberts, P. W., M. Khaire, and C. I. Rider
2011. "Isolating the symbolic implications of employee mobility: Price increases after hiring winemakers from prominent wineries." *American Economic Review Papers and Proceedings*, 101(3): 147-151.

Rubin, D. B.
2001. "Using propensity scores to help design observational studies: application to the tobacco litigation." *Health Services and Outcomes Research Methodology*, 2:169-188.

Samila, S., A. Oettl, and S. Hasan.
2016. "Helpful Thirds and the Durability of Collaborative Ties", Working Paper

Shapiro, C.
1983. “Premiums for high quality products as returns to reputations.” *Quarterly Journal of Economics*, 98: 659-680.

Simmel, G.
1955. Conflict and the Web of Group Affiliations. K. Wolff and R. Bendix, eds. (First published in 1922.) Glencoe, IL: Free Press.

Sørensen, A. B.
1996. “The structural basis of social inequality.” *American Journal of Sociology*, 101: 1333-1365.

Spence, M.
1973. *Market Signaling*. Cambridge, MA: Harvard Univ. Press.

Stiglitz, J. E. and B. C. Greenwald.
1986. "Externalities in economies with imperfect information and incomplete markets." *Quarterly Journal of Economics*, 101: 229–264.

Stovel, K., B. Golub, and E. Meyersson Milgrom.
2011. “Stabilizing Brokerage” *Proceedings of the National Academies of Science*, 108(4): 21326-21332.

Stovel, K. and L. Shaw.
2012. “Brokerage.” *Annual Review of Sociology*, 38: 139-158.

Sultan, A.
2010. “Lemons and certified pre-owned cars in the used car market.” *Applied Economics Letters*, 17: 45-50.

Waldman, M.
1990. “Up-or-out contracts: a signaling perspective.” *Journal of Labor Economics*, 8: 230-250.

Zuckerman, E. W.
1999. “The categorical imperative: Securities analysts and the illegitimacy discount.” *American Journal of Sociology*, 104: 1398-1438.

Figure 1. Certification of offering value.

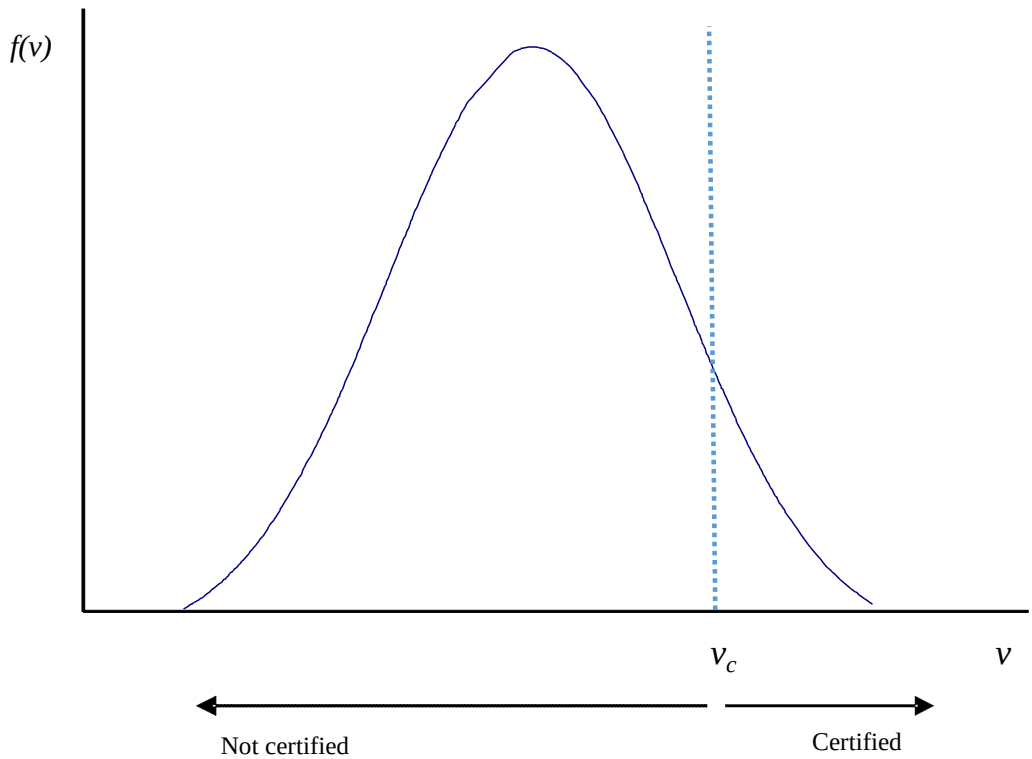


Figure 2. Matching buyers and sellers.

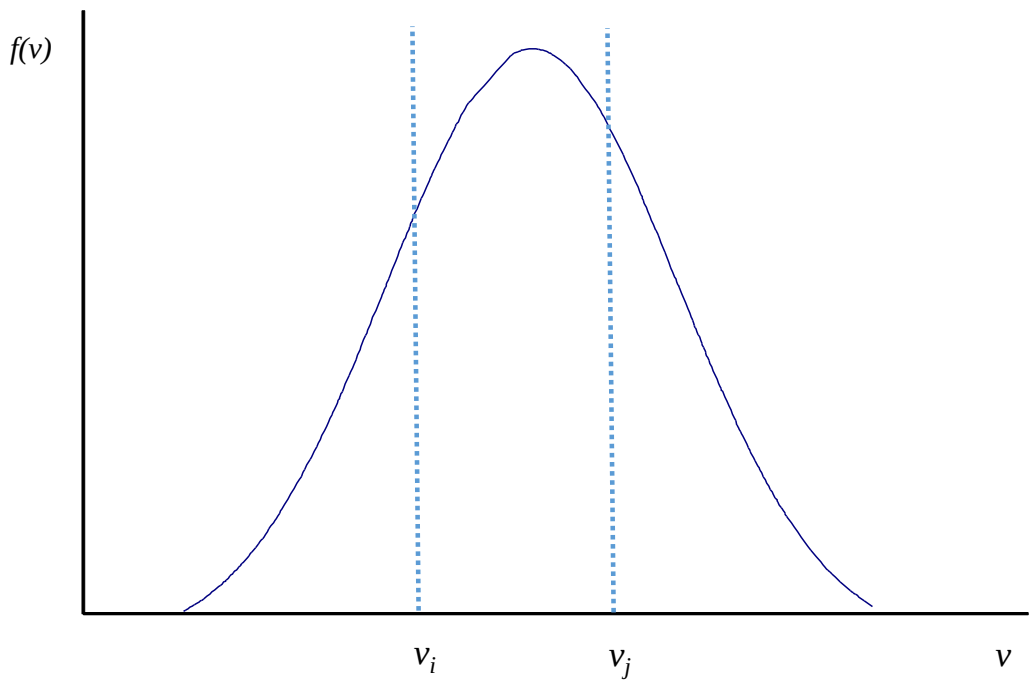


Figure 3. Possible outcomes of empirical analysis.

