A Two-Sided Entry Model with Manufacturer-Retailer Contracts

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Abstract

We construct and estimate a two-sided, asymmetric-information entry model where there exists a contractual, revenue-sharing agreement between the two sides. Using a unique dataset describing the two-sided entry decisions of clothing manufacturers into a retail department store, we recover the economic determinants driving the observed contractual and entry patterns. Estimation results show that the entry of a manufacturer can generate important spillovers for the sales of other manufacturers. In counterfactual experiments, we find that the nature of the contract minimizes the adverse effects of asymmetric information and that manufacturer profits would increase if they could reveal their private information.

Keywords: Two-sided entry, incomplete information, manufacturer-retailer contracts, MPEC, spillovers

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1. Introduction

In this paper, we construct and estimate a two-sided, asymmetric-information entry model where there exists a contractual, rent-sharing agreement between the two sides. This setting is common in the retail sector, where individual manufacturers enter into contracts with retail stores. In particular, we analyze the two-sided entry decisions of clothing brands in a Chinese retail department store and estimate a structural model which specifies the profit sharing agreement between the two sides.

In our context, entry decisions can only be made if the entry benefits both parties. If the department store wants to attract a manufacturer's brand, it has to offer a favorable contract. Similarly, a manufacturer can only sell in the department store with the store's permission. Information asymmetry, however, often exists between the two sides. The department store, for example, may only have partial information on the product quality of each potential entrant brand. A contract designed to facilitate entry and alleviate the economic inefficiency due to the information asymmetry, therefore, is important from the store and manufacturers' perspective.

The primary goal of this paper is to investigate the economic determinants of the observed patterns of entry in the data and to study the implications of information asymmetry on contract design. To achieve this goal, we model the division of sales revenue specified in a manufacturer-retailer contract, the entry decision of manufacturers, and post-entry market outcomes. Gaining a deeper understanding of how entry decisions are made requires a consideration of the incentives of both manufacturers and the department store. Although each manufacturer only considers its own profit from entry, the store has to evaluate the impacts of the entry on the overall store profit. By specifying and estimating an entry model that incorporates the considerations from manufacturers and the store, we are able to study the economic determinants of firm entry that cannot be identified in standard entry models. With results that quantify these determinants, we can further examine the economic factors that drive the design of the contracts that we observe in the data. In particular, we are interested in the determinants of the share of revenue that is transferred to manufacturers as well as understanding how information asymmetry affects contracts and profits.

The starting point for our analysis is a unique dataset which contains information about the manufacturers in the professional women's clothing category who are potential entrants to a major department store in the Chinese city of Shanghai. To quantify the impacts of entry on the profitability of the department store and manufacturers, we rely on three sources of information: the observed entry and exit decisions of the manufacturers, the annual sales revenue of each contracted manufacturer, and the contracted-level of revenue transfer from the store to manufacturers. This final data source, which describes the revenue-sharing agreement, makes our research unique in comparison with previous studies. Another rich feature of our data is that we obtain the complete list of brand attributes, both objective and subjective, for each potential entrant brand based on the store's evaluation. Therefore, we effectively have the information on the "demand shock" that is the store's knowledge but traditionally treated as unobserved heterogeneity in the literature.

Given this data, we can develop a two-sided entry model that allows for both asymmetric information and revenue sharing between the store and manufacturers. The unique nature of our data facilitates clean identification of the model's parameters. The sales data helps identify the relationship of substitution and complementarity among the various types of brands in the women clothing category. Data on the revenue transfer and entry decisions of manufacturers allow us to separately identify manufacturers' cost of entry from the spillovers effects of entry on the store's profit.

As documented in the previous literature on firm entry, allowing for substitution and complementarity between entrants may generate multiple equilibria. An additional complication is that our model involves a large number of manufacturer brands differentiated along multiple product attributes. These complexities pose potential challenges to estimating models of this class. To tackle this problem, we use the concept of Bayesian Nash equilibrium and specify a set of equilibrium probabilities of brand entry, under the constraint that each player's conjecture about other players' entry matches with their actual entry probabilities. We then apply the method of mathematical programming with equilibrium constraints (MPEC) developed in Su and Judd (2010) for model estimation, allowing us to estimate the structural parameters of our model where entry probabilities are subject to the constraints derived from the Bayesian Nash equilibrium. As the brand sales and revenue transfers are only observed conditional on entry, another challenge for our model estimation is the selection issue (Heckman, 1979). Our solution is to use the control function approach, introduced in Heckman and Robb (1985, 1986), to semi-parametrically correct for the selection bias in outcome equations.

Our results show that the entry of a manufacturer will impose significant externalities on the revenue of other manufacturers. The store classifies entering manufacturer brands as either low-end, medium-end, or high-end and we find that the strategic relationship between brands across these tiers is asymmetric. While the sales of low-end brands increase with the entry of medium-tiered brands, the entry of low-end brands does not have much impact on the sales of other brands. The entry of a high-end brand, on the other hand, will increase the sales of other high-end brands but hurt the sales of low-end brands. Thus, gaining one high-end brand will help attract other high-end brands to enter and pressure existing low-end brands to leave, facilitating the store's stated current strategy of moving upscale. Furthermore, we find that high-end brands also generate positive spillovers on other product categories sold in the store. While in previous research the externalities from a brand are assumed to have no direct impact on the manufacturer's entry decision, in our model the externalities are allowed to change the transfer offer in the contract. Finally, to validate our structural model approach, we compare the aggregate benefits from the entry estimated using our model with the brand scores used by the store, which have not been directly used in estimation. We find the two measures to be highly consistent with each other and have a correlation of 0.85, providing strong evidence for the validity of our structural model.

Based on the estimation results, we conduct two counterfactual experiments to study the impacts of different types of contracts on the store and manufacturers' profit. Our first counterfactual experiment suggests that the contingent component of contractual transfers plays a critical role in negating the adverse selection problem generated by asymmetric information. We also show that contracts allowing the store and manufacturers to share risks can generate a higher joint manufacturer-store profit. As such, the current contract is suboptimal from a social welfare perspective. Our second counterfactual experiment illustrates that, under the current contract, it is mutually beneficial for the store and manufacturers to reduce the degree of information asymmetry. Therefore, the current contract provides an incentive for manufacturers to reveal their private information.

Although our analysis focuses on the brand entry in a department store, the modeling and estimation strategies developed in this study may be easily extended to other empirical contexts where economic decisions are made through mutual agreements involving multiple economic agents. For example, Ho (2009) considered the formation of hospital networks involving revenue bargaining between health care insurers and health care providers. Other empirical applications include the matching of venture capitalists to entrepreneurs (Sorenson (2007)) and the entry of retail stores into shopping malls (Victorino 2010)).

The remainder of the paper is organized as follows. Section 2 places our paper in the context of the existing literature and Section 3 discusses the data and motivates the necessity of modeling both the two-sided entry decisions and the contract terms. Sections 4 and 5 outline the model and estimation details, respectively. Section 6 presents the estimation results, Section 7 discusses our counterfactual exercises, and Section 8 concludes.

2. Related Literature

This paper is closely related to the empirical literature on firm entry and exit. Since the contributions of Bresnahan and Reiss (1990, 1991), there has been a growing body of empirical studies that apply the framework of static discrete-choice entry games to investigate various interesting economic phenomena. An early example is Berry (1992), who studied the decisions of operating specific routes of airlines to infer the determinants of city pair profitability. Other studies include the quality choice of motels along U.S. interstate highways in Mazzeo (2002), the effects of incompatibility on demand for banks' ATM network (Ishii 2005), the complementarity between stores in shopping centers (Vitorino 2010), the location choice of retailer stores (Seim 2006, Ellickson, Houghton and Timmins 2010), and the recent work on the entry decisions of Wal-Mart (Jia 2007, Zhu and Singh 2009). The standard assumption in this stream of literature is that entry is a one-sided decision made by firms who compete against one another in the market in a non-cooperative game theoretic context.

When entry decisions involve multiple parties, another strand of the literature explores the economic concept of stable equilibrium in the contexts of one-on-one, one-to-many, and many-to-many matching games. Well-known theoretical studies such as Koopmans and Beckmann (1957), Gale and Shapley (1962), Shapley and Shubik (1972), and Becker (1973) have characterized the concept of stable matches, with or without transfers. Recent empirical works have applied the matching framework to marriage (Choo and Siow 2006) and dating (Hitsch et al 2010a, 2010b). Sorensen (2007) applied the two-sided matching model to estimate the influence and sorting of venture capitalists investing on entrepreneurial companies, and Bajari and Fox (2007) exploited the same idea to investigate the efficiency of FCC spectrum auctions. Ho (2009) modeled the negotiation process between insurance plans and hospitals to determine the equilibrium health care networks and division of profits. Our modeling approach is similar to hers; however, we exploit the unique data on the revenue transfer from the department store to manufacturers to also identify and estimate additional economic factors, such as spillovers of brand entry on other categories that contribute to the entry. We also differ from the above studies by explicitly modeling the information asymmetry between the two parties, and investigate how the information asymmetry influences the structure of contracts which will determine the outcomes from entry.

The empirical context of our study is a recent retail system which has become increasingly popular. In a traditional retail channel structure, a retailer typically sells multiple differentiated products produced by multiple manufacturers. In our retail system, however, branded manufacturers set up selling counters and hire their own sales staff to sell their products inside retail stores. In return, they are paid a manufacturer transfer based on a revenue sharing contract. This system, which has been commonly adopted in department stores both in Asian and U.S. markets, has been the focus of recent papers such as Jerath and Zhang (2009) and Chan et al (2010).

There exists a rich literature focusing on the agency theory and use principal-agent models to explain the primary motives for contracting. A strand of this literature uses transaction costs to explain the efficiency of different types of contracts. Masten and Saussier (2002) review the empirical contracting literature and compare the relative contributions of each approach in explaining actual contract practice. More relevant to our research, Gould, Pashigian and Prendergast (2005) empirically examine the externality from anchor stores on other stores within shopping malls. They find evidence that this is the primary driver for the observed difference in contract terms for different types of stores.

Market equilibrium in games involving large number of heterogeneous players is in general too complicated to fully characterize and difficult to estimate. To circumvent these difficulties, typical strategies involve making simplifying model assumptions. Berry (1992) considered the conditions in the airline profit function under which a unique equilibrium in the number of airlines in each city-pair market exists. Mazzeo (2002) assumed a sequential entry game to impose additional structure in the model. A recent approach proposed in the literature is to estimate the model based on the necessary conditions of market equilibrium. This includes the moment inequalities estimator developed in Pakes et al (2006), the maximum score estimator in Fox (2009), and the bounds approach using sufficient and necessary conditions outlined in Ciliberto and Tamer (2009). Recently, Su, and Judd (2010) proposed an approach, mathematical programming with equilibrium constraints (MPEC), for structural model estimation. In the context of entry game, under the Bayesian Nash equilibrium each player's expectation about competitors' entry has to match with the equilibrium entry probabilities actually observed.[2] Several empirical researches have applied this methodology (for examples see Dube, Fox, and Su 2009 and Vitorino 2010). The MPEC approach is ideally suited for our needs, and as such, we use MPEC to estimate our two-sided entry model.

[2] A similar concept is exploited in Seim (2006).

3. Data

The data comes from a large department store in Shanghai, China, located at a central business district with convenient transportation. It sells hundreds of categories ranged from men's, women's, and children's clothing to other products such as shoes, travel luggage, cosmetics and household electronics. Based on interviews with the store management, we understand that it is a middle-ranked department store, of which prices and store image are about the medium level among all department stores in Shanghai. The department store is equivalent to Macy's in the U.S. We were told that the management's long-term strategy is to attract more high-end brands in order to generate a more up-scaled image for the store.

