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When the weak are mighty: A two-sided matching approach to alliance performance

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Abstracts

Research Summary: Network centrality is an important determinant of alliance performance. However, estimating how each alliance member's centrality affects alliance performance is challenging because the end market might value each partner's contribution differently. We solve this empirical question with a two-sided matching model that accounts for the partners' endogenous selection and estimates the effect of each side's centrality and input quality on performance. We implement the method in the novel context of the Thoroughbred horse industry, in foal-sharing alliances between buyers and suppliers. We find that buyer centrality has a larger marginal effect on the alliance performance than the supplier centrality because buyers, who on average are less central in our context, are more likely to diffuse valuable information to the end market.

Managerial Summary: Alliance partners often struggle with identifying what their contributions and their partner's contribution are to the alliance performance. We use a new method to identify each side's contribution to their alliance. Our findings offer a few recommendations to firms forming similar alliances. First, we

Authors' names are in alphabetical order. All authors contributed equally to this work.

find that the less central partner in the business network has greater impact on the alliance performance due to their ability to diffuse more valuable information to the market. Second, our results suggest that product input quality that is relatively unknown impacts alliance performance more than low and average quality. Alliance partners may benefit more from experimenting with unknown inputs. Third, more central actors may reduce spending on mass communications if valuable information comes to the market through their less central partners.

KEYWORDS

alliance performance, centrality, information diffusion, networks, two-sided matching

1 | INTRODUCTION

Strategy scholars have long studied the relationship between network centrality and performance (e.g., Gulati, Nohria, & Zaheer, 2000). Firms form networks of relationships with other business partners such as suppliers and distributors, and horizontal partnerships. Network centrality captures the extent of involvement a firm has in a business network (Bell, 2005; Borgatti, 2005). A firm can use its centrality to gain access to resources and information (Bell, 2005; Knoke & Burt, 1983; Wasserman & Faust, 1994), and influence information diffusion throughout a network (Borgatti, 2005). Much of the previous research on networks focuses on the positional benefits of centrality, including what the end market infers from firms' position in the industry network (Lin, Yang, & Arya, 2009; Stuart, Hoang, & Hybels, 1999; Zaheer, Gözübüyük, & Milanov, 2010). However, centrality is also vital in facilitating information diffusion resulting in innovations and new business opportunities (e.g., Aral, 2016; Granovetter, 1973; Rogers, 1995).

Firms are embedded in industry networks, ensuring that their network centrality impacts alliance formation (Ahuja, Polidoro, & Mitchell, 2009; Powell, Koput, & Smith-Doerr, 1996) and their performance (Rowley, Behrens, & Krackhardt, 2000). Each alliance partner's respective network ties can diffuse information about the final product to the end market (Hansen, 1999; Rogers, 1995) and allows the end market to infer information from these ties (Lin et al., 2009; Stuart et al., 1999), which in turn determines alliance performance. Still, the end market may value differently the separate contributions from the alliance partners. Therefore, in alliances, each partner's network centrality might impact alliance performance differently.

It is thus a long-lasting empirical question to estimate each partner's direct contribution to the performance of the alliance (e.g., Anderson, 1990; Lunnan & Haugland, 2008). Answering this question is fraught with empirical challenges because unobserved characteristics, such as endogenous quality and network centrality, are easily confounded in the partner selection and performance estimations. Regressing performance on partners' characteristics exposes the coefficients to omitted variable biases if unobserved characteristics influence partner selection and alliance performance (Greve, Mitsuhashi, & Baum, 2013; Shaver, 1998; Sørensen, 2007).

In this paper, we investigate the relationship between network centrality and alliance performance in the context of alliances between partners fulfilling different roles. Firms can execute alliances by fulfilling different roles in a variety of ways - for instance, biotech and pharmaceutical firms (Mindruta, Moeen, & Agarwal, 2016), designers and manufacturers (Ni & Srinivasan, 2015), or suppliers and purchasers (McEvily, Zaheer, & Fudge Kamal, 2017). We use a rigorous method to empirically estimate the contributions from suppliers and buyers on alliance performance while accounting for the mutual selection of partners in the alliance. Specifically, we jointly estimate a performance equation with a two-sided matching model to address the alliance partners' mutual selection. Our method captures the effect of unobserved characteristics by comparing the matches resulting from the selection and corresponding performance across multiple markets (Chen, 2013; Honoré & Ganco, 2020; Park, 2013; Sørensen, 2007). The model estimates performance explicitly without assuming the drivers of selection automatically explain alliance performance (e.g., Mindruta, 2013).

We employ a two-sided matching model to study buyer and supplier's effects on auction prices, in the novel context of the Thoroughbred horse industry with foal-sharing alliance contracts. In each foal-sharing alliance, the supplier, which is a stud farm that owns sires (male horses), agrees with a buyer, which is a nursery that owns dams (female horses) to match a sire and a dam to co-produce an offspring to sell at auction to the end market, the bidders. The offspring sells as a yearling, a horse that is 1 year old. The partners operate as joint owners of the offspring in the end market at auction: they create the new product, share information about the product within the alliance, and sell the product at auction.

The industry provides a rich empirical setting with exogenous quality measures of the inputs, in the form of genetic characteristics for the parents of the offspring, allowing us to disentangle the effects of centrality from input quality. We also capture a financial performance measure in the form of an auction price at the alliance level. The information revealed to the market becomes aggregated in a market price (e.g., Hayek, 1945; Smith, 1982), which we use as the outcome of the alliance. The price reveals through an English auction mechanism the valuation assigned by the end-market bidders to the new product, the yearling horse.

Our empirical setting is particularly well suited for estimation with a two-sided matching model. First, the institutional setting has a fixed annual cycle with eight major auctions held every year. In this industry, all firms participate in the market, and no firm can wait for a different market, which fits the assumptions of the matching model. Second, the industry is also characterized by role specialization that places firms either as buyers or suppliers (nurseries and stud farms). Thus, we can use a model with two distinct sides. Third, each unique match between a sire and a dam represents a contract with fixed equity terms that remain constant across all agents and transactions (60% to the dam owner, the nursery, 40% to the sire owner, the stud farm). Therefore, we use a model with nontransferable utility. Fourth, each year, the buyers, the nurseries, are limited to one transaction for each horse while the suppliers, the stud farms, can have many transactions per horse, which allows us to use a one-to-many matching model. Thus, the identification properties of this setting are particularly well suited for separately measuring the buyer and supplier partner contributions.

