NBER WORKING PAPER SERIES

COUNTERFEITERS: FOES OR FRIENDS? HOW DO COUNTERFEITS AFFECT DIFFERENT PRODUCT QUALITY TIERS?

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Working Paper 16785
http://www.nber.org/papers/w16785

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2011

I warmly acknowledge support from the Kauffman Foundation Grants. I am grateful to Josh Lerner, Eric Anderson, Philippe Aghion, Meghan Busse, Shane Greenstein, Angela Lee, Jin Li, Keith Maskus, Ivan Png, Scott Stern, K. Sudhir, Catherine Tucker and Florian Zettlemeyer for helpful discussions; to seminar participants at the Kellogg School of Management, Yale School of Management, University of Colorado, and Quantitative Marketing and Economics conference for comments. Cooperation from the Chinese Quality and Technology Supervision Bureau (QTSB) and the companies we interviewed and surveyed are gratefully acknowledged. The results in this paper do not necessarily represent the views of QTSB or of the National Bureau of Economic Research.

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NBER Working Paper No. 16785
February 2011, Revised July 2013
JEL No. L25,L26,L6

ABSTRACT

A key concern about counterfeits and weak intellectual property protection is that they may hamper innovation by displacing legitimate sales. This paper combines a natural policy experiment with randomized lab experiments to estimate the heterogeneous impacts of counterfeiting on the sales and consumer purchase intent of branded products of various quality levels. I collect new product-line-level panel data (1993-2004) on Chinese shoe companies. I identify heterogeneous effects of counterfeit entry on sales of authentic products of three quality tiers. In particular, counterfeits have both advertising effects for a brand and substitution effects for authentic products, and the effects linger for a few years. The advertising effect dominates the substitution effect for high-end authentic-product sales, and the substitution effect outweighs the advertising effect for low-end product sales. The positive effect of counterfeits is most pronounced for high-fashion products (such as women's high-leg boots and dress shoes), for shoes tailored to young customers, and for high-end products of brands that were not yet well-known at the time of counterfeiter entry. Analogous heterogeneous effects of counterfeiting on consumer purchase intent for branded products of three quality tiers are also discovered in lab experiments with stimuli on shoes, handbags, and sunglasses.

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Imitation is the sincerest flattery.
– C. C. Colton (*Lacon*, 1780-1832)

1 INTRODUCTION

Counterfeits are illegal products that infringe upon others' brands. They affect many industries and can have a large influence on brands' innovative incentives through affecting authentic sales. Bate et al. (2012) find that 41.5% of the failures in drugs' active ingredients are due to counterfeits. In fiscal year 2009, U.S. Customs and Border Protection seized more than $260 million worth of counterfeits, and counterfeit footwear accounted for 40% of the total seizures (Schmidle 2010). In fact, counterfeit footwear has topped the seizure list for four years. While counterfeits worry firms, there may be heterogeneous effects due to the presence of counterfeits, especially for different quality tiers, for different product types, and for brands at different life stages. Only a few researches have directly studied the impacts of counterfeits. Grossman and Shapiro (1988a,b) theorize about the implications of counterfeits for international trade. Qian (2008) offers the first econometric study of the *average treatment effects* of counterfeiting on authentic-product differentiation and self-enforcement expenditures. In order to effectively guide priorities and directions of innovation and enforcement strategies, it is crucial to understand the sales impacts of counterfeits on authentic products of different quality tiers and types and on brands of different life-stages or natures. However, this topic has been largely unexplored in the past literature partly due to a lack of data.

Empirical studies of counterfeits (and in general underground economics) are constrained by their illicit nature (Thursby et al. 1991). Due to severe counterfeiting infringements, the Chinese footwear sector has a strong incentive to investigate the effects of counterfeiters. I gather internal and external data on Chinese shoe brands to analyze the sales effects of counterfeiting on different quality tiers. I significantly extend the brand-level panel data in Qian (2008) to footwear product-line details within each of the 31 brands (including multinational brands operating in China as well as Chinese national brands)[1] and obtain product-line-level sales data from 1993-2004 for the first time. As a result, I am able to go beyond the general impacts of counterfeiting on brands' marketing norms and study its sales impacts, a topic that directly sheds light on the *incentives* and *directions* of innovation. I introduce a new IV to address the endogeneity of counterfeiting: the preexisting ties between brand and product-line managers and enforcement officials based on their biographic matches. This paper further identifies the *heterogeneous effects* of counterfeits on sales of authentic products *at different*

[1]Most brands in China are concentrated in the leather and sport shoes sector (as compared to other parts of the footwear industry) which has annual sales of approximately 6 billion USD. Some Chinese brands, e.g., Li-ning and Anta, occupy Chinese market shares nearly as large as that of Nike.

quality tiers, of *different product types*, and of brands *at different life-stages*. I chart the longer-term effects by quality tier over time.

I probe into the heterogeneous sales impacts. In particular, I disentangle the separate effects of the life stage of a brand and of the quality tiers within a brand portfolio. Within each type of brands and each class of products, the counterfeiting effects are separately identified at the quality-tier level through the difference-in-difference-in-difference simultaneous equation estimations. The combination of field and lab data generates insights at both the aggregated market level and the individual sampled consumer level. I leverage IV strategy to identify occasions in which counterfeiters enter the market because of exogenous policy shocks that are unrelated to the brand's sales prospects – "randomized" entry – to infer entry impacts. I analyze short-term and long-term sales impacts of counterfeiting through a unique panel dataset. The field data uncover that counterfeits exhibit both negative substitution and positive spillover effects on authentic sales. The net effect is positive for high-end authentic products and negative for low-end authentic products, even within the *same brand*. Furthermore, the positive marginal effect of counterfeits on authentic sales is most pronounced for high-fashion products (including dress shoes for men and women and women's high-leg boots), for shoes tailored to young customers, for high-end shoes of newer brands that were not well-known at the time of counterfeiter entry or that did not own multiple sub-brands.

