

The Rise of Modern Retail in China: An Anatomy of the Footwear Industry (Preliminary and Incomplete)

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Abstract

We analyze the transformation of retail and production activities within a set of Chinese footwear manufacturing firms. We combine administrative and survey data to document the substantial increase in the number of brand-name chain stores, often called “modern” retail, from 2006 to 2013 in this industry. The growth is accompanied by rising market share of high quality firms and more prevalent domestic outsourcing activities. We then illustrate empirically that the entrepreneur’s comparative advantage determines these observed specialization patterns in manufacturing, “traditional”, and “modern” retail, both in the cross-section and overtime. We construct and quantify a model of non-homothetic demand, retail segment choice, and industry dynamics that account for the salient features of this transition process. We find that the changing relative factor prices can account for about half of the expansion of the modern retail in our data. The income effect is quantitatively small.

1 Introduction

There is large cross-country productivity differences in retail trade. Using comprehensive nationally representative surveys of establishments from six developing countries, Lagakos (2016) shows that these economies have retail productivity, measured as value added per worker, far below the U.S level. In particular, a large fraction of this difference is explained by the lack of “modern” retail segment in developing countries.

This paper investigates the rising modern retail segment in China. With China’s income per capita level quickly approached that of the upper middle-income countries, it provides a unique opportunity to study the *transition* process from a traditional, localized retail system to “modern” retail that primarily relies on chain stores. We combine administrative and survey data to document the related empirical patterns in the Chinese footwear industry. We characterize the individual firm-level manufacturing and retail activities both in the cross-section and overtime. We then construct and quantify a model of non-homothetic demand, retail segment choice, and industry dynamics that account for the salient features of this transition process.

We allow for several distinctive supply and demand side economic forces interact in a fast-growing economy like China. On the supply side, the modern retail technology is more capital intensive than the traditional channel. Entrepreneurs of comparative advantages in modern retail gradually reallocate their resources in response to changing factor market prices in the economy. On the demand side, we allow consumers to have non-homothetic demand and to be influenced by quality ladders differently in each retail segment. Finally, the manufactured intermediate goods are traded both home and abroad. Thus the domestic retail segment choice also depends on the export demand. In sum, the rising domestic income, tighter factor markets, and declining relative export demand all contribute to the rising modern retail in the Chinese footwear industry.

Our analysis proceeds in three steps. We first provide descriptive evidence that the Chinese footwear producers substantially increased their retail activities in the past

decade. This increase is primarily driven by the establishment and utilization of retail stores, while the traditional retail channel experienced less growth. We also show that the firms which build on their retail stores increasingly specialized and outsourced a large share of the goods sold. Overall, the industry also had much faster growth in its domestic sales relative to exports.

Second, we use a set of figures and regressions to empirically illustrate that entrepreneurs differ in terms of their comparative advantage both within retail and versus manufacturing. We find that, firms with larger retail capital tends to outsource while firms of higher physical efficiency focus on production. As a consequence, for firms that use primarily the modern retail technology, their physical efficiency explains little of the variation in domestic sales. Their retail capital, proxied by the number of retail stores, on the other hand is highly correlated with domestic sales both in level and growth. In contrast, physical efficiency is the key determinant of firms which specialize in goods production and exporting.

Third and most importantly, we develop a dynamic model to quantify the importance of labor cost escalation, retail capital rental, and consumer demand in the transition from manufacturing to retail. We first utilize our detailed survey of each firm's production output and input information to measure each firm's physical efficiency. We then use our model to explain the firm's activity allocation, the choice of retail technology, as well as the joint distribution of sales, production, physical efficiency, and retail capital in the data. We implement the Simulated Method of Moments to estimate the structural parameters of our model. Our estimates imply that the relative factor price is key to the expansion of the modern retail and the income effect plays a minor role. Quantitatively our model mechanisms can account for all the increase of the rising share of the modern retail by firm number and about half of the increase by sales in the Chinese footwear industry from 2006 to 2013. The fast-rising retail capital price turns out to be the main factor that hinders the further development of the modern retail. If the retail capital

price remained unchanged between 2006 and 2013, the sales share of the modern retail in our model would be more than 10 percentage points larger.

Our paper contributes to a broad set of literature. First, our work is related to the literature that investigates the changing retail technology, in particular, the small literature that focused on developing economies. Basker (2012), Foster, Haltiwanger, and Krizan (2006), Hortascu and Syverson (2015) systematically investigated the role of new formats and technologies (such as chains and scanners) in productivity growth in the U.S. retail sector. In the developing country context, Atkin et al (2018) evaluated the welfare gains of consumers due to entry of large foreign retail chains like Walmart. Lagakos (2016) uses establishment level data across six developing countries and illustrates that the lack of modernization can be driven by the lack of complementary transportation methods. Our data and model complements those studies by providing a more detailed and dynamic characterization of how the modern retail segment grew overtime and identify additional forces behind it.

Second, our work also contributes to the literature that emphasizes demand as the major driving force of firm's survival and growth. Foster, Haltiwanger, and Syverson (2008) pioneered this empirical investigation with the U.S Census data. They find that firm's demand shifter instead of physical efficiency is more important to explain new entrant growth and long-run survival. Their findings were confirmed in Hottman, Redding, and Weinstein (2016) using detailed bar-code data of a large number of products. These empirical patterns motivate the theoretical models of Arkolakis (2010), Gourio and Rudanko (2014), Fitzgerald, Haller, and Yedid-Levi (2017) that put customer capital at the center of firm dynamics. However, since only total sales, and sometimes total quantity, are used in these studies, it is hard to evaluate the mechanisms of how demand evolve differently across entrepreneurs and overtime. Our unique survey provides both production and retail channel information for each firm, thus allowing us to directly micro-found and quantify the specific mechanism.

Finally, The broad transformation from the goods producing manufacturing sector to the service sector happened in a large number of developed economies (Herrrendorf et al, 2014). Although our focus is on the retail segment of a specific industry, we believe our theoretical channels are applicable to a much broader set of consumption goods industries. Our theoretical channel is especially related to Acemoglu and Guerrieri (2008) which relies on cross-sector capital intensity differences to generate the relative price effect. Although we rely on entrepreneur’s allocation of resources within her firm and quantify these decisions using our micro-level data.

2 Modern Retail in China: A Case Study

The Chinese retail sector experienced dramatic changes in the past few decades. It traditionally features a mix of state dominated department stores and small private entrepreneurs that typically co-agglomerated in “commodity market”. Since the late 1990s, the Chinese government gradually deregulated the entry of its retail sector. As a result, large-scale foreign big box chain stores start to emerge in a handful large Chinese metropolitans. However, it was not until the early 2000s that Chinese private entrepreneurs start to use chain retail stores as a business growth strategy to penetrate new geographic markets.

Footwear industry provides an interesting opportunity for us to investigate in greater details the retail format commonly used in Chinese consumption goods market. During 2011 to 2013, we conduct a firm survey of footwear firms in Wenzhou, China. The region is one of the major footwear production centers and accounts for close to one third of the total national output. We surveyed 303 firms based random stratified sampling. We stratify based on firm size. Since most of the domestic retail activities are concentrated in large firms, so we disproportionately oversampled large firms based on our research question. To study these firms’ dynamic behaviors, we also collected information retro-

spectively, which results in a five year panel of 2006, 2009, 2011, 2012, and 2013 ¹.

Our survey has the unique feature of collecting both production/financial and *sales* information for each firm. In particular, we surveyed each firm’s sales channel and its related volume/price. In the case where firms sell to domestic retail market, we also collect the information in terms of its number of stores and the stores’ specific function (i.e. for local distribution or directly to consumers). Overall, to our knowledge, our survey is one of the first to comprehensively trace each firm’s output to the final consumer in its various pathways. In our sample, firms sell their products broadly through three different sales modes: export processing, domestic processing, and domestic stores. While targeting different markets, export processing and domestic processing share the similarity that firms process final output for other brand names. Chinese exporters in footwear are almost always processors. In contrast, most of the domestic-oriented firms rely on opening stores. The stores have subtle function differences though. One type is completely focused on reaching the final consumers and establish firm brand recognition. We label these stores “retail stores”. On the other hand, a second type of stores are often used to distribute products to local small vendors or to department stores. We label these stores “distribution stores”. In Table 1, we report the sales channels and the number of stores that firms have used in our sample and their relative importance overtime. For easy overtime comparison, we restrict our sample to the balanced panel of the 251 firms which survive all the sample periods, but the unbalanced panel has very similar patterns. One could easily observe that while export remains important, domestic sales channel has improved way more dramatically from 2006 to 2013. In particular, the domestic stores with retail function has more than doubled its total sales in quantity, which parallels the increase in total number of stores in Table A.1.