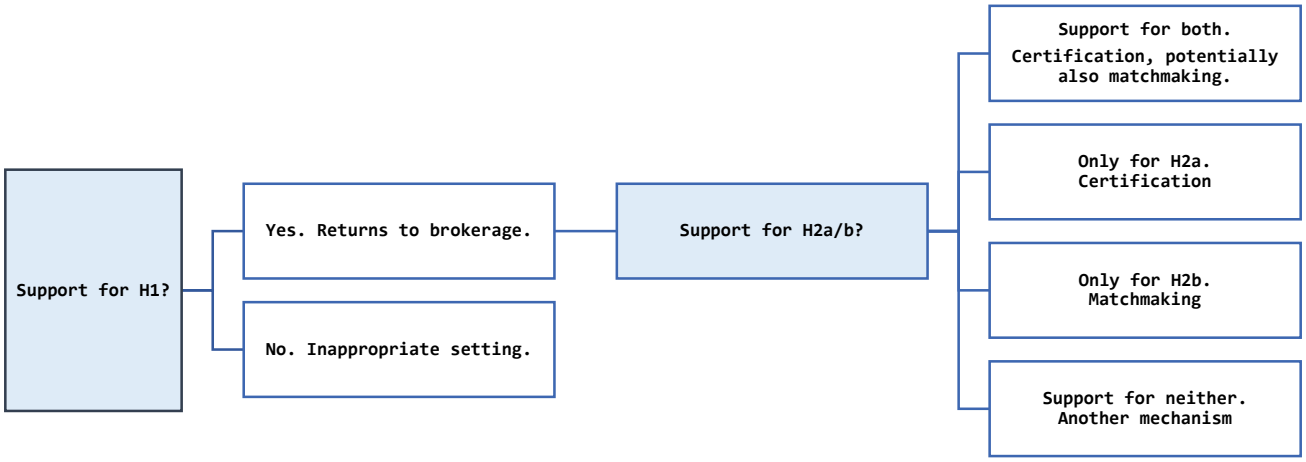


Figure 4. The market for placement agent services in U.S. venture capital fundraising.

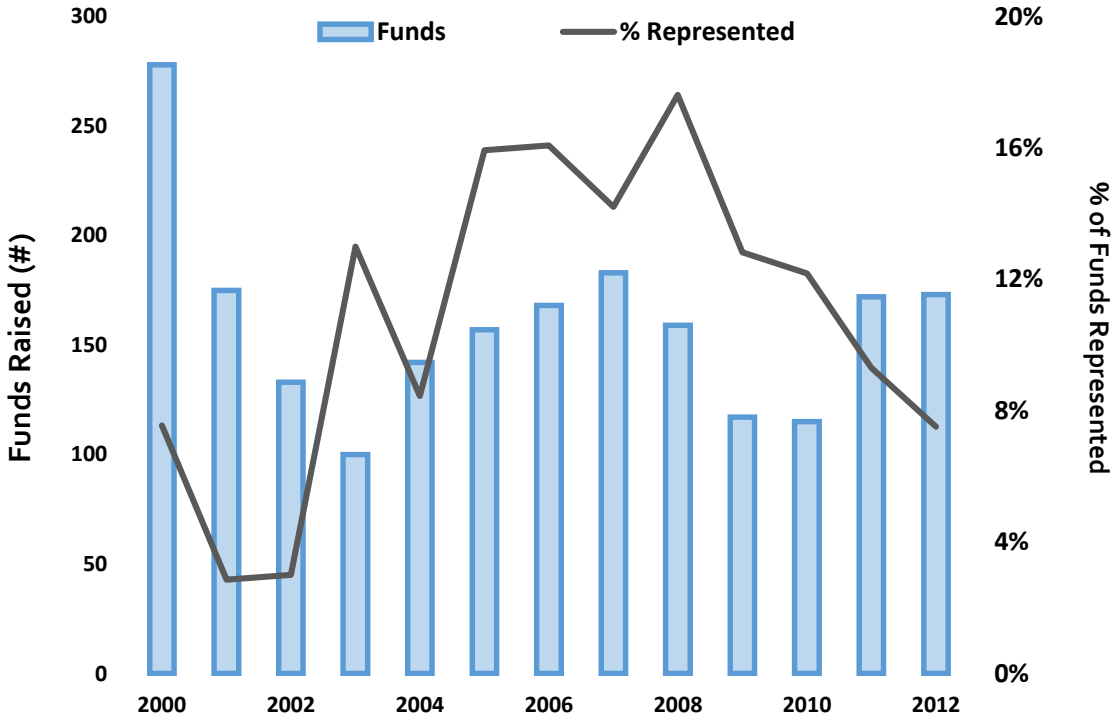


Table 1. Summary statistics for seller value analysis (n = 2,072 funds).

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Fund Number of LPs	4.24	7.42	0	81	1										
2	GP Invs Prior 5 yrs	26.27	41.34	0	424	0.39	1									
3	GP IPOs Prior 5 yrs	7.94	20.59	0	296	0.47	0.68	1								
4	GP M&As Prior 5 yrs	18.02	38.51	0	286	0.37	0.74	0.69	1							
5	GP Prior LPs	0.49	1.59	0	30	0.26	0.34	0.27	0.34	1						
6	GP Fund Count	2.87	5.13	0	67	0.27	0.55	0.38	0.53	0.64	1					
7	GP Centrality	1.2	26.19	0	1190.01	0.08	0.07	0.1	0.07	0	0.02	1				
8	Vintage	2005.71	3.94	2000	2012	-0.17	0.01	-0.13	0.13	0.05	0.16	-0.03	1			
9	Fund Used PA	0.11	0.31	0	1	0.11	-0.05	-0.05	-0.05	-0.02	-0.05	-0.01	0.06	1		
10	Fund Used Top PA	0.03	0.17	0	1	0.16	0.02	0.02	-0.01	0	-0.01	0	0.01	0.51	1	
11	Fund Used Non-Top PA	0.08	0.27	0	1	0.03	-0.06	-0.07	-0.06	-0.02	-0.05	-0.01	0.06	0.84	-0.05	1

