PRL
7/25/06
1:15 PM

Pricing and Marketing Impacts of Entry by Counterfeiters and Imitators

Yi Qian*

June 27, 2006

Abstract

Counterfeit and imitative products appear similar to authentic products but usually have lower quality. However, unlike imitation, counterfeiting infringes upon intellectual property rights by claiming a brand name that it does not own. I model the pricing, quality, and marketing strategies of producers of authentic and counterfeit goods in a setting of oligopolistic competition under both complete and asymmetric information. This model explains the effects of both counterfeit and imitative entry with different parameter specifications. I collect data from Chinese shoe companies from 1993-2004 to test the theoretical predictions. Exploiting the discontinuity of government enforcement efforts for the footwear sector in 1995 and the differences in authentic companies' relationships with their local governments, I use both regular instrumental variable (IV) and IV-Bayesian Hierarchical Changepoint Model techniques (Qian, 2005) to measure the effects of counterfeit entry on authentic manufacturers' prices, qualities, and profits. The empirical results are consistent with the theoretical predictions. First, low-quality counterfeit entrants induce authentic producers to both produce higher quality products and raise prices. Second, there is empirical evidence for the presence of asymmetric information, under which authentic prices rise further to signal quality (or authenticity). However, this price-signaling effect diminishes over time. Third, other costly non-price devices are used for signaling and reducing counterfeit sales.

JEL Classification: F23,L15,C11,C42,D21,O12,O14,O34

Key words: Counterfeit, Imitation, Intellectual Property Rights, China, Pricing, Marketing, Signaling, Strategy, IV, Bayesian Hierarchical Model, Shoes.

---

*Comments are appreciated and can be sent to yiqian@kuznets.fas.harvard.edu. I am grateful to Josh Lerner, Philippe Aghion, Richard Caves, and Richard Cooper for their constant advice and encouragement; to Gary Chamberlain, Sarah Ellison, Ray Fisman, Richard Freeman, Caroline Hoxby, William Kerr, Michael Kremer, Don Lessard, Ben Olken, Ariel Pakes, Jim Stock, Lucy White, Hui Xie, Pai-Ling Yin, and participants at the NBER Productivity Seminars, Harvard Seminars on Theory, Development, I.O., International, Econometrics, and Organizational Economics, and seminars at MIT Sloan, Kellogg, Brown, RAND, SUNY, and Georgia Tech for helpful comments; to Vincent Chen for helpful discussions in early stage of the project; to Adam Block, Davin Chor, K.E. Duffin, Mercedes Delgado-Garcia, and Jean Roth for comments on drafts; and to my beloved parents for encouragement. Financial support from the Harvard CID Grants and IO Research Grants, and cooperation from the Chinese Quality and Technology Supervision Bureau and the companies I interviewed and surveyed are gratefully acknowledged.

1 Introduction

Brand names have significant economic value and a long history. From stone seals dating to 3,500 B.C. in the Middle East, to the familiar brands of our times like BMW or Nike, brand names remain popular because they offer a guarantee of quality that generic products often do not match. The inherent value that brand names carry generate incentives for imitation and counterfeiting. As a cover story in *BusinessWeek* declares, "the global counterfeit business is out of control" (February 7, 2005). The World Customs Organization estimates that 512 billion *USD* of traded world merchandise in 2004 may have been counterfeits (*BusinessWeek*, 2005). Therefore, the effects of counterfeits on market prices, original product output, and original producers' marketing strategies are important issues to address. However, they remain puzzles and the economics of counterfeiting seems to be a black box.

What is "counterfeit"? The Merriam-Webster Dictionary defines this adjective as "made in imitation of something else with intent to deceive." Counterfeiting is characterized by its infringement of Intellectual Property Rights (IPR) by claiming another's brand name and is therefore illegal. Counterfeiters usually produce products that are inferior to the authentic goods (Grossman and Shapiro, 1988), and attempt to pass them off as authentic. In contrast, imitative goods, e.g. store-brand food, are more honest about their differences from originals in terms of quality and product source. This legality is the key difference between imitative and counterfeit goods. However, like counterfeits, imitative goods typically do not incur R&D costs, but reverse-engineering costs. Some counterfeits are sold in a very different market from authentic goods (*e.g.* street corners instead of shopping malls) and therefore, are revealed as different even though they closely resemble the authentics. Would these count as counterfeits? The answer is yes, as long as they are products that violate the IPR and are marketed under brand names their producers do not own. In addressing the pricing and marketing impacts of counterfeits, I model different layers of asymmetric information: (1) counterfeiters fool consumers into believing that the product is authentic; and (2) some purchasers of counterfeits are not fooled, but they intend to fool their friends into thinking they are high class who can afford authentic products.

To study the impacts of counterfeits on market prices and authentic manufacturers' strategies, I develop a vertical differentiation model with entry and test the predictions using a new panel dataset that I collected from shoe companies in China. The main contributions of this study are twofold. First, I develop a theoretical framework that is general enough to include entry by imitators and counterfeiters, flexible enough to explain the pricing and other marketing effects of new entry, and handle both complete and asymmetric information situations. I derive the price and quality combinations that the authentic producer chooses before and after a new entry. The authentic producer will produce a higher quality product and charge a higher price if the entrant's quality is below a cutoff value. Under asymmetric information, by which I mean there is a fraction of consumers who cannot distinguish counterfeits from authentic goods when they are sold at the same price, and a probability that a consumer who wears counterfeits cannot be discerned by others, I examine the interactions among the original producers' marketing strategies. I conjecture that authentic firms can upgrade quality to escape direct competition from counterfeits and can invest in IPR enforcement activities to combat counterfeits. They may raise prices above the full-information level to signal quality, and adopt non-price signaling strategies such as establishing licensed stores, attaching holograms, *etc.*. These costly devices help authentic firms to foster their local monopoly position and push up their prices. All of these strategies will widen the parameter range for an increase in authentic price post-entry. The model also sheds light on companies' choices of product quality and on consumer surplus pre- and post-entry. Because the model is meant to predict empirical results and provide generalizable explanations for the results, I relegate detailed derivations for the model with asymmetric information to a separate paper (Qian, 2005).

The second contribution of the paper is empirical, namely gathering survey data to probe into the black box of counterfeit impacts, providing suitable instruments for various levels of counterfeit entry and sales for different brands, and applying cutting-edge Bayesian techniques to take into account the different timing with which each authentic company responds to counterfeit entry. There is a dearth of empirical studies of counterfeits or underground economics in general: the very definition of counterfeit implies "under the table" and difficult to measure. Since China faces serious counterfeit problems–around 10% of sampled shoe commodities were fake in 1998 according to the Chinese Quality and Technology Supervision Bureau– the Chinese footwear sector has a strong incentive to investigate the effects of entry by imitators or counterfeiters. I conducted surveys of Chinese shoe companies to analyze empirically the pricing and marketing effects of counterfeits. Under agreements with the authentic companies that I would keep their data confidential and provide them with results and further analyses at their request, I obtained annual data for these companies' prices, production costs, financial statements, marketing strategies, and enforcement investments from 1993-2004.[1] I also gathered data on the detailed characteristics of each type of shoe for each brand from the annual product catalogs. Counterfeiters infringe upon brands of both Multinational Corporations (MNC)

[1] I collected and analyzed city-level data as well. I found that the authentic prices do not vary a lot across regions (they differ by approximately 1 USD), which accounts for the transportation costs approximately.

and local enterprises. My data include a few MNC in China with world-renowned brands, while the other brands are Chinese in origin. I also gathered the prices, costs, quantities, and several dimensions of product characteristics of counterfeits from each authentic company's "brand protection" office, and cross-validated these data with the Quality and Technology Supervision Bureau.

A key difficulty in empirically measuring entry effects on prices, profits, and other marketing outcomes is that entry is often endogenous to these outcomes. This endogeneity problem is especially serious for counterfeit entry, because the higher the authentic producer's markup and the more valuable a brand, the more likely counterfeiters will enter to copy the brand. Under such circumstances, counterfeit entry will be positively correlated with authentic prices and profits. However, a causal link cannot be inferred from this positive correlation, even if my theoretical model is correct in predicting that entry induces the authentic producer to improve quality and increase price. In order to identify how counterfeit entry contributes to authentic quality improvement and price rise, one approach is to compare companies that have similar characteristics and yet face different entry threats. For instance, it is useful to compare two branded companies, one of which experienced counterfeits and one that did not. However, companies that appeal to counterfeiters differently may not be comparable. My IV identification strategy allows me to find occasions in which counterfeiters of a brand enter for exogenous reasons that are not related to the brand holder's price and quality prospects. In short, I seek instrumental variables that predict counterfeiters' tendencies to make "randomized" entry decisions[2].

I exploit the change in government enforcement efforts to monitor footwear trademarks around 1995 to instrument for counterfeit entry in the Chinese shoe industry. The government reallocated enforcement resources away from footwear due to a series of accidents in several other sectors, notably gas explosions and food poisonings. Counterfeiters entered the shoe markets soon after. In addition, this policy change introduced more likelihood of entry by counterfeits to authentic companies that have poor relationships with the local government than it did to authentic companies with strong ties to the government. The rationale and legislation details are explained in Section 3.2, with the basic story as follows: After the enforcement legislation change, the monitoring of counterfeits became decentralized to the company level, carried out primarily through authentic manufacturers' own initiatives to protect their own brands. However, only the government has authority to remove the reported counterfeit localities. Therefore, companies that have poor relationships with their local governments received less attention and experienced more counterfeits. I use the interaction between the enforcement legislation change and a proxy for the relationship between an authentic company

[2] The part of entry decision that is uncorrelated with authentic price, quality, or profitability.

and local government to identify entry effects (detailed in Section 3.2). While an IV methodology addresses the endogeneity concerns, there may be remaining biases in the estimates resulting from the heterogeneity in the timing of responding to entry among the sampled companies. I apply the IV estimation in a Bayesian Hierarchical Changepoint Model (IV-BHCM) (Qian, 2005) to account for this and to provide estimates for the entry effect on prices and for the average response time.

Besides the IV techniques, the panel structure of my data enables me to better correct potential omitted variables bias and helps to improve precision in the entry effect estimator. The panel analyses have the advantage of testing pre- and post-entry price (or market outcomes) changes within the same company. The pre-entry price (or market outcomes) trend of an authentic company serves as a natural control for its post-entry price (or market outcomes) trend. In addition, the study of multiple-branded companies makes the results generalizable.

The empirical results from both regular IV and IV-BHCM confirm my theoretical predictions. In particular, the prices of the authentic manufacturers who were infringed upon rose, on average, 2 years after their counterfeits entered the market. Authentic shoe quality, mostly in materials, technology, and appearance, was also greatly improved. In addition, the original companies took measures to protect their brands. They sent their employees to monitor the market, and established licensed stores to signal their quality and authenticity. The prices of the generic brands without counterfeits follow a smooth and slightly upward time trend, while the counterfeit prices remained level. Investing in enforcement activities and establishing licensed stores are also shown to be effective in deterring counterfeit entry or at least reducing counterfeit sales. Companies' own enforcement activities and various differentiation mechanics lead to a "self-enforcing" intellectual property that is prevalent even in advanced and highly institutionalized contexts. A most recent article in the *Wall Street Journal* illustrates how branded companies (Fendi as an example) implement holograms in their products to distinguish from fakes (Passariello, 2006). China therefore provides a most interesting case to study this phenomenon of general interests.

Prior literature on the effects of entry on incumbent price has been inconclusive. The general intuition is that entry would impose competition on the incumbent, thereby forcing incumbent prices and output to decrease. For instance, Fudenberg and Tirole (2000) predict that the threat of entry can lead an incumbent to set low prices for network goods. Scandizzo (2001) argues that the price and profits of original firms will decrease and consumer welfare will increase. The more skewed the income distribution is towards the poor in a nation, the greater the welfare effect and the smaller the profit effect. In practice, however, we do not always see entry accompanied by a drop in authentic prices. There are empirical analyses (Caves, *et. al.*, 1992; Frank and Salkever, 1997) and a theoretical model (Frank and Salkever, 1997) documenting and explaining an increase in branded drug prices after generics entered the U.S. pharmaceutical market. However, their model cannot be directly adopted to explain my data due to the notable differences between generic drugs and counterfeit shoes.[3] In particular, counterfeiters attempt to infringe upon brands and may generate asymmetric information complexities.

Therefore, I take into account asymmetric information and build on the literature of quality uncertainty. Price is the conventional signal for product quality, but Nelson (1974) points out the importance of advertisement as a form of non-price signal for quality. Milgrom and Roberts (1986) argue that prices are better signals for quality than non-price signals (notably advertisements) unless repeated purchase is assumed. Despite the sophistication of the previous literature, the models only considered a monopolistic market and took quality as exogenously given. Metrick and Zeckhauser (1999) use a simplified vertical differentiation framework to model competition under asymmetric information. However, their models are still confined to exogenous quality, and they derive equilibrium market shares in a price-pooling equilibrium, which is helpful for explaining certain sector equilibria but not applicable to most counterfeit markets. I argue that quality choices and non-price signaling devices can play important roles in the price rivalry context. Markets with price competition and with quality choices have many practical ramifications, the Chinese footwear industry being one example, and the theoretical predictions derived from my model can have important implications for business strategies and public policies.

The rest of the paper is organized as follows: Section 2.1 sets up the benchmark model; Section 2.2 summarizes the model under asymmetric information and the subsequent implications; Section 3 describes the empirical research design, including identification strategies and data, followed by empirical analyses and results in Section 4. Discussion and conclusions are laid out in Section 5. Appendix includes figures and tables.

[3]First, the pharmaceutical market has complicated demand structures. Typically, doctors who prescribe medicines do not directly pay for them, and studies show that doctors tend to prescribe branded drugs even when generics are available. The health care system further makes drug demand inelastic. This is not the case in other industries. Second, the vast majority of Chinese consumers are very price-sensitive because their income level (in PPP terms) is lower than that of the Americans. The switch of these consumers to counterfeits will thus leave less market base for charging a higher authentic price. Third, generics can be considered perfect substitutes for branded drugs in terms of functionality or quality, but this is not usually true with counterfeits. The last point goes back to the key differences between counterfeits and generics/imitative goods, discussed in the previous paragraph.

2 VDIC Model–Vertical Differentiation with Imitation and Counterfeiting

I build upon a vertical differentiation model to explain the pricing and marketing effects of new entry. In particular, I consider oligopolistic competition under quality differentiation. The traditional models consider two producers, each producing one pre-determined quality, high or low. I, however, introduce quality options for the authentic producer, who chooses quality according to which would yield more profits. This endogenization of quality setting by the authentic producer helps to explain her pricing and marketing strategies in response to new entry. For semantic ease, I use female pronouns for authentic incumbent and male pronouns for entrant. I first analyze price competition with given quality (one per firm) under Bertrand and Stackelberg games, and then I look at the *ex ante* choice of quality. In addition, my model analyzes the responses both in symmetric and asymmetric information settings, with the latter fitting better with practical conditions and explaining the authentic companies' signaling strategies well. In sum, my model enriches the set of instruments the authentic producers can use to combat counterfeits: prices, quality, signaling devices, and enforcement activities. The solution to the model with multiple firms is available upon request, and the intuition is very similar to the duopoly intuition. Relevant competition occurs mainly among firms that are adjacent in the quality hierarchy, and counterfeit entry affects the infringed brands most.