While the sales channel is the primary focal point of our survey, large literature of Industrial Organization and International Trade also document quality differentiation

¹For the firms which enter after 2006, our sample is unbalanced. We report the overall number of observations and the descriptive statistics in our Appendix A.

Table 1: Modes of Sales (Millions of Pairs)

Year	Export Processing	Domestic Processing	Domestic Stores	
			Retail Stores	Distribution Stores
2006	22.1	3.5	8.8	3.3
2009	24.3	3.6	13.7	4.0
2011	26.8	3.2	18.1	4.8
2012	25.1	2.7	18.8	5.1
2013	25.8	2.9	19.0	5.7

as another key feature of consumption goods industry. We accordingly also collected a comprehensive sets of input information, including detailed intermediate input price and physical quantity, so we can carefully control this important source of product and firm heterogeneity. Table 2 reports the overall distribution of both input prices. Several features stand out. First, the overtime variation in input prices is small once we adjust for inflation. In fact, the nominal input price traces the inflation rate quite closely. Second, the distribution of the firm’s input prices are very dispersed, the interquartile range between the 25th and 75th percentiles are typically closely 100%. The difference between 10th and 90th percentiles are even more dramatic. This indicates large degree of quality differentiation across firms and controlling for these in our empirical analysis is important.

Table 2: Input Price Distribution (Log)

Year	p10	p25	p50	p75	p90
2006	2.15	2.49	2.95	3.45	3.87
2009	2.33	2.68	3.11	3.64	3.98
2011	2.47	2.82	3.26	3.74	4.06
2012	1.88	2.72	3.22	3.77	4.09
2013	1.87	2.77	3.25	3.81	4.14

With these basic data information introduced, we now proceed to formally define the term “modern retail” in our analysis. In the empirical literature, “modern retail” has often been used interchangeably with large “chain stores” but it is often vague in the

detailed threshold one should adopt.². We similarly use the store number to define a firm’s classification into the “modern retail” segment. However, we further refine this measure by also supplementing the information of each firm’s input price, a proxy for quality differentiation. We adopt it based on the observation that the retail stores are not only used to access the consumers but also to distance a firm’s product from its competing varieties. More specifically, we conduct a two-way clustering analysis based on the number of stores and input prices for all firms that sell domestically. Our clustering algorithm detects two distinctive types based on k-mean, with the one type of firms with significantly larger number of stores and higher input prices. We label this high type (red dots) as “modern retail” and the rest low type (blue dots) firms as “traditional retail”. Figure 1 reports the scatter plot of the analysis. We think this classification is reasonable. In particular, we find it reassuring that our definition of “modern retail” overlaps strongly with our independently surveyed function of each firm’s stores. As reported in Table 3, almost all high type firms report using their stores to directly sell to consumers. While the vast majority of the low type firms simply use their stores for local distribution. It is also worth noting that all of our empirical analysis holds if we define “modern retail” *only* based on the number of stores a firm operate³.

Table 3: Validation of Modern Retail Firms

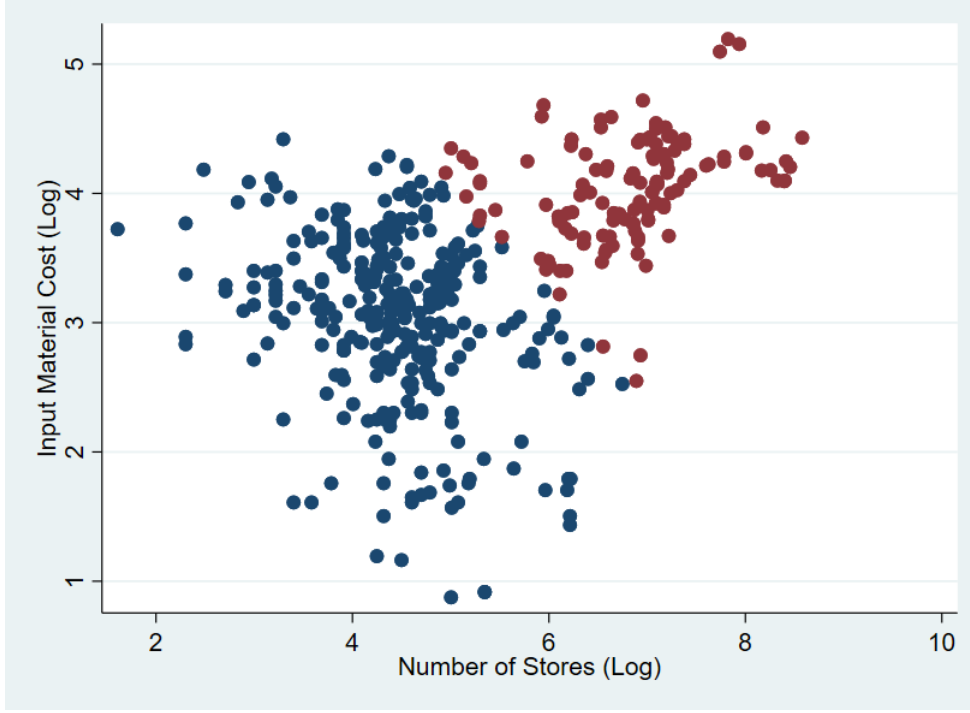
	Store for Retail	Store for Distribution
Traditional Retail	37%	63%
Modern Retail	95%	5%

Based on our definition of the “modern retail” firms, they account for 47.4% of the total domestic sales in quantity in 2006. The fraction increase to 58% during 2011 - 2013. The open question is then what are the determinants of the modern retail segment development in China.

²When there is a lack of information in the number of stores, researchers have also defined the “modern retail” segment based on the size of retail establishment.

³These alternative results are reported in Appendix A.

Figure 1: Clustering Analysis of the Modern Retail Firms



3 Empirical Analysis

In this section, we document a few additional important empirical patterns that distinguish the “modern retail” firms from their “traditional retail” counterparts. These facts help to motivate the necessary features we will need to incorporate in our structural model for quantitative analysis.

Fact 1: Modern retail firms has the lowest measured physical TFP but the largest domestic sales among all producers.

Since we collected information of each firm’s physical output and input, we can estimate the firm’s production function and construct physical TFP with our estimates⁴. Our

⁴Controlling for the quality differentiation is particularly important for the estimation of production function in a differentiated good industry, as emphasized by De Loecker and Goldberg (XXX) and Verhoogen (XXX). We will provide the details of the production function estimation in Appendix XXX.

constructed physical TFP is not *quality-adjusted* in the sense that we allow higher quality products to use *more* inputs for each unit of physical output. In Table 4, we report the distribution of sales, TFP, and the number of stores for all types of firms. In the first panel, we include the firms that operate in the domestic modern retail segment. In the second panel, we have the firms that operate in the domestic traditional retail segment. In the third panel, we have the firms that either completely export or exclusively process products for other domestic firms. These firms do not have any stores by definition.

When we compare across these three types of firms, interesting pattern emerges. First, the firms in modern retail turn out be the largest overall. Some of them export, but their primary source of income is domestic. On the other hand, these firms turn out to have lower physical TFP despite their larger scale. This indicate that demand side factors such as quality and retail stores play a predominant role in determining firm size compared with physical efficiency. Second, the firms in traditional retail have higher physical TFP, but by definition have much less stores. Their total and domestic sales are smaller than the first type. Finally, we find that the third type of firms have even slightly higher measured physical TFP and comparable total sales with the second type. Overall, the later two types have much higher (15% - 20%) physical TFP, but a lot lower in their retail capital. These patterns indicate that firms are heterogeneous in multiple dimensions and have comparative advantages in different market segments.

Fact 2: The growth in sales of exporters and traditional retail firms is highly correlated with TFP changes, this connection is significantly weaker for modern retail firms.

