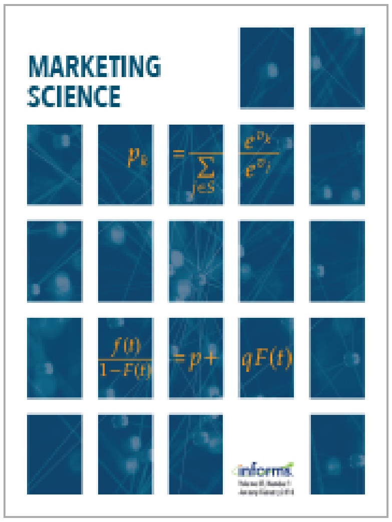

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Jian Ni, Kannan Srinivasan

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Matching in the Sourcing Market: A Structural Analysis of the Upstream Channel

Jian Ni
Carey Business School, Johns Hopkins University, Baltimore, Maryland 21202, jni@jhu.edu

Kannan Srinivasan
Tepper School of Business, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, kannans@cmu.edu

Building on the structural two-sided matching model, we develop a framework to study the sourcing market in the context of marketing firms matching with manufacturers. Both sides prefer partners that could generate significant values with better sourcing process abilities. Moreover, experienced manufacturers are preferred by the branded marketing firms who may even be willing to compensate the matching intermediary more for facilitating that preference. Empirical research, measuring the values of such matching and the intermediary's pricing (through commission) on observed marketing firms' characteristics and the low-cost manufacturers and the deals that result, is problematic, when some of the characteristics are only partially observed and the matching is endogenous. With the matching model, we can control for endogenous matching. We find evidence of positive assortative matching of pairs' size on both sides of the market. We also find that manufacturers' location and tenure, and whether the marketing firms are listed, are important factors in identifying the preferred matching partners and the related ranking. Without controlling for endogenous matching, the intermediary's pricing equation estimates are biased, especially for the marketing firms that specialize in luxury products.

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1. Introduction

During the past several decades, a number of firms have sourced some parts of their products or even the entire product to specialized manufacturers and largely focused on marketing and design. This business strategy is common, especially in the consumer goods, consumer electronics, and apparel industries. In the case of electronic components such as electronic circuit boards, firms design the product but completely outsource fabrication to production facilities in regions such as Taiwan and South Korea. Shoe and clothing production in their entirety is often outsourced to third-party manufacturers from emerging markets such as China, Bangladesh, and Vietnam. Consequently, firms are largely reduced to marketing, i.e., the companies design, innovate, and market the products but no longer engage, in any meaningful way, in manufacturing by themselves (Einhorn 2009). They pair with suitable manufacturers who can produce for them through the help of specialized intermediaries such as Li & Fung. Some of the best-known examples are Liz Claiborne and Nike, who follow this strategy for almost all of their products.

These marketing firms operate in highly competitive markets and face market demands to deliver high-value products that are subject to frequent modifications or short product life cycles. Apart from obviating the need to incur capital expenditure in production facilities, companies easily ramp up or down to the vagaries of market demand while shifting the risk of asset ownership to the manufacturers. Manufacturers, who focus on production, enjoy the strategic advantages arising from scale, especially low production cost in emerging markets. For example, Foxconn, which is famous for producing Apple's products, has become the largest electronic contract manufacturing company in the world. This type of matching-style marketing strategy involves substantially less risk and offers the potential of a sustainable boost not only in sales but also in profitability for the marketing firms and the manufacturers. During the past 20 years, this business model has been embraced across a large number of industries and by numerous medium-sized firms.

Success, however, critically depends on finding a matching partner. The marketing firms operate largely in developed markets whereas the manufacturing firms operate in emerging and less developed markets where information is not readily available.[1] Therefore, finding a suitable matching partner poses challenges for the manufacturer and the marketing firms. Both sides of the market must spend substantial resources to gather information and monitor each other to mitigate the potential risk involved in matching. Often this matching process is facilitated by upstream intermediaries, such as Li & Fung, who specialize at facilitating the matching between the two sides, and provide service to both parties for a fee. In doing so, they coordinate the upstream channel and expedite the supply of products to meet consumers' rapidly evolving demands.

A good match yields significant payoffs to the marketing firm and the manufacturer. The opportunity cost of a bad match is substantial; therefore, the price (in the form of commissions fee)[2] charged by the intermediary may well be due to this significant risk premium. The intermediary, who has a deep understanding of the economics of both sides and often manages the manufacturers' network, can charge the marketing firms a higher price through successful coordination. The size and scope of this service is evidenced by the tens of billions of dollars in revenue for the leading market intermediaries. This is different from traditional outsourcing, which is structured as a bilateral relationship negotiated between a manufacturer and a firm. The partnership between the marketing firms and the manufacturers is built on the matching intermediary's platform governed not only by legal agreements but, more important, by market-based economic incentives. The knowledgeable matching intermediary helps the two sides eliminate concerns about the other side of the market by providing information and monitoring operations. The pricing strategy adopted by such an intermediary could be a fixed-amount fee or a percentage-based fee, or both.

While there is an expansive literature on the downstream channel issues in marketing literature, there is far less research on the upstream channel issues such as outsourcing, which has undergone enormous changes. Understanding the factors in determining the matching and organizing the sourcing market is very important. The matching in the sourcing process and the related pricing adopted by the matching intermediaries to coordinate the upstream channel merit examination and are the central focus of this paper.

[1] The recent discussion about Foxconn offers an interesting example. The company's enormous transactions point to the gigantic size and scope of production in China. Though Foxconn is subject to the stringent standards of the London and Hong Kong Stock Exchange regulations, business press continues to express concern about the lack of information on operations and labor issues of the company. The problem is exacerbated for lesser known companies.

[2] Throughout the paper, we use the term "price" and "commission" interchangeably.

In summary, matching of marketing firms with manufacturing firms is an important and enormous upstream channel issue that has received little research attention. In examining the issue, we offer three key contributions. First, the matching of the marketing and manufacturing firms is impacted by some of their characteristics more than others. Second, the intermediary's commission is a proxy for its informational value contribution. Here we measure the impact of the determinants of this pricing. Third, the joint matching and commission analysis poses estimation challenges. We adopt a matching model to overcome this issue.

Note that matching between the marketing firms and the manufacturer is not random. Brand recognition, the type of product, and the size of the marketing firms play important roles in the manufacturers' choices. A big branded firm is likely to have better terms, making it more attractive to the manufacturer; such a marketing firm might also place more constraints on product delivery. These firms' characteristics plus other factors, such as whether the firm is public or private, may affect how much benefit the manufacturers will receive. On the other hand, the marketing firms also screen potential manufacturers and match only with those who are valuable for their business. Large size, long tenured manufacturers are generally considered less risky and more reliable. However the potential popularity of the big manufacturer could impact the lead time and capacity for receiving new orders. Similarly, manufacturers are evaluated by the marketing firms (with the help of the intermediary) based on characteristics such as size, location, and tenure, and are then ranked accordingly.

Clearly, these characteristics could also have a significant impact on the matching outcome and the intermediary's pricing strategy. When the intermediary's pricing strategy is the only focus, such endogeneity issues could be resolved if there are some plausible instrument variables that influence the matching only, but not the post-matching outcome. As we discuss in §4.1, because such data is not available, the approach becomes infeasible. To understand the matching preference and the intermediary's pricing in the sourcing process, we adopt a full-information approach using the two-sided matching model in which pairings between marketing firms and low-cost manufacturers are coordinated by the matching intermediary as part of a stable assignment, and the matching intermediary receives a commission. We jointly estimate the matching model and an equation representing determination of the ex post commission as the outcome of the matching process priced by the intermediary, allowing correlation between the matching model errors and the matching outcome.[3] The joint estimation allows us to

[3] Unlike Ackerberg and Botticini (2002), who supplement the contract choice equation with an ordered Probit matching equation

correct for selection bias in estimating the commission equation, following Sørensen (2007).

The interdependence among the players in the matching model presents numerical difficulties for joint estimation. We use a Gibbs sampling algorithm to obtain Bayesian inference with data augmentation (Gelfand and Smith 1990, Geweke 1999, Tanner and Wong 1987, Albert and Chib 1993, Yang et al. 2003). Sørensen (2007) and Chen (2009) applied this method to a two-sided matching model.

We obtain data from the outsourcing apparel industry where sourcing is prevalent and matching is considered critical. This is one of the largest outsourced manufacturing industries with revenue of $311 billion in the U.S. (Rees and Hathcote 2004), and in which seasonality and fashion trends often necessitate short contracts. Apparel marketing firms perform design and marketing functions but outsource actual apparel production to foreign firms. Though branded companies such as the Gap are the main players in the apparel sourcing arena, there is a significant amount of private label apparel designed and labeled by retailers such as Kohl's, JCPenney, and Sears and produced by lower cost apparel contractors.

Our results are as follows: (1) There is positive assorted matching between two sides in this sourcing market in terms of size. The medium-sized firms and similar-sized manufacturers are the most preferred partners though the large firms matching with large manufacturers closely follow; (2) Key characteristics such as manufacturers' location, tenure, and whether the marketing firms are listed are important determinants for the matching partners; (3) The informational opacity between the matching partners provides the matching intermediary pricing power in the supply chain. Such effect could be underestimated if endogenous matching is not accounted for, especially for marketing firms that specialize in luxury products.

The remainder of the paper is organized as follows: §2 provides the model specification. Section 3 presents the empirical estimation. Section 4 describes the institutional setting and the data. Section 5 presents and interprets the empirical results. Section 6 summarizes this paper, discusses its limitations, and suggests possible avenues for future research.

2. Model

As in the college admission setting (Gale and Shapley 1962), there is always an equilibrium matching in our model. These types of two-sided matching models have been applied to the marriage and labor markets, in which players are divided into two sides and each participant chooses a partner(s) from the other side. In marketing, Yang et al. (2009) estimate a structural two-sided matching model of free agent signings by NBA teams and team choices by NBA players, and assesses the value of brand alliance. Other examples include Sørensen's (2007) study of matching between venture capitalists and the companies in which they invest, Chen's (2009) analysis of the bank loan market, Park's (2013) merge and analysis of incentives and outcomes in the financial industry, and Uetake and Watanabe's (2013) study of bank acquisition with externality.

