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INFORMATION ASYMMETRY, MANUFACTURER–RETAILER CONTRACTS, AND TWO-SIDED ENTRY*

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We investigate the economic determinants of contract structure and entry with transfer contracts, which specify that manufacturers directly sell their products in retail stores while retailers collect sales revenue and return a transfer to the manufacturers. Using a unique data set describing entry decisions of clothing manufacturers into a retail department store, we estimate a two-sided, asymmetric-information entry model. We compare profit estimates under transfer contracts to counterfactual profit estimates under common alternative contract formats. Results show that, when adverse selection is present, transfer contracts dominate other contract formats from the retailer's perspective; otherwise, the common alternative contract formats dominate.

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.[2] 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 article examines transfer contracts, which have been widely used by department stores in Asian countries, including China. Under this contract format, 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. Although 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 article is to investigate the economic determinants of contract-format choice and to estimate the impacts on both manufacturer and retailer profits from using a transfer

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[2] Such contracts have a long history in the agricultural sector under the form of "crop-sharing."

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. We focus on the information asymmetry between manufacturers and the retail store and assume that the retail store faces uncertainty regarding some attributes of the manufacturer that affect sales revenue and manufacture costs; that is, these attributes are private information for manufacturers. This type of information asymmetry can lead to adverse selection problems that, through interviews with the store management, we believe to be the major concern of the store when deciding on contract offers.[3]

Our main interest is not to propose new contract designs; instead, this article compares the profit 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 impacts is important for both policymakers 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 on the sales revenue of a brand and the cost of its manufacturer are correlated with each other, which lead to different degrees of adverse selection in brand 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 data set 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 help identify the sales revenue function. Data on brand entry and the revenue transfer allow us to separate the manufacturers' cost function from the "spillover effects" of brand entry on the store's profit that comes from categories outside 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.

Our results show that the attributes of a manufacturer's brand have different effects on the store and manufacturer profits. For example, a better fit between a brand and the majority of consumers in the store will increase the brand's sales revenue but will also increase the manufacturer cost and have 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 0.44 million RMB,[4] which is very significant in comparison with the average brand sales revenue 1.5 million RMB.

Our data provide a direct and simple way to validate our structural model—we compare the expected sales revenue and manufacturer transfers estimated using our model with brand scores used by the store, which were not 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 profits, we use our estimation results to conduct counterfactual experiments. We analyze the

[3] In addition, as discussed in Section 3, various features of our data suggest the existence of both uncertainty and asymmetric information, which motivates our use of a two-sided, asymmetric-information, entry model.

[4] Chinese dollar. One RMB is about U.S.$0.16.

impacts of transfer contracts on profits with both vertical and share contracts under different levels of adverse selection, represented by different degrees of the correlation between the store's uncertainties on the sales revenue of a brand and the cost of its manufacturer. We show the sensitivity of the store's profit to changes in this correlation under both share and vertical contracts. Transfer contracts, as a solution to the adverse selection problem, dominate the other contracts when the correlation is positive, assuming the magnitude of demand shocks (to the store) is not too large. This finding offers an explanation of why transfer contracts are widely adopted in China. When adverse selection is not a substantial problem, however, share contracts are typically a better option for the store. We also examine the impact of contract structure on the joint channel value, that is, the sum of the store's and manufacturers' profits. Even in the absence of adverse selection, transfer contracts dominate. In addition, as adverse selection becomes more prevalent, the joint channel value will generally decrease with share and vertical contracts but remain constant under transfer contracts, resulting in even larger total welfare gains from transfer contracts.

The remainder of the article is organized as follows: Section 2 places our article in the context of the existing literature, and Section 3 discusses the data. Sections 4 and 5 outline the model and estimation details, respectively. Section 6 presents the estimation results, Section 7 combines these results with a counterfactual exercise to analyze the impact of adverse selection on contract-format choice, and Section 8 concludes.

2. RELATED LITERATURE

This article 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. With access to richer data, the empirical literature on vertical relationships has grown recently. Villas-Boas (2007), for example, studies vertical contracts between manufacturers and retailers in the supermarket industry, and develops a method to test different nonnested models of the vertical relationship, when wholesale prices are not observed. Draganska et al. (2010) extend 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) use a bilateral oligopoly bargaining model to help estimate input costs of distributors in the multichannel television market and conduct counterfactual experiments to compare the welfare implications of à la carte and bundling pricing. Ho (2009) models the negotiation process between insurance plans and hospitals to study how equilibrium hospital networks and the division of profits are determined. Ho and Lee (2017) introduced the concept of Nash-in Nash with Threat of Replacement to capture the incentives of an insurer to exclude certain medical providers. Empirical studies in this stream mostly do not have data on the transfers between channel members, with a few exceptions. Mortimer (2008), for example, uses 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 uses 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 would complicate our analysis and is not the objective of this article. We also depart 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 (2010) and Li et al. (2016).[5]

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 department stores in Shanghai, roughly equivalent to Macy's in the United States. 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 30 and above. The category occupies the whole fourth floor in the seven-storied store building. Clothing in this category generally has a formal style, and the quality of materials and design are important for consumers. Compared with other clothing categories, it also has 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, implying that manufacturers have more influence on demand than the department store does. 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.[6] Unfortunately, although they may influence sales, we do not observe factors such as location within the store or floor space.

3.1. *Brand List and Attributes.* From the beginning of the sample period, the store maintained a complete list of the manufacturers (including those who never entered during the period) that it considered as potential entrants. This implies that we observe the complete choice set of the store. Altogether, there are 119 unique manufacturers in the list. To facilitate management and contracting decisions, the store also maintains a list of brand and manufacturer attributes. Previous research typically treated these attributes as unobserved product attributes. In contrast, our data allow 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.[7]

[5] 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 (e.g., Berry, 1992; Mazzeo, 2002; Seim, 2006; Ishii, 2008; Jia, 2008; 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 noncooperative manner. In our model, however, the entry of a manufacturer brand has to be mutually agreed to by the department store and the manufacturer. This approach is related to some recent empirical work that applies the matching framework to marriage (Choo and Siow, 2006), venture capitalists (Sorensen, 2007), dating (Hitsch et al., 2010a, 2010b), and FCC spectrum auctions (Bajari and Fox, 2013).

[6] 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.

[7] *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.

TABLE 1
DEFINITION OF BRAND ATTRIBUTES

Brand Attribute	Definition
Origin	The origin of manufacturers: Inland China medium/large city, Hong Kong/Taiwan, Japan, Korea, and European countries and the United States
Fit	The fit of a brand with the majority of the store's customers
Capital	Supplier's registered capital
Production	Supplier's production capability: subcontract or self-production
Agency	Brand manufacturer or agent of the manufacturer
Coverage	Market coverage, represented by the fraction of nine comparable department stores in the local market selling the brand
Image	Brand image evaluation
Area	Average area of selling counters in the nine comparable department stores in the local market
Extra	Selling in selected five major cities other than Shanghai

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.

3.2. *Manufacturer–Store Contracts.* The store manager showed us some sample contracts. The contract structure is standardized, consisting of many terms, including details about manufacturers' hiring and training of sales employees and their contribution to store-wide promotions. The most important term, however, specifies that the store collects all sales revenue and returns a transfer to the manufacturer at the end of the payment cycle.[8] The determination of the actual transfer to manufacturers in contracts is complicated and nonlinear. 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% in the samples that we viewed), again differing 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 the next section, 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 allow 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, despite considerable research effort, 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. Thousands of clothing brands exist in China each year, yet none has a worldwide reputation (Dai and Zhang, 2010). Brand popularity, product quality, and the cost of materials fluctuate every year. Brand entry and exit rates are also very high in this industry. 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 assuming that contracts are renewed annually, starting in April and ending in March next year.[9]

[8] A payment cycle can be monthly, quarterly, and biannually.

[9] For those brands that enter later than September in a year, we assign 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.

TABLE 2

ATTRIBUTE VARIABLES AND SUMMARY STATISTICS FOR BRANDS THAT EVER ENTER AND BRANDS THAT NEVER ENTER

Attribute Variable	Definition	Brands that Ever Enter		Brands that Never Enter	
		Mean	SD	Mean	SD
Origin	1 if foreign brand, 0 otherwise	0.223	0.417	0.230	0.422
Fit	1 if good fit, 0 otherwise	0.405	0.492	0.479	0.501
Capital	1 if registered capital 100+ million RMB (agent) or 500+ million RMB (owner), 0 otherwise	0.591	0.493	0.418	0.494
Production	1 if self-production, 0 if subcontract	0.637	0.482	0.732	0.444
Agency	1 if brand manufacturer, 0 if agent	0.953	0.2111	0.962	0.192
Coverage	Fraction of nine comparable stores selling the brand	0.517	0.263	0.409	0.269
Image	1 if good brand image, 0 otherwise	0.251	0.435	0.391	0.489
Area	1 if mean operational area 50+ m^2, 0 otherwise	0.540	0.500	0.506	0.501
Extra	1 if selling in two or more cities	0.405	0.492	0.172	0.378

TABLE 3

ATTRIBUTE VARIABLES AND SUMMARY STATISTICS FOR ENTERING BRANDS BY YEAR

Attribute Variable	Year-1 Entering Brands (58)		Year-2 Entering Brands (58)		Year-3 Entering Brands (49)		Year-4 Entering Brands (50)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Origin	0.172	0.381	0.276	0.451	0.245	0.434	0.200	0.404
Fit	0.293	0.459	0.414	0.497	0.469	0.504	0.460	0.503
Capital	0.466	0.503	0.586	0.497	0.653	0.481	0.680	0.471
Production	0.534	0.503	0.655	0.480	0.673	0.474	0.700	0.463
Agency	0.931	0.256	0.948	0.223	0.959	0.200	0.980	0.141
Coverage	0.492	0.267	0.502	0.283	0.528	0.268	0.551	0.231
Image	0.190	0.395	0.276	0.451	0.286	0.456	0.260	0.443
Area	0.448	0.502	0.500	0.504	0.612	0.492	0.620	0.490
Extra	0.362	0.485	0.414	0.497	0.449	0.503	0.400	0.495

3.3. *Summary Statistics and Preliminary Evidence of Information Asymmetry.* For the purpose of model estimation, we redefine the brand and manufacturer attributes. Except for the variable *coverage*, which is defined as the percentage of the nine designated department stores selling the brand, all other variables are dummy variables. Table 2 lists the variables that we use in the estimation and provides some summary statistics broken out by whether the brand ever entered or never entered the store. The characteristics are quite different for several attributes across entry status. Table 3 compares the average attributes of entrant brands across the four years and indicates that the composition of brands varied considerably from year to year, but without any clear trend.