Table 2. Seller value analysis (DV = Number of investors).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			PS 0	CEM 1	CEM+PS 1	CEM 2	CEM+PS 2	CEM+PS 2
GP Invs Prior 5 yrs	0.071***	0.069***	0.076***	0.076***	0.075***	0.14***	0.083**	0.083**
	(0.014)	(0.014)	(0.017)	(0.017)	(0.017)	(0.051)	(0.036)	(0.035)
GP Invs Prior 5 yrs (sq)	-0.00023***	-0.00022***	-0.00021***	-0.00024***	-0.00021***	-0.00092	-0.00052	-0.00055
	(0.000037)	(0.000037)	(0.000040)	(0.000042)	(0.000040)	(0.00059)	(0.00034)	(0.00034)
GP IPOs Prior 5 yrs	0.18***	0.18***	0.087*	0.15***	0.087	0.13*	0.24***	0.22***
	(0.035)	(0.035)	(0.052)	(0.041)	(0.053)	(0.072)	(0.079)	(0.076)
GP IPOs Prior 5 yrs (sq)	-0.00050**	-0.00050**	0.00078	-0.00040*	0.00080	-0.00048	-0.0030*	-0.0030*
	(0.00021)	(0.00021)	(0.00077)	(0.00022)	(0.00078)	(0.0013)	(0.0016)	(0.0017)
GP M&As Prior 5 yrs	-0.012	-0.0083	0.049*	0.013	0.049*	-0.041	0.045	0.049
	(0.020)	(0.020)	(0.028)	(0.025)	(0.028)	(0.030)	(0.059)	(0.058)
GP M&As Prior 5 yrs (sq)	0.000014	0.00000085	-0.00049***	-0.000075	-0.00049***	0.00041**	-0.00041	-0.00048
	(0.00011)	(0.00011)	(0.00018)	(0.00013)	(0.00018)	(0.00020)	(0.00064)	(0.00064)
GP Centrality	-0.38***	-0.38***	-0.17	-0.36***	-0.18	0.20	-0.24	-0.052
	(0.13)	(0.13)	(0.34)	(0.13)	(0.34)	(0.69)	(0.71)	(0.70)
GP Centrality (sq)	0.00032***	0.00033***	-0.0067	0.00030***	-0.0068	-0.013	-0.0024	-0.030
	(0.00011)	(0.00011)	(0.013)	(0.00011)	(0.013)	(0.16)	(0.18)	(0.18)
Fund Used PA		2.58***	2.29***	2.55***	2.28***	2.60***	2.07***	
		(0.46)	(0.39)	(0.49)	(0.39)	(0.45)	(0.45)	
Fund Used Top PA								4.07***
								(0.94)
Fund Used Non-Top PA								1.26***
								(0.47)
GP Fund Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GP Prior LP Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.434	0.445	0.483	0.449	0.483	0.448	0.431	0.447
Clusters	90	90	90	86	86	81	80	80
Observations	2072	2072	1824	2045	1801	1254	1161	1161

Robust standard errors clustered by the intersection of year and fund type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Summary statistics for across-buyer value analysis (n = 637 funds).

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Fund Net IRR	3.17	17.64	-100	223.7	1										
2	GP Invs Prior 5 yrs	32.97	38.76	0	269	0	1									
3	GP IPOs Prior 5 yrs	12.13	25.46	0	225	-0.01	0.73	1								
4	GP M&As Prior 5 yrs	21.07	38.52	0	286	0.08	0.69	0.73	1							
5	GP Prior LPs	0.55	1.1	0	12	0.01	0.36	0.25	0.25	1						
6	GP Fund Count	3.24	5.19	0	55	0.04	0.62	0.36	0.43	0.58	1					
7	Vintage	2004.18	3.12	2000	2010	0.18	-0.06	-0.18	0.1	0.11	0.17	1				
8	GP Centrality	2.73	47.16	0	1190.01	0.01	0.09	0.11	0.09	0.02	0.02	-0.05	1			
9	Fund Used PA	0.18	0.39	0	1	0.05	-0.07	-0.08	-0.07	0.01	-0.07	0.17	-0.02	1		
10	Fund Used Top PA	0.07	0.25	0	1	0.02	0.02	0.02	-0.01	-0.01	-0.02	0.07	-0.01	0.57	1	
11	Fund Used Non-Top PA	0.11	0.32	0	1	0.04	-0.1	-0.11	-0.08	0.01	-0.06	0.15	-0.01	0.76	-0.1	1

Table 4. Across-buyer value analysis (DV = Fund returns).

	(1)	(2)	(3) PS 0	(4) CEM 1	(5) CEM+PS 1	(6) CEM 2	(7) CEM+PS 2	(8) CEM+PS 2
GP Invs Prior 5 yrs	0.0091	0.010	-0.058	0.038	0.13	0.071	0.13	0.12
	(0.070)	(0.071)	(0.18)	(0.072)	(0.10)	(0.11)	(0.11)	(0.11)
GP Invs Prior 5 yrs (sq)	-0.00012	-0.00014	0.00042	-0.00026	-0.00087	-0.00027	-0.00071	-0.00069
	(0.00038)	(0.00038)	(0.0011)	(0.00039)	(0.00066)	(0.00075)	(0.0018)	(0.0018)
GP IPOs Prior 5 yrs	-0.21**	-0.21**	-0.22	-0.33**	-0.37***	-0.027	-0.14	-0.13
	(0.096)	(0.095)	(0.15)	(0.13)	(0.13)	(0.21)	(0.24)	(0.24)
GP IPOs Prior 5 yrs (sq)	0.00090*	0.00094*	0.00090	0.0015**	0.0026**	-0.0027	0.0016	0.0015
	(0.00051)	(0.00050)	(0.0015)	(0.00063)	(0.0011)	(0.0024)	(0.0036)	(0.0036)
GP M&As Prior 5 yrs	0.16**	0.17**	0.17**	0.26***	0.21***	0.32***	0.15	0.15
	(0.068)	(0.069)	(0.072)	(0.091)	(0.062)	(0.12)	(0.12)	(0.12)
GP M&As Prior 5 yrs (sq)	-0.00043	-0.00046	-0.00041	-0.00079**	-0.00085**	-0.0016***	0.00060	0.00063
	(0.00028)	(0.00028)	(0.00045)	(0.00036)	(0.00034)	(0.00053)	(0.0014)	(0.0014)
GP Centrality	0.62	0.62	-2.04	0.70	-1.91	-7.01**	-5.50***	-5.64***
	(0.52)	(0.52)	(1.25)	(0.48)	(1.25)	(2.90)	(1.76)	(1.75)
GP Centrality (sq)	-0.00053	-0.00053	0.081***	-0.00059	0.080***	1.29**	0.74	0.77
	(0.00044)	(0.00044)	(0.030)	(0.00040)	(0.029)	(0.63)	(0.47)	(0.47)
Fund Used PA		1.42	2.30	2.39	3.57**	3.72*	2.75	
		(1.60)	(1.54)	(1.65)	(1.48)	(1.87)	(1.71)	
Fund Used Top PA								2.22
								(1.87)
Fund Used Non-Top PA								3.12
								(2.31)
GP Fund Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GP Prior LP Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.157	0.158	0.195	0.172	0.219	0.255	0.272	0.272
Clusters	68	68	66	56	54	45	44	44
Observations	637	637	525	563	464	345	293	293

Robust standard errors clustered by the intersection of year and fund type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Summary statistics for within-buyer value analysis (n = 5,900 LP-fund commitments).