Motivated by Fact 1, we further investigate how firm's sales quantity overtime variation is correlated with its measured TFP changes. In Table 5, we report the results of fixed effect regressions of domestic sales in quantity on the measured physical efficiency, controlling for a full set of year dummies, input prices, and firm fixed effects. We report the results of the three types of firms, modern retail, traditional retail, and exporters/OEM separately in columns 1 to 3. The contrast between columns (1) - (3) illustrate the increasing impact

Table 4: Firm Heterogeneity in the Cross-Section 2011-2013

	Sales (10,000CNY)	Domestic Sales (10,000CNY)	Physical TFP	Number of Stores
Firms with Modern Retail				
p25	10643	8365	-.124	456
p50	21211	18592	.053	839
p75	40685	35050	.219	1217
Firms with Traditional Retail				
p25	2386	1764	-.014	50
p50	3800	3000	.222	80
p75	6000	4640	.478	130
Exporting and OEM Firms with No Stores				
p25	2305	0	-.002	0
p50	4550	0	.171	0
p75	8337	0	.410	0

of physical efficiency when we move from modern retail segment towards the producers who primarily conduct only manufacturing activities. While the elasticity of sales with respect to the TFP is 0.347 for the modern retail firms, it almost tripled for traditional retail and exporters at 0.947 and 1.160.

Table 5: Domestic Sales Growth vs TFP

	(1) Traditional Retail	(2) Modern Retail	(3) Export and Domestic Processing
TFP	0.947*** (0.191)	0.347 (0.256)	1.160*** (0.113)
lnpm	-0.190* (0.111)	0.142 (0.128)	-0.015 (0.044)
Observations	116	114	278

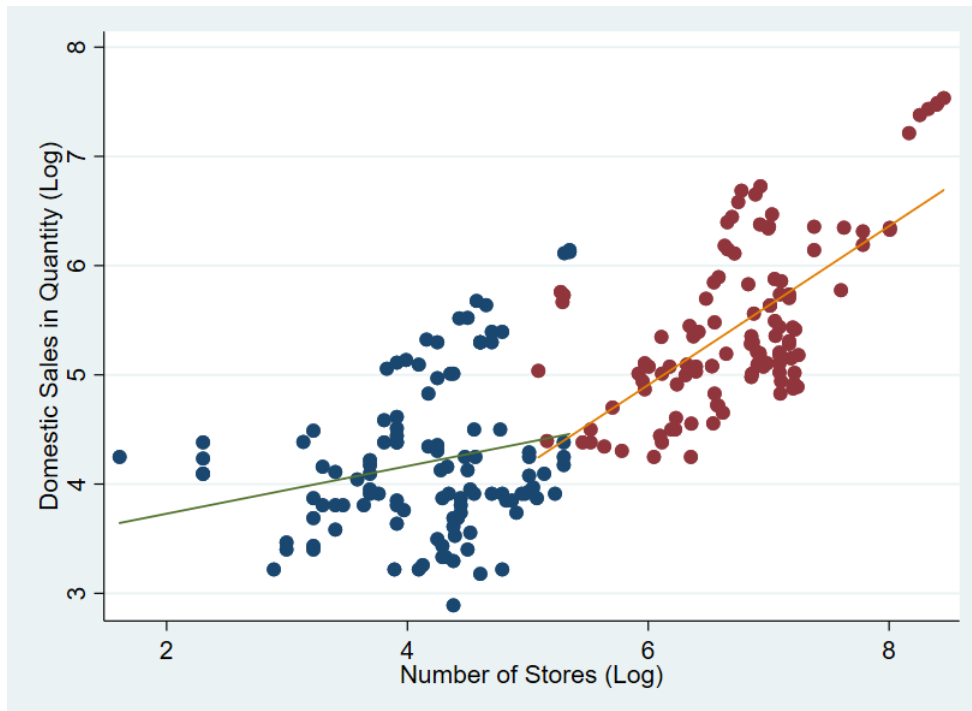
Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Fact 3: Domestic sales is strongly correlated with the number of retail stores in the modern retail segment in the cross-section and overtime. The correlation is much weaker in traditional retail.

In Figure 2, we scatter plot the log domestic sales in quantity vs the log number of stores that a firm operate. The red represents the modern retail firms, while blue represents the traditional retail firms. The estimated elasticity is around 0.731 for the modern segment and 0.214 for the traditional segment⁵. In other words, while the log retail sales is strongly correlated with the number of stores for modern retail firms, this relationship is a lot flatter for traditional retail firms. The evidences indicate that the stores in these two retail segments could use quite heterogeneous technologies for different functions.

Figure 2: Domestic Sales vs Number of Stores



⁵We also fit the scatter plots with a flexible local polynomial curve with confidence intervals. The differential relationship is robust.

Fact 4: The probability of a firm outsourcing is increasing in its number of retail stores and decreasing in its measured tfp (controlling for input price). The probability of a firm processing for other firms, in contrast, is increasing in its measured tfp (controlling for input prices).

In table 6, we report the cross-sectional pattern of firm's outsourcing and OEM decisions.⁶ In column 1, we report the coefficients of a Probit model of the firm's discrete outsourcing decision. We find that it is negatively related to measured TFP. Conditional on TFP, it is positively related to the number of retail stores, the proxy for retail capital. These again indicate that firms tend to exploit their comparative advantage. Similarly, column 2 provides the Probit estimates of the discrete OEM/processing decision. Again the probability that a firm is processing for other firms is positively correlated with measured TFP but negatively correlated with retail capital.

Table 6: Firm Outsourcing and Processing Decisions

	(1)	(2)
	Prob. of Outsourcing	Prob. of Processing
ln(store)	0.822*** (0.222)	-0.351*** (0.082)
TFP	-0.386 (0.470)	1.145*** (0.290)
lnpm	0.486 (0.340)	0.985*** (0.215)
Observations	294	294

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Overall, all of these empirical facts indicate that the Chinese footwear firms have a

⁶These decisions are quite persistent in our data and potentially involve long-term considerations and sunk costs, thus it is hard to investigate overtime changes with a short panel.

rich set of decisions to make in its production and retail activities. Firm's sales performance are determined by different factors in the processing, traditional retail, and modern retail segments. Entrepreneurs decide on which segment to operate based on their comparative advantages. We will next construct a simple model that is consistent with these basic elements and provide some theoretical intuitions for the overtime transition of this industry.

4 A Simple Model

We consider an economy where factor prices are exogenous. In the simple model, we assume a representative manufacture that produces Q units of homogenous intermediate goods. Q will be endogenously determined by firm production in the full-blown model. There are a large number of firms and the same number of differentiated final goods. Each firm produces one variety of final goods. Firms can convert intermediate goods costlessly into final goods in a one-to-one fashion. The right of making differentiated final goods is exclusive: Final goods i can only be produced by firm i . Such an exclusive right grants each firm the monopoly power over its own goods. Design, brand name and sales network are among many channels through which firm can build up the exclusive right.

4.1 Households

We adopt the standard logit model to model consumer preferences. Individual consumer k has the indirect utility function for each variety i in segment j as

$$u_{ki}^j = \chi_i^j R - \sigma \log p_i^j + \epsilon_{ki}. \quad (1)$$

Here, variety i indicates different varieties of footwear, and segment j denotes traditional (c) and modern (d) sales channels in our context. χ_i^j is the segment-specific demand shifter, which can be interpreted as the consumer's valuation of each variety's quality in

segment j . R represents exogenous consumers' income. $\sigma > 1$ is the price elasticity. p_i^j denotes the retail price of variety i sold through channel j . ϵ_{ki} represents consumer k 's idiosyncratic taste over different varieties and is drawn from identical and independent type-I extreme value distribution.