Before providing evidence that there exists information asymmetry between the store and manufacturers, we first note the extent of the uncertainty regarding the profitability of brand entry for the store. The R^2 from a simple ordinary least squares regression of sales revenue on brand/manufacturer attributes, tier dummies, and store-assigned brand scores is 0.32, suggesting that most of the variation in sales revenue is unpredictable for the store.[10] Furthermore, as can be seen in Table 4 we observe quite a few manufacturer brands entering and exiting the store over the four-year sample period. Among the total of 215 entrants in the data,[11] we observe 48 exits, which corresponds to an exit rate of 22.3%, illustrating substantial uncertainty in the

[10] An analogous regression when the dependent variable is store profit (i.e., sales revenue less transfers) yields an R^2 of 0.14. When including brand fixed effects, which is a richer information set than that available to the store, the analogous R^2 statistics are 0.47 and 0.35.

[11] Repeated entry of the same brand is counted as a separate entry.

TABLE 4
ENTRY AND EXIT PATTERN OF MANUFACTURER BRANDS

Brand Types	Number of Entrants	Number of Exits	Exit Rate
Total	215	48	22.3%
Two or more years of presence	125	29	23.2%
Three of more years of presence	61	14	23.0%

industry. Finally, Table 4 is also suggestive that the store has limited ability to learn about manufacturers, as 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. All these observations are consistent with the store manager's observation that brand popularity, product quality, and the cost of materials are constantly fluctuating in the industry.

Certain institutional details suggest that some of factors determining store uncertainty can be observed by the manufacturer, that is, that information asymmetry exists. Each 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 agents. They are also selling in multiple geographical markets across the nation so that the manufacturers can aggregate the sales information to obtain more precise information on consumers' preferences for their brands. Furthermore, because product quality and design are constantly changing within brands in the clothing market in China, the store's ability to use past brand sales in the store to learn about manufacturers is limited. In addition, quality is difficult to monitor and to contract upon. The store mainly acts as a platform for manufacturers to sell directly to consumers and, as such, its ability to affect sales is limited. Although the store can decide the location and ambience of the store, which can influence the store traffic and who are store customers, these factors are typically stable, and manufacturers can obtain reliable information based on past store sales. Therefore, the uncertainty of the manufacturers regarding how the store may impact their sales should be much less than the store's uncertainty regarding the performance of manufacturers.

Given our assumption that we observe the same information set as the store, information asymmetry is also directly testable in the data. In the absence of information asymmetry, the store (and we as researchers) should be able to predict exactly who will enter and not enter conditional on brand characteristics and a transfer offer. Although actual transfers are only observed conditional on entry, optimal transfers should only be a function of observable brand characteristics. Therefore, a simple, reduced-form test of information asymmetry is to see if entry decisions can be perfectly predicted using the store's information set. Not surprisingly, the results of this test suggest that information asymmetry exists. In particular, a Probit regression of entry on brand/manufacturer attributes, tier dummies, and store-assigned brand scores yields a pseudo-R^2 of only 0.13.[12]

Finally, we note that although the institutional details suggest that manufacturers have more information about the demand for their brands, we will consider a version of our model that allows both sides to have private information. This model is presented in the Appendix, and the key conclusions drawn from our primary specification are robust to this extension.

4. A TWO-SIDED ENTRY MODEL WITH ASYMMETRIC INFORMATION

We model the entry decisions of manufacturers as a two-sided entry game based on transfer contracts. The entry model differs from the recent literature on vertical contracting relationships between upstream and downstream firms (e.g., Mortimer, 2008; Ho, 2009; Crawford and

[12] We thank a referee for noting that if there are multiple equilibria to the game that determines entry this could also contribute to the low R^2. We discuss the possibility of multiple equilibria in Subsection 5.3.

Yurukoglu, 2012; Grennan, 2013) 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 and that there is information asymmetry between the store and manufacturers. In this section, we will discuss the model setup and derive the optimal transfer contracts and the manufacturers' entry decision.

4.1. *Model Setup.*

4.1.1. *Structure of the game.* The game has three stages. The store has a list of manufacturers as potential entrants, and, 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. A justification of this assumption is the following: During interviews with the store management, we were told that the store has a distinct locational advantage and reputation. Manufacturers compete for the opportunity to sell in the store. The department store therefore has a large bargaining power when negotiating a 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.[13]

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 then 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. Although we recognize the potential benefits (and costs) of extending the model to a dynamic framework, various features of the Chinese clothing industry suggest that the static assumption may be a good approximation of reality in our application. The sunk cost of entry is limited to simply setting 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. As discussed above, Table 4 shows the exit rate of manufacturers by tenure length. It can be seen in the table that the exit rate does not depend on the tenure length of entrants, providing further support for the static model assumption. This is also suggestive that store learning does not play a significant role in store decision making. Another potential concern may be that the store would try to extract more surplus from incumbent manufacturers; however, we do not see evidence of this in the data, as the rate of surplus extraction remains constant within firms over time.[14]

4.1.2. *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 brand k's sales revenue and costs in period t.[15] As discussed above, this is the complete list of variables that the store uses to evaluate the profitability of a brand's entry. We therefore assume that there is no additional information for the store that is unknown to us as

[13] 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. See Sieg (2000) for a similar modeling approach applied to take-it-or-leave-it settlement demands in medical malpractice lawsuits.

[14] We tested whether the ratio of the store's payoff-to-sales ratio changed between the first year of entry for a brand and the second year when the brand was an "incumbent." We find that, on average, the amount extracted was constant over the two years; the magnitude of the change is small, the sign of the change varies by calendar years, and the difference is not statistically different from zero.

[15] Each period in our model is one year. We use year dummies to capture the effects of time-varying factors on demand and costs.

researchers.[16] Since x_{kt} is evaluated based on the market information available to everyone, we also assume that this is public information to all manufacturers.[17]

To model the information asymmetry, we assume that a manufacturer may possess private information about its brand that is unobserved by the store and by 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 consumers. This demand-side private information is represented by a random variable, ξ_{kt}. On the cost side, private information may include labor, capital, and shipment costs, which are represented by a random variable, ω_{kt}. These two variables represent demand and cost shocks to the store. Suppose the two shocks 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 observe, represented by another random variable υ^o_{kt}. We assume that the store and other manufacturers know the distribution from which ξ_{kt}, ω_{kt}, and υ^o_{kt} are drawn, but do not know the exact values. The store thus cannot perfectly predict manufacturers' entry decisions; instead, it forms expectations about all manufacturers' entry decisions, conditional on contract offers. We assume that the information asymmetry is only one-sided. As such, the store has no private information unobservable to the manufacturers. Finally, we note that in estimation we do not impose asymmetric information but rather test for its presence.

4.1.3. *Sales revenue specification.* Let x^d_{kt} x_{kt} be a subset of variables that may affect the sales of brand k. We specify a reduced-form function for the brand's sales revenue, if it enters in period t, as the following:

$$S_{kt}\left(x^d_{kt}\right) = x^d_{kt}\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} I\left\{x^{d,l}_{k't} == x^{d,l}_{kt}\right\} I_{k't} + \xi_{kt} + \varepsilon_{kt}, \tag{1}$$

where S_{kt} is the realized sales revenue and $I_{k't} \equiv I\{k' \text{ enters in year } t\}$, $I\{.\}$ is an indicator function.

The first component $x^d_{kt}\beta$ on the right-hand side captures the effects of brand attributes on sales, which is public information for the store and manufacturers.[18] We define the interaction effect among entering brands on sales revenue at the brand-attribute level. Let $x^{d,l}_{kt}$ and $x^{d,l}_{k't}$ denote the values of brand attribute $l, l = 1, \dots, L$, for brand k and brand k'. Then $\sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}I_{k't}$ represents the number of other entering brands having the same value attribute l as brand k. Therefore, the second component captures the sum of interaction effects at each brand attribute level. Note that ε_{kt} is an idiosyncratic ex post demand shock that is unobserved by everyone, including the manufacturer, prior to entry. Following Pakes et al. (2015), this shock could be either an expectation error (due to imperfect information) or a measurement error of revenue.

[16] Although the store has a strong incentive to make sure that they accurately measure manufacturer characteristics, it remains a possibility that some characteristics are measured with error. Although this would affect the interpretation of the effect of the attributes on sales, it should not affect the key conclusions drawn in the article, as they rely on the store's expectation of manufacturer-specific sales and entry. Although, store management has assured us that they have shared all brand-characteristic data with us, if there are brand characteristics they did not share, we will overstate the variance of the manufacturers' private information.

[17] 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.

[18] Although some potential features, such as location and space, are unobserved, they may be captured in a reduced-form way by our sales equation. For example, if the agreed-upon location is a function the brand attributes, x^d, then a manufacturer that has better brand attributes may be offered a more desirable location and thus will have a higher sales revenue. The β term in the sales revenue function will then reflect the combined, reduced-form effect of x^d on sales, S_{kt}.

Since ξ_{kt} is a private information, the manufacturer's expectation of its sales revenue, prior to entry, is $E^1(S_{kt}) = x^d_{kt}\beta + E^2(\sum_{l=1}^{L}\gamma_l \sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}I_{k't}) + \xi_{kt} = x^d_{kt}\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} \times I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}p_{k't} + \xi_{kt}$, where $p_{k't} = E^2(I_{k't})$ is the store's belief that brand k' will enter. Unconditional on entry, the store's expectation of sales revenue is $E^2(S_{kt}) = x^d_{kt}\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}p_{k't}$.[19]

4.1.4. *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 the largest revenue and is a major store-traffic generator. Let x^s_{kt} 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 resulting from k's entry.

