Information Asymmetry, Manufacturer-Retailer Contracts, and Two-Sided Entry

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Abstract

We investigate the economic determinants of contract structure and entry in an empirical setting with transfer contracts, which specify that manufacturers directly sell their products in retail stores while retailers collect the sales revenue and return a transfer to the manufacturers. Using a unique dataset describing the entry decisions of clothing manufacturers into a retail department store, we estimate a two-sided, asymmetric-information entry model. We then use this model to compare welfare estimates under transfer contracts to counterfactual welfare estimates obtained under common alternative contract formats. Results show that transfer contracts dominate other contract formats when adverse selection is severe. We also find that, even in the absence of adverse selection, it is mutually beneficial for the retail store and the manufacturers to reduce information asymmetry.

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

1. Introduction

In a typical retail channel, it is required that upstream manufacturers reach a contractual, rent-sharing agreement with downstream retailers before their products can sell in retail stores. Three types of contracts are commonly observed in the retail industry: vertical contracts, share contracts, and transfer contracts. Under vertical contracts, product ownership is transferred from manufacturers to retailers, who are the residual claimants of the gain or loss from selling to end consumers, under agreed wholesale prices. This is the traditional type of contract adopted in the retail sector and has been widely studied in the economics literature. Share contracts, in contrast, let manufacturers keep the ownership and retailers are paid by a share of sales revenue in return for selling in their stores. They have recently become the dominant mechanism adopted by online retail platforms, such as the Marketplace at Amazon.com and Apple and Android app stores, to split revenue with third-party sellers or software developers.

This paper examines transfer contracts, which have been widely used by department stores in Asian countries, including China. In a transfer contract, manufacturers directly sell their products in retail stores, while retail stores collect the sales revenue and return a transfer to the manufacturers. The most important terms in the contract specify the retailer’s targeted sales revenue and a transfer amount. When sales are less than the target, the difference will be deducted from the transfer; when sales exceed the target, the manufacturer is paid almost all of the excess. This essentially guarantees that the retailer’s return is not greatly affected by demand fluctuations. While transfer contracts are a recent innovation for rent-sharing in the retail sector, they are effectively very similar to fixed-rent contracts, which have been typically used between shopping mall developers and store owners.

Our goal in this study is to investigate the economic determinants of contract-format choice and to estimate the welfare impacts on manufacturers and retailers from using a transfer contract in comparison with vertical and share contracts. Our empirical analysis examines the entry decisions of clothing manufacturers into a major retail store in the Chinese city of Shanghai. Our analysis focuses on the information asymmetry between manufacturers

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2 Such contracts have a long history in the agricultural sector under the form of “crop-sharing”.
and the retail store. We assume that the retail store faces uncertainty regarding some attributes of the manufacturer that affect sales revenue and manufacture costs, i.e., these attributes are private information for manufacturers. This type of information asymmetry can lead to adverse selection problems, which through interviews with the store management, we believe is the major concern of the store when deciding on contract offers.

Our main interest is not to propose new contract designs; instead, this paper compares the welfare impacts of the transfer, vertical, and share contracts under information asymmetry. Given that these three types of contracts have been widely adopted in different industries, understanding their welfare impacts is important for both policy makers and for retailers and manufacturers when choosing between contract formats. Based on the estimation results, we compare the equilibrium outcomes under the three types of contracts. We explore different forms of information asymmetry, in terms of how the two uncertainties are correlated with each other within brands, which lead to different degrees of adverse selection in manufacturer entry. Understanding the impact of adverse selection on profits is informative about why different contract formats are chosen in different economic environments.

To address these questions, we develop a two-sided model, in which the store makes simultaneous take-it-or-leave-it offers to all manufacturers and, conditional on the offers, manufacturers make entry decisions. By specifying and estimating such a two-sided entry model under information asymmetry, we are able to study the economic determinants of contract offers and firm entry that cannot be identified in standard entry models.

To estimate our model, we use a unique dataset containing information about manufacturers in a women’s clothing category who are potential entrants to a major department store in Shanghai. Estimation relies on three sources of information: the observed entry and exit decisions of manufacturers, the actual revenue transfer from the store to manufacturers, and the annual sales revenue of each contracted manufacturer. The rich nature of our data facilitates clean identification of model parameters. Brand entry and sales data helps identify the sales revenue function. Data on brand entry and the revenue transfer allows us to separate manufacturers’ cost function from the “spillover effects” of brand entry on the store’s profit that comes from categories outside the women’s clothing.
Another unique 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 data on the store’s information set regarding each potential entrant and based on that we can infer the magnitude of the store’s uncertainties regarding the entrant’s sales revenue and costs.

Our results show that the attributes of a manufacturer’s brand have different effects on the store and manufacturer profits. The better a brand fits with the majority of consumers in the store, for example, will increase the brand’s sales revenue, but will also increase the manufacturer cost and has a negative spillover effect on the sales of other categories sold in the store. Other brand attributes also have significant impacts on sales revenue, manufacturer cost, and spillovers. The standard deviation of the manufacturers’ private information is estimated as 0.4 mil. RMB\(^3\), which is very significant in comparison with the average brand sales revenue 1.5 mil. RMB. To validate our structural model, we compare the expected store profit and sales revenue estimated using our model with brand scores used by the store, which had not been directly used in estimation. We find the measures to be highly consistent with one another, providing strong evidence for the validity of our model.

To analyze the effects of the interaction of asymmetric information and contract design on welfare, we use our estimation results to conduct two counterfactual experiments. The first counterfactual experiment compares the welfare impacts of transfer contracts with both vertical and share contracts under different levels of adverse selection. We show that transfer contracts dominate the other contracts when adverse selection is severe, represented either by a high positive correlation between manufacturers’ private information on own brand sales and the production cost, or by a large proportion of manufacturers incurring loss if they enter. This finding offers an explanation why transfer contracts are widely adopted in China. When the adverse selection problem is at lower levels, however, share contracts are a better option for the store. Finally, vertical contracts would benefit manufacturers more at lower levels of adverse selection, but they are much

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\(^3\) Chinese dollar. One RMB is about US $0.16.
worse than the other contracts for both the store and manufacturers when adverse selection is severe.

Our second counterfactual experiment illustrates that, even when adverse selection is not an issue, it is mutually beneficial for the store and the manufacturers to reduce the degree of information asymmetry under transfer contracts. This could potentially be achieved through quality monitoring by the government or by other third parties. Reducing information asymmetry will increase the number of brands available to consumers in the store and we show that the welfare improvements are very substantial, even if only part of the information is revealed.

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 belongs to the broad literature on the efficiency and welfare impacts from different types of vertical relationship between upstream manufacturers and downstream retailers or distributors. A large theoretical literature in both economics and marketing has explored this topic. Due to a lack of detailed data, however, the literature on empirical studies of vertical relationships is more recent. Villas-Boas (2007), for example, studied vertical contracts between manufacturers and retailers in the supermarket industry, and developed a method to test different non-nested models of the vertical relationship, when wholesale prices are not observed. Draganska et al (2010) extended this framework by proposing a Nash bargaining model to determine wholesale prices and how margins are split in the retail channel. With a similar approach, Crawford and Yurukoglu (2012) used a bilateral oligopoly bargaining model to help estimate input costs of distributors in the multichannel television market. Based on the estimation results they conducted counterfactuals to compare the welfare implications of à la carte and bundling pricing. Ho
(2009) modeled the negotiation process between insurance plans and hospitals to study how equilibrium hospital networks and the division of profits are determined. Empirical studies in this stream mostly do not have data on the transfers between channel members, with a few exceptions. Mortimer (2008), for example, used the contract information from home video retailers to study the efficiency improvements in the video rental industry following the change from linear-pricing contracts between retailers and movie distributors to revenue-sharing contracts. Grennan (2013) also used data on buyer-supplier transfers to analyze bargaining and price discrimination in a medical device market.

All of the above studies assume that upstream and downstream firms have full information, which is acknowledged in Crawford and Yurukoglu (2012) as a strong assumption. The main innovation of our model is that it allows the department store to have uncertainty regarding both the sales revenue and the manufacturer cost for an entering brand. The store is aware of this information asymmetry issue when deciding contract offers. Therefore, our study can be viewed as a complement to the existing empirical research on vertical relationships. We abstract away from manufacturers’ pricing decisions. This is because we observe thousands of products in the professional women’s clothing category and rapid changes in product assortments in the store due to seasonality. Modeling manufacturers’ pricing decisions will complicate our analysis and is not the objective of this study. This paper also departs from the previous literature by studying a unique empirical setting, under which branded manufacturers set up selling counters and hire their own sales staff to sell products. This “store-within-a-store” business model is an innovation from the traditional retail system, and has been commonly adopted in department stores both in Asian and U.S. markets. It has been the focus of some recent studies in marketing such as Jerath and Zhang (2009) and Chan et al (2010).  