Our study focuses on one product category, the professional women's clothing, which mainly targets professional women aged thirty and above. The category occupies the whole fourth floor in the seven-storied store building. Clothing in this category generally has a more formal style and uses higher quality materials. We choose professional women's clothing because there are more brands and more variation in product attributes in the data. The data provide information about the monthly sales revenue of all brands sold in the store from January 2005 to April 2009. We also observe contract information of all entrant brands during the period. These include brand identities, contract periods (starting year/month and ending year/month), and the actual revenue transfers from the store to manufacturers. In addition, we observe the full list of all candidate brands (including those who never entered during the period) and a list of brand and manufacturer attributes for every brand evaluated by the store management. As we will explain below, these unique features of the data are important for identifying the structural parameters in our two-sided entry model.

3.1 Brand Attributes and Tiers

From the beginning of the sample period, the store maintained a complete list of brands it considered as potential entrants. This implies that we have the complete choice set of the store. There are altogether 119 brands in the list. To facilitate management and contracting decisions, the store also maintains a list of brand and manufacturer attributes.

Some of these attributes, such as the origin of manufacturers and the number of other stores selling the same brand in the local market, are objectively measured. Some are subjective evaluations from the store management, such as the fit with the store image and the image of the brand. In previous research, these subjective attributes were unobserved and treated as an unobserved product attribute or quality. In contrast, our data allows us to quantify how the store evaluates these attributes. Since we have the complete list of attributes that the store uses in judging a brand, we as researchers have the same information as the store.

Table 1 lists the brand attributes and their definitions.[3] Attributes including origin, fit, coverage, image, area and extra are related to market demand; other attributes including capital, production and agency are more likely related to the cost side.

[Table 1 here]

Based on the brand and manufacturer attributes the store further classifies all candidate brands into three tiers, the low-end (L), medium (M) and high-end (H) brands. There are 22 high-end brands, 51 medium brands and 46 low-end brands in the list of candidate brands. We do not know the criterion used for the classification. Based on statistical cluster analysis, tier H brands are characterized by a high ratio of foreign brands, high brand image and large in-store operational area. We are told by the store manager that foreign brands tend to be priced higher and are viewed as high-end clothing by most consumers, although most of these are in fact manufactured in Mainland China. Tier M brands have good fit with the store's image and large coverage in other comparable department stores. In contrast, tier L brands are low in all dimensions.

3.2 Manufacturer-Store Contracts

The entry of a brand requires that the manufacturer and the department store agree upon a contract. The store showed us some samples. The contract structure is standardized,[4]

[3] *Image* is the combination of several subjective brand attributes including *brand quality*, *brand prestige*, *image of the selling counter*, and *overall price image*. These attributes are highly correlated in our data suggesting their evaluations are driven by the same underlying factors. We combine them into a single attribute, *Image*, to avoid the collinearity problem in model estimation.

consisting of many detailed terms including manufacturers' hiring and training of sales employees and contribution to store-wide promotions. The most important term, however, specifies that the store collects all sales revenue and returns a transfer to the manufacturer at the end of month. There are several reasons why a transfer contract instead of a rent contract is adopted by the store. First, this helps the store prevent manufacturers from avoiding or delaying a payment to the store. The transfer contract also facilitates store-wide promotions. For example, customers under the store loyalty program can directly redeem coupons for everything sold inside the store, which would be difficult to implement if customers paid manufacturers directly. Additionally, under such arrangement the store records all transaction and price information, which is useful in monitoring a brand's performance and deterring excessive competition between brands. We were also told that, due to its locational advantage and reputation, the department store under study has large bargaining power when negotiating contract with manufacturers and hence can dictate the contract terms.

The determination of the actual transfer to manufacturers in contracts is very complicated and highly non-linear. The fundamental design is that, for every month in a year, the store specifies in the contract an amount of transfer to the manufacturer and expected sales revenue, both of which are differentiated across brands. When the actual sales revenue in a month is less than the expectation, the transfer will be deducted by the difference. If the sales revenue is higher than the expectation, the manufacturer will obtain a high share of the extra revenue (ranged from 70 to 90 percent), again differentiated across brands. This transfer design essentially guarantees that the store's return is not much affected by sales fluctuations. In the model that we will discuss in later section, we term the transfer amount specified in the contract the deterministic transfer, and the difference between the actual and the expected sales revenue the contingent transfer. We will also show that such transfer design has important economic consequences in manufacturers' entry decisions.

We define the time of an entry as the first month a brand is observed to generate sales in the store. About 50% of the entries occurred in April. Almost all entering brands are

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[4] Based on our knowledge this is a contract structure commonly adopted by department stores in Mainland China.

observed to have multiple contracts, implying that contracts are extended after they expired. About half of the contracts have a contract length between 9 and 13 months and 12-month contracts are most common, accounting for 27% of all contracts. Based on these observations, we simplify our model assuming that contracts are renewed annually, starting in April and ending in March next year[5].

3.2 Summary Statistics and Reduced-Form Evidence

For the purpose of model estimation, we redefine the brand and manufacturer attributes. Table 2 lists the variables we use in the estimation and provides some summary statistics. Except the variable *rcoverage*, which is defined as the percentage of coverage in the 9 designated department stores, all others are dummy variables.

[Table 2 here]

Table 3 reports some statistics of the number of entries, percentage of brands who ever enter in the three tiers, the average annual sales revenue, actual transfers to manufacturers, store revenues (sales revenue net of transfers), and transfer rates (manufacturer transfers divided by annual sales revenue) for each brand in each year. A surprising observation is that H-tiered brands, which the store considers important for its long-term strategy, generate lower sales revenue than M-tiered brands. However, H-tiered brands have the highest manufacturer transfer rates. L-tiered brands have the lowest transfers, but the store revenue generated from these brands is almost the same as that from H-tiered brands. With the highest transfer rate, H-tiered brands still have the lowest entry rate. On the other hand, M-tiered brands have the largest presence in the store and also the highest entry rate.

The comparison of sales revenues and transfer rates indicates that the store is willing to offer higher transfers to high-end brands even though the medium tier is the largest direct contributor for store profit. Given the higher profitability, it is interesting that the store does not offer more to other M-tiered brands to induce entry. This is not because of lack

[5] For those brands that enter later than September in a year, we assume them as entries in the next year. In the data these account for about 5% of all entry observations.

of choice since the entry rate of M-tiered brands is only about 50%. One plausible explanation is the spillover effect from a brand's entry on the profit of other categories. Even though M-tiered brands may better match with the needs of the store's customers, the most profitable consumers are those with high purchasing power who tend to buy many other products in the store. By carrying high-tiered brands the store is able to attract more of these consumers; hence, the profit of H-tiered brands, as perceived by the store, comes not only from their own sales but also from the fact that their buyers will spend more on other categories. The manager revealed to us that, by inducing more high-end brands in the women's clothing category to enter, the goal is to attract more profitable customers.

[Table 3 here]

We use reduced-form regressions to examine how sales revenue, entry probability and manufacturer transfer rate are related to brand attributes and within-category competition. We run an OLS regression with annual brand sales revenue (mil. RMB) as the dependent variable, using all 9 attribute variables as explanatory variables. We also include in the regression the number of brands entering in each tier interacting with the tier identity of the focal brand. For example, N_{LL}, N_{LM} and N_{LH} represent the number of low-end entering brands when the focal brand is low-end, medium and high-end, respectively. The entry numbers are endogenous. Also, there is a selection issue since the regression is conditional on brand entry. However, our objective for this exercise is to use simple analysis to motivate the need to develop a more structural model. We also run a logit regression for observed brand entry (1 if entry and 0 otherwise), and another OLS regression for the manufacturer transfer rate. For the latter regression, the dependent variable is the log odds of transfer rate, i.e., ln(transfer rate) – ln(1-transfer rate). For both regressions we use the same set of covariates as in the sales regression.

The estimation results in Table 4 show that brands with foreign origin (*dorigin*), a good fit with store (*dfit*) and large coverage in other selected markets (*dextra*) tend to predict larger sales in the store. Brands with good fit and good brand image (*dcounter*) are less likely to enter; brands with large registered capital (*dcapital*), large local market coverage (*rcoverage*) and large market coverage in other selected markets are more likely to enter.

Finally, manufacturers with higher registered capital (*dcapital*) receive higher transfer rate but those with larger operational area (*darea*) receive less. There are some counter-intuitive results. For example, *dfit* is shown to negatively affect a brand's entry probability but positively affect sales revenue. Yet the coefficient for *dfit* in the transfer rate regression is negative (although statistically insignificant). If the attribute helps increase sales, the store should offer a higher transfer rate to manufacturers to induce entry.

[Table 4 here]

The lack of competition effect on sales revenue (coefficients from N_{LL} to N_{HH} in the first column) is somewhat surprising, given that all the brands are closely located on the same floor. One possible reason for the insignificant results is that the reduced-form regressions have not taken into account the strategic interactions between entry and transfer rate decisions. The number of entrants in each tier is an endogenous variable determined by transfers. It is necessary to correct this endogeneity bias to obtain consistent estimates. Therefore, we need a more structural model that specifies the observed entry and manufacturer transfers as the equilibrium outcomes of two-sided negotiations, which will allow us to estimate the three outcomes in an integrated approach.

4. A Model of a Two-Sided Entry Game

The two-sided nature of the entry game requires modeling the decisions of both the store and manufacturers. We consider a static model of brand entry under information asymmetry between the store and manufacturers. The store has a list of candidate brands as potential entrants. We assume that, at the beginning of each period, the store offers a contract to each candidate brand in this choice set. The contract specifies a transfer to the corresponding manufacturer that consists of a deterministic and a contingent component.

This is a take-it-or-leave-it contract.[6] Conditional on the offer, manufacturers will simultaneously decide to accept the offer and enter the department store or not.

In this section, we will first discuss the information sets of the store and manufacturers as well as their respective profit functions. Then we will derive the optimal transfer from the store, and the decision rule for manufacturers' entry.

4.1 Model Setup

Information asymmetry among players: Let x_{kt} be a vector of variables including all brand attributes (origin, market coverage, brand image and so on) and time-varying factors relating to brand sales revenues and costs across periods.[7] As discussed above, this is the complete list of variables that the store uses to evaluate the profitability of a brand's entry; therefore it corresponds to the entire information set of the store when it decides its contract offer to the manufacturer of brand *k*. That is, our model assumes that the store does not have any additional information unknown to us as researchers. Since x_{kt} is evaluated based on the market information available to everyone, we also assume that this is public information to all manufacturers.

However, the manufacturer may possess private information about its brand that is unobserved to both competing brands and the store. On the demand side, this private information is related to product quality that is unobserved to other players. It is represented by a random variable ξ_{kt}. On the cost side, this may include some cost shocks in production and shipment, represented by a random variable ω_{kt}, as well as the value of the manufacturer's outside option that the store cannot fully observe, represented by another random variable υ_{kt}^{o}. Therefore, each player does not know the exact payoff of other players if they enter and cannot perfectly predict their actions. We assume that the store and other manufacturers know the distribution from which the private information shocks are drawn, but do not know the values of the shocks themselves. The store forms a

[6] In reality there may be multiple rounds of negotiation between the store and manufacturers. The contract in our model can be viewed as the offer in the final stage of negotiation.

[7] Each period in our model is one year. We use year dummies to capture these time-varying factors.

belief about all manufacturers' entry likelihood, and each manufacturer forms a belief about other manufacturers' entry likelihood, conditional on contract offers. They will apply these beliefs when calculating their own expected profits.