4.1.5. *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} 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

$$C_{kt} = x^c_{kt}\alpha^c + \omega_{kt}, \tag{2}$$

where ω_{kt} is private information for the manufacturer. Unconditional on entry, the store's prior expectation of the manufacturer's cost is $x^c_{kt}\alpha^c$, as ω_{kt} is mean zero in expectation.

A manufacturer's entry decision also depends on the outside option value it receives if it chooses not to enter. For example, if the manufacturer has already sold in other department stores or set up its 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^o_{kt} x_{kt} be a set of brand attributes and time-varying factors that are related to the outside option. We specify this value as

$$\Pi^o_{kt} = x^o_{kt}\alpha^o + \upsilon^o_{kt}, \tag{3}$$

where υ^o_{kt} is only known by the manufacturer. Unconditional on entry, the store's prior expectation about the outside option value is $x^o_{kt}\alpha^o$.

4.2. *Transfer Offers and Entry Decisions.* With the above primitives, 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.[20] 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 the store's expectation of sales revenue, that is, $S^*_{kt} = E^2(S_{kt})$. If the manufacturer enters, it will receive the following transfer payment:

$$T_{kt} = T^*_{kt} + (S_{kt} - S^*_{kt}) + \tau_{kt}, \tag{4}$$

[19] Conditional on entry, the expected sales revenue from the store's perspective is $E^2(S_{kt}) + E(\xi_{kt}|I_{kt} = 1)$, where $I_{kt} \equiv I\{k \text{ enters in year } t\}$.

[20] 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 categories.

where $(S_{kt} - S^*_{kt})$ is the deviation of the sales revenue (which we observe in the data) from the targeted sales. This is a simplification from actual contracts.[21] The last component, τ_{kt}, is an error term reflecting the difference between the actual payment to manufacturers and what the contracts specify. To our knowledge, this difference arises from various sources. One example is that the dollar value of products returned by customers is recorded in S_{kt} but will be deducted from the actual transfer. As another example, the store occasionally runs promotions by offering discounts to loyalty card holders. The dollar value of discounts will reduce sales revenue in data but the transfers paid to manufacturers will be calculated based on the full value. Adding this measurement error helps us to rationalize why actual transfers deviate from what our model predicts based on actual sales revenue in the model estimation. We assume that τ_{kt} is unknown to both the store and the manufacturer before entry and independently distributed from other random variables with mean zero. We call $(S_{kt} - S^*_{kt}) + \tau_{kt}$ the "contingent transfer."

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 spillovers on other categories. That is,

$$V^s_t = \sum_k [S_{kt} - T^*_{kt} - (S_{kt} - S^*_{kt}) - \tau_{kt} + x^s_{kt}\delta] I_{kt}, \tag{5}$$

where $I_{kt} \equiv I\{k \text{ enters in year } t\}$.

As the S_{kt} terms cancel, the uncertain factors that the store faces are τ_{kt} and the entry decisions of manufacturers. Let Ψ^s_t denote the information set of the store, including brand and manufacturer attributes and the contract offers, and let $p_{kt} = E(I_{kt}|\Psi^s_t)$ be the probability that manufacturer k will enter, which we will derive below. Since $E(\tau_{kt}|\Psi^s_t) = 0$, the store's expected value from the entry of all brands can be written as $E(V^s_t|\Psi^s_t) = \sum_k [S^*_{kt} - T^*_{kt} + x^s_{kt}\delta] p_{kt}$. Employing the definition of S^*_{kt}, the store's expected value is given by

$$E(V^s_t|\Psi^s_t) = \sum_k \left[x^d_{kt}\beta + \sum_{l=1}^{L} \gamma_l \sum_{k'} I\left\{ x^{d,l}_{k't} == x^{d,l}_{kt} \right\} p_{k't} - T^*_{kt} + x^s_{kt}\delta \right] p_{kt}. \tag{6}$$

The optimal deterministic transfer can be derived from the first-order condition of $E(V^s_t|\Psi^s_t)$ with respect to T^*_{kt} that gives the following:

$$T^*_{kt} = x^d_{kt}\beta + 2\sum_{l=1}^{L} \gamma_l \sum_{k'} I\left\{ x^{d,l}_{k't} == x^{d,l}_{kt} \right\} \; p_{k't}\frac{\partial p_{kt}}{\partial T^*_{kt}} + x^s_{kt}\delta - \frac{p_{kt}}{\partial p_{kt}/\partial T^*_{kt}}. \tag{7}$$

This is an implicit function, as T^*_{kt} also appears on the right-hand side of the equation.

In standard entry games in the previous literature, manufacturers compete against one another to enter markets with the objective of maximizing own profits. The spillovers generated for other categories play no role in each manufacturer's entry decision. This type of noncooperative 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 categories will receive a higher transfer, as shown by the term $x^s_{kt}\delta$ in the above equation, and consequently is incentivized to enter. Our store in this two-sided game will therefore reduce the economic inefficiency caused by excessive or

[21] 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, instead of all, of the deviation of sales from target sales. See Subsection 3.2 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 the contract sample that the store showed us.

insufficient entry. On the other hand, the store has the incentive to extract surplus from manufacturers, represented by the last term $-\frac{p_{kt}}{\partial p_{kt}/\partial T^*_{kt}}$, which is negative since $\partial p_{kt}/\partial T^*_{kt}$ is positive. The manufacturer hence will receive a return lower than the aggregate benefits from its entry. The net impact on social welfare when compared with noncooperative entry is therefore indeterminate.

Let Ψ^k_t denote the information set of manufacturer k. It includes brand and manufacturer attributes that are also known by the store, and ξ_{kt}, ω_{kt}, and ν^o_{kt} that are the manufacturer's private information. Since by assumption $E(\tau_{kt}|\Psi^k_t) = 0$, we have $E(T_{kt}|\Psi^k_t) = T^*_{kt} + \xi_{kt}$ and, therefore, the expected profit conditional on entry is

$$E\left(\Pi_{kt}|\Psi^k_t\right) = T^*_{kt} - x^c_{kt}\alpha^c + \xi_{kt} - \omega_{kt}. \tag{8}$$

The manufacturer will compare this profit with the outside option value, that is, Π^o_{kt}. Its entry probability function thus is

$$p_{kt} = Pr\left(T^*_{kt} - x^{co}_{kt}\alpha^{co} \geq v_{kt}\right), \tag{9}$$

where $v_{kt} \equiv \omega_{kt} + \nu^o_{kt} - \xi_{kt}$ and $x^{co}_{kt}\alpha^{co} = x^c_{kt}\alpha^c + x^o_{kt}\alpha^o$.

It can be seen from the store's expected value function (Equation (6)) and the manufacturer's expected profit function (Equation (8)) that setting a targeted sales revenue higher than the store's expectation (thus reducing $S_{kt} - S^*_{kt}$) 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 understates 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.

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 evaluate the expected entry profit in comparison with the option of not to enter.

We note that the imperfect-information shock to revenue, ε_{kt} (that is unknown to both the store and the manufacturers) does not play a role in decision making for either side. On the manufacturer side, this is due to the model's assumption of risk neutrality. On the store side, this is because the store is protected from risk by the contract structure.[22]

Finally, it is worth noting that our model allows for mechanisms other than manufacturer private information to affect entry. For example, even in the absence of the private information shock, v_{kt}, entry would not take place if the optimal transfer offer were not high enough to cover a manufacturer's (commonly known) outside option, $x^{co}_{kt}\alpha^{co}$. However, as discussed above, the only unobservables that directly affect entry (i.e., ω_{kt}, ν^o_{kt}, and ξ_{kt}) are manufacturer private information. We weaken this assumption in the Appendix, where we consider a model where the store has private information and draw similar conclusions regarding the benefits of the transfer-contract format.

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

[22] Although the model does assume that the store is also risk neutral, the transfer contract ensures that the manufacturer bears no risk from the shock ε_{kt}. In the alternative contract structures considered in Section 7, the store will bear some risk from ε_{kt}.

conditional on entry. In this section, we will outline the model estimation approach and 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, ν_{kt}, is distributed as *normal*$(0,\sigma^2)$ and i.i.d. across brands and periods. The standard deviation σ represents the magnitude of information asymmetry between the store and manufacturers, which will have a direct impact on transfer offers and the entry probability. We define the deterministic part of the manufacturer profit as $\bar{\Pi}_{kt} = T^*_{kt} - x^{co}_{kt}\alpha^{co}$. Based on the distribution assumption, the entry probability function of brand k can then be written as $p_{kt} = \Phi(\bar{\Pi}_{kt}/\sigma)$, where Φ is the CDF of the standard normal distribution. The larger the uncertainty σ, the smaller the entry probability conditional on T^*_{kt}. Therefore, even though the store wants, say, high-end brands to enter by offering a contract better than other brands, we will still observe a low entry rate among high-end brands.

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, ξ_{kt}, there is a selection issue in model estimation: The expectation of ξ_{kt} conditional on the entry is no longer zero, that is, $E(\xi_{kt}|I_{kt}=1) > 0$. 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 $E(\xi_{kt}|I_{kt}=1)$. 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}.[23]

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

$$S_{kt} = x^d_{kt}\beta + \lambda(p_{kt}) + \varepsilon^*_{kt}, \tag{10}$$

where $\varepsilon^*_{kt} = (E(\xi_{kt}|I_{kt}=1) - \lambda(p_{kt})) + (\xi_{kt} - E(\xi_{kt}|I_{kt}=1)) + \varepsilon_{kt}$. Given that $E(\xi_{kt}|I_{kt}=1) - \lambda(p_{kt})) = 0$, and $E(\xi_{kt} - E(\xi_{kt}|I_{kt}=1)) = 0$, we have $E(\varepsilon^*_{kt}|I_{kt}=1) = 0$.