Our study is also related to the empirical literature on firm entry and exit. Since Bresnahan and Reiss (1990, 1991), there has been a growing body of empirical studies that apply static discrete-choice entry games to investigate various interesting economic phenomena (for examples, Berry 1992, Mazzeo 2002, Ishii 2005, Seim 2006, Jia 2007, Zhu and Singh 2009, Vitorino 2012, Ellickson et al 2013). The standard assumption is that entry is a one-sided decision made by firms who compete against one another in the market in a non-cooperative manner. In our model, however, the entry of a manufacturer brand has to be mutually agreed by the department store and the manufacturer. This approach is related to some recent
3. Data

The department store that provides us data is located at a central business district in Shanghai with convenient transportation. Based on interviews with the store management, we understand that store prices and store reputation are at a medium level among all department stores in Shanghai, roughly equivalent to Macy’s in the U.S. It sells hundreds of categories ranging from men’s, women’s, and children’s clothing to other products such as shoes, travel luggage, cosmetics and household electronics. Our study focuses on one clothing category that targets professional women aged thirty and above. Clothing in this category generally has a more formal style and uses higher quality materials. The category occupies the whole fourth floor in the seven-storied store building. We choose professional women’s clothing because, relative to other categories, 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. Manufacturers keep ownership of the products and set up selling counters inside the store. They are responsible for hiring and training sales representatives, setting prices, and running promotions. The entry of a brand requires that the manufacturer and the department store agree upon a transfer contract, which typically involves a negotiation. We observe partial contract information for all of the entering brands. These include brand identities, contract periods (starting year/month and ending year/month), and the actual annual revenue transfers from the store to manufacturers.\(^5\)

3.1 Brand Attributes and Tiers

From the beginning of the sample period, the store maintained a complete list of the manufacturers (including those who never entered during the period) it considered as potential entrants. This implies that we have the complete choice set of the store. Altogether, there are 119 unique manufacturers in the list. To facilitate management and contracting

\(^5\) Due to confidentiality reasons, we are unable to observe other contract information, including the targeted sales revenue and targeted transfer details specified in the contract.
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. Others, such as the fit with the store image and the image of the brand, are difficult to measure. Previous research treats these attributes as an unobserved product attribute or quality (for researchers). 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. 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.

Based on the brand and manufacturer attributes the store further classifies manufacturer brands into three tiers: high-end (tier H), medium (tier M) and low-end (tier L) brands. There are 22 tier H brands, 51 tier M brands, and 46 tier L brands. We do not know the criterion used for the classification. A statistical cluster analysis shows that tier H brands are characterized by a high ratio of foreign brands, high brand image and large in-store operational area. 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 store manager showed us some sample contracts. The contract structure is standardized, 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.

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6 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.
at the end of the payment cycle. 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 targeted sales revenue, both of which differ across brands. When the actual sales revenue in a month is less than the target, 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 (ranging from 70 to 85 percent in the samples that we observe), again differ across brands. This transfer design essentially guarantees that the store’s return is not much affected by sales fluctuations. In the model that we present in Section 3, we term the transfer amount specified in the contract the “deterministic transfer”, and the difference between the actual and the targeted sales revenue the “contingent transfer”. Our data allows us to observe the total transfer (i.e. the sum of the deterministic and contingent transfer) for all matches, but we do not observe the deterministic and contingent components separately.

During interviews, the store manager discussed his view on why such a contract is adopted and stated that, no matter how much research has been done, the department store still has large uncertainty regarding the profitability of bringing a brand into the store because of the volatile nature of the industry. Many thousands of clothing brands exist in China, yet none has a worldwide reputation (Dai and Zhang, 2010). Brand popularity, product quality, and the cost of materials fluctuate every year. The manager suggested that transfer contracts could help protect the store from these uncertainties.

We define the time of an entry as the first month a brand is observed to generate sales in the store. About half of the entries occurred in April and about half of the contracts have a contract length between 9 and 13 months, where 12-month contracts are most common and account for 27% of all contracts. Based on these observations, we simplify our model

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7 A payment cycle can be monthly, quarterly and bi-annually.
assuming that contracts are renewed annually, starting in April and ending in March next year.\textsuperscript{8}

3.3 Summary Statistics

Over the 4-year sample period, we observe quite a few manufacturer brands entering and exiting the store. Table 2 shows the exit pattern based on the number of years after entering the store. A total of 215 entrants are in the data,\textsuperscript{9} among which we observe 48 exits, which corresponds to an exit rate of 22.3%. This illustrates the volatile vertical relationships in the industry. A noteworthy feature of the data is that the exit rate does not vary depending on the tenure length of the entrants: the exit rate is 23.2\% for brands that have entered for two or more years and 23\% for brands that have entered for three or more years. This is consistent with the store manager’s observation that brand popularity, product quality, and the cost of materials are constantly fluctuating in the industry. It is also an important observation which provides guidance for our modeling approach detailed in Section 4.

For the purpose of model estimation, we redefine the brand and manufacturer attributes. Table 3 lists the variables we use in the estimation and provides some summary statistics. Except the variable \textit{coverage}, which is defined as the percentage of the nine designated department stores selling the brand, all others are dummy variables.

Table 4 reports some statistics of the number of entrants, entry rate, average annual sales revenue, actual annual transfers to manufacturers, store revenues (sales revenue net of transfers), and transfer rates (manufacturer transfers divided by annual sales revenue) for each of the three tiers. A surprising observation is that H-tiered brands generate lower sales revenue than M-tiered brands, but they have the highest manufacturer transfer rates. With the highest transfer rate, the entry rate of H-tiered brands is still the lowest. On the other

\textsuperscript{8} 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. The exit of a brand is defined analogously.

\textsuperscript{9} Repeated entry of the same brand is counted as a separate entry.
hand, M-tiered brands have 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 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. Consumers may be attracted to the store by the professional women’s clothing and, once they are in the store, they may shop for other categories that brings the store extra revenue. 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. The store is able to attract more of these consumers by carrying high-tiered brands. 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 4 here]

4. A Model of a Two-Sided Entry Game

The two-sided entry game in this study follows the recent literature on vertical contracting relationships between upstream and downstream firms (e.g. Mortimer 2008, Ho 2009, Crawford and Yurukoglu 2012, and Grennan 2013). It differentiates from the traditional entry model by highlighting that the entry of a manufacturer brand has to be agreed upon by the manufacturer and the store based on the contract offer. We consider a static game under information asymmetry between the store and manufacturers. In this section, we will discuss the model setup, derive the optimal transfer paid by the store, and derive the manufacturers’ optimal entry decision.

4.1 Model Setup

Structure of the Game: The game has three stages. The store has a list of manufacturers as potential entrants. In stage one, the store offers a contract to each manufacturer 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.
justification of this assumption is the following: during interviews with the store management, we were told that the store has distinct locational advantage and reputation and that because of the economic growth in China, especially in Shanghai, demand for the professional women’s clothing has been growing rapidly. Manufacturers compete for the opportunity to sell in the store. The department store therefore has a large bargaining power when negotiating contract with manufacturers and hence can dictate the contract terms. We also learned that the store uses a default contract design and presents the manufacturer its offers first. Contract renewal also follows the same process.\textsuperscript{10}

In stage two, manufacturers simultaneously decide whether or not they will accept the contract offers. If they do, their brands will enter and sell in the store. Finally, in stage three actual sales are realized. The store collects the sales revenue, and transfers part of the revenue to manufacturers based on the contract offers.

The game is static and the store and manufacturers make decisions independently each period. Various features of the Chinese clothing industry suggest that this assumption may be a good approximation of reality in our application. The sunk cost of entry is simply to set up a selling counter inside the store, which is negligible relative to the sales revenue and the operation and production costs. As such, current entry and exit decisions may not have important impacts on future entry and exit. Also, there are large fluctuations in brand popularity, product quality, and the cost of materials over time; current performance of a brand thus may not help the store to learn the brand’s future sales. Some evidence can be found from the data: Table 2 shows that the exit rate of manufacturers does not depend on the tenure length of entrants, providing further support for the static model assumption.

\textbf{Information Sets of the Store and Manufacturers:} 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 the brand’s sales revenue and costs.\textsuperscript{11} As discussed above, this

\textsuperscript{10} 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.

\textsuperscript{11} Each period in our model is one year. We use year dummies to capture the effects of time-varying factors on demand and costs.
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. We assume that there is no 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.\(^\text{12}\)

To model the information asymmetry, we assume that a manufacturer may possess private information about its brand that is unobserved to the store and other manufacturers. On the demand side, this private information is related to the product quality and, for fashion clothing, how fast the manufacturer can innovate the style and design of its products that are attractive to most consumers. This demand-side private information is represented by a random variable, $\xi_{kt}$. On the cost side, private information may include some cost shocks for labor, capital and shipment, which are represented by a random variable, $\omega_{kt}$. We allow $\xi_{kt}$ and $\omega_{kt}$ to be correlated. If the two are positively correlated, an entrant who enters because of low cost will also have low product quality, implying that the store will face the classical adverse selection problem. There is also a shock to the manufacturer’s outside option value that the store cannot fully observe, represented by another random variable $\psi_{kt}^o$. We assume that the store and other manufacturers know the distribution from which the private information variables are drawn, but do not know the exact values. Each player in the game thus cannot perfectly predict manufacturers’ entry decisions. The store forms a 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.