The probability that consumer k would select variety i is

$$s_i^j = \frac{\exp(\chi_i^j R - \sigma \log p_i^j)}{\sum_{i,j} \exp(\chi_i^j R - \sigma \log p_i^j)}. \quad (2)$$

s_i^j is the market share (in terms of quantity) of variety i in segment j . Simple comparative statics give

$$\frac{\partial s_i^j}{\partial \chi_i^j} = s_i^j R > 0, \quad (3)$$

$$\frac{\partial^2 s_i^j}{\partial \chi_i^j \partial R} = s_i^j > 0. \quad (4)$$

(3) shows that varieties with higher qualities occupies higher market share, and (4) shows that such relationship is stronger as income increases.⁷

4.2 Sales Channels

Firm i converts the intermediate goods (either produced by themselves or purchased from OEM) into the i th final goods and then choose to sell it through traditional or modern channels. For traditional channel, the sales technology is

$$x_i^c = z^c l_i^c, \quad (5)$$

where x_i^c and l_i^c denote the quantity of goods sold through the traditional channel and the labor input for the traditional channel. z^c is the efficiency of the traditional channel. An example of traditional channel is the “commodity exchange markets” described above. The unit sales cost of traditional channel is w/z^c .

⁷As in Khandelval (2010), we assume there are a large number of varieties and no one can influence the market equilibrium price and quantity. Thus, the market share of any variety is negligible.

Firms may also use their own sales channel such as direct sales stores. Our interviews with Chinese footwear entrepreneurs suggest that modern channel plays a critical role in blocking counterfeit goods, building up brand name, gathering and processing consumer feedback, and improving logistics management. Despite all these advantages over traditional channel, modern channel was not adopted by most footwear manufacturers in the 1990s, a period when most shoes were sold through traditional channel. The proportion of the footwear manufacturers using modern channel as their main sales channel increased to about a third in 2013 when the survey was conducted. For the modern channel, the sales technology is

$$x_i^d = z^d k_i^d, \quad (6)$$

where x_i^d is the quantity of goods sold through modern channel, k_i^d denotes retail capital for modern channel and z^d is the efficiency of the modern channel. The unit sales cost of modern channel is r/z^d .

Two remarks are in order. First, both sales channels may use retail capital and more specifically, retail stores. The stark assumptions on sales technology are introduced to obtain analytical results that may shed light on our main mechanism. The full-blown model will adopt Cobb-Douglas sales technology with capital and labor for both traditional and modern channels. Second, we assume away firm heterogeneity in z^c and z^d , which will be introduced into the full-blown model for quantitative purposes.

The optimal pricing of goods i sold through channel j is determined by

$$\max_{p_i^j} (p_i^j - uc^j) x_i^j.$$

Here,

$$x_i^j = s_i^j (Q - Q^e), \quad (7)$$

where Q and Q^e represent total intermediate goods produced and exported, respectively. Both Q and Q^e are constant in the simple model. $Q - Q^e$ is the quantity of goods sold

in the domestic market.

$$uc^j = \begin{cases} p + \frac{w}{z^c} & \text{if } j = c \\ p + \frac{r}{z^d} & \text{if } j = d \end{cases} \quad (8)$$

represents the unit cost of traditional- and modern-channel goods (including production and sales cost).

The FOCs lead to

$$p_i^j = \frac{\sigma}{\sigma - 1} uc^j. \quad (9)$$

The sales profits from traditional and modern channel are

$$\pi_i^j = \frac{uc^j}{\sigma - 1} s_i^j (Q - Q^e). \quad (10)$$

We assume that firms can only operate in one sales channel (i.e., C and D are mutually exclusive). This assumption is consistent with the fact that most firms specialize in one sales channel in our sample. It also simplifies substantially the following analysis. We will allow firms to operate in both sales channels as a robustness check. Under the assumption that firms have to choose between traditional and modern channels, their choice will simply depend on which sales channel delivers more profits. Specifically, (9) and (??) show that firm i would choose modern channel if

$$\Delta\chi_i \equiv \chi_i^d - \chi_i^c > \frac{(\sigma - 1)}{R} \log \left(\frac{p + r/z^d}{p + w/z^c} \right)^{\sigma-1} \equiv \tilde{\chi}. \quad (11)$$

It is straightforward that $\partial\tilde{\chi}/\partial r > 0$, $\partial\tilde{\chi}/\partial w < 0$ and $\partial\tilde{\chi}/\partial R < 0$ – i.e., lower interest rate, higher wage rate or higher income would push more firms to choose modern channel. The effect of p is ambiguous. In what follows, we will consider a special case where the unit sales cost is equalized across the two sales channels: $r/z^d = w/z^c$. There, $\partial\tilde{\chi}/\partial p = 0$.

(11) also reveals a sorting mechanism that works on the demand side. If $\chi_i^d - \chi_i^c$ increases in the quality of the variety, only varieties with sufficiently high quality will be sold through the modern channel.

4.3 Market Clearing

The total expenditure on final goods is $R = R^c + R^d$, where $R^j = \sum_{i \in j} p_i^j s_i^j (Q - Q^e)$. The goods market clearing condition is

$$R = (Q - Q^e) \left(\sum_{i \in c} p_i^c s_i^c + \sum_{i \in d} p_i^d s_i^d \right). \quad (12)$$

(12) solves the intermediate goods price p .

Lemma 1 *The equilibrium intermediate goods price exists and is unique.*

The detailed proof is in the appendix.

Let $X^j \equiv \sum_{i \in j} s_i^j (Q - Q^e)$ denote the quantity of goods sold through channel j .

Lemma 2 *Fixing p , $\partial X^d / \partial r < 0$, $\partial X^d / \partial w > 0$ and $\partial X^d / \partial R > 0$.*

To see the results, let us first differentiating X^d with respect to r yields

$$\frac{\partial X^d}{\partial r} = \underbrace{\sum_{i \in EX^d} s_i^d (Q - Q^e)}_{\text{extensive margin}} + \underbrace{\sum_{i \in INC^d} \frac{\partial s_{ij}^d}{\partial \log p_i^d} \frac{\partial \log p_i^d}{\partial r} (Q - Q^e)}_{\text{intensive margin}} \quad (13)$$

where EX^d denotes the set of firms entering or exiting the modern sales channel due to $\partial \tilde{\chi} / \partial r$; INC^d denotes the set of firms staying in the modern sales channel. (13) illustrates the three channels through which r may affect X^d . The first term on the RHS captures the effect that moves firms between traditional and modern channels. As discussed above, since $\partial \tilde{\chi} / \partial r < 0$, a lower r would make more firms to switch from traditional to modern channel. This would increase X^d . The second term captures the intensive margin. Since $\partial s_i^j / \partial \log p_i^j = -\sigma s_i^j$, together with the fact that a lower r lowers both firm's unit cost of modern-channel goods and their retail price ($\partial p_i^d / \partial r > 0$), we confirm that $\partial X^d / \partial r < 0$. The proof for $\partial X^d / \partial w > 0$ and $\partial X^d / \partial R > 0$ is analogous.

The effects of r , w and R on X^d under endogenous p is more involved. We invoke the assumption of equal unit sales cost across traditional and modern channels, $r/z^d = w/z^c$,

to guarantee $dX^d/dp = 0$. To see this, note that when firms face exactly the same sales costs across the two channels, any variation in the intermediate goods price would have zero effect on the modern retail price relative to the traditional retail price, which is always equal to one. This establishes our main proposition.

Proposition 1 *In the neighborhood of $r/z^d = w/z^c$, $dX^d/dr < 0$, $dX^d/dw > 0$ and $dX^d/dR > 0$.*

The proposition shows that lower r , higher w or R will lead to an expansion of the modern channel.

5 The Full-Blown Model

We enrich the simple model by introducing the following elements: (i) firm production of intermediate goods; (ii) heterogeneity of sales efficiency in both traditional and modern channels; (iii) imperfect substitution between the traditional and modern sales channels. The full-blown model will serve as a workhorse for quantitative exercises in the next section.

5.1 Production

We maintain the assumption that each firm can costlessly convert the intermediate goods into its own final goods in a one-to-one fashion. The right of making differentiated final goods is exclusive: Final goods i can only be produced by firm i . Such an exclusive right grants each firm the monopoly power over its own goods. Design, brand name and sales network are among many channels through which firm can build up the exclusive right.

Denote x_i the quantity of final good i . Firms with $q_i \neq x_i$ will trade in the intermediate goods market. Those with $q_i > x_i$ sell the intermediate goods and, hence, are considered as OEMs. Those with $q_i < x_i$ undertake outsourcing. $x_i = x_i^c + x_i^d$, where x_i^c and x_i^d denote the quantity of final good i sold by traditional and modern channel, respectively.

The aggregate intermediate goods output is

$$Q = \int e_i^\kappa q_i di, \quad (14)$$

where e_i represents the quality of the intermediate goods.