Sales revenue specification: Let $x_{kt}^{d} \subset x_{kt}$ be a subset of variables that may affect the sales of brand *k*, and let I_{-kt} be a vector of indicators of entry of all candidate brands other than *k*, where $I_{jt} = 1$ if brand *j* enters in period t and 0 otherwise. Also, let $R(k)$ and $R(j)$ be the brand tier (L, M or H) of brand *k* and another brand *j*, respectively. We specify a reduced-form function for *k*'s sales revenue; if *k* enters in period t, the function captures the impacts on sales revenue from *k*'s own brand attributes as well as from the entry of other brands:

$$S_{kt}(x_{kt}^{d}, I_{-kt}) = x_{kt}^{d}\beta + \sum_{j \neq k} \gamma_{R(j)R(k)} I_{jt} + \xi_{kt} + \epsilon_{kt} \tag{1}$$

where S_{kt} is the realized sales revenue. The first component on the right hand side captures the stand-alone sales, and the second component captures the interaction effects of the entry of other brands on its sales. It allows the effect of a brand's entry on the sales of the others to be asymmetric depending on the tiers of every pair of brands, i.e., $\gamma_{R(j)R(k)}$ may be different from $\gamma_{R(k)R(j)}$. Also, depending on the values of coefficients, brands *k* and *j* can be substitutes (when $\gamma_{R(j)R(k)}$ is negative) or complements (when $\gamma_{R(j)R(k)}$ is positive). For our three brand-tiers (L, M, and H), we have 9 tier-interactive parameters: γ_{LL}, γ_{LM}, γ_{LH}, γ_{ML}, γ_{MH}, γ_{HL}, γ_{HM}, and γ_{HH}. Finally ϵ_{kt} is an idiosyncratic demand shock that is unobserved by everyone, including manufacturer *k*. Following Pakes et al (2006), these ex-post sales shock could be either an expectation error (due to incomplete information) or a measurement error of revenue. Let manufacturer *k*'s belief of the entry probabilities of all other brands –*k* be p_{-kt}, and assume that its expectation of ϵ_{kt} is 0 at the beginning of period t. Manufacturer *k*'s expectation about sales revenue can be expressed as:

$$E^{1}(S_{kt}) = x_{kt}^{d}\beta + \sum_{j \neq k} \gamma_{R(j)R(k)} p_{jt} + \xi_{kt} \tag{2}$$

Since the store has the same information as manufacturer k regarding other brands $-k$, its belief of the entry probabilities of $-k$ is also p_{-kt}. Assume that the store's expectation of ξ_{kt} is 0 before entry, its expectation of sales revenue is:

$$E^2(S_{kt}) = x_{kt}^d\beta + \sum_{j \neq k} \gamma_{R(j)R(k)} p_{jt} \tag{3}$$

Entry cost specification: In reality, the cost of entry for manufacturer k may include fixed costs (e.g. setting up the selling counter and hiring and training sales employees) and marginal cost of production. However, we do not observe data on the quantity of goods sold, and as such, it is difficult to separate the two components. Consequently, we assume a lump-sum entry cost faced by the manufacturer upon entry. Let $x_{kt}^c \subset x_{kt}$ be a set of brand attributes and time-varying factors that are related to the cost of selling in the store. The entry cost function is specified as

$$C_{kt} = x_{kt}^c \alpha^c + \omega_{kt} \tag{4}$$

where ω_{kt} is the cost shock which is private information for manufacturer k. The store's expectation of the entry cost of manufacturer k is $x_{kt}^c \alpha^c$, as ω_{kt} is zero in expectation.

A manufacturer's profit is the transfer from the store, which we denote by T_{kt}, minus the entry cost. Its entry decision also depends on the outside option value if it chooses not to enter. For example, if the manufacturer has already sold in other department stores or set up own specialty store in the same local market, its outside option value may be higher, reflecting the fact that selling in this store can cannibalize the sales in these other locations. The outside option value will also impact the contract offer. Let $x_{kt}^o \subset x_{kt}$ be a set of brand attributes and time-varying factors that are related to the outside option. We specify this value as

$$\Pi_{kt}^o = x_{kt}^o \alpha^o + \upsilon_{kt}^o \tag{5}$$

Again we assume that υ_{kt}^o is only known by manufacturer k and hence the store's expectation about the outside option value of manufacturer k is given by $x_{kt}^o \alpha^o$.

Spillover effect on other categories: As the department store sells other product categories targeting the same consumers who buy from women's clothing, the store has to evaluate the influence of the entry of a brand on the sales of other categories. A brand helps the store to attract consumers with high purchasing power and generates positive spillovers on other products will be evaluated favorably. This argument is quite pertinent to women's clothing as it is one of the largest categories in store and is a major store-traffic generator. Let $x_{kt}^{s} \subset x_{kt}$ be a set of brand attributes and time-varying factors that are related to these spillovers. We use $x_{kt}^{s}\delta$ to capture the store's expectation about the spillover effect which will result from k's entry.

4.2 Transfer Offers and Entry Decisions

With the primitives set up in the model, we can now formally model the store-manufacturer contracts. We assume that the store offers a take-it-or-leave-it contract to every manufacturer at the beginning of each period. The objective of the store is to choose an optimal set of contracts to maximize the expected aggregate store value.[8] We assume that the store specifies a deterministic transfer in the contract. It also specifies a "targeted" sales figure, which is its expected sales revenue as a function of its expectations about the entry decisions of other manufacturers as in equation (3). If a brand enters, the manufacturer will receive the deterministic transfer and the deviation of the actual sales from the targeted sales, i.e., the demand shocks ξ_{kt} and ε_{kt}. Based on the observation of the sample contracts, we believe this simplification is a good approximation of the reality.[9]

[8] We use store "value" instead of "profit" because it measures not only the profit from the entry of a brand but also its spillovers on the sales revenue of other brands and other categories.

[9] In the actual contract, the store specifies the transfer and targeted sales at the monthly level. We aggregate to the annual level in model estimation. Also, the transfer in the contract is as a fraction of the targeted sales revenue. In terms of the effect on the entry this is the same as specifying a fixed amount of transfer in our model. Finally, since the store's information x_{kt} is public information to manufacturer *k*, it is infeasible for the store to bias its expectation of sales revenue in the contract. Even if it can, there is no economic incentive to bias the expectation since the entry decision solely relies on how much store will keep and how much the manufacturer will obtain from the transfer.

Define Ψ_t^s as the information set of the store, including brand and manufacturer attributes and the deterministic transfers it offers to all manufacturers. For the store, conditional on entry, the expected value from the entry of all brands is the total expected sales revenue deducted by the total deterministic transfers specified in contracts, together with the aggregate spill-overs of women clothing brands on other categories. Therefore,

$$E(V_t^s|\Psi_t^s) = \sum_k [x_{kt}^d\beta + \sum_{j\neq k}\gamma_{R(j)R(k)}p_{jt} - T_{kt}^* + x_{kt}^s\delta]p_{kt} \quad (6)$$

where V_t^s is the aggregate value of the store and T_{kt}^* is the deterministic transfer. For each brand k, the expected entry probabilities p_{kt} and p_{-kt} are separable in the equation because by assumption the stochastic components ξ_{kt} and ϵ_{kt} are independent across brands.

To determine the optimal transfer offer, we use the first-order condition of store value function V_t with respect to the transfer T_{kt}^*. That is,

$$\frac{\partial E(V_t^s|\Psi_t^s)}{\partial T_{kt}^*} = -p_{kt} + \left(x_{kt}^d\beta + \sum_{j\neq k}\gamma_{R(j)R(k)}p_{jt} - T_{kt}^* + x_{kt}^s\delta\right)\frac{\partial p_{kt}}{\partial T_{kt}^*}$$
$$+ \sum_{j\neq k}\frac{\partial S_j\left(p_{kt}, p_{-j\backslash k,t}\right)}{\partial T_{kt}^*}p_{jt}$$
$$= 0$$

where $S_j\left(p_{kt}, p_{-j\backslash k,t}\right)$ is manufacturer j's expected sales revenue as a function of the entry probabilities of all other brands excluding brands j. Since $\frac{\partial S_j(p_{kt}, p_{-j\backslash k,t})}{\partial T_{kt}^*} = \gamma_{R(k)R(j)}\frac{\partial p_{kt}}{\partial T_{kt}}$, from the above condition the optimal deterministic transfer can be derived as

$$T_{kt}^* = x_{kt}^d\beta + \sum_{j\neq k}(\gamma_{R(j)R(k)} + \gamma_{R(k)R(j)})p_{jt} + x_{kt}^s\delta - \frac{p_{kt}}{\partial p_{kt}/\partial T_{kt}^*} \quad (7)$$

Under general conditions, T_{kt}^* is an implicit function as it also appears on the right-hand side of the equation via $\frac{p_{kt}}{\partial p_{kt}/\partial T_{kt}^*}$.

In the determination of T_{kt}^*, there are two brand-interaction terms. The first term $\sum_{j\neq k}\gamma_{R(j)R(k)}p_{jt}$ captures the expected interaction effects of all other brands j on brand k, and the second term $\sum_{j\neq k}\gamma_{R(k)R(j)}p_{jt}$ represents the expected interaction effects of brand k on all other brands. These capture the store's consideration of the entry of a brand on the sales revenue of the whole category. The term $x_{kt}^s\delta$ represents the spillover effect on the profit of other product categories. The last term $-\frac{p_{kt}}{\partial p_{kt}/\partial T_{kt}^*}$ in the above equations captures the effect of changing transfer on the entry probability of a brand. As $\partial p_{kt}/\partial T_{kt}^*$ is positive, the whole term is negative. This represents a trade-off in the store's decision. Large transfers will increase a brand's entry probability, but will decrease the store's revenue, conditional on entry.

In a standard one-sided entry game, manufacturers compete against one another to enter markets with the objective of maximizing own profits. The externality imposed on other brands in the same category or the spillovers generated for other categories play no role in each manufacturer's entry decision. This type of non-cooperative competition may lead to excessive or insufficient entry at equilibrium in comparison with the social optimal. However, in our two-sided entry game the store coordinates the entry. A brand generating higher benefits to other brands in the same category or other categories will receive a higher transfer and is therefore incentivized to enter. Our store in this two-sided game hence will reduce the economic inefficiency due to excessive or insufficient entry. On the other hand, the store has the incentive to extract surplus from manufacturers, which is implied by the last term in equation (7). The manufacturer hence will receive lower return than the aggregate benefits from its entry. The net impact on social welfare when compared with non-cooperative entry therefore is indeterminate.

Given deterministic transfer T_{kt}^*, the expected profit of brand k at the beginning of period t, conditional on entry, is

$$\begin{aligned}\Pi_{kt} &= T_{kt}^* + \xi_{kt} - C_{kt}\\ &= T_{kt}^* - x_{kt}^c\alpha^c + \xi_{kt} - \omega_{kt} \qquad (8)\end{aligned}$$

Define $\nu_{kt} \equiv \xi_{kt} - \omega_{kt}$ as the profit shock that is the private information of manufacturer k. Given Π_{kt}, the manufacturer will evaluate this option with the outside option value, i.e., Π^{o}_{kt}. It will enter if and only if

$$T^{*}_{kt} - x^{c}_{kt}\alpha^{c} - x^{o}_{kt}\alpha^{o} \geq \nu^{o}_{kt} - \nu_{kt} \tag{9}$$

To summarize, our modeling framework captures the two-sided decisions involved in the entry game. The store first determines the deterministic transfer offers to all manufacturers based on its beliefs of the entry probabilities of manufacturers conditional on the transfer. On the one hand, it takes account of the within-category brand interaction effects and out-of-category spillover effects from the entry of brands. The external benefits from the entry of a brand will be internalized benefiting the manufacturer through a higher transfer offer. On the other hand, there is an incentive for the store to extract surplus from manufacturers through contract offers. There is uncertainty regarding the entry because of the store's limited information regarding sales revenue and the entry cost of a brand. However, under this type of transfer contracts the store is protected from the risk of unobserved demand shocks. Based on the transfer offer, a manufacturer compares the profit of entry, which is a function of its beliefs about the entry of all other brands, with its outside option value. From the manufacturer's perspective, the entry of other brands is also uncertain because it has limited information regarding the sales revenue and entry costs of other manufacturers.