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Fund Net IRR	3.41	12.2	-100	72.2	1										
2	GP Invs Prior 5 yrs	57.31	50.95	0	269	0.12	1									
3	GP IPOs Prior 5 yrs	28.72	42.91	0	225	0.06	0.82	1								
4	GP M&As Prior 5 yrs	42.69	57.39	0	286	0.15	0.71	0.71	1							
5	GP Prior LPs	1.04	2.15	0	30	0.06	0.35	0.18	0.22	1						
6	GP Fund Count	5.16	6.5	0	55	0.12	0.57	0.33	0.41	0.66	1					
7	GP Centrality	6.68	81.73	0	1190.01	0.01	0.08	0.09	0.08	0.01	0	1				
8	Vintage	2003.89	3.17	2000	2010	0.22	-0.14	-0.27	0.05	0.12	0.2	-0.08	1			
9	Fund Used PA	0.19	0.4	0	1	0.07	-0.12	-0.14	-0.11	-0.09	-0.11	-0.03	0.17	1		
10	Fund Used Top PA	0.1	0.3	0	1	0.07	-0.01	-0.04	-0.08	-0.05	-0.05	-0.02	0.09	0.67	1	
11	Fund Used Non-Top PA	0.1	0.29	0	1	0.03	-0.14	-0.15	-0.06	-0.07	-0.09	-0.02	0.15	0.67	-0.11	1

Table 6. Within-buyer value analysis (DV = Fund returns).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
			PS 0	CEM 1	CEM+PS 1	CEM 2	CEM+PS 2	CEM+PS 2	CEM 3	CEM+PS 3	CEM+PS 3
GP Invs Prior 5 yrs	0.088	0.095	0.24**	0.073	0.092	0.20**	0.19	0.19	0.079	0.22**	0.22**
	(0.067)	(0.067)	(0.10)	(0.071)	(0.089)	(0.099)	(0.13)	(0.13)	(0.063)	(0.087)	(0.085)
GP Invs Prior 5 yrs (sq)	-0.00041	-0.00047	-0.0015	-0.00045	-0.00028	-0.0011	-0.0017	-0.0017	-0.00060*	-0.0022***	-0.0021***
	(0.00032)	(0.00032)	(0.00095)	(0.00032)	(0.00069)	(0.00073)	(0.0016)	(0.0016)	(0.00033)	(0.00080)	(0.00077)
GP IPOs Prior 5 yrs	-0.21***	-0.22***	-0.50***	-0.26***	-0.38***	-0.15	-0.072	-0.075	-0.23***	-0.16*	-0.17*
	(0.069)	(0.070)	(0.15)	(0.083)	(0.13)	(0.12)	(0.13)	(0.13)	(0.080)	(0.093)	(0.096)
GP IPOs Prior 5 yrs (sq)	0.00087**	0.00096**	0.0042	0.0010**	0.0025**	-0.00034	-0.00084	-0.00082	0.0011**	0.0015	0.0015
	(0.00037)	(0.00038)	(0.0028)	(0.00042)	(0.00095)	(0.00087)	(0.0016)	(0.0016)	(0.00049)	(0.0011)	(0.0011)
GP M&As Prior 5 yrs	0.11*	0.12*	0.17**	0.19**	0.20**	0.16*	0.28***	0.28***	0.20**	0.15**	0.15**
	(0.061)	(0.063)	(0.081)	(0.084)	(0.083)	(0.083)	(0.078)	(0.078)	(0.090)	(0.060)	(0.060)
GP M&As Prior 5 yrs (sq)	-0.00021	-0.00026	-0.00084*	-0.00042	-0.0011**	-0.00045	-0.0015***	-0.0015***	-0.00051	-0.00028	-0.00028
	(0.00023)	(0.00024)	(0.00048)	(0.00030)	(0.00044)	(0.00032)	(0.00045)	(0.00045)	(0.00033)	(0.00049)	(0.00049)
GP Centrality	-0.46	-0.46	-2.08	0.11	-0.11	-3.59**	-4.17***	-4.11***	-0.56	-1.72	-1.58
	(0.48)	(0.47)	(1.82)	(0.67)	(1.70)	(1.62)	(1.35)	(1.36)	(0.75)	(1.87)	(1.89)
GP Centrality (sq)	0.00038	0.00038	0.096	-0.000096	-0.24	0.59	0.69*	0.68*	0.00047	0.19	0.16
	(0.00040)	(0.00040)	(0.36)	(0.00056)	(0.34)	(0.48)	(0.34)	(0.36)	(0.00063)	(0.53)	(0.53)
Fund Used PA		2.38*	2.90**	3.06**	3.94***	3.67**	3.26**		4.08**	3.73***	
		(1.42)	(1.28)	(1.50)	(1.30)	(1.63)	(1.40)		(1.70)	(1.34)	
Fund Used Top PA								3.68*			4.73**
								(1.89)			(1.82)
Fund Used Non-Top PA								2.84			2.62*
								(2.18)			(1.47)
GP Fund Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GP Prior LP Count Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Type Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LP Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.338	0.341	0.426	0.411	0.455	0.518	0.503	0.503	0.448	0.422	0.424
Clusters	66	66	65	54	53	42	41	41	46	46	46
Observations	5900	5900	4056	5026	3947	3189	2586	2586	1469	1233	1233

Robust standard errors clustered by the intersection of year and fund type. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A

Placement Agents Distinguished by Reputation (Top versus Other).