All firms can produce the common intermediate goods with a Cobb-Douglas production technology subject to quality adjustment:

$$q_i = e_i^{-\kappa} k_i^\alpha (z_i l_i)^\beta,$$

where $\alpha > 0$, $\beta > 0$, $\kappa > 0$, $\alpha + \beta \in (0, 1)$; q_i , k_i , and l_i denote the quantity of intermediate goods produced by firm i , its production capital and labor; z_i captures the labor-augmented technology. The intermediate goods market is competitive. Denote p the price of the “standard” intermediate goods (with $e_i = 1$) to one. The price of the i th intermediate goods is equal to $e_i^\kappa p$. While we observe firm-level material price, which is informative about e_i^κ , it is hard to back out e_i^κ as it is intertwined with firm TFP. We will later structurally estimate κ , which captures the magnitude of quality heterogeneity across firms. Moreover, the estimated TFP in the empirical section above does not control for quality heterogeneity. Our structural estimation can shed light on the extent to which the difference in the estimated TFP across the two channels can be accounted for by quality heterogeneity.

Denote \tilde{r} the rental price for production capital, which may differ from the rental price for retail capital r . Firms choose k_i and l_i by

$$\max_{\{k_i, l_i\}} p k_i^\alpha (z_i l_i)^\beta - \tilde{r} k_i - w l_i.$$

The FOCs imply

$$q_i = p^{\frac{\alpha+\beta}{1-\alpha-\beta}} \left(\frac{\alpha^\alpha \beta^\beta}{\tilde{r}^\alpha w^\beta} \right)^{\frac{1}{1-\alpha-\beta}} z_i^{\frac{\beta}{1-\alpha-\beta}}. \quad (15)$$

5.2 Imperfect Substitution between Sales Channels

We next extend (1) by adding channel-specific idiosyncratic preferences.

$$u_{ki}^j = \chi_i^j R - \sigma \log p_i^j + \xi_k^j + (1 - \gamma) \epsilon_{ki}, \quad (16)$$

where $\gamma \in [0, 1]$ and ξ_k^j represents consumer k 's idiosyncratic taste over different segments and is also drawn from identical and independent type-I extreme value distribution. The within-segment correlation in the utility level is governed by γ . When $\gamma = 0$, the household optimal choice reduces to the standard logit model. We further assume that χ_i^j increases in e_i – i.e., higher-quality goods are associated with stronger demand.

The probability that consumer k would select variety i conditional on channel j is

$$\begin{aligned} s_{i|j} &= \frac{\exp((\chi_i^j \gamma R - \sigma \log p_i^j) / (1 - \gamma))}{\sum_{i' \in j} \exp((\chi_{i'}^j R - \sigma \log p_{i'}^j) / (1 - \gamma))} \\ &\equiv \frac{\exp((\chi_i^j R - \sigma \log p_i^j) / (1 - \gamma))}{D_j}. \end{aligned}$$

The segment sales share, s_j , is equal to

$$s_j = \frac{D_j^{1-\gamma}}{\sum_{j'} D_{j'}^{1-\gamma}}.$$

So, the market share (in terms of quantity) of variety i sold through channel j is

$$s_i^j = \frac{\exp((\chi_i^j R - \sigma \log p_i^j) / (1 - \gamma)) D_j^{1-\gamma}}{\sum_{j'} D_{j'}^{1-\gamma}}. \quad (17)$$

5.3 Sales Channels

We allow both sales channels to adopt Cobb-Douglas technology. Specifically,

$$x_i^j = e_i^{-\kappa} (k_i^j)^{\omega^j} (\hat{z}_i^j l_i^j)^{1-\omega^j}, \quad (18)$$

where k_i^j , l_i^j denote capital and labor input for the corresponding sales channel, \hat{z}_i^j is labor-augmenting sales technology and ω^j captures capital intensity of sales channel. The unit sales cost of sales channel is $r^{\omega^j} w^{1-\omega^j} e_i^\kappa / z_i^j$, where $z_i^j \equiv \omega^{j\omega^j} ((1 - \omega^j) \hat{z}_i^j)^{1-\omega^j}$. Sales and production costs are both proportional to the quality index of the goods.

Table 7: Patterns of Production and Sales

	$\pi_i^c \geq \pi_i^d$	$\pi_i^c < \pi_i^d$
$x_i < q_i$	OEM + traditional channel	OEM + modern channel
$x_i > q_i$	outsourcing + traditional channel	outsourcing + modern channel

The unit sales cost in (8) becomes

$$uc_i^j = \begin{cases} \left(p + \frac{r^{\omega^c} w^{1-\omega^c}}{z_i^c}\right) e_i^\kappa & \text{if } j = c \\ \left(p + \frac{r^{\omega^d} w^{1-\omega^d}}{z_i^d}\right) e_i^\kappa & \text{if } j = d \end{cases}. \quad (19)$$

The pricing equation (9) and profits (10) are now

$$p_i^j = \frac{\sigma/(1-\gamma)}{\sigma/(1-\gamma)-1} uc_i^j, \quad (20)$$

$$\pi_i^j = \frac{uc_i^j}{\sigma/(1-\gamma)-1} s_i^j (Q - Q^e). \quad (21)$$

Firm i would choose modern channel if

$$\Delta\chi_i \equiv \chi_i^d - \chi_i^c > \frac{(\sigma-1)}{R} \log \left(\frac{p + r^{\omega^d} w^{1-\omega^d}/z_i^d}{p + r^{\omega^c} w^{1-\omega^c}/z_i^c} \right)^{\sigma-1} \equiv \tilde{\chi}_i. \quad (22)$$

The full-blown model also allows us to study firm decisions on OEM vs. outsourcing. The following table shows the four types of firms classified by their production and sales modes. For example, the firms with $\Delta\chi_i \leq \tilde{\chi}_i$ have a comparative advantage in the traditional channel. Among the traditional-channel firms, those associated with high TFP would thus do OEM and belong to the category of “OEM + traditional channel”. Some of the firms would choose the modern channel when the variations in factor prices and income change their comparative advantage.

It is also straightforward that the sales of firms in the category of “OEM + traditional channel” are more responsive to their TFP as opposed to the sales of firms in the category of “outsourcing + modern channel”, which, in turn, are more responsive to their retail capital. This is exactly what we found in the empirical analysis.

6 Quantitative Exercise

6.1 Calibration

Table XXX in the appendix shows that labor share is stable among the footwear manufacturers over the sample period. β is thus calibrated to 0.51 to match the average labor share between 2011 and 2013. $\alpha + \beta$ is set to 0.90, implying $\alpha = 0.39$. We can also use the estimated α and β in the productivity regressions. The results are robust. We assume $\log z_i$ to follow normal distribution with mean zero and variance σ_z^2 , which is calibrated to match the standard deviation of $\log q_{it}$ averaged over 2011-13. Since $1 - \alpha - \beta = 0.1$, we get $\sigma_z = 0.094$.

The rental price for production is set to match the aggregate capital return of 10% plus capital depreciation of 5% (see, e.g., Bai, Hsieh and Qian, 2006; Hsieh and Song, 2015). This gives $\tilde{r} = 0.15$. The wage rate, w , is calibrated to match the observed aggregate capital-labor ratio of 0.93 for production, where capital is measured by the value of machines (10 thousand Yuan). Since $K/L = (\alpha w / (\beta r))^{1-\alpha-\beta}$, we have $w = 0.13$. We set Q^e such that exports account for 49% of the total intermediate goods, which is the average share for 2011-13. We don't have good data to back out r , the rental price for retail capital. So we simply let $r = \tilde{r}$. As shown in (19), r cannot be separately identified from z_i^c and z_i^d . The level of r will be absorbed by the mean of retail productivity that will be structurally estimated below.

We have shown before that the number of retail stores and sales quantity are highly correlated among modern-channel firms and much less so among traditional-channel firms. We regress $\log k_{it}^j$ (proxied by the number of retail stores) on $\log x_{it}^j$, with year dummies included, and the interaction term between the dummy variable (1 for modern channel and 0 for traditional channel) and $\log x_{it}^j$. The coefficients of $\log k_{it}^c$ and the interaction term are 0.54 and 0.33 (with standard error of 0.09 and 0.10). This implies $\omega^c = 0.54$ and $\omega^d = 0.87$. We can also run regressions separately for traditional- and modern-channel firms. The results are very robust.