Therefore, $S_{kt} - S^*_{kt} = \lambda(p_{kt}) + \varepsilon^*_{kt}$, and the actual transfer conditional on the entry therefore can be written as

$$T_{kt} = T^*_{kt} + \lambda(p_{kt}) + \tau^*_{kt}, \tag{11}$$

where $\tau^*_{kt} = \varepsilon^*_{kt} + \tau_{kt}$. As $E(\varepsilon^*_{kt}|I_{kt}=1) = 0$ and, by assumption, $E(\tau_{kt}|I_{kt}=1) = 0$, therefore $E(\tau^*_{kt}|I_{kt}=1) = 0$.

Finally, we define

$$I_{kt} = p_{kt} + e^*_{kt}. \tag{12}$$

This applies to every manufacturer unconditional on entry. We have $E(e^*_{kt}) = 0$ as $E(I_{kt}) = p_{kt}$.

[23] In model estimation we employ a polynomial of degree 5. We experimented with different degrees in estimation and found only trivial differences between parameter estimates when the degree goes above 5.

5.3. *Estimation Strategy.* We use the nonlinear least square method to estimate Equations (10)–(12) 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, and we employ the Mathematical Programming with Equilibrium Constraints (MPEC) approach developed in Su and Judd (2012).[24]

Given the sales revenue error, ε^*_{kt}, defined in Equation (10), the transfer error, τ^*_{kt}, defined in Equation (11), and the entry error, e^*_{kt}, defined in Equation (12), we choose the structural parameters $\theta' = \{\alpha',\ \beta',\ \gamma', \delta',\ \sigma\}'$ and a set of deterministic transfers $T^* = \{T^*_{kt}, \forall k, \forall t\}$ to minimize the average squared residuals across the three equations subject to the constraints provided by the first-order condition for optimal transfers. That is,

$$\theta, T^* = \underset{\theta, T^*}{\operatorname{argmin}} \sum_{t=1}^{T}\sum_{k} e^{*2}_{kt}/N + \sum_{t=1}^{T}\sum_{k} \varepsilon^{*2}_{kt}/n + \sum_{t=1}^{T}\sum_{k} \tau^{*2}_{kt}/n \tag{13}$$

$$\text{s.t.}\ \ T^*_{kt} = x^d_{kt}\beta + \frac{2}{\sigma}\phi\left(\frac{T^*_{kt} - x^{co}_{kt}\alpha}{\sigma}\right)\sum_{l=1}^{L}\gamma_l \phi \sum_{k'} I\left\{x^{d,l}_{k't} == x^{d,l}_{kt}\right\}\ \Phi\left(\frac{T^*_{k't} - x^{co}_{k't}\alpha}{\sigma}\right)$$

$$+ x^s_{kt}\delta - \sigma\phi\frac{\Phi\left(\frac{T^*_{kt} - x^{co}_{kt}\alpha}{\sigma}\right)}{\phi\left(\frac{T^*_{kt} - x^{co}_{kt}\alpha}{\sigma}\right)},\quad \forall\, k,\quad \forall\, t,$$

where N is the total number of candidate brands and n is the total number of entering brands from all T periods. The constraint for T^*_{kt} comes from Equation (7).

A potential issue arises if there are multiple equilibria; that is, given the interaction effects, γ, it is possible that more than one T^* could satisfy the equilibrium constraint in (7). To address this, we assume that a unique equilibrium is observed in the data. Therefore, the equilibrium played is identified by our observable outcomes. If there is more than one set of T^* that satisfies the equilibrium constraint, the estimator will choose the one that minimizes the criterion function.[25]

To obtain standard errors, we adopt a parametric bootstrapping method (Hall 1994). Given estimates for θ and T^*, we calculate the residuals $\hat{\varepsilon}^*_{kt}$ and $\hat{\tau}^*_{kt}$. 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 the entry decision of every brand. We then treat the simulated outcomes as data and reestimate our model.

Finally, we have to decide which variables to include 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^{co}_{kt}. 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^d_{kt}. 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

[24] Several recent papers have applied this methodology. For example, Dube et al. (2012) use the MPEC method to estimate the model of Berry et al. (1995) by imposing the constraints that the observed market share is equal to the predicted market share.

[25] There could (in theory) also be multiple roots to Equation (7) as it is a first-order condition, which, as usual, provides only necessary conditions for maximization. Choosing the root that maximizes the criterion function is appropriate on the basis that profit-maximizing behavior will be identified by the data.

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.* We have six sets of structural parameters to estimate: cost and outside option value parameters (α), brand attribute parameters determining demand (β), polynomial parameters for the control function (λ), interaction effect parameters (γ), spillover parameters (δ), and the standard deviation of the combined stochastic terms (σ) that represents the magnitude of the information asymmetry. 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.

Conditional on manufacturer transfers, the cost parameters α can be identified from the observed entry across brands. For example, if we observe a brand with a high x^c entering the store at a level of transfer offer lower than the others, this can only be rationalized in our model that x^c is negatively correlated with the entry cost or outside option value of the manufacturer, that is, $\alpha < 0$. If there were no selection issue, the parameter β 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, β has to be jointly identified with λ. The parameter vector β is identified by the relationships between manufacturers' sales revenue and their brand attributes, and the interaction parameter γ is identified by the variation of brand attributes across different entering brands at different entry years. The set of polynomial parameters in the control function, λ, is identified from the relationship between sales revenue and p_{kt}. Note that an exclusion restriction regarding variables that affect the probability of entry, but do not affect demand, is utilized to identify λ. The three cost variables, *capital*, *production*, and *agency*, all affect the entry probability (through the cost function) but are assumed to not shift demand.

Furthermore, the variation in transfers across brands with different brand attributes identifies the spillover parameters, δ. Conditional on parameters α, β, and γ, we can calculate the optimal transfer offer when the spillovers are zero. After controlling for selection (i.e., conditional on the parameter λ), the deviation of the actual transfer from this optimal transfer identifies δ. 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 σ 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 (β). Among the significant estimates, a brand's good fit with the store image (*fit*) yields 0.819 million RMB higher annual sales revenue.[26] The positive coefficient on *coverage* suggests that a brand is likely to sell well if it has large penetration in the local market. The coefficient for *extra* is also positive and has a large magnitude. The results in the second column show that the coefficients for *coverage, image*, and *extra* are significantly negative, indicating that customers substitute between brands with similar values of these attributes. In contrast, the parameters for *origin* and *area* are significantly positive, implying a complementary relationship. One potential explanation is that the entry of foreign brands with larger selling areas (which are typically more high-end and expensive) helps attract customers who have higher consumption power.

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

TABLE 5
STRUCTURAL MODEL ESTIMATES

Variables	Sales Revenue (β)	Brand Interaction (γ)	Cost and Outside Option Value (α)	Out-of-Category Spillovers (δ)	Polynomial Terms (λ)	Scale (σ)
Constant	0.8175		0.8983***	0.4496	−1.4325**	
	(0.6855)		(0.2390)	(0.6097)	(0.7273)	
*Year*2	0.0116		0.0384			
	(0.1158)		(0.1177)			
*Year*3	0.1241		0.1729			
	(0.1270)		(0.1281)			
*Year*4	0.1111		0.1644			
	(0.1188)		(0.1184)			
Origin	0.8500	0.0301***	0.1130	0.5700**		
	(0.6732)	(0.0102)	(0.1705)	(0.2347)		
Fit	0.8193***	0.0095	0.5908***	−0.1595		
	(0.2252)	(0.0160)	(0.0943)	(0.1031)		
Capital			0.1713***			
			(0.0453)			
Production			−0.1075**			
			(0.0457)			
Agency			−0.4846***			
			(0.1818)			
Coverage	0.3493*	−0.0229**	0.1448	−0.2728**		
	(0.1982)	(0.0116)	(0.1499)	(0.1177)		
Image	−0.6492	−0.0272*	0.1364	0.0323		
	(0.6185)	(0.0159)	(0.1367)	(0.2303)		
Area	0.1131	0.0284***	0.1241	−0.3022**		
	(0.1453)	(0.0087)	(0.1051)	(0.1203)		
Extra	0.9455*	−0.0287***	0.6876*	0.0101		
	(0.5717)	(0.0089)	(0.3568)	(0.3884)		
P					14.4714***	
					(2.5501)	
P^2					−24.3171***	
					(1.5678)	
P^3					−20.7754***	
					(2.1028)	
P^4					10.5496***	
					(2.1426)	
P^5					47.3647***	
					(2.3939)	
SD of stochastic term (σ)						0.4387***
						(0.0368)

NOTE: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

The third 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. The positive coefficient on *capital* suggests that manufacturers with larger capital bases have larger entry costs. Finally, production with own facility (*production*) and entering without an agent both decrease the manufacturer's costs.

The fourth column illustrates the effect of brand attributes on spillovers to other categories. Being a foreign brand (*origin*) will have positive spillovers. It is interesting to see that the coefficient for *fit* is negative, although insignificant, suggesting that the store will not offer higher manufacturer transfers to brands with good fit (who are mostly medium-tier brands), probably because these brands do not help attracting profitable customers who are the target of the store's strategy of moving upscale. The coefficient for *area* is also negative, perhaps indicating that occupying a large selling area reduces the capacity of the store to sell other products on the same floor. Note that these coefficients have a large magnitude that is comparable with the coefficients in the sales revenue and cost functions, suggesting that, for the store, cross-category spillovers are an important factors in contract offer decisions.