5. Estimation

We estimate the parameters of our structural model using three observed market outcomes – brand entry, manufacturer transfers, and sales revenue, where the transfers and revenue are observed conditional on entry. The key challenge to our model estimation is that a manufacturer's entry depends on its beliefs about other manufacturers' entry and vice versa. Likewise, the store transfer offer depends on its beliefs about the entry of all manufacturers and how they will respond to the change in its offer. In this section, we will outline the MPEC approach in model estimation and how we control for the selection issue imbedded in the entry game. Finally, we will discuss the identification of the model's parameters.

5.1 Empirical Specification

We assume that the profit shock $\nu_{kt} \equiv \xi_{kt} - \omega_{kt}$ (see equation (8)) is distributed i.i.d. Type I extreme value with scale parameter σ across brands and periods. This distribution is a common knowledge to the store and to all brands[10]. For identification purpose, we assume that the shock in the outside option value, ν_{kt}^{o}, is also i.i.d. Type I extreme value with the same scale parameter σ as ν_{kt}.

Let $\overline{\Pi}_{kt} = T_{kt}^{*} - x_{kt}^{c}\alpha^{c} - x_{kt}^{o}\alpha^{o}$ be the difference between the deterministic profit of entry and the deterministic part of the outside option value (see equation (9)). Based on the Type I extreme value distribution assumptions, the entry probability function of brand k has the logit specification $p_{kt} = \frac{\exp(\overline{\Pi}_{kt}/\sigma)}{1+\exp(\overline{\Pi}_{kt}/\sigma)}$. Therefore, we have

$$\frac{\partial p_{kt}}{\partial T_{kt}^{*}} = p_{kt}(1 - p_{kt})/\sigma \tag{10}$$

Given p_{kt}, T_{kt}^{*} can be directly calculated using equations (7) and (10). Let $x_{kt}^{co} = x_{kt}^{c} \cup x_{kt}^{o}$, i.e., the union of the variables affecting the manufacturer's entry cost and outside option value, and define $x_{kt}^{c}\alpha^{c} - x_{kt}^{o}\alpha^{o} = x_{kt}^{co}\alpha$, where α is a set of parameters[11]. The structural model parameters we will estimate are $\theta = \{\alpha', \beta', \delta', \sigma, \gamma'\}'$.

5.2 Entry Probability and the Bayesian-Nash Equilibrium

Let p_{kt}^{*} be the belief of the store or other manufacturers regarding k's entry. Based on the Type I extreme value distribution assumptions, the belief can be written as the following:

[10] Since the manufacturer transfer data is now integrated with the entry probability, the error variance has its scale determined by the transfer. Hence, we do not need to normalize the scale parameter of the error as in previous research on entry games.

[11] Since the entry cost function and the outside option value function always appear together in the entry probability function and transfer function, if x_{kt}^{c} and x_{kt}^{o} share common variables, their effects on cost and outside option value cannot be separately identified.

$$p^*_{kt} = \Phi(p^*_{-kt}, x_{kt})$$
$$= \frac{\exp\left(x^d_{kt}\beta/\sigma + \sum_{j\neq k}\left(\gamma_{R(j)R(k)} + \gamma_{R(k)R(j)}\right)p^*_{jt}/\sigma + x^s_{kt}\delta/\sigma - \frac{1}{1-p^*_{kt}} - x^{co}_{kt}\alpha/\sigma\right)}{1+\exp\left(x^d_{kt}\beta/\sigma + \sum_{j\neq k}\left(\gamma_{R(j)R(k)} + \gamma_{R(k)R(j)}\right)p^*_{jt}/\sigma + x^s_{kt}\delta/\sigma - \frac{1}{1-p^*_{kt}} - x^{co}_{kt}\alpha/\sigma\right)} \tag{11}$$

This expression makes clear the simultaneity issues that arise in the game. Suppose there are K candidate brands. Conditional on model parameters θ and x_{kt}, the beliefs will be the p*'s as the solution of K non-linear simultaneous equations as in equation (11). We apply the Bayesian-Nash equilibrium concept, which states that at the equilibrium, each player's beliefs of the entry probabilities of other players are consistent with their actual entry probabilities. Therefore p^*_{kt} in the above equation can be substituted by the entry probability predicted by our model when the market is at equilibrium. This becomes the equilibrium constraint that we can use to calculate the entry probabilities. This specification motivates our use of the MPEC approach as we will explain later.

5.3 Selection-Bias Correction

We have specified the sales revenue function and the manufacturer transfer function. These observations are only available if a manufacturer enters. Since manufacturer k will decide entry based on the unobservable shock ξ_{kt}, there is a selection issue in model estimation: the expectation of ξ_{kt} conditional on brand k's entry is no longer zero, i.e., $E(\xi_{kt}|I_{kt} = 1) > 0$. Therefore, to estimate the sales revenue and manufacturer transfer models, we must correct for the potential selection bias induced by the underlying entry game.

One strategy, as proposed in the classic Heckman selection model, is to obtain a consistent estimate of $E(\xi_{kt}|I_{kt} = 1)$ based on the distributional assumption on ξ_{kt} and entry condition in equation (9). However, this does not have a closed-form expression in our model, since the entry probability function p_{kt} is a non-linear function of all other entry probabilities $p_{-k,t}$ (see equation (11) above). We choose an alternative approach by employing the propensity-score-based control-function approach described in Heckman and Robb (1985, 1986) to approximate $E(\xi_{kt}|I_{kt}=1)$. The idea is to treat this conditional expectation term as a function of profit index from entry. Given the one-on-one correspondence between the profit index and entry probability, it can be equivalently expressed as a function of entry probability, $\lambda(p_{kt}^*)$, where p_{kt}^* satisfies the equilibrium condition in equation (11). In practice this function can be approximated flexibly by a polynomial function of p_{kt}^*[12].

Therefore, the sales revenue equation, conditional on brand k enters, can be written as

$$S_{kt} = x_{kt}^d\beta + \sum_{j\neq k}\gamma_{R(j)R(k)}I_{jt} + \xi_{kt} + \varepsilon_{kt}$$

$$= x_{kt}^d\beta + \textstyle\sum_{j\neq k}\gamma_{R(j)R(k)}I_{jt} + \lambda(p_{kt}^*) + \varepsilon_{kt}^* \tag{12}$$

where $\varepsilon_{kt}^* = \varepsilon_{kt} + (\xi_{kt} - \lambda(p_{kt}^*))$. Since $\xi_{kt} - \lambda(p_{kt}^*)$ is a mean-zero approximation error, by definition $E(\varepsilon_{kt}^*|I_{kt}=1)=0$.

Define $\tau_{kt} = \sum_{j\neq k}\gamma_{R(j)R(k)}\left(I_{jt} - p_{kt}^*\right) + \varepsilon_{kt}$. Under the assumption that the stochastic components in the sales and cost functions are independent across manufacturers, $E(\tau_{kt}|I_{kt}=1)=0$. The actual transfer conditional on brand k enters can be similarly written as

$$T_{kt} = x_{kt}^d\beta + \sum_{j\neq k}\left(\gamma_{R(j)R(k)} + \gamma_{R(k)R(j)}\right)p_{jt}^* + x_k^s\delta - \frac{\sigma}{1-p_{kt}^*} + \xi_{kt} + \tau_{kt}$$

$$= x_{kt}^d\beta + \textstyle\sum_{j\neq k}\left(\gamma_{R(j)R(k)} + \gamma_{R(k)R(j)}\right)p_{jt}^* + x_k^s\delta - \frac{\sigma}{1-p_{kt}^*} + \lambda(p_{kt}^*) + \tau_{kt}^* \tag{13}$$

where $\tau_{kt}^* = \tau_{kt} + (\xi_{kt} - \lambda(p_{kt}^*)$. Again $E(\tau_{kt}^*|I_{kt}=1)=0$.

Finally, define $e_{kt}^* \equiv I_{kt} - p_{kt}^*$ (14)

By the definition of Bayesian Nash equilibrium, $E(e_{kt}^*)=0$.

[12] Please refer to Appendix I for derivation.

5.4 Estimation Strategy

We use the nonlinear least square (NLS) method to estimate a 3-equation system simultaneously. We set up our model estimation as a constrained optimization problem, which is the mathematical programming with equilibrium constraints (MPEC) approach developed in Su and Judd (2010)[13]. Given the entry error e_{kt}^* defined in equation (14), the sales revenue error ε_{kt}^* defined in equation (12), and the transfer error τ_{kt}^* defined in equation (13), we choose the structural parameters $\theta' = \{\alpha', \beta', \delta', \sigma, \gamma'\}'$ and a set of entry probabilities $p^* = \{p_{kt}^*, \forall k, \forall t\}$ to minimize the average squared residuals across the three equations subject to the equilibrium entry probability constraints. That is,

$$\theta, p^* = \underset{\theta, p^*}{\operatorname{argmin}} \sum_{t=1}^{T} \sum_{k} {e_{kt}^*}^2 / N + \sum_{t=1}^{T} \sum_{k} {\varepsilon_{kt}^*}^2 / n + \sum_{t=1}^{T} \sum_{k} {\tau_{kt}^*}^2 / n$$

$$s.t.\ p_{kt}^* = \Phi(p_{-kt}^*, x_{kt})\ \forall k, \forall t \tag{15}$$

where N is the total number of candidate brands, and n is the total number of entering brands, in all T periods.

By using state-of-the-art constrained optimization programs developed by numerical scientists, the MPEC algorithm chooses the structural parameters and the endogenous variables (equilibrium entry probabilities p^* in our model) to minimize the average squared residual. We find this algorithm very efficient in terms of the computation time[14].

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[13] Su and Judd (2010) showed that their MPEC estimator is consistent, asymptotically normal and computationally efficient, and its finite-sample properties are superior to other estimators. Several empirical researches have applied this methodology. For examples, Dube, Fox, and Su (2009) use the MPEC method to improve the efficiency of estimators in Berry, Levinsohn, and Pakes (1995) by imposing the constraints that the observed market share is equal to the predicted market share.

[14] In comparison, one could adopt a two-stage algorithm by estimating θ only. At the inner stage, conditional on any trial of θ, one would first numerically compute the solution p^* from the equilibrium constraint and then calculate the criterion function value. At the outer stage, one would search for the optimal θ to minimize the criterion function value.

To correct the selection-bias, we employ a Chebyshev polynomial of degree 5 in our estimation[15]. The control function method is a two-step approach. We first find a consistent estimate for p_{kt}^* from a reduced-form logit regression of brand entry on all available brand attributes and period dummies and use it to construct the polynomial terms. After estimating the model, we then update the polynomial using the newly-estimated p_{kt}^* and re-estimate the model. We then iterate on this process.[16]

When constructing standard errors for our estimates, a complication arises as the polynomial control function is constructed based on the estimates from previous iteration. Therefore, a closed-form asymptotic distribution for the parameter estimates is difficult to derive. We adopt a parametric bootstrapping method. Given estimates for θ and p^*, we calculate the residuals ε_{kt}^* and τ_{kt}^*. We then resample them with replacement for every candidate brand and calculate the sales revenue and transfers if they enter. Based on the simulated transfers we then simulate entry decision of every brand. We then treat the simulated outcomes, which include entry and the sales revenue and transfers after that, as data and re-estimate our model. We repeat this procedures 100 times and use the bootstrapping estimates to compute the significance of our estimates for θ.

Finally, we have to determine the variables to be used in the sales function and the cost and outside value function. Some brand attribute variables including *dcapital* (supplier's registered capital), *dproduction* (self-production or subcontract) and *dagency* (brand owner or agent) should affect the entry cost, therefore we include them in x_{kt}^{co}. Some other variables such as *dimage* (brand image), *dorigin* (origin of manufacturers), and *darea* (mean operation area in comparable department stores) clearly should influence demand, hence they are included in x_{kt}^{d}. However, not all brand attribute variables have such a clear classification. We test different model specifications. For example, we test whether the three attributes *dcapital*, *dproduction* and *dagency* also influence the demand

[15] We experiment with different degrees in the estimation and find there is only trivial difference between parameter estimates when the degree goes above 5 and so adopt the polynomial of degree 5.

