Strategic Management Journal
Strat. Mgmt. J., **37**: 206–231 (2016)
Published online EarlyView in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.2448
Received 31 August 2013; *Final revision received 18 November 2014*

A TWO-SIDED MATCHING APPROACH FOR PARTNER SELECTION AND ASSESSING COMPLEMENTARITIES IN PARTNERS' ATTRIBUTES IN INTER-FIRM ALLIANCES

DENISA MINDRUTA,[1] MAHKA MOEEN,[2] and RAJSHREE AGARWAL[3]*
[1] *Department of Strategy and Business Policy, HEC, Paris, France*
[2] *Department of Strategy and Entrepreneurship, University of North Carolina, Chapel Hill, North Carolina, U.S.A.*
[3] *Department of Management and Organization, University of Maryland, College Park, Maryland, U.S.A.*

Research summary: *Strategic alliances are undertaken to create value through complementarities of resources and capabilities of the partner firms. This paper uses a recently developed estimator of matching games, i.e., the maximum score estimator, to advance strategic management research on partner selection in strategic alliances, with a focus on the formation of research alliances in the biopharmaceutical industry. We contribute to the literature in three ways. First, we develop a matching framework to study strategic alliances, taking a market perspective that explicitly incorporates key features of alliance formation: two-sided decision making; quest for complementarities between indivisible and heterogeneous partner attributes; and competition on each side of the market for partners on the other side of the market. Second, we assess the relative performance of the maximum score and standard discrete choice estimators by performing simulations based on known functional relationships in various matching scenarios. Third, within the context of biopharmaceutical research alliances, we hypothesize and find support using the maximum score estimator for complementarity in partner size and in upstream research capabilities.*

Managerial summary: *A critical question facing managers who seek to benefit from strategic alliances is "whom to ally with". Typically, each party seeks a partner whose attributes reinforce their own. This paper explains that the interaction of these preferences leads to a market-wide sorting of alliance partners. Since the value created by an alliance is driven by attributes of all alliance partners, firms cannot successfully bid financial resources to get access to their most preferred partner. Instead, managers need to understand the market-wide competition and invest in the "right" mixture of attributes to make their firm more attractive in the market for alliance partners. Using this framework, we highlight firms' sizes and research capabilities as two drivers of partner selection and sorting in bio-pharmaceutical research alliances.*

Keywords: alliance formation; partner selection; matching models; complementarities; empirical methods
*Correspondence to: Rajshree Agarwal, 4512 Van Munching Hall, University of Maryland, College Park, MD 20742. E-mail: rajshree@umd.edu
All authors contributed equally and the names are listed in random order.

INTRODUCTION

Strategic alliances create value through the combination of resources and capabilities that reside across firm boundaries. They are undertaken particularly when indivisibility, heterogeneity, and complexity of what is being transacted requires

significant and repeated interactions and coordination of activities (Arora, Fosfuri, and Gambardella, 2001; Capron and Mitchell, 2012). Partner selection is a critical consideration, as value creation is contingent on whether prospective partners represent synergies in the relevant attributes (Ahuja, Polidoro, and Mitchell, 2009; Alcacer, Cantwell, and Gittelman, 2009; Mitsuhashi and Greve, 2009). In this context, most studies of alliance formation use either a focal firm or a dyadic perspective, abstracting away from the *market* for strategic alliances. Theoretically, they fail to accommodate the fundamental issue that firms face competition for allying with their most preferred partner (MacDonald and Ryall, 2004). Indeed, a firm seeking a preferred partner is constrained by the partner's preferences and opportunities for realizing higher value in a different alliance. Empirically, partner choice and complementarities between partners' attributes are almost universally tested with single-agent discrete choice models, which implicitly make a strong behavioral assumption that a firm chooses partners independently from and unconstrained by other firms (Train, 2009). Thus, extant research gaps relate to theoretical and empirical modeling of how *matching* may drive alliance formation.

In this paper, we discuss a matching theory of alliances as fundamental for the strategic analysis of "who collaborates with whom." By taking a market perspective, matching models permit the integration of two-sided decision making in voluntary collaborations; quest of complementarities between heterogeneous and indivisible partner attributes; and competition in partner choice (Becker, 1973; Mitsuhashi and Greve, 2009; Mortensen, 1988). The theoretical crux of the paper lies in the following insight: complementarity in partner attributes is a necessary condition for alliance formation, but not sufficient for how partners are selected. Rather, it is the competition among firms and the resultant interdependent choices that impact the sorting of alliance partners and the extent of value creation in the alliance (Cabral and Pacheco de Almeida, 2014). The empirical crux follows from the above theoretical considerations. Ignoring the effect of the market-wide interdependencies by modeling partner selection through a focal or even dyadic firm perspective in discrete choice model estimation can result in erroneous inferences, because the stochastic terms no longer satisfy the structural assumptions of the discrete choice estimators. Matching models enable identification of complementarities in attributes of partnering firms based on the maximization of joint value creation after accounting for all opportunities for value creation between all realized and potential alliances in the market. In this paper, we use the maximum score estimator (Fox, 2010a,b) in order to identify which combinations of attributes are complements or substitutes in alliance formation and assess their relative importance in driving partner selection. We explain the theoretical similarities and differences of this approach and the standard single-agent binary choice models. We demonstrate in a simulation setting with known parameters that the maximum score estimator uncovers the true relationships between partner attributes with minimal bias, while logit estimates have high bias.

We also develop new theory in the biopharmaceutical context and test our hypotheses with data on these research alliances in the 1996–2006 time period. We hypothesize and find support for complementarity between biotechnology and pharmaceutical firm's sizes and in capabilities in upstream research. Unlike the past literature characterizing biopharmaceutical alliances as occurring between small and large firms, we show that complementarities in partners' size result in top-down sorting, such that the largest biotechnology firm allies with the largest pharmaceutical firm, and the smallest biotechnology firm allies with the smallest pharmaceutical firm. Likewise, we observe top-down sorting in partners' research capabilities.

Our paper contributes to the literature by demonstrating how matching models are appropriate for studying strategic alliances, as they enable identification of theoretical relationships and reduce the likelihood of false inferences based on erroneous model specifications. Consider our empirical result regarding top-down sorting of partnerships based on their research capabilities. A focal or even dual firm perspective may lead to the inference that firms with similar levels of research capabilities *prefer* each other due to the perceived similarities in research routines or stock of knowledge. Instead, the inference from matching models is that market interdependencies result in firms with lower research capability having to settle on partners with lower research capability, *in spite of* their preferences, because the firms with better research capabilities were not available to them.

These sorting effects also have implications for alliance performance inferences, separate from a selection effect. In addition to resource

DOI: 10.1002/smj

complementarities of partner firms (i.e., selection effect due to ex-ante anticipation of value creation), there is an enhanced performance effect arising due to assortative matching, given that the benefits of alliances increase in the quality of the partner resources (i.e., selection effect due to sorting). Overall, matching models focus on how partners' attributes interact to create increasing returns when firms compete in the market for alliances, thus allowing researchers to identify better the role of the alliance in creating joint value.

While our paper utilizes matching models in the context of strategic alliances, we contribute more generally by helping demonstrate the application of a *two-sided market* perspective for issues related to strategic management. Indeed, to the extent that strategy researchers focus on markets—whether factor, intermediate, or final product—that are *not* characterized by assumptions that underpin perfectly competitive market conditions, matching models can apply to a whole host of questions, including selection in mergers and acquisitions, buyer–supplier relationships, investor-investee relationships, matching of human capital and firms, and top management teams and board composition.

PARTNER SELECTION AND VALUE CREATION IN ALLIANCE FORMATION: A BRIEF REVIEW

Characteristics of markets for strategic alliances

Strategic alliances are voluntary cooperative relationships between two or more independent organizations for value creation through access to capabilities (Ahuja, 2000; Capron and Mitchell, 2012). When firms enter the "markets for strategic alliance partners," the choice of a partner—whom, among the various options, should a firm ally with —relates to what capabilities are being combined in an alliance (Ahuja *et al.*, 2009; Oxley, 1997). The two-sided voluntary nature of the decision implies that both partners must agree to ally with each other, thus preferences of both firms matter. Moreover, beyond considerations of additive fit (i.e., seeking a partner that possesses resources/capabilities lacked by a focal firm), complementarity in partner attributes is critical for joint value creation and partner choice. Complementarity arises when the combination of partners' attributes leads to a supermodular joint production function, i.e., the incremental change in the output resulting from increasing one firm's attribute of interest is augmented when the firm is allying with a partner having higher levels of the other attribute of interest (Milgrom & Roberts, 1995; Parmigiani & Mitchell, 2009). For continuous differentiable functions, complementarity is represented by the cross-partial derivative of the joint production function with respect to the two attributes: if the cross-partial derivative is positive, the two attributes are complements, and if negative, then they are substitutes. Complementarity may occur regardless of whether partners' attributes are different or the same; i.e., complementarity may arise because either (1) the marginal output of an attribute X of a firm increases when the firm allies with a partner having more of an attribute Y, or (2) more of the same attribute X in both partners results in greater gains. In the alliance literature, researchers have used *complementarities* to mean only the first kind, and *similarity* or *compatibility* to denote the second kind (e.g., Dussauge, Garrette, and Mitchell, 2000; Rothaermel and Boeker, 2008).

Another relevant feature of the market for strategic alliances is the competition for partners deemed to have attractive attributes given the scope of collaboration. For example, capacity constraints in the number of alliances that firms can undertake at a time is a key factor leading firms compete for securing an alliance with scarce desirable partners. Furthermore, even if capacity constraints are not an issue, a firm might decide to limit the number of partnerships for reputational reasons (Stuart, 1998). Taken together, these features of strategic alliances imply that two firms form an alliance when (1) both firms anticipate complementarities among their respective attributes and (2) either firm cannot create higher value with other available firms in the market.

Review of literature and its underlying theoretical assumptions

In our brief review, we examine whether the papers summarized in Table 1 abstract away from the above characteristics that affect partner selection within the "market for strategic alliances" framework. Papers that adopt a focal firm perspective seek to answer the question: "whom does the focal firm choose to collaborate with?" By taking a unilateral perspective of a focal firm seeking alliance partners, studies listed in Panel A of Table 1 assume away the

DOI: 10.1002/smj

characteristics of the markets for strategic alliances discussed above. The focus of such studies is on the "main effects" of either focal or partner firm characteristics on alliance formation. Examples of factors that affect the choice of partners include market- or firm-specific uncertainty (Beckman *et al.*, 2004), ability in new product development (Rothaermel, 2002), or status (Stern *et al.*, 2014).

Studies in Panel B incorporate considerations of partner "fit", while still focusing on one partner's perspective. These studies have inferred partner fit due to technological and market overlap (Diestre and Rajagopalan, 2012; Dushnitsky and Shaver, 2009; Mitsuhashi and Greve, 2009; Mowery *et al.*, 1998), prior ties (Podolny, 1994), geographic proximity (Alcacer *et al.*, 2009; Sorenson and Stuart, 2001), and similarity in status and reputation (Hallen, 2008; Li and Rowley, 2002; Podolny, 1994; Sorenson and Stuart, 2001). Theoretical explanations of fit in these papers assume congruence in partner preferences but abstract away from competition for alliance partners.

Studies represented in Panel C employ a dyadic perspective, in that they hypothesize about "what pairs of firms choose to collaborate with each other". These studies explicitly examine the question of how "fit" in partner attributes drives alliance formation, and specifically model alliance formation as jointly determined by both partner preferences. Researchers have studied various aspects of interdependence among firms, including resource similarity (Rothaermel and Boeker, 2008), prior relationships (Gulati, 1995; Gulati and Gargiulo, 1999), geographic proximity (Reuer and Lahiri, 2014), and similarity in structural positions within networks (Ahuja *et al.*, 2009; Chung *et al.*, 2000; Gulati and Gargiulo, 1999). Studies in this tradition have also raised the possibility that alliance partners might substitute each other resources (Chung *et al.*, 2000; Rothaermel and Boeker, 2008).

The papers reviewed above vary in the extent to which they incorporate complementarities and the bilateral nature of decision-making, but they all abstract away from competition for desired partners. We note that some studies do acknowledge that markets for alliances create different opportunities and impose different constraints for different firms in their partner choice (Ahuja, 2000). For example, studies that examine status homophily note that low-status firms may be constrained in their access to high-status firms (Stuart, 1998). However, as Greve *et al*. (2013) note, a proper theoretical treatment of the issue requires the use of matching logic and consideration of outside options for allying firms.