We assume markups of 1.2, close to the estimates in the literature. Since markups are $\frac{\sigma/(1-\gamma)}{\sigma/(1-\gamma)-1}$, we set $\sigma = 6(1 - \gamma)$, where γ will be structurally estimated. Our main findings turn out to be robust to different values of markups.

6.2 Structural Estimation

We structurally estimate seven parameters that govern the distributions of unobservable sales efficiency, goods quality and preferences in traditional and modern channels. Specifically, we normalize $\log z_i^c = 0$ and assume $\log \hat{z}_i^d$ to be drawn from normal distributions with mean $E_{\log z^d}$ and variance $\sigma_{\log z^d}^2$. Three remarks are in order. First, allowing heterogeneity in retail efficiency for the traditional channel has negligible effects on our estimates, which are presented in the appendix. Second, the estimated value of $E_{\log z^d}$ should be interpreted with caution as it may also be affected by retail capital rental price. Third, the appendix also allows sales efficiency to be correlated with TFP. The correlation is estimated by targetting the observed correlation between z_i and x_i^d . The results are similar. This is primarily because the correlation between z_i and x_i^d is close to zero.

Goods quality, $\kappa \log e_i$, follows normal distribution with zero mean and variance κ^2 . We assume

$$\log \chi_i^j = \theta^j \kappa \log e_i, \quad (23)$$

with θ^j to be estimated. The variance of preference over goods sold through the traditional and modern channel is thus equal to $(\theta^c \kappa)^2$ and $(\theta^d \kappa)^2$, respectively.

The last two parameters are R in the indirect utility function, which is a function of household income, and γ that governs the substitutability between goods sold through the two channels.

We target thirteen empirical moments. For both modern- and traditional-channel firms, we use the standard deviation of their sales quantity ($\log x_i^c$ or $\log x_i^d$). (17) and (19) show that the sales dispersion disciplines the preference dispersion, θ^j , and the sales

efficiency dispersion, $\sigma_{\log z^d}$. We next use the proportion of modern-channel firms and their sales quantity share. The two moments are informative for the mean and variance of modern sales efficiency, $E_{\log z^d}$ and $\sigma_{\log z^d}$, household income R and the substitutability parameter γ , as one can see from (17) and (22).

The observed material price dispersions for traditional- and modern-channel firms reflect the quality heterogeneity and, hence, disciplines the magnitude of κ . The firms that produce higher-quality goods are associated with lower estimated TFP and more likely to use the modern channel. In our model, such selection leads to a gap of the estimated TFP between modern- and traditional-channel firms, which is the seventh empirical moment and mainly affected by κ .

To estimate θ^j , we run the following regressions:

$$\log p_{it}^j = b_0^j + b_1^j \log x_{it}^j + \varepsilon_{it}^j. \quad (24)$$

Year dummies are added. We ask the model to fit the estimated b_1^j . Note that the model predicts

$$\log p_i^j = \text{constant} - \frac{1-\gamma}{\sigma} \log x_i^j + \frac{R}{\sigma} e_i^{\theta^j \kappa}$$

where we use (23) to substitute out χ_i^j . By the pricing equation (20), we have

$$\frac{1-\gamma}{\sigma} \log x_i^j = -\log \left(p + \frac{r^{\omega^j} w^{1-\omega^j}}{z_i^j} \right) - \kappa \log e_i + \frac{R}{\sigma} e_i^{\theta^j \kappa}. \quad (25)$$

Since χ_i^j is correlated with x_i^j , the estimate of b_1^j would be biased away from $(1-\gamma)/\sigma$.⁸

$$\lim \hat{b}_1^j = -\frac{1-\gamma}{\sigma} + \frac{\text{cov}(\log x_i^j, \log \chi_i^j)}{\text{var}(\log x_i^j)}. \quad (26)$$

The estimated b_1^j is informative about θ^j and $\sigma_{\log z^d}$. While higher quality leads to higher material and retail prices, its effect on sales quantity is ambiguous. If θ^j is sufficiently large, the demand enhanced by higher quality through $\frac{R}{\sigma} e_i^{\theta^j \kappa}$ would dominate the associated higher cost through $\kappa \log e_i$ in (25), resulting in positive $\text{cov}(\log x_i^j, \log \chi_i^j)$ that

⁸That is the reason why we cannot directly back out $(1-\gamma)/\sigma$ by the regression.

attenuates the estimates of b_1^j . Since high-quality goods are more likely to be sold through the modern channel, the bias tends to be stronger for b_1^d than b_1^c . This can explain the significantly negative correlation between p_i^c and x_i^c but much weaker and even positive correlation between p_i^d and x_i^d . The magnitude of $\sigma_{\log z^d}$ matters too. More variations in the retail efficiency weaken the bias. The difference in θ^j also affects firm decisions through (11) and (22). If $\theta^c = \theta^d$, preference intensities would not affect firm's choice on sales channel.

We group goods into terciles by their quality in the modern channel. The market shares of different quality groups help to identify the income measure, R , and the substitutability parameter, γ . Specifically, we use the sales quantity shares of the high- and middle-quality group. A lower R or γ (more quality substitutability) would lead to a lower market share of the high-quality group.

The last two empirical moments are the differences of the average retail (material) price between the traditional and modern channels. They are informative about the difference between θ^j . In the extreme case where θ^j are identical, (11) and (22) imply no quality sorting between the two sales channels. The material price gap would disappear accordingly. The retail price gap would be reduced and solely determined by the sales cost difference between the modern and traditional channels.

We use Simulated Method of Moments (SMM) to estimate the eight parameters by targeting the ten moments. Appendix B lays out the detailed procedures for implementing SMM. The results are reported in the following table.

Our estimates confirm that sales channels are very different on both demand and supply sides. Both the proportion of modern-channel firms and their sales share are sensitive to $E_{\log z^d}$. The dispersion of modern-channel efficiency is statistically significant and quantitatively sizable. Lowering $\sigma_{\log z^d}$ mainly affects the proportion of modern-channel firms and the estimated b_1^d in (24). A less dispersed retail efficiency distribution leads to fewer firms with high modern retail efficiency and, thus, fewer firms choosing the

Table 8: Estimated Parameters

		Estimates	S.E.
$E_{\log z^d}$	Mean of $\log z_i^d$	-1.09	0.05
σ_{z^d}	Standard deviation of $\log z_i^d$	0.24	0.09
κ	Quality heterogeneity	0.62	0.02
θ^c	Traditional-channel demand intensity	0.45	0.02
θ^d	Modern-channel demand intensity	0.46	0.02
R	Income measure	6.76	0.93
γ	Substitutability	0.43	0.07

Table 9: Targeted and Simulated Moments

	Data	Model
Standard deviation of $\log x_i^c$	0.87	0.73
Standard deviation of sales quantity ($\log x_i^d$)	0.96	0.90
Proportion of modern-channel firms	0.31	0.35
Sum of x_i^d / Sum of x_i^c and x_i^d	0.58	0.62
Standard deviation of material price (traditional)	0.69	0.60
Standard deviation of material price (modern)	0.52	0.66
Difference of $\log z_i$ between two channels	-0.14	-0.21
Estimated b_1^c in (24)	-0.25	-0.43
Estimated b_1^d in (24)	0.02	-0.01
Market share of high-quality group (modern)	0.06	0.03
Market share of middle-quality group (modern)	0.87	0.73
Mean of $\log(p_i^d)$ - Mean of $\log(p_i^c)$	0.64	0.16
Difference of mean log material price between two channels	0.91	0.21

modern channel. Lower $\sigma_{\log z^d}$ also increases the degree of the variations in x_i^d contributed by the demand-side effect. This would bias further upwards the estimated b_1^d .

The estimation of κ is more precise. As discussed above, κ governs the dispersion of material price. A lower κ has two additional major effects on the empirical moments. First, it reduces the difference of the estimated TFP between modern- and traditional-channel firms, which does not take into account quality heterogeneity. In fact, our model suggests no difference of “true” TFP (adjusted by quality heterogeneity) between modern- and traditional-channel firms. Second, the magnitude of κ affects the estimated b_1^d in (24). A small κ would weaken the demand-side effect, resulting in a more negative correlation

between sales quantity and retail price.