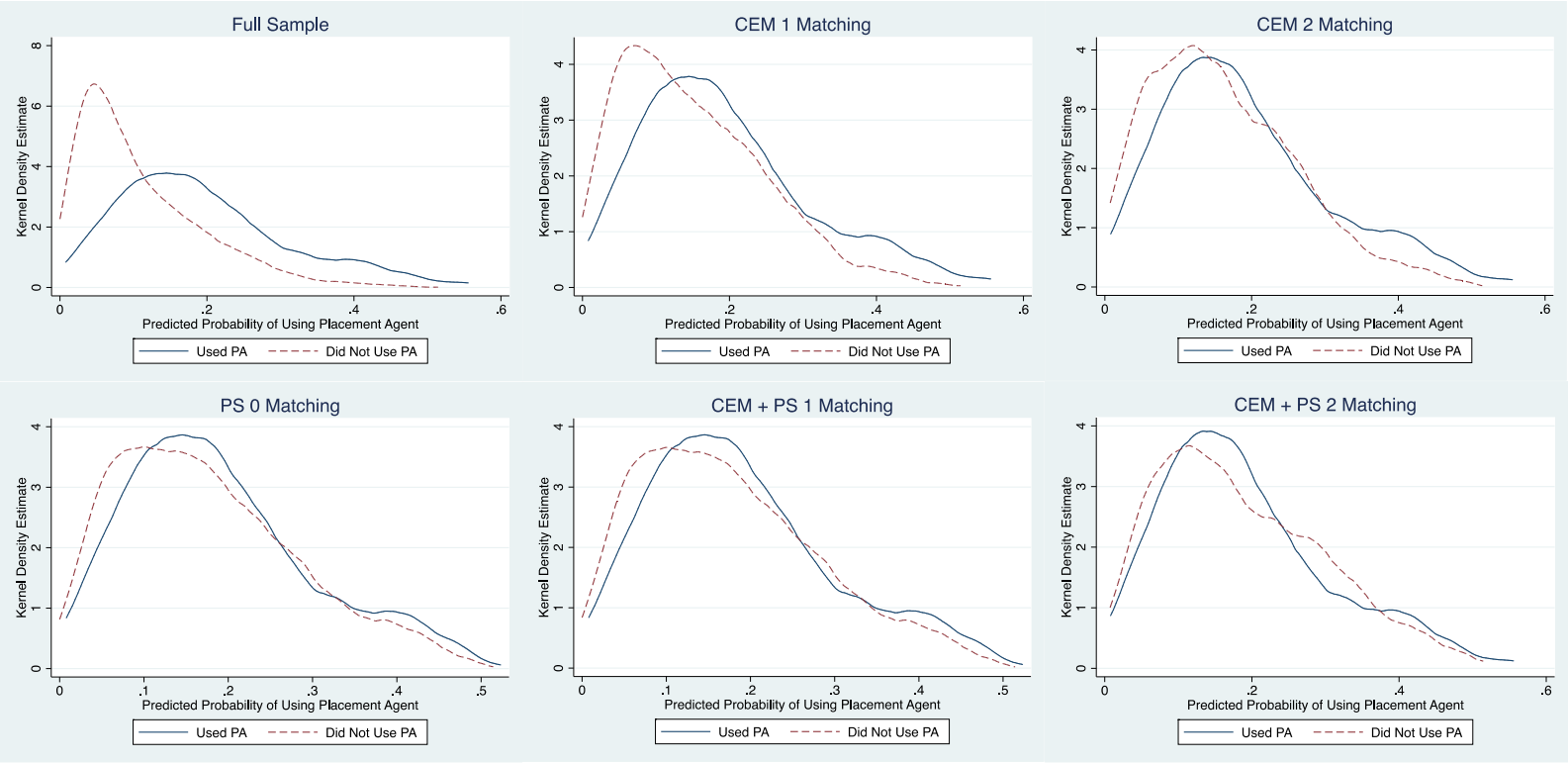
Top Placement Agents		
Campbell Lutyens	JP Morgan Chase & Co (fka Bear Stearns)	Park Hill Group
Credit Suisse Private Fund Group	Lazard Private Fund Advisory Group	Probitas Partners
Denning & Company	MVision Private Equity Advisers	Somerset Capital
Eaton Partners	Merrill Lynch PE Placement	UBS Investment Bank Private Funds Group
Gold Bridge Capital	Monument Group	

Other Placement Agents		
Almeida Capital	Edinburgh Financial General & Holding	Mercury Capital Advisors
Alternative Investment Source	European American Funds Associates	Moravia Capital
Apple Lane Group	Evercore Private Funds Group	Morgan Joseph & Co.
Aquitaine Investment Advisors	FPG Partners	Morgan Stanley Global Financial
Arch Street Advisors	Far Hills Group	NML Capital
Ariane Capital Partners	Farrell Marsh & Co.	NovaFund Advisors
Asset Management Services	First National Capital Markets	Prevail Capital
Atlantic American Partners	Fortress Group	Purple Capital
Atlantic-Pacific Capital	Gladstone Securities	Somerset Capital
Benedetto Gartland & Company	Greenhill & Co.	Source Capital Private Equity
Bentley Associates	Griffin Financial Group	Sparring Partners
BerchWood Partners	Harken Capital	Stanwich Advisors
Cabrera Capital Markets	Hudson Partners	TBLI Group
Candela Capital	J.P.Morgan Cazenove	Thomas Capital Group
Capstone Partners	JP Morgan Securities Inc.	Touchstone Group
Centenium Advisors	Kildare Capital	Trailhead Capital
Champlain Advisors	Knight Capital Partners	Trout Group
Chatsworth Securities	Koonce Securities	Troy Investment Associates
Citi Alternatives Distribution Group	Liberty Global Partners	Unspecified
Cue Capital	Liora Partners	Wetherly Capital
Diamond Edge Capital Partners	Mallory Capital Group	William Blair Funds Placement Group
E.L.K. Capital Advisors	Marwood Group	Young America Capital
EdgeLine Capital Partners		