The relevance of these assumptions is exemplified by the debate across recent papers published in the *Strategic Management Journal*. Diestre and Rajagopalan (2012) take the biotechnology start-up firm's perspective to conclude that start-ups can choose among pharmaceutical firms with better complementary capabilities and lower appropriability hazards. In response, Mason and Drakeman (2014), executives in biotechnology firms argue that given competition among several thousand biotechnology firms to partner with one of at most 100 pharmaceutical firms, it is likely that the biotechnology start-ups cannot choose their preferred partner. Clearly, both biotechnology and pharmaceutical firms' perspectives matter, as do complementarities between their attributes and the competition both within pharmaceutical firms and within biotechnology firms for allying with the best available partner. These issues, core to partner selection in the context of alliances, are largely underaddressed in the literature. A matching theory of alliances can fill this gap.

MATCHING MODELS OF ALLIANCE FORMATION: THEORY AND EMPIRICAL ESTIMATION

Matching models solve the problem of finding a suitable "assignment" (i.e., a structure of who matches with whom) in markets where transactions involve heterogeneous agents that have preferences over whom to transact with and that compete for a limited supply of desirable partners (Koopmans and Beckmann, 1957; Roth and Sotomayor, 1990). Matching governs the formation of many relationships in real-life markets.[1] It may be accomplished

[1] In economics, finance, and sociology, and to a limited extent in strategy, researchers have used the matching framework to examine school choice (Gale and Shapley, 1962); employer–employee matches (Coleman, 1991); marriages (Becker, 1973); mergers and acquisitions (Akkus, Cookson, and Hortacsu, 2015; Ozcan, 2015); startups–VC investors (Sorensen, 2007); IPO underwriters (Fernando, Gatchev, and Spindt, 2005); bank lenders (Chen and Song, 2013); CEOs and firms (Gabaix and Landier, 2008; Mackey, Molloy, and Morris, 2014; Pan, 2015; Tervio, 2008); buyer–supplier relationships (Chatain, 2014; Fox, 2010b; Ostrovsky, 2008); firm–university relationships (Banal-Estanol, Macho-Stadler, and Perez-Castrillo, 2015; Mindruta, 2013); alliances (Song, 2009; Yang, Shi, and Goldfarb, 2009), sponsorship of sport teams (Yang and Goldfarb, 2015), and social networks (Baccara *et al.*, 2012).

Table 1. Review of scholarly work on partner selection

Scholarly work	Empirical unit of analysis	Counterfactual choice set	Econometric specification
(A) Focal firm perspective; no partner complementarity			
Baum, Calabrese, and Silverman (2000), Beckman, Haunschild, and Phillips (2004), Geringer (1991), Hitt *et al.* (2000, 2004) and Rothaermel (2002)	Focal firm	Not applicable	Random effects negative binomial; Poisson or GLS; correlation analysis; negative binomial
Stern, Dukerich, and Zajac (2014)	Dyad	Full list of unrealized alliances	Discrete time event history
(B) Focal firm perspective; partner complementarity matters			
Shah and Swiminathan (2008)	Focal firm	Not applicable	t-tests in experiment
Alcacer *et al.* (2009), Diestre and Rajagopalan (2012), Hoetker (2005), Li and Rowley (2002), Li *et al.* (2008) and Podolny (1994)	Dyad	Full list of unrealized alliances	Logit; conditional logit; multinomial logit
Hallen (2008), Mitsuhashi and Greve (2009), Mowery, Oxley, and Silverman (1998) and Sorenson and Stuart (2001)	Dyad	Subset of unrealized alliances	Logit; rare events logit; selectivity-corrected probit
(C) Dyadic perspective; partner complementarity matters			
Ahuja *et al.* (2009), Chung, Singh, and Lee (2000), Garcia-Pont and Nohria (2002), Gimeno (2004), Gulati (1995), Rosenkopf, Metiu, and George (2001), Rosenkopf and Padula (2008) and Rothaermel and Boeker (2008)	Dyad	Full list of unrealized alliances	Logit; negative binomial; competing risks; random effects probit
Gulati and Gargiulo (1999), Reuer and Lahiri (2014) and Sorenson and Stuart (2008)	Dyad	Subset of unrealized alliances	Logit or conditional logit; random effects probit

through a centralized system as in the matching of medical interns and residents in U.S. hospitals (Roth, 1984) or through a decentralized, "often invisible" process (Stovel and Fountain, 2009), where the acceptance and rejection rules are not directly observable, but the final configuration of pairings is. We focus our exposition below on decentralized matching processes as they better reflect alliance formation, and discuss its theoretical underpinning and empirical estimation approaches.

Two-sided matching models: theoretical underpinnings

We start with the theoretical model for one-to-one alliances where each firm allies with only one partner. This includes the case of the same firm engaging in multiple alliances within different "markets." For example, a firm may engage in a marketing alliance and an R&D alliance in the same year; however, each of these partnerships represents matches in different contexts, undertaken for different purposes. To facilitate the exposition, we consider a generic alliance between a pair of upstream and downstream firms, labeled $\boldsymbol{U_i}$ and $\boldsymbol{D_i}$. The model incorporates bilateral preferences as complementarities in the joint production (i.e., value creation) function, f ($\boldsymbol{U_i}$, $\boldsymbol{D_i}$). The identification of the joint production function is the focus of empirical estimation.

Let $\boldsymbol{v}$ denote the revenue that a firm receives from a match and t the transfer payment it has to make to the other alliance partner. With the inclusion of transfer payments, the model (known in the literature as a game with transferable utility) allows for situations where firms can lower prices to attract higher quality partners or conversely, trade away quality in order to obtain a higher share of the surplus. Transfer payments are subject to negotiation between participating firms. For the brevity of exposition, we assume that downstream firms make a transfer to upstream firms, but we allow transfers to be positive or negative. The upstream firm $\boldsymbol{U_i}$'s net payoff from a match is $\boldsymbol{v}_{\mathrm{U}}(\boldsymbol{U_i}, \boldsymbol{D_i}) + t_{UiDi}$ and the downstream firm $\boldsymbol{D_i}$'s net payoff is $\boldsymbol{v}_{D}(\boldsymbol{U_i}, \boldsymbol{D_i}) - t_{UiDi}$. The joint surplus is the

DOI: 10.1002/smj

summation of payoffs:

$$f\left(\boldsymbol{U_i},\boldsymbol{D_i}\right) = \boldsymbol{v}_{\mathrm{U}}\left(\boldsymbol{U_i},\boldsymbol{D_i}\right) + \boldsymbol{v}_{D}\left(\boldsymbol{U_i},\boldsymbol{D_i}\right) \quad (1)$$

Within a matching perspective, whether downstream firm $\boldsymbol{D_i}$ chooses upstream firm $\boldsymbol{U_i}$ depends upon $\boldsymbol{D_i}$*'s* payoff from partnering with $\boldsymbol{U_i}$ relative to its payoff from partnering with any other possible upstream firms who are also willing to work with $\boldsymbol{D_i}$. Likewise, the upstream firm $\boldsymbol{U_i}$*'s* willingness to accept a partnership with $\boldsymbol{D_i}$ depends upon its own utility from the relationship as well as its "effective" choice set (i.e., the set of downstream firms willing to ally with $\boldsymbol{U_i}$, given their own alternatives). These conditions lead to the equilibrium characterization of assignment games, namely, "pairwise stability". Intuitively, pairwise stability means that neither firm in an observed alliance would be willing to separate and ally with a different partner, because the revenues of both firms in an actual match, net of transfer payments, are higher than the payoffs they would get from any other counterfactual partnership in the market. Formally, a pairwise stable configuration of alliances is defined by two properties.

First, the payoffs of each partner in a match are large enough to make alliancing superior to not participating in the market. Let $\boldsymbol{v}_{\mathrm{U}}(\boldsymbol{U_i})$ denote the revenue of an upstream firm when acting on its own. For all matches $(\boldsymbol{U_i},\boldsymbol{D_i})$, voluntary participation entails the following:

$$\boldsymbol{v}_{\mathrm{U}}\left(\boldsymbol{U_i},\boldsymbol{D_i}\right) + t_{UiDi} > \boldsymbol{v}_{\mathrm{U}}\left(\boldsymbol{U_i}\right) \quad (2)$$

$$\boldsymbol{v}_{\mathrm{D}}\left(U_i,D_i\right) > t_{UiDi} \quad (3)$$

As inequalities (2) and (3) show, transfers impose a lower bound on participation in the market for alliances and define the class of unacceptable partnerships.

Second, for any two observed matches $(\boldsymbol{U_i}, \boldsymbol{D_i})$ and $(\boldsymbol{U_j}, \boldsymbol{D_j})$, the following holds:

$$\boldsymbol{v}_{\mathrm{U}}\left(\boldsymbol{U_i},\boldsymbol{D_i}\right) + t_{UiDi} > \boldsymbol{v}_{\mathrm{U}}\left(\boldsymbol{U_i},\boldsymbol{D_j}\right) + \boldsymbol{\mathcal{T}}_{UiDj} \quad (4)$$

$$\text{where } \boldsymbol{\mathcal{T}}_{UiDj} = \boldsymbol{v}_{\mathrm{D}}\left(\boldsymbol{U_i},\boldsymbol{D_j}\right) - \left(\boldsymbol{v}_{\mathrm{D}}\left(\boldsymbol{U_j},\boldsymbol{D_j}\right) - t_{UjDj}\right)$$

In interpreting condition (4), $\boldsymbol{\mathcal{T}}_{UiDj}$ can be thought of as the maximum transfer that firm $\boldsymbol{D_j}$ is willing to pay to upstream firm $\boldsymbol{U_i}$ when it contemplates switching from its current equilibrium partner $\boldsymbol{U_j}$ to ally with $\boldsymbol{U_i}$. The maximum transfer is bounded by the revenue $\boldsymbol{v}_{\mathrm{D}}(\boldsymbol{U_i}, \boldsymbol{D_j})$ that $\boldsymbol{D_j}$ can obtain in the counterfactual partnership with $\boldsymbol{U_i}$ and the net payoff $\boldsymbol{v}_{\mathrm{D}}(\boldsymbol{U_j}, \boldsymbol{D_j}) - t_{UjDj}$ that $\boldsymbol{D_j}$ enjoys in the relationship with its actual partner $\boldsymbol{U_j}$. The key idea in the inequality (4) is that even if firm $\boldsymbol{D_j}$ offers to pay $\boldsymbol{U_i}$, the maximum transfer, firm $\boldsymbol{U_i}$ still prefers to pair up with $\boldsymbol{D_i}$ and receive t_{UiDi}, instead of partnering with $\boldsymbol{D_j}$ and receiving $\boldsymbol{\mathcal{T}}_{UiDj}$.

Relationships (1) to (4) indicate that neither unilateral preferences for a particular partner nor dyad-level acceptance are sufficient conditions for an alliance to occur. Instead, each dyad-level decision is constrained by the opportunity cost of forgone partnerships. In one-to-one matching games with transfers, pairwise stable equilibrium assignments are unique and guaranteed to exist (Roth and Sotomayor, 1990). Further, the equilibrium assignments are also optimal; i.e., they maximize the global sum of value created by all pairs in the market (Becker, 1973).

Maximum score estimator methodology for matching models

Drawing on the theoretical underpinnings described above, the maximum score estimator, described in this section, identifies two main features of the joint production function: (1) the nature of relationships (complementarity versus substitutability) between the characteristics of the partners and (2) the relative importance of a relationship in explaining the sorting patterns governing partner selection. While matching theory has a long and rich history, empirical techniques that incorporate its full logic have only recently begun to be used. Largely, this is because of the difficulty of estimating market outcomes, in which all decisions are interrelated and have to be modeled at once. This aspect creates a "curse of dimensionality" because the calculation of matching probabilities entails evaluating a high-dimensional integral over the density of error terms, and this integral cannot be broken down in smaller dimensional integrals as when decision are independent (Fox and Bajari, 2013). Furthermore, an equilibrium selection rule would have to be imposed in order to account for the probability of a particular configuration of alliances to occur among all possible market-wide configurations (Fox, 2010a). As we explain in more detail later, turning the estimation into a one-sided or a dyadic choice model cannot capture the endogeneity

DOI: 10.1002/smj

of match formation at market level. Among the various matching model estimation techniques, the maximum score identification approach developed by Jeremy Fox and his colleagues represents very recent class of models that address the computational challenges of modeling matching games (Fox, 2010a,b; Fox and Bajari, 2013; Fox and Yang, 2012).[2] For comprehensive details, we refer interested readers to the sources, while providing the logic in this section.