2.1 Benchmark Setup

2.1.1 Pre-entry

A product can be described as a bundle of characteristics: quality, brand, time, appearance, availability, consumer information about its existence and quality, and so on. Each consumer has a ranking of the mix of characteristics. In a vertically differentiated product space, all consumers agree on the most preferred combinations of characteristics and, in turn, on the preference ordering. The attribute most typically studied is quality. Most people agree that higher quality is preferable, *ceteris parabis*. For instance, a lighter and more powerful computer is preferable to a bulkier and less functional one; a more comfortable and stylish pair of shoes is preferred to a less comfortable and ugly pair. At equal prices and locations, each bundle of characteristic has a set desirability. Following the tradition of vertical differentiation models, I characterize a good with a quality index s_i, where i indexes company i. In the shoe example, this index includes various shoe characteristics such as materials used for a pair of shoes, their sturdiness, ventilation, flexibility, cushioning, responsiveness, appearance, etc. There is at first one original producer with the option of producing two qualities: $s_L = s, s_H = M * s,$ where $M > 1$. When the monopolist produces several qualities, we often consider these different qualities as representing different "goods". For now, I confine myself to a single quality/product monopolist. The additional unit costs of producing the Ms quality versus the s quality is c. The producer decides which quality to produce by comparing the respective profits that would result from each production plan.

Each consumer consumes one unit of a product or none, and derives utility $U = V * s_i - P_i$ if one unit with quality s_i is consumed at price P_i, and U equals zero if the consumer does not buy any unit:

$$U = \begin{cases} V * s_i - P_i & \text{if} \quad \text{one unit is consumed} \\ 0 & \text{if} \quad \text{zero units are consumed} \end{cases}$$

U can be thought of as the surplus derived from the consumption of the good. Notice that utility is separable in quality and price. All consumers prefer high quality, given the same price. However, consumer heterogeneity in taste is captured by V in the model: a higher V indicates more willingness to purchase a given quality. One can model V as distributed in the economy according to a density $f(V)$ with cumulative distribution function $F(V)$ on the real line $[0, +\infty)$, where $F(0) = 0$ and $F(+\infty) = 1$. $F(V)$ is therefore the fraction of consumers with a taste parameter less than V.

Assumption A1: The consumer taste for quality, V, is distributed uniformly in the interval $[0, 1]$.

An interesting transformation of the preference function reveals an alternative interpretation of V as the inverse of the marginal rate of substitution between income and quality. In deciding whether to buy a good of quality s_i, a consumer checks whether he derives positive utility, equivalently, whether $U' = s_i - (1/V) * P_i$ is positive. Here, all consumers derive the same utility (or surplus) from the product, but they have different incomes, which induce different marginal rates of substitutions (MRS) between income and quality ($\frac{1}{V}$). Wealthier consumers have a lower MRS because they face budget constraints that are less tight, and, therefore, have a higher V. This is the utility first introduced by Gabszewicz and Thisse (1979, 1980) and Shaked and Sutton (1983).

Let us derive the demand function based on the preference initially defined, if quality s_a, with $s_H = Ms, s_L = s$, is offered on the market. The lowest valuation among consumers who purchase is $\underline{V}s_a - P_a = 0$, implying that $\underline{V} = \frac{P_a}{s_a}$. This yields the demand

$$D(P_a) = \begin{cases} \int_{\underline{V}}^{1} f(V)dV = 1 - \underline{V} = 1 - \frac{P_a}{s_a} & \text{if } 0 \leq P_a < s_a \\ 0 & \text{otherwise} \end{cases}$$

The producer maximizes profits $\Pi_a^M = (P_a - c_a) * D(P_a)$ $w.r.t.$ P_a:

$P_a^M = \frac{s_a + c_a}{2}$, and $\Pi_a^M = \frac{(c_a - s_a)^2}{4s_a}$; $D_a^M = 1 - \frac{s_a + c_a}{2s_a}$,

and $CS^M = \int_{\frac{P_a}{s_a}}^{1} Vs - \frac{s_a + c_a}{2} f(V)dV = \frac{(s_a - c_a)^2}{8s_a}$.

2.1.2 Post-entry

When entry occurs with a product of quality $s_c = m * s, m \leq 1$, the entrant and incumbent play a duopoly game. Let P_a, P_c be the prices for the incumbent and entrant goods, respectively. I assume counterfeit quality is exogenously given because counterfeiters have limited technologies available relative to authentic producers. For instance, they cannot import fancy materials and equipment because they are not registered companies and have no permits for imports.

I first assume that consumers have perfect information on qualities. This simplifying assumption captures some circumstances where counterfeits are sold in very different markets from the authentics, notably by someone with a boxful of shoes wandering around street corners, or are made of very inferior materials that one can detect instantly. We do see these circumstances in China, India, Jordan, UK, and the U.S. (Canal street in NY, for instance) and so on; however, these are certainly not the exclusive channels for counterfeit transactions. Many articles and news stories reveal how consumers are conned into buying counterfeits.[4] Therefore, I will relax the perfect information assumption in the next section.

Suppose the incumbent produces a good with quality $s_a, (a = H, L)$, as denoted generally in the previous section. Then the consumer who is completely indifferent between purchasing the incumbent and entrant product has a valuation: $\underline{V} * s_a - p_a = \underline{V} * ms - p_c$, which implies $\underline{V} = \frac{p_a - p_c}{s_a - ms}$.

In a Bertrand setting, the optimal duopoly prices are set by both producers simultaneously maximizing

$$\begin{aligned} \Pi_a^D &= (P_a - c_a)(1 - \tfrac{P_a - P_c}{s_a - ms}); \\ \Pi_c^D &= P_c(\tfrac{P_a - P_c}{s_a - ms} - \tfrac{P_c}{ms}). \end{aligned}$$

Therefore, the reaction functions are

$$\begin{aligned} P_a^* &= \tfrac{P_c + s_a - ms + c_a}{2}; \\ P_c^* &= \tfrac{msP_a}{2s_a} \end{aligned}$$

resulting in equilibrium prices

$$\begin{aligned} P_a^{DB} &= \tfrac{2s_a(s_a - ms + c_a)}{4s_a - ms}; \\ P_c^{DB} &= \tfrac{(s_a - ms + c_a)ms}{4s_a - ms}. \end{aligned}$$

In a Stackelberg setting, the incumbent is the leader and sets her price first, taking into account that the entrant will set his price according to hers. It is easy to see from the previous calculations that, given any incumbent price P_a, the profit-maximizing price for the entrant is $P_c =$

[4] One piece of news I read last year in the Chinese media reports that a lady bought a pair of Nike shoes on sale, but only one month later, they fell apart. Her happiness in catching the sale turned into indignation, and she sued the NIKE branch in Shanghai. She then found out that the pair she got was a counterfeit version.

$\frac{msP_a}{2s_a}$. The incumbent therefore sets her price by maximizing

$$\Pi_a^{DS} = (P_a - c_a)(1 - \frac{P_a - \frac{msP_a}{2s_a}}{s_a - ms}),$$

yielding

$$\begin{array}{lll} P_a^{DS} & = & \frac{s_a(s_a-ms)}{2s_a-ms} + \frac{c_a}{2} \\ P_c^{DS} & = & \frac{ms(s_a-ms)}{4s_a-2ms} + \frac{msc_a}{4s_a} \\ D_a^{DS} & = & \frac{1}{2} - \frac{(2M-m)c_a}{4M(M-m)s} \\ CS^{DS} & = & \frac{Ms-c_a}{2} - \frac{M(M-m)s}{2M-m} + \frac{(2M(M-m)s+(2M-m)c_a)^2}{32M^2(M-m)s} > CS^M. \end{array}$$

Notice that consumer surplus increases because the entrant product captures the lower end of the market, where consumers could not have afforded the incumbent products, and/or consumers derive more utility from the possible quality upgrade of incumbent product.

2.1.3 Main Predictions

It is worth noticing that if the incumbent offers the same quality before and after entry, then her profit-maximizing price will have to drop when there are entrants. Formally,

Lemma 1 $P_a^D(s_a, ms) < P_a^M(s_a)\ \forall s_a$.

Proof: We look at both Bertrand and Stackelberg games. As derived before, $P_a^{DB} - P_a^M = \frac{2s_a(s_a-ms+c_a)}{4s_a-ms} - \frac{s_a+c_a}{2} = \frac{ms(c_a-3s_a)}{8s_a-2ms}$. Under the assumption that $s_a \geq s, m \leq 1$, the denominator is always positive. Notice also that non-negative utility obtained from a good with quality s_a implies that $Vs_a - P_a \geq 0$; this is to say that $P_a \leq Vs_a$. Under assumption A.1, V can maximally be 1, and therefore $P_a \leq s_a$. Non-negative profit on the authentic firm side restricts $c_a \leq P_a \leq s_a$. Therefore, the numerator of the above expression has to be negative, indicating that $P_a^{DB} \leq P_a^M$.

Similarly in the Stackelberg game, $P_a^{DS} - P_a^M = \frac{s_a(s_a-ms)}{2s_a-ms} + \frac{c_a}{2} - \frac{s_a+c_a}{2} = \frac{-ms*s_a}{4s_a-2ms}$. It is obvious that this is negative. This implies that $P_a^{DS} \leq P_a^M$. *Q.E.D.*

I now examine closely possible incumbent price rises after counterfeit entry, as evinced in the Chinese shoe industry data from 1993-2004 and the Indian experience with shoe prices in the 1980s.

Lemma 2 *Without entrants, s is offered instead of Ms iff $\frac{c}{s} \geq M - \sqrt{M}$.*

Proof: When the incumbent is a monopoly in the market, she would choose s over Ms iff $\Pi_L > \Pi_H$. That is, $\frac{(s)^2}{4s} > \frac{(Ms-c)^2}{4Ms}$.

This implies: $M + \sqrt{M} \geq \frac{c}{s} \geq M - \sqrt{M}$

However, we already know that $c < P < Ms$ to ensure positive producer markup and consumer utility. Thus, the upper bound (first inequality) is trivially satisfied. *Q.E.D.*

The intuition of this Lemma is that when higher quality would raise costs more than it would yield profits, the monopoly incumbent offers a lower quality.

Lemma 3 *With new entry, Ms is offered by the incumbent instead of s iff $\frac{c}{s} \leq cutoff_1$.*

Proof: With new entry, if the incumbent still produces s, then the equilibrium $P_a^{DB}(s) = \frac{2(1-m)s}{4-m}$, and $\Pi_a^{DB}(s) = \frac{4(1-m)s}{(4-m)^2}$.

If the incumbent now produces Ms, then the equilibrium becomes:

$P_a^{DB}(Ms) = \frac{2M(M-m)s+2Mc}{4M-m}, \Pi_a^{DB}(Ms) = \frac{4M^2(M-m)s-2M(2M-m)c}{(4M-m)^2}$

The condition for $\Pi_a^{DB}(Ms) \geq \Pi_a^{DB}(s)$ is

$\frac{c}{s} \leq \frac{2(M-m)M^2(4-m)^2-2(1-m)(4M-m)^2}{(2M-m)M(4-m)^2} \equiv \text{cutoff}_1^{DB}$

Similarly for the Stackelberg setting, if s is offered, then equilibrium

$P_a^{DS}(s) = \frac{(1-m)s}{2-m}$ and $\Pi_a^{DS}(s) = \frac{(1-m)s}{4-2m)}$;

whereas the equilibrium with Ms is

$P_a^{DS}(Ms) = \frac{c}{2} + \frac{M(M-m)s}{2M-m}$ and $\Pi_a^{DS}(Ms) = \frac{(2M(M-m)s-(2M-m)c)^2}{8M(2M-m)(M-m)s}$.

$\Pi_a^{DS}(Ms) \geq \Pi_a^{DS}(s)$ leads to

$\frac{c}{s} \leq \frac{2M(M-m)}{2M-m} - \sqrt{\frac{(1-m)4M(M-m)}{(2-m)(2M-m)}} \equiv \text{cutoff}_1^{DS}$ *Q.E.D.*.

Entry pushes the incumbent to alleviate competition by introducing a higher quality, provided that the additional costs are not too high.

Proposition 1 *Under the conditions specified in Lemmas 2 and 3, the price of the original good rises if the entrant quality s_c is below a certain cutoff value, which is an increasing function of M and s.*

Proof: Lemmas 2 and 3 outline the case where the incumbent produces a low quality product without entry but is induced to produce the high quality product after entry. Under this scenario, the producer initially enjoys a monopoly price $P_L = \frac{s}{2}$ and later charges $P^{DB} = \frac{2M(M-m)s+2Mc}{4M-m}$ if a Bertrand game is played, or $P^{DS} = \frac{c}{2} + \frac{M(M-m)s}{2M-m}$ if a Stackelberg game is played. The original prices rise after entry if

$P^{DB} \geq \frac{s}{2} \Leftrightarrow s_c = ms \leq \frac{4M((M-1)s+c)}{4M-1} = \text{cutoff}_2^{DB}$

(Note that this can also be solved as $s \leq \frac{4Mc}{4M(1+m-M)-m}$)

or $P^{DS} \geq \frac{s}{2} \Leftrightarrow s_c = ms \leq \frac{2M((M-1)s+c)-mc}{2M-1} = \text{cutoff}_2^{DS}$

($\Leftrightarrow s \leq \frac{(2M-m)c}{2M(1+m-M)-m}$)

$$\begin{aligned}\frac{\partial cutoff_2^{DB}}{\partial M} &= \frac{4(2M-1)s+4c}{4M-1} - \frac{16M(M-1)s+16Mc}{(4M-1)^2} \geq 0;\\ \frac{\partial cutoff_2^{DB}}{\partial s} &= \frac{4M(M-1)}{4M-1} > 0;\end{aligned}$$

It is almost identical to check the comparative statics for the Stackelberg cutoff. The threshold values for s_c increases as M or s rises. *Q.E.D.*

This proposition predicts that the incumbent is induced to improve qualities and raise prices after new entry in the market, provided that the entrant's product quality is less than a certain value relative to the incumbent's product quality. It is also worth noting the conditions on the incremental cost of introducing the higher quality (including R&D costs and production costs) in order to have the price increase. The cost has to be large enough to dissuade the incumbent firm from investing in higher quality as a monopoly (Lemma 2), yet still be surmountable (Lemma 3) so that the incumbent is willing to produce the higher quality when faced with the new entrant's competition. This can be further linked to the findings by Aghion, *et al.* (2004) that firms sometimes innovate to escape competition. If the entrant's quality is very high relative to Ms, then competition could still be fierce even if the incumbent upgrades quality to Ms. The incumbent may be better off engaging in limit pricing strategies. It is only when an entrant's quality is below a threshold that the incumbent sees enough innovation gains to justify additional costs. The theoretical result that the threshold value for the entry quality, cutoff$_2$, is increasing in M and s is again very intuitive. In particular, higher Ms implies larger gap between the counterfeit quality and the high authentic quality. It therefore allows for a wider range of entrant product quality where the incumbent finds it profitable to improve her product quality. In this light, entry quality values above the cutoff can be considered the "*indolence interval*" and any values below, the "*activation interval*".