[16] We find that the structural parameter estimate of θ and p_{kt} are close enough to each other after 3 iterations and hence stop at the third iteration.

and out-of-category spillovers and find none of them significant. Therefore, they are dropped from the demand and spillovers functions.

5.5 Model Identification

In a standard entry game model where only entry is observed, identification mainly comes from the variation in observed entries in different markets and variation in market characteristics. It requires sufficient variation in the data to identify the substitution or complementarity relationship among entrants. In our case, market outcomes such as sales revenue provide additional identifying power. Furthermore, the data on manufacturer transfers can be used to identify the spillover effects of the entry of brands on outside categories in our empirical context.

We have four sets of structural parameters to estimate: brand attribute parameters determining demand (β), brand-interaction parameters determining demand (γ), cost and outside option value parameters (α), and spillovers parameters on outside categories (δ). If there were no selection issue, parameters β and γ could be identified from the sales revenue data alone. However, since the selection-bias correction comes from the entry decision and the transfer amount are also determined by the brand attributes and the expected entry from different brand tiers, β and γ are jointly identified from the entry data and the sales revenue and transfer observation.

Conditional on manufacturer transfers, the cost parameters α can be identified from the observed entry across brands. For example, if we observe a brand entering the store at a level of transfer offer lower than the others, this can only be rationalized in our model by the low entry cost or low outside option value of that manufacturer.

Finally, the variation in transfers across brands identifies the out-of-category spillovers. Conditional on parameters α, β, and γ, we can calculate the optimal transfer offer, when the spillovers are zero. The deviation of the actual transfer from this optimal transfer identifies the spillovers parameters, δ.

6. Results

Table 5 reports the estimation results from the model. The demand-side and cost-side coefficient estimates show the relative importance of different brand attributes in determining the brand's sales potential and entry cost. The effects on sales due to the entry of other brands also play an important role in manufacturer's entry decision. There is also evidence that brands with some desired attributes are able to generate positive spillovers to other product categories.

The first column in Table 5 reports estimates of the parameters for sales revenue (β). Most estimates of brand attributes are statistically significant. A brand's good fit with the store image (*dfit*) yields 0.844 million RMB[17] higher annual sales revenue. Another important variable is *dextra,* which suggests that a brand is likely to sell well if it already has a large presence in other big cities, an indication of its popularity nationwide. However, a brand's local market coverage (*rcoverage*) is insignificant. Since this variable is a proxy for both the popularity of a brand and the degree of competition the store faces in the local market, its insignificance may suggest that the two effects cancel out with each other. Being a foreign brand (*dorigin*) and having a large selling area (*darea*) also have a positive effect on sales revenue. Finally, good brand image (*dimage*) helps brand generate higher sales revenue in this store.

[Table 5 here]

The second column in Table 5 reports the estimated parameters for manufacturer's entry cost (and the outside option value). A brand's fit with store (*dfit*) again has a large effect on costs. The coefficient of r*coverage* is negative but insignificant, which suggests that the cost-saving of delivery, transportation, and inventory-holding from a large presence in the local market may be offset by the high opportunity cost from potential entry. The positive sign of the coefficient for *dproduction* suggests that it is more costly for a manufacturer to produce the good themselves compared with subcontracting production.

[17] We re-scale brand sales revenue and manufacturer transfers in model estimation; each unit of the estimated coefficients represents one million RMB.

The positive coefficient for *dimage* implies a high production cost or high outside option value for a brand with good prestige.

The third column illustrates the effect of brand attributes on spillovers to other categories. Here, two attribute variables, *dorigin* and *rcoverage,* are significantly positive. The entry of a foreign brand generates a total of 0.183 million RMB benefit annually on products in other categories. Although neither of the effects of *rcoverage* is significant at the demand or cost side, the benefit from the entry of a brand with large market coverage is substantial in terms of the ability of generating positive out-of-category spillovers. It is also interesting to see that the coefficient for *dfit* is significantly negative and has the largest magnitude, suggesting that the store will offer lower manufacturer transfers to brands with good fit (who are mostly medium-tier brands), probably because these brands do not help attracting the profitable customers associated with the store's stated strategy of moving upscale.

Finally, the lower panel in Table 5 reports the structural parameter estimates of the interaction effects (substitutability and complementarity) on a brand's sales revenue due to the entry of other brands in the same category. We first examine the effects within the same brand tier. Although all brands selling on the same store floor are directly competing with each other, no brands at each tier are substitutes (the effect of medium brands (M) is negative but insignificant). Interestingly, high-end brands (H) are complements ($\gamma_{HH} = 0.091$), implying that the entry of a high-end brand benefits the sales of other high-end brands. This is probably because there are only a few high-end brands in the store; the entry of another high-end brand will make it more likely that customers with high purchasing power visit the store, which will benefit the others of the same tier. The pattern of cross-tier interaction effects is mixed. The entry of medium brands benefits the revenue of low-end brands ($\gamma_{ML} = 0.026$), probably because the latter can use low prices to induce those customers who are attracted to the store to buy the former brands to switch. The entry of high-end brands also benefits medium brands ($\gamma_{HM} = 0.013$), probably due to the same reason. However, the impact of the entry of high-end brands on low-end brands is negative ($\gamma_{HL} = -0.038$), suggesting that, on the one hand, high-purchasing-power consumers will not switch from high-end to low-end brands; on the other hand, the targeted consumers of low-end brands may stay away as the store moves upscale with more high-end brands. This finding is consistent with Vitorino (2010), who finds that in a shopping mall lower-level department stores are hurt by the entry of an upscale department store.

The estimate of scale parameter (σ), which is not reported in Table 5, is 0.497 mil. RMB. As reported in Table 3, the average brand sales revenue in the data is 1.493 mil. RMB, suggesting that the store's uncertainty about manufacturers' sales and cost is not trivial.

We also examine the fit of our model by comparing the actual entry probabilities, sales revenue and transfers with model predictions based on the estimation results. Table 6 reports the results. Overall, the equilibrium outcomes predicted in our model match quite well with the actual data. In particular, the model predicts that H-tiered brands generate lower sales revenue than M-tiered brands, but receive a higher transfer rate. The model also predicts lower entry probabilities for H-tiered brands. Both of these predictions are consistent with our data.

[Table 6 here]

6.1 Model Validation

Based on observed attributes, the store assigns a score for every potential entrant brand. The objective of assigning scores is to help manager's decision-making when negotiating the entry with manufacturers. We do not know how the score is determined; however, the higher the score implies the more valuable is the brand.[18] This score has not been used in our estimation model; therefore it offers us a unique opportunity to test the validity in our structural model. If our model is a good representation of how decisions are made in reality, the score should be consistent with of the economic value related to the entry of a brand for the store and manufacturers.

[18] Based on our conversation with the store manager, we understand that the score is a weighted sum of the list of brand attributes the store has collected. We use the brand attributes in our model; however, the weight associated with each brand attribute is unknown to us and has not been used in the estimation.

However, it is not clear to us what economic value is represented by the brand score. The first obvious possibility is that it measures the expected demand of the brand once it enters the department store. As a test we plot the brand score (at the x-axis) against the expected sales revenue based on model estimates (at the y-axis; in mil. RMB) for each brand in Figure 1. Although the relationship is positive and quite strong (the correlation coefficient is 0.518), it is widely scattered across brands, suggesting that sales revenue may not be the only determinant of the value of a brand. Additional factors that are considered in our model include the entry cost of the manufacturer, and the spill-over effects on the sales of other brands within the category and on other categories. Since these factors have a direct linkage with the profit to the store and the entry probability, they should also be incorporated in the brand score. We test this assumption by calculating the aggregate value of a brand upon entry, which is the sum of the expected sales revenue, its effects on the sales revenue of other brands multiplied by their entry probabilities, and the spill-overs to other categories, deducted by the expected entry cost of the brand. Figure 2 shows the relationship between brand scores (at the x-axis) and the aggregate values for all candidate brands (at the y-axis; in mil. RMB). The relationship is close to an upward-sloping curve and much less scattered. The correlation coefficient between the two is 0.851, implying that the aggregate value of entry predicted from our model has a high fit with the brand score assigned by the store. Since the scores have an important effect on transfer offers and hence on manufacturers' entry decisions, this result greatly enhances our confidence in the validity of the structural model in terms of approximating how business decisions are made in our empirical context.

[Figure 1 here]

[Figure 2 here]

7. Counterfactual Experiments

One of the unique features we observe in the contract is that, in addition to the transfer stated prior to entry, there is a contingent component in the final transfer depending on how the actual sales revenue exceeds or falls behind the projection. As such, the store enjoys a certain amount of protection from the risks associated with brand entry. This type of contract is not unique and is widely used by department stores that adopt the store-within-a-store system. This form of contact naturally suggests two questions. Why do department stores choose such a contract? And, what are the economic consequences of adopting such a contract?

To address these questions we conduct a series of counterfactual experiments. Our first counterfactual experiment shows that, even when the store is risk-neutral, under information asymmetry it is better off using such type of contracts than other risk-sharing contracts. This exercise also helps us explore the economic consequences of adopting such a contract, not only for the store but also for manufacturers. We follow up with another counterfactual experiment to calculate the profit impact on manufacturers and the store when such information asymmetry is reduced.

7.1 Counterfactual Experiment I: Risk-Sharing Contracts

In the first counterfactual experiment, we assume that the store adopts some of the risk and shares ξ_{kt} with each manufacturer in the transfer. The same sales revenue projection is specified in the contract; but the store will now retain a fraction (s) of the difference between the actual and the projected sales (ξ_{kt}), while the rest $(1-s)$ belongs to the manufacturer. We vary s from 10% to 100% and simulate the market outcomes in different scenarios of risk-sharing.

In estimating our model, we only estimated the variance of the profit shock, ν_{kt}, which is the difference between the demand shock, ξ_{kt}, and the cost shock ω_{kt}. Letting r denote the ratio of the variance of ξ_{kt} relative to that of ν_{kt}, we investigate the robustness of the results from the counterfactual experiment by also varying the value of r from 0.1 to 0.99[19]. The change of the contract leads to a change in the store's belief about the entry likelihood of manufacturers. Given the structural parameter estimates of our model, we simulate the entry decisions of manufacturers, the store's expected value, the

[19] We choose 0.99 instead of 1 because of a technical reason when simulating ξ_{kt}. Nevertheless, $r = 0.99$ is a good approximation to the case where there is only demand shock. See Appendix II for the description of our simulation procedure.

manufacturers' profit, as well as other market outcomes subject to the equilibrium constraints. We do this for each combination of r and s and report the results in Tables 7, 8, and 9.

We also plot the expected store value in Figure 3. The contour line is shown in the bottom plane and each horizontal axis represents the store share (s) and the magnitude of ξ_{kt} (r), respectively. It is decreasing monotonically as the store retains a larger share of ξ_{kt} (s increases) or ξ_{kt} has a larger magnitude (r increases). The store value in all scenarios is smaller than that under the current contracts without risk-sharing (34.1609 mil. RMB). Furthermore, when s is small, the store value is quite stable under different values of r (e.g. the store value is 34.09 mil. RMB at r=0.1 and 33.51 mil. RMB at r=0.99 when s is 10%. See the first row of Table 7). However, when the store's share is large (e.g. s=100%. See the last row of Table 7), the expected store value decreases rapidly with increasing r. When r=0.99 and s=100%, the store value is even negative (assuming positive transfer offers) and hence there will be no contract agreement and the market will break down. These simulation results suggest that it is less profitable for the store to share the risk with manufacturers; therefore, the current contract structure is optimal from the store's perspective. This finding offers a coherent explanation for why department stores in the current retail system choose such type of contracts.