Fox (2010a) proves that the joint value creation function (Equation 1) is identified under some very general conditions and proposes a technique to estimate the unknown parameters. The underlying approach draws on a necessary condition derived from the pairwise stability condition (see Equations 1–4 above). Specifically, any two alliances ($\boldsymbol{U_i}$, $\boldsymbol{D_i}$) and ($\boldsymbol{U_j}$, $\boldsymbol{D_j}$) in a pairwise stable configuration should satisfy the following inequality:

$$f\left(U_i,D_i\right)+f\left(U_j,D_j\right)>f\left(U_i,D_j\right)+f\left(U_j,D_i\right) \quad (5)$$

This relationship, referred to by Fox (2010a) as the local production maximization inequality, means that the sum of values created by any two pairs ($\boldsymbol{U_i}$, $\boldsymbol{D_i}$) and ($\boldsymbol{U_j}$, $\boldsymbol{D_j}$) belonging to a pairwise stable configuration is greater than or equal to the sum of values created by the counterfactual pairs ($\boldsymbol{U_i}$, $\boldsymbol{D_j}$) and ($\boldsymbol{U_j}$, $\boldsymbol{D_i}$) obtained by swapping partners.

The coefficient estimates are obtained by maximizing the number of inequalities that satisfy relationship (5), written for all possible pairs of observed and counterfactual alliances in the market. To show the mathematical formula of the estimator, let the joint production function f take the general expression:

$$\begin{aligned} f\left(U_i,D_i\right) &= f\left(U_i,D_i|\beta\right)+\varepsilon_{UiDi} \\ &= \prod_{\beta}\left(X_{Ui}*X_{Di},\ X_{Ui},X_{Di}\right)+\xi_{Ui}+\xi_{Di}+\varepsilon_{UiDi} \end{aligned} \quad (6)$$

where X_{Ui} and X_{Di} represent the vector of upstream and downstream firms' attributes, respectively, ξ_{Ui} and ξ_{Di} are respectively upstream and downstream firm fixed effects, and ε_{UiDi} are match-specific errors. The term (X_{Ui}*X_{Di}) denotes the interactions between the observed attributes of partners in a match. There is no assumption about the distribution of ε_{UiDi}.

Also, let $\boldsymbol{h}$ be a market index, which takes values from 1 to M, where M is the total number of observed markets (M could be 1 when the estimation is done in a large market). Let $\boldsymbol{N_h}$ be the total number of alliances in a market $\boldsymbol{h}$. Within each market, we denote upstream firms by $\mathbf{U^h_i}$, $\mathbf{i}=1,\ \ldots\ \boldsymbol{N_h}$. and downstream firms by $\mathbf{D^h_i}$, $i=1,\ \ldots\ \boldsymbol{N_h}$. The estimates $\widehat{\beta}$ are obtained by numerically computing the global maxima of the function that counts the number of correctly predicted inequalities for all combinations of realized and counterfactual matches within all M markets:

$$\begin{aligned} Q(\beta) = \sum_{h=1}^{M}\sum_{1<i,j<Nh} 1\Big[&f\left(U_i^h,\ D_i^h\ |\beta\right) \\ &+f\left(U_j^h,\ D_j^h\ |\beta\right)>f\left(U_i^h,\ D_j^h\ |\beta\right)\Big] \\ &+f\left(U_j^h,\ D_i^h\ |\beta\right)\Big] \end{aligned} \quad (7)$$

where 1[.] is an indicator with a value of 1 if the inequality in the parenthesis is true and 0 otherwise.

Using the local production maximization inequality (5) as the basis of estimation does not require researchers to calculate the equilibrium outcome of a matching game or the equilibrium selection rules when dealing with multiple equilibria. The estimator is asymptotically consistent when estimation is conducted using many independent markets or one large market (Fox, 2010b).[3]

[2]Given the richness of the contexts explored through the lens of matching models, several recent papers represent ongoing econometric advances in the area (see Choo and Siow (2006) for one-to-one matching; see Chiappori, Salanie, and Weiss (2012), Dupuy and Galichon (2014), and Galichon and Salanie (2015) for alternative approaches to estimating more general matching models with transferable utility). Graham (2011) provides an overview of recent empirical methods. Our exposition here is based on what is currently state of the art, and we encourage researchers interested in using matching models to stay abreast with future development in the area.

[3]Fox (2010b) proves consistency under Manski (1975)'s rank order property. Assuming, for simplicity, only two alliances in a market, the rank order property states that if firms prefer to be in the configuration A of matches {(U_1, D_1), (U_2, D_2)} as opposed to being in the configuration B of pairings {(U_1, D_2), (U_2, D_1)}, then the probability of observing configuration A is higher than the probability of observing B, after the configuration-specific error terms are drawn. We refer readers to Fox (2010a, 2010b) and Fox and Bajari (2013) for an in-depth discussion of the technical assumptions behind the rank property condition in the presence of pair-specific unobservables and configuration-specific unobservables.

Identification of complementarities and assortative matching in partner attributes

As noted earlier, positive (negative) cross-partial derivatives of the alliance joint production function indicate that the two attributes are complements (substitutes). Thus, the signs of the maximum score estimates of the production function enable researchers to infer complementarity or substitution in partners' attributes. Further, the coefficient estimates allow researchers to assess the relative importance of complementarities and substitutions that occur on different sets of partners' attributes when matching is multidimensional (Fox, 2010a). This feature is particularly relevant in alliance formation where firms have to make trade-offs between attributes as partners come in "bundles" of attributes that are not fungible.

In studying partner selection, researchers are also interested in another important feature of matching markets, i.e., the presence of assortative matching patterns. Assume partners on each side of the market are characterized by only one attribute. In the presence of positive assortative matching, firms scoring highest on this dimension on each side will seek each other as partners, leaving the second highest firms to select each other, and so forth. Likewise, in the presence of negative assortative matching, the firm scoring lowest on a dimension on one side will seek the firm that scores highest on the other side, leaving the second lowest firm to ally with second highest firm, and so forth. First analyzed and proven by Becker (1973), assortative matching and complementarity (substitutability) are interrelated. The nature of sorting patterns depends on how attributes of the partners combine in the joint production function. The intuition is that when two attributes are complements, the incremental value created is higher when the top-down sorting along these attributes occurs. Therefore, complementarity in partners' attributes leads to positive assortative matching of firms in alliances. Likewise, substitution in partners' attributes leads to negative assortative matching.

In reality, firms may match on multiple dimensions, with some being more important than others, and some being complements and other substitutes. However, it is difficult to characterize in a simple way the intricate patterns of "who matches with whom" that emerge in a multidimensional space of attributes. Therefore, as a general closed-form mathematical expression for multidimensional matching does not exist in the literature, most prior empirical work has analyzed unidimensional sorting (Dupuy and Galichon, 2014). Nonetheless, because it relies on a necessary condition satisfied in equilibrium, the maximum score estimator does not require a multidimensional characterization of the equilibrium outcome per se. Instead, for firms with multiple attributes, inferences about which cross-side attributes are complements and which ones are substitutes in the joint payoff function enable inferences, ceteris paribus, of the sorting patterns underlying the pairwise stable configuration of observed alliances.

While our exposition in the paper solely focuses on one-to-one alliances, we discuss extensions to one-to-many and many-to-many alliances in Appendix S1.

Features and limitations of the maximum score estimator

When studying partner selection and complementarities in partners' attributes, researchers often do not have complete data about the choice set facing each firm, or their preferences; the contractual details of the alliances, including transfer payments between potential partners; and the alliance performance or a quantitative measure of the actual value created. A chief advantage of the maximum score estimator is that because the identification of relationships is based on observed characteristics of each alliance partner, and the equilibrium outcome of the realized alliances, it enables researchers to estimate features of the joint value creation function with the best available data, while incorporating the endogeneity of partner selection to competition in the market. Further, the consistency of matching score estimator ensures that researchers can draw correct inferences from the estimates, even if there are missing data on some firms or some alliances, as long as there are no systematic sample selection issues in the data construction (Fox, 2010b).

The method allows for a flexible specification of the production function: it can contain polynomial expressions of higher order; attributes can be continuous (firm size or age) or discrete measures (number of product lines); attributes can be pair-specific (geographical proximity or knowledge similarity). In practical terms, the key aspect relates to researchers' ability to build these variables for both observed and counterfactual alliances. The

DOI: 10.1002/smj

function does not have to be globally super- or sub-modular in pairs of attributes.

Given that the "main effects" of firm characteristics X_{Ui} and X_{Di} cancel out in inequality (5), only dyadic or combinations of partner characteristics can be estimated. This feature may limit its applicability in contexts where researchers are interested in estimating the magnitude of the match production function (which includes the part arising from the un-interacted characteristics of the partners), such as when the evaluation of the efficiency and total contribution of alliance markets is at stake, or when researchers examine the value from participation versus nonparticipation in the market for alliances. Nevertheless, even if the true joint value production function includes main effects, their absence from the Equation 6 does not bias the matching estimates as they only affect the level of the output $\boldsymbol{f}(\boldsymbol{U}_i, \boldsymbol{D}_i)$ across alliances. Main effects may be identified in cases when data on self-matched firms exist or when researchers have information on transfers (Akkus *et al.*, 2015).

Further, as we specified in Equation 6, the estimates are obtained for the deterministic part of the production function. As common in econometric estimation, the researcher may not observe all relevant variables in the joint value creation. Similarly to a standard regression, whether or not the estimator remains consistent depends on the behavior of unobservables (ξ_{Ui}, $\xi_{Di,}$ and ε_{UiDi} in Equation (6)). The method is consistent to unobserved firm-effects ξ_{Ui} and ξ_{Di} and other unobservable factors that are valued similarly by agents on the same side of the market because they cancel out in the local maximization condition. The estimator is inconsistent if some of the attributes of firms on one side interact in the production function with the fixed effects of firms on the other side of the market or with the match-specific errors. The estimator does not make any assumptions about the distribution of errors ε_{UiDi}, but on the whole, researchers may want to consider carefully whether the presence of match-specific heterogeneity could make the problem empirically intractable.

There are also three cautionary notes related to implementation of the method. First, the method requires researchers to delineate properly the boundaries of the market(s) and ensure that firms are assigned to the appropriate side of the market. While an improper definition of market may break the consistency because the optimization will be done over false inequalities, the method is robust to including a subset of the inequalities imposed by the theory (Fox, 2010b) and defining markets conservatively. Second, because the joint production function, as with all utility functions, does not have a natural scale or level, scale normalization is required, which can be done by setting one of the β estimates to be ± 1. Such scale normalization causes the baseline relationship to become the "unit of measurement," implying that coefficients for the other relationships are interpreted in comparison to the impact of the baseline relationship on the joint value. Third, the method relies on numerical optimization for obtaining the estimates. The recommended optimization algorithm is differential evolution (Fox and Santiago, 2014), a global maximization routine that behaves well in maximizing step functions such as the objective function in Equation (7). Similar to most numerical optimization routines, the method is computationally intensive and researchers need to run robustness checks to find the global optimum.

Boundary conditions of the maximum score estimator

In considering the method, researchers need to be aware of the boundary conditions of using the maximum score methodology in empirical applications. The behavioral assumption behind the methodology is that the configuration of observed alliances satisfies the pairwise stability condition. This condition may not hold in empirical contexts in which assortative matching may have been thwarted by the presence of frictions in the market due to search costs, incomplete information about the characteristics of the potential partners, or bounded rationality of decision makers. With search costs, the question is whether agents are willing to wait for the most attractive partners that would match with them. The theoretical literature shows that matching remains assortative when search costs are introduced under various formulations in the model, such as when stronger complementarities exists among pairs (Shimer and Smith, 2000) or when search costs are partner-independent (Atakan, 2006). In these situations, it is possible that the method will uncover only very strong complementarities, thus "underestimating" the extent of synergies between partners. Researchers may want to turn to the literature on dynamic matching (or search models in labor economics) to model

DOI: 10.1002/smj

explicitly the impact of search costs on match formation and dissolution.

To assess whether frictions from informational asymmetries are important, researchers must first ask whether the model can be improved with better data. A more serious concern is whether some agents in the market have idiosyncratic private advantages in their information on potential partners. This might lead to situations where firms ranking low on observed attributes are chosen over ones ranking high purely based on informational concerns. Most often, however, alliance formation is preceded by a "courtship" period, which serves, among other things, to improve the partners' reciprocal assessment of their qualities. Moreover, in many markets, uncertainty on the potential partner is often mitigated by third-party referrals. If, on the other hand, alliances are formed under conditions of persistent uncertainty about the "true" attributes, then the assortative properties of the assignment problem might be seriously undermined by adverse selection and moral hazard problems. In aggregate, in extreme cases of idiosyncratic informational asymmetries, we would no longer observe assortative matching, and the method will yield insignificant results.