Appendix B. Seller Value Analysis Balance Tests for Number of LPs

	Full Sample				CEM 1				CEM 2			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	20.81	26.91	0.04	0.40	20.81	27.63	0.03	0.35	21.10	19.32	0.35	1.29
GP IPOs Prior 5 yrs	5.04	8.28	0.03	0.28	5.04	7.35	0.07	0.34	5.23	4.65	0.55	0.79
GP M&As Prior 5 yrs	11.90	18.74	0.01	0.49	11.90	20.41	0.00	0.28	11.30	11.54	0.90	1.12
GP Prior LPs	0.39	0.50	0.31	0.23	0.39	0.57	0.14	0.22	0.31	0.26	0.37	1.11
GP Fund Count	2.10	2.96	0.02	0.19	2.10	3.54	0.00	0.29	1.91	1.91	0.98	0.94
GP Centrality	0.68	1.27	0.76	0.00	0.68	1.25	0.74	0.00	0.71	0.53	0.00	1.08
Vintage	2006.40	2005.60	0.01	0.59	2006.40	2006.40	1.00	1.00	2006.30	2006.30	1.00	1.00
early	0.23	0.38	0.00	0.58	0.23	0.23	1.00	0.99	0.24	0.24	1.00	1.00
late	0.26	0.14	0.00	1.01	0.26	0.26	1.00	0.97	0.23	0.23	1.00	1.00
general	0.50	0.47	0.44	1.04	0.50	0.50	1.00	1.00	0.52	0.52	1.00	1.00
CA	0.34	0.36	0.55	0.95	0.34	0.35	0.80	0.99	0.35	0.33	0.54	1.02
MA	0.10	0.11	0.54	0.89	0.10	0.10	0.77	0.94	0.09	0.12	0.26	0.79
NY	0.16	0.12	0.18	1.14	0.16	0.13	0.38	1.02	0.16	0.15	0.70	1.07

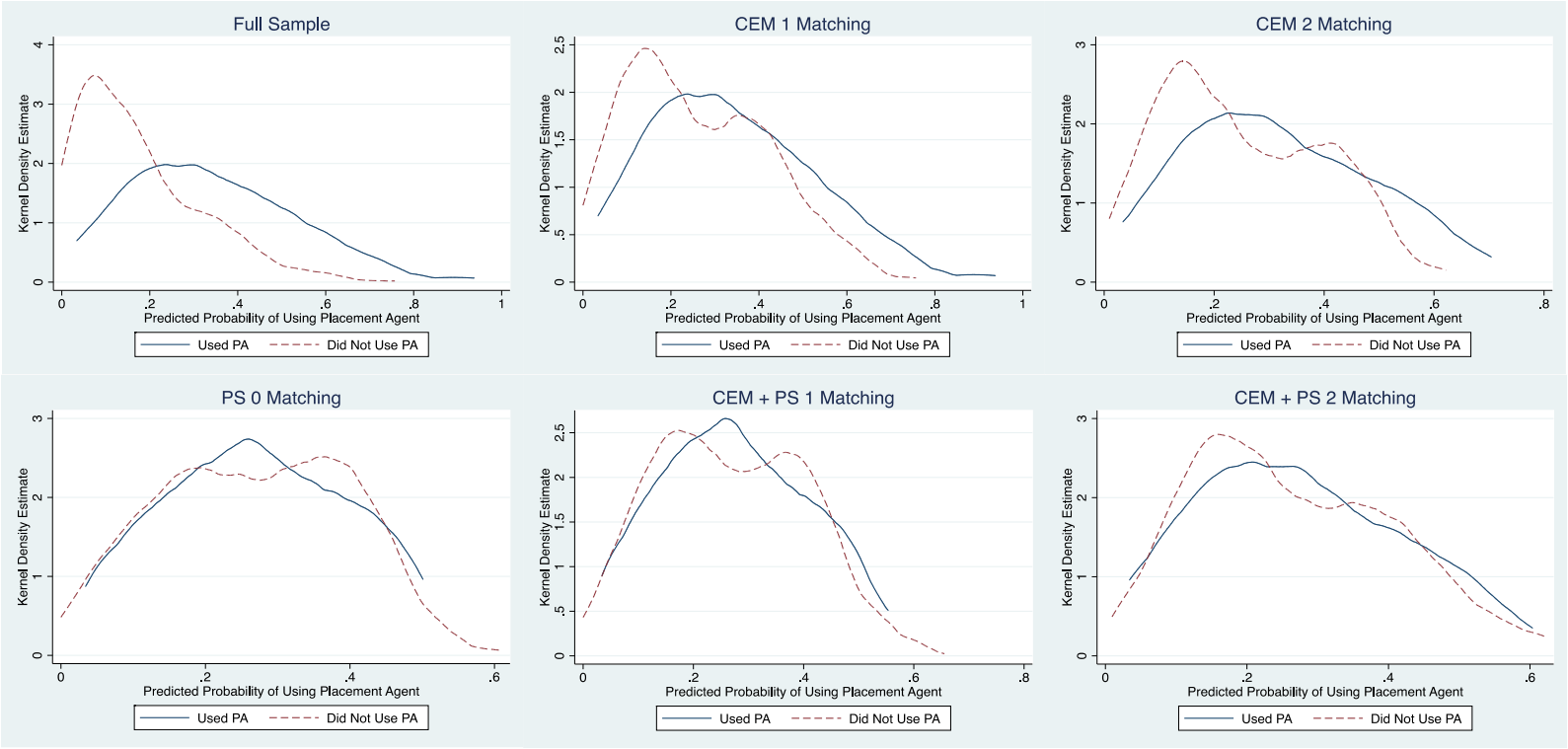
	PS 0				CEM + PS 1				CEM + PS 2			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	20.25	20.68	0.87	0.84	20.25	20.71	0.86	0.83	19.62	18.56	0.63	1.12
GP IPOs Prior 5 yrs	4.80	5.26	0.66	0.84	4.80	5.25	0.67	0.83	4.52	4.40	0.89	1.05
GP M&As Prior 5 yrs	10.69	11.51	0.68	0.74	10.69	11.53	0.67	0.73	9.51	9.68	0.91	0.94
GP Prior LPs	0.38	0.38	0.95	1.00	0.38	0.38	0.95	1.00	0.30	0.28	0.76	0.95
GP Fund Count	2.05	2.05	1.00	0.90	2.05	2.05	0.99	0.90	1.80	1.77	0.83	0.96
GP Centrality	0.67	0.67	0.95	0.65	0.67	0.67	0.93	0.66	0.71	0.73	0.90	0.99
Vintage	2006.40	2006.20	0.65	0.84	2006.40	2006.20	0.66	0.84	2006.30	2006.10	0.74	1.03
early	0.24	0.27	0.44	0.76	0.24	0.27	0.42	0.78	0.25	0.26	0.83	0.97
late	0.26	0.24	0.65	1.02	0.26	0.23	0.59	1.04	0.24	0.22	0.76	1.08
general	0.51	0.49	0.78	1.00	0.51	0.50	0.81	1.00	0.52	0.52	0.94	1.01
CA	0.34	0.35	0.85	0.97	0.34	0.35	0.83	0.96	0.35	0.36	0.92	0.99
MA	0.10	0.10	0.94	0.97	0.10	0.10	0.93	0.96	0.09	0.09	0.94	0.98
NY	0.15	0.15	1.00	1.00	0.15	0.15	0.99	1.00	0.16	0.15	0.95	1.02