2.2 Asymmetric Information Implications

In the asymmetric information case, I assume that there is a fraction, γ, of consumers who can distinguish between authentic qualities s and Ms, but may not be able to tell counterfeits from their authentic counterparts at the same price. The other $1-\gamma$ fraction of consumers are experts in shoes and know exactly the quality of any pair of shoes they are purchasing. This relaxed assumption is not unfounded. In particular, authentic producers tend to provide detailed information about their products in order to build reputation and brand recognition. Counterfeiters, on the other hand, mostly try to mimic the appearance of authentics to extract short-term windfalls. This fraction, γ, of consumers perceive any product as authentic with a prior probability b. Assume further that a higher authentic quality could facilitate consumers in detecting counterfeits, leading to a lower fraction of confused consumers.

Assumption A2 $\gamma_{Ms} < \gamma_s$.

The rationale for this assumption is intuitive. For example, counterfeit shoes usually imitate different levels of authentic products using the same inexpensive materials, typically rubber or PU or imitative leather, although they may have different stylish appearances to resemble the different types of authentics. When the authentic producer adopts a higher quality, notably better materials (*e.g.* crocodile skins instead of cow skins) to produce its shoes, it may be easier for even non-expert consumers to detect the differences between authentics and counterfeits. This drop in γ indicates that the authentic producer is less affected by counterfeits in two dimensions, by increasing its own quality: first, she faces less competition from counterfeits with a more different product, and second, the widened quality gap helps to disentangle information friction so that counterfeits can fool fewer consumers. As we see in Qian (2005), the drop in γ is also important for providing incentives to counterfeit producers to choose a separating equilibrium pricing strategy because he now would enjoy a diminished fraction of consumers in the pooling equilibrium and may be better off charging a lower price than the authentic's to increase market share.

To incorporate the case in which purchasers themselves are not fooled but try to fool others (signal their high status, etc.), I modify the utility derived from the authentic and counterfeit goods:

$$U_a = V * s_a - p_a + u; \tag{1}$$

$$U_c = V * s_c - p_c + (1 - \lambda) * u + \lambda * f; \tag{2}$$

where subscript a still refers to the authentic incumbent and c refers to the counterfeit entrant; $u \geq 0$ is the utility of a consumer derived from being perceived as high class by wearing authentics; and $f \leq 0$ stands for the disutility from being recognized by others as wearing counterfeits; λ is the probability of being discerned. Other assumptions remain as specified earlier.

In this scenario, the authentic producer is more likely to provide a higher quality product when counterfeits enter. Even without a quality change, she may choose to set a higher than full-information price to signal her product's superior quality relative to the counterfeit's. The detailed derivations clearly lay out the conditions for the separating equilibra to prevail, and the various parameter spaces with price dynamics (Qian, 2005). The model intuitions and predictions will also be tested in the empirical section.

Proposition 2 *In the asymmetric information case, entry can induce the incumbent price to rise under a wider range of parameter values than those proposed in Proposition 1: the entry pushes the original producer to produce a higher quality; and, even if the original producer retains the same* *quality, she may charge a high price to signal superior quality and to distinguish herself from the entrant.*

Proof: Please see Qian, 2005

Enforcement activity against counterfeits (either publicly lobbying or privately funding spot-checks) is another combating measure many authentic companies take in China. In the Chinese shoe market, authentic firms send their own employees to walk around the market as consumers and track down counterfeit sellers. They then report the discoveries to the local Quality and Technology Supervision Bureau and have them close down these counterfeit sources and outlaw illegal companies. Intuitively, these enforcement investments increase the odds that counterfeits will be confiscated and major counterfeit producers will be jailed. Most times, successful enforcement cases are announced in newspapers to caution consumers and deter future counterfeits. The risk of such penalties reduces incentives for counterfeiting and favors the separating equilibrium. The effects of enforcement on deterring counterfeits and on authentic prices will be examined both theoretically and empirically (Section 5).

Proposition 3 *Enforcement Activities add risks and costs to counterfeiters, thereby favoring a separating equilibrium where authentic prices are higher than generic ones.*

Proof: Please see Qian, 2005.

Self-invested enforcement activities are adopted in branded companies in the Western nations as well. As a recent article in the *Wall Street Journal* reports, luxury-goods companies like LVMH Moet Hennessy Louis Vuitton SA target not only manufacturers and sellers of counterfeits, but also the landlords, shipping companies, and any other part of the supply chain that leads to the sale of counterfeit wares (Galloni, 2006).

In practice, the authentic producers also adopt alternative signaling devices besides price to signal their high qualities. Such signaling devices include establishing licensed stores and designing fancy trademark stickers or packaging. Intuitively, these signaling devices help to establish a separating equilibrium where the authentic products can distinguish themselves from the counterfeits. At the same time, they could also push up marginal costs of authentic goods, thereby making it more likely for authentic product prices to rise after counterfeit entry.

Proposition 4 *Non-price signals relax the conditions for separating equilibrium, and push up marginal costs of authentic products. Authentic prices are more likely to rise under these circumstances. These signaling devices take on more important roles when they provide actual information about authenticity.*

Proof: Please see Qian, 2005.

In addition, once we naturally assume that λ is an increasing function in the quality gap between authentic and counterfeit products and in signaling devices such as holograms, etc., and γ is a decreasing function in these devices. That is, a higher quality gap and more signaling devices make authentics and counterfeits less alike so that counterfeits confuse fewer people–larger $\lambda(\frac{M}{m}, l, T)$ and smaller $\gamma(\frac{M}{m}, l, T)$. Then this assumption enhances the proposition that authentic producers may decide to improve quality and adopt signaling devices post-entry.

The propositions hold true for imitations as well. A simplification for imitations is that $u = f = \lambda = 0$. Honest imitative entry (*e.g.* generic drugs) is apparently analyzed in the benchmark model. Imitations that are not honest about their quality generate asymmetric information and their effects are summarized in Section 2.2. I further solved the model with multi-firm competition instead of two-firm oligopoly (duopoly), and the intuitions remain similar. Other extensions are in Qian (2005).

3 Empirical Research Design

3.1 Theoretical Implications For Empirics

The theoretical model predicts that if entrant quality is lower than a certain level relative to incumbent quality, new entry can provide incentives for the incumbent to offer a higher quality product and raise price. In the case of counterfeit entry with quality uncertainty, price could increase additionally due to signaling for quality or authenticity. Other signaling devices such as licensed stores, advertisements, and holograms can help consumers to distinguish authentics from counterfeits and push up authentic prices. Together with enforcement activities, these measures can be effective measures to combat counterfeits. I gather data to test these predictions one by one. In this section 3, I describe the empirical research design, including the identification strategy, survey methods and data. The econometric analyses and results will be discussed in Section 4.

3.2 Identification Problem and Solutions

Suppose entry was exogenous (randomly assigned to companies). Then the research question of its effects on an authentic producer's marketing strategies can be simply addressed with OLS regressions of price or other market variables of interests on the binary indicator variable of entry. This assumption, however, may not hold because entry is more likely to occur if the original producer has a larger markup, the brand is more popular, and trademark laws against counterfeiting are weaker. This endogeneity problem will lead to biased estimates in the simple regression suggested above. The identification strategy I adopt comes from enforcement changes in Chinese trademark law in the footwear industry. It is therefore useful to briefly review the history of the legislation and enforcement.

On the legislation side, the Chinese copyright and trademark laws were restored after 1976. China signed the TRIPS agreements and modified the "Details of Trademark Laws Implementations" in 1993. On the enforcement side, since 1985, the Chinese government has established the Quality and Technology Supervision Bureau (QTSB), with a branch in each city, to supervise product qualities and outlaw counterfeit localities. The Bureau has enlarged its personnel and funding since 1991 in joint efforts with legislations to protect IPR and to monitor product quality. Due to a series of accidents arising from low quality or counterfeit cottons,[5] agricultural products, gas tanks, and alcohol, the Chinese government issued notifications in late 1994 and early 1996 to enhance quality supervision and combat counterfeits in seven main sectors prone to hazardous materials: pharmaceuticals, agricultural products (including fertilizers, pesticides, and other materials or instruments), fiber and cotton (paying special attention to those bacteria-infected or bleached counterfeits), food, tobacco, alcohol, and gas. The majority of the Bureau workforce and funding went into these sectors, leaving loopholes for counterfeits to enter the footwear industry. In the early 90s, 5% of the Bureau's resources were devoted to the leather shoe sector. This number, however, fell to 0.8% after 1995 (Bureau yearbooks). As seen in the data, authentic companies experienced significant counterfeit entry after this loosening of governmental monitoring and enforcement: most entry occurred in 1996. This exogenous policy shock provides a natural experiment to study the effects of counterfeit entry in the Chinese shoe industry. The brandname companies that were infringed upon set up their own "brand-protection" offices to make up for the lack of government monitoring of counterfeits. The company fixed-effects regression of log of company enforcement investment on a legislation dummy is positive and significant at the 5% level (coefficient=3.2). However, the authentic companies still had to get the government to outlaw the counterfeit sites once their own enforcement employees

[5]Some counterfeit cottons carry bacteria and spread infectious diseases.

discovered them. This is where relationships with local government (the QTSB in particular) come into play.

Before the enforcement change, the Quality and Technology Supervision Bureau conducted regular inspections in the shoe markets and factories. They confiscated and shut down counterfeit localities right on the spot. The monitoring mechanism was therefore quite uniform across different brands. After the enforcement change, however, companies that had a good relationship with the government received more attention and faster responses when they reported counterfeit cases. All else being equal, this would reduce the incentives of counterfeiters to infringe these brands. This company-level variation is helpful in exploring the variation in the effect of enforcement change on counterfeit entry and sales for different brands and, in turn, the effect on different authentic prices. The challenge is to obtain a proxy for such a relationship.

Since the late 1980s, all registered companies were *required* to meet the standards set by the International Standards Organization (ISO). For the shoe industry, ISO sets standards for the basic equipment a company uses and basic quality of products. The QTSB is in charge of the ISO certification. For some companies, one month was sufficient for obtaining the ISO certificate, but for others, the application date and grant date were over 300 days apart. Among these companies that spent a long time to fulfill the ISO requirements, some are small companies and some are medium or large ones. In my interviews with companies, I was told that the standards were rather basic and the differences in application times were largely due to bureaucracy. I reviewed summaries of ISO criteria, and confirmed that they were indeed basic. Chinese consumers hardly notice these ISO certificates, myself included. Therefore, ISO does not signal product quality or influence prices in any other way besides through affecting counterfeit entry and quantity[6]. I use the number of work days it took each company to pass the ISO requirements as a proxy for its relationship with the local government (or how fast it managed through the bureaucracies). There were two waves of ISO standards that the sampled shoe companies had to comply with, one in 1994 and the other in 2000. I obtained the application and grant dates for each company in both waves. I then constructed a variable (named "*iso*") that equals the number of work days between the application and grant dates of the 1994-wave ISO up to the year 2000, and equals the number of work days to get the 2000-wave ISO certificate after 2000. The correlation between the number of days to obtain both waves of ISO certificates is very high, .96, suggesting that the relationship between a company and the government is rather steady in the period under examination. There is also no significant correlation between

[6] Many sectors are privatized in China, the footwear industry included. None of the companies in my sample is state-owned. Shoe prices are also freely set by demand and supply in the market.

this relationship proxy and the company's market share, sales, product quality or production cost. I will further the discussions of the IV criteria and its validity in Section 4.2.1.

3.3 Data

Data collection comprises a large part of my effort to address this research question. The choice of studying the footwear industry to examine counterfeit effects is based on several additional considerations, besides the identification convenience discussed in the previous section. First, shoes are daily necessities as well as fashion products (worn on a person, visible to other people). Consumers care about both the quality and appearance of their shoes. The valuations of appearances and brand names make possible potential markets for counterfeits. With economic development, the Chinese fashion industry (footwear included) grew. By the late 1980s, many Chinese-originated brands found their niche in the market. The flourishing of brand names also instigated counterfeit entry, raising many interesting questions to tackle. Second, the footwear industry plays an important role in Chinese manufactures and exports. Domestically, it employs approximately 300,000 workers. From 1994 to 2005, the Chinese footwear industry grew 8-fold. It had a total output of 6.2 billion pairs in 2003, which is a 60% share of the total global market. Of this, leather shoe output has been averaging 2.6 billion pairs since 2003, exporting .9 billion pairs, amounting to 4.3 billion USD. These exports are sent to 200 countries in all five continents. The major markets are Europe, America, and Japan, with an average export price of 5 USD per pair. The average price in the international market for some famous Chinese brandname shoes has risen to 40 USD after these brandnamed companies established their licensed stores abroad.

Most of the branding and counterfeiting occur in the leather and sport shoe sectors of the footwear industry, mainly because other handmade shoes have very small price-cost margins and no brandname. I identified the complete list of registered (authentic) leather and sport shoe companies in China from *Kaiboxin* Consulting in Beijing, and ranked them according to their market shares in each year. I then randomly drew 10 companies from each of the four categories with random number generators: I. multinational corporations in China; II. Chinese-originated brand name companies that are classified as first-class medium scale according to the Chinese standard (Chinese National Bureau of Statistics, 1995); III. Chinese-originated branded companies that are classified as second-class medium scale; and IV. Chinese-originated branded companies that are classified as small scale. I have received data from 31 out of these 40 authentic companies covering the period 1993-2004.

There are no observable differences between the respondents and the non-respondents, based on the variables I managed to obtain from the consulting firm (e.g. market shares, age). I collected data on counterfeits from the "brand-protection" offices of each authentic company, the Industrial and Commercial Bureau of China, and the Quality and Technology Supervision Bureau. For every data point, I got cross-references and confirmations to the extent possible.

For each company, relevant data are their product prices, domestic sale quantities, costs, and total sales. Ideally, I wanted to have data for these four variables broken down by each type of shoe a company produces. On average, each company produces over 10 different types of shoes: male winter (with fur or cotton), male summer, male regular (with regular leather, suitable for spring or autumn), female winter (including fur- and cotton-made), female summer, female regular, female knee boots, female mid-leg. Each type is produced at three different qualities (high, medium and low) according to their materials and fabrication techniques. However, most of the companies do not have such detailed data available (either because of limitations in computer storage, or difficulties in accessing old and detailed documents, or concerns over confidentiality). After persistent contacts with the companies, they agreed to provide me with data on the average prices, costs and sales for three qualities (high, medium, and low) of their shoe products.