Our results indicate that the respective buyers' (the nursery) and suppliers' (the stud farm) network centralities contribute positively to the alliance outcome. The buyer's centrality effect is three times larger than the supplier's centrality effect. In our context, the buyers are, on average less central than the suppliers. Based on our empirical and anecdotal evidence, we argue that the most plausible mechanism underlying the results is information diffusion because the bidders attach a higher marginal value to buyers' centrality as observed in the larger effect of the buyers' centrality on alliance performance. If the bidders inferred higher value based on network centrality, without relying on direct information diffusion, the effect of suppliers' centrality on alliance performance should have been larger. Specifically, we think that the more central partner might have overly diffused the information about the product, making the information from the relatively less central partners more valuable to the end market. The effect is even more pronounced in situations where the end market is particularly in need of direct information (such as a mismatch of input quality from the two partners or new geographical partners entering an auction).

To summarize, our paper's contribution is three-fold. We use a new empirical method of identifying each partner's contributions to the alliance performance by employing a two-sided matching model. The model accounts for endogeneity due to unobserved characteristics that affect selection and performance. We empirically disentangle the respective benefits, such as quality and network centrality, alliance members bring to the alliance. We find that, despite being the less central partner in the business network, buyers exert a greater influence, at the margin, on alliance performance.

2 | ALLIANCE PERFORMANCE, INFORMATION DIFFUSION, AND NETWORK CENTRALITY

Firms can use alliances to access high-quality inputs and to create and sell new products (Hoetker, 2005). Firms self-select into such alliances to increase their respective performance (e.g., Greve et al., 2013; Mindruta, 2013; Shaver, 1998). The partners' main goal is to maximize the joint value of the alliance (e.g., Hagedoorn, 1993; Hamel, Doz, & Prahalad, 1989; Teece, 1992). Therefore, potential alliance partners compete for the partner most capable of providing the highest quality inputs (Das & Teng, 2000; Hennart & Reddy, 1997; Mindruta, 2013; Nistor & Selove, 2020) and more generally, for desirable partners (Chatain & Plaksenkova, 2019; Honoré & Ganco, 2020). Furthermore, each partner might bring different levels of contributions to the alliance. Research on inter-organizational relationships tends to use one party to proxy for the entire relationship and overlooks each partner's separate contributions (Graebner, Lumineau, & Fudge Kamal, 2020; Lumineau & Oliveira, 2018). This simplification might lead to erroneous conclusions about each firm's contribution to the alliance performance. For example, some of the partners' resources might be of similar quality while other resources might show different quality levels between partners, or a partner may lack a resource altogether. Therefore, in this paper, we examine the partners' mutual selection and each partner's separate contributions to the alliance performance while taking into account that these firms are part of a larger network of firms in the industry.

Firms are embedded in industry networks that they can use to select their alliance partners (Ahuja et al., 2009; Powell et al., 1996) and increase their performance (Rowley et al., 2000). Foundationally, network ties are conduits of information such that network participants diffuse and gather information through their network ties (Podolny, 2001). Seminal work established that weaker ties might bring valuable information to a network participant and might play a unique role in disseminating information to a broader network (Granovetter, 1973). Network centrality captures the position of network participants within the structure of their ties. Central participants diffuse information that is more easily recalled and shared more readily

TABLE 1 Seminal work on networks and their application in alliance research

Main mechanism	Network literature	Performance-related alliance literature
Information diffusion	Granovetter (1973), Rogers (1995), Podolny (pipes, 2001)	Rowley et al. (2000)
Information inference	Asch (1940), Merton (1968), Podolny (prism, 2001)	Lin et al. (2009), Stuart et al. (1999)

(Asch, 1940; Merton, 1968; Podolny, 2001). In contrast, less central participants help diffuse innovation to the broader network, enabling innovations to gain more traction (Rogers, 1995). The role of less central ties in networks is "particularly important in the diffusion of innovations because their links reach out into the entire system, while an interlocking network is more ingrown in nature" (Rogers, 1995, p. 295).

Two possible mechanisms of network centrality affect alliance performance. The network centrality of alliance partners can capture the information diffusion to the end market and can also reflect the end market's information inference about the product. Table 1 lists the seminal papers using each mechanism.[1] On one hand, information diffusion between the network and the end market positively affects alliance performance because both strong and weak ties share valuable information (Rowley et al., 2000). On the other hand, information inference from the end market positively affects alliance performance because the end market observes the network ties between central actors and examines past performances to make their purchasing decision (Lin et al., 2009; Stuart et al., 1999). More broadly, information inference in alliances also occurs through media coverage and press releases (Castellucci & Ertug, 2010).

Our paper disentangles the effect of each alliance partner's centrality on the alliance performance while controlling for quality and accounting for mutual selection in the alliance formation. We focus on buyers and suppliers that combine their inputs to create a product sold to the end market. Their respective network centrality can play two roles: directly diffuse information about the product to the end market or allow the end market to infer information about the products. In both cases, centrality of alliance partners can affect the end market's purchasing decisions. However, buyers' and suppliers' respective effect on the alliance performance might vary based on their centrality. Prior work about information diffusion suggests that less central partners might be able to diffuse valuable information (e.g., Hansen, 1999; Rogers, 1995). In contrast, prior work about information inference suggests that more central partners might have a more prominent role as the end market infers better resources from each firm's network position as centrality increases (e.g., Stuart et al., 1999). We use a context where on average the buyer is less central than the supplier to test whether each side's centrality impacts performance, and whether one side's marginal effect is larger than the other. If the supplier's centrality has a larger effect than the buyer centrality, the effect goes beyond a direct transmission of information and suggests information inference due to its more central position in the industry.

[1]For a detailed review of the literature on information diffusion and inference, refer to Table A1 in the Appendix. In Table A1, we include papers on information inference as a mechanism where actors in a network infer information about quality from network centrality and papers that use status where the end market infers information from other non-network sources to determine the quality and hierarchy of firms.

However, if buyer centrality has a larger effect than the supplier partner's centrality, information diffusion is a more plausible explanation, beyond information inference. The end market attaches a higher marginal value to the buyer information than to the supplier information. Suppliers in central positions regularly diffuse information about their new products and might overwhelm the end market with redundant information. In the next sections, we provide a thorough description of the context and method that allow us to discuss which explanation is more plausible and how these findings might inform future work.

3 | THE THOROUGHBRED HORSE INDUSTRY

The Thoroughbred horse industry focuses on horse breeding and horse sales at auction (Cassidy, 2007), estimated at $122 billion in economic impact in the United States (American Horse Council, 2018). The largest drivers of economic activity for the horse industry are stud fees and auctions. Thus, a firm's primary goal is to match horses with bloodlines known for producing successful racehorses and to sell the newly bred horses for profit. The auction bidders who buy the horses train them for racing and might breed them when their racing career is over.

We focus on yearlings,[2] one-year-old horses, created in "foal-sharing contracts," a well-defined alliance arrangement. Foal-sharing contracts are contracts in which both the nursery and the stud farm own a fixed share (60:40) of the foal (the offspring) by breeding a dam to a sire (Campbell, 2000; Hall, 1998; Kropp, Landen, & Donath, 1985). In these contracts, the suppliers are stud farms, which have multiple transactions per horse every year and dominate the economic market for breeding. The buyers are nurseries, who own the dams and are limited to producing one offspring per dam each year. Nurseries and stud farms collaborate, in foal-sharing alliances, to create offspring: they make the best genetic match expected to be successful, share information about the new horse, and auction it off together when the horse becomes 1 year old (yearling).