Finally, the estimate of scale parameter (σ), which is reported in Table 5, is 0.439 million RMB. The average brand sales revenue in the data is 1.493 million RMB, suggesting 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. Note that if the store had no uncertainty regarding manufacturer's sales and costs, the selection–correction procedure would not be required. As can be seen in the fifth column of Table 5, the coefficients on the selection correction terms are statistically significant, which is suggestive of the importance of controlling for the selection caused by the store's uncertainty.[27]

We note that a limitation of the model is that it abstracts away from potential store capacity constraints. This is due to the fact that we do not observe information on whether capacity constraints bind. To partially address this, we consider a robustness check whereby we re-estimate the model dropping the year where entry was highest, as the store may have reached the maximum constraint in that year but was unlikely to have reached it in other years. The results are presented in Table A2 and show that most of the statistically significant parameter estimates are reasonably similar to what we obtain from our baseline estimates, suggesting that capacity constraints are unlikely to be a key determinant of our results.

6.1. *Model Validation.* Before turning to our counterfactual exercise, we take advantage of a unique feature of our data that allows us to conduct a simple external validity test. As discussed in Section 3, the store assigns a score for every potential entrant 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. 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 million RMB) for each brand in Figure 1. The positive and strong relationship (the correlation coefficient is 0.735) suggests that the brand score is a good measure of a brand's sales potential from the store's perspective. We also compare the transfer offer T^*_{kt} the model predicts with the brand score. Figure 2 shows that there is also a strong and positive correlation (0.771), suggesting that the store is using brand scores to decide the transfer offers.[28] Although these results enhance our confidence in the validity of the structural model in terms of approximating how business decisions are made in our empirical context, we note that it is possible that other models could also do well under this type of external-validity exercise.

7. ADVERSE SELECTION AND CONTRACT FORMAT

In this section, we investigate how contract format affects the profit 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 what type of contract dominates the others from the store's

[27] We also estimate a version of the model without controlling for selection. The results, which are presented in Table A1, are quite different.

[28] 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 ($E(S_{kt}|I_{kt}) - T^*_{kt}$). The relationship is positive, with a correlation coefficient of 0.344. However, the relationship is weaker than that with sales revenue and transfer offers.

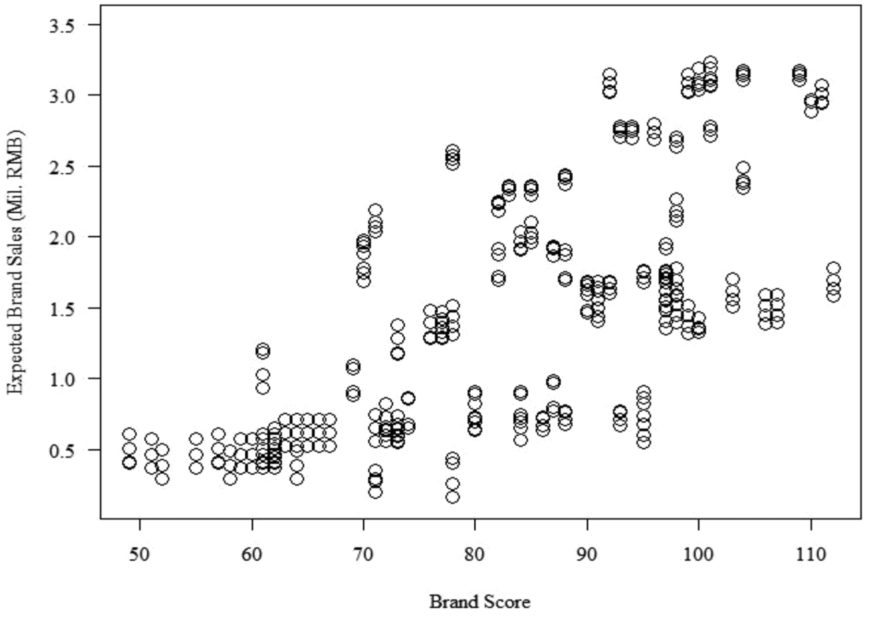

FIGURE 1

EXPECTED SALES REVENUE VERSUS BRAND SCORE

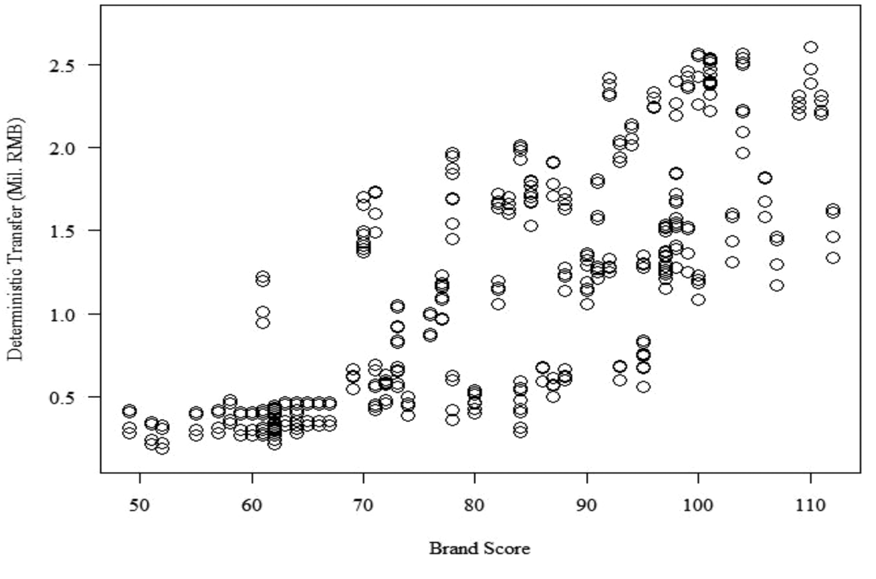

FIGURE 2

OPTIMAL TRANSFER OFFER VERSUS BRAND SCORE

perspective and how the adoption of such a contract will influence the joint profit of both the store and the manufacturers.

7.1. *Vertical and Share Contracts.* To conduct these counterfactual experiments, we must first derive the optimal offers under vertical contracts and share contracts, the corresponding expected store values, and the predicted market outcomes.

7.1.1. *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.[29] The manufacturer will accept the offer only if the profit is higher than the production cost and the outside option value:

$$W_{kt} - x_{kt}^{co}\alpha \geq \nu_{kt}^{o} + \omega_{kt} \equiv \mu_{kt}. \tag{14}$$

Assuming that the cost shock (to the retailers) μ_{kt}, which is the sum of the manufacturer's private information about its outside option value and its entry costs, has a normal distribution with standard deviation σ_μ,[30] the store expects that the manufacturer will accept the offer with probability

$$p_{kt}(W_{kt}) = \Phi\left(W_{kt}/\sigma_\mu - x_{kt}^{co}\alpha/\sigma_\mu\right). \tag{15}$$

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

$$\begin{aligned} \max_{\{W_{1t},\ldots,W_{kt}\}} E(V_t^s|\Psi_t^s) = \sum_k \int \Bigg[& x_{kt}^d\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} I\left\{x_{k't}^{d,l} == x_{kt}^{d,l}\right\} p_{k't} + x_{kt}^s\delta + \xi_{kt} - W_{kt}\Bigg] \\ & * I\left\{W_{kt} - x_{kt}^{co}\alpha^{co} - \mu_{kt} \geq 0\right\} dF(\xi_{kt}, \mu_{kt}), \end{aligned} \tag{16}$$

where F is the joint distribution function of the demand shock (to the store) ξ_{kt} and μ_{kt}.[31]

7.1.2. *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:

$$s_{kt} \cdot E\left(S_{kt}|\Psi_t^k\right) - x_{kt}^{co}\alpha \geq \mu_{kt}. \tag{17}$$

The expectation operator E denotes the manufacturer's expectation conditional on its information set Ψ_t^k. That is, $E(S_{kt}|\Psi_t^k) = x_{kt}^d\beta + \sum_{l=1}^{L}\gamma_l\sum_{k'} I\{x_{k't}^{d,l} == x_{kt}^{d,l}\}p_{k't} + \xi_{kt}$. Substituting into the above equation, the store's (and other manufacturers') predicted probability that the manufacturer k will enter is

$$\begin{aligned} p_{kt}(s_{kt}) = \int I \Bigg\{ & s_{kt} \cdot \left(x_{kt}^d\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} I\left\{x_{k't}^{d,l} == x_{kt}^{d,l}\right\} p_{k't} + \xi_{kt}\right) - x_{kt}^{co}\alpha - \mu_{kt} \geq 0 \Bigg\} \\ & \times dF(\xi_{kt}, \mu_{kt}). \end{aligned} \tag{18}$$

[29] This is equivalent to the case that the store offers the manufacturer a wholesale price for each unit of product and commits to purchasing a fixed quantity at the beginning of each period. Due to the production and shipping lead time, it is common practice in many industries, including the clothing industry, that retailers have to place purchase orders before a selling season starts.

[30] 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.

[31] As ξ_{kt} and μ_{kt} may be correlated, I cannot simply be replaced by the entry probability function p here.

The objective of the store is to offer an optimal share to each of the manufacturers such that it can maximize its expected value:

$$
\begin{aligned}
(19)\quad \max_{\{s_{1t},\ldots,s_{kt}\}} E(V_t^s|\Psi_t^s) = {} & \sum_k \int \left[(1-s_{kt}) \left(x_{kt}^d \beta + \sum_{l=1}^{L} \gamma_l \sum_{k'} I\left\{ x_{k't}^{d,l} == x_{kt}^{d,l} \right\} p_{k't} + x_{kt}^s \delta \right) + \xi_{kt} \right] \\
& * I\left\{ s_{kt} \cdot \left(x_{kt}^d \beta + \sum_{l=1}^{L} \gamma_l \sum_{k'} I\left\{ x_{k't}^{d,l} == x_{kt}^{d,l} \right\} p_{k't} + \xi_{kt} \right) - x_{kt}^{co} \alpha - \mu_{kt} \geq 0 \right\} \\
& \times dF(\xi_{kt}, \mu_{kt}).
\end{aligned}
$$

To calculate the store's expected value, we simulate $\{\xi_{kt}^{sim}, \mu_{kt}^{sim}\}$, $sim = 1, \ldots, NS$, under different assumptions about how ξ_{kt} and μ_{kt} are correlated. We then calculate the expected value under vertical contracts (using Equation (16)) and under share contracts (using Equation (19)), as the average of the store value under each simulation draw.[32]

Finally, we note that as the demand and cost functions described in Section 4 were not derived from primitives, we assume that they are policy invariant for the purpose of our counterfactual simulations. Given the counterfactuals we consider, this is likely a reasonable assumption; for example, we assume that changing the contract structure would not affect the manufacturers' outside options or the effect of brand attributes on sales.