I then coded and compiled product-level data from the annual catalogs that I requested from the companies and stores. These product catalogs are also helpful in better controlling for quality and costs. I compiled a dataset of different shoe characteristics, consisting of materials, comfort, decorative patterns on the shoes, support and cushioning effects, ventilation, etc. I have corroborated the unit production cost data with the corresponding material, machinery, and labor (wage) costs of the shoes, and found that the data companies provided were reliable.

While interviewing the companies, I learned that those infringed upon by counterfeits invest in enforcement activities by sending their own employees to monitor counterfeits, lobbying at the local government level to outlaw counterfeit localities, and organizing anti-counterfeit conferences. The companies also uniformly tell me that establishing licensed stores for their brands is a very good strategy to signal their quality and to ward off counterfeits. In order to set up a licensed store, a company has to get approval from the Industrial and Commercial Bureau. The application requires legal documents about the brands from the company. The formal approval certificate has to be displayed in each licensed store. Therefore, the counterfeiters are not able to mimic this business strategy. In fact, establishing a fake licensed store will only help the authentic company and the local government to track down the counterfeits and no counterfeiter has the incentive to do so. I therefore obtained data on enforcement expenditures, personnel, and the number of licensed stores to test empirically the effectiveness of these strategies in deterring entry. In addition, I obtained their advertisement costs to control for the differences in various brand information for consumers.

To control for the overall economic environment and consumer purchasing power, I extracted the GDP per capita PPP, GDP growth, Consumer Price Index, household consumption, and total consumption as a share of GDP for China in the sampled years from the World Development Indicator (WDI) database. I also extracted the annual Gini coefficients in China from the UN Human Development Reports.

4 Empirical Analyses and Results

In this section, I start with testing the benchmark model of the pricing effects of counterfeit entry with OLS (Section 4.1). To deal with potential endogeneity problems, instrumental variable analyses are carried out for pricing and marketing impacts of counterfeit entry in Section 4.2. I test the presence of asymmetric information as well as the entry effects on prices: higher authentic price due to both quality change and signaling, respectively. In particular, I further carry out stratification analyses with the instrumental variable in the strata of different levels of entrant qualities. Section 4.3 summarizes the results from the Instrumental Variable estimation with the Bayesian Hierarchical Changepoint Model (Qian, 2005). This method estimates pricing and marketing effects more precisely by taking into consideration the heterogeneity of response time (to fake entry) across authentic firms. Section 4.4 analyzes the changes in authentic leather and sport shoe quality after counterfeit entry. Last but not least, I test the effectiveness of the authentic companies' enforcement and signaling strategies for combating counterfeits in Section 4.5. I explore the decision to enter as a counterfeiter based on the previous year's authentic sales and other appealing features as well as the relevant macro-economic environment.

4.1 Testing Entry Effects on Prices with OLS – Table 1

To test the pricing effects of counterfeit entry, I start with some plots and OLS, I then proceed to rigorous econometric analyses. I first plotted the price (deflated) trends for each company and its counterfeits over the sampled time period. Many of the infringed upon companies experienced some initial drop in prices. However, their highest and medium prices shifted up shortly after the counterfeits enter the market. The price of the lowest quality product of the authentic companies witnessed less dramatic jumps: it increased moderately for some companies, or stayed level for others. The counterfeit prices in general remained constant. The price-cost margin for high-end products tends to widen after entry for many of these authentic companies. Figure 1 shows the trend for a representative company that experienced noticeable counterfeit entry since 1996. As a comparison, I also plotted the deflated price trends for the sampled companies whose brands attracted no counterfeits during the same period. Their price trends were very smooth, and there were no shifts comparable to those I identified for the infringed brands. Figure 2 shows a representative company in this group that has similar starting prices as the company in Figure 1. There are some initial price declines in most companies immediately upon counterfeit entry, before these authentic manufacturers were able to improve quality or engage in other countervailing strategies. To show the price dynamics pre- and post-entry more formally, I regressed the log of deflated authentic prices on a set of dummies indicating the years relative to fake entry (from 5 years prior entry to 5 years afterward), and plotted the coefficients on these time lines (the green line in Figure 3). The pattern is similar to the single company plots – rather smooth price movements prior to entry, an initial drop upon entry, and an upward drift shortly after entry, finally leveling off possibly due to diminished signaling effects. The coefficient on the dummy indicating 1-year after entry is negative in the figure although some companies had raised prices already. This is mainly due to the heterogeneous response times for different companies. In contrast, a counterfactual experiment based on the price trend pre-entry[7] shows a smooth and slightly upward trend in authentic price over time, as plotted in the dashed red line. I also plot the cost trend in the yellow line in Figure 3, and found an upward jump two years after counterfeit entry. As another comparison, Figure 4 shows that the deflated price trend for the footwear industry in the American market in the contemporary period has been smooth and even declining (American Apparel and Footwear Association Study, *ShoeStats*, 2005).

From the theoretical model presented in Section 3, I derive the change in prices of the authentic producer: $\Delta P = P_H^D - P_L^M = \frac{2M((M-1-m)s+c)}{4M-m}$. The comparative statics are $\frac{\partial \Delta P}{\partial M} > 0$; $\frac{\partial \Delta P}{\partial c} > 0$; $\frac{\partial \Delta P}{\partial m} < 0$. This guides my most basic regression Model 1:

$$log(P_{a,t}) = \beta_0 + \beta_1 * \text{Entry}_{a,t-2} + \beta_2 * M_{a,t} + \beta_3 * m_{a,t} + \beta_4^T * \text{YearDum}_t + \beta_5^T * \text{FirmDum}_a + \epsilon_{a,t}$$

where $M_{a,t} = log(c_{a,t}) - log(c_{a,t-1})$ is the cost difference as well as a proxy for the quality difference between the best authentic products in the current year and previous year, respectively, for

[7]I regressed the actual coefficients on these year dummies on the years before entry, and predicted the coefficients in the counterfactual experiment (*i.e.*, no entry) from this regression.

the same authentic company. $m_{a,t} = \frac{s_{c,t}}{s_{a,t}}$ is the quality of the counterfeit product as a fraction of the authentic counterpart. I also use the first difference in log prices as an alternative dependent variable to check the robustness of results.

Both the standard and clustered standard error regressions yield these empirical results: $\hat{\beta}_1 > 0, \hat{\beta}_2 > 0, \hat{\beta}_3 < 0$ (Column 1 in Table 1). These three statistically significant coefficients confirm the theoretical predictions. In particular, after controlling for the unit costs for upgrading authentic quality and the counterfeit quality as a fraction of authentic quality, the counterfeit entry induced authentic price to rise by a factor of 1.17 on average ($\hat{\beta}_1 = .16$, response variable is the log of deflated price). The greater the quality and cost differentials between the post- and pre-entry authentic product, the higher the current authentic price (positive $\hat{\beta}_2$). In addition, just as the model predicted, the higher counterfeit quality is relative to authentic quality, the smaller the price increase we expect to see for the authentic product (negative $\hat{\beta}_3$).

To address the concern that prices can rise due to positive demand shifts, I control for the company's domestic sale quantities and a set of macroeconomic variables. Price can also be correlated with a company's prestige, which I control for by including the age of the company, defined by the present year minus the incorporation year. I further control for the macro-economic environment by using annual data on Chinese real GDP per capita PPP, growth rate, Gini coefficient, total consumption as a share of GDP (denoted as Cshare), and deflated household consumption (denoted as dfhhc) in that year. Prices, domestic sale quantities, deflated household consumption, and GDPpcPPP are converted to logarithms in order for the data distributions to be better approximated as normal distributions (Model 2). Furthermore, regressions on log terms capture the rates of change in variables, instead of their levels which vary across companies. Column 2 of Table 1 shows that the coefficient on the entry variable remains statistically significant and positive as predicted in the theoretical model. The negative coefficient on the domestic sale quantity variable provides some evidence that demand shift may not be a good explanation for the price increase, although it cannot entirely rule out that possibility. Positive demand shocks would logically raise both domestic price and sale quantities, and lead to a positive correlation between these two variables. In addition, the coefficients on the log of GDP per capita PPP, growth, Gini coefficient, and consumption as a share of GDP are positive, statistically significant at 5% levels, indicating that the increase in income and consumption, economic growth, and the widening in income inequality correlate with an increase in the log of the highest price of authentic companies. This is intuitive because richer consumers are willing to pay more for most ranges of normal goods, and can afford more luxury products.

Regression analyses were also carried out on the log of the first difference of authentic prices, with the same set of control variables (Model 3). As listed in Column 3 of Table 1, results are similar as before with a significant coefficient on the entry of counterfeits, suggesting a 12.7% rise in authentic price after entry (coefficient=.12), after controlling for unit authentic cost changes and all the other variables.

In addition, it is evident from the shoe characteristics data I collected that there have been improvements in authentic shoe quality after counterfeit entry, both in terms of materials and technologies the authentic companies adopt to produce shoes. The regular leather shoes have been upgraded to special leather: imported snake, crocodile, and kangaroo skins as well as domestic cow and sheep skins. The authentic companies have also imported Italian machines to press beautiful patterns on the shoes. This not only confirms the theoretical predictions, but also helps to tease out the confounding effect: if the price jumps were due to a brand effect, that should affect the price of the same product, not a higher quality one. Detailed empirical analyses of quality changes are discussed in Section 4.4. Let us finish analyzing the price changes first.

4.2 Testing Pricing Effects and Asymmetric Information with IV Estimation and Stratification Analyses

In this section, I first verify the instrumental variables' validities in Section 4.2.1. I then discuss the IV estimation results when various authentic strategies and outcomes are regressed on lagged counterfeit entry in Section 4.2.2. In the next subsection 4.2.3, I try to test the effects of non-price signals on the authentic prices. Section 4.2.4 carries out stratification analyses on companies that experience entrants of various qualities. With these analyses, one gets some insights about the presence and effect of asymmetric information in the Chinese shoe market and the pricing and signaling dynamics. Section 4.3 improves on the estimates by jointly modeling the heterogeneity of response time and price outcomes, based on the IV-BHCM. Section 4.4 analyzes the authentic shoe quality changes post-entry. Finally, Section 4.5 searches for the determinants of counterfeit entry, and Section 4.6 does some robustness checks and provides additional tests for entry effects on high-, mid- and low-end authentic prices.

4.2.1 IV Criteria

As explained in Section 3.2, the 1994 Notification 52 (for fiber and cotton quality supervision) and 1996 Notification 10 (for gas and other major hazardous products) reallocated government resources to ensure quality and combat counterfeits in the seven sectors where counterfeits can have severe safety consequences. The governmental attention paid to the shoe industry has been diverted significantly. I use this enforcement change and its interaction with the relationship between a company and government (proxied by the days it took the company to pass ISO) as instrumental variables for counterfeit entry.

Because the enforcement change was due to a series of accidents which took place in other industries, it is randomly assigned. The IV exclusion restrictions are also fulfilled because tightened government enforcement elsewhere is not expected to affect shoe prices directly. The relationship proxy does not correlate with counterfeit entry directly in the first step of IV regression. Since authentic prices are set by market equilibrium, and the ISO time proxies for the relationship of a company with only the Quality and Technology Supervision Bureau, this proxy is therefore not expected to affect prices directly either. The first stage of IV estimation shows clearly that the instruments are highly correlated with the endogenous variables: fake entry and fake sale quantities as a share of authentic sale quantities (Table 2). This first stage regresses counterfeit entry or sale quantities as a fraction of authentic quantities on the indicator variable for the loosened attention to the footwear industry, which takes on a value 1 for years 1995 onwards and 0 otherwise, the interaction variable between the legislation change indicator and relationship proxy, the relationship proxy, and year trend. I only included these most important instruments because additional weaker instruments can reduce the effectiveness of IV and fail to correct for endogeneity bias. As shown in Columns 2 and 4 in Table 2, the legislation dummy and the interaction variable are highly correlated with the counterfeit entry or sales and statistically significant at the 1% level. The relationship proxy itself, however, does not carry statistically significant coefficients. This means that a company's relationship with the local government correlates with its counterfeit entry only after the loosening of the governmental enforcement efforts in the footwear sector. This is exactly as we expected in Section 3.2, confirming that this relationship proxy fulfills both the relevance and the exclusion restrictions. The overall Wald Chi-square test for the instruments are highly significant.

For robustness checks, I tried alternative specifications of this first stage IV regression. Column 1 of Table 2 exhibits the estimation using the government enforcement dummy (loose) as a sole instrument. Column 3 documents the regression of counterfeit entry on the interaction variable, relationship proxy, and year and company fixed effects. The high F-stat (49.3) again indicates that the instruments are strongly correlated with the endogenous entry variable. The coefficient on the interaction variable, which is the main instrument, is statistically significant at the 5% level even after taking out the year fixed effects.

4.2.2 IV Regressions for Various Authentic Strategies and Outcomes

My theoretical model provides predictions on fake entry effects on the authentic company's strategy profile, as defined by $\sigma_a = (P_a, s_a, Ads_a, l_a, T_a, Enf_a)$. I carry out IV regressions with year and company fixed effects to test the counterfeit entry effect on each of these strategy proxies that I have data for and on the authentic profits and export revenues. The only variable that I do not have data for is T_a, the costs of holograms (variable cost signals). Panel B of Tables 7 and 8 report positive and significant entry effects on quality, as measured by the log of deflated production costs and the overall quality rank. Table 2b reports results for the entry effects on all the other authentic strategies and outcomes. Entry induces authentic price to rise two years later (Column 1), while it significantly initiates authentic companies' combating responses by investing in enforcement activities and establishing licensed stores starting from the year following entry (Columns 3,4). Advertisement costs were not significantly influenced by counterfeits (Column 2), plausibly due to two opposing forces: 1. being counterfeited can be a form of advertisement for the brand; 2. low-quality counterfeits could ruin the brand reputation, and the authentic company has to invest more in advertising and inform consumers about the differences between its products and the counterfeits. There is no significant effect of counterfeit entry on authentic profits or export revenues (Columns 5 and 6).

Exploring further the story of licensed stores, I regressed the number of licensed stores an authentic company establishes on the lagged year number of licensed stores (essentially testing the change in number of licensed stores), lagged year fake entry, log GDP per capita PPP, economic growth, Gini coefficient, and the counterfeit quality as a fraction of authentic quality, year trend, and company fixed effects. Results demonstrate that the number of licensed stores is positively (statistically significant at 1% level) correlated with the lagged year counterfeit quantities and the current year Gini coefficient. The intuition is that the prevalence of counterfeits in the market induces incumbents' countervailing responses. According to the interviewed companies, one effective measure is to establish licensed stores. In particular, the lagged year counterfeit entry carries a large coefficient in the regression on the log number of licensed stores. Selling original products in a licensed store at a higher price (because building or renting a place to set up a licensed store pushes up fixed and marginal costs) is profitable if consumers find it worthwhile to have this separating device, which can be considered as an information service. The number of licensed stores is positively correlated with income distribution – the higher the Gini coefficient, the more wealthy people there are to afford luxury products, or who are willing to pay more for famous brands.