COMPARISON OF MATCHING MODEL METHODOLOGY WITH ALTERNATIVE METHODS

Discrete choice models, particularly logit and probit, are the predominant empirical approach in the alliance formation literature (Please see Table 1). While discrete choice models may be appropriate in contexts where a focal firm faces few constraints in forming alliances with the preferred partner(s) and researchers observe transfer payments, their applicability is limited in contexts characterized by firms constrained by competition for desirable partners. We now turn to the reasons why, by juxtaposing discrete choice models with the maximum score methodology as they relate to both theoretical underpinnings and empirical specification. We then provide a simulation that assesses the relative performance of the two estimation techniques.

Limitations of binary choice models in studying alliance formation in matching markets

We focus on the core features of the typical discrete choice models used in the extant literature. These models start from the "utility" that a firm derives from choosing a partner from the set of alternatives available in the market. The behavioral assumption is that a firm chooses the partner that provides it with the greatest utility. In the terminology used previously in the paper, this is akin to imposing that $\boldsymbol{U_i}$'s payoff $\nu_{U}(\boldsymbol{U_i}, \boldsymbol{D_i}) + t_{UiDi}$ from its actual alliance with $\boldsymbol{D_i}$ is greater than its payoff $\nu_{U}(\boldsymbol{U_i}, \boldsymbol{D_j}) + t_{UiDj}$ from a potential, unrealized alliance with any other firm $\boldsymbol{D_j}$. A firm's utility is typically written as a function of focal firm characteristics, the characteristics of firms in the pool of potential partners, and an additively separable error term. The probability for an alliance to occur is a multidimensional integral over the density of error terms in the model. Researchers make various assumptions to calculate this higher order integral. Most of the applications we reviewed followed a standard logit approach in which firms choose their most preferred partner independently of other firms, and errors across alternatives are assumed uncorrelated and distributed type I extreme value. These assumptions do not hold in an "alliance market" with rivalry constraints on partner choice because the probability of two firms to ally depends on who allies with whom in the rest of the market. In short, the major shortcoming of the standard discrete choice models is their inability to accommodate the complex structure of correlated errors that emerges due to the constraints in the partner-choice decisions imposed by the preferences and alliance opportunities of all firms participating in the market.[4]

There are other limitations in the way researchers have typically used the discrete choice estimators for modeling partner choice in matching markets. For example, these estimation approaches fail to accommodate mutual choices. This is a consequence of the assumption that the utility function reflects preferences of firms on one side of the market choosing among potential partners on the other side. Specifications that include dyadic covariates (such as when the utility is a function of the interacted characteristics of the partners) do not solve

[4] An empirical approach referred to as "constraining the choice set" in the existing alliance literature refers to the practice of utilizing a subset of unrealized alliances (Hallen, 2008; Sorenson and Stuart, 2001) as opposed to the full set. This empirical approach addresses the potential autocorrelation of errors resulting from inclusion of the same firms across multiple counterfactual dyads and does not relate to the more fundamental aspects of choice constraints that we highlight, as resulting from interdependencies in decisions.

this problem inasmuch as, by construction, the underlying utility comparison across alternatives is still based on a one-sided choice perspective. Another issue in the use of standard discrete choice models arises due to researchers' lack of information regarding transfer payments in realized and unrealized alliances. From a theoretical standpoint (see Equation 4), the full specification of a firm's utility from an alliance contains a transfer payment term. Data limitations require researchers to estimate the probability of alliance formation without including transfer payments in the equation. These terms are relegated to the error terms and assumed to be uncorrelated with the other variables in the model. Table 2 summarizes the features of the standard discrete choice and the maximum score estimators.

As our discussion suggests, standard discrete choice models may be appropriate when conforming to one of the following theoretical assumptions: (1) the focal firm makes choices that involve homogenous or closely substitutable partners *or* (2) the focal firm chooses among heterogenous partners, but choices are unconstrained by rivalry or mutual acceptance. We want to note that estimation techniques based on more advanced forms of discrete choice models can be developed by imposing a set of theory-driven simplifying assumptions about the matching structure of the data. For example, for a one-to-one (marriage) matching game with transferable utility, Choo and Siow (2006) propose a technique for estimating aggregate marriage probabilities based on a model that borrows some assumptions from conditional

Table 2. Comparison of binary choice and matching models

	Matching models	Binary choice models
Theoretical underpinnings		
In which types of markets are the models suitable?	A market in which the focal firm's choices are constrained by competition. Potential partners are heterogeneous in both preferences and attributes	A market in which firms do not face rivalry constraints in choosing their preferred partner, or a market in which the focal firm chooses among homogenous (or closely substitutable) partners
Whose perspectives are accounted for?	All partners	The focal firm
What is being optimized?	Sum of the individual payoff (utility minus transfer payments) of partners	The individual payoff (utility minus transfer payments) of the focal firm
How are outcomes in the market determined?	Complementarities and competition lead to sorting of all partners into observed alliances	Unconstrained choices by the focal firm
What are the equilibrium implications?	Joint payoff maximization is subject to "sorting" and the observed matches represent efficient market outcomes	No discussion of equilibrium implications because of single-firm perspective
Empirical specification issues		
What is the purpose of the estimation?	Determining how the variables of interest impact joint payoff function, and thus partner selection	Determining how the variables of interest impact the probability of partner selection. The probability function is a transformation of the individual payoff function
What is the choice set?	Choice set is determined by mutual attractiveness and competition for the "best partner"	All firms in the market
What relationships are estimated?	The impact of dyad-level relationships (arising from complementarity or substitutability) on the joint production function	The impact of main effects and dyad-level relationships on the probability of alliance formation
How are complementarities inferred from the model?	Based on cross-partial derivative of the joint utility function	Based on cross-partial derivative of the probability function

DOI: 10.1002/smj

logit. The technique can be used when agents have discrete characteristics only and information on both matched and unmatched agents is available in the data. Graham (2011) discusses other approaches.

Simulation: comparing relative performance of the empirical methodologies

In this section, we assess the relative performance of the maximum score matching estimator and logit models in a simulation where the true complementarities in partner attributes are known. The simulated data entail upstream–downstream alliances between 50 agents on each side and for 25 markets in four matching scenarios: one-to-one, one-to-many (where firms on one side may have up to 5 or 10 partners), and many-to-many matching (where firms on each side have up to 10 partners). We assumed an additive separable match production function in the following form:

$$f\left(\mathrm{U_i}, \mathrm{D_i}|\beta\right) = \beta_1 \cdot \mathrm{x_{Ui}} * \mathrm{x_{Di}} + \beta_2 \cdot \mathrm{y_{Ui}} * \mathrm{y_{Di}} + \beta_3 \cdot \mathrm{z_{Ui}} * \mathrm{z_{Di}} + \varepsilon_{\mathrm{uidi}} \quad (8)$$

We set $\beta_1 = 1$ for scale normalization and $\beta_2 = 5$ and $\beta_3 = 3$ to capture complementarities in attributes. We included pair-specific error terms $\varepsilon_{\mathrm{uidi}}$ distributed extreme value type I. We made the match formation process progressively "noisy" by varying the location parameter in the

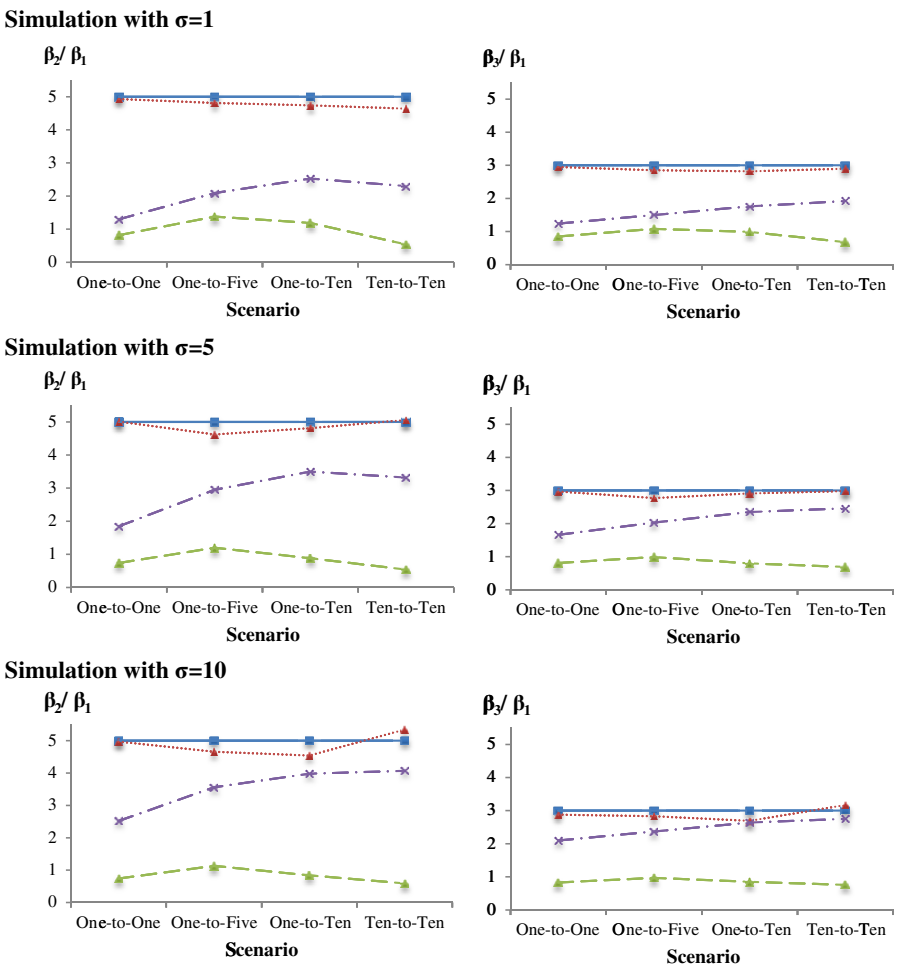

Figure 1. Comparison of estimation techniques in simulation.
Notes: (1) Vertical axes represent mean value over 100 runs of simulation, (2) error terms follow extreme value type I distribution with different σ values, (3) —■—, True Value; ···▲···, Maximum Scoore; - -▲- -, Relogit-Dyadic Covariates; - -×- -, Relogit-Main and Dyadic Covariates.

DOI: 10.1002/smj

distribution of error terms to take values of 1, 5, and 10. Using a standard normal distribution to draw randomly values of attributes, we calculated the match production function, and used a linear programming procedure to generate the optimal matching assignment (Koopmans and Beckmann, 1957; Shapley and Shubik, 1971). We followed this procedure over 100 runs. Appendix S2 provides the details of the simulation setup.

When assessing the relative performance of different methods in inferring complementarities between partners' attributes, the coefficients β_1, β_2, and β_3 represent the cross-partial derivatives of the match production function. We estimated parameters β using the maximum score estimator and two specifications of logit with a rare events correction for a subset of counterfactual alliances (King and Zeng, 2001). The first logit specification, which includes only dyadic interaction terms, mimics the matching production function. The second specification, which includes main and dyadic covariates, follows the commonly-used way of running logit, despite being theoretically misspecified in this context.

Figure 1 reports the results. Because differences in scale normalization affect the absolute values of the estimates across the two techniques, we report the ratios of coefficients as they are invariant to scale. Across all specifications, the maximum score estimation method performs remarkably well in estimating the true values of the coefficients. However, the logit estimates depart from the true values of the coefficients regardless of inclusion of main effect terms, relaxing capacity constraints, or introduction of error-term noise. While the estimated values in some specifications for one-to-many and many-to-many scenarios are closer to the true values when compared with the logit estimates in the one-to-one scenario, the logit estimates continue to have a high bias. In contrast, the maximum score method coefficients remain close to the true values in all scenarios. Similar patterns are observed when different levels of error-term noise are introduced in the simulation. Although logit estimates become closer to the true values as we increase the noise level and relax capacity constraints, we caution against a generalization regarding improvements of logit under these circumstances. This observation should be interpreted in the light that modeling the friction as a match-specific iid extreme value error term imposes a structure favorable to logit estimation. Accordingly, simulations with other error distributions and payoff functions may not show similar improvements. Overall, this simulation shows high performance of maximum score relative to logit in assessing complementarity levels.