7.2. *Adverse Selection under Information Asymmetry.* Before turning to the simulation results, we consider the theoretical factors influencing which contract format dominates. Adverse selection is a primary concern for the store when information asymmetry exists. Under vertical contracts, the problem will arise if manufacturers who accept payments W_{kt} because of low μ_{kt} also have low ξ_{kt} in the sales revenue function. As the likelihood that $I\{W_{kt} - x_{kt}^{co}\alpha^{co} - \mu_{kt} \geq 0\}$ in Equation (16) is larger for those with low ξ_{kt}, the store's expected value will be lower than if μ_{kt} and ξ_{kt} are uncorrelated, that is, no adverse selection. Share contracts require manufacturers to bear part of the consequence if sales revenue is low. Since the share s_{kt} is smaller than 100%, however, the adverse selection problem is only partially solved. In contrast, transfer contracts force manufacturers to bear 100% of the demand uncertainty ξ_{kt}. Equation (6) shows that, given the same σ (standard deviation of $\upsilon_{kt} \equiv \xi_{kt} - \mu_{kt}$), the store's expected value is independent from how μ_{kt} and ξ_{kt} are correlated. The adverse selection problem thus is solved.

Naturally, adverse selection will be the most severe when ξ_{kt} and μ_{kt} are perfectly correlated. However, many of the 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 ξ_{kt} and μ_{kt} are uncorrelated, then adverse selection is not an issue.

Solving the adverse selection problem comes at a cost to the store. For the same reason that transfer contracts protect the store against adverse selection (i.e., they force manufacturers to bear 100% of the demand uncertainty, ξ_{kt}), they do not allow the store to benefit from the entry of brands who have high ξ's. In contrast, with share contracts, the store will extract some of the surplus from manufacturers who choose to enter because they have high ξ's.

We have only estimated σ, the standard deviation of the combined stochastic terms $\nu_{kt} \equiv \xi_{kt} - \mu_{kt}$. In the baseline 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 ξ_{kt} and μ_{kt} from

[32] When we analyze the market outcomes under vertical and share contracts in counterfactual experiments, we assume that if there are multiple sets of equilibrium, the store can choose the equilibrium that maximizes its expected value, which pins down a unique equilibrium.

TABLE 6

MARKET OUTCOMES UNDER COUNTERFACTUAL CONTRACTS AND CORRELATIONS BETWEEN SALES REVENUE AND COST—$\sigma_\xi^2 = \sigma_\mu^2$

Correlation between Sales and Cost	Store Value (million RMB)			Manufacturers' Total Profit (million RMB)			Joint Channel Value (million RMB)			Number of Entrants		
	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer
0	32.74	31.61	32.72	11.80	11.01	16.29	44.54	42.61	49.01	42.53	44.32	48.19
0.1	32.68	30.53	32.72	11.87	11.40	16.29	44.55	41.93	49.01	42.60	44.55	48.19
0.2	32.69	29.24	32.72	11.95	12.36	16.29	44.64	41.60	49.01	42.79	45.51	48.19
0.3	32.43	27.74	32.72	12.05	12.85	16.29	44.48	40.59	49.01	42.73	45.29	48.19
0.4	32.18	25.94	32.72	12.15	13.79	16.29	44.33	39.73	49.01	42.72	45.68	48.19
0.5	31.86	23.70	32.72	12.32	14.62	16.29	44.18	38.33	49.01	42.79	44.06	48.19
0.6	31.54	21.09	32.72	12.58	14.64	16.29	44.11	35.73	49.01	43.03	41.44	48.19
0.7	30.96	17.50	32.72	12.99	14.74	16.29	43.95	32.24	49.01	43.39	38.38	48.19
0.8	29.93	12.43	32.72	13.78	15.75	16.29	43.71	28.18	49.01	44.02	35.19	48.19
0.9	27.09	4.90	32.72	15.96	9.46	16.29	43.04	14.36	49.01	45.69	18.33	48.19

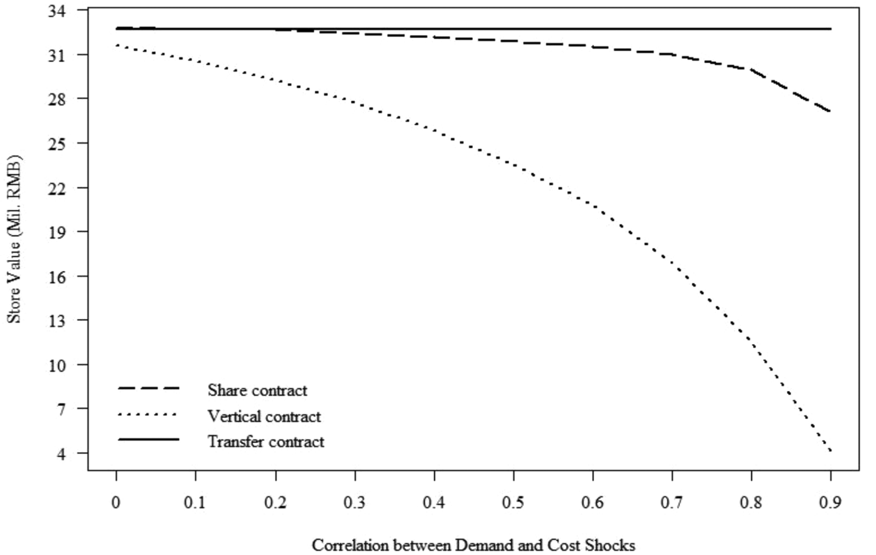

FIGURE 3

CHANGE IN THE STORE VALUE AS THE CORRELATION BETWEEN DEMAND AND COST SHOCKS VARIES, $\sigma_\xi^2 = \sigma_\mu^2$

0 to 0.9, indicating different degrees of adverse selection.[33] Under each counterfactual contract scenario, we calculate in year 4, the last year of our data, the optimal deterministic transfer offers $T^* = \{T_{14}^*, \dots, T_{K4}^*\}$ derived in Subsection 4.2, the optimal lump-sum payments $W^* = \{W_{14}^*, \dots, W_{K4}^*\}$, or share rates $s^* = \{s_{14}^*, \dots, s_{K4}^*\}$, as described above. Based on these optimal contract offers, we simulate manufacturers' entry decisions and sales revenue, manufacturers' profits, and the store's value conditional on entry. Table 6 reports the detailed results.

Figure 3 graphically illustrates how the store's value under the three contract formats changes following the increase of the correlation between ξ's and μ's. The first notable result is that the store's value under transfer contracts remains constant as the correlation varies, confirming that this contract structure can fully solve the adverse selection problem. In contrast, the store's value decreases with a larger correlation under share and vertical contracts. In particular, the

[33] As the correlation changes, we adjust σ_ξ and σ_μ such that the standard deviation of ν_{kt} remains σ.

TABLE 7
MARKET OUTCOMES UNDER COUNTERFACTUAL CONTRACTS AND CORRELATIONS BETWEEN SALES REVENUE AND COST—$\sigma_{\xi}^2 = 0.5\sigma_{\mu}^2$

Correlation between Sales and Cost	Store Value (million RMB)			Manufacturers' Total Profit (million RMB)			Joint Channel Value (million RMB)			Number of Entrants		
	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer
0	32.57	32.10	32.72	12.44	12.93	16.29	45.01	45.03	49.01	42.85	45.97	48.19
0.1	32.33	31.16	32.72	12.59	12.79	16.29	44.92	43.95	49.01	42.77	44.66	48.19
0.2	32.18	30.16	32.72	12.78	13.56	16.29	44.96	43.72	49.01	42.91	45.12	48.19
0.3	31.87	29.03	32.72	12.97	13.98	16.29	44.83	43.01	49.01	42.84	44.71	48.19
0.4	31.68	27.58	32.72	13.26	15.04	16.29	44.94	42.62	49.01	43.08	45.10	48.19
0.5	31.44	25.94	32.72	13.65	15.18	16.29	45.09	41.11	49.01	43.41	43.26	48.19
0.6	31.25	24.03	32.72	14.12	15.98	16.29	45.36	40.01	49.01	43.89	42.25	48.19
0.7	30.70	21.48	32.72	14.92	15.96	16.29	45.62	37.44	49.01	44.38	38.91	48.19
0.8	29.79	18.64	32.72	16.27	17.02	16.29	46.06	35.67	49.01	45.36	36.26	48.19
0.9	27.91	14.53	32.72	18.96	19.20	16.29	46.87	33.73	49.01	46.77	33.10	48.19

store value under vertical contracts is very sensitive to increases in the correlation. The value change under share contracts is less dramatic because, first, the store only bears part of the sales revenue loss and, second, brands with very low ξ's will choose not to enter.

Transfer contracts bring the highest store value in most of the scenarios. Only in the absence of adverse selection (i.e., when the correlation is close to 0) do share contracts bring the store a higher value than transfer contracts. Compared with transfer contracts, share contracts enable the store to extract surplus from brands who have high ξ's. This benefit may overcome the loss due to adverse selection if the correlation between the demand and cost shocks is low. However, when the correlation is positive, transfer contracts (which fully solve the adverse selection problem) are the best contract choice for our store.