Partners select each other based on the genetic quality of the sire and dam, the position of the firm in the industry network for information, and other criteria such as dams' past pregnancies and farms' managerial capabilities. The performance of the alliance, the yearling price, is determined at auctions held in the second half of each year that draw many end-market bidders. Stakes are high in the alliance because these yearling horses are valuable.[3] The breeding network of firms found at auctions is highly influential as it directly represents the ties necessary to create horses for auction receipts from bidders. Thus, the activities related to the auctions are essential to disseminate information about the horses (i.e., sires, dams, and foals) and represent a significant bell-weather to the overall health of the industry (Cassidy, 2007).

3.1 | Information environment

The full potential of a yearling horse's racing ability is unknown as these horses have not trained or raced yet. In our context, auction bidders evaluate many horses up for auction in that

[2]An offspring is considered a *foal* once it is born and nurses. After the offspring is weaned from its dam it is referred to as a *weanling*, until it reaches its first birthday (January 1) when it becomes known as a *yearling*.
[3]On average, a yearling is worth about $50,000, but they can be worth millions.

year and also gather information in a small amount of time.[4] Buyers and suppliers in foal-sharing contracts diffuse information about their horses, such as the offspring's attitude and the veterinarian care, in addition to the publicly available bloodlines.

3.1.1 | Auction bidders in the larger business network

Thoroughbred horse auctions create excitement for the industry. Auctions are a typical English auction format where the auctioneer presents an opening bid, and subsequent bids from bidders increase in value. The auction itself is a social experience where the industry converges on the auction grounds to trade yearling horses.

At the auctions, bidders purchase horses to train and race them. High profile bidders are top trainers and owners associated with famous horse racing and breeding firms.[5] Many auction bidders choose to be discreet so as not to draw attention and start a bidding war. Bidders prefer side conversations to gather information from stud farms and nurseries under the shaded area of the barns. They also engage in subtle bidding cues from the paddock rather than the more visible auction gallery. Bid spotters are situated throughout the auction pavilion so that they can detect whether a tip of the hat, glasses, or a subtle nod in a crowded area indicates a bid. After the final bid, the auction companies settle the sale directly with the bidders or their agents. If the winning bidder uses an agent, the new owner's identity may not be revealed until years later during the racing career of the horse. The full network between bidders and the yearling horses they are considering is not observable. Fortunately, all the breeding alliances of yearlings created for auction provide a close approximation of a full network of ties in this industry that proxies for the intertwined social and business networks. In this industry rooted in tradition, where a handshake and formal contracts can span generations, most players have a business tie with other industry players through breeding contracts.

The industry has annual breeding and auction cycles: business ties in the previous year capture connections for each player in the industry to the most extensive available network. The business connections firms make in the year before each auction usually represent many years of repeated business dealings and proxy for the information diffusion of the full network of connections in this industry. In an interview we conducted, one bidder reflected they revisit prior breeders from the past because they found that "some [breeders] are easier to buy from."

Bidders tend to follow the same process every year. Prospective bidders and yearlings offered for sale arrive on the auction grounds 2 days before the sale, and the activity culminates with placing bids in the actual auction. Nurseries and stud farms promote information about the yearlings through their business network of acquaintances, often gained through the prior year's dealings. Cot Campbell, a famous racehorse owner, writes,

> Logistically, the inspection and reinspection of those animals and the research and preparation for their purchase are demanding with severe time constraints. In addition, you know practically everyone at the sale. You are constantly stopping to

[4]Some bidders boast that they are able to inspect 150 yearlings a day. However, many will also argue that decision fatigue sets in after viewing 50 horses and they are less effective in their scrutiny. Inspections are also frequently interrupted by informal meetings.

[5]For example, in 2006, a Bloodhorse list of top 10 bidders at the yearling auctions shows large operations with separate divisions for racing and breeding respectively. Two of the most famous bidders represented the firms Darley and Coolmore, which also have breeding divisions.

> shake hands, be told some hot item [yearling], or answer a question about the progress of a horse you bought in the past that may provide germane guidance on one of the offerings of this sale. (Campbell, 2000, p. 142)

The inspection involves visiting an owner's temporary stable on the auction grounds and requesting to see the horse of interest. Prospective bidders watch the horse walk in an oval, and the horse stands for an inspection as the offspring sells before beginning any training. Moreover, the prospective bidder has an opportunity to ask the breeder for information about the horse's temperament and get an estimate of the horse's potential reserve price (a minimum price for the horse to clear the auction). Importantly, bidders rely on direct ties for assessment of the horse, "Unless it is your closest friend, never ask another [bidder] what he thinks of a horse" (Campbell, 2000, p. 167). Bidders also consider competition with other potential bidders. Jeffrey Bloom, in the 2019 documentary *All In*, describes at the auction that, "You have to wait in line to buy a potentially two-million-dollar horse." Realizing that their most preferred horse might be above their budget, bidders gather information and finalize their shortlists before the auction.

During the actual auction, bidders continue to seek information and bid discreetly from the holding area. The holding area also contains stud farm representatives available to share any valuable updates about their horse. Cot Campbell states (2000, p. 147), "…while I'm waiting for my next [yearling]… I may[…] walk 'out back' and chew the fat with someone." Later, he writes, "I hurried up to watch [a yearling] sell. On the way, someone stopped me and I became engrossed in a juicy tidbit of gossip."

These social and business interactions are particularly important when the information made public about the yearlings is scarce or conflicting. For example, horses that come up for auctions in a different state than the one they were born raise questions about their expected quality for racing. Similarly, bidders need more information for a horse whose parents are not an obvious genetic match of input quality. Bidders must reconcile whether breeders were overly optimistic in these costly or risky decisions. In these situations, information shared in a social setting from trusted partners can help determine how high bidders should bid on the yearlings.

3.1.2 | Stud farms' information to bidders

Stud farms, the suppliers in our empirical setting, play an essential role in the industry. Will Farish, of the renowned Lane's End Stud farm, remarks, "stallions are 'the breadwinners.' Stallions tend to get most of the attention." (Patton, 2012) Stud farms often host open houses to allow prospective bidders and fans to visit iconic champions of the sport of racing. The richest and highest-profile horseraces in America, such as the Kentucky Derby and Breeders Cup Classic, emphasize male horses.[6] Male horses that win these top races become attractive sires. Ethnographer Cassidy (2007, p. 88) writes, "The stallion is the most valuable category of bloodstock." Justify, a recent triple crown winner, had his breeding rights sell for an estimated $75 million (Rovell, 2018). The trainer of the horse, Bob Baffert, recently missed buying a yearling that became a top two-year-old racehorse because he was so focused on the sires of the yearlings rather than both sire and dam (Cherwa, 2019). Baffert said "Jill [his wife] is always telling me, 'Do not be a sire snob,' but sometimes we let it get away from us."