PARTNER SELECTION AND COMPLEMENTARITIES IN THE BIOPHARMACEUTICAL INDUSTRY

Interfirm alliances in the biopharmaceutical industry have been extensively studied in strategy (Arora *et al.*, 2009; Lane and Lubatkin, 1998) and particularly in studies of partner selection (Diestre and Rajagopalan, 2012; Rothaermel and Boeker, 2008; Song, 2009). We use this context to showcase the substantive theoretical questions that may be addressed using matching models, because it demonstrates key features of a matching market; i.e., alliances between upstream (largely biotechnology) and downstream (largely pharmaceutical) firms permit accessing capabilities and firms face competitive constraints in their choice of partners. We focus on assessing complementarities in three attributes of partners: size, research capability, and drug development capability. This approach in theorizing and estimating complementarities in partners' attributes leads to novel insights, made possible by the matching model theoretical logic and the maximum score estimation.

Competitive constraints in the market for biopharmaceutical alliance partners

The biopharmaceutical context is characterized by competition in the market for alliance partners on either side. The pharmaceutical side of the market resembles an oligopolistic market, providing biotechnology firms with a limited number of available partners to ally with (Mason and Drakeman, 2014; Stuart, Hoang, and Hybels, 1999). The scarcity in availability of pharmaceutical partners is exacerbated by the fact that challenges related to learning and integrating partners' knowledge and general complexities of alliance management may cause pharmaceutical firms to limit the number of concurrent alliance partners. Because knowledge creation and transfer within alliances relate to contact between human capital (Sampson, 2007), the opportunity costs of entering into too many alliances relate to divided access and reduced

DOI: 10.1002/smj

quality of interaction (Aggarwal, 2014). Indeed, pursuing a large number of research alliances is associated with negative R&D performance for a pharmaceutical firm (Hoang and Rothaermel, 2010).

On the biotechnology side, while aggregate numbers may suggest that there are numerous biotechnology firms in the market that may be considered as potential partners, not all firms are equally sought after. Biotechnology firms are typically specialized in a specific therapeutic area, and at any point in time, there are a limited number available to ally with a pharmaceutical firm seeking a specific expertise. Moreover, while biotechnology firms typically lack past performance records, they nonetheless exhibit significant variation in riskiness and potential value to partners, as associated with signals of technological expertise or pipeline viability (Rothaermel, 2002; Stern *et al.*, 2014). Indeed, once biotechnology firms provide tangible evidence of their technological discovery, not only do they typically receive multiple alliance offers from pharmaceutical firms (Giovannetti and Morrison, 2000), but also they enjoy high bargaining power in the alliance (Adegbesan and Higgins, 2011). Hence, this context demonstrates a key feature of matching markets, in that firms face competitive constraints in their choice of highly differentiated partners.

Complementarities in partners' sizes

Among the characteristics of the markets for technology in the biopharmaceutical context, a salient feature is that biotechnology firms are on average smaller than pharmaceutical firms, and alliances represent avenues for resource constrained small biotechnology firms and resource rich large pharmaceutical firms to discover and develop drugs jointly (Baum *et al.*, 2000; Diestre and Rajagopalan, 2012). However, heterogeneity in size within each population merits closer theoretical attention to the role of size in partner selection. While a simple generalization of large and small firms forming an alliance may imply that the largest of pharmaceutical firms is likely to match with the smallest of biotechnology firms, presence of complementarities in size may show that the largest of pharmaceutical firms is likely to match with the largest of biotechnology firms.

There are multiple benefits of size in drug discovery and development projects, given long cycles of experimental trial and error processes. Larger size indicates greater access to financial and human capital as well as returns to scale in a firm's research spending due to the potential for leveraging common resource inputs, such as knowledge repositories and equipment, across multiple research programs (Henderson and Cockburn, 1994; Macher and Boerner, 2006). Moreover, large size usually implies more scientists, which enable not only access to more depth and breadth of the scientific personnel, but also superior routines for coordination and knowledge creation.

Given benefits of scale, firms on each side will seek partners who are larger relative to alternative options. From a biotechnology firm's perspective, allying with a large pharmaceutical firm implies greater access to financial capital and general resources, enabling an engagement in projects of larger scale. Moreover, affiliation with a large pharmaceutical firm may provide a biotechnology firm with more legitimacy (Stuart *et al.*, 1999), as a result of which it can seek resources from other external sources. Absent access to a large resource base, biotechnology firms typically have to restrict the scale/number of their research projects. Larger pharmaceutical partners reduce these resource constraints that often hinder biotechnology firms. From a pharmaceutical firm's perspective, allying with a larger biotechnology firm provides access to a larger pool of scientific expertise (Stern *et al.*, 2014). Moreover, larger biotechnology firms have established more effective problem-solving routines, which further enable their drug-discovery efforts. They are also likely to have practices that facilitate communication and knowledge transfer across their boundaries, a feature lacked by many small firms, though critical for alliance success (Adegbesan and Higgins, 2011).

On each side, the benefits of allying with a larger partner are more salient when the focal firm is large: the benefits of a larger pharmaceutical partner accrue more to a larger biotechnology firm, who is typically involved in advanced-stage projects and requires additional valuable resources. Similarly, the benefits of allying with a large biotechnology partner are more relevant for a larger pharmaceutical firm, who is more likely to leverage its partner's knowledge over a larger research base and make best use of its resources. At the alliance level, an increase in the size of combined resources of the two partners leads to higher potential for joint value creation and scale economies. Not only can partners

DOI: 10.1002/smj

spread the cost of research equipment and labs over a larger base of research activity, but also they can benefit from knowledge spillover from one program to another.

Taken together, partners' sizes have a reinforcing effect on joint value production and become sources of complementarity. These complementarities, in the presence of competition on each side for larger partners, imply positive sorting in the partner selection process. Larger biotechnology firms will match with larger pharmaceutical firms, and system-wide interdependencies will lead to smaller biotechnology firms allying with smaller pharmaceutical firms. Thus, we suggest:

Hypothesis 1: Upstream and downstream firms' sizes are complements in value creation.

Complementarities in partners' research capabilities

Research capability refers to the extent of a firm's expertise in the scientific base of biopharmaceutical context. While scholars have noted that similarity in the knowledge bases of the two partners increases the likelihood of alliance formation (Mowery *et al.*, 1998; Rothaermel and Boeker, 2008) as well as knowledge transfer within the alliance (Lane and Lubatkin, 1998), an understudied research area relates to how firms with heterogeneous levels of research capability partner up.

Firms with higher level of research capability have more basic ingredients to come up with a large and diverse set of novel combinations of knowledge, thereby enhancing their chances of drug discovery. This expertise may relate either to technology-specific aspects, such as the biotechnology or chemistry knowledge or to application-specific aspects, such as knowledge of diseases, human body, and toxicology. Beyond the technical expertise aspects, research capabilities reflect an accumulation of past learning-by-doing in managing research projects and assessing prospects of different technological trajectories. Drug discovery and development projects typically entail intensive communication and coordination between collaborators, and prior experience in managing similar processes increases a firm's research capability. Further, firms typically have to choose between multiple technological routes, and a firm's past experiences in dealing with these situations enable a better assessment of which route to pursue. In line with these arguments, existing literature has shown that research capability in the biopharmaceutical context is associated with more drug discovery and patenting (Henderson and Cockburn, 1996; Rothaermel and Hess, 2007), more drug development (Hoang and Rothaermel, 2010), and commercial success (Nerkar and Roberts, 2004).

These benefits of research capability imply that firms on each side of the market will seek partners with higher levels of research capability relative to alternative options. From a pharmaceutical firm's perspective, the heterogeneity in the research capabilities of biotechnology may make them more or less attractive partners. Although the scientific knowledge residing in individual scientists of a biotechnology firm may be a point of strength, these inputs of the research process are often difficult to measure ex-ante. Accordingly, pharmaceutical firms are likely to seek biotechnology firms partners that are able to signal their research capability through research accomplishments and tangible outcomes such as patents or viable drug pipelines (Adegbesan and Higgins, 2011; Rothaermel, 2002). These biotechnology firms are then considered to be in a superior position to engage in research projects and leverage their research capabilities, which in turn increase the chances of alliance success.

From a biotechnology firm's perspective, the research capability of pharmaceutical firms in related biotechnology domains such as biochemical processes, toxicology, and knowledge of diseases and human body are considered valuable, even though the pharmaceutical firms may not possess the focal biotechnology knowledge. Indeed, these are the types of knowledge that a biotechnology firm may lack, whereas a pharmaceutical firm may leverage these research capabilities from its existing operations. Even if a pharmaceutical partner is only involved in downstream drug development, different activities such as running clinical trials, interpreting results of various animal and human experiments, and undertaking adjustments to reduce adverse drug effects are research-intensive. Therefore, all things being equal, it is likely that biotechnology firms prefer to form an alliance with a pharmaceutical partner with a better research record.

On each side, these benefits of allying with a research capable partner become more salient when the focal firm itself has higher levels of research capability. Better research capability is

DOI: 10.1002/smj

typically associated with a firm's absorptive capacity (Cohen and Levinthal, 1990), implying that firms with higher levels of research capability are better at understanding, evaluating, and integrating external knowledge of their partners (Arora and Gambardella, 1994). Indeed, existing research has noted that performance of research projects is enhanced when external sourcing of knowledge is accompanied by high internal research capability (Ceccagnoli, Higgins, and Palermo, 2014; Hoang and Rothaermel, 2010). Accordingly, anticipating greater prospects of assimilation of external knowledge of their partner, pharmaceutical (biotechnology) firms with better research capabilities have more incentive to seek partners with better research capability. These mutual preferences of research-capable firms on each side of the market are bolstered by the overall dynamics of research alliances focused on drug discovery and development. At the alliance level, alliance partners of higher research quality have higher opportunities for knowledge recombination across the two partners' knowledge bases and a more effective management of the research process, thereby leading to a reinforcing effect of partners' research capability for joint drug discovery and development.

Taken together, firm research capability becomes a key attribute leading to complementarities and enhancing joint value creation. Complementarities, in the presence of competition on each side for more research capable partners, imply a positive assortative matching in partners' research capabilities, so that pharmaceutical firms with high levels of research capability and biotechnology firms with high levels of research capabilities are more likely to ally, whereas pharmaceutical firms with low levels of research capability and biotechnology firms with low levels of research capability are more likely to partner up. Thus, we suggest:

Hypothesis 2: Upstream and downstream firms' research capabilities are complements in value creation.

Complementarities in partners' research and development capabilities

Another feature of markets for technology in the biopharmaceutical context is that transactions are driven by considerations of partners' comparative advantage (Arora *et al.*, 2001); i.e., pharmaceutical firms seek biotechnology firm's upstream research expertise in the focal biotechnology area whereas biotechnology firms seek pharmaceutical firm's downstream capabilities related to drug development. These comparative advantage considerations imply that drug development capability of a pharmaceutical firm and research capability of a biotechnology firm become important factors for partner selection. While the literature has noted the potential division of scientific labor creating an additive fit of these two capabilities as relevant for alliance formation, the extent to which they exhibit complementarities across partners is understudied.

Drug development capability refers to a firm's resources and capabilities in taking an investigational drug or a pharmaceutical compound through various stages of clinical trials, FDA approval, and product launch. Drug development capability may then be considered a critical downstream complementary asset for operations in the biopharmaceutical context (Macher and Boerner, 2006). Not only are complementary assets critical for commercial success and economic value appropriation (Teece, 1986), but also they may shape the direction of a firm's innovative activities (Helfat, 1997). There are, however, high sunk cost investments as well as time compression diseconomies involved in development of these capabilities. In particular, drug development capability is accumulated as a result of years of running clinical trials, establishing a network of hospital and physician collaborators, extensive data management across clinical trials, and seeking regulatory approval. Although pharmaceutical firms have accumulated these capabilities over time, biotechnology firms lacking these capabilities use alliances as a means to gain access to them.

From the perspective of a biotechnology firm contemplating an alliance to overcome its lack of drug development capability, the higher a pharmaceutical firm's drug development capability, the more attractive it becomes as a partner (Diestre and Rajagopalan, 2012). This preference to collaborate with a pharmaceutical firm with high drug development capability is enhanced when the biotechnology firm itself has better research capabilities. As mentioned for Hypothesis 2, a higher level of research capability increases the likelihood of successful drug discovery. Thus, biotechnology firms with higher levels of research capability have higher stakes, as they perceive the prospects of turning their lead molecules to a successful drug to be really high. Accordingly, the higher the level of a biotechnology firm's research capabilities, the more likely

DOI: 10.1002/smj

that it seeks a pharmaceutical partner with a higher level of drug development capability.

As noted above, pharmaceutical firms prefer biotechnology firms with higher research capability (Rothaermel, 2002). Importantly, when a pharmaceutical firm itself has better drug development capability, it perceives a research-capable biotechnology firm even a more valuable partner. Although a pharmaceutical firm has already incurred the sunk costs of accumulating development capabilities, these capabilities are nonscale free (Levinthal and Wu, 2010). Because the forgone opportunity costs are higher for a pharmaceutical firm with better drug development capability, it wants to ensure that it puts its capability at its best use. Therefore, the higher the level of a pharmaceutical firm's drug development capability, the more likely that it seeks a biotechnology partner with better research capability.