The estimation of θ^j is also precise. While the estimated values of θ^j are very close, the quality sorting across the two sales channels remains significant. The average material price of goods sold through the modern channel is about 20% higher than that through the traditional channel. Nevertheless, the predicted material price gap is far smaller than that of 91% in the data. This is the major discrepancy between the predicted and observed moments.

The effects of R and γ are qualitatively similar. Both affect the proportion of modern firms, their sales share and the market shares of high- and middle-quality groups in the modern channel. Moreover, a lower R or γ would weaken the bias in the estimation of b_1^j in (24). We will conduct robustness checks by fixing the value of γ and estimating R only. The preliminary results show that our main findings are robust.

6.3 Counterfactuals

Our model suggests that changes in factor prices and income growth may contribute to the growing number of modern-channel firms and their rising sales share since 2006. We then conduct a model-based accounting exercise to illustrate the quantitative importance of each force.

China experienced a rapid wage growth over the past two decades. According to China Statistical Yearbook, the average wage growth is 13.9% per annum for urban workers between 2006 and 2013. The median wage in our survey suggests a more modest annual growth of 9.4%. We use the average of two numbers for the wage growth in our counterfactuals. On the retail capital side, our survey shows a dramatic increase of 120% in the median rental price for retail stores (annual growth of 11.9%) in the sample period. While this is in line with the land and housing price boom in China since the early 2000,⁹

⁹Fang, Gu, Xiong, and Zhou (2015) show that housing prices in real terms grew at an annual rate of 13.1% in the first-tier cities, 10.5% in the second-tier cities, and 7.9% in the third-tier cities between 2003 and 2013.

the rental price increase might be partially driven by the locality effect. For instance, more retail stores were opened in prime locations. The rental price for urban households exhibit a much more modest increase of 29% (annual growth of 4.3%) in the period. Again, we use the average of two numbers for the retail capital rental price growth in our counterfactuals. We then calibrate w and r in 2006 so that w_{13}/w_{06} and r_{13}/r_{06} match the targeted wage and rental price growth.

On the production capital side, which is not directly related to firm decision on sales channel, our survey shows that production capital grew in tandem with revenue of intermediate goods (calculated by factory gate price). The median average revenue product of capital declined by barely one percent from 2006 to 2013. Some recent estimates show a dramatic decline in China's aggregate returns to capital since the mid 2000s (i.e., Bai and Zhang, 2016; Chen et al., 2019). Bai, Hsieh and Song (2016) argue that this is primarily driven by the financial deregulation on local governments, which mainly benefit state-owned enterprises.¹⁰ This is in line with the small change in the average revenue product of capital in our survey: All the firms are privately owned. The rental price for production capital in 2006, \tilde{r}_{06} , is therefore set equal to \tilde{r}_{13} .

R cannot be directly measured as it is an indicator of income in the indirect utility. But we know that higher R would lead to higher market share of high-quality goods sold through the modern channel. So, R_{06} is calibrated to match the market share of high-quality group of 80% in 2006, which is 8 percentage points lower than the average in 2011-2013, in the model with \tilde{r}_{06} , r_{06} and w_{06} . As an external validity check, we find that changing R has little impact on the market shares in the traditional channel. This is exactly what we see in the sample: The traditional channel had highly stable market shares of high- and middle-quality groups.

The following table reports the counterfactual results. The proportion of modern-channel firms and their sales quantity increase by 5 and 11 percentage points in our

¹⁰See also the literature reviewed in Song and Xiong (2018).

Table 10: The Importance of Wages, Rental Prices, Income per Capita

Counterfactual Exercises I				
	Data		Model	
	2006	2011-2013	“2006”	benchmark
Proportion of modern-channel firms	0.26	0.31	0.28	0.34
Proportion of modern-channel sales	0.47	0.58	0.57	0.62

Counterfactual Exercises II				
	high r only	high w only	high R only	high w and R
Proportion of modern-channel firms	0.09	0.64	0.28	0.64
Proportion of modern-channel sales	0.35	0.73	0.60	0.75

sample and by 6 and 5 percentage points in our estimated model. In words, our model can well explain the increase in the modern-channel share by firm number and about half of the increase by sales quantity.

If there were only increase in the rental price of retail capital ($w_{13} = w_{06}$ and $R_{13} = R_{06}$), the proportion of modern-channel firms and sales quantity would decline by 19 and 22 percentage points. If there were only increase in the wage rate ($r_{13} = r_{06}$ and $R_{13} = R_{06}$), the shares would increase by 36 and 16 percentage points. If there were only increase in income ($r_{13} = r_{06}$ and $w_{13} = w_{06}$), the share by firm number would not change but the share by sales quantity would increase by 3 percentage points. These exercises suggest a quantitatively small income effect. In contrast, the effects of factor prices are much larger.

Increases in the wage rate and income are hard to disentangle conceptually. In the last column of the above table, we fix the retail capital rental price only – i.e., $r_{13} = r_{06}$. The model-channel share by firm number and sales quantity would increase to 64% and 75%, respectively, due to the wage and income growth. In other words, the fast-rising retail capital price appears to be the main factor that hinders the expansion of the modern channel. If the retail capital price remained unchanged, we would expect to see a substantially larger modern retail sector in 2013.

6.4 Robustness Check

We fix the value of γ to be 0.20 and 0.80. Our main results appear to be very robust with lower γ . Higher γ (lower substitutability) tends to weaken the quantitative effects. In particular, the variations in the factor prices and income growth can only lead to one percentage point increase in the sales share of the modern channel. The effect on the share of the modern channel by firm number is still quantitative sizable: The increase is about six percentage points. The order of the quantitative importance of the retail capital price, wage rate and income remain unchanged. The income effect plays, again, a minor role in the rise of the modern channel.

7 Conclusion

The modernization of the retail sector is happening in a large number of emerging economies. China is no exception. However, the detailed mechanisms behind it have not been empirically investigated extensively so far. Our paper provides one of the first micro-level studies of this process in the footwear industry of China. We illustrate novel empirical patterns of within-firm transition based on entrepreneurial comparative advantage. We also quantify the role of capital deepening, wage growth, and export demand in the overtime growths of the industry level retail activities.

Despite the fact that our study relies primarily on data from one specific industry, we believe our model mechanisms can be applied to the broader manufacturing, in particular, consumption goods sector. A natural next step is to extend our data effort to a more comprehensive set of industries and endogenize the key equilibrium objects such as interest rate and wages.

The other important lesson we learned from our analysis is how government policies affect the speed of this change. Since the export market and the domestic retail market

Table 11: Robustness Check: Estimation

Estimated Parameters					
		$\gamma = 0.2$		$\gamma = 0.8$	
		Estimates	S.E.	Estimates	S.E.
$E_{\log z^d}$	Mean of $\log z_i^d$	-1.08	0.05	-1.11	0.04
σ_{z^d}	Standard deviation of $\log z_i^d$	0.25	0.10	0.25	0.06
κ	Quality heterogeneity	0.62	0.02	0.62	0.02
θ^c	Traditional-channel demand intensity	0.45	0.02	0.45	0.02
θ^d	Modern-channel demand intensity	0.46	0.02	0.46	0.02
R	Income measure	9.68	0.26	2.43	0.07

Targeted and Simulated Moments			
		Data	Model
			$\gamma = 0.2$ $\gamma = 0.8$
Standard deviation of $\log x_i^c$		0.87	0.70 0.70
Standard deviation of sales quantity ($\log x_i^d$)		0.96	0.88 0.91
Proportion of modern-channel firms		0.31	0.36 0.31
Sum of x_i^d / Sum of x_i^c and x_i^d		0.58	0.68 0.54
Standard deviation of material price (traditional)		0.69	0.60 0.60
Standard deviation of material price (modern)		0.52	0.65 0.67
Difference of $\log z_i$ between two channels		-0.14	-0.17 -0.22
Estimated b_1^c in (24)		-0.25	-0.40 -0.36
Estimated b_1^d in (24)		0.02	0.00 0.02
Market share of high-quality group (modern)		0.06	0.04 0.04
Market share of middle-quality group (modern)		0.87	0.73 0.72
Mean of $\log(p_i^d)$ - Mean of $\log(p_i^c)$		0.64	0.13 0.17
Difference of mean log material price between two channels		0.91	0.17 0.22

is intrinsically related due to entrepreneur's investment and production decision, trade policies such as export subsidies can have the unintended consequence of slowing down domestic market integration.