[6]Female horses can also enter these races; however, few enter, and even fewer win.

Stud farms are deliberate in trying to influence these perceptions and thus saturate the market with information. They run long advertising campaigns, host open houses, and public tours where prospective breeders can inspect sires up close. Ethnographic research on this industry indicates that "The feat [of offering a successful sire] is achieved by advertising in the broadest sense" Cassidy (2007, p. 88). The stables are ornately decorated with stained-glass windows and lighting that makes the sires' haircoat gleam.

> To the modern [sire] manager, racing is not just a test of the breed, or even a gambling medium, but also a prolonged advertising campaign. The contemporary popularity of breeding theories such as dosage [an index that rates a horses' pedigree for speed, similar to AEI], which concentrate on the contribution of the stallion at the expense of the dam, depends on this, the current orientation of the yearling market. Cassidy (2007, p. 88)

3.1.3 | Nurseries' information to bidders

In contrast to visiting a stud farm, a visit to a nursery provides a very different experience. Within the alliance, nurseries and stud farms share information and decisions about the progress and care of the foal. Because of the nurseries' smaller scale, outside visitors such a bidders are often only invited by the owner or dam manager. To inspect a dam and its offspring, one might walk several acres across a field or disrupt a farmworker's day to groom and walk yearlings for the visitor. Prospective bidders gain insight about the water sources in the land or the climate of the nursery, which could potentially limit the growth of an offspring.

At the auction itself, bidders tend to have strong preferences for professionally presented yearlings with well-developed physical attributes. Direct observation and a connection to the nursery might provide more perspective. For example,

> Zenyatta, a hall of fame racehorse, was famously presented at auction with a skin fungus, which is quite common. David Ingordo, the winning auction bidder, (Lintner, 2018) recounts, "Hip 703 at the 2005 Keeneland September Yearling Sale had a skin disease on her 'which, at the end of the day, on a scale of one to 10, it's a 1 of an issue [...]. It happens when the horses come from the farm to the sale. [...] When the bidding stopped at $60,000] I thought I had bought the wrong horse."

The nurseries use a personalized way to diffuse information. Instead of holding large open houses or intense advertising campaigns like the stud farms, they rely on their limited ties to the business community to cultivate personalized relationships with other breeders and auction bidders. Cassidy (2007, p. 106) notes information from a nursery might even reveal a "proof of friendship or respect: "I wouldn't tell everyone this, Joe, but the Storm Cat [sire name] is the guy you want to be looking at. Him and the Rahy [another sire] filly."

To summarize, stud farms engage in extensive advertising campaigns (Conley, 2003); however, nurseries can leverage their direct ties to diffuse information. On the one hand, prospective bidders are likely to hear the same information through the network about the sire. Bidders might get overwhelmed by the flow of information about the potential hundreds of yearlings from that sire, which decreases the marginal value of a piece of information. On the other hand, as illustrated above, gaining information from nurseries is more challenging. Making a connection with a nursery is more time consuming and more costly on the auction grounds. Moreover, the information might not have been heard many times, which increases its marginal value. Overall, anecdotal evidence supports the greater marginal value of the information diffused by the less central firms, which are nurseries in our context.

4 | DATA

4.1 | Sample and data collection

We carried out a comprehensive data collection that combined several sources to assemble the dataset on foal-sharing contracts. We obtained proprietary data on auction entries of yearling horses from *Blood-Horse Auction Edge*, a publication produced before auctions. The publication includes the breeder names (the alliance partners) and the characteristics of the horses, including the quality of their genetic lines (Fudge, 2013). We retrieved auction prices publicly available from each auction company. We complemented our dataset with information about the stud farms compiled by *The Stallion Register*.

We selected all the foal-sharing contracts by identifying the yearlings with both a stud farm and a nursery listed as co-owners.[7] We focused on the period after the 2008 recession began so that the studied contracts are part of the same economic environment. Hence, the data used for estimation in the matching model range from the years 2009 to 2014. The resulting dataset includes 800 yearlings sold at eight major U.S. auctions.

4.2 | Dependent variables

The dependent variable is the *auction price* of the yearling produced and sold in a foal-sharing contract between a stud farm and a nursery. This alliance-level measure captures the performance of the alliance relationship (Geringer & Herbert, 1991). The measure conveys realized information aggregated in a market price (e.g., Hayek, 1945; Smith, 1982).

4.3 | Independent variables

We use two different measures for sire and dam quality. Each of these measures is well established in the Thoroughbred horse breeding industry: they represent the information available on the quality of each genetic family. Racehorse genetic families get evaluated by their performance on the racetrack (Tesio & Spinola, 1958). Sire quality incorporates the performance of their offspring. In contrast, dam quality reflects her racing record, as dams produce only one offspring each year, limiting the data available on the progeny for the end market.

[7]Yearlings created internally in a nursery (with both the dam and the sire belonging to the same company) are excluded from this analysis. Those horses are considered internal transactions and are not alliances because the owner of the farm reaps 100% of the profit.

4.3.1 | Sire quality

Firms and auction houses carefully track sire quality: its most robust indicator is called the "Average Earnings Index" (AEI). The AEI represents the number of winners each sire produces, weighted by the purse money their offspring won and then compared to other similar sires. The distribution of sire quality is skewed because sires at the beginning of their stud career have zero or very low AEI (little or no available information about offspring racing). Moreover, the AEI might have a nonlinear relationship with the yearling price. We break down this variable into five categories entered as five dummies into the model from category 0 to category 4. Category 0 is the omitted category in the model and thus, serves as a baseline to interpret the results.[8]

4.3.2 | Dam quality

Dams have a limited amount of offspring over their reproductive lifespan, so the industry relies on the dam's racing record instead of her offspring's record. We use the index for the winning record called "Class Performance Index" (CPI), a weighted measure based on the quality of races that the dam won relative to the race records of other horses who raced in the same period. If a dam has never raced, her quality measure is zero. Dam quality has a skewed distribution because some dams have never raced while a handful of dams have won major races. Moreover, the relationship between dam quality and the yearling price might not be linear. We break down the measure of dam quality into five dummy variables from category 0 to category 4, with category 0 being the omitted category in the model.[9]

4.3.3 | Eigenvector centrality

The nurseries and stud farms that enter foal-sharing agreements are also part of a larger business network, including all inter-firm business relationships for breeding (foal-sharing agreements and spot market transactions). On average, each year, there are around 5,000 breeders in the market producing yearlings. The nodes in the network are the breeders, and the ties are all the yearlings created that year.[10] We use all available transactions between 2008 and 2013 to create a full network following the usual practice of measuring a network previous to the outcome (e.g., Banerjee, Chandrasekhar, Duflo, & Jackson, 2013; Schilling & Phelps, 2007; Zaheer & Soda, 2009). In the Thoroughbred horse industry, foal-sharing contracts follow yearly markets: breeders produce horses to sell at annual yearling auctions. Thus, we observe all the breeders in a network for a market in a given year, which allows us to use the previous year's network to capture the network of relationships in the industry.[11]

[8]The categories are the following: category 0 when AEI is 0; category 1 when AEI is strictly greater than zero and less than or equal to 1; category 2 when AEI is strictly greater than 1 and less than or equal to 1.5; category 3 when AEI is strictly greater than 1.5 and less than or equal to 2; and category 4 when AEI is greater than 2.