In addition to mutual preferences of biotechnology firms with high research capability and pharmaceutical firms with high drug development capability to ally, there are sources of enhanced joint value creation at the alliance level as a result of these matches. Many tasks across the drug discovery and development stages have to be pursued in parallel, as many requirements of the development process can be anticipated ex-ante and taken into account during the discovery stage, and new findings during the development process require revising activities in the discovery process. When alliance partners pool higher levels of research capability and drug development capability, these interactions between the two stages may be managed more smoothly. Indeed, the literature has suggested that the positive effect of research capability on pharmaceutical sales is increased when combined with development capability and product-market experience (Nerkar and Roberts, 2004).

Hence, research capability of biotechnology firms and drug development capability of pharmaceutical firms exhibit reinforcing effects in a partnership. These complementarities—in the presence of competition on one side for more research-capable partners and on the other side for better drug development capability—imply a positive assortative matching in biotechnology firm's research capability and pharmaceutical firm's drug development capability, so that pharmaceutical firms with high levels of drug development capability and biotechnology firms with high levels of research capabilities are more likely to ally. Thus, we suggest:

> *Hypothesis 3: Upstream firm's research capabilities and downstream firms' drug development capabilities are complements in value creation.*

Data description

We base our analysis on interfirm alliances reported in the *ReCap* database during 1996–2006, a period representing significant alliance activity to permit the estimation of the coefficients for every year. The time period of our sample compares well to those used in other studies: Rothaermel and Boeker (2008) studied the industry during the 1998–2001 period, and Diestre and Rajagopalan (2012) the 2002–2007 period. Additional data on firm attributes (e.g., size, geographic location, patent stock, etc.) were compiled from a variety of sources such as the *BioScan Directory*, the *Bloomberg Private Firms' directory*, *Compustat*, *Directory of Corporate Affiliations, drugs@FDA, Hoover's*, *LexisNexis*, and the *NBER* 2006 patent databases.

We define each year as a separate "market" within which the alliances are formed. To enable identification of each side of the market, we focus on nonequity research collaborations with a licensing component between a biotechnology firm (upstream) and a pharmaceutical firm (downstream). Consistent with prior literature (Arora *et al.*, 2009; Hoang and Rothaermel, 2010), we consider firms as pharmaceutical if they or one of their antecedent firms were founded prior to 1976 (the founding year of Genentech, the first biotechnology regime firm) and as biotechnology firms otherwise. Research alliances are an appropriate context because the knowledge characteristics represent indivisibility and complexity and firms care about the identity of their partners. Moreover, licensing alliances are characterized by one party's licensing of another firm's knowledge, which enables us to draw a clear boundary between the two sides of the market.

In the context of our study, a pharmaceutical firm could engage in multiple alliances in any year. Careful reading of the scope of each alliance revealed that multiple alliances in the same year constituted different transactions (different disease areas, technologies, stages of development, etc.). We thus concluded that the payoff of a pharmaceutical–biotech alliance does not depend

DOI: 10.1002/smj

on the characteristics of the other alliances that a pharmaceutical firm makes in the same year. Also, in any given year, biotechnology firms did not engage in more than one alliance (of the type we examine here). These features of the data are consistent with a one-to-many matching with additive separable payoffs across partnerships made by a pharmaceutical firm with multiple partners. Our final alliance sample consists of 614 alliances between 101 pharmaceutical and 335 biotechnology firms. On average, we observe 56 alliances per year.

Variables

Technological overlap

This pair-specific attribute is measured by the number of common U.S. patent subclasses related to pharmaceutical and biotechnology areas (patent classes 514 and 435) between the two firms' patent portfolio in the 10-year window prior to the alliance divided by the maximum number of overlaps in the sample. The number of overlapping technology fields represent similarities in firms' knowledge bases (Diestre and Rajagopalan, 2012; Rothaermel and Boeker, 2008; Song, 2009). We use data from the *NBER 2006* patent database for all patent-based variables and account for organizational structure and acquisition history of firms.

Firm size

We measure firm size using the (logged) number of employees in the focal year. Our primary data sources for firm size are the *Directory of Corporate Affiliations* and *Compustat* historical databases. In cases where the number of employees at the year of alliance was not available, we instead searched for the number of employees at the closest available year.

Research capabilities

We use the (logged) number of a firm's patents in the U.S. patent subclasses related to pharmaceutical and biotechnology (patent classes 514 and 435) in the 10-year window prior to the alliance (Hoang and Rothaermel, 2010; Nerkar and Roberts, 2004). We apply a 10 percent depreciation to allow for more recent patents to have greater weights. In research-intensive industries, patenting is a good indicator of research capabilities.

Drug development capabilities

We use the (logged) number of a firm's FDA-approved drugs that were on the market in the 10-year window prior to the alliance (Diestre and Rajagopalan, 2012; Macher and Boerner, 2006). We use data on firm's approved drugs from the *drugs@FDA* database. Similar to the patent measures, we account for the organizational structure and acquisition history of firms and assume a 10 percent depreciation rate.

Geographic proximity

This is a pair-specific attribute measured as a dummy variable equal to 1 if the alliance partners are located in the same state (for U.S. firms) or the same country (for foreign firm), and 0 otherwise.

Number of prior alliances

This is a pair-specific attribute measured as the number of times the two partner firms had an alliance in the preceding 10 years. We draw on all biotechnology alliances (including research, manufacturing and distribution, etc.) recorded in the *ReCap* database.

Table 3 provides the descriptive statistics and the correlation matrix. These alliances vary considerably in terms of partner's size, research capability, drug development capability and geographic location. In supplementary analysis, we confirm that descriptive statistics for each market resemble that of the entire sample.

Results

Table 4 provides the maximum score estimation results. We estimate the coefficients using a template code in Mathematica provided by Santiago and Fox (2014). Coefficient estimates are obtained by applying the Differential Evolution routine for numerical optimization. We ran the procedure 20 times with different parameters for the routine (e.g., initial values, number of search points, scaling factor) to ensure reaching a global maximum. Confidence intervals are calculated using the subsampling procedure (Politis, Romano, and Wolf, 1999) across 200 random samples of four markets at a time. The results are robust to using 200 random samples of five markets at a time. We include multiplication of firm-level attributes

DOI: 10.1002/smj

Table 3. Descriptive statistics for biopharmaceutical alliances

Variable	Mean	s.d.	1	2	3	4	5	6	7	8
1. Technological overlap	0.025	0.055	1							
2. Biotech size	4.528	1.227	0.28	1						
3. Pharma size	10.255	1.329	0.15	0.01	1					
4. Biotech research capability	1.589	1.087	0.60	0.39	0.00	1				
5. Pharma research capability	5.038	1.594	0.26	0.01	0.49	0.03	1			
6. Pharma drug development capability	2.244	1.142	0.17	0.00	0.48	0.00	0.59	1		
7. Geographic proximity	0.071	0.258	0.01	0.01	−0.02	0.00	0.05	0.01	1	
8. Number of prior alliances	0.128	0.413	0.09	0.10	0.12	0.08	0.12	0.11	0.03	1

or pair-specific terms in order to assess complementarity. Under this specification of the matching equation, a positive coefficient suggests that the two attributes are complements (increasing return in joint value production), while a negative coefficient suggests that the two attributes are substitutes.

For scale normalization, we set the coefficient for technological overlap to equal 1. Inclusion of our baseline variable (i.e., technological overlap) is consistent with the literature highlighting the importance of knowledge similarity between alliance partners for alliance formation (Lane and Lubatkin, 1998; Mowery *et al.*, 1998; Rothaermel and Boeker, 2008). The baseline indicates that each firm perceives higher benefits from allying with a partner that is closer in the knowledge space rather than a partner that is more distant. We compare the magnitude of other coefficients to this baseline.

As seen in Table 4, 73 percent of the 5,214 inequalities in the model are predicted correctly, which shows that the estimation performs reasonably well given the observed attributes of firms included in the model. Column 1 in Table 4 shows presence of statistically significant (at 95% level) complementarities in partner firms' sizes and partner research capabilities, corroborating Hypotheses 1 and 2. However, in contrast to Hypothesis 3, we don't find empirical support for presence of complementarity between a biotechnology firm's research capability and a pharmaceutical firm's drug development capability. We have examined robustness of this nonfinding using alternative measures such as a firm's experience in downstream alliances and a firm's experience in late-stage alliances and could not find evidence in support of Hypothesis 3.

We also infer that geographic proximity and number of prior alliances lead to increasing returns in joint value production function. Both of these findings are consistent with the earlier literature highlighting the role of geographic proximity (Alcacer *et al.*, 2009; Reuer and Lahiri, 2014) and prior ties (Gulati, 1995) for partner selection. We note that the presence of a prior alliance between two firms may be considered either an indication either of unobserved pair-specific heterogeneity or of preferences to ally with a former partner; i.e., a structural state dependence in choice (Dube, Hitsch, and Rossi, 2010). These two explanations are difficult to disentangle empirically in our context. To ensure that our results are not driven by inclusion or exclusion of prior ties in the analysis, we drop this control variable in Model 2. The statistical significance and relative importance of our variables of interest are not sensitive to exclusion of this variable.

In addition to identifying complementarities, the magnitude of coefficient estimates allows us to assess the relative importance of partner attributes in creating joint value. Table 4, Column 2 shows the effect of one standard deviation change in the covariate on the joint value, when evaluated relative to the effect of changing the baseline by one standard deviation. Results show that, when included, prior alliances dominate other considerations. The next important complementarity arises between partners' research capabilities, indicating that firms with higher levels of research capability benefit when allying with a partner with high levels of research capability. The next important covariate is geographic proximity, which enhances joint value creation. Finally, synergies emerging from size and technological overlap also matter, in that order.

We also compare these results with estimates from logit models, shown in Table 5. Coefficients in logit represent cross-partial derivatives of the underlying utility function and can be directly used

DOI: 10.1002/smj

Table 4. Matching model estimations of complementarities in partner attributes

Relationship	Model 1		Model 2	
	Coefficient	Relative importance of covariates	Coefficient	Relative importance
Technological overlap	1	**0.05**	1	**0.05**
Biotech size × pharma size	**1.00** (0.25; 1.74)	**1.64**	**1.88** (0.54; 3.22)	**3.06**
Biotech research capability × pharma research capability	**3.08** (0.88; 5.28)	**5.34**	**5.44** (1.65; 9.25)	**9.43**
Biotech research capability × pharma drug development capability	0.41 (−1.34; 2.16)	Not significant	0.75 (−1.48; 2.99)	Not significant
Geographic proximity	**16.14** (4.88; 27.41)	**4.16**	**23.56** (7.18; 39.95)	**6.08**
Number of prior alliances	**29.84** (7.12; 52.28)	**12.3**	–	–
% correctly predicted inequalities	73%		70%	

95% confidence intervals in parentheses. Bold values indicate coefficient estimates within the 95% confidence interval.

Table 5. Logit estimations of likelihood of alliance formation

	Model 1		Model 2	
	Coefficient	Std. dev.	Coefficient	Std. dev.
Technological overlap	−1.342	1.126	−1.601	1.140
Biotech size × pharma size	0.007	0.027	0.018	0.027
Biotech research capability × pharma research capability	0.034	0.033	0.040	0.033
Biotech research capability × pharma drug development capability	0.018	0.038	0.026	0.038
Geographic proximity	0.694***	0.163	0.722***	0.163
Number of prior alliances	0.658***	0.106	–	–
Biotech size	−0.060	0.281	−0.151	0.283
Pharma size	0.042	0.128	0.007	0.129
Biotech research capability	−0.186	0.146	−0.208	0.147
Pharma research capability	0.111 *	0.059	0.114 *	0.059
Pharma drug development capability	0.013	0.075	0.011	0.074
Constant	−4.424	1.286	−4.139	1.293
% correctly predicted realized alliances	17.9%		11.4%	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

to infer complementarities. The estimates show complementarity in geographic proximity and number of previous alliances. However, the logit models are not able to uncover the complementarities in partners' sizes and research capabilities. In supplementary analyses, similar results hold for the rare events logit specification with a random subset of counterfactual alliances.