We assume that the information asymmetry is only one-sided. As such, the store has no private information unobservable to the manufacturers. Certain features of the store-manufacturer relationship suggest the appropriateness of this assumption. The manufacturer operates as a store-within-a-store and takes full responsibility for setting prices, running promotions for its brand, and hiring, training, and compensating sales

\(^\text{12}\) Some of the brand attributes, such as brand image, are subjectively ranked by the store. The ranking is still mostly based on the market information also available to all manufacturers, even though the store may process the information differently from manufacturers.
agents. The store’s ability to affect the brand’s performance is quite limited. Therefore, the uncertainty of the manufacturers regarding how the store may impact their sales once they enter should be much less than the store’s uncertainty regarding the performance of manufacturers. Consequently, we choose to model a form of information asymmetry that is most relevant to our empirical context.

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

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

(1)

where \( S_{kt} \) is the realized sales revenue. The first component on the right hand side captures the effects of brand attributes on sales, and the second component captures the effects of the entry of other brands on sales. We allow the effect to be asymmetric depending on the tiers of every pair of brands, i.e., \( \gamma_{R(j)R(k)} \) may be different from \( \gamma_{R(k)R(j)} \). 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). Finally \( \varepsilon_{kt} \) is an idiosyncratic ex-post demand shock that is unobserved by everyone, including the manufacturer, prior to entry. Following Pakes et al (2006), this shock could be either an expectation error (due to imperfect information) or a measurement error of revenue.

Let the manufacturer’s belief of the entry probabilities of all other brands be \( p_{-kt} \). We assume that the expectation of \( \varepsilon_{kt} \) is 0, and \( \xi\)'s are independent across manufacturers. Therefore, the manufacturer’s expectation of its sales revenue, prior to entry, can be expressed as:

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

(2)
Since the store has the same information as manufacturer $k$ regarding other brands, its belief of the entry probabilities is also $p_{-kt}$. Unconditional on entry, the store’s expectation of the sales revenue is:\(^{13}\)

$$E^2(S_{kt}) = x^d_{kt} \beta + \sum_{j \neq k} Y_{R(j)R(k)} P_{jt}$$ \tag{3}

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

**Cost and outside option specifications:** In reality, the cost of selling in the store for the manufacturer may include fixed costs (e.g. cost of hiring and training sales employees) and production cost (e.g. material and labor costs). 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 per-period cost faced by the manufacturer if it enters. Let $x^c_{kt} \subset x_{kt}$ be a set of brand attributes and time-varying factors that are related to the cost of selling in the store. The cost function is specified as

$$C_{kt} = x^c_{kt} \alpha + \omega_{kt}$$ \tag{4}

where $\omega_{kt}$ is a random variable that is private information for the manufacturer. Unconditional on entry, the store’s prior expectation of the manufacturer’s cost is $x^c_{kt} \alpha$, as $\omega_{kt}$ is mean zero in expectation.

A manufacturer’s 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

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\(^{13}\) Conditional on entry, the expected sales revenue of brand $k$ in period $t$ from the store’s perspective is $E^2(S_{kt}) + E(\xi_{kt} | I_{kt} = 1)$. 

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 other locations. 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

\[
\Pi_{kt}^o = x_{kt}^o \alpha^o + v_{kt}^o
\]  

(5)

Again we assume that \( v_{kt}^o \) is only known by the manufacturer. Unconditional on entry, the store’s prior expectation about the outside option value is \( x_{kt}^o \alpha^o \).

4.2 Transfer Offers and Entry Decisions

With the primitives set up in the model, we can now formally model the store and manufacturer decisions. The objective of the store is to choose an optimal set of contract terms to maximize the expected store value.\(^{14}\) The store specifies a “deterministic” transfer offer, \( T_{kt}^* \), and a “targeted” sales amount, \( S_{kt}^* \), in the contract. We assume that \( S_{kt}^* \) is given by sales revenue as in equation (3), i.e., \( S_{kt}^* = E^2(S_{kt}) \). If the manufacturer enters, it will receive \( T_{kt}^* \) and a “contingent” transfer which is the deviation of the actual sales from the targeted sales \( (S_{kt} - S_{kt}^*) \).\(^{15}\) This assumption is a simplification of the actual contracts but, based on our observation of the sample contracts, we believe that it is a good approximation of the reality.\(^{16}\)

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\(^{14}\) 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.

\(^{15}\) The targeted sales revenue, which is also unobserved to us, may not be the expected revenue of the store but it does not affect our results. For example, specifying \( S_{kt}^* = E^2(S_{kt}) + E(\xi_{kt} | I_{kt} = 1) \) would make no difference as this would simply add a constant to the contingent transfer, which would then result in the same amount being deducted from the (optimal) deterministic transfer. What is key is that marginal changes in \( \xi_{kt} + \epsilon_{kt} \) are borne by the manufacturer. More details are below.

\(^{16}\) 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 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. Furthermore, the manufacturer retains a very high percentage, rather than all, of the deviation of sales from target sales. See Section 4.2 for more details. We do not observe the percentage specified in all contracts, but the assumption of 100% retention is a close approximation to the percentage we observe from contracts that the store showed us.
For the store, the value from the entry of all manufacturers is the total sales revenue deducted by the payment to the manufacturer, which is the sum of deterministic and contingent transfers, together with the spill-overs on other categories. That is,

\[ V_t^s = \sum_k [S_{kt} - T_{kt}^* - (S_{kt} - S_{kt}^*) + x_{kt}^s \delta] I_{kt} \]  

(6)

As the \( S_{kt} \) terms cancel, the only uncertainty that the store faces is the entry decisions of manufacturers, conditional on contract terms \( T_{kt}^* \) and \( S_{kt}^* \). We let \( \Psi_t^s \) denote the information set of the store, including brand and manufacturer attributes and the contract offers. The store’s expected value from the entry of all brands can be written as

\[ E(V_t^s | \Psi_t^s) = \sum_k [S_{kt}^* - T_{kt}^* + x_{kt}^s \delta] p_{kt} \]

where \( p_{kt} = E(I_{kt} | \Psi_t^s) \) is the probability that manufacturer \( k \) will enter, which we will derive below. Employing the definition of \( S_{kt}^* \), the store’s expected value is given by:

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

(7)

To determine the optimal deterministic transfer offer, the first-order condition of store value function \( V_t^s \) with respect to the transfer \( T_{kt}^* \) gives the following,

\[-p_{kt} + \left( x_{kt}^d \beta + \sum_{j \neq k} Y_{R(j)R(k)} p_{jt} - T_{kt}^* + x_{kt}^s \delta \right) \frac{\partial p_{kt}}{\partial T_{kt}^*} + \sum_{j \neq k} \frac{\partial S_j(p_{kt}, p_{-j\backslash k}, t)}{\partial T_{kt}^*} p_{jt} = 0 \]

where \( S_j(p_{kt}, p_{-j\backslash k}, t) \) is the expected sales revenue of manufacturer \( j \), as a function of the entry probabilities of other brands. Since \( \frac{\partial S_j(p_{kt}, p_{-j\backslash k}, t)}{\partial T_{kt}^*} = Y_{R(k)R(j)} \frac{\partial p_{kt}}{\partial T_{kt}^*} \), the optimal deterministic transfer can be written as:

\[ T_{kt}^* = x_{kt}^d \beta + \sum_{j \neq k} (Y_{R(j)R(k)} + Y_{R(k)R(j)}) p_{jt} + x_{kt}^s \delta - \frac{p_{kt}}{\partial p_{kt} / \partial T_{kt}^*} \]  

(8)

\( T_{kt}^* \) is an implicit function as it also appears on the right-hand side of the equation via \( \frac{p_{kt}}{\partial p_{kt} / \partial T_{kt}^*} \).
There are two brand-interaction terms in the above expression. The first term
\[ \sum_{j \neq k} \gamma_j R(j) R(k) p_{jt} \]
captures the effect of other brands on the sales of brand \( k \), and the second term
\[ \sum_{j \neq k} \gamma_k R(k) R(j) p_{jt} \]
represents the effect of brand \( k \) on the sales of 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
\[ -\frac{p_{kt}}{\partial p_{kt}/\partial T_{kt}^*} \]
captures the effect of changing the deterministic transfer on the entry probability of a brand, which is negative since \( \partial p_{kt}/\partial T_{kt}^* \) is positive.
This represents a trade-off in the store’s decision. Larger transfers will increase a brand’s
entry probability but also decrease the store’s revenue conditional on entry.