4.2.3 IV Regressions on Log Authentic Prices

The IV estimations are repeated for the regression models 1 to 3 in Section 4.1, and the results corroborate the previous conclusions qualitatively: The coefficients on counterfeit entry are positive and significant. Notably, in the IV regressions with year trend and company fixed effects but no other control variables, the coefficients on the instrumented entry dummy lagged by two or more years are all positive and significant at the 5% level (Columns 3 and 5 in Table 3). Results are robust when including year fixed effects, with IV3 as specified in Table 2.

Section 2.2 outlines the theoretical predictions from the model under asymmetric information. The first prediction is that prices can rise to signal quality. Empirically, we would like to disentangle the price increase into two parts: the part due to quality improvement, and the part due to signaling effect. To tease out these two parts, I include the log of unit production costs as a control variable. Costs are directly linked with quality, because higher quality requires more expensive materials and technologies. The part of the price increase due to quality improvement is reflected by a positive coefficient on the cost variable, and the signaling part is reflected by a positive coefficient on the entry variable in the same regression.

The IV regression of the log authentic prices on the fake entry dummy with no lag shows a negative but insignificant coefficient on the entry dummy (Column 1 and 2, Table 3). This indicates that it takes time for the authentic companies to respond to counterfeit entry. When regressing log authentic prices on the entry dummy lagged by 2 years and the other control variables, the lagged entry variable, log authentic cost, and Gini coefficient all carry positive coefficients and are significant at the 5% levels. Counterfeit entry has induced authentic price to rise by 8% on average two years after entry, even after controling for cost (proxying for quality) (Column 4, Table 3). This provides evidence for price signaling effects: prices rise above a level explained by the quality improvements. However, the signaling effects fade away when log authentic prices were regressed on the 4-year lagged entry variable (Column 6, Table 3). This seems to support the predictions in Bagwell and Riordan (1991) and echo findings in Curry and Riesz (1988) that, in the durables market, firms may first signal high quality with a price higher than the full-information optimal price, then decrease the price as information diffuses. It is worth noting the positive and significant coefficients on the age variable. This interesting result suggests that as an authentic brand has been on the market longer (older age), more information is released to the consumers (corresponding to a bigger λ and smaller γ in my theoretical model), so that counterfeit entry would impose less influence on the authentic prices.

I further test the effects of other marketing strategies, which authentic producers adopted, on their prices. Figures 5 shows a representative case where the licensed stores correlated with a decline in the counterfeit sale quantities. The authentic sale quantities dropped after counterfeits entered, but plateaued soon after. To test the influence of information and non-price signals on the authentic price, I added the log of advertisement costs and log of number of licensed stores to the right hand side of the regression model. This is unlikely to bias estimates since Table 2b shows no statistically significant correlations between entry lagged by two years and log advertisement costs or log number of licensed stores.

$log(P_{a,t}) = \beta_0 + \beta_1 * Entry_{a,t-2} + \beta_2 * log(c_{a,t}) + \beta_3 * m_{a,t} + \beta_4 * logoutput_{a,t} + \beta_5 * logGDPPPP_t + \beta_6 * loggrow_t + \beta_7 * gini_t + \beta_8 * loghhc_t + \beta_9 * Cshare_t + \beta_{10} * age_{a,t} + \beta_{11} * lstore_{a,t} + \beta_{12} * log(ads)_{a,t} + \beta_{13} * Year_t + \beta_{14}^T * FirmDum_a + \epsilon_{a,t}$ (Model 4, Table 4)

where $lstore$ is the log number of licensed stores established by the authentic producer a, $log(ads)_a$ is the log of advertisement costs for the brand a. Similar to the age variable, $log(ads)$ helps to capture the information disseminated to consumers about the brand products. Which part of an advertisement is informative and which part is purely for signaling is impossible to separate in the data. However, based on interviews and my personal observations, it is true that companies engage in more advertisment campaigns to inform consumers about their product features after counterfeit entry.

Column 1 in Table 4 lists the results from Model 4 using the 2-years lagged entry. Entry is shown to raise authentic price in addition to quality upgrading by 2% on average, statistically significant at the 5% level. The improved quality (proxied by log of authentic cost) still explains most of the price change. There are also positive coefficients on the log number of licensed stores and advertisement costs, which are statistically significant at the 10% and 5% levels, respectively. Signaling devices and information on products can help consumers to distinguish authentics from counterfeits, and in turn reinforce local monopoly position. The additional costs of building or renting licensed stores and advertisements can also lead to price rise. The coefficients on the income distribution (Gini) are again positive and statistically significant at the 5% level. The coefficients on the log of authentic domestic sales quantity bear negative and statistically significant coefficients across all specifications, again ruling out demand effects for the price rise.

4.2.4 Stratification Analyses (Column 2 and 3, Table 4)

In order to zoom in the effects of entry with different levels of product quality, I carried out similar regression specifications on the two subsamples of companies: Stratum 1, the companies whose counterfeit quality as a fraction of authentic quality are less than the fifth quintile lower bound value of m (.3); and Stratum 2, the companies whose counterfeit quality fractions are greater than or equal to .3. The regression outputs are laid out in Columns 2 and 3 of Table 4, respectively. In both strata, the log of domestic sale quantity of authentics is negatively correlated with their prices.

Column 2 in Table 4 shows that, in the stratum with low-quality entrants, the log number of licensed stores significantly increases the log of authentic price, by 1%. The log cost for high-quality authentic products, and the counterfeit entry indicator variable both bear statistically significant positive coefficients. Entry induces price to rise by 5% on average for signaling. Log of advertisement costs bears a positive coefficient and significant at the 5% level. The Gini also carries positive coefficient, significant at 5% level.

Column 3 in Table 4 shows that, in the stratum of companies with high-quality entrants, the number of licensed stores does not have a statistically significant relationship with the authentic price, although the coefficient is positive. Consumers may be actively choosing counterfeits if their quality is good enough. In addition, the higher the counterfeit quality with respect to the authentic quality (bigger m value), the larger the drop in authentic price due to price competition. Age takes on a positive coefficient, significant at the 5% level. Companies that had been in the market for a longer time tend to endure less adverse entry effects.

These results are consistent with the theoretical model predictions. In particular, in the group of companies whose counterfeit quality exceeds a certain level, the counterfeit entry exerts a lot of competitive pressure, so that authentics find that even a quality upgrade may not help them to escape competition, and the authentic price cannot rise as high. For companies whose authentic quality far exceeds the counterfeit quality, asymmetric information has a more important role to play in pricing. Licensed stores and ads prevent consumers from being fooled by the appearance of counterfeits and, in a separating equilibrium, the authentic price is more responsive to the number of licensed stores.

4.3 Bayesian Model for Response Times and Prices – IV-BHCM

The price trend plots in the appendix clearly show that different authentic companies have different response time for adjusting their pricing strategies after counterfeit entry. This heterogeneity of response times among companies cannot be appropriately estimated in the traditional approach of a regression with lagged variables, which requires that the change point be specified in advance and assumed identical for all companies. Without modeling the response time and its variabilities, the effect of counterfeit entry will be under-estimated. My simulations show that this under-estimation can be quite serious (30-40% downward bias from the true estimator) (Qian, 2005). I use a Bayesian hierarchical model (BHM) to jointly model the pricing profile and the (latent) response time, and it is therefore called a Bayesian Hierarchical Changepoint Model (BHCM). In addition, I implement the instrumental variable estimation in the Bayesian framework to account for both the endogeneity problem (with IV) and the heterogeneity in response time (with BHCM). Further motivation and details of the model estimations follow those described in my paper "IV Estimation in BHCM"(2005). Table 5 compares the estimates from OLS, regular IV, and IV-BHCM in regressions of log authentic price on entry and control covariates, excluding the cost variable. The overall entry effect estimated from OLS is .12, after controlling for company fixed effects;[8] the regular IV addressed the endogeneity concern and resulted in an effect estimate of .29. However, because regular regression does not take into account the different response times across companies, it tends to underestimate the entry effect. The coefficient on entry from the IV-BHCM is equal to .41, implying that entry induces authentic prices to rise by a factor of 1.51 on average. All these effect estimates are statistically significant at the 5% level. Table 6 compares the estimates from OLS, regular IV, and IV-BHCM, with an additional control variable of authentic quality (as proxied by log cost). As before, the cost variable explains away most of the price increase. The price signaling effect due to entry is estimated to be 2% under both versions of IV estimation. The average response time for an authentic company to raise its price is 2 years on average.

4.4 Quality Changes after Entry

Using the data on shoe characteristics that I gathered from the product catalogs, I ranked the various dimensions of quality according to the costs of materials used. For instance, the variable for surface material takes on value 1 if it is made of plastic leather,...,4 if regular cow skin,..., and 14

[8]The omitted variable biases potentially enter OLS in two directions: 1. upward bias due to brand effects, which correlate with the price outcome and counterfeit entry positively; 2. downward bias due to management effects, which are positively correlated with the price outcome but negatively correlated with the brand's counterfeit entry. In particular, a brand with good management may ward from counterfeits effectively as well as maintaining high-standard products with relatively high prices. In fact, when simply regressing log prices on the fake entry dummy and a year trend, the entry coefficient is very large (=.78). While the company fixed effects help to control for the omitted brand effects, they do not control for the time-variant management effects. The resulting OLS entry coefficient is therefore biased downward, as compared to the IV estimates.

if crocodile skin. Similar procedures are carried out to generate the variables for side and bottom materials. I constructed the variable for appearance by summing up three dummy variables: fine, elegant, and patterns, each taking on value 1 if a pair of shoes contain these characteristics and 0 otherwise. I then constructed a variable for functionality by summing up the following indicator variables: versatility, cushioning (whether a pair of shoes has cushioning effects), absorption (whether it can absorb sweat), countering athlete's foot, softness, comfort, sturdiness, warmth, friction (for protection on slippery ground), and additional features for sport shoes such as durability, flexibility, and support. I also constructed a variable indicating the technologies applied to make shoes, embodied in equipment. Before counterfeit entry, all the companies used domestic equipment. However, after entry, many of them imported Italian[9] production lines, pattern-pressing machines, and equipment to make shoe bottoms with cow skins. Some companies even adopted nano-technologies. I first constructed a dummy variable for each type of equipment, and then summed them to generate the "equipment" variable. I generated the variable "workmanship" to indicate whether the shoes were made with detailed and careful work. Finally, I summed the values of these different characteristics variables to obtain the overall quality proxy.

I applied Wilcoxon ranksum tests on these categorical variables and on overall quality one by one, and tabulated the pre- and post-entry medians and the ranksum test p-values in Tables 7 (for leather shoes) and 8 (for sport shoes). The tables clearly show that the authentic producers used fancier surface and side materials and improved the shoe appearances tremendously (especially for leather shoes) after counterfeit entry. Equipment and technologies were improved significantly as well. There is no matching improvement in the functionality (both at the aggregate level and the detailed characteristics level), possibly due to the fact that the companies always describe their products as having good characteristics: mobility, versatility, having cushioning effects, etc.. The overall quality is shown to be better after entry, with an extremely low p-value in the Wilcoxon ranksum test. I also carried out IV regressions for the continuous variable for overall quality in the leather and sport shoes sectors, with the interaction between the loosening in government enforcement efforts and the relationship proxy as the IV, controlling for year and company fixed effects. I found statistically significant coefficients on the quality measures (log deflated production costs and the overall quality rank), significant at the 1% level (Panels B in Tables 7 and 8). In particular, the coefficients on counterfeit entry in the regressions for overall quality ranks indicate that the overall authentic quality shifts up by 15 percentile after the brand experienced counterfeits (the modes of the distributions for quality ranks were approximately equal to 20).

[9] Italy has a famous cluster of shoe manufacturers.

4.5 Predicting Entry

What attracts counterfeit entry? What suppresses counterfeit entry or sales? I attempted to explore the stigma of entry by regressing the counterfeit entry, sale quantities divided by authentic quantities, and log sales, respectively, in separate specifications, on the government enforcement change dummy, the relationship proxy between the company and the government, the interaction between the legislation dummy and relationship proxy, age of the authentic brand, previous year authentic sales, number of licensed stores, enforcement investment and costs to produce the authentic product, and the current year log GDP per capita PPP, economic growth rate, Gini coefficient, total consumption as a share of GDP, log of deflated household consumptions, and a year trend, controlling for company fixed effects (Table 9). The log GDP per capita PPP variable is included in light of Khan's (2004) finding that IPR might be endogenous to development level, which would then correlate with the counterfeit entry. While the coefficients on this variable are positive, they are not statistically significant. The positive coefficients on Gini, however, are significant at the 5% level for predicting counterfeit entry and sales. The lagged year authentic sales are positively correlated with counterfeit sales and the age of brand is negatively correlated with counterfeit entry and sales. (Column 1 and 3 in Table 9). It is reassuring to see the highly significant positive coefficients on the enforcement legislation dummy and its interaction with the relationship proxy, and insignificant coefficients on the relationship proxy by itself. All these results confirm the validity of the instruments adopted in the previous sections. The empirical analyses here also provide some evidence that the strategies companies take to fight counterfeits are quite effective. In particular, an additional lagged year licensed store helps to reduce counterfeit sale quantities as a fraction of an authentic quantities by 2% on average, statistically significant at the 5% level. It also helps to deter entry by .001 on average, although significant only at the 10% level. Lagged year enforcement costs are also shown to be negatively correlated with counterfeit entry, sale quantities, and log sales. An additional 10,000 yuan invested in enforcement reduces fake sales by .3% on average, significant at the 5% level.

4.6 Robustness Checks and Estimations on Other Authentic Prices and Total Profits

Data on the two waves of ISO application and grant dates show no clear pattern of relationships related to company size, fame, or other characteristics. In addition, the time it took each company to pass through either wave of ISO did not change much over time. However, I carried out alternative specifications using only the number of days to pass through the 1994 ISO as a relationship proxy. I repeated the first stage IV estimation including year dummies instead of year trend to check the robustness of results. Because the government enforcement loosening indicator variable is a linear combination of the year dummies after 1995, I had to drop it in order to include the year dummies. The interaction variable between enforcement change indicator and relationship proxy is still significantly correlated with the counterfeit entry at the 3% level, and the overall F-stat for the first stage estimation is significant also (reported in Panel B of Table 10).

I apply this alternative specification of IVs to analyze the entry effects on log authentic prices for high-, mid- and low-end products. As Table 10 shows, counterfeit entry leads to a 10% increase in high prices on average, significant at the 5% level, a 3% rise in prices of the mid-end authentic products, significant only at the 10% level, and no significant impact on the low-end prices. The age of the company and the log of number of licensed stores are shown to correlate highly with authentic prices. The longer the company has been on the market, the higher its prices. This could be due to consumer loyalty or company characteristics (such as reputation and fame) that are correlated with both age and price. Licenced stores (in logs) assist in raising log prices of high-end products by 6%, of mid-range products by 3%, and low-end products by 2% on average, either through enhancing local monopoly position or through higher marginal costs.