[9]The categories are the following: category 0 when CPI is 0; category 1 when CPI is strictly greater than zero and less than or equal to 1; category 2 when CPI is strictly greater than 1 and less than or equal to 2.6; category 3 when CPI is strictly greater than 2.6 and less than 5; and category 4 when CPI is greater than or equal to 5.

[10]A cell in the network matrix is any yearling produced by two breeders, a stud farm and a nursery—not by two horses.

[11]In this context we know when the contracts start and end. Moreover, the industry operates on a yearly basis which implies the networks are limited to a yearly window (Cassidy, 2007).

We compute eigenvector centrality for firms involved in a foal-sharing agreement[12] using nwcommands in STATA (Grund, 2015). Eigenvector centrality has been used extensively in recent research as a proxy for information diffusion and information inference in networks in different contexts (see Table A1 for a review). Eigenvector centrality is an intuitive measure of centrality as it accounts for the numbers of ties that can be used for information diffusion as well as how these ties are themselves well connected to the rest of the network (Jackson, 2010). In our context, the eigenvector centrality measures the importance of a firm's connections in the Thoroughbred industry by weighing how well-connected all their connections are in the business network. Thus, it can represent both the directly diffused information flow through the network to the bidders and the inferred information by the bidders. In the model, we used the standardized stud farm centrality and the standardized nursery centrality to compare their coefficients (i.e., mean of zero and standard deviation of 1).

Lastly, all models include year and auction dummies as control variables in the performance equation to account for time and auction house effects that could bias the results.

5 | METHOD

Correctly estimating the effect of a strategic decision on performance is a known challenge to nonexperimental work in the field of strategy (Shaver, 1998). This challenge is more difficult in the study of strategic alliances because, in contrast to decisions a firm can make on its own, alliances rely on at least two firms agreeing first on entering the relationship and then making decisions in the alliance. Each partner's unobserved characteristics affect both the selection of their counterpart and the overall alliance performance. The performance estimation is likely biased if it does not account for selection based on unobserved characteristics. Furthermore, a reduced form estimation with instrumental variables (e.g., iv probit) would miss the fact that the prospective partners compete to obtain the counterpart most likely to increase the alliance performance. The partners' choices are interdependent, meaning that once a partner is selected, she might not be available for the next partner. Thus, we implement a two-sided matching model that captures the essence of the sorting in the Thoroughbred alliance market.

Two-sided matching models differ based on whether they allow the transfer of utility between matched agents (Chen, 2020; Chiappori & Salanié, 2016; Ganco, Honoré, & Raffiee, 2018). In the Thoroughbred horse industry context, the revenue-sharing rule for foal-sharing alliances is fixed with no possible transfer (i.e., 60% for the nursery and 40% for the stud farm) (Campbell, 2000). Each party cannot offer a higher share of the existing foal-sharing agreement to pair up with a better dam or sire. Therefore, we use a two-sided matching model with nontransferrable utility that incorporates a performance equation developed by Sørensen (2007).[13]

[12]If a yearling belongs to more than one nursery (or stud farm), we use the maximum over all the nurseries (or stud farms).

[13]Prior work in strategy has used the maximum-score estimation; however, this technique has been applied for transferrable utility models (e.g. Fox, 2018; Mindruta, 2013).

5.1 | Model equations

Let I_t and J_t denote respectively the finite and disjoint sets of sires and dams in market t, where $t = 1, 2, ..., T$. A market is a year in our context. The model is composed of four equations:

$$P_{ij} = \alpha_0 + S_i\alpha_1 + D_j\alpha_2 + C_{ij}\alpha_3 + e_{ij} \equiv U_{ij}\alpha + e_{ij} \tag{1}$$

$$M_{ij} = I(\text{sire } i \text{ mates with dam } j) \tag{2}$$

$$R^s{}_i = S_i\beta + f_i \tag{3}$$

$$R^d{}_j = D_j\gamma + g_j \tag{4}$$

The first equation provides the price estimation. P represents the price at auction of the yearling resulting from the match between sire i and dam j under the foal-sharing agreement. S represents the vector of sire characteristics, including the stud farm network centrality. D represents the vector of dam characteristics, including the nursery network centrality. C represents the vector of controls. The last three equations jointly estimate the selection between a sire and a dam. I is the indicator function. $R^s{}_i$ and $R^j{}_j$ are the respective sire and dam latent rankings, which lead to $M_{ij} = 1$ when sire i pairs up with dam j.[14] All the error terms, f_i, g_j, and e_{ij} are normally distributed, and their correlation is modeled to include unobserved characteristics (see Appendix). The matching process reaches a pairwise stable equilibrium with no pair of agents preferring to deviate from their current match to form another match (see the Appendix for a formal description).

5.2 | Model application to the Thoroughbred horse industry

In the Thoroughbred horse industry, nurseries and stud farms want to match their horse with a horse that maximizes their payoff. Moreover, because of the competition in the market, the realized matches are considered the highest payoff match each agent could obtain. The model reveals the characteristics of the agents who created these realized matches. Sires and dams with certain characteristics are at the top of the respective rankings, whereas sires and dams lacking these characteristics are lower. The positions in the rankings are relative and depend on each horse characteristics and its owners' network structure. Sires and dams match starting with the top in each ranking.

The performance part of the model estimates the price obtained at auction by the yearling produced from the sire and dam match. Unobserved characteristics can influence the auction price and the match. For instance, a sire with an AEI of 1.5 might match with a dam with a CPI of 15 and produce an offspring sold for \$200,000. In another market, similar horses might produce an offspring sold for \$50,000. Such large discrepancies in auction prices signal an essential effect of unobserved characteristics.[15]

[14]For each alliance, the performance outcome and match is at the horse level: the match is between a sire and a dam whose offspring is sold at auction as a yearling. The decision makers who set up the match are, respectively, the stud farms and nurseries.

The model identifies the discrepancies in outcome despite having the same observed characteristics and corrects the estimates based on the correlations between the error terms (Chen, 2013; Sørensen, 2007). The implicit assumption underlying the correction is that the distribution of agents across markets is uncorrelated to these unobserved characteristics (Sørensen, 2007).