[Table 7 here]

[Figure 3 here]

The key driver of this result lies in the potential adverse selection behavior from manufacturers. The demand shock ξ_{kt} is completely borne by manufacturer k under the current contract, while only part of it goes to the manufacturer's profit under risk-sharing contracts. Consider a manufacturer with negative ξ_{kt} who will not enter under the current contract. With the risk-sharing contract, the manufacturer may receive positive profit since part of the negative shock is absorbed by the store. Similarly, a manufacturer with a positive shock may enter under the current contract but not under risk-sharing contracts. This is a standard adverse selection problem for the store, and the magnitude of which will be amplified with larger demand shocks (i.e. larger r). As evidence, simulation results show that the average ξ_{kt} for all entering brands in each scenario is decreasing as either r or s grows. It will result in a profit loss for the store under risk-sharing contracts. To conclude, when there is asymmetric information between the store and manufacturers, the contingent component of the current contract acts as a useful protection for the store against adverse selection from manufacturers.

The feasibility of implementing such type of contracts, however, requires that department stores have sufficient market power to enforce such contracts onto manufacturers. This is because manufacturers' total profit in Table 8, in contrast, increases monotonically when s or r increases. In each of the scenarios this profit is also larger than that under the current contract (34.5 mil. RMB). This increase comes from two sources: first, transfers offered by the store will increase as either r or s becomes larger and, second, consequently the number of entrants also increases.

[Table 8 here]

[Figure 4 here]

This is a rather surprising finding. As r or s increases under risk-sharing contracts, adverse selection becomes a bigger problem. Why then is the store willing to offer higher transfers to candidate brands? To understand the underlying reason, first note that the store is facing an upward-sloping entry probability function (i.e., the higher the transfer offered in contract the larger is the entry probability). Therefore, there is an incentive for the store to extract manufacturers' profit through transfers. As shown in equation (7), the deterministic transfer in the current contract is lower than the value for the store from the entry of brand k, which is the sum of the first three terms on the right-hand side. At the optimal level, the marginal benefit of increasing the transfer offer has to be equivalent to the marginal cost. Under risk-sharing contracts the marginal effect of the transfer on the entry probability is larger than that without risk-sharing.[20] If the difference between the store value from entry and the deterministic transfer under the current contract, is larger

[20] The derivative of the entry probability with respect to transfer offer is $p_{kt}(1-p_{kt})/\sigma$. As σ is reduced when the store shares the risk with the manufacturer, the marginal effect of increasing transfer on entry will become larger.

than the loss due to adverse selection, i.e., $s * E[\xi_{kt}|I_{kt} = 1, s]$[21], the marginal benefit of increasing transfer under risk-sharing contracts will dominate the marginal cost. Consequently, the store is willing to offer a higher deterministic transfer when s is larger than zero, and manufacturers will enjoy a higher profit and more will enter the store. This result illustrates a trade-off from the perspective of policy makers – allowing for risk-sharing contracts will, on the one hand, make the adverse selection problem worse but, on the other hand, facilitate firms' entry and enhance the social welfare. Table 9 reports the manufacturers-store joint profit under different (r, s) scenario. The joint profit under the current contract (68.7 mil. RMB) is always lower than that under risk-sharing contracts except at the extreme case of (r=0.99 and s=100%). At different levels of r, the joint profit is maximized with s in the range of 50% to 60%, suggesting that from the social welfare perspective risk-sharing contracts dominate the current contract.[22]

[Table 9 here]

7.2 Counterfactual Experiment II: The Value of Information

In the above experiment, we illustrate how asymmetric information between manufacturers and the store may explain the adoption of the contract structure we observe in the data. In the second counterfactual experiment, we examine the impact on manufacturers and store profits when some of manufacturers' private information becomes public information. Since the store has significant market power, manufacturers may be concerned that the revelation of private information can lead to the store extracting more manufacturers' surplus. We will show that this assumption is invalid under the current contract without risk-sharing. Indeed, we show that it is mutually beneficial to both manufacturers and the store when the magnitude of asymmetric information is reduced.

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[21] When s is positive, $E[\xi_{kt}|I_{kt} = 1, s]$ is found to be negative from our simulation study.

[22] With a larger number of entrants in the department store, consumers have more choices and, because of more intensive competition among manufacturers on the same store floor, are more likely to find lower prices. It is therefore reasonable to assume that the consumer welfare will also increase under risk-sharing contracts.

In our second counterfactual experiment, we consider what happens when part of ξ_{kt}[23] becomes known to the store and other manufacturers. Correspondingly, the magnitude of the manufacturer's private information is reduced. We consider 4 scenarios of information revelation: after the information is revealed, the store's uncertainty becomes 95%, 90%, 85% and 80% of the estimated scale parameter σ, respectively[24]. The reduced store uncertainty leads to a new set of equilibrium outcomes including transfer offers and entry probabilities.

We numerically calculate the new equilibrium outcomes in each of the scenarios and Table 10 reports some of the simulated outcomes. What is interesting is that, as uncertainty is reduced from the original level (100% scenario) to a lower level, the store is willing to offer a higher deterministic transfer in the contract and hence attracts more entrants. The reason is similar to why the store is willing to offer a higher transfer under risk-sharing contracts. With lower uncertainty, the marginal effect of increasing transfers on the entry probability becomes higher. If the average value of brand entry to the store is sufficiently large, this also implies a bigger benefit to increasing transfer. As a result of increased transfers, the total number of entrants and total manufacturers' profit also increases. Although the store's value from each entrant (after deducted transfers) is reduced, in contrast to the risk-sharing case, its total value increases from the 100% scenario to the 80% scenario, mainly driven by the increased entry. Therefore, the reduced information asymmetry creates a win-win situation for both parties, implying an improvement of social welfare. This is true even though the private information would also become available to rival manufacturers. This finding suggests that manufacturers under the current contract will have an incentive to reveal their private information if it can be verified through some mechanisms. For example, they can let the store get access to their sales data in other stores, or they can pay an independent marketing research firm to verify their sales and profit claims. Either way can help reduce the store's uncertainty

[23] We assume that the demand shock ξ_{kt} is 50% of the total profit shock, i.e., with scale parameter of $\sqrt{0.5}\sigma$.

[24] Please refer to Appendix III for simulation details.

regarding the product quality and sales potential.[25] In contrast, we assume in another simulation that the store takes all of the demand shocks in the contract, and find that the store will offer a lower transfer to manufacturers as more information is revealed. As the store's profit increases, total manufacturers' profit is reduced and fewer brands will enter.[26] All of these results therefore suggest that the current contract structure may help induce information revelation from manufacturers hence reduce the extent of asymmetric information, which may be another reason why department stores choose to adopt such type of contracts.

[Table 10 here]

8. Conclusion

This paper studies an entry game involving two-sided decisions from economic agents, and applies the model to study the entry of manufacturers in the professional women's clothing category into a Chinese department store. We investigate the economic determinants of the observed entry pattern in the data, using detailed information on transfer offers from the store to manufacturers and brand sales conditional on entry. We structurally model, under information asymmetry between manufacturers and the store, the store's decision of how much transfer is offered in contracts and how this affects the entry decisions of manufacturers. Our model helps us to quantify the magnitude of the effect an entering brand has on other brands within and outside the category, and how these externalities will be incorporated in the manufacturer's entry decision through the transfer offer.

Based on the estimation results, we study the impacts of different types of contracts on the store and manufacturers' profit. When information asymmetry exists between manufacturers and the store, sharing risks (from the store's perspective) in contracts will

[25] Manufacturers with low ξ's do not have incentive to reveal such information; however, failing to agree to do so like the others will reveal that their products are of low quality.

[26] Detailed results are not presented here to save space. They are available from the authors upon request.

lead to adverse selection in manufacturers' entry decisions. Our first counterfactual experiment suggests that the contingent component of transfers in the current contract is crucial to protect the store from the potential loss caused by adverse selection. However, we also show that risk-sharing contracts generate a manufacturers-store joint profit higher than under the current contract; therefore, the current contract is suboptimal from a social welfare perspective. Our second counterfactual experiment illustrates that, under the current contract, it is mutually beneficial for the store and manufacturers to reduce the degree of information asymmetry, implying that the current contract may provide an incentive for manufacturers to reveal their private information.

The modeling and estimation strategies developed in this study can be extended to other empirical contexts where economic decisions have to be made through contracts involving multiple agents. For future research, it may be valuable to also model other strategic decisions, such as pricing and technology investment, in addition to firms' entry decisions. Finally, in this paper, we have abstracted away from the dynamics of entry and exit decisions as well as the store's learning of the true brand quality. A potential avenue for future research would be to incorporate forward-looking behavior into this framework.

Table 1: Definition of brand attributes

Brand Attribute	Definition
origin	The origin of manufacturers: Inland China medium/large city, Hong Kong/Taiwan, Japan, Korea, and European countries and US
fit	Brand fitness with the store’s targeted customers
capital	Supplier’s registered capital
production	Supplier's production capability: subcontract or self-production
agency	Brand manufacturer or agent of the manufacturer
coverage	Market coverage, represented by the number of 9 comparable department stores in the local market selling the brand
image	Brand image evaluation
area	Average area of selling counters in the 9 comparable department stores in the local market
extra	Selling in selected 5 major cities other than Shanghai

Table 2: Attribute variables and summary statistics

Attribute	Definition	Mean	Std. Dev
dorigin	1 if foreign brand, 0 otherwise	0.227	0.421
dfit	1 if good fit, 0 otherwise	0.445	0.499
dcapital	1 if registered capital 100+ million RMB (agent) or 500+ million RMB (owner), 0 otherwise	0.496	0.502
dproduction	1 if self-production, 0 if subcontract	0.689	0.465
dagency	1 if brand manufacturer, 0 if agent	0.958	0.201
rcoverage	(number of selling stores)/9	0.458	0.272
dimage	1 if good brand image, 0 otherwise	0.328	0.471
darea	1 if mean operational area 50+ m^2, 0 otherwise	0.521	0.502
dextra	1 if 2+ entries in selected comparable stores of 5 cities	0.277	0.450

Table 3: Summary statistics of entry, sales, transfers, and store revenue

Brand Tier	Average Number of Annual Entries	Entry Rate from Choice Set	Sales Revenue (mil. RMB)	Manufacturer Transfers (mil. RMB)	Store Revenue (mil. RMB)	Manufacturer Transfer Rate
H	8.75	0.398	1.467	1.209	0.258	0.846
M	25.25	0.495	1.816	1.375	0.441	0.762
L	19.75	0.429	1.091	0.669	0.422	0.628
Total	53.75	0.452	1.493	1.089	0.404	0.726

Table 4: Reduced-form regression results of sale revenue, brand entry and manufacturer transfer rate

Variable	Sales Revenue	Brand Entry	Manufacturer Transfer Rate
constant	1.363	-2.691	7.053***
dorigin	0.287*	-0.065	0.471
dfit	0.525***	-1.048***	-0.248
dcapital	0.093	0.507**	0.455*
dproduction	0.129	-0.464	0.237
dagency	-0.277	0.232	-0.202
rcoverage	0.070	1.655***	-0.474
dimage	0.283	-0.895***	0.122
darea	0.155	-0.027	-0.657**
dextra	0.536***	0.890***	0.242
N_{LL}	-0.004	0.095**	-0.045
N_{LM}	-0.016	0.002	-0.034
N_{LH}	-0.028	0.012	0.013
N_{ML}	-0.009	-0.018	-0.132*
N_{MM}	0.002	0.104	-0.132*
N_{MH}	0.002	0.029	-0.103
N_{HL}	-0.006	0.006	-0.044
N_{HM}	-0.008	0.000	0.006
N_{HH}	-0.046	0.217*	-0.053

***: significant at 1% level; **: significant at 5% level; *: significant at 10% level

Table 5: Structural parameter estimates of the two-sided entry model

Variable	Sales Revenue (β)	Entry Cost and Outside Option Value (α)	Out-of-Category Spillovers (δ)
constant	0.173	0.075	0.280
dorigin	0.149*	0.199	0.183**
dfit	0.844***	0.771***	-0.451
dcapital		-0.102*	
dproduction		0.376**	
dagency		-0.234	
rcoverage	-0.181	-0.177	0.260**
dimage	0.276**	0.381**	-0.147
darea	0.228**	0.008	-0.041
dextra	0.253**	0.002	0.082

Interaction Effects (γ)		Brand Tier		
		L	*M*	*H*
Brand Tier	*L*	-0.007	0.018	0.011
	M	0.026**	-0.003	-0.029
	H	-0.038*	0.013*	0.091*

***: significant at 1% level; **: significant at 5% level; *: significant at 10% level

Note: The interaction effect parameters LL, LM and LH, for example, represent the effects of the entry of a low-end brand on the sales revenue of another low-end brand, medium-end brand and high-end brand, respectively.