To further illustrate this point, we conduct the same counterfactual exercise but no longer assume that the standard deviations for ξ_{kt} (σ_ξ) and μ_{kt} (σ_μ) have equal magnitude. In Table 7, we assume that $\sigma_\xi = 0.5^*\sigma_\mu$, and in Table 8 we assume that $\sigma_\xi = 2^*\sigma_\mu$. When $\sigma_\xi = 0.5^*\sigma_\mu$, the variance of the demand shock is small, and therefore the cost of eliminating adverse selection by using transfer contracts is small. Accordingly, the transfer contract is always optimal from the store's perspective, which can be seen in Table 7. In contrast, when we assume that $\sigma_\xi = 2 * \sigma_\mu$, the variance of the demand shock is large, and using transfer contracts to eliminate adverse selection requires forgoing a lot of surplus extraction. In that case, the transfer contract is only optimal from the store's perspective when there are considerable levels of adverse selection, that is, the correlation between ξ_{kt} and μ_{kt} is greater than 0.7, as can be seen in Table 8.

This result 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 have a stronger incentive to adopt transfer contracts. With a more established quality monitoring and information system in the retail channel, adverse selection may be a lesser concern in developed economies like the United States or European countries. Therefore, share contracts may be a better choice for retailers.

Although Figure 3 suggests the dominance of transfer contracts over the alternative formats, from the store's perspective, this conclusion may be dependent on brand attributes. We therefore further investigate the performance of each brand under the three contract formats. To do this we divide brands into below-median value and above-median value. The above-median value brands have higher sales revenue, spillovers, and entry costs compared with the below-median

TABLE 8

MARKET OUTCOMES UNDER COUNTERFACTUAL CONTRACTS AND CORRELATIONS BETWEEN SALES REVENUE AND COST—$\sigma_\xi^2 = 2\sigma_\mu^2$

Correlation between Sales and Cost	Store Value (million RMB)			Manufacturers' Total Profit (million RMB)			Joint Channel Value (million RMB)			Number of Entrants		
	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer	Share	Vertical	Transfer
	33.52	30.42	32.72	12.68	8.80	16.29	46.21	39.22	49.01	45.58	41.54	48.19
0.1	33.43	29.39	32.72	12.62	9.26	16.29	46.05	38.65	49.01	45.48	42.24	48.19
0.2	33.38	28.10	32.72	12.58	9.83	16.29	45.96	37.93	49.01	45.40	42.97	48.19
0.3	33.31	26.63	32.72	12.47	10.33	16.29	45.79	36.97	49.01	45.23	43.55	48.19
0.4	33.18	24.60	32.72	12.38	11.02	16.29	45.56	35.62	49.01	45.02	44.15	48.19
0.5	33.08	22.12	32.72	12.23	11.89	16.29	45.31	34.00	49.01	44.82	44.53	48.19
0.6	32.99	18.82	32.72	12.05	13.24	16.29	45.05	32.05	49.01	44.75	45.41	48.19
0.7	32.87	14.48	32.72	11.74	12.41	16.29	44.61	26.89	49.01	44.51	40.74	48.19
0.8	32.49	8.71	32.72	11.18	13.30	16.29	43.67	22.00	49.01	43.96	38.66	48.19
0.9	31.71	0.30	32.72	9.93	2.72	16.29	41.64	3.02	49.01	42.79	8.08	48.19

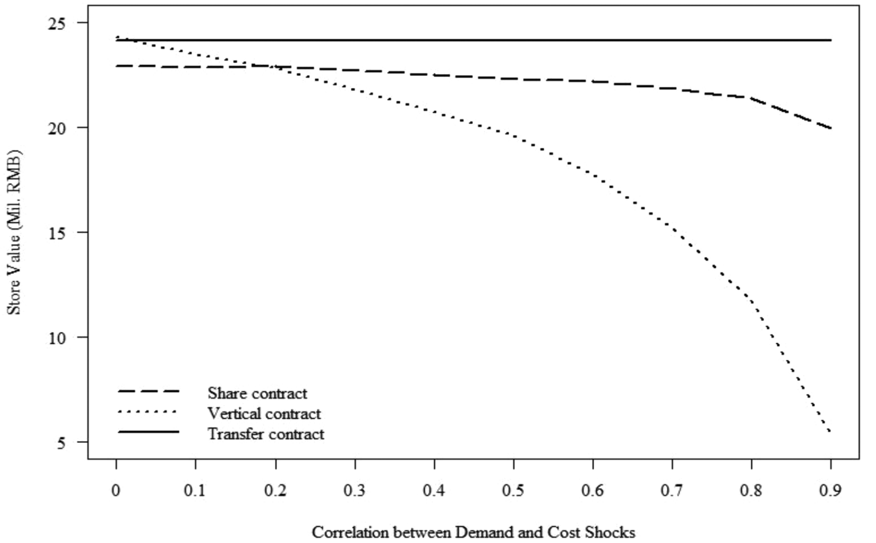

FIGURE 4

CHANGE IN THE STORE VALUE AS THE CORRELATION BETWEEN DEMAND AND COST SHOCKS VARIES—HIGH-VALUED BRANDS, $\sigma_\xi^2 = \sigma_\mu^2$

brands. They also bring a higher joint channel value (i.e., the sum of the store's value and manufacturers' profit) when they enter the store. We then repeat the exercise of Figure 3 separately for each of these two groups. The store value from the entry of high-valued brands under each of the three contract formats is illustrated in Figure 4. Note that, when there is no adverse selection, vertical contracts bring a slightly higher store value than transfer contracts. This suggests that, when the candidates are high-valued brands, the store should consider using vertical contracts as long as there is no adverse selection. When most of the candidates are low-valued brands, however, the store should use share contracts when adverse selection is not very severe, as illustrated in Figure 5. When adverse selection is a serious issue, however, the best contract format for the store is transfer-contract format.

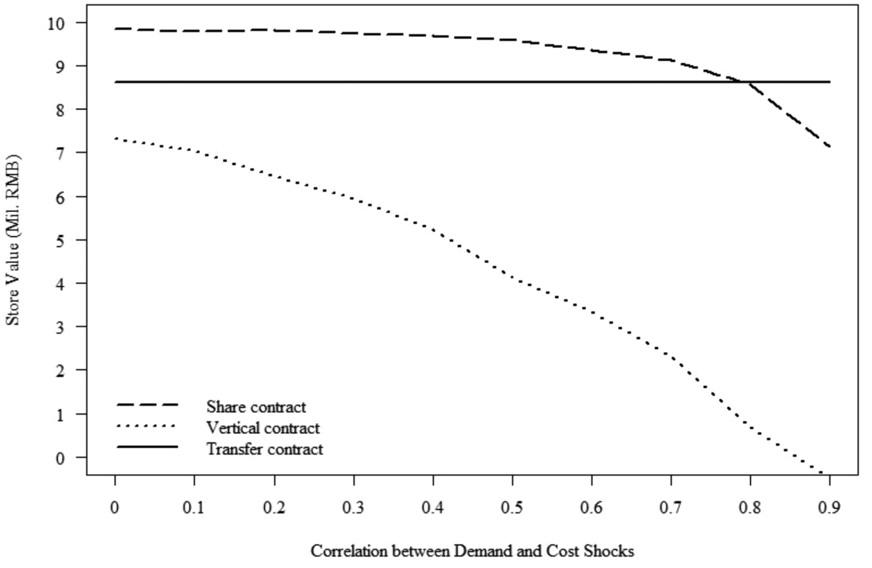

FIGURE 5

CHANGES IN THE STORE VALUE AS THE CORRELATION BETWEEN DEMAND AND COST SHOCKS VARIES—LOW-VALUED BRANDS, $\sigma_\xi^2 = \sigma_\mu^2$

Other results from Table 6 show that, when the correlation between the demand and cost shocks increases, manufacturers' total profit under vertical and share contracts may also increase. This is because the optimal lump-sum payment or the optimal share that the store offers to each manufacturer increases. Although it seems counterintuitive that the store offers can increase as the adverse selection problem worsens, the rationale is that the store has an incentive to attract brands with high ξ's to enter. When the correlation is high, those with high ξ's will choose not to enter (since they also have high μ's), unless they receive sufficiently high payments. As the store cannot distinguish brands, it has to make higher offers to all candidate brands. In contrast, the joint channel profit under vertical or share contracts is lowest when adverse selection is most severe. Under transfer contracts, the joint channel value is constant and always higher than the other contract formats.

We note that in the share- and vertical-contract formats, the store's profits are affected by the revenue shock, ε_{kt}. This is in contrast to the transfer contract. As the model effectively assumes risk neutrality on the part of the store, we can view the results as a lower bound of the attractiveness of the transfer contract. Similarly, although we do not formally model moral hazard, the transfer contract would provide the store with the most protection from moral hazard, again suggesting that the results may be a lower bound of the attractiveness of the transfer contract.

Finally, we consider an extension of the model that allows the store to have private information. Assuming that ξ_{kt} and μ_{kt} are independent, the store value is always the highest under transfer contracts. The details of that model and further discussion of the results are presented in the Appendix.

In summary, our results illustrate how transfer contracts can effectively solve the adverse selection issue and bring a higher value to the store. This provides an explanation for why department stores adopt this contract format when adverse selection is a major concern. However, solving the adverse selection problem with transfer contracts comes at a cost, as transfer contracts do not allow the store to capture as much surplus from manufacturers with high unobservable quality. As such, when adverse selection problems are minimal, transfer contracts can be dominated by alternative formats, from the store's perspective.

8. CONCLUSION

This article 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 profit impacts on both manufacturers and retailers from these alternative contract formats. A key focus of our analysis is the information asymmetry between manufacturers and retailers, which can lead to an adverse selection problem.

To address this question, 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 shed light on the economic conditions that determine both the choice of contract format and the welfare maximizing format. We demonstrate how, from the store's perspective, transfer contracts dominate the other two contract types when adverse selection is present. When adverse selection is not an issue, however, vertical or share contracts can be a better choice, depending on the value of the candidate brands.

The modeling and estimation strategies developed in this study can be extended to other empirical contexts where economic decisions have to be made through contracts involving multiple agents. For future research, it may be valuable to also model other strategic decisions, such as pricing and technology investment, in addition to firms' entry decisions. Finally, in this article, 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.