5.3 | Model assumptions and features

The matching model we use in this paper follows previous empirical work on matching models with nontransferable utility (Chen, 2013; Honoré & Ganco, 2020; Ni & Srinivasan, 2015; Park, 2013; Sørensen, 2007). Partners belong to *two distinct sides* and want to maximize the value of each match independently of other matching decisions. To do so, they compete to ally with promising counterparts for each match. In our setting, breeding and raising an offspring is costly, and alliance partners run for-profit businesses. The model assumes that all firms have the same value-maximizing goal and, thus, the same preferences over partners.

The model is a *one-to-many matching model*, which means that each sire matches to many dams while each dam matches to one sire.[16] His actual number of yearlings, called a *quota*, restricts the number of matches for each sire in a market (given year) to make the estimation tractable and realistic. Once the quota fills up, the next sire in the ranking becomes a potential match for the next dam.

Each agent is assumed to have complete information about the other side's set of agents. The context fits this assumption of complete information quite well because farm owners meet multiple times a year at auctions to learn about genetic lines and other firm characteristics (e.g., Cassidy, 2007). Furthermore, these horse characteristics are available in the *Blood-Horse* publications that lead up to the next breeding season.

5.4 | Estimation

The estimation is computationally intensive. The model considers the formation of each possible dyad and how the formation of each dyad influences formation of all other dyads. We overcome this computational difficulty by using a Bayesian estimation with data augmentation and Gibbs sampling (Gelfand, Hills, Racine-Poon, & Smith, 1990; Geweke, 1999). Gibbs sampling, which is a Markov chain Monte Carlo algorithm, is used to draw on each variable's conditional density obtained from applying the Bayes rule to each variable's prior density. Data augmentation uses latent variables, latent rankings as parameters. Thus, the difficult integration problem becomes a simulation exercise (Chen, 2013; Park, 2013; Sørensen, 2007). In the Appendix, we present the densities and the application of the Bayes rule to solve the model (i.e., obtain the conditional posterior densities) and list the mathematical assumptions supporting the use of Gibbs sampling and data augmentation.

[15]These unobserved characteristics to researchers are observed to potential partners in their matching decision.

[16]The American Jockey Club prevents the use of reproductive technological advances such as cloning, artificial insemination or embryo transfer to alter the natural reproductive tendencies of *Equus*. Thus, the one-to-many setting is exogenous.

TABLE 2 Descriptive statistics and correlation matrix with *p*-value ($n = 800$)

	Variable	Mean	*SD*	Min	Max	1	2	3	4	5
1	Dam quality	2.04	3.27	0.00	35.78	1.00				
2	Nursery eigenvector centrality	0.02	0.02	0.00	0.23	0.01	1.00			
3	Sire quality	1.43	0.68	0.00	3.31	0.19	0.20	1.00		
4	Stud farm eigenvector centrality	0.18	0.09	0.00	0.33	0.07	0.21	0.08	1.00	
5	Yearling's price (logged)	10.31	1.46	6.91	14.00	0.22	0.20	0.42	0.29	1.00

TABLE 3 OLS regression results (DV = yearling's logged price, $n = 800$)

	Coef.	Std. err.	*p*-Value	M.E.	δ	Identified set
Dam quality 1	−0.24	0.12	.04	−21.38		
Dam quality 2	−0.07	0.11	.53	−6.49		
Dam quality 3	0.17	0.12	.15	18.39		
Dam quality 4	0.35	0.15	.02	42.55		
Nursery eigenvector centrality	0.06	0.04	.15	6.17	0.17	[−0.33, 0.06]
Sire quality 1	−0.63	0.18	.00	−46.65		
Sire quality 2	−0.53	0.17	.00	−41.01		
Sire quality 3	−0.03	0.17	.84	−3.35		
Sire quality 4	1.19	0.17	.00	227.62		
Stud farm eigenvector centrality	0.27	0.04	.00	31.17	1.08	[0.02, 0.27]
Constant	9.80	0.21	.00			
R-squared	0.46					

Note: P-values are obtained from two-sided tests. Year dummies and auction dummies were included. δ was computed with psacalc and R max = 1. δ represents the magnitude of the unobserved characteristics. The values in the identified set were computed using psacalc with R max = 1 and δ set at 1 for the lower bound and 0 for the upper bound. Note that the identified set of nursery network centrality includes 0, which indicates that its effect on price can be eliminated by unobserved characteristics. The test shows support for the use of the matching model.

6 | RESULTS

Table 2 presents descriptive statistics. Our sample is made up of 800 offspring produced from the match between 309 sires and 800 dams and sold at auction as yearlings from 2009 to 2014. Dam's quality is, on average, 2.04 with a large standard deviation of 3.27, while the sire's quality, as measured by AEI, is, on average, 1.43 (standard deviation of 0.68). The nurseries have an average eigenvector centrality of 0.02 (standard deviation of 0.02), which is small compared to the eigenvector centrality of stud farms, with an average of 0.18 (standard deviation of 0.09). In the regressions and model, we use a standardized eigenvector centrality measure to compare the nurseries and stud farms' centrality effects. Table 2 presents the correlation matrix. All independent variables correlate positively with the logged price variable.

Table 3 presents the results obtained with an OLS regression of the yearling's logged price. Sire top quality and stud farm eigenvector centrality positively relate to the auction price. Dam top quality also positively relates to the auction price. Interestingly, on both sides, low quality is negatively associated with auction price suggesting that auction bidders would instead buy a horse whose parents' quality is unknown rather than settle for low quality.

As discussed in the method section, we suspect that these OLS model results are biased because they do not account for the alliance market sorting that occurs based on observed and unobserved characteristics. We use the method developed by Oster (2019) to measure the effect of the unobserved characteristics on the auction price. We compute δ, the size of the unobserved characteristics. We find that unobserved variables as small as 0.17 for the nursery centrality would eliminate its effect on price (i.e., with a potential R-squared of 1). This analysis confirms that unobserved variables significantly impact the nursery's centrality effect. By contrast, the unobserved variables would have to be 1.08 as large as the effect of stud farm centrality to eliminate its effect on the price, suggesting a limited bias of the stud farm's effect.