Table 6: Data fit: entry probability, sales revenue and transfers

Brand	Entry Probability		Sales Revenue (mil. RMB)		Transfer (mil. RMB)	
Tier	Real Data	Two-Sided Model	Real Data	Two-Sided Model	Real Data	Two-Sided Model
L	0.429	0.481	1.091	1.102	0.669	0.647
M	0.495	0.433	1.816	1.775	1.375	1.377
H	0.398	0.397	1.467	1.546	1.209	1.242
Total	0.452	0.445	1.493	1.490	1.089	1.087

Table 7: Expected store value (mil. RMB) under risk-sharing contract

		Proportion of the variance of demand shock: r									
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
Share to the store: s	10%	34.0880	34.0410	33.9947	33.9254	33.8749	33.8266	33.7686	33.6844	33.6348	33.5054
	20%	33.9571	33.7492	33.5976	33.3963	33.1746	32.9236	32.6649	32.3980	32.1299	31.4833
	30%	33.7700	33.3818	32.9817	32.5226	32.0371	31.4641	30.8891	30.3134	29.6880	28.2413
	40%	33.5059	32.8392	32.1391	31.3441	30.5060	29.5430	28.5479	27.4784	26.4289	23.9617
	50%	33.2004	32.2063	31.1252	29.9335	28.6292	27.2154	25.7374	24.1396	22.6721	19.0837
	60%	32.8317	31.4480	29.9490	28.3285	26.5641	24.6518	22.6198	20.5741	18.7567	14.3574
	70%	32.4428	30.6100	28.6698	26.6028	24.2736	21.8661	19.3325	16.8819	14.9611	10.1450
	80%	31.9899	29.7575	27.3683	24.7584	21.9656	19.0518	16.0583	13.2773	11.3495	6.5554
	90%	31.5341	28.7942	25.9090	22.8768	19.5988	16.2048	12.8445	9.8100	7.8936	3.0677
	100%	31.0431	27.8475	24.4101	20.9041	17.2312	13.4354	9.7285	6.4126	4.4419	--

Table 8: Expected total manufacturer profit (mil. RMB) under risk-sharing contract

	Proportion of the variance of demand shock: r										
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
Share to the store: s	10%	35.0222	35.3083	35.6979	36.1273	36.4684	37.0282	37.2937	37.8692	38.1501	38.7225
	20%	35.3083	36.0825	36.8702	37.7352	38.5794	39.5076	40.4195	41.3377	42.3071	43.8229
	30%	35.7969	36.8695	38.1173	39.4514	40.7880	42.2455	43.7255	45.2440	46.8170	48.7128
	40%	36.0606	37.7295	39.3902	41.1953	43.0660	45.0748	47.1287	49.2700	51.3986	54.0363
	50%	36.5260	38.4949	40.6349	42.9296	45.3083	47.8783	50.5115	53.1477	55.6960	58.8849
	60%	36.9714	39.3124	41.8624	44.6188	47.5100	50.5756	53.7233	56.7060	59.3371	62.3663
	70%	37.2383	40.1941	43.0955	46.2440	49.5659	53.0897	56.6309	59.8132	62.1938	64.4682
	80%	37.6323	40.7655	44.1145	47.7299	51.4862	55.3859	59.2318	62.4928	64.3052	65.2334
	90%	37.9955	41.5017	45.2507	49.1709	53.2054	57.4334	61.4671	64.7719	66.1286	66.3785
	100%	38.3251	42.1516	46.2229	50.4656	54.8384	59.1755	63.4690	66.8347	68.0593	--

Table 9: Expected store-manufacturer joint profit (mil. RMB) under risk-sharing contract

	Proportion of the variance of demand shock: r										
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
Share to the store: s	10%	69.1102	69.3493	69.6926	70.0527	70.3433	70.8548	71.0623	71.5536	71.7849	72.2279
	20%	69.2654	69.8317	70.4678	71.1315	71.7541	72.4312	73.0844	73.7357	74.4370	75.3062
	30%	69.5669	70.2513	71.0990	71.9740	72.8250	73.7096	74.6147	75.5574	76.5050	76.9540
	40%	69.5665	70.5687	71.5294	72.5394	73.5721	74.6178	75.6766	76.7484	77.8276	77.9980
	50%	69.7264	70.7012	71.7601	72.8632	73.9374	75.0937	76.2489	77.2873	78.3681	77.9686
	60%	69.8031	70.7604	71.8114	72.9473	74.0741	75.2275	76.3431	77.2801	78.0938	76.7238
	70%	69.6811	70.8041	71.7653	72.8468	73.8395	74.9558	75.9634	76.6951	77.1550	74.6132
	80%	69.6223	70.5231	71.4828	72.4884	73.4519	74.4378	75.2901	75.7701	75.6547	71.7887
	90%	69.5296	70.2959	71.1597	72.0477	72.8042	73.6382	74.3116	74.5819	74.0222	69.4461
	100%	69.3682	69.9990	70.6329	71.3697	72.0695	72.6109	73.1975	73.2473	72.5012	--

Table 10: Market outcomes with decreasing information uncertainty

	Mean Transfer (mil. RMB)	Store Value (mil. RMB)	Total Manufacturer Profit (mil. RMB)	Total Entry Value (mil. RMB)	Number of Entries	Store Value per brand (mil. RMB)	Mean Manufacturer Profit (mil. RMB)
100% Scenario	1.1608	33.916	32.322	66.238	52.7	0.6444	0.6141
95% Scenario	1.1755	34.216	32.802	67.019	53.6	0.6285	0.6118
90% Scenario	1.1910	34.585	33.280	67.865	54.7	0.6127	0.6086
85% Scenario	1.2062	34.831	33.828	67.658	55.8	0.5974	0.6067
80% Scenario	1.2226	35.125	34.401	68.525	56.9	0.5822	0.6047