In standard entry games in the previous literature, 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 consequently is incentivized to enter. Our store in this
two-sided game will therefore reduce the economic inefficiency caused by 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 (8). The manufacturer hence
will receive a return lower than the aggregate benefits from its entry. The net impact on
social welfare when compared with non-cooperative entry therefore is indeterminate.

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

\[ \Pi_{kt} = T_{kt}^* + \xi_{kt} - C_{kt} = T_{kt}^* - x_{kt}^c \alpha^c + \xi_{kt} - \omega_{kt} \quad (9) \]

The manufacturer will compare this profit with the outside option value, i.e., \( \Pi_{kt}^o \). Its entry
probability function thus is

\[ p_{kt} = Pr(T_{kt}^* - x_{kt}^c \alpha^c \geq v_{kt}) \quad (10) \]
where $v_{kt} \equiv \omega_{kt} + v_{kt}^o - \xi_{kt}$ is the private information for the manufacturer and $x^c_{kt} \alpha^c = x^c_{kt} \alpha^c + x^o_{kt} \alpha^o$.

To summarize, our modeling framework captures the two-sided decisions involved in the entry game under information asymmetry. 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. Because the store has limited information regarding sales revenue and the cost of a brand, it cannot fully extract the manufacturer surplus; however, under transfer contracts the store is also protected from the risk caused by the uncertainties. Manufacturers expect to receive the deterministic transfer and the contingent transfer, and evaluate such benefits in comparison with the option of not to enter. Finally, it is also clear from the store value function (equation (7)) and the manufacturer’s profit function (equation (9)) that setting a targeted sales revenue higher than the store’s expectation (thus reducing the contingent transfer $S_{kt} - S'^*_{kt}$) will have the same effects on the store’s expected value and the manufacturer’s entry probability as decreasing the deterministic transfer $T'^*_{kt}$ by the same amount. As such, it does not matter if the store over- or under-states the target sales in the contract. It also does not matter if it sets the target sales equal to the expected sales unconditional on entry or expected sales conditional on entry.

5. Estimation

We estimate the parameters of our structural model using three observed market outcomes – brand entry, manufacturers’ actual transfers, and sales revenue. The latter two are observed conditional on entry. In this section, we will outline the model estimation approach and how we use the equilibrium constraints to simplify estimation. We also discuss how we control for the selection issue. Finally, we will discuss identification of the model’s parameters.

5.1 Empirical Specification

We assume that the combined stochastic term, $v_{kt} \equiv \xi_{kt} - \omega_{kt} - v_{kt}^o$, (see equation (10)) is distributed as $\text{normal}(0, \sigma^2)$ and $i.i.d.$ across brands and periods. This distribution is a common knowledge to the store and to all manufacturers. Define $\bar{P}_{kt} = T'^*_{kt} - x^c_{kt} \alpha^c$ as
the difference between the deterministic part of the profit and the deterministic part of the cost and outside option value for the manufacturer. Based on the distribution assumption, the entry probability function of brand $k$ is $p_{kt} = \Phi \left( \frac{\bar{\Pi}_{kt}}{\sigma} \right)$, where $\Phi$ is the CDF of the standard normal distribution. 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, we can substitute this entry probability function when calculating the expected store value and manufacturers’ profits.

### 5.2 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 its private information $\xi_{kt}$, there is a selection issue in model estimation: the expectation of $\xi_{kt}$ conditional on the entry is no longer zero, i.e., $E(\xi_{kt}|l_{kt} = 1) > 0$. Therefore, to estimate the sales revenue and manufacturer transfer models, we must correct for the potential selection bias induced by the underlying entry game. We choose an estimation strategy by employing the propensity-score-based control-function approach described in Heckman and Robb (1985, 1986) to approximate $E(\xi_{kt}|l_{kt} = 1)$. The idea is to treat this conditional expectation term as a function of profit from entry. Given the one-to-one correspondence between profit and entry probability, it can be equivalently expressed as a function of entry probability, $\lambda(p_{kt})$. In practice this function can be approximated flexibly by a polynomial function of $p_{kt}$.

Therefore, the realized sales revenue equation (1), conditional on brand $k$ entering, can be written as

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

where $\varepsilon_{kt}^* = (E(\xi_{kt}|l_{kt} = 1) - \lambda(p_{kt})) + (\xi_{kt} - E(\xi_{kt}|l_{kt} = 1)) + \varepsilon_{kt}$. Conditional on entry, $E(\xi_{kt}|l_{kt} = 1) - \lambda(p_{kt}) = 0$ and $E(\xi_{kt} - E(\xi_{kt}|l_{kt} = 1)) = 0$, therefore $E(\varepsilon_{kt}^*|l_{kt} = 1) = 0$. 

19
Given the sales revenue equation (11) and the targeted sales equation (3), the contingent transfer, which is the difference between the actual and the targeted sales revenue, is \( S_{kt} - S_{kt}^* = \sum_{j \neq k} Y_{R(j)R(k)}(I_{jt} - p_{kt}) + \lambda(p_{kt}) + \epsilon_{kt}^* \). The actual transfer conditional on the entry therefore can be written as

\[
T_{kt} = T_{kt}^* + \lambda(p_{kt}) + \tau_{kt}^*
\]  

(12)

where \( \tau_{kt}^* = \sum_{j \neq k} Y_{R(j)R(k)}(I_{jt} - p_{jt}) + \epsilon_{kt}^* \). Conditional on the entry, \( E(\tau_{kt}^* | I_{kt} = 1) = 0 \) since \( E(I_{jt} | I_{kt} = 1) = p_{jt} \), and \( E(\epsilon_{kt}^* | I_{kt} = 1) = 0 \).

Finally, we define

\[
I_{kt} = p_{kt} + e_{kt}^*
\]  

(13)

This applies to every manufacturer unconditional on entry. We have \( E(\epsilon_{kt}^*) = 0 \) since \( E(I_{kt}) = p_{kt} \).

### 5.3 Estimation Strategy

We use the nonlinear least square (NLS) method to estimate equations (11) to (13) simultaneously. The optimal deterministic transfer \( T_{kt}^* \) is not observed from data, but it influences \( S_{kt} \), \( T_{kt} \), and \( I_{kt} \) as outlined in our model above. One could use a nested fixed point algorithm to solve for \( T_{kt}^* \) at each iteration of the optimization routine. However, a computationally simpler way is to set up estimation as a constrained optimization problem, which is the mathematical programming with equilibrium constraints (MPEC) approach developed in Su and Judd (2012).\(^{17}\) Given the sales revenue error, \( \epsilon_{kt}^* \), defined in equation (11), the transfer error, \( \tau_{kt}^* \), defined in equation (12), and the entry error, \( e_{kt}^* \), defined in equation (13), we choose the structural parameters \( \theta' = \{\alpha', \beta', \delta', \sigma, \gamma'\}' \) and a set of deterministic transfers \( T^* = \{T_{kt}^*, \forall k, \forall t\} \), to minimize the

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\(^{17}\) Su and Judd (2012) 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 (2012) 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.
average squared residuals across the three equations subject to the equilibrium constraints of optimal transfers. That is,

\[ \theta, T^* = \arg\min_{\theta,T^*} \sum_{t=1}^{T} \sum_{k} e_{kt}^* / N + \sum_{t=1}^{T} \sum_{k} \epsilon_{kt}^2 / n + \sum_{t=1}^{T} \sum_{k} \tau_{kt}^2 / n \]

s.t. \( T_{kt}^* = x_{kt}^d \beta + \sum_{j \neq k} \left( \gamma_{R(j)R(k)} + \gamma_{R(k)R(j)} \right) \cdot \phi \left( \frac{T_{kt}^* - x_{kt}^0 \alpha}{\sigma} \right) + x_{kt}^s \delta - \sigma \cdot \phi \left( \frac{T_{kt}^* - S_{kt}^0 \alpha}{\sigma} \right) \)

\[ \forall k, \forall t \] (14)

where \( N \) is the total number of candidate brands, and \( n \) is the total number of entering brands, in all \( T \) periods. The equilibrium constraint for \( T_{kt}^* \) comes from equation (8).

A potential issue arises if there are multiple equilibria, i.e., there could be multiple \( T^* \) that satisfy the equilibrium constraint in (14). To solve this problem, we make the assumption that a unique equilibrium is observed in the data. Conditional on this assumption, the equilibrium played is identified by our observable outcomes. If there are more than one set of \( T^* \) that satisfy the equilibrium constraint, the estimator will choose the one that minimizes the criterion function. That is, on the basis that the data can identify which equilibrium is played, we choose the \( T^* \) that best fits the data.