We resolve the unobserved characteristics bias by using the two-sided matching model. The first pane of Table 4 presents the results of the performance outcome equation of the model. A dam of top quality positively impacts the yearling's price ($\alpha_2 = 1.19$ and p-value = .00). On average, a yearling produced by a top-quality dam sells for a price 229.84% higher than a yearling produced by a dam of quality 0. A dam of low quality negatively impacts the price obtained at auction than a dam of quality zero. Low and average race results are worse than not having raced (categories 1 and 2 with $\alpha_2 = -0.70$ and p-value = .00, and $\alpha_2 = -0.56$ and p-value = .00). Low quality decreases the price, respectively, by 50.23% and 43.15%. Similar results appear on the stud farm side: a sire of top quality increases the price by 35.68% ($\alpha_1 = 0.31$ and p-value = .04) while a sire of low quality (category 1) decreases the price by 23.13% ($\alpha_1 = -0.26$ and p-value = .03). Overall, the quality results are qualitatively similar to the results from the OLS, but the nursery side has a larger effect on the auction price. The quality effects are consistent with previous research on risk-taking for unknown quality compared to negative returns for low quality (Dranove, Kessler, McClellan, & Satterthwaite, 2003; Lewis & Carlos, 2019).

In addition to dam and sire quality, we estimate the effect of network centrality of the nursery and stud farms on the alliance outcome. We find that the nursery centrality has a positive effect on price ($\alpha_2 = 0.26$ and p-value = .00): the increase of one centrality unit increases the auction price by 29.85%. Stud farm centrality has a positive but smaller effect than nurseries on auction price ($\alpha_1 = 0.10$ and p-value = .04): the increase of one centrality unit raises the auction price by 10.09%.

The centrality measures are standardized, which allows us to compare the two sides. The marginal effect of the nursery is almost three times larger than the marginal effect of the stud farm. A t-test (p-value = .00) indicates that the nursery centrality effect is significantly larger than the stud farm centrality. However, for large samples, most t-tests are significant, and thus, it is more meaningful to estimate the effect size (Coe, 2002). Using a pooled standard deviation, we find that the nursery effect is 2.4 standard deviations larger than the effect of the stud farm. The large size of the effect indicates that the nursery and stud farm centrality effects are indeed different.

The second pane of Table 4 presents the results obtained from the matching estimation[17] needed to obtain a correct estimate of the performance. Briefly, we find that dams and sires of top quality have a probability advantage of 10.26% and 20.17% over dams and sires of no known quality, respectively. While these marginal probabilities have large positive effects, they must be interpreted with caution because the p-values are large. Stud farms tend to dislike dams that do not belong to the top-quality category (e.g., dam quality 3, $\gamma = -0.28$ with p-value = .08). Nurseries tend to prefer less central stud farms ($\beta = -0.08$ with p-value = .04).

[17]The results computed over 41,427 pairs.

TABLE 4 Results with standardized eigenvector centrality from performance outcome equation and matching equation

		Mean	*SD*	*p*-Value	M.E. or P.A.
Price	Constant	9.93	0.25	.00	
Equation	Dam quality 1	−0.70	0.20	.00	−50.23
	Dam quality 2	−0.56	0.18	.00	−43.15
	Dam quality 3	−0.12	0.20	.53	−11.59
	Dam quality 4	1.19	0.20	.00	229.84
	Nursery eigenvector centrality	0.26	0.05	.00	29.85
	Sire quality 1	−0.26	0.12	.03	−23.13
	Sire quality 2	−0.09	0.11	.43	−8.40
	Sire quality 3	0.17	0.12	.16	18.08
	Sire quality 4	0.31	0.15	.04	35.68
	Stud farm eigenvector centrality	0.10	0.05	.04	10.09
Match	Dam quality 1	−0.17	0.18	.33	−9.84
Equations	Dam quality 2	−0.07	0.15	.64	−4.09
	Dam quality 3	−0.28	0.16	.08	−15.48
	Dam quality 4	0.10	0.18	.59	5.51
	Nursery eigenvector centrality	−0.02	0.06	.76	−1.08
	Sire quality 1	0.09	0.09	.31	5.21
	Sire quality 2	0.09	0.08	.25	5.35
	Sire quality 3	0.02	0.09	.84	1.03
	Sire quality 4	0.18	0.13	.15	10.34
	Stud farm eigenvector centrality	−0.08	0.04	.02	−4.74
	κ	0.42	0.22	.06	
	Λ	−0.27	0.21	.10	
	$1/\sigma^2_{\nu}$	0.87	0.05	.00	

Note: The sample contains 800 matches. *P*-values are obtained from two-sided tests except for λ whose *p*-value is obtained from a one-sided test because of its truncated distribution. Year dummies and auction dummies are included in the performance outcome equation. Mean and Std. Dev. are the mean and standard deviation of the parameters' simulated posterior distributions. They are computed on a draw thinning of 1,218 draws. The marginal effects (M.E.) for the performance outcome equation are computed as follows: $100 \times (e^{\gamma} - 1)$. The probability advantages (P.A.) of the matching equation parameters are computed as follows: {2 * [normal cumulative distribution function $(X_i\beta - X_{i'}\beta)/2\hat{\ }.5\} - 1 \ \forall\ i \neq i'$ using a 10-percentage point increase for continuous variables.

In Table 4, we also report κ and λ, the correlations between the error term in the performance outcome equation, and the error terms in the rankings. They are large with small *p*-values, implying that unobserved characteristics for dams, sires, and their respective owners affect the matching and auction prices. Furthermore, $1/\sigma^2_{\nu}$ also exhibits a large value (*p*-value = .00), which suggests that unobserved characteristics not attributable to either side but rather attributable to the yearling or transaction also affect the results. These three indicators justify the use of the matching equation while estimating the performance.

We identify two context-specific situations where the auction bidders would more highly value information than usual. First, we identify yearling horses sold in a different geographical market than the state where they were born: the entry into a new geographical market leads to a scarce information environment for the auction bidders. The auction bidders could not have easily directly observed the offspring before the auctions. Thus, the owners would have to activate their network more intensively to promote the offspring. Alternatively, the bidders would place a greater marginal value on the information they receive through the network. As expected, the results in Table A2 indicate that the nursery side eigenvector centrality exhibits a larger effect than in our main model, with the centrality effect of the nursery remaining larger than the stud farm effect.

Second, we separately select a subsample of yearlings whose genetic parent quality is mismatched. These are horses created by pairing a dam from the top two tiers of quality with a sire from the lowest two tiers of quality or vice-versa. The quality mismatch prompts the bidders to search for more information on why the alliance partners selected such mismatched quality parents to place a high or low bid. A mismatch occurs when a dam of quality 3 or 4 pairs with a sire of quality 0 or 1 and vice-versa. We exclude the middle category of quality. The results, in Table A3, indicate that the nursery eigenvector effect is slightly larger than in the main model. The nursery eigenvector effect is significantly different than the eigenvector effect of the stud farm.

Overall, information diffusion is more likely to drive these results than information inference in situations where more information is needed such as different state of birth, and quality mismatch. If inference dominated, the effect of the more central of the two partners should be higher, meaning that the bidders infer more information from the most central network position because they lack direct information. In contrast, we observe than the nursery eigenvector centrality effect is larger than the stud farm, indicating that information diffusion is driving the effect.