I further test the effects of counterfeit sale quantity on authentic prices. Because counterfeit sale quantity as a share of authentic sale quantity has a skewed distribution, I take log transformations. I instrument for this log quantity share variable, instead of the entry dummy, with the same set of IV in testing the pricing effects. Column 4 of Table 10 reports positive and statistically significant coefficients on the log of counterfeit quantity share, company's enforcement investments, number of licensed stores, and company age. A tripling of counterfeit sale quantity share would induce an increase in the high-end authentic product price by approximately 4%.

I use this same IV to test the entry effects on the profits of authentic companies, and did not find statistically significant entry effects with different sets of control covariates. However, the coefficients on counterfeit entry are positive and equal to approximately .77 (indicating doubling profits post-entry, since the response variable is log profits). When controlling for the authentic quality (proxied by the high-end cost), most of these positive effects on profits are shown to come from quality upgrades, statistically significant at the 10% level. Log advertisement costs (coeff=.61) and Gini coefficients (coeff=.08) are shown to be positively correlated with profits, statistically significant at the 5% level in all specifications.

Robustness checks were also carried out using squared and cubic terms of year trend in the regression, and key results remain similar, with the year effects dwindling.

5 Discussion and Conclusion

Pricing and marketing impacts of counterfeits are urgent concerns for business managers and policy makers. This paper develops a vertical differentiation model for imitative and counterfeit entry to predict and explain the pricing and marketing responses of authentic incumbents to new entry. Panel data on Chinese shoe companies are compiled to estimate empirically pricing and marketing impacts of counterfeit entry. In particular, I identify an exogenous change in government enforcement efforts in monitoring footwear trademarks occurring since 1995 and its differential impacts on counterfeit entry for branded companies with varying degrees of closeness with the local government. Using the interaction between legislation change and relationship proxy as an IV, I obtained empirical results consistent with theoretical predictions. This study is the first attempt to combine theory and empirics to unveil the economics of counterfeits in the literature.

My analyses show that counterfeit entry may exert downward pressure on prices by lowering expected quality in the pooling equilibrium. More importantly, however, counterfeit entry also induces the original producer to offer a higher quality product at a higher price. This suggests a successful business strategy to mitigate copycat competition: innovation. There is also evidence revealing that authentic producers use a high price to signal quality when first introducing a new product. In addition, an authentic company's non-price signaling devices push up costs or reinforce its local monopoly position, thereby help its products to sustain a high price. The average response time for authentics to raise prices is approximately 2 years after counterfeit entry, as estimated by the IV-BHCM. Lastly, enforcement activities and licensed stores are shown to deter counterfeit entry or reduce counterfeit sales.

This paper is a first step in exploring the complex impacts of counterfeits. The modeling and empirics naturally lead to the next step of welfare calculations. I am continuing to gather data on market shares and sales at the product-level. Merging with the prices and characteristics data from this research, I will carry out structural estimations to conduct welfare analyses, both in terms of consumer surplus changes after counterfeit entry and in terms of efficiency gains (or losses) that result from shifting the burden of monitoring counterfeits from the government to individual companies. Furthermore, I plan to estimate structural entry models to better understand counterfeiters' decisions for market entry.

References

Aghion, P., Blundell, R., Griffith,R., Howitt, P., and Prantl, S. (2004), "Firm Entry, Innovation and Growth: Theory and Micro Evidence" *Working paper,* **Harvard University**, Aug.

Bagwell, K. and Riordan, M. H. (1991), "High and Declining Prices Signal Product Quality", *The American Economic Review,* **81:1**, 224–239.

Caves, R.E., Whinston, M. D. and Hurwitz, M. A. (1991), " Patent Expiration, Entry and Competition in the U.S. Pharmaceutical Industry: An Exploratory Analysis", *Brookings Papers on Economic Activity,* .

Chinese National Bureau of Statistics (1995), *Codebook for the Third Chinese National Industrial Census*, National Bureau of Statistics.

Curry, D. J. and Riesz, P. C. (1988), " Prices and Price / Quality Relationships: A Longitudinal Analysis", *Journal of Marketing,* **52**, 36-51.

Frank, R.G. and Salkever, D.S. (1997), "Generic Entry and the Pricing of Pharmaceuticals", *Journal of Economics & Management Strategy,* **6:1**, 75–90.

Fudenberg, D. and Tirole, J. (2000), "Pricing a Network Good to Deter Entry", *The Journal of Industrial Economics,* **48:4**, 373–390.

Gabszewicz, J. and Thisse, J.-F. (1979), "Price Competition, Quality and Income Disparities", *Journal of Economic Theory,* **20:** 340-359.

Gabszewicz, J. and Thisse, J.-F. (1980), "Entry (and Exit) in a Differentiated Industry", *Journal of Economic Theory,* **22:** 327-338.

Galloni, A. (2006), "Bagging Fakers and Sellers", *Wall Street Journal,* January 31, B1-2.

Gordon, W. and Watt, R. (2003), *The Economics of Copyright,* Edward Elgar Publishing limited.

Grossman, G. and Shapiro, C. (1988), "Counterfeit Product Trade", *American Economic Review,* **78**, 59-75.

Khan, B.Z. (2004), "Does Copyright Piracy Pay? The Effects of U.S. International Copyright Laws on the Marke for Books, 1790-1920", *NBER Working Paper Series,* **10271**.

Milgrom, P. and Roberts, J. (1986), “Price and Advertising Signals of Product Quality ”, *Journal of Political Economy* , **94** , 796-821.

Metrick, A. and Zeckhauser, R. (1999), “Price Versus Quantity: Market-Clearing Mechanisms When Consumers are Uncertain about Quality”, *Journal of Risk and Uncertainty,* **17:3**, 215–242.

Nelson, P. (1974), “Advertising as Information, ”, *Journal of Political Economy,* **82:4**, 729-754.

Passariello, C. (2006), “Holograms Tell Fake From Fendi”, *The Wall Street Journal,* Feb. 22, 2006, B1, B2.

Qian, Yi (2005), “Instrumental Variable Estimation in Bayesian Hierarchical Changepoint Model” *working paper,* **Harvard University**.

Quality and Technology Supervision Bureau of China (1991-2004), *Year Books,*.

Scandizzo, S. (2001), “Counterfeit Goods and Income Inequality” *IMF Working Paper,* **WP/01/13**, January.

Shaked, A., and Sutton, J. (1983), “Natural Oligopolies” *Econometrica,* **51:5**, 1469-1483.

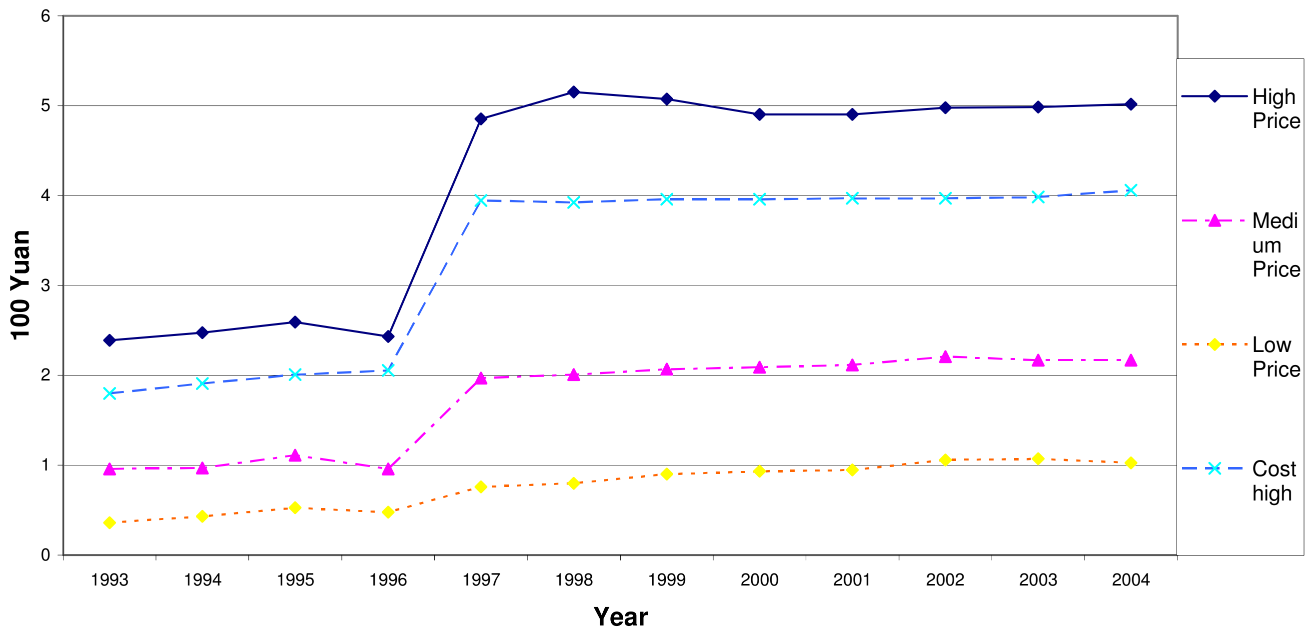

Fig.1: Deflated Prices and Costs for an Infringed Chinese Brand (FakeEntry=1996). This figure presents the price and cost of high-end product, the prices of medium-end and low-end products of the Chinese-originated brand, deflated at 1995 CPI.

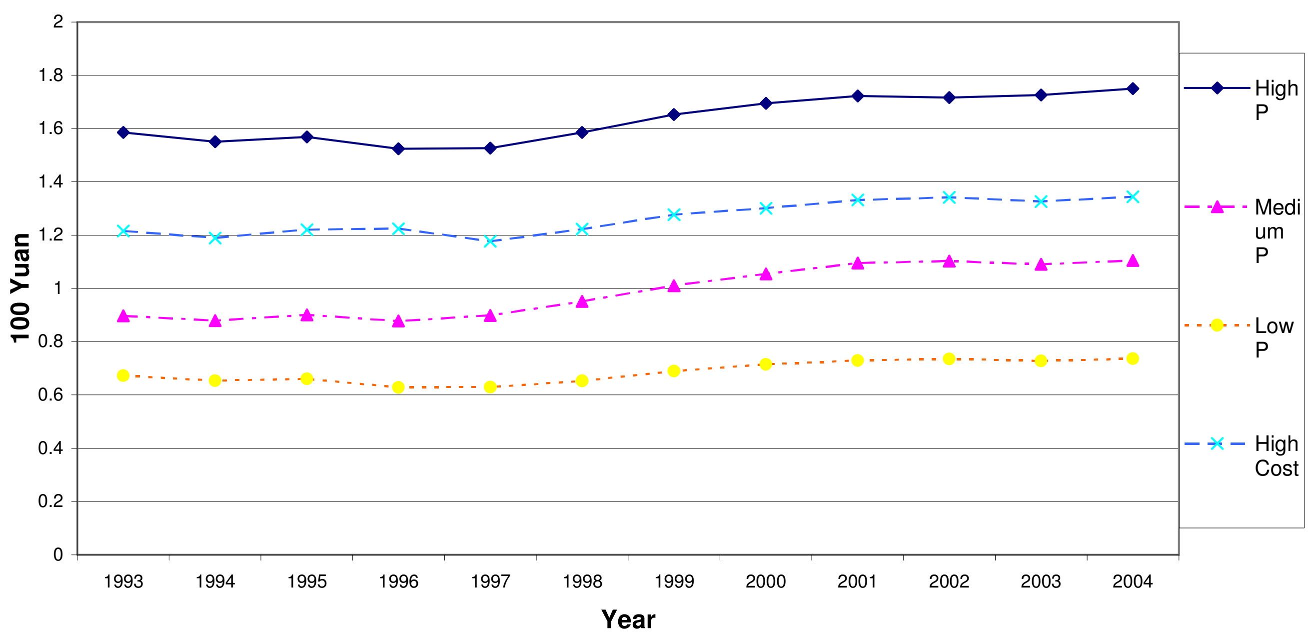

Fig.2: Deflated Prices for a Non-infringed Chinese Company. This figure presents the time trends of the authentic prices for the high-end, medium-end, and low-end products, and the costs of authentic high-end product, all deflated at 1995 CPI.

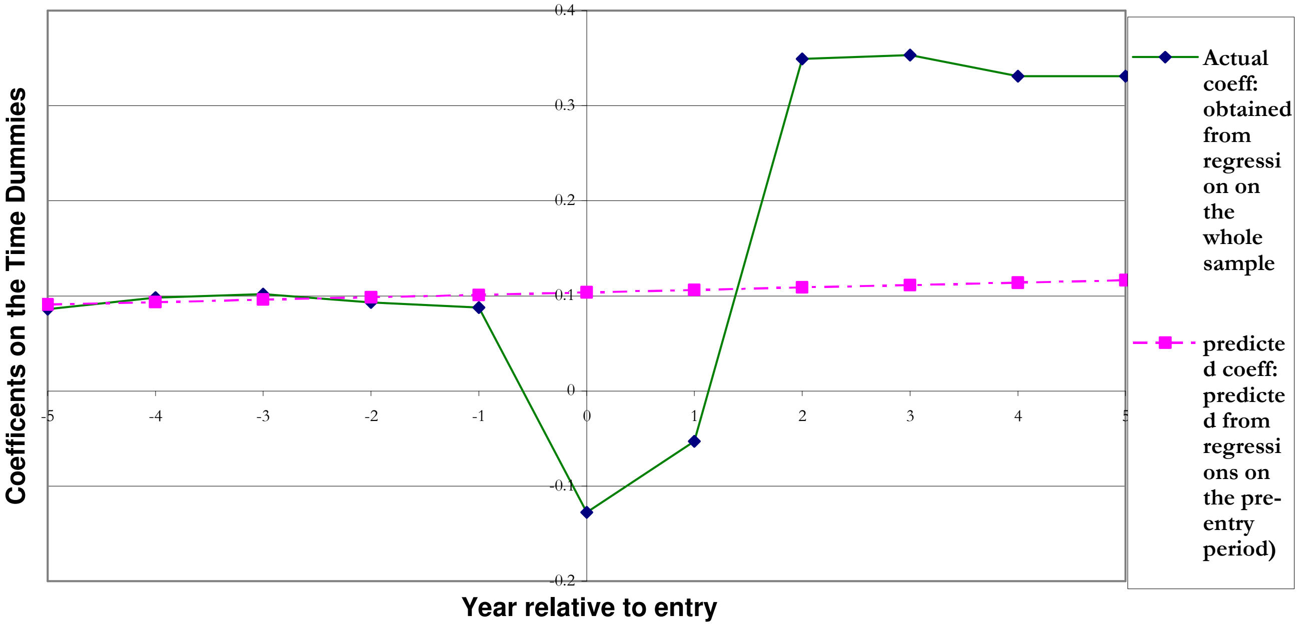

Fig.3: Time Plot of Average Log Deflated Authentic Prices. This figure plots the regression coefficients on the dummies (indicating the year relative to counterfeit entry), with log deflated authentic price as the response variable.