To correct for the selection bias, we employ a polynomial of degree 5 in our estimation.\(^{18}\) The estimation procedure involves an iterative process. We first use a trial \( T^* \) to construct the polynomial terms in the control function. After estimating \( \theta \) and \( T^* \) from the model, we then update the polynomial using the newly-estimated \( T^* \) and re-estimate the model. We iterate this process until converges.\(^{19}\) 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. To address this issue, we use a bootstrap

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

\[ \text{We find that the structural parameter estimate of } \theta \text{ and } T^* \text{ are close enough to each other after 5 iterations and hence stop at the fifth iteration.} \]
procedure to resample the data 100 times and estimate the parameters for each resample dataset. To resample the data, we adopt a parametric bootstrapping method (Hall 1994). Given estimates for $\theta$ and $T^*$, we calculate the residuals $\hat{e}_{kt}^*$ and $\hat{t}_{kt}^*$. We then resample them with replacement for every candidate brand and calculate the sales revenue and transfers if they enter. Based on the estimated entry probabilities, we also simulate entry decision of every brand by drawing from a uniform distribution. We then treat the simulated outcomes, which include entry and the sales revenue and transfers after that, as data and re-estimate our model.

Finally, we have to decide the variables to be used in the sales function and the cost and outside value function. We use year dummies in the sales revenue and entry cost functions to capture the market-level demand and cost fluctuations in the clothing industry. Regarding brand attributes, some variables including capital (supplier’s registered capital), production (self-production or subcontract) and agency (brand owner or agent) should affect the cost, and therefore we include them in $x_{kt}^{co}$. Some other variables such as image (brand image), origin (origin of manufacturers), and area (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 capital, production and agency also influence the demand and out-of-category spillovers and find none of them significant. Therefore, they are dropped from the demand and spillovers functions.

5.4 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 model. In our case, market outcomes including sales revenue and actual transfers provide additional identifying power.

We have five sets of structural parameters to estimate: cost and outside option value parameters ($\alpha$), brand attribute parameters determining demand ($\beta$), brand-interaction
parameters determining demand ($\gamma$), polynomial parameters for the control function ($\lambda$), spillovers parameters on outside categories ($\delta$), and the standard deviation of the combined stochastic terms ($\sigma$).

Conditional on manufacturer transfers, the cost parameters $\alpha$ 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. If there were no selection issue, the parameters $\beta$ and $\gamma$ could be identified from the sales revenue data alone, assuming that there is sufficient variation in the attributes of entering brands. However, since the selection-bias correction comes from entry, $\beta$ and $\gamma$ are jointly identified with $\lambda$. The parameter vector $\beta$ is identified by the relationships between manufacturers’ sales revenue and their brand attributes, and $\gamma$ is identified by the relationships between manufacturers’ sales revenue and the number of entrants in different brand tiers, across different years. $\lambda$ is identified from the relationship between sales revenue and $p_{kt}$, which can be calculated once $\alpha$ is estimated.

Furthermore, the variation in transfers across brands with different brand attributes identifies the spillover parameters, $\delta$. Conditional on parameters $\alpha$, $\beta$, and $\gamma$, we can calculate the optimal transfer offer, when the spillovers are zero. The deviation of the actual transfer from this optimal transfer identifies $\delta$. That is, if we observe a high transfer relative to the optimal transfer without spillovers, we can infer that the spillovers are positive. Finally, since we observe actual transfers, we can use the relationship between the observed entries and transfers to estimate $\sigma$ instead of normalizing the parameter as in standard entry models.

6. Results

Table 5 reports the estimation results from the model. The first column reports estimates of the parameters for sales revenue ($\beta$). Among the more precisely estimated coefficients,
a brand’s good fit with the store image (fit) yields 0.546 million RMB$^{20}$ higher annual sales revenue. Another important variable is extra, 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. Having a large selling area in the store (area) also has a positive effect on sales revenue.

[Table 5 here]

The second column in Table 5 reports the estimated parameters for the manufacturers’ cost function and the outside option value. A brand’s fit with store (fit) again has a large effect on costs. Being a foreign brand (origin) also increases cost. The negative sign of the coefficient for capital suggests that a manufacturer with a larger capital base can lower their production costs. A large presence in other big cities (extra), while increasing sales revenue, also increases the production cost. Finally, having a large selling area in the store (area) increases costs.

The third column illustrates the effect of brand attributes on spillovers to other categories. While not statistically significant, it is interesting to see that the coefficient for fit is negative, 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. The effect of coverage is positive, suggesting the substantial benefit from the entry of a brand with large market coverage.

The lower panel in Table 5 reports the structural parameter estimates of the interaction effects on a brand’s sales revenue due to the entry of other brands in the same category. The estimates are insignificant, perhaps reflecting the lack of data that can help pin down the estimates: our estimation relies on the variation in the number of brands in different brand tiers that entered in the four years of the sample period. We may be able to obtain more precise results if we have a longer time-series.

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$^{20}$ We re-scale brand sales revenue and manufacturer transfers in model estimation; each unit of the estimated coefficients represents one million RMB.
Finally, the estimate of scale parameter ($\sigma$), which is reported in Table 5, is 0.414 mil. RMB. As reported in Table 3, the average brand sales revenue in the data is 1.493 mil. RMB. This suggests that the store’s uncertainty about manufacturers’ sales and cost is not trivial, and that it is important to model the information asymmetry in the model.

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 much 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 brand and manufacturer 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. 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 the economic value for the store related to the entry of a brand.

It is not clear to us what economic value is represented by the brand score so we test its correlations with several measures. 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. The positive and strong relationship

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21 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.
(the correlation coefficient is 0.857) suggests that the brand score is a good measure of a brand's sales potential from the store's perspective. We also calculate the correlation between brand scores and actual sales revenue. While the relationship is still positive and strong (the correlation coefficient is 0.518), it is widely scattered across brands, suggesting that the scores cannot fully predict the actual brand sales. This provides evidence that the store has large uncertainty regarding predictive sales.

We also compare the expected store profit from each candidate brand, which is the difference between the expected sales revenue conditional on entry and the deterministic transfer \( (E(S_{kt}|I_{kt}) - T_{kt}^*) \). Figure 2 shows the relationship between brand scores (at the x-axis) and the expected store profits (at the y-axis; in mil. RMB). The relationship is positive, with a correlation coefficient of 0.607, implying that the store profit predicted from our model has a good fit with the brand score assigned by the store. Finally, since the scores have an important effect on transfer offers and hence on manufacturers’ entry decisions, we also compare the correlation with the deterministic transfer offer, as predicted in our model, and find the correlation coefficient to be 0.894. These results greatly enhance 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

In this section, we investigate how contract format impacts the welfare of manufacturers and retailers under information asymmetry. We focus on the three most common contract formats adopted in the retail sector: transfer contracts, vertical contracts, and share contracts. We conduct a series of counterfactual experiments under different scenarios of information asymmetry. The results provide insight on when each type of contract dominates the others from the store’s perspective, and how the adoption of such a contract will influence total welfare of both the store and the manufacturers.
We also conduct a counterfactual experiment to address a specific policy question: what if the Chinese government (or other groups) could monitor the quality of manufacturers’ products and effectively help reduce the store’s uncertainty? We consider the welfare impacts of such a policy change. Given the volatile nature of the Chinese clothing industry, it has been argued that government intervention is critical for not only protecting consumers’ welfare, but also for protecting the interests of manufacturers and retailers. However, it has also been argued that this may restrict the entry of manufacturer brands and reduce the industry profit. Our results provide insight on this important policy question.

7.1 Market Outcomes under the Three Contracts

To conduct our first counterfactual analysis, we must derive the optimal offers under vertical contracts and share contracts, the corresponding expected store values, and the predicted market outcomes.

**Vertical Contracts:** We assume that under vertical contracts the store offers manufacturer $k$ a lump-sum payment, $W_{kt}$, for the ownership of its products sold in store. The manufacturer will accept the offer only if the profit is higher than the production cost and the outside option value:

$$W_{kt} - x_k c o α ≥ ν^0_{kt} + ω_{kt} = μ_{kt}$$

(15)

Assuming that $μ_{kt}$, which is the sum of the manufacturer’s private information about their outside option value and their costs, has a normal distribution with standard deviation $σ_μ$, the store expects that the manufacturer will accept the offer with probability:

$$p_{kt}(W_{kt}) = \Phi(W_{kt}/σ_μ - x_k c o α/σ_μ)$$

(16)

For the store, its objective is to make the optimal offer to individual manufacturers such that it can maximize the expected value. That is,

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22 Compared with $σ$, which is the standard deviation of $ν_{kt}$, $σ_μ$ does not account for the variation in $ξ_{kt}$, the stochastic demand component.
\[
\max_{(W_{i},...,W_{k})} E\left(V_{i}^{t} | \Psi_{i}^{t}\right) = E\left(\sum_{k}[S_{ki} - W_{ki} + x_{kt}\delta] * I_{kt} | \Psi_{i}^{t}\right)
\]

Sales revenue \( S_{kt} \) is a function of the entry of other brands, \( I_{jt} \). Under the assumption that \( \mu 's \) across brands are independent, we can first integrate out \( \mu 's \) of other brands and substitute into the above expression to get

\[
\max_{(W_{i},...,W_{k})} E\left(V_{i}^{t} | \Psi_{i}^{t}\right) = \sum_{k} \left[ x_{kt}^{d}\beta + \sum_{j\neq k} \gamma_{R(j)R(k)} p_{jt} (W_{jt}) + x_{kt}\delta + \xi_{kt} - W_{kt} \right] * I_{kt} \left\{ W_{kt} - x_{kt}\alpha - \mu_{kt} > 0 \right\} dF(\xi_{kt}, \mu_{kt})
\]