Figure 1: Actual sales revenue vs. brand score

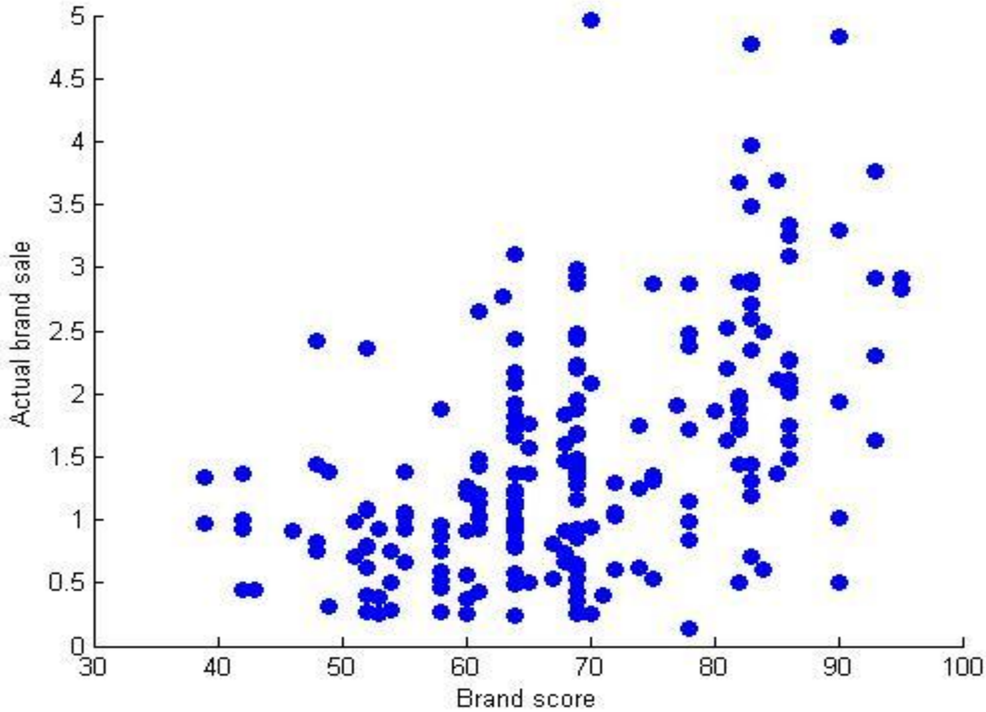


Figure 2: Expected aggregate value of entry vs. brand score

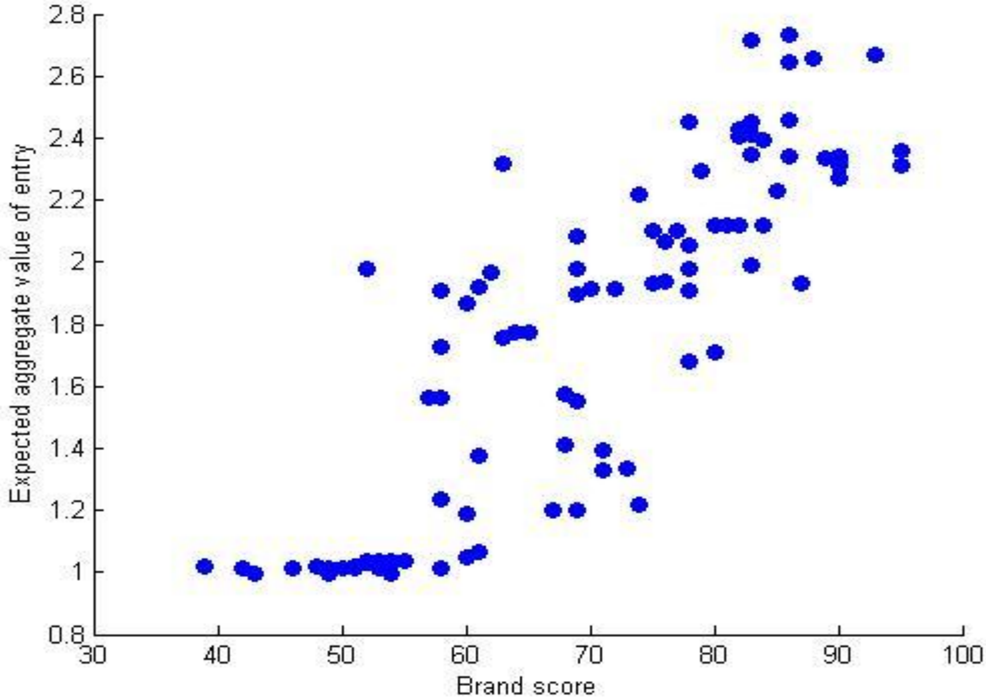


Figure 3: Expected store value (mil. RMB) under risk-sharing contract

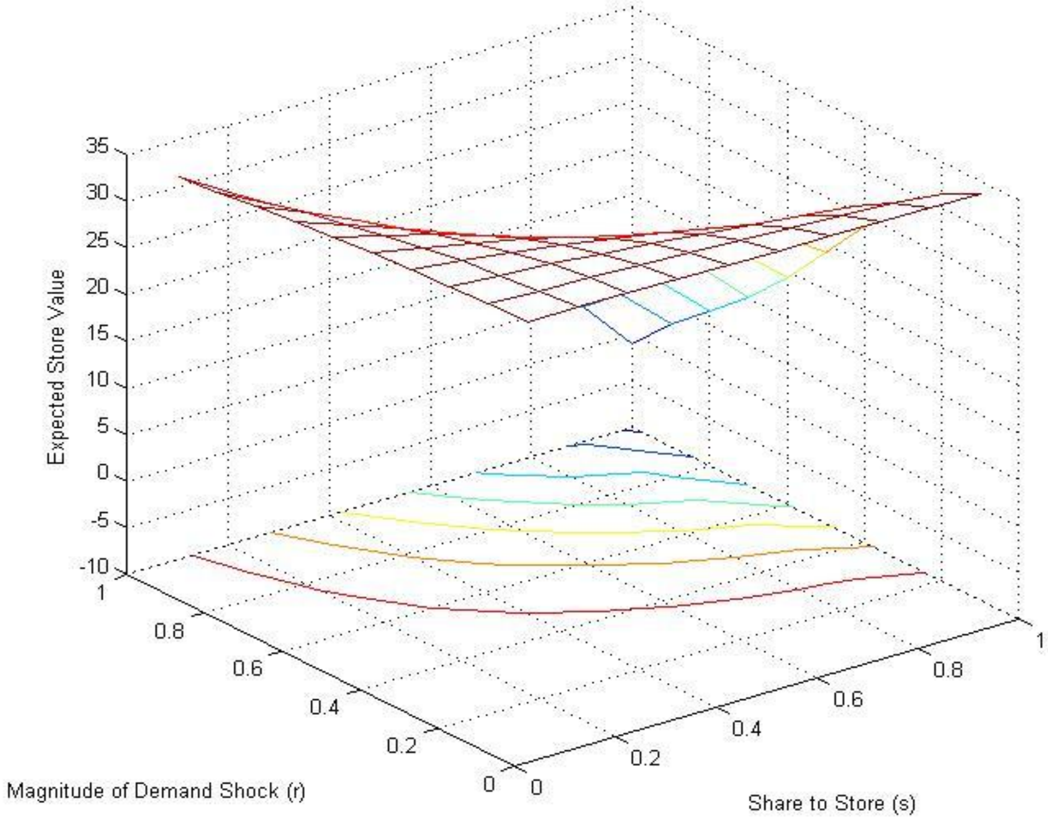
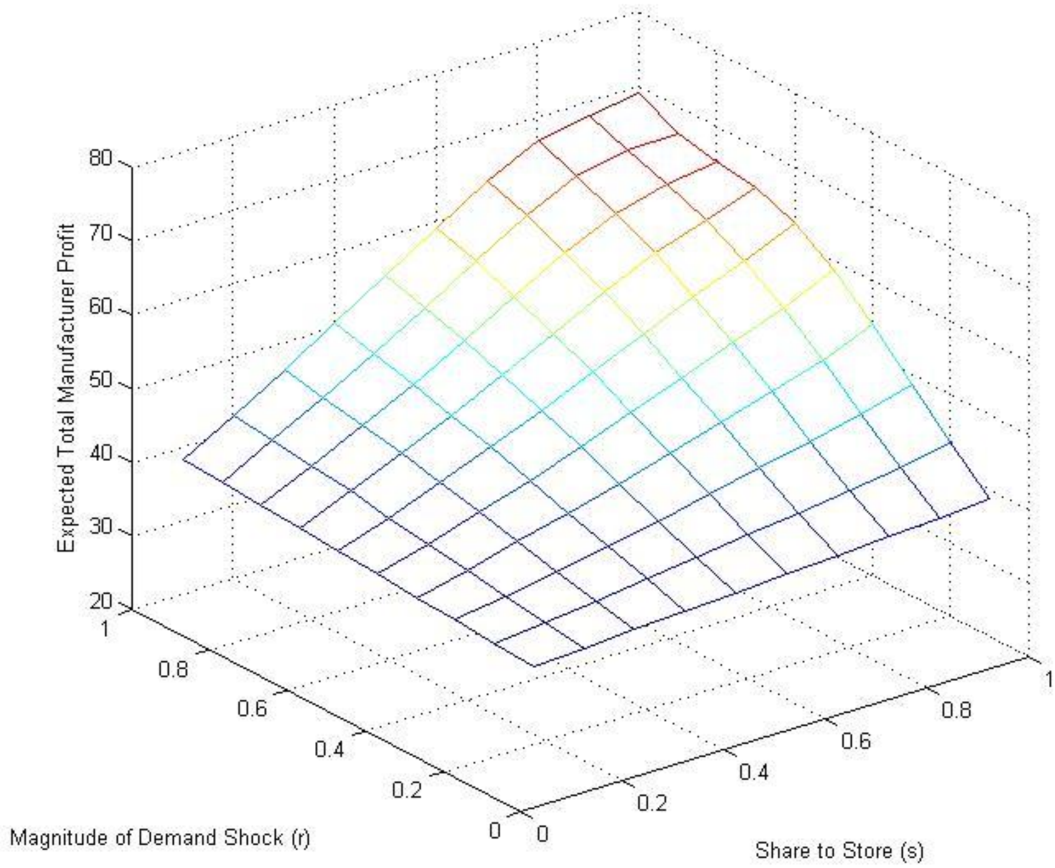


Figure 4: Expected total manufacturer profit (mil. RMB) under risk-sharing contract



Appendix I: Derivation of $E(\xi_{kt}|I_{kt}=1)$

Define $\bar{\Pi}_{kt}=T^{*}_{kt}-x^{co}_{kt}\alpha$ as the deterministic part of manufacturer's k's entry profit. As

$$E(\xi_{kt}|I_{kt}=1)=E(\xi_{kt}|\Pi_{kt}\geq 0)$$

$$=E(\xi_{kt}|\xi_{kt}\geq -\bar{\Pi}_{kt}+\omega_{kt})$$

$$=\int_{-\infty}^{\infty}\int_{-\bar{\Pi}_{kt}+\omega_{kt}}^{\infty}\frac{\xi_{kt}f(\xi_{kt},\omega_{kt})}{p(\xi_{kt}\geq-\pi_{kt}+\omega_{kt})}d\,\xi_{kt}d\omega_{kt}$$

where $f(\xi_{kt},\omega_{kt})$ is the joint distribution density of ξ_{kt} and ω_{kt}, this conditional expectation is a function of $\bar{\Pi}_{kt}$. Therefore, $E(\xi_{kt}|I_{kt}=1)=g(\bar{\Pi}_{kt})$, where g is some function. Since $p_{kt}=\dfrac{\exp(\bar{\Pi}_{kt})}{1+\exp(\bar{\Pi}_{kt})}$, there is an one-on-one correspondence between $\bar{\Pi}_{kt}$ and p_{kt}. This implies that

$$E(\xi_{kt}|I_{kt}=1)=g(\Phi^{-1}(p_{kt}))\equiv\lambda(p_{kt}).$$

At equilibrium, p_{kt} can be replaced by the equilibrium entry probability p^{*}_{kt}. Therefore, for a consistent estimator of p^{*}_{kt}, say $\hat{p}^{*}_{kt}$, this expectation can be written as $E(\xi_{kt}|I_{kt}=1)=\lambda(\hat{p}^{*}_{kt})+\varsigma_{kt}$, where $\varsigma_{kt}\equiv\lambda(p^{*}_{kt})-\lambda(\hat{p}^{*}_{kt})$ is a mean zero approximation error. In model estimation, we use polynomial to approximate the function $\lambda(.)$.

Appendix II: Simulation procedure of section 7.1 (Counterfactual experiment I: Risk-Sharing Contracts)

The key to this experiment is the ability to draw ξ_{kt} under different values of r such that the entry probability of each brand is still the logit specification in equation (11) under different risk-sharing contracts. Let μ_{kt} be the manufacturer's profit shock net of the stochastic component in the outside option value (i.e., $\mu_{kt} = \nu_{kt} - \nu_{kt}^0$). Under our distribution assumptions, μ_{kt} is logistic distributed. Cardell (1997) proposes a so-called generalized logistic (GL) distribution and shows that a GL-distributed random variable is the difference between two logistic random variables with the same scale parameter. For each (*r*,*s*) combination, we adopt his procedure by first applying the inverse transform method, given the CDF of GL distribution in Theorem 2.2 of Cardell (1997), to draw from a GL distribution with scale parameter $\sigma^* = \sqrt{1 - r * s * (2 - s)}\sigma$ (i.e., GL(σ^*), $\sigma^* < \sigma$) and then multiplying the draw by a factor of $\lambda = \sqrt{1 - r * s * (2 - s)}$ to get a draw of ξ_{kt} (i.e., $\xi_{kt} = \lambda * \mathrm{GL}(\sigma^*) \equiv \mathrm{GL}(\lambda, \sigma^*)$). We also draw for the manufacturer a new logistically distributed random variable, μ_{kt}^*, with the same scale parameter σ^*. Their sum will be a logistically distributed random variable with the original scale parameter σ. That is, $\mu_{kt} = \xi_{kt} + \mu_{kt}^*$, where $\mu_{kt} \sim logistic(\sigma)$, $\xi_{kt} \sim \mathrm{GL}(\lambda, \sigma^*)$ and $\mu_{kt}^* \sim logistic(\sigma^*)$.

Under risk-sharing contract, manufacturer *k*'s entry profit given any T_{kt}^* (net of the outside option) is $\Pi_{kt} = T_{kt}^* - \bar{C}(x_{kt}^c) + \mu_{kt}^*$. Define I_{kt} as the indicator of entry which equals 1 if Π_{kt} is positive and 0 otherwise. The ex-ante entry probability $p_{kt}^* = E[I_{kt} = 1 | T_{kt}^*]$ from store's perspective is defined in equation (11) with σ replaced by the new scale parameter σ^*. Let T_t^* be the vector of the deterministic transfers offered to all candidate brands, then the store's expected profit is (see equation (6))

$$E(V_t^s | \Psi_t^s, T_t^*) = \sum_k E\{[\bar{S}(x_{kt}^d) + S_k(p_{-kt}) - T_{kt}^* + \varphi(x_{kt}^s) + s * \xi_{kt}] p_{kt}\}.$$

Given each draw of ξ_{kt}, we search in each (r, s) scenario for the optimal level of deterministic transfer (T_{kt}^{*}) for each manufacturer that will maximize the average store value. We then calculate the manufacturer's entry profit given T_{kt}^{*} and the draw of μ_{kt}^{*} to simulate their entry decisions. We draw 1,000 times for each manufacturer and calculate the mean store value and average profit for each manufacturer.

Appendix III: Simulation procedure of section 7.2 (Counterfactual Experiment II: The Value of Information)

Let ξ^*_{kt} be the revealed information. We can rewrite the previously unknown profit shock as $\mu_{kt} = \xi^*_{kt} + \mu^*_{kt}$, where $\mu^*_{kt} = (\xi_{kt} - \xi^*_{kt}) - \omega_{kt} - \nu^o_{kt}$ is the new profit shock after ξ^*_{kt} is known.

We assume that the revealed information ξ^*_{kt} is GL-distributed as in section 7.1 so that the new profit shock μ^*_{kt} is still logistically distributed. We draw ξ^*_{kt} and μ^*_{kt} from these distributions. Specifically, we start from the 80% scenario to draw the unknown demand shock ξ_{kt} from a GL distribution and μ^*_{kt} correspondingly. We next draw the revealed demand shock ξ^*_{kt} when moving from 85% scenario to 80% scenario. We repeat this process sequentially for moving from 90% scenario to 85% scenario and moving from 95% scenario to 90% scenario. Given these draws, we obtain the unknown demand shock $(\xi_{kt} - \xi^*_{kt})$, the revealed demand shock as well as μ^*_{kt} in each scenario.

Given each draw, we search in each scenario the optimal level of deterministic transfer (T^*_{kt}) for each manufacturer that will maximize the average store value. We then calculate the manufacturer's entry profit given T^*_{kt} and simulate their entry decisions. We draw 1,000 times for each manufacturer and calculate the mean store value and average profit for each manufacturer.

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