Full Sample
CEM 1 Matching
CEM 2 Matching
PS 0 Matching
CEM + PS 1 Matching
CEM + PS 2 Matching
Kernel Density Estimate
Predicted Probability of Using Placement Agent
Used PA
Did Not Use PA

Appendix C. Across-Buyer Value Analysis Balance Tests for Fund Returns

	Full Sample				CEM 1				CEM 2			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	27.45	34.20	0.09	0.66	27.45	31.10	0.32	0.94	24.28	24.11	0.95	1.10
GP IPOs Prior 5 yrs	7.73	13.11	0.04	0.30	7.73	9.19	0.44	0.57	6.03	6.15	0.93	0.83
GP M&As Prior 5 yrs	15.24	22.37	0.07	0.67	15.24	21.45	0.09	0.69	11.07	15.24	0.19	0.55
GP Prior LPs	0.56	0.54	0.88	0.76	0.56	0.64	0.51	0.82	0.35	0.36	0.84	0.86
GP Fund Count	2.49	3.41	0.09	0.22	2.49	3.93	0.02	0.49	2.07	2.11	0.88	0.71
GP Centrality	0.88	3.14	0.64	0.00	0.88	2.72	0.67	0.00	0.91	0.81	0.44	0.84
Vintage	2005.30	2003.90	0.00	0.52	2005.30	2005.30	1.00	1.00	2005.00	2005.00	1.00	1.01
early	0.22	0.36	0.01	0.63	0.22	0.22	1.00	1.00	0.24	0.24	1.00	1.01
late	0.25	0.12	0.00	1.24	0.25	0.25	1.00	1.01	0.19	0.19	1.00	1.01
general	0.53	0.52	0.91	0.99	0.53	0.53	1.00	1.01	0.57	0.57	1.00	1.00
CA	0.43	0.39	0.37	1.06	0.43	0.36	0.19	0.97	0.43	0.36	0.24	0.98
MA	0.10	0.14	0.34	0.78	0.10	0.12	0.56	0.80	0.08	0.13	0.22	0.67
NY	0.11	0.09	0.51	1.20	0.11	0.11	0.96	0.99	0.12	0.16	0.30	0.72

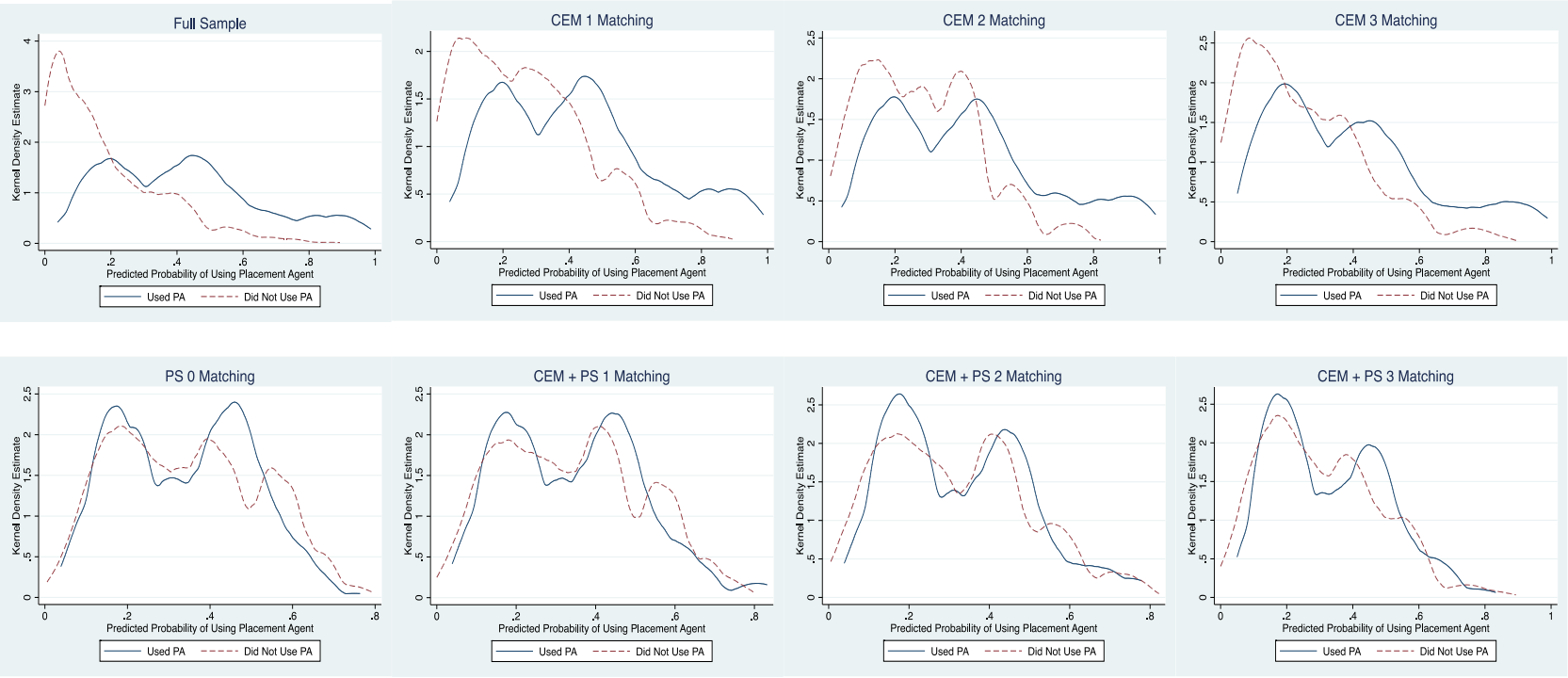
	PS 0				CEM + PS 1				CEM + PS 2			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	27.79	26.09	0.69	1.06	26.10	26.50	0.92	0.86	21.11	22.88	0.59	0.82
GP IPOs Prior 5 yrs	7.94	7.45	0.81	0.87	7.49	7.64	0.94	0.94	5.32	5.85	0.72	0.90
GP M&As Prior 5 yrs	14.51	13.33	0.70	0.80	13.77	13.45	0.92	0.86	11.29	11.23	0.98	1.00
GP Prior LPs	0.41	0.38	0.82	1.20	0.41	0.39	0.80	1.22	0.30	0.25	0.57	1.12
GP Fund Count	2.46	2.25	0.49	1.11	2.33	2.28	0.89	0.98	1.88	1.93	0.87	0.93
GP Centrality	0.90	0.86	0.84	0.83	0.89	0.88	0.96	0.84	0.90	0.87	0.83	0.98
Vintage	2004.90	2004.90	0.93	0.91	2004.90	2004.90	0.99	0.95	2004.90	2004.70	0.68	0.81
early	0.28	0.29	0.91	0.98	0.27	0.29	0.75	0.93	0.28	0.29	0.85	0.97
late	0.17	0.17	0.98	0.99	0.14	0.14	0.99	1.00	0.11	0.12	0.79	0.92
general	0.55	0.54	0.90	1.00	0.59	0.57	0.78	1.05	0.62	0.59	0.73	1.00
CA	0.45	0.44	0.90	1.03	0.45	0.46	0.89	0.99	0.46	0.44	0.79	0.94
MA	0.13	0.13	0.94	0.99	0.12	0.13	0.81	0.94	0.11	0.12	0.82	0.84
NY	0.13	0.12	0.80	1.05	0.13	0.11	0.69	1.13	0.12	0.14	0.76	0.89