(17)

where \( F \) is the joint distribution function of \( \xi_{kt} \) and \( \mu_{kt} \), and \( I_{kt} \) is an indicator function for entry.\(^{23}\)

**Share Contracts:** Under this contract format, the store offers a revenue share \( s_{kt} \) to each manufacturer. Thus, the store takes \((1-s_{kt}) \cdot S_{kt}\) and the manufacturer takes \( s_{kt} \cdot S_{kt}\). The manufacturer will accept the offer only if its share of revenue less its costs is higher than its outside option value:

\[
s_{kt} \cdot E^{k}(S_{kt}) - x_{kt}^{co}\alpha \geq \mu_{kt}
\]

(18)

The expectation operator \( E^{k} \) denotes the manufacturer’s expectation conditional on its information set, including the demand shock, \( \xi_{kt} \). Let \( p_{jt}(s_{jt}) \) be the expected entry probability of a manufacturer \( j \), which is common to both the store and manufacturer \( k \). Note that \( p_{jt}(s_{jt}) \) is not a function of \( j 's \) private information, \( \xi_{jt} \). We can then write

\[
E^{k}(S_{kt}) = x_{kt}^{d}\beta + \sum_{j\neq k} \gamma_{R(j)R(k)} p_{jt}(s_{jt}) + \xi_{kt}
\]

(19)

Substituting this into Equation (18), the store’s (and other manufacturers’) predicted probability that the manufacturer \( k \) will enter is

\(^{23}\) As the stochastic components \( \xi_{kt} \) and \( \mu_{kt} \) may be correlated, \( I \) cannot simply be replaced by the entry probability function \( p \) here.
\[ p_{kt}(s_{kt}) = \int \{ s_{kt} \cdot (x_{kt}^{d} \beta + \sum_{j \neq k} \gamma_{R(j)R(k)} p_{jt}(s_{jt}) + \xi_{kt}) - x_{kt}^{co} \alpha - \mu_{kt} \geq 0 \} dF(\xi_{kt}, \mu_{kt}) \] (20)

Let \( P(s) \) be the collection of \( p_{kt}(s_{kt}) \) for all manufacturers. This vector of equilibrium entry probabilities (conditional on share offers, \( s \)) can be calculated as a fixed point from the above expression. The objective of the store is to offer an optimal share to each of the manufacturers such that it can maximize its expected value.

\[
\max_{\{s_{kt}, \ldots, s_{kt}\}} E \left( V^{s}_{t} | \Psi^{s}_{t} \right) = E \left( \sum_{k} \left\{ (1 - s_{kt}) \cdot S_{kt} + x_{kt} \delta \right\} \right)
\]

\[
= \sum_{k} \int \left\{ \left\{ (1 - s_{kt}) \cdot \left( x_{kt}^{d} \beta + \sum_{j \neq k} \gamma_{R(j)R(k)} p_{jt}(s_{jt}) + \xi_{kt} + x_{kt}^{\delta} \right) \right\} \right\} \right\} dF(\xi_{kt}, \mu_{kt})
\] (21)

Note that multiple equilibria may exist in this setup, as more than one set of \( P(s) \) may satisfy the equilibrium condition in Equation (20). A similar issue may also exist under vertical contracts. When we analyze the market outcomes under vertical and share contracts in counterfactual experiments, we assume that if there are multiple sets of equilibrium \( \{p_{1t}, \ldots, p_{Kt}\} \), the store can choose the equilibrium that maximizes its expected value, which pins down a unique equilibrium in the counterfactual experiments. That is, the store chooses lump-sum payments \( \{W_{1t}, \ldots, W_{Kt}\} \) or share rates \( \{s_{1t}, \ldots, s_{Kt}\} \), together with entry probabilities \( \{p_{1t}, \ldots, p_{Kt}\} \), subject to the constraint in Equation (16) or in Equation (20), that will maximize the expected store value function.

To calculate the store’s expected value, we simulate \( \{\xi_{kt}^{sim}, \mu_{kt}^{sim}\}, sim = 1, \ldots, NS \), under different assumptions about how \( \xi_{kt} \) and \( \mu_{kt}^{sim} \) are correlated. We then calculate the expected value under vertical contracts (using Equation (17)) and under share contracts (using Equation (21)), as the average of the store value under each simulation draw.

Adverse selection is a primary concern for the store and will have the biggest impact on the store under vertical contracts. If manufacturers who accept payments \( W_{kt} \) because of low \( \mu_{kt} \) also have low \( \xi_{kt} \) in the sales revenue function, the store will face an adverse
selection problem.\textsuperscript{24} In contrast, transfer contracts force manufacturers to bear 100\% of the demand uncertainty $\xi_{kt}$, which solves the problem. Share contracts require manufacturers to bear part of the consequence if sales revenue is low thus offering only a partial solution.

Naturally, adverse selection will be the most severe when $\xi_{kt}$ and $\mu_{kt}$ are perfectly correlated. However, many exogenous factors that affect the production cost (e.g. labor and material costs) may be uncorrelated with demand fluctuations. Likewise, there may be brand-specific factors that will affect demand (e.g. a creative product design or marketing campaign) and are uncorrelated with the production cost. If $\xi_{kt}$ and $\mu_{kt}$ are uncorrelated, adverse selection is not an issue. From the store’s perspective, it is unclear whether transfer contracts dominate vertical and share contracts in cases of moderate adverse selection. The fact that the latter contracts are commonly adopted in the retail industry probably indicates that the type of contracts chosen depends on the specific circumstances.

We explore how the correlation between $\xi$ and $\mu$ impacts the welfare of the store and manufacturers when different types of contracts are chosen. Note that in our estimation, we only estimate $\sigma$, the standard deviation of the combined stochastic terms $\nu_{kt} \equiv \xi_{kt} - \mu_{kt}$. In the counterfactual experiment, we assume that the standard deviations for $\xi_{kt}$ ($\sigma_{\xi}$) and $\mu_{kt}$ ($\sigma_{\mu}$) have equal magnitude and we vary the correlation between $\xi_{kt}$ and $\mu_{kt}$ from 0 to 0.9, indicating different degrees of adverse selection.\textsuperscript{25} Under each scenario, we calculate the optimal deterministic transfer offers $T^* = \{T^*_1t, ..., T^*_Kt\}$ derived in Section 3.2, and the optimal lump-sum payments $W = \{W_{1t}, ..., W_{Kt}\}$ and share rates $s = \{s_1t, ..., s_{Kt}\}$, as described above. Based on these optimal contract offers, we simulate manufacturers’ entry decisions, sales revenue, manufacturers’ profits, and the store’s value.\textsuperscript{26} Table 7 reports the results.

\textsuperscript{24} Mathematically, this can be seen in Equation (17).

\textsuperscript{25} As the correlation changes, we adjust $\sigma_{\xi}$ and $\sigma_{\mu}$ such that the standard deviation of $\nu_{kt}$ remains $\sigma$.

\textsuperscript{26} Sales Revenue and manufacturer profits are simulated conditional on entry.
The first notable result is that the store’s value under vertical contracts is always lower compared with share contracts or transfer contracts. This is particularly true when the correlation between $\xi$’s and $\mu$’s is high. This result raises the question of why vertical contracts are used in many traditional retail settings. One possible explanations is that manufacturers may have large market power, so that the retailer is not able to dictate the contract format. In fact, the table shows that, when the correlation is at lower levels ($\rho$ from 0 to 0.5), manufacturers’ total profit under vertical contracts is higher than the other contracts. As $\rho$ increases, however, adverse selection becomes a bigger issue and the store will offer lower $W$, and as a result, manufacturers’ total profit will become much lower than in the other contract formats.

Second, the store’s value under transfer contracts is surprisingly low compared with share contracts, when $\rho$ is less than 0.8. As discussed above, unlike transfer contracts, share contracts only partly address the adverse selection problem by making manufacturers bear part of the loss if the entry is unprofitable. However, the advantage of using share contracts is that the store can extract from manufacturers part of the surplus generated from high $\xi$’s. It is infeasible for the store to do this under transfer contracts, since the store cannot discriminate manufacturers by setting different levels of deterministic transfers based on manufacturers’ private information. Our results suggest that, when adverse selection is not too severe, share contracts dominate transfer contracts for the store. The finding also offers an explanation why transfer contracts are popular among department stores in China: due to the lack of quality monitoring and established brands, adverse selection is a major issue in China’s clothing industry. As such, department stores in China have a stronger incentive to adopt transfer contracts.