We develop a structural matching model of the sourcing market facilitated by the matching intermediary. Marketing firm preferences and the contract manufacturer are central to the way they are paired and are known to all parties. The largely transparent rules of the matching game managed by the intermediary determine equilibrium matching. The first part of our model is built on a two-sided matching model to control for endogenous matching. With minor modifications, this model forms the basis for an empirical model of market sorting, which generalizes existing models, such as the Probit, by allowing for interaction between the choices made by different agents. The second part of our model investigates the determinants of the commission charged by the intermediary, including the marketing firm's and the manufacturer's characteristics and the features of the resulting deal.

Usually marketing firms contact the intermediary with a new order. Then intermediary representatives recommend manufacturers from their established network; they assess the manufacturers to match the marketing firm's needs. Often the marketing firms follow the intermediary's recommendation and carefully evaluate the manufacturers based on their needs. Intermediaries meticulously cultivate a reputation for integrity, and diligently avoid any biased recommendation. The two-sided matching process takes place before the commission is finalized.[4] Thus the marketing firm and the manufacturer take into account the expectation of the intermediary's price when deciding whether to accept the match. This is a function of the agents' characteristics. Consideration of such commission is reflected in the agents' payoffs during the matching process. These payoffs are the expected value of the marketing firms and the manufacturers from the matching. Once the matching is set, the marketing firms pay the total amount of the sourcing goods including the commission fee to the

to address endogenous matching, we use the structural matching model to understand the underlying preferences of the matching sides. A Probit model does not capture the sorting that is the source of identification of the matching model (Sørensen 2007).

[4] Sometimes matching is done together with the negotiation of the value of sourcing (and the commission fee).

intermediary. Manufacturers are paid by the intermediary afterwards.[5]

The matching model is designed to facilitate understanding of the matching preference of both sides, the value of the matching deals, and the determinants of the intermediary's price (i.e., commission). The matching model enables us to correct for selection bias in understanding the value chain and the intermediary's price by jointly estimating the matching model and the commission equation. If the marketing firms with particular characteristics tend to match with some manufacturers that are desirable for unobservable reasons, the estimated coefficient for the marketing firms' characteristics in the commission equation will reflect the effects of the unobserved downstream manufacturers' characteristics, thus biasing the coefficient upwards. Therefore, we can better understand the matching partners' preference, quantify the value generated in the sourcing process, and assess the intermediary's pricing strategy.

2.1. Agents and Matches

Let the finite and disjoint sets, I_t and J_t, denote the marketing firms and manufacturers in market t, respectively, where $t = 1, \ldots, T$. In the empirical implementation of the model, players include all of the marketing firms and all of the manufacturers that operate in one specific market. The manufacturers can access the lists of potential orders placed by the marketing firms through the intermediary. The capacity and abilities of the manufacturers within the intermediary's sourcing network are also available to the marketing firms. In market t, firm i can contract with several (n_{it}) manufacturers; manufacturer j can only deal with one marketing firm. The model is a special case of the many-to-one two-sided matching model, also known as the college admission model (Gale and Shapley 1962, Roth and Sotomayor 1990).

The set of all potential deals (or matches) is given by $M_t = I_t \times J_t$. A matching, μ_t, is a set of matches such that $(i, j) \in \mu_t$ if and only if marketing firm i and manufacturer j are matched in market t. For a fixed $i \in I$, denote $\mu_t^{\mathrm{mf}}(i) = \{j \mid (i, j) \in \mu_t\}$ as the set of manufacturers that work for firm i in market t, and for a fixed $j \in J$, denote $\mu_t^{\mathrm{mf}}(j) = \{i \mid (i, j) \in \mu_t\}$ as the set of firms that contract with manufacturer j in market t. This implies $(i, j) \in \mu_t \Leftrightarrow j \in \mu_t^{\mathrm{mf}}(i) \Leftrightarrow i \in \mu_t^{\mathrm{mf}}(j)$.

2.2. Preferences

The matching between the marketing firm and the manufacturer(s) is the equilibrium outcome of a two-sided matching process, shown below

$$m_{ij} = I(\text{firm } i \text{ contracts with manufacturer } j). \tag{1}$$

The two sides make their decisions based on their evaluation of each other. Let R_i^f be the payoff manufacturer j expects to receive if it manufactures for firm i; denote R_j^m as the payoff firm i expects to receive if it contracts with the manufacturer j in the set $\mu_t(i)$. Consequently, $\sum_{j \in \mu_t(i)} R_j^m$ is the total payoff if firm i contracts with several manufacturers. Each manufacturer prefers firm i to firm i' if and only if $R_i^f > R_{i'}^f$, and each firm prefers manufacturer j to manufacturer j' if and only if $R_j^m > R_{j'}^m$. In our model, the possible payoffs are the values generated for either side. They are always strictly ranked and there are no ties among any two agents in either side of the matching market.

In the apparel sourcing market, manufacturers' expected added-value R_i^f is influenced by the firm i's characteristics, whereas R_j^m is a function of manufacturer j's characteristics, as specified below

$$R_i^f = F_i'\beta + \eta_i, \qquad \eta_i \sim N(0, \sigma_\eta^2), \tag{2}$$

$$R_j^m = M_j'\gamma + \delta_j, \qquad \delta_j \sim N(0, \sigma_\delta^2), \tag{3}$$

where F_i and M_j are the vector of firm i's characteristics and manufacturer j's characteristics, respectively. Both sides have strong economic incentives to choose their partners. When a marketing firm contracts with a manufacturer, the firm not only reimburses the manufacturer financially but also provides design, expert advice, monitoring, and endorsement based on reputation. On the other hand, qualified manufacturers help improve marketing firm performance. These mutually-beneficial practices generate non-negligible values in the sourcing process.

Marketing firms are ranked by manufacturers and manufacturers are ranked by marketing firms based on these payoffs, which are functions of the relevant characteristics. The rankings by the sourcing partners, facilitated by the intermediary, imply vertical heterogeneity on both sides. The underlying assumption for the matching outcome is that the marketing firms have preference ordering over the manufacturers, and the manufacturers have matching preference ordering over the marketing firms.[6] Therefore, the market is fully sorted.

[5] The manufacturers and the marketing firms cannot contact each other without the help of the intermediary before the matching is set. The matching partners do not have the resources to search for, identify, and evaluate their counterparts, whereas the intermediary specializes in doing so. Usually the communications happen between the marketing firms and the intermediary or between the manufacturers and the intermediary. Consequently, we do not build transfer payments into our matching model. Intermediaries, whose revenues are in the billions of dollars, diligently guard and cultivate their reputation for effective matching. Reputation risk essentially mitigates any attempt by low quality manufacturers to pay off intermediaries for matching with quality marketing firms.

[6] Conversations with apparel industry executives confirm this as a valid assumption. Both sides access the detailed information and statistics of marketing firms and manufacturers, provided and managed by the intermediary.

The total added value of each matching is denoted as $s_{ij} = R_i^f + R_j^m$, which depends on the characteristics of the marketing firm and the contract manufacturer. Because of the institutional setting and tractability concerns, we do not endogenize the division of the pair-specific surplus between the two sides and are unable to include pair-specific characteristics. In our model, as long as the magnitudes of the pair-specific surplus are not large enough to change the preference ordering, we still account for vertical heterogeneity on both sides of the market. This is especially true when the matching is completed with the help of the matching intermediary since it deals with a large set of clients, and reputation concerns limit its ability to favor one particular client. In the empirical implementation, preference (payoff) ordering is assumed as the index that reflects the surplus of each firm/manufacturer to its counter partner. If the pair-specific surplus has absolute values smaller than the difference between the two levels of valuations and the preference ranks are distinct integers, then the preference ordering is still determined entirely by the payoffs specified above. For the same reason, the lack of deal-specific characteristics is of less concern, especially after we include category-specific characteristics, such as industry tenure, in our application.

2.3. Equilibrium Matching

A matching achieves equilibrium if it is stable, that is, if there is no blocking coalition of agents. A coalition of agents is blocking if they prefer to deviate from the current matching and form new matches among themselves. Formally, μ_t is an equilibrium matching in market t if and only if there does not exist $\tilde{I} \subset I_t$, $\tilde{J} \subset J_t$, and $\tilde{\mu}_t \neq \mu_t$ such that $\tilde{\mu}_t(i) \subset \tilde{J} \cup \mu_t(i)$ and $\sum_{j\in\tilde{\mu}_t(i)} R_j^m > \sum_{j\in\mu_t(i)} R_j^m$ for all $i \in \tilde{I}$, and $\tilde{\mu}_t(j) \in \tilde{I}$ and $R^f_{\tilde{\mu}_t(j)} > R^f_{\mu_t(j)}$ for all $j \in \tilde{J}$. This group-stability equilibrium always exists in the type of college admission model we considered here as proved in Roth and Sotomayor (1990) and it is equivalent to the pair-wise stability. Eeckhout (2000) shows that in a one-to-one two-sided matching model, the equilibrium matching is unique if there is vertical heterogeneity on both sides of the market. The following proposition shows that this sufficient condition also applies to our many-to-one two-sided matching model.

Proposition 1. *The equilibrium matching is unique in the many-to-one two-sided matching game when there is vertical heterogeneity on both sides of the market.*

The proof of Proposition 1 is in Appendix A. The unique stable matching of the model is characterized by a set of inequalities. This comes from the fact that there is no blocking pair of firm-manufacturer. For each marketing firm, stability requires that its worst contracting-manufacturer be better than any other manufacturer whose corresponding marketing firm is worse than this firm. Similarly, for each manufacturer, stability requires that its marketing firm be better than any other firm whose worst contracting-manufacturer is worse than this manufacturer. We obtain the upper and lower bounds on the agents' preference ranks in the corollary, below.

Corollary 1. *The equilibrium matching is characterized by the upper and lower bounds on the agents' preference ranks, $\bar{R}_i^f$, $\bar{R}_j^m$, $\underline{R}_i^f$, and $\underline{R}_j^m$, such that*

$$\mu_t = \mu_t^e \quad \Leftrightarrow \quad \begin{cases} R_i^f \in (\underline{R}_i^f, \bar{R}_i^f), & \forall\, i \in I_t \\ \text{and} & \\ R_j^m \in (\underline{R}_j^m, \bar{R}_j^m), & \forall\, j \in J_t \end{cases}, \tag{4}$$

where μ_t^e represents the unique equilibrium matching in market t.

We then use the characterization of the equilibrium matching in our estimation detailed in §3.