In the Appendix in Tables A4 and A5, we present results obtained with more draws in the Gibbs sampling as recommended by Bayesian research (e.g., Cowles & Carlin, 1996). We also show and discuss our results when using two alternative network measures (Wasserman & Faust, 1994) and analyze models that include controls for reputation (Ebbers & Wijnberg, 2010).

7 | DISCUSSION

We find evidence that the buyers' and suppliers' network centrality positively influences the price bidders pay at auctions. The effect of the buyer firms' network centrality is larger than the effect of the suppliers' despite the suppliers being more central on average in this industry. Based on anecdotal evidence and additional empirical tests, we believe that the underlying mechanism is information diffusion because the bidders attach a higher marginal value to buyers' centrality. If information inference drove the results, the effect of supplier centrality on alliance performance should have been larger.

Overall, qualitative evidence suggests that buyers, which are the nurseries in our context, diffuse information of greater marginal value. Making a connection with a nursery is more time consuming and more costly than being exposed to a large marketing campaign from a stud farm. The nurseries might not disseminate the information many times, which increases the information's marginal value. In contrast, stud farms diffuse a lot of information, which might become redundant and less valuable.

In analyses on subsamples with varying levels of need for information for bidders, the buyers' effect of the network centrality persists and even increases when there is an additional need for information. Thus, the results suggest that information diffusion is indeed an important driver of the large positive effect of the less central partner on alliance performance.

Our results for input quality effects are straightforward: top-quality positively affect the auction price. Interestingly, the effect of low quality on the auction price is worse than the effect of no quality information for each side. The bidders prefer to bet on unknown input quality rather than low or even average quality, consistent with previous research (Dranove et al., 2003; Lewis & Carlos, 2019).

7.1 | Contributions

First, we introduce an innovative empirical method of identifying the respective contributions of the alliance partners on the alliance performance while accounting for the alliance partners' mutual selection. We use a model that jointly estimates a performance equation with a two-sided matching model, a powerful tool for strategy research that will enhance the existing line-up of two-sided matching models (Chatain & Mindruta, 2017; Mindruta, 2013; Mindruta et al., 2016). Hence, we estimate the distinct effect of partners' characteristics on the outcome of the alliance free of endogeneity due to mutual selection.

Second, our model allows us to disentangle the marginal effect of each partner's inputs on alliance performance: we measure quality and centrality separately for each side. We contribute to the broader alliance literature that often considers network positions as an indicator of underlying quality (e.g., Podolny & Phillips, 1996). By disentangling the effect of input quality known to the market from unobserved product characteristics diffused by the network to the market, our work expands the discussion on signaling and identification of quality (e.g., Simcoe & Waguespack, 2011). Our study shows that even when input quality information is available, the network centrality of the firms still affects performance through information diffusion.

Third, our paper suggests a different reason for less central firms to be beneficial in an alliance: their ability to disseminate information whose marginal value is higher to the end market as it is less prevalent in the network. The results are in line with prior research on information diffusion (Hansen, 1999; Rogers, 1995) and offers a contrast to prior work suggesting that information inference from the most central partners' network position is the main driver of performace (Lin et al., 2009; Stuart et al., 1999). Interestingly, across the two sides of the alliance, our findings suggest that the less central partner has a greater marginal value for the relationship as a whole. Furthermore, our findings indicate that risks associated with less central partners in alliances (e.g., Das & Teng, 1999) may be overstated.

Moreover, our novel modeling approach allows us to estimate the effect of resources, input quality and centrality, on alliance performance when partners have resource quotas, unlike previous work on resource differentiation and scale-free resources (Levinthal & Wu, 2010; Teece, 1982). The alliance partners do not enjoy entirely scale-free resources, both stud farms and nurseries have limited capacity in their production. Thus, our matching model estimates coefficients relative to a baseline of the same side of the match (a nursery is compared to a similar nursery with a smaller centrality, all else equal), which sidesteps the problem of scale after the alliance partners match.

Our paper has important practical implications. For the Thoroughbred horse industry, our results suggest that stud farm advertising campaigns may have limited value for information dissemination for the alliance. Stud farms might be able to lower advertising costs and still reap the benefits of their foal-sharing contracts. In other contexts, such as in alliances between new ventures and established firms, our research suggests that entrepreneurs and managers could reap alliance benefits from less central partners' information diffusion.

7.2 | Limitations and future research

In this paper, we use a two-sided matching model coupled with performance equation that invokes several assumptions. First, we assume that all potential partners have the same objective and preferences over mating horses to create an offspring that sells in an auction to a successful bidder. This assumption fits the empirical reality of the Thoroughbred horse industry. Future papers interested in complementarities could use the maximum score estimation to show complementarity with nonzero cross-partial derivatives (Fox, 2018). Future work could also tackle multiple objectives for complex alliances such as access to technology, access to new markets, and the growth of brand equity.

Second, we assume that the markets during which both parties match are independent. The industry setting affords us a clean market structure by operating on a fixed annual cycle. However, qualitative work on alliances has investigated repeated alliances and their consequences (Faems, Janssens, Madhok, & Van Looy, 2008). Hence, research on dynamic matching models and their empirical estimations is an avenue for strategy research on alliances in different contexts where overlapping interactions prevent a clear identification of independent markets in modeling.

In our setting, both parties collaborate and share information as the yearling prepares for auction, and ultimately participate as joint sellers at the auction. Our modeling approach disentangles the marginal value of information for each side. Thus, our estimates do not capture a situation where one side has a disproportionate share of proprietary information about the new product. Future research could test a similar empirical framework in a setting where only one side of the alliance has proprietary knowledge of product development.

Our rich empirical setting offers multiple advantages for studying alliance performance in contexts with rich data availability—our setting benefits from multiple detailed sources of information such as *Blood-Horse* publications, and direct interactions of the end market at the auctions. The Thoroughbred horse industry is similar to many other industries that rely on advanced data collection and analyses. Previous literature used technological industries where employee information, patents, or product testing are available (e.g., Honoré, 2020; Mindruta et al., 2016; Moeen, 2017), and sports where training and performance data are tracked regularly by firms, partners, and competitors (e.g., Castellucci & Ertug, 2010). Future work may tackle industries where data collection is less expansive, and where participants in auctions do not directly interact with sellers such as telephone or online auctions.

8 | CONCLUSION

Potential partners' input quality and centrality jointly drive alliance performance. We advance scholarly understanding in this area by using a new rigorous empirical method, a two-sided matching model with a joint estimation of performance, to estimate the effect both partners' separate contributions to the alliance outcome. We find that buyers' and suppliers' top quality and unknown quality have a stronger positive effect on performance than low or average quality. Our results indicate that the buyer, who is on average the less central partner, has an important role in the alliance by diffusing information with a higher marginal value to the end-market bidders about the alliance's assets. Thus, our results suggest that, in this type of setting, less central firms are advantageous alliance partners.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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