A third result is that the contract-format choice also has other welfare implications. Share contracts dominate transfer contracts in terms of the total welfare, which is the sum of the store value and manufacturers’ total profit, even when $\rho$ is very high. Since the number of entrant brands is also higher under share contracts, consumers’ welfare should also be higher.

In summary, our results illustrate that, although transfer contracts can effectively solve the adverse selection issue, they do result in lower social welfare than share contracts. They
also result in lower store value when adverse selection is not too severe. Finally, since transfer contracts fix the store’s payment, a change in $\rho$ has no impact on the store’s value, manufacturers’ total profit, or the number of entrant brands. In contrast, under vertical contracts these outcomes are very sensitive to the change in $\rho$. Interestingly, under share contracts, the store’s value is quite stable as $\rho$ increases, suggesting that the contract format can help address a large part of the adverse selection problem.

[Table 7 here]

To further explore this issue, we consider an alternative scenario where we increase the severity of adverse selection. As a counterfactual exercise, we assume lower sales revenues, which makes entry less profitable for manufacturers and increases adverse selection.\footnote{Based on our estimation results, very few manufacturers will incur losses if entry is free.} We simulate market outcomes when brand-specific sales revenues are reduced by .75 mil. RMB, which corresponds to roughly a 40% reduction. Table 8 presents the results which show that transfer contracts are now preferred to share contracts under a greater range of value of $\rho$. The store’s value under share contracts is lower than transfer contracts when $\rho$ is larger than 0.4, and is essentially the same for $\rho$ is smaller than 0.4. The store’s value under vertical contracts is much lower than the other contracts, and will become negative when $\rho = 0.9$. Furthermore, the aggregate welfare under transfer contracts is always the highest, and manufacturers’ total profit and the number of entrant brands are also higher under transfer contracts for a large range of $\rho$. These results suggest that the adoption of transfer contracts also depends on the proportion of manufacturers who will bring loss upon entry, which is effectively another measure of the severity of the adverse selection problem.

[Table 8 here]

7.2 The Welfare Impacts of Revealing Information

We examine the welfare impacts on the store and on manufacturers when part of manufacturers’ private information becomes public. The government could potentially facilitate this by increasing its quality monitoring efforts and making the reports available to the store. Alternatively, third parties (e.g., Consumer Reports) or consumer reviews on
websites could also provide similar information. As transfer contracts effectively solve the adverse selection problem, it is unclear whether revealing information has value for the store. From manufacturers’ perspective, revealing information could hurt their interest if it leads to the store extracting more surplus. Furthermore, this information may increase the store’s ability to restrict brand entry, which may reduce consumers’ choices inside the store, reducing consumer welfare.

To explore these issues, we conduct a counterfactual experiment where we assume that some of the information contained in $\xi$’s is revealed. As only $v_{kt} \equiv \xi_{kt} - \omega_{kt} - v^0_{kt}$ matters to the store’s and manufacturers’ decisions under transfer contracts, we conduct the experiment assuming that $v_{kt}$ is the sum of two independent components, $v^k_{kt}$ that comes from a distribution $normal(0, x \cdot \sigma^2)$, and another $v^u_{kt}$ that comes from $normal(0, (1-x) \cdot \sigma^2)$. We simulate $v^k_{kt}$, and assume that it is made public so that the store’s expectations of the sales revenue and the entry probability will adjust accordingly. The variance of the manufacturer’s private information $v^u_{kt}$, representing the store’s new uncertainty, is now reduced to $(1-x) \cdot \sigma^2$. While varying $x$ from 0% to 50%, we calculate the new deterministic offer $T^*_kt$ and simulate the manufacturer’s entry and sales revenue conditional on entry.

The results are reported in Table 9. Contrary to the belief that the store will extract more surplus, the average deterministic transfer across manufacturers increases as more information is revealed. As the store’s uncertainty is reduced by half, the average transfer increases by 40,000 RMB and, as a result, manufacturers’ total profit increases by 1.1 mil. RMB and the number of brands selling in the store increases by seven, implying that consumers’ welfare should also increase. Although the store made higher transfer offers, it benefits most from the new information as its value increased by 2.7 mil. RMB. Consequently, the total welfare increases by 3.8 mil. RMB. Therefore, the reduced information asymmetry creates a win-win situation, with improvements in welfare for both the store and the manufacturers. This finding shows that manufacturers under the current transfer contract will have an incentive to reveal their private information, if the information can be verified either by the government or by third parties. Furthermore, as verifying information about a given manufacturers will increase welfare between that
manufacturer and other retail stores, the total benefits may be considerably larger than the benefits estimated here

[Table 9 here]

8. Conclusion

This paper investigates the economic determinants of observed entry and resulting transfer payments in an empirical setting involving transfer contracts. Making comparisons with both vertical and share contracts, we measure the welfare impacts on manufacturers and retailers from alternative contract structures. A key focus of our analysis is the information asymmetry between manufacturers and retailers, which can lead to an adverse selection problem.

To address these issues, we develop an entry game involving two-sided decisions from manufacturers and retailers, and apply the model to study the entry of manufacturers in the professional women’s clothing category into a Chinese department store. Based on the estimation results, we use counterfactual experiments to study the impacts of transfer contracts on the store’s and manufacturers’ profits, comparing the outcomes with those that would have occurred with vertical contracts and share contracts. This exercise helps us understand the economic conditions that determine the choice of contract forms from retailers and manufacturers. We also demonstrate that even when adverse selection is not an issue, reducing the extent of information asymmetry can significantly improve the welfare for retailers, manufacturers, as well as for consumers through a larger availability of brand choice inside the store.

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 or to investigate potential moral hazard issues that are beyond the scope of this study. 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.
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Appendix

Table 1: Definition of brand attributes

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

Table 2: Entry and exit pattern of manufacturer brands

<table>
<thead>
<tr>
<th>Brand Types</th>
<th>Number of Entrants</th>
<th>Number of Exits</th>
<th>Exit Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>215</td>
<td>48</td>
<td>22.3%</td>
</tr>
<tr>
<td>Two or more years of presence</td>
<td>125</td>
<td>29</td>
<td>23.2%</td>
</tr>
<tr>
<td>Three of more years of presence</td>
<td>61</td>
<td>14</td>
<td>23.0%</td>
</tr>
</tbody>
</table>
Table 3: Attribute variables and summary statistics

<table>
<thead>
<tr>
<th>Attribute Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>origin</td>
<td>1 if foreign brand, 0 otherwise</td>
<td>0.227</td>
<td>0.421</td>
</tr>
<tr>
<td>fit</td>
<td>1 if good fit, 0 otherwise</td>
<td>0.445</td>
<td>0.499</td>
</tr>
<tr>
<td>capital</td>
<td>1 if registered capital 100+ million RMB (agent) or 500+ million RMB (owner), 0 otherwise</td>
<td>0.496</td>
<td>0.502</td>
</tr>
<tr>
<td>production</td>
<td>1 if self-production, 0 if subcontract</td>
<td>0.689</td>
<td>0.465</td>
</tr>
<tr>
<td>agency</td>
<td>1 if brand manufacturer, 0 if agent</td>
<td>0.958</td>
<td>0.201</td>
</tr>
<tr>
<td>coverage</td>
<td>Fraction of nine comparable stores selling the brand</td>
<td>0.458</td>
<td>0.272</td>
</tr>
<tr>
<td>image</td>
<td>1 if good brand image, 0 otherwise</td>
<td>0.328</td>
<td>0.471</td>
</tr>
<tr>
<td>area</td>
<td>1 if mean operational area 50+ m², 0 otherwise</td>
<td>0.521</td>
<td>0.502</td>
</tr>
<tr>
<td>extra</td>
<td>1 if selling in two or more cities</td>
<td>0.277</td>
<td>0.450</td>
</tr>
</tbody>
</table>