Table 12: Robustness Check: Counterfactuals

Counterfactual Exercises I				
	$\gamma = 0.2$		$\gamma = 0.8$	
	“2006”	benchmark	“2006”	benchmark
Proportion of modern-channel firms	0.29	0.36	0.25	0.31
Proportion of modern-channel sales	0.62	0.68	0.53	0.54

Counterfactual Exercises II				
	high r only	high w only	high R only	high w and R
	$\gamma = 0.2$			
Proportion of modern-channel firms	0.10	0.64	0.29	0.65
Proportion of modern-channel sales	0.31	0.81	0.64	0.83
	$\gamma = 0.8$			
Proportion of modern-channel firms	0.08	0.60	0.25	0.60
Proportion of modern-channel sales	0.43	0.59	0.53	0.59

A Data Appendix

A.1 Data Summary Statistics

We report additional data summary statistics in this subsection.

Table A.1: Summary Statistics (Mean)

Year	Firms	Quant. of Sales (10,000)	No. of Stores	Production Workers
2006	251	155	183	496
2009	275	173	270	544
2011	294	195	323	596
2010	302	190	356	595
2013	303	199	361	614

A.2 Alternative Cutoffs for Private-Channel Firms

Table: Firm Numbers

	Full Sample				Balanced Panel			
	Cutoff: 50 Stores		Cutoff: 200 Stores		Cutoff: 50 Stores		Cutoff: 200 Stores	
	Traditional	Modern	Traditional	Modern	Traditional	Modern	Traditional	Modern
2006	42	68	79	31	42	68	79	31
2009	38	93	89	42	34	91	83	42
2011	32	114	99	47	28	106	87	47
2012	32	122	102	52	27	112	87	52
2013	27	128	101	54	24	115	85	54

Table: Modern Retail Share

	Full Sample		Balanced Panel	
	Cutoff: 50 Stores	Cutoff: 200 Stores	Cutoff: 50 Stores	Cutoff: 200 Stores
2006	87.2%	61.6%	87.2%	61.6%
2009	92.9%	69.0%	93.2%	69.5%
2011	94.4%	69.7%	94.5%	71.9%
2012	93.2%	70.1%	94.4%	72.8%
2013	95.6%	69.1%	95.7%	72.6%

A.3 Production Function Estimation

Consistent with the model, we have the value-added production function that

$$\ln[q_{it}(e_i)] = \alpha \ln(k_{it}) + \beta \ln(l_{it}) - \gamma \ln(e_i) + \ln(z_{it})$$

We can use two alternative empirical strategies to control for quality differences e_i . First, if we believe that quality is slow-evolving, then we can treat e_i as a permanent unobserved heterogeneity in a panel data setup. Second, we can also utilize material's unit input cost $c_m(e_i) = p_m \times e_i^{\gamma_m}$. Since we surveyed c_m , we can substitute $\ln(e_i) = \frac{1}{\gamma_m} [\ln(c_m(e_i)) - \ln(p_m)]$, thus

$$\ln[q_{it}(e_i)] = c_0 + \alpha \ln(k_{it}) + \beta \ln(l_{it}) - \frac{\gamma}{\gamma_m} \ln(c_m(e_i)) + \ln(z_{it})$$

In Table A.2, we report the production function estimates. It implies a labor coefficient $\beta = 0.534$ and capital coefficient $\alpha = 0.428$. We then can construct each producer's non-adjusted physical efficiency as $\ln(\hat{z}_{it}) \equiv \ln(z_{it}) - \gamma/\gamma_m \ln(c_m)$.

Table A.2: Production Function Estimates

	(1)	(2)
	With Input Cost	W/O Input Cost
L.lnv	0.603*** (0.094)	0.616*** (0.092)
lnl	0.517*** (0.144)	0.534*** (0.129)
L.lnl	-0.309** (0.123)	-0.321*** (0.115)
lnk	0.412*** (0.133)	0.428*** (0.107)
L.lnk	-0.247** (0.125)	-0.259** (0.117)
lnpm	-0.026 (0.102)	
L.lnpm	0.013 (0.107)	
Observations	866	869

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

B Simulated Method of Moments

This appendix explains our procedures for Simulated Method of Moments (see, e.g., Bloom, 2009).

1. Bootstrap: Denote K the total number of random samples generated by bootstrap. We use $K = 500$. Denote $g_{m,k}$ the m th moment in the k th sample. We will target $\frac{1}{K} \sum_k^K g_{m,k}$ – i.e., the moment averaged across K samples.
2. Generate the variance-covariance matrix of the bootstrapped moments, Ω . Under the estimating null, Ω is proportional to the variance-covariance matrix of the simulated moments.
3. Minimizing the weighted sum of the distance between the empirical and simulated moments:

$$\theta = \arg \min_{\theta} h(\theta)' \Omega^{-1} h(\theta)$$

where $h(\theta)$ is a vector with M elements and $h_m(\theta) = g_m(\theta) - \frac{1}{K} \sum_k^K g_{m,k}$.

4. The difference between the true and estimated parameter follows asymptotically a normal distribution with mean zero and the variance-covariance matrix of V , where $V = (DW^{-1}D')^{-1}$ and $D = \frac{\partial h(\theta)}{\partial \theta}|_{\theta=\theta}$. Note that D is a $N \times M$ matrix and V is a $N \times N$ matrix. The variance of the estimated parameters are on the diagonal of V .

C Endogenous Factor Prices

We then introduce endogenous factor prices and their dynamics. Assume that capital is owned by a representative financial intermediary, who earns rents and “consumes” investment goods. The intertemporal choice solves

$$\max_{\{C_t, I_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \rho^t d_t, \tag{27}$$

subject to

$$d_t = r_t K_t - I_t \geq 0, \quad (28)$$

$$K_{t+1} = I_t + (1 - \delta) K_t, \quad (29)$$

where $\rho \in (0, 1)$ is the discount factor, d_t stands for the “consumption” of the financial intermediary and δ is the capital depreciation rate. The subscript for time t is dropped when there is no source of confusion. The financial intermediary cannot borrow from outside, as shown by the inequality in (28).

Thanks to the linearity of the preference, the financial intermediary will save all its rental income if

$$\rho(1 + r_{t+1}) > 1. \quad (30)$$

So, $d_t = 0$ and $I_t = (r_t - \delta) K_t$ if (30) is satisfied. If the condition in (30) is reversed, the financial intermediary will downsize capital by selling it to the intermediate goods market until (30) becomes an equality.

Now we are ready to characterize the dynamics. Consider an economy with the initial capital stock $K_0 \rightarrow 0$. It is immediate that $r_0 \rightarrow \infty$. (30) is satisfied and capital grows according to (29), where $I_t = (r_t - \delta) K_t$ and $r_t = \alpha K_t^{\alpha-1} L^{1-\alpha} + \delta$. The economy will reach the steady state when $r^* \equiv 1/\rho - 1$. Denote $\hat{\chi}^{\max}$ the upperbound of $\hat{\chi}_i$. In the benchmark model, if $\hat{\chi}^{\max} < \hat{\chi}^*$, where $\hat{\chi}^*$ refers to $\hat{\chi}$ with $r = r^*$, there would be no modern channel in equilibrium dynamics. The whole dynamics would thus be similar to those in a standard neo-classical growth model.

If, instead, $\hat{\chi}^{\max} > \hat{\chi}^*$, there exists period t when r_t is sufficiently low such that the firms with $\hat{\chi}_i < \hat{\chi}^{\max}$ will switch from traditional to modern channel. Moreover, capital will evolve according to (29), where $I_t = (r_t - \delta) K_t$ and $r_t = \alpha K_t^{\alpha-1} L^{1-\alpha} + \delta$. The rise of traditional channel pushes capital out of the production sector, slows down the decline of the interest rate but speeds up the transition. The transitional dynamics will exhibit rising wage rate, falling interest rate, sales reallocation from traditional to

modern channel, and capital reallocation from production sector to sales. The transition will be complete when $r_t = r^*$.