DISCUSSION

We underscore that although small-firm advantages of biotechnology firms and large-firm advantages of pharmaceutical firms may constitute the rationale for alliance formation in biopharmaceutical context, complementarities in partners' sizes result in larger firms on each side to ally. Moreover, partners' sizes may be related to their relative bargaining power within an alliance, which is a key consideration in biopharmaceutical alliances (Adegbesan and Higgins, 2011). Positive assortative matching in firm's size implies that the equilibrium of a matching market enables firms on each side of the market to engage in an alliance in which they maintain high relative bargaining power. This issue has implications for a recent debate in *SMJ* regarding factors driving partner selection in biopharmaceutical

DOI: 10.1002/smj

alliances. Diestre and Rajagopalan (2012), taking a biotechnology firm's perspective, assume that biotechnology firms have agency in increasing their bargaining power through choice of their preferred pharmaceutical firm. However, Mason and Drakeman (2014), taking a pharmaceutical firm's perspective, assume full agency for pharmaceutical firms. Taking a matching model perspective, our results are consistent with both views. Indeed, positive assortative matching in partners' sizes provides a more nuanced view, whereby the bargaining power of a firm is not determined by a relative difference in size but by the outside options available to each partner for alternative partners.

Our finding regarding positive assortative matching in partners' research capabilities has implications for the literature noting similarity in partners' patenting propensity as a key factor for alliance formation (Rothaermel and Boeker, 2008). Matching models enable us to tease out the implications of assortative matching from firms' preferences in partnering with similar firms. The empirical evidence that similarity in patenting propensity increases the likelihood of alliance formation may not be as much an indication of firms preferring similar partners but as a market competition for alliance partners in quest for complementarity in research capabilities.

We don't find support for Hypothesis 3. This is an important nonfinding because prior literature has characterized biopharmaceutical alliances as driven by considerations of additive fit between partners' research and development capabilities. The use of matching methods enables us to examine specifically how pharmaceutical firms with heterogeneous levels of development capabilities and biotechnology firms with heterogeneous levels of research capability match. We thus make an important distinction in partners' attributes between complementarities (arising from cross-partial derivative of the joint value function) versus additive fit (match with a firm that possesses what you lack) considerations. Lack of complementarities in research and drug development capabilities does not mean that these are not critical for alliance formation; rather, it shows that once a partner satisfies the minimum required level of either research or drug development capability, assortative matching patterns do not govern partner selection and random matching may suffice.

CONCLUSION

Complementarities in partner attributes represent an important question in the strategic alliances literature, since value creation in alliances is contingent on them. In this paper, we discuss the theoretical and empirical applicability of matching models to the context of strategic alliances. Matching models are particularly conducive to the study of "who partners with whom," since alliances represent the transaction of indivisible and heterogeneous goods when the identity (i.e., partner attributes) of the agents of both sides of the market matter and when there is rivalry on each side of the market for the "best" available partner. The latter permits researchers to infer that realized matches result not only because of true preferences but also because of market constraints. While empirical estimation of matching models traditionally suffered from the curse of dimensionality, recent econometric advancements have significantly reduced the computational burden of estimating these models. Accordingly, we provide a theoretical and empirical comparison of the maximum score estimator with the dominant discrete choice estimators to highlight limitations that arise from fundamental assumptions in discrete choice models in their use for assessing complementarity in partner attributes. We apply the method to the biopharmaceutical alliance context, examining complementarities in the three key attributes of partners' sizes, research capabilities, and drug development capabilities.

While we primarily focused on value creation in alliances, the market perspective that we employ enables the incorporation of ex-ante value appropriation issues. Because the matching model relies on voluntary decision making, each firm enters into an alliance only if, net of transfer payments, it perceives higher utility from the alliance than being solo. Additionally, the equilibrium inequalities account for transfer payments within both realized and counterfactual alliances. Thus, equilibrium outcomes allow for firms being able to attract a desirable partner by offering a higher share of the value being created through higher transfer payments. Such transfer payments, nonetheless, are bound from below, as attractive partners are likely to find higher opportunities elsewhere in the market such that the value created from those alternatives, net of transfer payments, is still higher than the value appropriated from the focal alliance. The boundaries around value creation that are caused

DOI: 10.1002/smj

due to the alternative options for alliancing in the market dictate the bargaining around value appropriation among potential alliance partners. This key feature of the market perspective for strategic alliances thus permits value appropriation factors to be accounted for.

Contributions

We begin with the empirical contributions of the paper: We illustrate how maximum score estimators can be used to identify complementarities in partners' attributes in markets that conform to the theoretical characteristics of strategic alliances. We highlight the need for researchers to think through carefully which methodology is most appropriate for the underlying context, as the dominant binary choice specifications make assumptions that may render them inapplicable to contexts where complementarities and competition are important factors for partner selection. Particularly, in light of the high bias of the coefficients in the simulation setting and the divergence across logit estimates in the biopharmaceutical alliances context, an important implication of our study is that future researchers think through the methodological issues that impact support, or lack thereof, of their hypothesized relationships when studying factors influencing formation of strategic alliances. More generally, while the maximum score estimator is among the most recent advances in matching model estimation techniques, we increase the awareness among strategic management researchers of these methods with the hope that future methodological advances may diffuse quickly within our field.

Theoretically, our paper contributes to the literature by adopting a market perspective. Extant research has focused on complementarities in partner attributes as a chief driver of joint value creation. We show that, while complementarity in partner attributes is a necessary condition, it is not sufficient for partner selection. Instead, market interdependencies may constrain the choice set, such that some firms will not be able to ally with their most preferred partner. As a result, sorting governs partner selection, given complementarities. Taking a focal or dual firm perspective, extant studies tend to infer preferences from observed relationships. In highlighting the role of sorting, over and above complementarities, we show how studies may have made erroneous inferences regarding firm preferences: firms scoring low in their relative ranking to others may have to settle with the best available partner, in spite of their preferences. Extant studies on ex-ante alliance performance have highlighted the role of partner selection, emerging from the anticipation of complementarity in attributes. We show that there is an additional source of selection, caused because competition results in the sorting of firms based on the relative rankings of their attributes.

In terms of managerial implications, much is known about the strategic factors leading to higher performance. Less is known about how to compete for getting a better partner. Our study underscores that managers should think through how their investments in resources and capabilities may shape their attractiveness to partners that they seek. Given that partners represent an indivisible bundle of multiple attributes, the ordinal importance of attributes revealed by the matching method may allow mangers to invest differentially in attributes, based on which ones are more salient for complementarities and their own attractiveness to desirable partners. Further, as sorting amplifies the performance consequences, the variance in performance is higher in the presence of sorting rather than its absence. Thus, firms can create "what if" scenarios to assess the performance effect of sorting, separately from complementarities, and more accurately estimate what the appropriate transfer payment ought to be, so as to secure their preferred partner. Simply put, competition in the market for alliances disciplines managers to think about the size of the pie they can create through partnering, even as they worry in bilateral bargaining about their share of the pie (Chatain, 2011).

Future research opportunities

One avenue for future research is to go beyond dyads and study multipartner alliances and complementarities within and across the portfolio of alliances (Moeen, Somaya, and Mahoney, 2013), an area whose dearth of studies has been recently noted (Heidl, Steensma, and Phelps, 2014). The one-to-many and many-to-many matching framework incorporates such scenarios. Additionally, identification of strategic alliance contexts where the joint value creation of multiple partners results from interdependencies at a portfolio level would help create new theories that are context specific, but that nonetheless extend our understanding of factors that impact partner selection and complementarities in these situations. Thus, matching

DOI: 10.1002/smj

theory may be applicable within an ecosystem framework, wherein multiple firms contribute jointly by creating value through complementarities across the different partners' attributes. Further, while the focus of our study has been on the partner selection and ex-ante consideration of complementarities, the role that selection due to sorting plays in ex post alliance performance is deserving of attention. Finally, as indicated in the introduction, matching theory can apply to a variety of strategic management questions, as long as the market is characterized by multi-sided decision making by voluntary participants, quest for complementarities between indivisible and heterogeneous attributes, and competition on each side.

In sum, we hope that our paper has provided the basis for strategic management researchers to embrace the matching model logic when applicable, both in their theorizing and empirical applications. In doing so, our work may help researchers improve the answers, based on reliable research design. The use of matching models is in line with recent calls for identification, since they address selection and sorting effects, and permit researchers to distinguish the role of the distribution of exogenous partner characteristics from the role of the alliance as a "match production function." Thus, by assessing complementarities and substitutions of partner attributes, matching models permit better identification of the value creation through strategic alliances.

ACKNOWLEDGMENTS

We would like to thank Theodore Chronis for programming, and Heejung Byun, Justin Frake and Martin Goossen for research assistance. The manuscript has benefited from comments from the editors Ashish Arora and Will Mitchell, three anonymous reviewers, Thomas Astebro, Carnahan, Olivier Chatain, J. Anthony Cookson, Jeremy Fox, and seminar participants at the 2014 ACAC conference, 2014 Academy of Management Meeting, HEC Paris, National University of Singapore, and University of Maryland.

REFERENCES

Adegbesan JA, Higgins MJ. 2011. The intra-alliance division of value created through collaboration. *Strategic Management Journal* **32**(2): 187–211.

Aggarwal V. 2014. Alliance portfolios and resource competition: how a firm's partners' partners influence the benefits of collaboration. Working Paper, INSEAD, Fontainebleau, France.

Ahuja G. 2000. The duality of collaboration: inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal* **21**(3): 317–343.

Ahuja G, Polidoro F, Mitchell W. 2009. Structural homophily or social asymmetry? The formation of alliances by poorly embedded firms. *Strategic Management Journal* **30**(9): 941–958.

Akkus O, Cookson A, Hortacsu A. 2015. The determinante of bank mergers: a revealed preference analysis. *Management Science* (Forthcoming).

Alcacer J, Cantwell J, Gittelman M. 2009. Are licensing markets local? An analysis of the geography of vertical licensing agreements in bio-pharmaceuticals. Working paper. Harvard Business School, Harvard University, Boston, MA.

Arora A, Fosfuri A, Gambardella A. 2001. *Markets for Technology: The Economics of Innovation and Corporate Strategy*. MIT Press: Cambridge, MA.

Arora A, Gambardella A. 1994. Evaluating technological information and utilizing it: scientific knowledge, technological capability, and external linkages in biotechnology. *Journal of Economic Behavior & Organization* **24**(1): 91–114.

Arora A, Gambardella A, Magazzini L, Pammolli F. 2009. A breath of fresh air? Firm type, scale, scope, and selection effects in drug development. *Management Science* **55**(10): 1638–1653.

Atakan AE. 2006. Assortative matching with explicit search costs. *Econometrica* **74**(3): 667–680.

Baccara M, İmrohoroğlu A, Wilson AJ, Yariv L. 2012. A field study on matching with network externalities. *American Economic Review* **102**(5): 1773–1804.

Banal-Estañol A, Macho-Stadler I, Pérez-Castrillo D. 2015. Endogeneous matching in university-industry collaboration: theory and empirical evidence from the UK, Barcelona GSE *Working Paper* Series 704, Pompeu Fabra University, Barcelona, Spain.

Baum JA, Calabrese T, Silverman BS. 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal* **21**(3): 267–294.

Becker GS. 1973. A theory of marriage: Part I. *Journal of Political Economy* **81**(4): 813–846.

Beckman CM, Haunschild PR, Phillips DJ. 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. *Organization Science* **15**(3): 259–275.

Cabral L, Pacheco de Almeida G. 2014. The distributional properties of interorganizational value. Working paper, HEC, Paris, France.

Capron L, Mitchell W. 2012. *Build, Borrow or Buy: Solving the Growth Dilemma*. Harvard Business Press: Boston, MA.

Ceccagnoli M, Higgins MJ, Palermo V. 2014. Behind the scenes: sources of complementarity in R&D. *Journal of Economics and Management Strategy* **23**(1): 125–148.

Chatain O. 2011. Value creation, competition, and performance in buyer-supplier relationships. *Strategic Management Journal* **32**(1): 76–102.

Chatain O. 2014. Estimating value creation from revealed preferences: application to value-based strategy. Working paper, HEC, Paris, France.

Chen J, Song K. 2013. Two-sided matching in the loan market. *International Journal of Industrial Organization* **31**(2): 145–152.

Chiappori PA, Salanié B, Weiss Y. 2012. Partner choice and the marital college premium. Working paper, Columbia University: New York, NY.

Choo E, Siow A. 2006. Who marries whom and why. *Journal of Political Economy* **114**(1): 175–201.

Chung S, Singh H, Lee K. 2000. Complementarity, status similarity and social capital as drivers of alliance formation. *Strategic Management Journal* **21**(1): 1–22.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1): 128–152.

Coleman JS. 1991. Matching processes in the labor market. *Acta Sociologica* **34**(1): 3–12.