Table 4: Summary statistics of entry, sales, transfers, and store revenue

<table>
<thead>
<tr>
<th>Brand Tier</th>
<th>Average Number of Annual Entries</th>
<th>Entry Rate from Choice Set</th>
<th>Sales Revenue (mil. RMB)</th>
<th>Manufacturer Transfers (mil. RMB)</th>
<th>Store Revenue (mil. RMB)</th>
<th>Manufacturer Transfer Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>19.75</td>
<td>0.429</td>
<td>1.091</td>
<td>0.669</td>
<td>0.422</td>
<td>0.628</td>
</tr>
<tr>
<td>M</td>
<td>25.25</td>
<td>0.495</td>
<td>1.816</td>
<td>1.375</td>
<td>0.441</td>
<td>0.762</td>
</tr>
<tr>
<td>H</td>
<td>8.75</td>
<td>0.398</td>
<td>1.467</td>
<td>1.209</td>
<td>0.258</td>
<td>0.846</td>
</tr>
<tr>
<td>Total</td>
<td>53.75</td>
<td>0.452</td>
<td>1.493</td>
<td>1.089</td>
<td>0.404</td>
<td>0.726</td>
</tr>
</tbody>
</table>
Table 5: Structural model estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sales Revenue (θ)</th>
<th>Cost and Outside Option Value (α)</th>
<th>Out-of-Category Spillovers (δ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>1.752***</td>
<td>1.876***</td>
<td>-0.165</td>
</tr>
<tr>
<td>year2</td>
<td>0.138</td>
<td>-0.032</td>
<td></td>
</tr>
<tr>
<td>year3</td>
<td>0.272</td>
<td>0.055</td>
<td></td>
</tr>
<tr>
<td>year4</td>
<td>0.281*</td>
<td>0.141</td>
<td></td>
</tr>
<tr>
<td>origin</td>
<td>0.103</td>
<td>0.278**</td>
<td>0.017</td>
</tr>
<tr>
<td>fit</td>
<td>0.546***</td>
<td>0.589***</td>
<td>-0.116</td>
</tr>
<tr>
<td>capital</td>
<td></td>
<td>-0.239*</td>
<td></td>
</tr>
<tr>
<td>production</td>
<td></td>
<td>0.158</td>
<td></td>
</tr>
<tr>
<td>agency</td>
<td></td>
<td>-0.186</td>
<td></td>
</tr>
<tr>
<td>coverage</td>
<td>-0.108</td>
<td>0.122</td>
<td>0.390*</td>
</tr>
<tr>
<td>image</td>
<td>0.217</td>
<td>0.006</td>
<td>-0.021</td>
</tr>
<tr>
<td>area</td>
<td>0.256**</td>
<td>0.323***</td>
<td>-0.108</td>
</tr>
<tr>
<td>extra</td>
<td>0.631***</td>
<td>0.251**</td>
<td>0.194</td>
</tr>
<tr>
<td>Std Dev of Stochastic Terms (α)</td>
<td></td>
<td>0.414***</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Brand Interaction Effects (γ)</th>
<th>Brand Tier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L</td>
</tr>
<tr>
<td>Brand Tier</td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>0.014</td>
</tr>
<tr>
<td>M</td>
<td>-0.001</td>
</tr>
<tr>
<td>H</td>
<td>-0.011</td>
</tr>
</tbody>
</table>

*** 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: Model fit: entry probability of all candidate brands, sales revenue and transfers for entering brands

<table>
<thead>
<tr>
<th>Brand Tier</th>
<th>Entry Probability</th>
<th>Sales Revenue (mil. RMB)</th>
<th>Transfer (mil. RMB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Real Data</td>
<td>Model Prediction</td>
</tr>
<tr>
<td>L</td>
<td>0.429</td>
<td>0.458</td>
<td>1.091</td>
</tr>
<tr>
<td>M</td>
<td>0.495</td>
<td>0.446</td>
<td>1.816</td>
</tr>
<tr>
<td>H</td>
<td>0.398</td>
<td>0.370</td>
<td>1.467</td>
</tr>
<tr>
<td>Total</td>
<td>0.452</td>
<td>0.436</td>
<td>1.493</td>
</tr>
</tbody>
</table>
Table 7: Market Outcomes under Counterfactual Contracts and Correlations between Sales Revenue and Cost

<table>
<thead>
<tr>
<th>Correlation between Sales and Cost</th>
<th>Store Value ($mil. RMB)</th>
<th>Manufacturers' Total Profit ($mil. RMB)</th>
<th>Total Welfare ($mil. RMB)</th>
<th>Number of Entrants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Share</td>
<td>Vertical</td>
<td>Transfer</td>
<td>Share</td>
</tr>
<tr>
<td>0</td>
<td>14.687</td>
<td>14.149</td>
<td>14.315</td>
<td>12.707</td>
</tr>
<tr>
<td>0.1</td>
<td>14.680</td>
<td>13.681</td>
<td>14.315</td>
<td>12.723</td>
</tr>
<tr>
<td>0.2</td>
<td>14.670</td>
<td>13.127</td>
<td>14.315</td>
<td>12.743</td>
</tr>
<tr>
<td>0.3</td>
<td>14.657</td>
<td>12.461</td>
<td>14.315</td>
<td>12.766</td>
</tr>
<tr>
<td>0.4</td>
<td>14.640</td>
<td>11.643</td>
<td>14.315</td>
<td>12.796</td>
</tr>
<tr>
<td>0.5</td>
<td>14.616</td>
<td>10.615</td>
<td>14.315</td>
<td>12.835</td>
</tr>
<tr>
<td>0.6</td>
<td>14.579</td>
<td>9.287</td>
<td>14.315</td>
<td>12.892</td>
</tr>
<tr>
<td>0.7</td>
<td>14.518</td>
<td>7.523</td>
<td>14.315</td>
<td>12.985</td>
</tr>
<tr>
<td>0.9</td>
<td>13.976</td>
<td>2.556</td>
<td>14.315</td>
<td>13.399</td>
</tr>
</tbody>
</table>
Table 8: Market Outcomes under Counterfactual Contracts and Correlations between Sales Revenue and Cost, with Brands Sales Lowered by $.75 mil. RMB

<table>
<thead>
<tr>
<th>Correlation between Sales and Cost</th>
<th>Store Value ($mil. RMB)</th>
<th>Manufacturers’ Total Profit ($mil. RMB)</th>
<th>Total Welfare ($mil. RMB)</th>
<th>Number of Entrants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Share</td>
<td>Vertical</td>
<td>Transfer</td>
<td>Share</td>
</tr>
<tr>
<td>0</td>
<td>0.945</td>
<td>0.652</td>
<td>0.945</td>
<td>0.814</td>
</tr>
<tr>
<td>0.1</td>
<td>0.945</td>
<td>0.604</td>
<td>0.945</td>
<td>0.815</td>
</tr>
<tr>
<td>0.2</td>
<td>0.945</td>
<td>0.551</td>
<td>0.945</td>
<td>0.816</td>
</tr>
<tr>
<td>0.3</td>
<td>0.945</td>
<td>0.491</td>
<td>0.945</td>
<td>0.818</td>
</tr>
<tr>
<td>0.4</td>
<td>0.944</td>
<td>0.423</td>
<td>0.945</td>
<td>0.819</td>
</tr>
<tr>
<td>0.5</td>
<td>0.943</td>
<td>0.348</td>
<td>0.945</td>
<td>0.821</td>
</tr>
<tr>
<td>0.6</td>
<td>0.941</td>
<td>0.264</td>
<td>0.945</td>
<td>0.824</td>
</tr>
<tr>
<td>0.7</td>
<td>0.937</td>
<td>0.174</td>
<td>0.945</td>
<td>0.828</td>
</tr>
<tr>
<td>0.8</td>
<td>0.929</td>
<td>0.080</td>
<td>0.945</td>
<td>0.838</td>
</tr>
<tr>
<td>0.9</td>
<td>0.901</td>
<td>-0.147</td>
<td>0.945</td>
<td>0.874</td>
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</tbody>
</table>
Table 9: Market Outcomes under Reduced Uncertainty of the Store

<table>
<thead>
<tr>
<th>Reduction in Uncertainty</th>
<th>Average Transfer ($mil. RMB)</th>
<th>Store Value ($mil. RMB)</th>
<th>Manufacturers' Total Profit ($mil. RMB)</th>
<th>Total Welfare ($mil. RMB)</th>
<th>Number of Entrants</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>2.117</td>
<td>14.315</td>
<td>12.831</td>
<td>27.146</td>
<td>41.460</td>
</tr>
<tr>
<td>5%</td>
<td>2.121</td>
<td>14.487</td>
<td>12.971</td>
<td>27.457</td>
<td>41.951</td>
</tr>
<tr>
<td>10%</td>
<td>2.125</td>
<td>14.666</td>
<td>13.108</td>
<td>27.774</td>
<td>42.583</td>
</tr>
<tr>
<td>15%</td>
<td>2.129</td>
<td>14.863</td>
<td>13.237</td>
<td>28.100</td>
<td>43.152</td>
</tr>
<tr>
<td>20%</td>
<td>2.133</td>
<td>15.076</td>
<td>13.359</td>
<td>28.436</td>
<td>43.816</td>
</tr>
<tr>
<td>25%</td>
<td>2.137</td>
<td>15.313</td>
<td>13.480</td>
<td>28.794</td>
<td>44.592</td>
</tr>
<tr>
<td>30%</td>
<td>2.141</td>
<td>15.577</td>
<td>13.594</td>
<td>29.171</td>
<td>45.370</td>
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<tr>
<td>35%</td>
<td>2.145</td>
<td>15.871</td>
<td>13.698</td>
<td>29.569</td>
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<tr>
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<td>2.149</td>
<td>16.201</td>
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<td>29.989</td>
<td>46.966</td>
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<tr>
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<td>2.153</td>
<td>16.575</td>
<td>13.864</td>
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<td>47.831</td>
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<tr>
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<td>2.156</td>
<td>16.999</td>
<td>13.920</td>
<td>30.919</td>
<td>48.794</td>
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Figure 1: Expected sales revenue vs. brand score

Figure 2: Expected ex-ante store profit vs. brand score