Full Sample
CEM 1 Matching
CEM 2 Matching
PS 0 Matching
CEM + PS 1 Matching
CEM + PS 2 Matching
Kernel Density Estimate
Predicted Probability of Using Placement Agent
Used PA
Did Not Use PA

Appendix D. Within-Buyer Value Analysis Balance Tests for Fund Returns within LP Portfolios

	Full Sample				CEM 1				CEM 2				CEM 3			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	45.14	60.24	0.00	0.93	45.14	51.69	0.00	1.29	46.00	41.07	0.00	2.05	48.58	50.06	0.52	1.68
GP IPOs Prior 5 yrs	16.08	31.76	0.00	0.26	16.08	20.00	0.00	0.54	16.22	13.73	0.01	1.08	17.23	21.42	0.01	0.57
GP M&As Prior 5 yrs	30.22	45.69	0.00	1.02	30.22	40.66	0.00	1.19	32.36	32.20	0.93	1.84	29.83	36.98	0.01	1.50
GP Prior LPs	0.65	1.14	0.00	0.24	0.65	1.34	0.00	0.15	0.60	0.60	0.88	1.04	0.76	0.98	0.01	0.61
GP Fund Count	3.74	5.50	0.00	0.23	3.74	6.22	0.00	0.14	3.80	3.55	0.05	1.27	3.79	4.41	0.00	0.62
GP Centrality	0.85	8.08	0.01	0.03	0.85	6.98	0.01	0.03	0.86	0.88	0.57	1.15	0.93	11.86	0.03	0.05
Vintage	2005.00	2003.60	0.00	0.45	2005.00	2005.00	1.00	1.00	2005.00	2005.00	1.00	1.00	2004.50	2004.50	1.00	1.00
early	0.17	0.29	0.00	0.46	0.17	0.17	1.00	0.99	0.16	0.16	1.00	1.00	0.16	0.16	1.00	1.00
late	0.21	0.12	0.00	1.30	0.21	0.21	1.00	1.00	0.16	0.16	1.00	1.00	0.12	0.12	1.00	1.00
general	0.62	0.59	0.06	0.97	0.62	0.62	1.00	0.98	0.68	0.68	1.00	1.00	0.72	0.72	1.00	1.00
CA	0.43	0.42	0.46	1.01	0.43	0.40	0.09	1.03	0.41	0.40	0.59	1.05	0.46	0.41	0.07	0.98
MA	0.14	0.18	0.00	0.77	0.14	0.16	0.10	0.81	0.13	0.20	0.00	0.83	0.18	0.21	0.20	0.82
NY	0.13	0.10	0.00	1.26	0.13	0.10	0.00	1.15	0.15	0.15	0.84	0.98	0.13	0.14	0.45	0.97

	PS 0				CEM + PS 1				CEM + PS 2				CEM + PS 3			
	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/	Mean		t-test	V_e(T)/
Variable	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)	PA	No PA	p>|t|	V_e(C)
GP Invs Prior 5 yrs	29.08	29.37	0.80	0.81	31.09	30.65	0.72	0.93	27.93	29.24	0.26	0.90	33.21	33.01	0.91	1.08
GP IPOs Prior 5 yrs	8.50	9.11	0.27	0.82	9.53	9.84	0.62	0.70	8.08	8.47	0.48	0.78	9.88	10.29	0.64	0.74
GP M&As Prior 5 yrs	15.28	14.90	0.68	0.83	15.68	16.28	0.54	0.73	14.81	15.97	0.29	0.86	14.74	15.91	0.35	0.70
GP Prior LPs	0.52	0.51	0.90	1.05	0.54	0.55	0.80	0.88	0.46	0.43	0.45	1.06	0.61	0.62	0.98	1.10
GP Fund Count	2.80	2.71	0.35	0.91	2.87	2.80	0.50	0.87	2.61	2.54	0.50	1.03	2.84	2.77	0.58	0.93
GP Centrality	0.89	0.91	0.65	1.02	0.93	0.99	0.24	1.05	0.99	0.99	0.96	0.99	0.99	1.01	0.76	0.96
Vintage	2004.80	2004.70	0.76	0.98	2004.70	2004.80	0.49	0.92	2004.60	2004.50	0.34	0.95	2004.30	2004.20	0.77	1.04
early	0.19	0.20	0.83	0.96	0.19	0.20	0.74	0.94	0.20	0.20	0.74	1.02	0.17	0.18	0.47	0.98
late	0.23	0.21	0.31	1.04	0.20	0.18	0.16	1.22	0.15	0.12	0.16	0.99	0.13	0.12	0.70	1.05
general	0.58	0.59	0.50	1.05	0.61	0.63	0.39	1.13	0.65	0.67	0.46	0.86	0.71	0.70	0.75	1.01
CA	0.45	0.45	0.86	0.94	0.45	0.46	0.93	0.94	0.42	0.45	0.35	0.93	0.47	0.51	0.20	0.94
MA	0.17	0.18	0.52	1.00	0.17	0.15	0.39	0.89	0.17	0.19	0.52	0.90	0.21	0.23	0.36	0.89
NY	0.10	0.09	0.70	0.98	0.09	0.10	0.62	1.04	0.11	0.12	0.84	1.00	0.07	0.09	0.44	0.85


Full Sample
CEM 1 Matching
CEM 2 Matching
CEM 3 Matching
PS 0 Matching
CEM + PS 1 Matching
CEM + PS 2 Matching
CEM + PS 3 Matching
Kernel Density Estimate
Predicted Probability of Using Placement Agent
Used PA
Did Not Use PA