Diestre L, Rajagopalan N. 2012. Are all 'sharks' dangerous? New biotechnology ventures and partner selection in R&D alliances. *Strategic Management Journal* **33**(10): 1115–1134.

Dube JP, Hitsch GJ, Rossi PE. 2010. State dependence and alternative explanations for consumer inertia. *RAND Journal of Economics* **41**(3): 417–445.

Dupuy A, Galichon A. 2014. Personality traits and the marriage market. *Journal of Political Economy* **122**(6): 1271–1319.

Dussauge P, Garrette B, Mitchell W. 2000. Learning from competing partners: outcomes and durations of scale and link alliances in Europe, North America and Asia. *Strategic Management Journal* **21**(2): 99–126.

Dushnitsky G, Shaver JM. 2009. Limitations to inter-organizational knowledge acquisition: the paradox of corporate venture capital. *Strategic Management Journal* **30**(10): 1045–1064.

Fernando CS, Gatchev VA, Spindt PA. 2005. Wanna dance? How firms and underwriters choose each other. *Journal of Finance* **60**(5): 2437–2469.

Fox JT. 2010a. Identification in matching games. *Quantitative Economics* **1**(2): 203–254.

Fox JT. 2010b. Estimating matching games with transfers. Working paper, University of Michigan, Ann Arbor, MI.

Fox JT, Bajari P. 2013. Measuring the efficiency of an FCC spectrum auction. *American Economic Journal: Microeconomics* **5**(1): 100–146.

Fox JT, Santiago D. 2014. A toolkit for matching maximum score estimation and point and set identified sub-sampling inference. Working paper, University of Michigan: Ann Arbor, MI.

Fox JT, Yang C. 2012. Unobserved heterogeneity in matching games. NBER working paper 18168, National Bureau of Economic Research, Cambridge, MA.

Gabaix X, Landier A. 2008. Why has CEO pay increased so much? *Quarterly Journal of Economics* **123**(1): 49–100.

Gale D, Shapley LS. 1962. College admissions and the stability of marriage. *American Mathematical Monthly* **69**: 9–15.

Galichon A, Salanie B. 2015. Cupid's invisible hand: social surplus and identification in matching models. Working paper. Available at SSRN: http://ssrn.com/abstract=1804623 (accessed 3 November 2015).

Geringer JM. 1991. Strategic determinants of partner selection criteria in international joint ventures. *Journal of International Business Studies* **22**(1): 41–62.

Garcia-Pont C, Nohria N. 2002. Local versus global mimetism: the dynamics of alliance formation in the automobile industry. *Strategic Management Journal* **23**(4): 307–321.

Gimeno J. 2004. Competition within and between networks: the contingent effect of competitive embeddedness on alliance formation. *Academy of Management Journal* **47**(6): 820–842.

Giovannetti G, Morrison S. 2000. *Convergence: The Biotechnology Industry Report*. Ernst & Young: Palo Alto, CA.

Graham BS. 2011. Econometric methods for the analysis of assignment problems in the presence of complementarity and social spillovers. In *Handbook of Social Economics* (Volume 1), Benhabib J, Bisin A, Jackson M (eds). Elsevier N.V.: Amsterdam, The Netherlands; 965–1052.

Greve HR, Mitsuhashi H, Baum JAC. 2013. Greener pastures: outside options and strategic alliance withdrawal. *Organization Science* **24**(1): 79–98.

Gulati R. 1995. Social structure and alliance formation patterns: a longitudinal analysis. *Administrative Science Quarterly* **40**(4): 619.

Gulati R, Gargiulo M. 1999. Where do interorganizational networks come from? *American Journal of Sociology* **104**(5): 1439–1493.

Hallen BL. 2008. The causes and consequences of the initial network positions of new organizations: from whom do entrepreneurs receive investments? *Administrative Science Quarterly* **53**(4): 685–718.

Heidl RA, Steensma HK, Phelps C. 2014. Divisive faultlines and the unplanned dissolutions of multipartner alliances. *Organization Science* **25**(5): 1351–1371.

Helfat CE. 1997. Know-how and asset complementarity and dynamic capability accumulation: the case of R&D. *Strategic Management Journal* **18**(5): 339–360.

Henderson R, Cockburn I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal* **15**(S1): 63–84.

Henderson R, Cockburn I. 1996. Scale, scope, and spillovers: the determinants of research productivity in drug discovery. *RAND Journal of Economics* **27**(1): 32–59.

Hitt MA, Ahlstrom D, Dacin MT, Levitas E, Svobodina L. 2004. The institutional effects on strategic alliance

partner selection in transition economies: China vs. *Russia. Organization Science* **15**(2): 173–185.
Hitt MA, Dacin MT, Levitas E, Arregle JL, Borza A. 2000. Partner selection in emerging and developed market contexts: resource-based and organizational learning perspectives. *Academy of Management Journal* **43**(3): 449–467.
Hoang H, Rothaermel FT. 2010. Leveraging internal and external experience: exploration, exploitation, and R&D project performance. *Strategic Management Journal* **31**(7): 734–758.
Hoetker G. 2005. How much you know versus how well I know you: selecting a supplier for a technically innovative component. *Strategic Management Journal* **26**(1): 75–96.
King G, Zeng L. 2001. Logistic regression in rare events data. *Political Analysis* **9**(2): 137–163.
Koopmans T, Beckmann M. 1957. Assignment problems and the location of economic activities. *Econometrica* **25**(1): 53–76.
Lane PJ, Lubatkin M. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* **19**(5): 461–477.
Levinthal DA, Wu B. 2010. Opportunity costs and non-scale free capabilities: profit maximization, corporate scope, and profit margins. *Strategic Management Journal* **31**(7): 780–801.
Li SX, Rowley TJ. 2002. Inertia and evaluation mechanisms in interorganizational partner selection: syndicate formation among US investment banks. *Academy of Management Journal* **45**(6): 1104–1119.
Li D, Eden L, Hitt MA, Ireland RD. 2008. Friends, acquaintances, or strangers? Partner selection in R&D alliances. *Academy of Management Journal* **51**(2): 315–334.
MacDonald G, Ryall MD. 2004. How do value creation and competition determine whether a firm appropriates value? *Management Science* **50**(10): 1319–1333.
Macher JT, Boerner CS. 2006. Experience and scale and scope economies: trade-offs and performance in development. *Strategic Management Journal* **27**(9): 845–865.
Mackey A, Molloy JC, Morris SS. 2014. Scarce human capital in managerial labor markets. *Journal of Management*, **40**: 339–421.
Manski CF. 1975. Maximum score estimation of the stochastic utility model of choice. *Journal of Econometrics* **3**(3): 205–228.
Mason R, Drakeman DL. 2014. Fishing for sharks: partner selection in biopharmaceutical R&D alliances. *Strategic Management Journal* **35**(10): 1564–1565.
Milgrom P, Roberts J. 1995. Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics* **19**(2): 179–208.
Mindruta D. 2013. Value creation in university-firm research collaborations: a matching approach. *Strategic Management Journal* **34**(6): 644–665.
Mitsuhashi H, Greve HR. 2009. A matching theory of alliance formation and organizational success: complementarity and compatibility. *Academy of Management Journal* **52**(5): 975–995.
Moeen M, Somaya D, Mahoney JT. 2013. Supply portfolio concentration in outsourced knowledge-based services. *Organization Science* **24**(1): 262–279.
Mortensen DT. 1988. Matching: finding a partner for life or otherwise. *American Journal of Sociology* **94**(1): 215–240.
Mowery DC, Oxley JE, Silverman BS. 1998. Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Research Policy* **27**(5): 507–523.
Nerkar A, Roberts PW. 2004. Technological and product market experience and the success of new product introductions in the pharmaceutical industry. *Strategic Management Journal* **25**(8–9): 779–799.
Ostrovsky M. 2008. Stability in supply chain networks. *American Economic Review* **98**(3): 897–923.
Oxley JE. 1997. Appropriability hazards and governance in strategic alliances: a transaction cost approach. *Journal of Law, Economics, and Organization* **13**(2): 387–409.
Ozcan Y. 2015. Innovation and acquisition: two-sided matching in M&A markets. Working paper, Kellogg School of Management, Northwestern University, Evanston, IL.
Pan Y. 2015. The determinants and impact of executive-firm matches. Working Paper. Available at http://ssrn.com/abstract=1571892 (accessed 3 November 2015).
Parmigiani A, Mitchell W. 2009. Complementarity, capabilities, and the boundaries of the firm: the impact of within-firm and interfirm expertise on concurrent sourcing of complementary components. *Strategic Management Journal* **30**(10): 1065–1091.
Podolny JM. 1994. Market uncertainty and the social character of economic exchange. *Administrative Science Quarterly* **39**(3): 458–483.
Politis D, Romano J, Wolf M. 1999. *Subsampling*. Springer: New York.
Reuer JJ, Lahiri N. 2014. Searching for alliance partners: effects of geographic distance on the formation of R&D collaborations. *Organization Science* **25**(1): 283–298.
Rosenkopf L, Metiu A, George VP. 2001. From the bottom up? Technical committee activity and alliance formation. *Administrative Science Quarterly* **46**(4): 748–772.
Rosenkopf L, Padula G. 2008. Investigating the microstructure of network evolution: alliance formation in the mobile communications industry. *Organization Science* **19**(5): 669–687.
Roth AE. 1984. Stability and polarization of interests in job matching. *Econometrica* **52**(1): 47–57.
Roth AE, Sotomayor MA. 1990. *Two-Sided Matching: A Study in Game-Theoretic Modeling and Analysis*. Cambridge University Press: Cambridge, UK.
Rothaermel FT. 2002. Technological discontinuities and interfirm cooperation: what determines a startup's attractiveness as alliance partner? *IEEE Transactions on Engineering Management* **49**(4): 388–397.
Rothaermel FT, Boeker W. 2008. Old technology meets new technology: complementarities, similarities, and

alliance formation. *Strategic Management Journal* **29**(1): 47–77.
Rothaermel FT, Hess AM. 2007. Building dynamic capabilities: innovation driven by individual-, firm-, and network-level effects. *Organization Science* **18**(6): 898–921.
Sampson RC. 2007. R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. *Academy of Management Journal* **50**(2): 364–386.
Santiago D, Fox JT. 2014. A toolkit for matching maximum score estimation and point and set identified subsampling inference. Working paper, University of Michigan: Ann Arbor, MI.
Shah RH, Swaminathan V. 2008. Factors influencing partner selection in strategic alliances: the moderating role of alliance context. *Strategic Management Journal* **29**(5): 471–494.
Shapley LS, Shubik M. 1971. The assignment game I: the core. *International Journal of Game Theory* **1**(1): 111–130.
Shimer R, Smith L. 2000. Assortative matching and search. *Econometrica* **68**(2): 343–369.
Song K. 2009. Drug R&D alliances and innovation: a two-sided matching model of the licensing market in the biotechnology-pharmaceutical industry. Working paper, University of California, Irvine, CA.
Sørensen M. 2007. How smart is smart money? A two-sided matching model of venture capital. *Journal of Finance* **62**(6): 2725–2762.
Sorenson O, Stuart TE. 2001. Syndication networks and the spatial distribution of venture capital investments1. *American Journal of Sociology* **106**(6): 1546–1588.
Sorenson O, Stuart TE. 2008. Bringing the context back in: settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly* **53**(2): 266–294.
Stern I, Dukerich JM, Zajac E. 2014. Unmixed signals: how reputation and status affect alliance formation. *Strategic Management Journal* **35**(4): 512–531.
Stovel K, Fountain C. 2009. Matching. In *The Oxford Handbook of Analytical Sociology*, Hedstrom P, Bearman P (eds). New York, NY; 365–390.
Stuart T. 1998. Network positions and propensities to collaborate: an investigation of strategic alliance formation in a high-technology industry. *Administrative Science Quarterly* **43**(3): 668–698.
Stuart TE, Hoang H, Hybels RC. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* **44**(2): 315–349.
Teece DJ. 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. *Research Policy* **15**(6): 285–305.
Terviö M. 2008. The difference that CEOs make: an assignment model approach. *American Economic Review* **98**(3): 642–668.
Train K. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press: New York, NY.
Yang Y, Goldfarb A. 2015. Banning controversial sponsors: understanding equilibrium outcomes when sports sponsorships are viewed as two-sided matches. *Journal of Marketing Research* **52**(5): 593–615.
Yang Y, Shi M, Goldfarb A. 2009. Estimating the value of brand alliances in professional team sports. *Marketing Science* **28**(6): 1095–1111.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. Extension to one-to-many and many-to-many alliances.

Appendix S2. Comparing relative performance of the empirical methodologies in a simulation.

DOI: 10.1002/smj