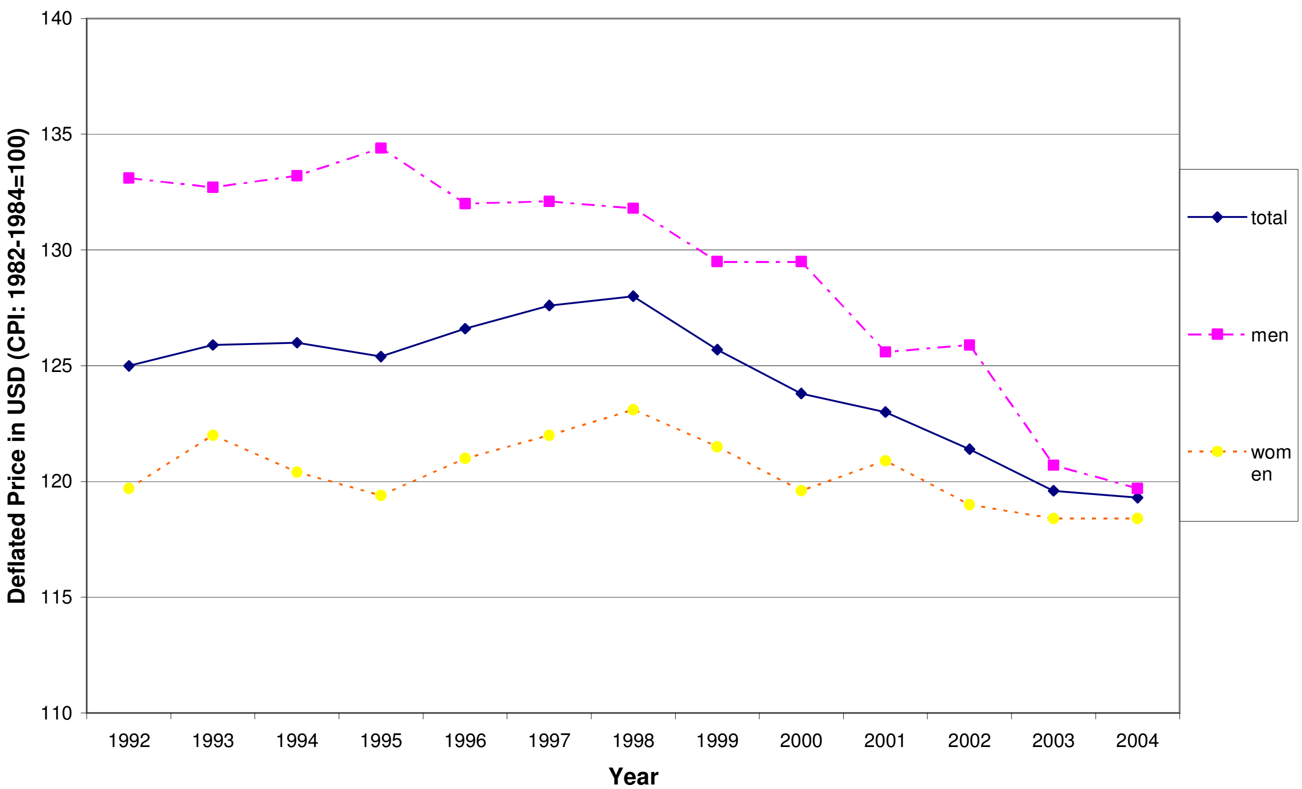

Fig.4: Time Trends of Deflated U.S. Footwear Prices. This figure presents the trends of deflated average prices in America, for all shoes, men's shoes, and women's shoes, respectively. **Source: American Apparels and Footwear Association.**

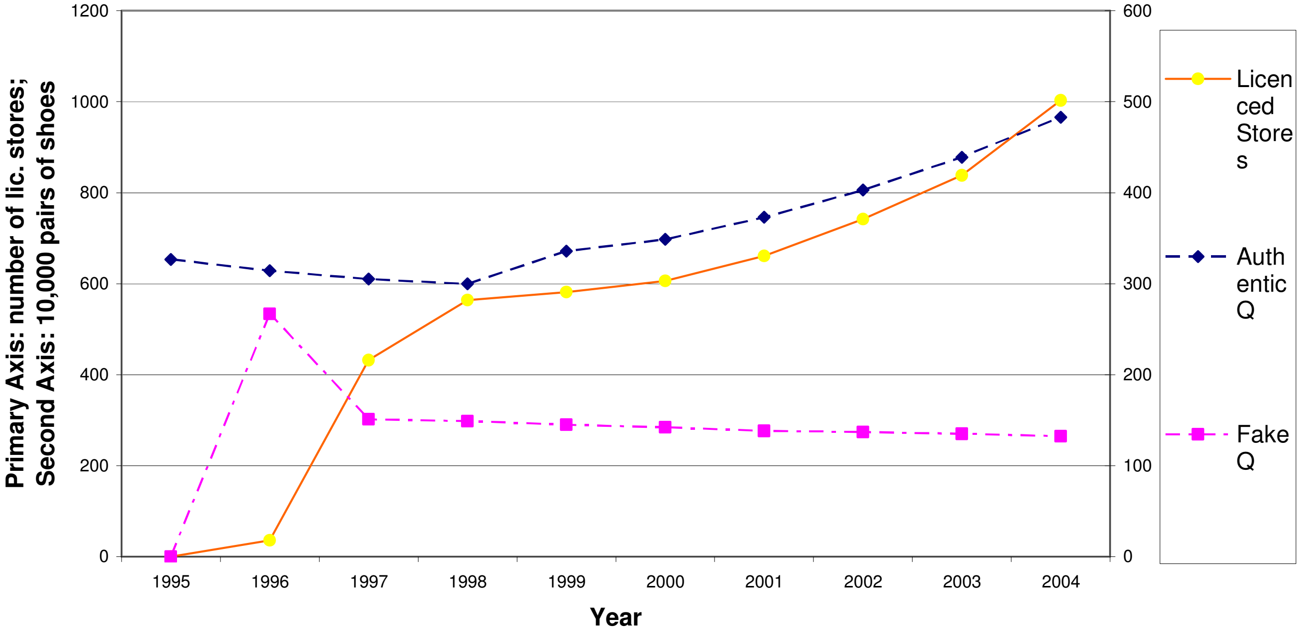

Fig.5: A Famous US MNC in China (Entry=1996). This figure presents the sale quantities of authentic and counterfeit products of a famous MNC brand, and the authentic producer's number of licensed stores in China.

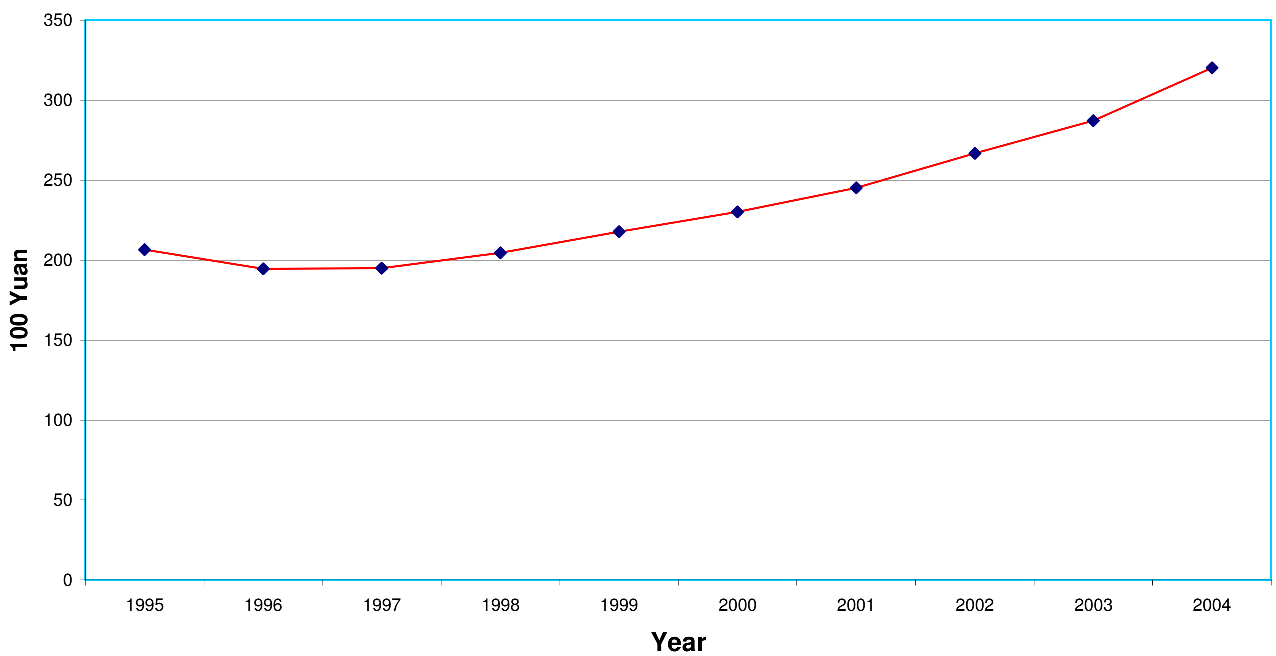

Fig.6: Time Trend of Deflated Total Profits of a MNC (Entry=1996). This figure plots the deflated profits of a MNC in China over the years in the data. Counterfeiter of this brand entered in 1996.

Table 1. OLS Estimates for Counterfeit Effects on Authentic Prices

This table reports the OLS estimates of the counterfeit entry effect on the log of deflated authentic high-end prices. All models use company fixed effects. Each column represents a regression specification, with the dependent variable listed in the column header and coefficient estimates and standard errors on the relevant independent variables in the first column. Entry_{t-2} dummy equals 1 if counterfeit of a brand entered in year t-2; M is the authentic costs of high-end products of year t divided by that of year t-1, proxying for the quality differential among the authentic products; m is the counterfeit production cost divided by the authentic one, proxying for the quality gap; log(sale quantity) is the log of authentic domestic sale quantity. Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators*. Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent variable:	$\log P_t$		$log(P_t) - log(P_{t-1})$
	(1)	(2)	(3)
Entry_{t-2}	**.16****	**.15****	**.12****
	(.08)	(.07)	(.06)
M	1.38***	.88**	.56
	(.29)	(.31)	(.40)
m	-.69*	-.36*	-1.07
	(.43)	(.19)	(1.69)
log(sale quantity)		-.03	-.13*
		(.03)	(.07)
age		.02**	.02***
		(.01)	(.01)
log(GDPpcPPP)		2.88***	4.88**
		(.54)	(2.37)
Growth		.03***	.06*
		(.01)	(.03)
GINI		.15***	.11**
		(.04)	(.05)
(C/Y)		.01	.51**
		(.01)	(.23)
log(HHC)		.83**	.21
		(.36)	(.61)
year trend		.41***	.59**
		(.05)	(.29)
Year Fixed Effects	Y	N	N
No. of Obs.	370	370	370
R-square	.98	.97	.89

Table 2. The IVs' Relevances

This table reports the first stage of IV estimations. All models use company fixed effects. Counterfeit entry dummy (equals one if counterfeits are discovered for a brand) and counterfeit sale quantity as a fraction of authentic sale quantity are regressed on the set of I.V., with year trend and company fixed effects, in four separate regressions. Each column reports one regression specification. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses.Statistical significance levels: *-10%; **-5%; ***-1%.

IV1: Enforcement legislation change – Loose, a dummy which equals 1 in 1995 onwards, and year trend.

IV2: Interaction between legislation change and a company's relationship with its local government – Relation (Proxied by the number of work days between the application and grant dates of ISO certificate for an authentic company), Loose*relation, Loose, and year trend.

IV3: Interaction between legislation change and a company's relationship with its local government (Loose*relation), year and company dummies.

Dependent Variable:	Fake Entry			Fake Q/Auth. Q
	(1)	(2)	(3)	(4)
	IV1	IV2	IV3	IV2
Loose	.72***	.27***		.49***
	(.04)	(.05)		(.06)
Relation		.001	.001	.002
		(.001)	(.001)	(.001)
Loose*relation		.14***	.002***	.002***
		(.02)	(.000)	(.000)
year trend	-.000	.04**		-.02*
	(.000)	(.01)		(.01)
Year Fixed Effects	N	N	Y	N
No. of Obs.	370	370	370	370
Wald Chi2 (or F-stat)	135	179	49.3	51

Table 2b: IV Reg for Fake Entry Effects on Various Authentic Company's Business Strategies and Outcomes

This table reports the second stage of IV estimations. All models use year and company fixed effects. Counterfeit entry dummy Entry_{t-2} (or Entry_{t-1}) equals one if counterfeits are discovered in year $t-2$ (or $t-1$) for a brand. Various authentic outcome variables are regressed on the entry dummies, in separate regressions. Each column reports one regression specification. Column 1 reports entry effects on log authentic deflated high-end prices, Column 2 reports entry effects on log advertisement costs, 3 for log number of licensed stores, 4 for log enforcement investments, 5 for log profits, and 6 for log of export revenues of the authentic company. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses.Statistical significance levels: *-10%; **-5%; ***-1%. R-squre values from the two alternative regression specifications are similar, and I report the first specification R-square in the last line.