2.4. The Intermediary's Commission

The matching not only generates the surplus for the matching partners but also creates the benefit for the intermediary, who facilitates the deal in the value chain. The intermediary's commission from the successful matching is the benefit. Once the matching is successful, $m_{ij} = 1$, the commission is priced based on the value generated for both matching parties and the characteristics of the deal, as specified below

$$C_{ij} = \alpha_0 + \kappa R_i^f + \lambda R_j^m + D_{ij}'\alpha_3 + \nu_{ij}, \quad \nu_{ij} \sim N(0, \sigma_\nu^2), \tag{5'}$$

where C_{ij} is the commission[7] derived from the successful deal between firm i and manufacturer j; D_{ij}' is the deal-specific characteristics, such as the size and length of the deal. R_i^f and R_j^m are the payoff of the marketing firms and manufacturers, respectively, as specified in the previous section, and which are not perfectly observed.

Therefore we get

$$\begin{aligned} C_{ij} &= \alpha_0 + \kappa(F_i'\beta + \eta_i) + \lambda(M_j'\gamma + \delta_j) + D_{ij}'\alpha_3 + \nu_{ij} \\ &= \alpha_0 + F_i'\kappa\beta + M_j'\lambda\gamma + D_{ij}'\alpha_3 + \kappa\eta_i + \lambda\delta_j + \nu_{ij} \\ &= \alpha_0 + F_i'\alpha_1 + M_j'\alpha_2 + D_{ij}'\alpha_3 + \kappa\eta_i + \lambda\delta_j + \nu_{ij}. \end{aligned} \tag{5}$$

The error term $\kappa\eta_i + \lambda\delta_j + \nu_{ij}$ contains η_i and δ_j, the unobserved payoffs. Both sides' characteristics, such as tenure, location, and size, are important determinants of the intermediary's pricing in the sourcing market. Prior industry studies (Harvard Business

[7] Specifically, in the empirical analysis, we use the commission rate as the dependent variable, since the intermediary usually charges the firms on the percentage basis of the total deal size.

Cases 1996, 2002) also suggest that unobserved characteristics, such as the marketing firms' monitoring ability and risk, as well as the manufacturers' risk, operational efficiency, and information opacity influence the commission of the matching intermediary.

Because of the endogenous matching, the unobserved payoffs of a firm and a manufacturer influence the matching outcome, and therefore are likely to be correlated with its partner's characteristics. Consequently, the regressors in the commission equation are correlated with the error term. To correct this endogeneity, we could resort to variables that influence the matching but not the post-matching outcome, i.e., the commission. However in our data, any variable that influences the matching affects the error term of the intermediary's payoff through the unobservables. Therefore, the usual instrumental variables (IV) method is not feasible here. Manufacturers' capacity constraints influence the matching but not the post-matching outcome (the commission) and hence, could be an effective IV. Unfortunately, we do not have this information in our data. Moreover, our full-information approach helps us understand the matching preference and the associated pricing strategy used by the intermediary.[8]

A marketing firm with a better reputation and ability to work on the deal helps the manufacturers' operations and provides higher value, which leads to higher payoffs on both sides. Therefore, the matching intermediary is expected to charge a higher price for such deals. A firm's number of visits to the production plant reflects its effort and ability to monitor and guarantee a smooth transaction. A marketing firm's risk for a manufacturer comes from slow payment and possible withdrawal of the order. Apart from the firm's size, whether a firm is publicly traded and whether the marketing firm's brand is in the luxury category are the proxies for the lower risk of the sourcing deals.

The manufacturers' risk for a marketing firm is the uncertainty of timely product delivery, especially due to significant geographical dispersion leading to long logistical lead times. A manufacturer's location, tenure, and size are important elements to estimate the risk. A coastal location usually leads to faster delivery, and longer tenure likely reflects the ability to meet industry time commitments. Whether a manufacturer is publicly traded could serve as the proxy for a higher manufacturer's operational efficiency and limited information opacity since the listed manufacturer has more pressure from its investors to be more efficient and transparent. Moreover, smaller manufacturers, in general, pose larger information asymmetries because of their limited ability to track information.

[8] We thank an anonymous reviewer and the area editor for the insightful suggestion.

3. Estimation

A two-sided matching model presents numerical challenges when it comes to Estimation. This has been discussed in Sørensen (2007), among others. The proof of existence of the unique equilibrium allows us to use the efficient Maximum Likelihood Estimation (MLE) instead of the maximum score approach recently used in other applications (Fox 2010, Manski 1975, Yang et al. 2009). However MLE requires integrating a highly nonlinear function over thousands of dimensions. To overcome this challenge, we use a Gibbs sampling algorithm that performs Markov Chain Monte Carlo (MCMC) simulations to obtain Bayesian inference. We augment the observed data with simulated values of the latent data on the quality indexes so that the augmented data are straightforward to analyze. The method iteratively simulates each block of the parameters and the latent variables conditional on all of the others to recover the joint posterior distribution. This transforms a high-dimensional integration problem into a simulation problem, and overcomes the computational difficulty. The computational complexity of the estimation requires some compromises in model specifications. In particular, we do not allow for correlation among unobservables for the same agent over time and we leave out the dynamics of the matching process for future research.

3.1. Error Terms and Prior Distributions

Estimation of the post-matching commission equations is subject to the usual identification constraints in discrete choice models. Thus the variances, σ_η and σ_δ, are set to one to fix the scales, and the constant and market characteristics are excluded to fix the levels. To allow for correlation among the error terms, we denote $\varepsilon_{ij} = \kappa\eta_i + \lambda\delta_j + \nu_{ij}$, $\nu_{ij} \sim N(0, \sigma_\nu^2)$, then redefine Equation (5) as $C_{ij} \equiv A'_{ij}\alpha + \varepsilon_{ij}$, $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$, with

$$\begin{pmatrix} \varepsilon_{ij} \\ \eta_i \\ \delta_j \end{pmatrix} \sim N\left(0, \begin{bmatrix} \kappa^2 + \lambda^2 + \sigma_\nu^2 & \kappa & \lambda \\ \kappa & 1 & 0 \\ \lambda & 0 & 1 \end{bmatrix}\right). \tag{6}$$

The signs in the two-sided matching model are identified by λ. The match-specific variables, such as deal size and length, and whether special raw materials or special packaging is needed, enable identification in the spirit of Sørensen (2007). We experiment with different assumptions on the sign of λ and verify whether the results are significantly influenced by different assumptions. The rationale is the following: For the model to be identified, the sign of one of the parameters in β, γ, κ, λ must be specified, because both $(\beta, \gamma, \kappa, \lambda)$ and $(-\beta, -\gamma, -\kappa, -\lambda)$ would be admissible given the same observed (endogenous and exogenous) variables. When λ is positive, we obtain negative coefficient estimates for the preference-ranking equations. This is counter to what we would expect. Therefore, our estimated parameters of interest are consistent with nonpositive λ. Business practice suggests that marketing firms with higher unobserved value (lower unobserved risk, higher unobserved operational efficiency or lower levels of unobserved information opacity) are more likely to pay a higher commission for the intermediary and the matching partners, all else being equal.

The prior distributions are multivariate normal for β, γ, α, normal for κ, and truncated normal (on the right at 0) for λ. The means of these prior distributions are zeros, and the variance-covariance matrices are $10I$, where I is an identity matrix. The prior distribution of $1/\sigma_\nu^2$ is gamma, $1/\sigma_\nu^2 \sim G(2, 1)$. The above are diffused priors that include reasonable parameter values well within their supports. For any parameter, the variance of the prior distribution is at least 185 times the variance of the posterior distribution, which shows that the information in the Bayesian inference is substantial.

3.2. Conditional Posterior Distributions

In the model, the exogenous variables are F_i, M_j, and D_{ij}, which are abbreviated as X. The observed endogenous variables are the commission, C_{ij}, and the matching indicator, m_{ij}. The implicit rankings based on the payoffs for both matching partners are R_i^f and R_j^m. The parameters are β, γ, α, κ, λ, and $1/\sigma_\nu^2$, which are abbreviated as θ. In market t, we summarize the above variables as X_t, C_t, μ_t, and R_t^*, where μ_t embodies all of the m_{ij}'s and R_t^* denotes the ranks of the payoffs.

The joint density of the endogenous variables and the payoffs conditional on the exogenous variables and the parameters are as follows:

$$
\begin{aligned}
&p(C_t, \mu_t, R_t^* \mid X_t, \theta) \\
&= I(R_i^f \in (\underline{R}_i^f, \bar{R}_i^f), \forall i \in I_t \text{ and } R_j^m \in (\underline{R}_j^m, \bar{R}_j^m), \forall j \in J_t) \\
&\quad \cdot \prod_{(i,j)\in\mu_t} \phi(C_{ij} - A_{ij}'\alpha - \kappa(R_i^f - F_i'\beta) - \lambda(R_j^m - M_j'\gamma); 0, \sigma_\nu^2) \\
&\quad \cdot \prod_{i\in I_t} \phi(R_i^f - F_i'\beta; 0, 1) \times \prod_{j\in J_t} \phi(R_j^m - M_j'\gamma; 0, 1),
\end{aligned} \tag{7}
$$

where $I(\cdot)$ is the indicator function and $\phi(\cdot; \mu, \sigma^2)$ is the $N(\mu, \sigma^2)$ probability density function (pdf). To obtain the likelihood for the market t, $L_t(\theta) = p(C_t, \mu_t \mid X_t, \theta)$, we need to integrate $p(C_t, \mu_t, R_t^* \mid X_t, \theta)$ over all possible values of the preference ranks. Because of endogenous matching in the market, the bounds on each agent's preference ranks depend on other agents' preference ranks. Thus the integral cannot be factored into a product of lower-dimensional integrals. The Gibbs sampling algorithm with data augmentation transforms this high-dimensional integration into a simulation problem and makes the estimation feasible.

We assume the markets are independent due to both tractability concerns and the fact that every deal between the two sides is reached separately at different times. Therefore, the product of $p(C_t, \mu_t, R_t^* \mid X_t, \theta)$ for $t = 1, \ldots, T$ gives the joint density $p(C, \mu, R^* \mid X, \theta)$ for all markets. From Bayes' rule, the density of the posterior distribution of R^* and θ conditional on the data is

$$
\begin{aligned}
p(R^*, \theta \mid X, C, \mu) &= p(\theta)^* p(C, \mu, R^* \mid X, \theta) / p(C, \mu \mid X) \\
&\propto p(\theta)^* p(C, \mu, R^* \mid X, \theta),
\end{aligned} \tag{8}
$$

where $p(\theta)$ is the prior densities of the parameters. The conditional posterior distributions are detailed in Appendix C. They are truncated normal for R_i^f, R_j^m and λ, multivariate normal for β, γ, and α, normal for κ, and gamma for $1/\sigma_\nu^2$.