APPENDIX: AN ALTERNATIVE MODEL OF INFORMATION ASYMMETRY

The proposed entry model under transfer contracts assumes manufacturers have private information regarding demand. To test how this assumption affects the main results regarding which type of contracts is more profitable, we consider the alternative case where only the store has the private information regarding demand. Let the store's expectation of the sales of manufacturer k, conditional on the manufacturer entry and the information set x^d_{kt}, be $E^2(S_{kt}) = x^d_{kt}\beta + E^2(\sum_{l=1}^{L}\gamma_l \sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}I_{k't})$, where $I_{k't} \equiv I\{k' \text{ enters in year t}\}$, $I\{.\}$ is an indicator function. The actual sales are represented as $S_{kt} = x^d_{kt}\beta + \sum_{l=1}^{L}\gamma_l \sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\}I_{k't} + \tilde{\varepsilon}_{kt}$, where $\tilde{\varepsilon}_{kt}$ represents the deviation of the actual sales from the store's expectation.

Assume that the manufacturer obtains an unbiased but imperfect signal Z_{kt} about S_{kt} such that $Z_{kt} \sim N(E^2(S_{kt}), \sigma_\xi)$, and uses the signal to form its expectation of sales. The manufacturer's expectation can be expressed as $E^1(S_{kt}) = E^2(S_{kt}) + \xi_{kt}$, where the stochastic component ξ_{kt} represents the deviation of the expectation from the store's that is normally distributed with a standard deviation σ_ξ. It represents a prediction error for the manufacturer due to the incomplete information. The manufacturer only knows the expectation $E^1(S_{kt})$ and cannot distinguish it from ξ_{kt}. The store does not know the manufacturer's ξ_{kt}, only its distribution function. We still assume that the manufacturer still has private information regarding its own entry cost and its own outside option value.

Under this setup, the optimal deterministic transfer offer T^*_{kt} can be shown to be the same as Equation (7), and the entry probability is the same as Equation (9). The model estimation, therefore, is still based on Equations (10)–(12). Estimation results, therefore, remain unchanged.

In counterfactuals, however, actual sales and profits have to be adjusted in the following way:

(1) Transfer contracts: The store's expected value given T^*_{kt} remains the same. The manufacturer's expected profit net of the outside option value is $T^*_{kt} - x^{co}_{kt}\alpha^{co} - \mu_{kt}$, where $\mu_{kt} \equiv \omega_{kt} + \nu^{o}_{kt}$.
(2) Vertical contracts: ξ_{kt} does not enter Equation (16). Therefore, the optimal lump-sum payment W^*_{kt} differs from the case of manufacturers having private information on demand. The store's expected value will adjust by the change of W^*_{kt}. The manufacturer's expected profit net of the outside option value is $W^*_{kt} - x^{co}_{kt}\alpha^{co} - \mu_{kt}$.
(3) Share contracts: ξ_{kt} does not enter the first line of Equation (19) but remains the same in the second line. The optimal share s^*_{kt} thus differs from the case of manufacturers having private information on demand. The store's expected value will adjust by the change of s^*_{kt}. The manufacturer's expected profit net of the outside option value is $s^*_{kt} \cdot (x^d_{kt}\beta + \sum_{l=1}^{L} \gamma_l \sum_{k'} I\{x^{d,l}_{k't} == x^{d,l}_{kt}\} p_{k't} + \xi_{kt}) - x^{co}_{kt}\alpha^{co} - \mu_{kt}$.

In the simulation exercise, we only consider the case where ξ_{kt} and μ_{kt} are independent. This is because the former represents a random signal the manufacturer receives, so it is unlikely to correlate with the cost and outside option value shocks. We also assume that $\mathrm{var}(\xi_{kt})$ is equal to $\mathrm{var}(\mu_{kt})$, and that $\tilde{\varepsilon}_{kt}$ is i.i.d. across brands with expected value equal to 0.

We present the results in Table A3. The optimal deterministic transfer under transfer contracts is the same under either information asymmetry assumption, that is, whether the

TABLE A1
STRUCTURAL MODEL ESTIMATES—NO SELECTION CORRECTION

Variables	Sales Revenue (β)	Brand Interaction (γ)	Cost and Outside Option Value (α)	Out-of-Category Spillovers (δ)	Scale (γ)
Constant	0.2300		0.5813*	−0.3691	
	(1.1296)		(0.3058)	(0.8459)	
Year2	0.0843		0.0872		
	(0.1223)		(0.1048)		
Year3	0.2517*		0.1967*		
	(0.1303)		(0.1144)		
Year4	0.2162		0.2291**		
	(0.1322)		(0.1112)		
Origin	0.2490	0.0054	0.2979**	0.3769	
	(1.3208)	(0.0203)	(0.1438)	(0.5699)	
Fit	0.7833**	0.0120	0.5687***	−0.2059	
	(0.3655)	(0.0256)	(0.1392)	(0.1810)	
Capital			−0.1166		
			(0.1149)		
Production			0.1445		
			(0.1241)		
Agency			−0.2316		
			(0.2892)		
Coverage	0.2399	−0.0062	0.0305	0.6468*	
	(0.1973)	(0.0124)	(0.2120)	(0.3371)	
Image	0.5110	0.0143	0.2440	0.0537	
	(0.8065)	(0.0195)	(0.1502)	(0.3081)	
Area	0.1770	0.0142	0.2069	−0.0653	
	(0.1906)	(0.0232)	(0.1403)	(0.1327)	
Extra	0.2297	−0.0326	0.1202	0.2389	
	(1.2225)	(0.0233)	(0.1558)	(1.0950)	
SD of stochastic terms (σ)					0.4232***
					(0.0815)

NOTE: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

TABLE A2
STRUCTURAL MODEL ESTIMATES—OMITTING YEAR-2 DATA

Variables	Sales Revenue (β)	Brand Interaction (γ)	Cost and Outside Option Value (α)	Out-of-Category Spillovers (δ)	Polynomial Terms (λ)	Scale (σ)
Constant	0.7864		0.8648***	0.6256	0.4623	
	(0.8226)		(0.1685)	(0.7197)	(0.8973)	
Year3	0.1128		0.1389			
	(0.1164)		(0.1161)			
Year4	0.1181		0.1211			
	(0.1128)		(0.1105)			
Origin	0.4501	0.0173	0.1113	0.7478**		
	(0.7884)	(0.0115)	(0.1964)	(0.1374)		
Fit	0.9197***	0.0091	0.7175***	−0.0761		
	(0.2702)	(0.0192)	(0.1198)	(0.0776)		
Capital			0.0738**			
			(0.0294)			
Production			−0.0466			
			(0.0291)			
Agency			−0.3836***			
			(0.1114)			
Coverage	0.0992	−0.0273**	−0.1595	−0.4282***		
	(0.2735)	(0.0125)	(0.1969)	(0.1323)		
Image	−0.1861	−0.0085	0.0005	−0.1826*		
	(0.5366)	(0.0135)	(0.1429)	(0.1054)		
Area	0.0660	0.0293	0.1966	−0.2773		
	(0.2025)	(0.0227)	(0.1459)	(0.2652)		
Extra	0.9487	−0.0275*	0.8245**	−0.4486		
	(0.9558)	(0.0164)	(0.3780)	(0.4645)		
P					8.7725***	
					(2.8976)	
P^2					−24.4237***	
					(2.2244)	
P^3					−17.3829***	
					(1.8705)	
P^4					15.0747***	
					(1.8546)	
P^5					51.8096***	
					(1.9522)	
SD of stochastic term (σ)						0.3177***
						(0.0332)

NOTE: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

TABLE A3
MARKET OUTCOMES FROM COUNTERFACTUAL CONTRACTS UNDER ALTERNATIVE INFORMATION ASYMMETRY ASSUMPTIONS

Contracts	Store Value	Manuf. Profit	Channel Value	Entry
(A) Manufacturers Have Private Information on Sales				
Share	32.74	11.80	44.54	42.53
Vertical	31.61	11.01	42.61	44.32
Transfer	32.72	16.29	49.01	48.19
(B) Store Has Private Information on Sales				
Share	29.98	12.11	42.09	47.17
Vertical	31.70	11.04	42.73	44.37
Transfer	32.72	10.81	43.53	48.19

manufacturer or the store has private information regarding demand. Therefore, the expected store value is the same. The store value under share contracts is smaller when the store has the private information on sales. This is because, under the assumption that the store has private information, ξ_{kt} represents a prediction error for the manufacturer due to the lack of information, and, as such, the store does not benefit from entrants who have high ξ's.

When comparing the three types of contracts when the store has the private information on sales, the store value is always the highest under transfer contracts. This result is even stronger than the case where only manufacturers having the private information, where under some limiting cases the share contracts can be better than transfer contracts. This suggests that the result that transfer contracts dominate share and vertical contracts, from the store's perspective, is robust when we change the information asymmetry assumption.

Intuitively, vertical contracts that allow the store to take the residuals should be a better choice for the store if the store has the private information. Our model, however, shows that this is not always the case. The reason is the following: It can be shown that

$$EV_k^S\left(T_{kt}^*\right) = P_k^2\left(T_{kt}^*\right)/\partial P_k\left(T_{kt}^*\right)/\partial T_{kt}^*$$

under transfer contracts, and

$$EV_k^S\left(W_{kt}^*\right) = P_k^2\left(W_{kt}^*\right)/\partial P_k\left(W_{kt}^*\right)/\partial W_{kt}^*$$

under vertical contracts. Based on our estimation results, $P_k(T_{kt}^*) > P_k(W_{kt}^*)$, but $\partial P_k(T_{kt}^*)/\partial T_{kt}^* < \partial P_k(W_{kt}^*)/\partial W_{kt}^*$ when averaged across brands. Therefore, transfer contracts dominate vertical contracts for the store under either information asymmetry assumption.

Overall, when manufacturers have the private information on demand, vertical contracts are typically the worst contract-format choice for the store. When the store has the private information, however, share contracts are in general the worst. This is because the key benefit of share contracts in the manufacturer private information case was that they allowed the store to extract some of the unknown demand shock. However, in the store private information case, the demand shock is observable to the store.

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