Dependent variable:	$\log(\mathbf{P_t})$	$\log(\mathbf{Ads_t})$	$\log(\mathbf{Store_t})$	$\log(\mathbf{Enf_t})$	$\log(\mathbf{\Pi_t})$	$\log(\mathbf{Exp_t})$
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment Specification 1: Entry_{t-2}	**.37*** **	**.53**	**2.63**	**1.62**	**.21**	**2.68**
	(.10)	**(.39)**	**(2.62)**	**(1.91)**	**(.66)**	**(3.58)**
Treatment Specification 2: Entry_{t-1}	**.16**	**.52**	**4.36*** **	**2.73** **	**-2.44**	**1.65**
	(.30)	**(1.07)**	**(1.32)**	**(1.02)**	**(1.57)**	**(4.83)**
Year and Company Fixed Effects	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
No. of Obs.	**370**	**370**	**370**	**370**	**370**	**370**
R-square	**0.98**	**0.97**	**0.92**	**0.88**	**0.92**	**0.83**

Table 3. IV Estimates for Counterfeit Effects on Authentic Prices: entry dummy lagged by 0, 2, or 4 years

This table reports the IV estimates of the counterfeit entry effect on the log of deflated authentic high-end prices. All models use company fixed effects. Each column represents a regression specification, with counterfeit entry dummy defined at different lags as specified in the column header. For instance, Columns 3 and 4 correspond to $Entry_{t-2}$ dummy, which equals 1 if counterfeit of a brand entered in year t-2; logCost is the authentic costs of high-end products of year t, proxying for its quality; m is the counterfeit production cost divided by the authentic one, proxying for the quality gap; age is defined as the current year minus a company's incorporation year. log(sale quantity) is the log of authentic domestic sale quantity. Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators*. Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent variable:	Log deflated prices for high-end authentic products–$log(P_t)$					
	Current Year		2-year Lag		4-year Lag	
	(1)	(2)	(3)	(4)	(5)	(6)
Entry	.02	-.01	.43***	.08**	.25**	.06
	(.06)	(.01)	(.13)	(.04)	(.12)	(.05)
logCost		1.02***		.82***		.93***
		(.01)		(.05)		(.03)
m		-.22*		-.13		-.18*
		(.12)		(.19)		(.11)
age		.001**		.001		.001*
		(.000)		(.001)		(.000)
log(sale quantity)		.002		.01		-.01
		(.002)		(.01)		(.03)
log(GDPpcPPP)		.11		.04		.09
		(.15)		(.21)		(.12)
Growth		.001		.001		.002
		(.001)		(.001)		(.005)
GINI		.005*		.004**		.002
		(.002)		(.002)		(.006)
C/Y		.000		.003		.002
		(.001)		(.003)		(.003)
log(HHC)		.01		.08		.04
		(.02)		(.08)		(.08)
year trend	.00	-.01	.04***	-.01	.03***	.00
	(.00)	(.01)	(.01)	(.02)	(.01)	(.00)
No. of Obs.	370	370	370	370	370	370
R-square	.91	.96	.95	.98	.92	.97

Table 4. Stratified IV Estimations for $log(P_t)$ on Entry Dummy Lagged by 2 Years

This table reports the IV estimates on the counterfeit entry effect on the log of deflated authentic high-end prices. All models use company fixed effects. Each column represents a regression in a different stratum as specified in the column header. Column 2 refers to the stratum with low-quality counterfeit entrant, whose quality belongs to the lower four quintiles of the fake quality distribution. Again, production cost is used to proxy quality. High-quality entrant stratum consists of companies whose counterfeit quality is in the fifth quintile of the distribution. $Entry_{t-2}$ dummy equals 1 if counterfeit of a brand entered in year t-2; logCost is the authentic costs of high-end products; m is the counterfeit production cost divided by the authentic one; age is defined as the current year minus a company's incorporation year; log(store) is the log of number of authentic licensed stores; log(ads) is the log of authentic advertisement expenditure. log(sale quantity) is the log of authentic domestic sale quantity. Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators*. Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent variable:	Log deflated prices for high-end authentic products–$log(P_t)$		
	(1)	(2)	(3)
	Complete Sample	Low-quality Entrant Stratum	High-quality Entrant Stratum
$Entry_{t-2}$	.02**	.05**	-.002
	(.01)	(.02)	(.01)
logCost	.72***	.93***	.95***
	(.03)	(.01)	(.02)
m	-.10*	.02	-.66**
	(.06)	(.01)	(.18)
log(Store)	.002*	.01**	.001
	(.001)	(.00)	(.01)
log(ads)	.007**	.01**	.001
	(.003)	(.005)	(.01)
age	.01	.01	.03**
	(.03)	(.00)	(.01)
log(sale quantity)	-.01**	-.01**	-.01
	(.00)	(.005)	(.01)
log(GDPpcPPP)	.27	.42	-.36
	(.43)	(.62)	(.29)
Growth	-.00	-.002	-.003
	(.00)	(.003)	(.01)
GINI	.12***	.28***	.30
	(.03)	(.06)	(.51)
C/Y	.001	.001	-.00
	(.001)	(.001)	(.00)
log(HHC)	.02	.03	.01
	(.08)	(.05)	(.10)
year trend	-.01	-.02	.03
	(.07)	(.04)	(.03)
No. of Obs.	370	298	72
R-square	.99	.98	.90

Table 5. Comparing OLS, IV, and IV-BHCM Estimates without Controlling for Authentic Cost – Overall Entry Effect

This table compares the estimates on the counterfeit entry effect on the log of deflated authentic high-end prices from OLS, regular IV, and IV-BHCM, without controlling for authentic production cost (which proxies for quality). All models use company fixed effects. Each column represents a regression approach as specified in the column header, and lists the coefficient estimates on the included RHS variables. IV with the interaction of enforcement legislation change and relationship proxy is applied. For the OLS and regular IV, Entry_{t-2} dummy equals 1 if counterfeit of a brand entered in year t-2; Response time refers to the average number of years authentic companies responded to counterfeit entry, and only IV-BHCM provides estimate for it; m is the counterfeit production cost divided by the authentic one; age is defined as the current year minus a company's incorporation year; log(store) is the log of number of authentic licensed stores; log(ads) is the log of authentic advertisement expenditure; log(sale quantity) is the log of authentic domestic sale quantity. Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators*. Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent Variable:	Log deflated prices for high-end authentic products–$log(P_t)$					
	OLS		IV		IV-BHCM	
	(1)	(2)	(3)	(4)	(5)	(6)
Entry	.31***	.12***	.43***	.26**	.67***	.41**
	(.06)	(.04)	(.13)	(.11)	(.16)	(.12)
Response time					1.2***	1.6***
					(.14)	(.26)
m		-.91***		-2.3**		-1.7***
		(.27)		(1.1)		(.38)
log(Store)		.06***		.09**		.06***
		(.01)		(.05)		(.02)
log(ads)		-.04		.05		.00
		(.03)		(.10)		(.05)
age		.06**		.01		.02*
		(.02)		(.03)		(.01)
log(sale quantity)		-.04		-.18*		-.07
		(.03)		(.10)		(.05)
log(GDPpcPPP)		2.3		2.1		.88**
		(1.8)		(8.0)		(.24)
Growth		-.02		.05		.05***
		(.01)		(.06)		(.01)
GINI		-.05*		-.37*		-.1**
		(.03)		(.20)		(.03)
C/Y		.00		.05		.03**
		(.01)		(.04)		(.01)
log(HHC)		1.6		2.5		1.3**
		(4.3)		(1.8)		(.5)
year trend	.01	.34**	.04***	.46	-.001	.02
	(.01)	(.12)	(.01)	(.65)	(.001)	(.05)
No. of Obs.	370	370	370	370	370	370
R-square	.96	.96	.95	.98	.98	.98

Table 6. Comparing OLS, IV, and IV-BHCM Estimates, Controlling for Authentic Cost – Signaling Effect.

This table compares the estimates on the counterfeit entry effect on the log of deflated authentic high-end prices from OLS, regular IV, and IV-BHCM, controlling for the authentic production cost. All models use company fixed effects. Each column represents a regression approach as specified in the column header. IV with the interaction of enforcement legislation change and relationship proxy is applied. For the OLS and regular IV, Entry_{t-2} dummy equals 1 if counterfeits of a brand were present in year t-2; Response time refers to the average number of years authentic companies responded to counterfeit entry, and only IV-BHCM provides estimate for it; logCost is the log of authentic production cost; m is the counterfeit production cost divided by the authentic one; age is defined as the current year minus a company's incorporation year; log(store) is the log of number of authentic licensed stores; log(ads) is the log of authentic advertisement expenditure. log(sale quantity) is the log of authentic domestic sale quantity. Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators*. Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent variable:	Log deflated prices for high-end authentic products–$log(P_t)$		
	(1)	(2)	(3)
	OLS	IV	IV-BHCM
Entry	.03	.02**	.024**
	(.02)	(.01)	(.01)
Response time			2.0***
			(.48)
logCost	1.01***	.72***	.80***
	(.01)	(.03)	(.02)
m	-.02*	-.10*	-.03
	(.01)	(.06)	(.03)
log(Store)	.003	.002*	.007***
	(.005)	(.001)	(.001)
log(ads)	.002	.007**	.003
	(.001)	(.003)	(.002)
age	.01	.01	.03
	(.01)	(.03)	(.04)
log(sale quantity)	-.003	-.01**	-.002
	(.002)	(.00)	(.002)
log(GDPpcPPP)	.03	.27	.19
	(.10)	(.43)	(.42)
Growth	.00	-.00	.006***
	(.00)	(.00)	(.001)
GINI	.01**	.12**	.07***
	(.00)	(.03)	(.01)
C/Y	.00	.001	.00
	(.00)	(.001)	(.00)
log(HHC)	.01	.02	.06
	(.03)	(.08)	(.05)
year trend	-.01	-.01	-.03
	(.01)	(.07)	(.08)
No. of Obs.	370	370	370
R-square	.97	.99	.99

Table 7. Wilcoxon Ranksum Tests and IV Estimation on Leather Shoe Quality

Panel A tabulates the Ranksum test statistics for the leather shoe characteristics pre- and post- counterfeit entry. All the characteristics variables are categorical. Surface materials include 14 varieties, ranging from plastic leather to crocodile skin; Side materials include 7 varieties, ranging from plastic leather to baby cow skin; Bottom materials include 5 varieties, ranging from inferior PU to cow skin; Equipments include local and Italian equipments which include Italian production line, pattern-press equipments, and equipments to make the shoe bottom sturdy. Appearance variable is a sum of the dummies indicating whether a pair of shoes is fine, elegant, and with decorative patterns. Functionalities is an aggregate variable for various functional attributes, including adroit (a dummy equals one if a pair of shoes is adroit), absorption (a dummy equals one if a pair of shoes absorbs sweat), athleticfeet (a dummy equals one if a pair of shoes helps treat athletic feet), soft, cushion (a dummy equals one if a pair of shoes has cushion effects), comfort, sturdy, warm, friction (a dummy equals one if a pair of shoes protects from slippery grounds). Workmanship is a dummy that equals one if a pair of shoes is carefully and finely manufactured. Quality is the sum of all dimensions of shoe characteristics.
Panel B reports the IV estimate on the counterfeit entry effect on authentic quality, estimated by log deflated costs and the sum of various shoe characteristics, with the interaction of government enforcement change and relationship proxy as the main IV.

Panel A.

	Medium Value		Ranksum Test
	(1)	(2)	(3)
Quality dimensions	Pre-Entry	Post-Entry	p-value
Surface Material	Regular cow	Precious cow	.000***
Side Material	Regular cow	Sheep	.000***
Bottom Material	Regular	Regular (5% cow skin)	.72
Equipment	Local	Italian	.000***
Appearance	Fine	Elegant, Patterns	.000***
Functionality	6.06	6.08	.83
Workmanship	.93	.95	.26
Versatility	.096	.10	.77
Cushioning	.096	.1	.88
Quality	18.6	22.6	.000***

Panel B.

Dependent variable:	log Cost	Overall Quality
Entry_{t-2}	.45***	2.82***
	(.12)	(.51)
Company and Year Fixed Effects	Y	Y
No. Obs.	3336	3336
R-square	.95	.96

Table 8. Wilcoxon Ranksum Tests and IV Estimation on Sport Shoe Quality

Panel A tabulates the Ranksum test statistics for the authentic sport shoe characteristics pre- and post- counterfeit entry. All the characteristics variables are categorical. Surface and side materials include 6 varieties, ranging from inferior PU to real leather with materials for nets; Bottom materials include 4 varieties, ranging from TPU to special rubber; Equipments include local and Italian equipments which mainly refers to Italian production line. Appearance variable is a sum of the dummies indicating whether a pair of shoes is fine, and elegant. Functionalities is an aggregate variable for various functional attributes, including adroit (a dummy equals one if a pair of shoes is adroit), absorption (a dummy equals one if a pair of shoes absorbs sweat), athleticfeet (a dummy equals one if a pair of shoes helps treat athletic feet), soft, cushion (a dummy equals one if a pair of shoes has cushion effects), comfort, sturdy, warm, friction (a dummy equals one if a pair of shoes protects from slippery grounds), lasting (a dummy equals one if a pair of shoes lasts a long time), support (a dummy equals one if a pair of shoes supports ankle well), and flexibility. Workmanship is a dummy that equals one if a pair of shoes is carefully and finely manufactured. Quality is the sum of all dimensions of shoe characteristics.
Panel B reports the IV estimates of the counterfeit entry effect on authentic quality, estimated by log deflated costs and the sum of various shoe characteristics, with the interaction of government enforcement change and relationship proxy as the main IV.

Panel A.

	Medium Value		Ranksum Test
	(1)	(2)	(3)
Quality dimensions	Pre-Entry	Post-Entry	p-value
Surface Material	PU; net	Syn.leather;light net	.000***
Bottom Material	MD	TPR	.229
Air Pumps	none/middle	top/middle/back	.02**
Equipment	Local	Italian	.000***
Appearance	Fine	Fine/Elegant	.09*
Functionality	12	12	
Workmanship	1	1	
Versatility	1	1	
Supportiveness	1	1	
Quality	21.3	24.1	.000***

Panel B.

Dependent variable:	log Cost	Overall Quality
Entry_{t-2}	.30***	2.67***
	(.09)	(.25)
Company and Year Fixed Effects	Y	Y
No. Obs.	3336	3336
R-square	.92	.93

Table 9. Predicting Fake Entry, Quantities, and Sales

Counterfeit entry dummy (equalling one if counterfeits are discovered for a brand), counterfeit sale quantity as a fraction of authentic sale quantity, and counterfeit sales are regressed on the set of covariates in Column 1, with company fixed effects, in three separate regressions. Each column reports one regression specification. Loose is a dummy for government enforcement change, which equals one from 1995 onwards; Relation between a company and local government is proxied by the number of work days between the application and grant dates of ISO certificate for an authentic company; age is defined as the current year minus a company's incorporation year; lag lstore, lag sales, lag enforce, and lag cost are the lagged year number of licensed stores, sales, enforcement investment, and production cost for an authentic company; Real GDP per capita PPP, growth rates, consumption over income (C/Y), and household consumption (HHC) are obtained from the World Bank *World Development Indicators.* Gini coefficients are extracted from the UN Human Development Reports. Heteroskedasticity-consistent standard errors that correct for clustering at the company level appear in parentheses. Statistical significance levels: *-10%; **-5%; ***-1%.

Dependent Variable:	Fake Entry (1)	Fake Q/Auth. Q (2)	log Fake Sales (3)
Loose	.48***	.82***	6.70***
	(.07)	(.11)	(.61)
Relation	.001	.001	.19
	(.001)	(.001)	(.38)
Loose*Relation	.03**	.10**	.45**
	(.01)	(.04)	(.18)
age	-.45**	.01	-3.4***
	(.16)	(.01)	(.99)
lstore_{t-1}	-.001*	-.02***	-.01
	(.000)	(.005)	(.02)
Sales_{t-1}	.04	.01	.52**
	(.04)	(.05)	(.25)
enforce_{t-1}	-.000	-.01	-.003**
	(.000)	(.015)	(.001)
cost_{t-1}	.16	.27	-.25
	(.13)	(.20)	(.93)
log(GDPpcPPP)	3.4	2.55	18.3
	(3.1)	(4.36)	(19.5)
Growth	-.01	-.05	.02
	(.03)	(.05)	(.23)
GINI	.14**	.07	1.32***
	(.05)	(.08)	(.37)
C/Y	-.02	-.03	-.15
	(.02)	(.03)	(.16)
log(deflated HHC)	.95	1.70	8.5
	(.88)	(1.22)	(5.9)
year	.22	-.43	-.01
	(.24)	(.25)	(.08)
No. of Obs.	370	370	370
R-square	.87	.63	.66