3.3. Simulation

In the algorithm, the parameters and the preference ranks are partitioned into blocks. Each of the parameter vectors ($\beta, \gamma, \alpha, \kappa, \lambda$, and $1/\sigma_\nu^2$) and the preference ranks is a block. In market t the number of preference ranks is equal to the number of agents, $|I_t| + |J_t|$. Thus, altogether we have $\sum_{t=1}^{T}(|I_t| + |J_t|) + 6$ blocks. In each iteration of the algorithm, each block is simulated conditional on all of the others according to the conditional posterior distributions. The sequence of draws converge in distribution to the joint distribution.

Estimation results reported later are based on 20,000 draws from which the initial 2,000 are discarded to allow for burn-in. Visual inspection of the draws shows that convergence to the stationary posterior distribution occurs within the burn-in period. To formally examine whether the posterior simulator is correct and whether convergence has been achieved, several sets of tests are conducted. First, the Raftery-Lewis test (Raftery and Lewis 1992) using all of the draws shows that a small amount of burn-in and a total of 9,800 draws are needed for the estimated 95% highest posterior density intervals to have actual posterior probabilities between 0.94 and 0.96 with probability 0.95. This indicates that satisfactory accuracy can be achieved using the draws we have. Second, joint distribution tests of the posterior simulator (Geweke 2004) using first-moments and second-moments functions yield few rejections in tests of size 0.05, implying that the posterior simulator is correct. Finally, based on the first 10% draws after burn-in (2,001, 3,800) and the last 50% after burn-in (1,001, 20,000), Geweke's convergence diagnostic (Geweke 1992) is less than 1.85 in absolute value for all parameters, indicating that convergence of the MCMC algorithm is achieved.

4. Institutional Setting and Data

The appeal of doing business through global sourcing was clear even before the advent of the Internet era. By bringing together huge numbers of marketing firms and manufacturers and matching them to focus on their core strength, the sourcing market expands the choices available to marketing firms, gives manufacturers access to new customers, and adds significant value to all of the players. As the facilitator in the sourcing market, the intermediary extracts commissions from the deals and enjoys vast value spillover in the supply chain. The marketing firms and the manufacturers identify the factors that influence the value generated by the potential matching partners and rank them accordingly. The intermediary collects information and enables matching partners to cost-effectively accomplish the deal.

Upon being contacted by the marketing firms, intermediary representatives recommend the manufacturers that they have evaluated to most closely match the marketing firms' needs. The intermediary usually presents both sides with detailed information on the other side including factors such as the factory skill level, reliability of the manufacturers, average lead time, and the marketing firm name recognition during the matching process. However, the emerging market may be difficult for the marketing firms in terms of monitoring raw material selection, the desired product standard, quota availability, packaging, and cost, and for the manufacturers to get fast payment. The inability of the marketing firms to monitor the manufacturers' operation and the related possible unobserved risk leads to potentially severe information opacity. The matching intermediary leverages the strength of its extensive sourcing network and substantial prior knowledge across a number of manufacturers over a number of contracts to mitigate information asymmetries and create effective matching. Consequently, marketing firms rely on and select the manufacturer matched by the intermediary. The intermediary extracts rents primarily through a variable fee.

The intermediary in our study is the dominant player in the apparel sourcing market accounting for more than half of the volume of transactions, and enjoys enormous commissions reaching nearly $50 billion. Two other significant but smaller players constitute the set of intermediaries. In our data, marketing firms rarely used more than one intermediary partly because different intermediaries focus on different product categories. To that extent, the substantive analysis will remain unaffected by potential competition among different intermediaries. Straight commission is the only mechanism observed in our data; this is also the norm in the industry. Whereas the commission amount as the mean of sharing the value spillover in the sourcing market can be endogenous, its uniformity and format invariance eliminates the issue as a concern in our analysis.

For the reasons noted earlier, there is no incentive for manufacturers or marketing firms to bypass the intermediary. The intermediary serves a useful function that is hard to eliminate or substitute. Again, discussions with the intermediary firm executives confirm that this is not a major issue. Finally, intermediaries are sophisticated organizations and fully understand the enforceable legal obligations of the marketing firms in advanced economies.

4.1. Data Description

Our data come from one of the largest matching intermediaries specializing in making deals between marketing firms and manufacturers in the sourcing market between 2002 and 2005. The intermediary is nearly five times the size of its two local competitors. This intermediary assembles a broad manufacturer network that helps achieve better price and quality and works with more than 500 marketing firms, primarily in the U.S. and Europe. Some of its top clients included Kohl's, Express, Warner Brothers, The Limited, and Tommy Hilfiger. We match the marketing firms and the manufacturers in the data set to the related business reports to collect detailed characteristics of the matching partners.

The matching deals are divided into four markets (Women, Men, Children, and Sports apparel),[9] each containing the marketing firms and the manufacturers in the same year from one particular category. Data on firms' and manufacturers' characteristics are from the quarter that precedes the market. The matching of the marketing firms and manufacturers is given by the names of the matched agents recorded in our transaction data. The sample consists of 259 matches between 72 marketing firms and 218 manufacturers. Some marketing firms and manufacturers participated in more than one market. In the specified period, there are 102 market firms, and 259 manufacturers.

There are three groups of variables used in the matching model and the commission equation. The first group includes the following firm characteristics: whether the firm is publicly traded, whether

[9] The definition of the four categories of the apparel industry follows the tradition among the industry practice as confirmed by the executives and industry experts.

the brand offered by the firm is a luxury brand, the number of visits made by the firm to the manufacturer, and two size dummies. The size dummy for the small firm is normalized. These dummies enable us to detect nonlinear relationships between sizes and commissions. The second group includes the following manufacturer characteristics: whether the manufacturer is publicly traded, whether the manufacturer is in a coastal province (Guangdong, Fujian, Zhejiang, and Jiangsu), the International Organization for Standardization (ISO) qualification, whether the manufacturer always meets the delivery deadline, the manufacturer's tenure, and two size dummies. The third group consists of the match-specific variables such as deal size, deal length, whether the deal is the first-time transaction among the matching partners, whether the deal entails special requirements on raw material selection, and whether the deal includes special packing requirements. Table 1(A) presents summary statistics and the variable definitions of the marketing firms' characteristics, and the manufacturers and the matching deals in our sample, respectively. Whereas there are many more small manufacturers in the data compared with large and medium-size, about 23.5% of firms are big marketing firms, and 35.3% are small. We see a substantive variation of the commission rate (and the commission) charged by the intermediary, ranging from 0.4% to 9.3% with an average of 2.5%.

To understand the variation across the four different types of markets, we present the summary statistics of the characteristics of the deals and the related matching partners in Table 1(B). There are significant numbers of matching partners (46 marketing firms and 30 manufacturers) participating in more than one category. Note that the Men's and Women's apparel categories have fewer publicly-traded or luxury marketing firms compared to the Sports and Children's categories, whereas Men's and Women's have more manufacturers in the convenient coastal provinces and are also more likely to be publicly traded. Interestingly, there are more large marketing firms and manufacturers in the Children's category, compared to other categories. In the Women's apparel market, there are more medium-size marketing firms, but relatively more large manufacturers than in the other categories. The Sports category has the fewest large marketing firms and manufacturers. Even though the Men's category has more large marketing firms than the Women's, the number of large manufacturers actually reverse in these two categories. This suggests that, across different markets (categories), the matching between marketing firms and manufacturers might vary, though in aggregate the big marketing firms tend to connect with big manufacturers, as we discuss in §4.2 in more detail. Furthermore, manufacturers in the Children's category are historically more likely to have ISO qualification and to meet deadlines.

Table 1(A) Variable Summary Statistics and Definition

Variable	Number of obs.	Mean	Standard deviation	Min	Max	Definition
Firm characteristics						
Listed_Firm	102	0.196	0.399	0	1	Whether the firm is publicly traded
Luxury	102	0.206	0.406	0	1	Whether the firm's brand is a luxury brand
Firm_Visit	102	1.392	1.220	0	7	Number of firm visits
Medium_Firm[a]	102	0.412	0.495	0	1	Whether a medium size firm
Large_Firm	102	0.235	0.426	0	1	Whether a large size firm
Manufacturer characteristics						
Location	259	0.641	0.481	0	1	Whether the manufacturer is located in a coastal province
Tenure (year)	259	5.050	2.343	2	14	Tenure of the manufacturer
Listed_Manu	259	0.185	0.389	0	1	Whether the manufacturer is publicly traded
ISO	259	0.884	0.321	0	1	The ISO qualification
Deadline	259	0.927	0.261	0	1	Whether the manufacturer always meets the delivery deadline
Medium_Manu[b]	259	0.177	0.383	0	1	Medium size manufacturer
Large_Manu	259	0.104	0.306	0	1	Large size manufacturer
Matching deal characteristics						
Commission ($1,000)	259	27.558	32.418	1.400	531.065	Match-specific commission
Deal_Size ($100,000)	259	13.856	17.126	0.700	256.476	Size of the matching deal
Comm. rate (%)	259	2.495	1.306	0.355	9.333	Commission rate charged
Deal_Length (Month)	259	6.537	2.135	4	12	Length of the transaction
Material	259	0.120	0.325	0	1	Whether special raw material is needed
Packaging	259	0.151	0.358	0	1	Whether special packaging is needed

[a]The definition of firm size is created by the matching intermediary. Even though they do not explicitly provide the cut-off level of the firm size, conversation with sources implies that medium firms' annual sales (for a particular product) are between $4 to $20 million; large firms refer to more than $20 million in sales.

[b]The manufacturer size is defined by the matching intermediary. As in the case of firm size, conversation with sources implies that medium manufacturers' annual revenue (for a particular product) is between $1 to $5 million; large firms refer to more than $5 million in sales.

Table 1(B) Summary Statistics of the Deals (and Matching Partners) Across Markets

Variable	Men (54)	Women (92)	Children (63)	Sports (50)
Firm characteristics				
Listed_Firm	0.185 (0.392)	0.173 (0.381)	0.222 (0.419)	0.260 (0.443)
Luxury	0.167 (0.376)	0.184 (0.390)	0.222 (0.419)	0.260 (0.443)
Firm_Visit	1.389 (1.172)	1.478 (1.288)	1.270 (1.139)	1.560 (1.417)
Medium_Firm	0.407 (0.496)	0.445 (0.500)	0.429 (0.499)	0.420 (0.499)
Large_Firm	0.241 (0.432)	0.207 (0.407)	0.317 (0.469)	0.140 (0.351)
Manufacturer characteristics				
Location	0.685 (0.469)	0.674 (0.471)	0.556 (0.501)	0.640 (0.485)
Tenure (year)	4.944 (2.291)	5.011 (2.393)	5.492 (2.526)	4.680 (1.755)
Listed_Manu	0.204 (0.407)	0.261 (0.442)	0.095 (0.296)	0.140 (0.351)
ISO	0.907 (0.293)	0.880 (0.326)	0.937 (0.246)	0.800 (0.404)
Deadline	0.963 (0.191)	0.913 (0.283)	0.984 (0.126)	0.840 (0.370)
Medium_Manu	0.130 (0.339)	0.174 (0.381)	0.222 (0.419)	0.180 (0.388)
Large_Manu	0.093 (0.293)	0.109 (0.312)	0.143 (0.353)	0.060 (0.240)
Matching deal characteristics				
Commission ($1,000)	25.470 (7.581)	31.435 (53.137)	26.349 (10.095)	24.200 (7.225)
Deal_Size ($100,000)	11.565 (6.366)	16.277 (26.074)	13.143 (10.691)	12.774 (8.640)
Comm. rate (%)	2.696 (1.374)	2.302 (1.134)	2.597 (1.402)	2.509 (1.392)
Deal_Length (Month)	6.167 (1.871)	6.620 (2.218)	6.492 (2.094)	6.840 (2.298)
Material	0.056 (0.231)	0.207 (0.407)	0.095 (0.296)	0.060 (0.239)
Packaging	0.185 (0.392)	0.098 (0.299)	0.143 (0.353)	0.220 (0.418)

In terms of the matching deals, the Women's and Children's categories, on average, have larger transactions than other categories. The commissions charged for these categories are also higher, though the commission rate is not necessarily higher. Interestingly, the Men's category has, on average, the smallest deal size, but the commission rate is also the highest. Compared with the other categories, the Sports category has the longer deal length, though not by much. Matching deals in the Women's category are much more likely to use special materials, whereas the Sports category has more deals that require special packaging.

4.2. Model Free Inferences and Simple Model Results

Industry wisdom suggests that large marketing firms tend to match with large manufacturers and vice versa. Table 1(B) also suggests that large marketing firms are more likely to coexist with large manufacturers in markets such as the Children's category. The other markets exhibit coexistence of medium- to large-size marketing firms and medium- to large-size manufacturers. To further understand the matching pattern, we construct the size measures (using the firms'/manufacturers' total annual sales) for all matching parties and run two corresponding ordinary least squares (OLS) regressions using the matched pairs: the marketing firms' size on the manufacturers' characteristics and the manufacturers' size on the firms' characteristics.[10]

[10] Whereas we glean insights from these reduced-form regressions, the structural model is not a direct development of these findings.

Results in Tables 2(A) and 3(A) show that the coefficients on the sizes of the matching partners are positively significant in both cases, which confirms that large marketing firms tend to match with large manufacturers, and vice versa. Though these results are generated from the pooled data across the four markets, they suggest that firm and manufacturer size are positively correlated. Larger manufacturers have some advantage in the sourcing market because they are likely to have a larger capacity, more experienced workers, and better production facilities. They are also more likely to have better information to facilitate easier monitoring. However, a large manufacturer could face significant variance in demand, thus reducing the firm's ability to meet demand in a timely manner. This is very important in the context of sourcing. In addition, contracting with a large manufacturer means that a firm's control over the production process will be relatively small, especially when product customization is important. Therefore, the size of a manufacturer could have multiple effects on the payoff perceived by the marketing firms.

The regression in Table 2(A) also shows that a large marketing firm is positively correlated with a manufacturer in the coastal area partly because the location is more convenient. In making their contracting choices, firms are more likely to match with manufacturers with longer tenures, convenient locations, public listings, and broader experience. Table 2(A) shows that a publicly-traded manufacturer is likely to be matched with a big marketing firm. Though a large marketing firm tends to match with a manufacturer

Table 2(A) **Firm Size on Manufacturer's Characteristics**

Variable	Mean	Standard deviation
Constant	3.065	0.327***
Location	0.002	0.001*
Tenure (year)	0.004	0.003
Listed_Manu	0.005	0.001***
Ln(*Manu_Size*)	0.337	0.051***
ISO	0.003	0.001***
Deadline	0.004	0.004

*, Significance at the 10% level; **, significance at the 5% level; ***, significance at the 1% level.

Table 2(B) **Firm Size on Manufacturer's Characteristics in Every Category**

Variable	Men	Women	Children	Sports
Location	0.003	0.002*	0.002**	0.001
Tenure (year)	0.004	0.005**	0.004	0.002
Listed_Manu	0.011**	0.004	0.004	0.003*
Ln(*Manu_Size*)	0.421*	0.307*	0.382	0.301***
ISO	0.004	0.002	0.005**	0.002
Deadline	0.002	0.006*	0.003	0.004

Note. The dependent variable is the log of the firm's total annual sales.
*, Significance at the 10% level; **, significance at the 5% level; ***, significance at the 1% level.

Table 3(A) **Manufacturer Size on Firm's Characteristics**

Variable	Mean	Standard deviation
Constant	1.015	0.192***
Listed_Firm	0.002	0.001**
Luxury	0.004	0.005
Firm_Visit	−0.007	0.015
Ln(*Firm_Size*)	0.314	0.032***

*, Significance at the 10% level; **, significance at the 5% level; ***, significance at the 1% level.

Table 3(B) **Manufacturer Size on Firm's Characteristics in Every Category**

Variable	Men	Women	Children	Sports
Listed_Firm	0.003*	0.004*	0.002	−0.001
Luxury	0.004*	0.007**	0.003	0.002
Firm_Visit	−0.008**	−0.009	0.001	−0.004*
Ln(*Firm_Size*)	0.275*	0.321***	0.212***	0.208

Note. The dependent variable is the log of the manufacturer's total annual sales.
*, Significance at the 10% level; **, significance at the 5% level; ***, significance at the 1% level.

with ISO certification, the impact of a manufacturer's tenure (past history) on the firm's size is not obvious.

As for the manufacturers, Table 3(A) suggests that the big manufacturers are more likely to match with large publicly-traded marketing firms. Moreover, the luxury brand marketing firms seem unattractive to the big manufacturers. The size of a marketing firm plays an important role in manufacturers' choices.

We run the same regressions for every market and present the results in Tables 2(B) and 3(B). Longer-tenure manufacturers have a bigger impact on the marketing firms in the Women's category, whereas this may not be significant in the other categories. Though large manufacturers seem to have a greater influence on most firms, some marketing firms in the matching pairs of the Children's category are not necessarily coordinated with corresponding manufacturers. The marketing firms in the Children's category reach the deal with the manufacturers with convenient locations and those that meet ISO standards. As for the manufacturers, most of them seem to benefit from being with large marketing firms, although those in the Sports category may not do so. Manufacturers in the Men's and Women's categories are more likely to deal with luxury and listed marketing firms, though the likely firms in the Children's and Sports categories are not obvious. These results coupled with the fact that the matching between two sides is not random suggest that to understand why the matching partners choose each other in the sourcing market and the resulted commission, a structural matching model could be fruitful.

5. Two-Sided Model Results and Discussion

We first illustrate that positive assortative matching of sizes is indeed prevalent in our model. We then show that for agents on both sides of the market there are similar relationships between the payoff (preference) ranking and the size: after controlling for other factors, medium-sized agents are considered as having the highest payoffs, closely followed by the largest agents, and then the smallest agents at the bottom of the list. Consequently there are similar size rankings on both sides, which explain the positive assorted matching of sizes. Marketing firms' risks and contract manufacturers' risk are important factors in the perceived payoffs and the resulting ranking. Controlling for the endogenous matching has a non-negligible impact on estimates of the determinants of the commissions and the intermediary's corresponding pricing strategy in such a business-to-business sourcing market.

5.1. Matching Preference

We explore the pattern of the matching in our structural model. Table 4 reports the posterior means and standard deviations of the coefficients in the agents' ranking of the matching partners in the matching process as summarized in Equations (1) and (2). The coefficients for all of the size dummies are positive and significant. Notably, the 95% highest posterior density intervals of all of the coefficients do not include

Table 4 Estimates of the Preference Ranking Equations (from the Matching Model)

Variable	Mean	Standard deviation
Manufacturer preference (firm ranking of added-value)		
Listed_Firm	0.046	0.014***
Luxury	0.012	0.008
Firm_Visit	0.009	0.021
Medium_Firm	0.287	0.115***
Large_Firm	0.269	0.108***
Firm preference (manufacturer ranking of added-value)		
Location	0.014	0.003***
Tenure (year)	0.024	0.009***
Listed_Manu	0.004	0.026
ISO	0.009	0.011
Deadline	0.014	0.008*
Medium_Manu	0.302	0.159**
Large_Manu	0.286	0.085***
Correlation		
κ	0.169	0.044***
λ	−0.128	0.101
$1/\sigma_v^2$	1.421	0.049***

Note. The dependent variables are the rankings of the added-value.
*, Zero is not contained in the 90% posterior density intervals; **, zero is not contained in the 95% posterior density intervals; ***, zero is not contained in the 99% posterior density intervals.

zero, indicating that on both sides of the market, the smallest agents are considered the worst in terms of perceived payoff and consequent ranking. This suggests that the small marketing firms potentially suffer from low reputation.

Further examination of the coefficients reveals that, on both sides of the market, the medium-sized agents have the highest rank, though the magnitude is modest.[11] This is consistent with the raw matching pattern discussed in §4.2, where we see that, within some markets, the agents' size is not necessarily significantly correlated with their marketing partners' size. The largest agents are less attractive, but they closely follow the medium group, and are better than the smallest. In the sourcing market, this mirrors the fact that, as the size of a marketing firm increases, it becomes a lower risk with better payment ability, thus making it more attractive. However, larger firms typically have organizational hierarchies that make the partners difficult to deal with. The estimation results suggest that the negative effects could outweigh the advantages for the biggest firms over the medium-sized firms, in terms of risk and growth potential. Similarly, as the size of a manufacturer increases, it is more likely to meet the production criteria, deliver products quickly, and pose smaller information asymmetries. Yet, the largest manufacturers could be less attractive than the medium-sized because large manufacturers may not allow detailed product customization (and the corresponding specific production process), and often do not provide rapid turnaround times. In the markets we study, these disadvantages of the largest manufacturers outweigh the advantages of medium-sized firms.

On both sides of the market, size ranking is in the same order: medium, big, and small. Medium-sized firms match with medium-sized manufacturers because both groups are the top choices on their respective sides. Among the remaining agents, the large firms and the large manufacturers are the top candidates, and are matched. Finally, the small firms and small manufacturers are ranked lowest in added-value, and they seem to have few choices but to match with each other.

Notably, whether the firm is publicly traded has the largest impact on the ranking besides the size factor. Other than size, a manufacturer's tenure has the highest influence for the marketing firm's ranking. These results highlight the importance of the manufacturers' tenure and the marketing firms' status during the matching process. The coefficient of the firms' number of visits is positive, but zero is included in the 90% highest posterior density intervals. Together with the result in the OLS regression that the coefficient of firms' visits is negative but not significant, this suggests that the influence of the marketing firms' visits on their rank of the benefit brought by the matching partner is ambiguous. On one hand, firms' visits could be seen as their monitoring ability. Thus a firm is better off with more visits because it can better monitor the other party. On the other hand, a higher number of visits could mean that there are problems with the other party that need to be addressed. This suggests that marketing firms' visits do not influence manufacturers' matching preference. The coefficients of whether the firm is publicly traded or is a luxury brand are both positive and are in the direction surmised earlier. As for the manufacturers, tenure and location have a positive influence. These findings suggest that a manufacturer's attractiveness is positively related to its years of experience and logistical capability, as reflected by its location. The coefficient of whether the manufacturer is publicly traded is positive, indicating that a publicly-traded manufacturer might have an advantage in reaching a deal with the marketing firms. However, the fact that the 90% highest posterior density interval includes zero means that this may not be an important concern of the firms when they rank the manufacturers.[12] Whether

[11] We thank one anonymous reviewer for suggesting a cautious interpretation of the medium-size agents ranking highest, as the magnitude is modest.

[12] One important observation in the market we study is that more state-owned manufacturers (in terms of ratio) are publicly traded

the manufacturer has a history of not meeting deadlines has a positive impact on the firm's preference; meeting ISO standards is less relevant.

5.2. The Intermediary's Pricing: Determinants of the Commission

5.2.1. The Impact of the Matching Partners' and the Matching Deals' Characteristics. Because the matching generates benefits for firms and manufacturers, the intermediary's commission from this process is based on these agents' characteristics. In Table 5(A), we see a model without endogenous matching where a publicly-traded firm contributes to a higher commission and the luxury brand seems to have a negative impact on commission. In the structural matching model presented in Table 5(B), both factors have a positive impact on the commission. However, the 95% highest posterior density intervals for the variable of whether the firm is publicly traded include zero, showing that this characteristic may not have a substantial impact on the commission. The coefficients of firm size dummies are both negative and their 90% highest posterior density intervals do not include zero. This shows that larger firms charged lower commission fees, holding all else equal. The coefficient of the firm's number of visits is positive. This suggests that firms expending more effort in monitoring are also willing to pay a premium to the intermediary to find better partner manufacturers. Thus, interestingly, firms' desire to visit manufacturing factories allows the intermediary to charge a higher commission, though the visits have little impact on manufacturers' preference.

Manufacturers' tenure has a positive impact on the intermediary's commission. The longer the tenure, the higher the commission paid by the marketing firm. The 95% highest posterior density interval does not include zero, which suggests manufacturer's tenure has a nontrivial impact on the commission. Location of the manufacturers has a similar positive effect, but influence could be weak since the 95% highest posterior density interval includes zero. Whether a manufacturer is publicly traded weakens the intermediary's pricing power by reducing the commission. The result implies that publicly-traded manufacturers are attractive to the marketing firms, but do not necessarily benefit the intermediary. This could be due to the fact that many publicly-traded companies are known to the branded firms. Thus, the intermediary's additional informational value is limited. The coefficients of the manufacturer-size dummies are both positive and their 95% highest posterior density intervals do not include zero. This indicates that firms matching with larger manufacturers pay higher commissions, and contribute more to the value-generating process.

The coefficients of the deal size and length are negative. This implies that large and/or lengthy deals lead to lower commissions; however, the fact that the 95% highest posterior density intervals include zero suggests that the impact is negligible. Consequently, these seemingly attractive big and lengthy deals may not generate a higher value spillover in the sourcing chain. Special requirements for materials or packaging have positive and significant impacts on the commission. Though the analysis without the matching model provides similar results, the matching model further confirms the importance of these factors for the intermediary when pricing the commission in the matching process. Thus, in the sourcing market a special order that requires some attention, such as packaging and material, benefits the intermediary, in the form of commission.

5.2.2. The Role of Unobserved Factors. From the estimation results in Table 4, we find that the covariance, κ, between the error terms in the marketing firm's ranking equation and the commission equation is positive and does not include zero in its 95% highest posterior density interval. This suggests that the matching process is correlated with the intermediary's commission outcome. We substitute Equation (6) into the commission Equation (5) by considering the

Table 5(A) OLS Estimates of the Commission Equation

Variable	Mean	Standard deviation
Firm characteristics		
Listed_Firm	0.288	0.281
Luxury	−0.268	0.269
Firm_Visit	0.045	0.014***
Medium_Firm	−0.199	0.105*
Large_Firm	−0.205	0.087***
Manufacturer characteristics		
Location	0.021	0.194
Tenure (year)	0.108	0.041***
Listed_Manu	−0.041	0.052
ISO	0.049	0.039
Deadline	−0.033	0.046
Medium_Manu	0.212	0.101**
Large_Manu	0.239	0.105**
Deal-specific characteristics		
Deal_Size	−0.027	0.023
Deal_Length	−0.032	0.049
Material	0.046	0.022**
Packaging	0.072	0.023***
Constant	3.198	0.553***

Note. The dependent variables are the commission rate charged by the matching intermediary.

*, Zero is not contained in the 90% posterior density intervals; **, zero is not contained in the 95% posterior density intervals; ***, Zero is not contained in the 99% posterior density intervals.

companies, making them less attractive to the branded firms compared to privately-owned companies.

Table 5(B) Estimates of the Commission Equation Using Endogenous Matching

Variable	Mean	Standard deviation
Firm characteristics		
Listed_Firm	0.245	0.238
Luxury	0.114	0.059*
Firm_Visit	0.036	0.011***
Medium_Firm	−0.183	0.101*
Large_Firm	−0.217	0.072***
Manufacturer characteristics		
Location	0.018	0.117
Tenure (year)	0.121	0.049***
Listed_Manu	−0.021	0.043
ISO	0.041	0.044
Deadline	−0.021	0.029
Medium_Manu	0.176	0.102*
Large_Manu	0.217	0.124*
Deal-specific characteristics		
Deal_Size	−0.017	0.032
Deal_Length	−0.012	0.041
Material	0.044	0.026*
Packaging	0.077	0.033***
Constant	2.864	0.711***

Note. The dependent variables are the commission rate charged by the matching intermediary.

*, Zero is not contained in the 90% posterior density intervals; **, zero is not contained in the 95% posterior density intervals; ***, zero is not contained in the 99% posterior density intervals.

successful deals as follows to see the m_{ij}'s are correlated with the ε_{ij}'s

$$\begin{aligned} C_{ij} &= \alpha_0 + m'_{ij}F'_i\alpha_1 + M'_j\alpha_2 + D'_{ij}\alpha_3 + \varepsilon_{ij} \\ &= \alpha_0 + m'_{ij}F'_i\alpha_1 + M'_j\alpha_2 + D'_{ij}\alpha_3 + \kappa m'_{ij}\eta_i \\ &\quad + \lambda\delta_j + \nu_{ij}, \quad \nu_{ij} \sim N(0, \sigma_\nu^2). \end{aligned} \tag{9}$$

If the matching, m_{ij}, were in fact independent of ε_{ij}, as without the matching process in the random assignment between the two sides, then m_{ij} should be exogenous. However, the nonzero covariance of κ implies that m_{ij} is correlated with ε_{ij}. Therefore the OLS estimators of regressing the commission on the observed characteristics are biased and misleading.

Table 5(A) shows OLS estimates without the endogenous matching. Table 5(B) is from our structural matching model. The differences between these two groups are significant with the average absolute percentage difference at more than 10%. In addition, signs of some estimates actually reverse. Especially noteworthy is the impact of whether the marketing firm is a luxury brand.

The marketing firms' unobserved factors have two components that affect the commission in opposite directions. These components are: unobserved ability and unobserved risk.[13] If the first component dominates, then the unobserved firm attractiveness will be positively correlated with the commission; firms with high unobserved ability have higher unobserved quality but demand more effort from the matching intermediary to meet their needs. Therefore, the intermediary charges them a higher commission. On the other hand, if the unobserved risk dominates, then the unobserved firm attractiveness will be negatively correlated with the commission fee; firms with higher unobserved risk have lower unobserved quality and will be charged a high commission, all else being equal. The positive sign of κ indicates that unobserved ability dominates the unobserved risk to become the main component in firms' unobserved attractiveness.

Conventional wisdom suggests that the manufacturers unobserved factors have several components that affect the commission in the same directions: unobserved risk, unobserved information opacity, and operational efficiency (Stoll and Whaley 1983, Spulber 1996). From a broad perspective, operational efficiency can be considered part of information opacity. Manufacturers with lower unobserved risk or lower degrees of unobserved information opacity are more attractive but unknown to the marketing firms. Consequently, the matching intermediary is unable to charge the marketing firms high commission fees for matching with such manufacturers, whereas the marketing firms are willing to pay higher commission to manufacturers with known characteristics.[14] The negative sign of λ reinforces this negative correlation between manufacturers' unobserved factors and the commission from the deals involving such manufacturers.

The difference between the OLS estimates and estimates from the structural matching model is consistent with the signs of λ and κ. Because λ is negative, the higher unobserved attractiveness of the manufacturer means that the value spillover generated in the process for such transactions has a smaller unobserved factor. In the OLS regression of the commission equation, the effect of the smaller unobserved

[13] We refer to the factors unobserved by the econometrician and the matching partners, but observed by the intermediary. These could be the informational services provided by the intermediary to facilitate the matching (and the commission). Such informational provision is the intermediary's main focus, and is often settled before the deals are reached, even though some realization of the service (such as monitoring the matching parties' related behavior) could be after the deals are signed. Such unobservables influence the matching and the commission. However, if the factors are only unobserved by the econometrician, but not the matching partners, the positive correlation may not be interpreted as the information provided by the intermediary. If the unobservable influences the commission but not the matching, the value spillover captured by the commission could be underestimated. Unless we have additional information on the relevant variables, we can neither test this nor completely rule it out. Thanks to one anonymous reviewer for these insights.

[14] Conversations with industry executives confirms this insight obtained from our analysis.

factor is incorrectly attributed to the observed proxies, resulting in biased estimators of these factors. Similarly, since κ is positive, the reduced-form OLS regression overestimates the coefficients of these observed proxies, making the inference potentially misleading.

6. Conclusion

Enormous shifts in the upstream-channel structure in the past two decades, outsourcing production, and marketing focus have become important strategies in a number of key verticals. The strategies raise a number of important research issues but have not received any significant attention. Here we have taken a step to bridge this gap. In this paper, we investigate the matching partners' preference and the intermediary's associated pricing strategy (i.e., the commission) in the sourcing market. We show that there is endogenous matching in the sourcing market and the matching preference and that OLS estimation of the commission outcome is problematic when some characteristics of marketing firms and manufacturers are not perfectly observed. To control for the endogenous matching, we develop a two-sided matching model together with the commission equation. We obtain Bayesian inference using a Gibbs sampling algorithm with data augmentation. This transforms a high-dimensional integration problem into a simulation problem and overcomes the computational difficulty.

Using a sample of marketing firms and contract manufacturers from one leading intermediary, we find evidence of positive assorted matching of sizes in the market. That is, large marketing firms tend to match with large manufacturers, and vice versa. We then show that for agents on both sides of the market there are similar relationships between attractiveness and size. This leads to similar size rankings for both sides and explains the positive assorted matching of sizes. Controlling for the endogenous matching yields different estimates of the impact of the determinants of the intermediary's pricing. Furthermore, the two-sided matching model enables us to understand the factors that add value to the matching partners, which can point the way for agents who try to improve their standing. Our analysis suggests that factors such as whether the marketing firms are listed, the manufacturers' location, and tenure are important in ranking the matching partners' payoff from such matching.

Our analysis has a number of limitations. First, as noted earlier, data limitations prevent us from identifying exogenous variables that can serve as useful instruments and enable simpler estimation. Second, though the commission acts as a raw proxy for the informational value provided by the intermediary, direct visibility and measurement of these factors could yield additional interesting insights. Third, our results are derived from the apparel industry[15] and the results may not generalize to other markets.

Our study suggests several avenues for future research. First, our analysis focuses on the information opacity between marketing firms and manufacturers, and abstracts away the possible agent conflict between the matching intermediary and the clients. Even though this agent conflict concern is implicitly captured in our preference ranking construction, an explicit model of principal-agent conflict in the matching setting may yield additional theoretical and empirical insights. Second, it may also be fruitful to examine repeated matching between the same set of firms and manufacturers and the evolving commission structure. An interesting scenario may arise if we allow for dynamic matching. Switching partners across different deals could be more informative, and a forward-looking agent might foresee this and plan accordingly. We hope future research will address these issues.

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Appendix A. Proof of Proposition 1

This proof builds on Gale and Shapley (1962), Roth and Sotomayor (1990), and Eeckhout (2000). Our model is a special case of the college admission model, for which the existence of an equilibrium matching is established in the literature. We add vertical heterogeneity on both sides of the market to the model. Eeckhout (2000) shows that in a one-to-one two-sided matching model, the equilibrium matching is unique if there is vertical heterogeneity on both sides of the market. We show that this sufficient condition for uniqueness also applies to the many-to-one two-sided matching model.

We re-index the marketing firms and manufacturers based on the preference rank as follows: $i \succ_j i'$, $\forall\, i > i'$, $\forall\, j$,

[15] The apparel industry is one of the biggest in the world. It dwarfs categories such as coffee, ketchup, and yogurt. It is extensively outsourced especially to emerging markets worldwide. The intermediary in this market alone earns tens of billions of dollars in commission. This underscores the sheer size of this market. Therefore, arguably on its own merit, examination of the vertical is relevant. The same intermediary also operates in a number of significant verticals such as fashion accessories, furnishings, gifts, handicrafts, home products, promotional merchandise, toys, sporting goods, and travel goods. Thus, our analysis may be appropriate for these categories as well but the extent to which the characteristics impact value creation requires category-specific estimation. The electronic component industry is another massive vertical and examination of this category will shed light on the generalizability of our findings.

and $j \succ_i j'$, $\forall j > j'$, $\forall i$, where $i \succ_j i'$ denotes that manufacturer j prefers firm i to firm i' and $j \succ_i j'$ denotes that firm i prefers manufacturer j to manufacturer j'. Let n_{it} be the quota of firm i. The following J-step algorithm implies the unique equilibrium matching, in which there is perfect sorting. In step 1, manufacturer J matches with firm I. In step 2, manufacturer $J-1$ matches with firm I if $n_{It} \geq 2$, otherwise it matches with firm $I-1$. In step 3, manufacturer $J-2$ matches with firm I if $n_{It} \geq 3$, otherwise it matches with firm $I-1$ if $n_{It} + n_{I-1,t} \geq 3$, else it matches with firm $I-2$, etc.

First, μ is an equilibrium matching. Suppose not, then there exists at least one blocking pair (i', j') such that $i' > \mu(j')$ and $j' > \min\{j\colon j \in \mu(i')\}$. That is a contradiction, since by construction if $i' > \mu(j')$ then $j'' > j'$, $\forall j'' \in \mu(i')$, so $j' > \min\{j\colon j \in \mu(i')\}$ cannot be true. Second, the equilibrium matching is unique. Suppose not, then there exists $\tilde{\mu} \neq \mu$ such that $\tilde{\mu}$ is also an equilibrium matching. There is at least one match that is in μ but not in $\tilde{\mu}$. Now consider the first step in the algorithm that forms a match that is not in $\tilde{\mu}$. Name this match (i', j'). It follows that $\min\{j\colon j \in \tilde{\mu}(i')\} < j'$ and that $\tilde{\mu}(j') < i'$, since all of the matches formed in the previous steps are in both μ and $\tilde{\mu}$. Therefore, (i', j') is a blocking pair for $\tilde{\mu}$, a contradiction. $\square$

Appendix B. Proof of Corollary 1

The unique equilibrium matching is characterized by a set of inequalities, based on the fact that there is no blocking firm-manufacturer pair. For each firm, stability requires that its worst current partner manufacturer be better than any other firm whose current partner firm is worse than this firm. Similarly, for each manufacturer, stability requires that its current partner firm be better than any other firm whose worst current partner manufacturer is worse than this manufacturer.

Consider a matching in market t, μ_t. Suppose firm i and manufacturer j are not matched in μ_t. The matching (i, j) is a blocking pair iff $R_j^m > \min_{j' \in \mu_t(i)} R_{j'}^m$ and $R_i^f > R_{\mu_t(j)}^f$. Correspondingly, (i, j) is not a blocking pair iff $R_j^m < \min_{j' \in \mu_t(i)} R_{j'}^m$ or $R_i^f < R_{\mu_t(j)}^f$. Equivalently, (i, j) is not a blocking pair iff $R_j^m < \bar{R}_{ji}^m$ and $R_i^f < \bar{R}_{ij}^f$, where

$$\bar{R}_{ji}^m = \begin{cases} \min\limits_{j' \in \mu_t(i)} R_{j'}^m, & \text{if } R_i^f > R_{\mu_t(j)}^f \\ \infty & \text{otherwise} \end{cases} \quad \text{and}$$

$$\bar{R}_{ij}^f = \begin{cases} R_{\mu_t(j)}^f, & \text{if } R_j^m > \min\limits_{j' \in \mu_t(i)} R_{j'}^m \\ \infty & \text{otherwise} \end{cases}.$$

Now assume that firm i and manufacturer j are matched in μ_t. Firm i or manufacturer j is part of a blocking pair iff $R_j^m < \max_{j' \in f(i)} R_{j'}^m$ or $R_i^f < \max_{i' \in f(j)} R_{i'}^f$, where $f(i)$ is the set of manufacturers that do not currently partner with firm i but would prefer to do so, and $f(j)$ is the set of firms that do not currently contract with manufacturer j but would prefer to do so. These two sets contain the feasible deviations of the agents and are specified as

$$f(i) = \{j \in J_t \backslash \mu_t(i)\colon R_i^f > R_{\mu_t(j)}^f\} \quad \text{and}$$

$$f(j) = \Big\{i \in I_t \backslash \mu_t(j)\colon R_j^m > \min_{j' \in \mu_t(i)} R_{j'}^m\Big\}.$$

Therefore neither firm i nor manufacturer j is part of a blocking pair iff $R_j^m > \underline{R}_{ji}^m$ and $R_i^f > \underline{R}_{ij}^f$, where $\underline{R}_{ji}^m = \max_{j' \in f(i)} R_{j'}^m$ and $\underline{R}_{ij}^f < \max_{i' \in f(j)} R_{i'}^f$. This leads to the following characterization of the equilibrium matching:

$$\mu_t = \mu_t^e \quad \Leftrightarrow \quad \begin{cases} R_i^f \in (\underline{R}_i^f, \bar{R}_i^f), \quad \forall\, i \in I_t \\ \qquad\qquad \text{and} \\ R_j^m \in (\underline{R}_j^m, \bar{R}_j^m), \quad \forall\, j \in J_t \end{cases},$$

where $\underline{R}_i^f = \max_{j \in \mu_t(i)} \underline{R}_{ij}^f$, $\bar{R}_i^f = \min_{j \notin \mu_t(i)} \bar{R}_{ij}^f$, $\underline{R}_j^m = \underline{R}_{j, \mu_t(j)}^m$, and $\bar{R}_j^m = \min_{i \notin \mu_t(j)} \bar{R}_{ji}^m$. $\square$

Appendix C. Conditional Posterior Distributions

We obtain the conditional posterior distributions by examining the kernels of the conditional posterior densities.

The conditional posterior distribution of R_i^f is $N(\hat{R}_i^f, \hat{\sigma}_{R_i^f}^2)$ truncated to the interval $(\underline{R}_i^f, \bar{R}_i^f)$, where

$$\hat{R}_i^f = F_i'\beta + \frac{\kappa \sum_{j \in \mu_t(i)} [C_{ij} - A_{ij}'\alpha - \lambda(R_j^m - M_j'\gamma)]}{\sigma_\nu^2 + \kappa^2 n_{it}} \quad \text{and}$$

$$\hat{\sigma}_{R_i^f}^2 = \frac{\sigma_\nu^2}{\sigma_\nu^2 + \kappa^2 n_{it}}.$$

The conditional posterior distribution of R_j^m is $N(\hat{R}_j^m, \hat{\sigma}_{R_j^m}^2)$ truncated to the interval $(\underline{R}_j^m, \bar{R}_j^m)$, where

$$\hat{R}_j^m = M_j'\gamma + \frac{\lambda[C_{\mu_t(j), j} - A_{\mu_t(j), j}'\alpha - \kappa(R_{\mu_t(j)}^f - F_{\mu_t(j)}'\beta)]}{\sigma_\nu^2 + \lambda^2} \quad \text{and}$$

$$\hat{\sigma}_{R_j^m}^2 = \frac{\sigma_\nu^2}{\sigma_\nu^2 + \lambda^2}.$$

The prior distributions of β, γ, α, and κ are $N(\bar{\beta}, \bar{\Sigma}_\beta)$, $N(\bar{\gamma}, \bar{\Sigma}_\gamma)$, $N(\bar{\alpha}, \bar{\Sigma}_\alpha)$, and $N(\bar{\kappa}, \bar{\Sigma}_\kappa)$, respectively. The prior distribution of λ is $N(\bar{\lambda}, \bar{\Sigma}_\lambda)$ truncated on the right at 0. The prior distribution of $1/\sigma_\nu^2$ is gamma, $1/\sigma_\nu^2 \sim G(a, b)$, $a, b > 0$.

The conditional posterior distribution of β is $N(\hat{\beta}, \hat{\Sigma}_\beta)$, where

$$\hat{\beta} = -\hat{\Sigma}_\beta \bigg\{ -\bar{\Sigma}_\beta^{-1}\bar{\beta} + \sum_{t=1}^{T} \bigg[\sum_{(i,j) \in \mu_t} \frac{\kappa}{\sigma_\nu^2} F_i \Big(C_{ij} - A_{ij}'\alpha - \kappa R_i^f - \lambda(R_j^m - M_j'\gamma) \Big) - \sum_{i \in I_t} R_i^f F_i \bigg] \bigg\},$$

and

$$\hat{\Sigma}_\beta = \bigg\{ \bar{\Sigma}_\beta^{-1} + \sum_{t=1}^{T} \sum_{i \in I_t} \frac{\sigma_\nu^2 + \kappa^2 n_{it}}{\sigma_\nu^2} F_i F_i' \bigg\}^{-1}.$$

The conditional posterior distribution of γ is $N(\hat{\gamma}, \hat{\Sigma}_\gamma)$, where

$$\hat{\gamma} = -\hat{\Sigma}_\gamma \bigg\{ -\bar{\Sigma}_\gamma^{-1}\bar{\gamma} + \sum_{t=1}^{T} \bigg[\sum_{(i,j) \in \mu_t} \frac{\lambda}{\sigma_\nu^2} M_j (C_{ij} - A_{ij}'\alpha - \kappa(R_i^f - F_i'\beta) - \lambda R_j^m) - \sum_{i \in J_t} R_j^m M_j \bigg] \bigg\},$$

and

$$\hat{\Sigma}_\gamma = \bigg\{ \bar{\Sigma}_\gamma^{-1} + \sum_{t=1}^{T} \sum_{j \in J_t} \frac{\sigma_\nu^2 + \lambda^2}{\sigma_\nu^2} M_j M_j' \bigg\}^{-1}.$$

The conditional posterior distribution of α is $N(\hat{\alpha}, \hat{\Sigma}_\alpha)$, where

$$\hat{\alpha} = -\hat{\Sigma}_\alpha \left\{ -\bar{\Sigma}_\alpha^{-1}\bar{\alpha} - \sum_{t=1}^{T} \sum_{(i,j)\in\mu_t} \frac{1}{\sigma_\nu^2} A_{ij}(C_{ij} - \kappa(R_i^f - F_i'\beta) - \lambda(R_j^m - M_j'\gamma)) \right\},$$

and

$$\hat{\Sigma}_\alpha = \left\{ \bar{\Sigma}_\alpha^{-1} + \sum_{i=1}^{T} \sum_{(i,j)\in\mu_t} \frac{1}{\sigma_\nu^2} A_{ij} A_{ij}' \right\}^{-1}.$$

The conditional posterior distribution of κ is $N(\hat{\kappa}, \hat{\sigma}_\kappa^2)$, where

$$\hat{\kappa} = -\hat{\sigma}_\kappa^2 \left\{ -\frac{\bar{\kappa}}{\bar{\sigma}_\kappa^2} - \sum_{t=1}^{T} \sum_{(i,j)\in\mu_t} \frac{(C_{ij} - A_{ij}'\alpha - \lambda(R_j^m - M_j'\gamma))(R_i^f - F_i'\beta)}{\sigma_v^2} \right\},$$

and

$$\hat{\sigma}_\kappa^2 = \left\{ \frac{1}{\bar{\sigma}_\kappa^2} + \sum_{t=1}^{T} \sum_{i\in I_t} \frac{n_{it}(R_i^f - F_i'\beta)^2}{\sigma_v^2} \right\}^{-1}.$$

The conditional posterior distribution of λ is $N(\hat{\lambda}, \hat{\sigma}_\lambda^2)$ truncated on the right at 0, where

$$\hat{\lambda} = -\hat{\sigma}_\lambda^2 \left\{ -\frac{\bar{\lambda}}{\bar{\sigma}_\lambda^2} - \sum_{t=1}^{T} \sum_{(i,j)\in\mu_t} \frac{(C_{ij} - A_{ij}'\alpha - \kappa(R_i^f - F_i'\beta)(R_j^m - M_j'\gamma))}{\sigma_v^2} \right\},$$

and

$$\hat{\sigma}_\lambda^2 = \left\{ \frac{1}{\bar{\sigma}_\lambda^2} + \sum_{t=1}^{T} \sum_{j\in J_t} \frac{(R_j^m - M_j'\gamma)^2}{\sigma_v^2} \right\}^{-1}.$$

Denote $d = \sum_{t=1}^{T} |J_t|$ as the total number of deals across all of the markets. The conditional posterior distribution of $1/\sigma_v^2$ is $G(\hat{a}, \hat{b})$, where $\hat{a} = a + d/2$, and

$$\hat{b} = \left[\frac{1}{b} + \frac{1}{2} \sum_{t=1}^{T} \sum_{(i,j)\in\mu_t} (C_{ij} - A_{ij}'\alpha - \kappa(R_i^f - F_i'\beta) - \lambda(R_j^m - M_j'\gamma))^2 \right].$$

References

Ackerberg DA, Botticini M (2002) Endogenous matching and the empirical determinants of contract form. *J. Political Econom.* 110(3):564–591.

Albert J, Chib S (1993) Bayesian analysis of binary and polychotomous response data. *J. Amer. Statist. Assoc.* 88(422):669–679.

Chen J (2009) Two-sided matching in the loan market. Working paper, University of California, Irvine, Irvine.

Eeckhout J (2000) On the uniqueness of stable marriage matchings. *Econom. Lett.* 69(1):1–8.

Einhorn B (2009) Li & Fung: A factory sourcer shines. *Bloomberg Businessweek*. Accessed February 12, 2015, http://www.businessweek.com/magazine/content/09_21/b4132054330480.htm.

Fox J (2010) Estimating matching games with transfers. Working paper, University of Michigan, Ann Arbor.

Gale D, Shapley L (1962) College admissions and the stability of marriage. *Amer. Math. Monthly* 69(1):9–15.

Gelfand A, Smith A (1990) Sampling-based approaches to calculating marginal densities. *J. Amer. Statist. Assoc.* 85(410):398–409.

Geweke J (1992) Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. *Bayesian Statist.* 4:169–193.

Geweke J (1999) Using simulation methods for Bayesian econometric models: Inference, development and communication. *Econometric Rev.* 18(1):1–73.

Geweke J (2004) Getting it right: Joint distribution tests of posterior simulators. *J. Amer. Statist. Assoc.* 99(467):799–804.

Harvard Business Cases (1996) Li & Fung (Trading) Ltd. https://cb.hbsp.harvard.edu/cbmp/product/396075-PDF-ENG.

Harvard Business Cases (2002) Leveraged growth: Expanding sales without sacrificing profits. https://cb.hbsp.harvard.edu/cbmp/product/R0210E-PDF-ENG.

Manski CF (1975) Maximum score estimation of the stochastic utility model of choice. *J. Econometrics* 3(3):205–228.

Park M (2013) Understanding merger incentives and outcomes in the mutual fund industry. *J. Banking Finance* 37(11):4368–4380.

Raftery AE, Lewis S (1992) How many iterations in the Gibbs sampler? Bernardo JM, Berger JO, Dawid AP, Smith AFM, eds. *Bayesian Statistics*, Vol. 4 (Oxford University Press, Oxford, UK), 763–773.

Rees K, Hathcote J (2004) The U.S. textile and apparel industry in the age of globalization. *Global Econom. J.* 4(1):1–24.

Roth A, Sotomayor M (1990) *Two-Sided Matching: A Study in Game-Theoretic Modeling and Analysis*, Econometric Society Monograph Series (Cambridge University Press, Cambridge, UK).

Sørensen M (2007) How smart is smart money? A two-sided matching model of venture capital. *J. Finance* 62(6):2725–2762.

Spulber DF (1996) Market microstructure and intermediation. *J. Econom. Perspectives* 10(3):135–152.

Stoll HR, Whaley RE (1983) Transaction costs and the small firm effect. *J. Financial Econom.* 12(1):57–79.

Tanner MA, Wong WH (1987) The calculation of posterior distributions by data augmentation. *J. Amer. Statist. Assoc.* 82(398): 528–550.

Uetake K, Watanabe Y (2013) Entry by merger: Estimates from a two-sided matching model with externalities. Working paper, Yale University, New Haven, CT.

Yang S, Chen Y, Allenby G (2003) Bayesian analysis of simultaneous demand and supply. *Quant. Marketing Econom.* 1(3):251–275.

Yang Y, Shi M, Goldfarb A (2009) Empirically identifying the value of a brand alliance: An application to professional team sports. *Marketing Sci.* 28(6):1095–1111.