The lab experiments unravel such impacts at the consumer level and find that the presence of counterfeits increased consumers' purchase intent on the high-end-product stimuli and decreased that on the low-end-product stimuli of the brand being infringed. The written responses on purchase motivation also decipher the double-edged effects of counterfeits in increasing brand awareness and in substituting for the authentic product. These experiments complement the field studies by providing micro-foundations of the overall sales impacts based on individual attitudes. The combination of a natural policy experiment and manipulated lab experiments produces conclusions that are more likely to have both internal and external validity. The consistent results from the lab experiments in the U.S. demonstrate that the findings in the field panel data have implications beyond China.

In addition to the new research question, new data, and the approach of combining field studies with lab experiments, this study uncovers interesting findings that are surprising at first sight yet shed new light on the literature. The discovery and understanding of the heterogeneous impacts have important implications for guiding priorities for IPR enforcement policy. As a recent World Intellectual Property Organization study comments, "Governments are invariably resource constrained and completely eradicating violations of IPR law – like violations of other types of law – is out of reach for even the best-resourced states"(Fink et al. 2010). Advocates of IPR promote its stimulating effects on innovation as an engine for economic growth. Such stimulating effects are shown to be rather limited (Lerner 2009) with a generalizable conditional importance of patent only in countries of advanced education and development (Qian 2007, Kyle and McGahan 2011). The debate over IPR culminated in the TRIPs (Trade-Related Intellectual Property) negotiations, which were largely motivated by the desire to reduce trade in counterfeit goods. This study therefore contributes to the broader literature on how firm responses to the legal environment could have important moderating effects on the impact of IPR protection (Zhao 2006, Mortimer 2010, Qian 2008).

The findings suggest that counterfeiters can be both friends and foes to the authentic producers. The brands could optimize their self-enforcement efforts according to the particular adolescence stage the brand faces. At the early stages of brand development, counterfeiters could help increase brand awareness and penetrate the market, playing a role very similar to that of buzz agents. Strong brand awareness and familiarity may be a prerequisite for positive thoughts and feelings toward the brand (Keller 2003), and counterfeiting helps to establish or enhance strong brand awareness and familiarity. This also links to findings in Berger et al. (2010) that no publicity is bad publicity. As the brand grows and becomes prominent, such benefits of counterfeits dwindle and the authentic producers can enhance enforcement against counterfeits to weed out their business-stealing effects.

This was exactly Microsoft's strategy in China, as Bill Gates told an audience at the University of Washington: "Although about 3 million computers get sold every year in China, people don't pay for the software. Someday they will, though. And as long as they're going to steal it, we want them to steal ours. They'll get sort of addicted, and then we'll somehow figure out how to collect sometime in the next decade" (Piller 2006). Only after the majority of the consumers were "locked into" Microsoft softwares did Microsoft engage in furious enforcement campaigns in collaboration with the government to crack down on piracy and make the Chinese market adopt legitimate Microsoft software. By that point, Linux was far less of a competitor for Microsoft in China than in the U.S..

The heterogeneous sales impacts of counterfeits on different product lines yield additional managerial insights: the optimal level of enforcement may vary across the product lines within each brand. For instance, brands need not concern themselves too much with counterfeits that have a wide quality gap below their authentic counterparts, as these counterfeits capture a very different customer segment that would not purchase the authentic products anyways. Brands can also devote relatively fewer enforcement resources to high-fashion product lines and the high-end product lines designed for younger customers, as counterfeits can help set fashion trends and diffuse authentic innovation. This further promotes the product-innovation cycle.

This study contributes to the literature on whether counterfeits are always damaging. Based on her ethnographic research, Gasoline (2009) documented that the consumption of counterfeits stimulated consumers to purchase more branded purses. A stream of literature on online piracy has vigorously debated the effect of filesharing on original music sales in recent years, and Liebowitz (2006) and Oberholzer-Gee and Strumpf (2009) provide excellent surveys. Several empirical studies point to a negative effect of piracy and filesharing (Hui and Png 2003, Liebowitz 2006, Hong 2008), yet Oberholzer-Gee and Strumpf (2007) conclude the opposite, based on an uniquely matched dataset of music downloads and purchases. Along the same line, Mortimer et al. (2010) find that illegitimate redistribution of digital goods increases revenue from nondigital complementary products, notably live performances. At the consumer level, Rob and Waldfogel (2006) conducted surveys of undergrad students. Although they found that the average drop in album purchases due to downloading was \$0.2, consumer surplus increased due to the lower prices.

Illegal imitation can have other positive effects on authentic product sales. A commonly cited mechanism is network effects, where the consumer utility of a product is an increasing function in the size of the user base, and this argument is proposed particularly for software and book copyright cases (Takeyama 1991, Conner and Rumelt 1991, Khan 2004). Others suggest that imitation could serve as a signal for the original product's or idea's high quality (Castro et al. 2008, Biais and Perotti 2008). All these mechanisms speak to the advertising effect of counterfeits. In short, the literature has not provided generalizable guidance on the sales effects of counterfeits.

The rest of the paper is organized as follows. First, I discuss the natural policy experiment. Second, I describe the field data. Third, I provide empirical analyses and results. Finally, I draw out policy implications. Figures and tables are included in the end.

2 Natural Experiment

The ideal experiment to test the sales impact of counterfeits would randomly assign a set of brands to be infringed by counterfeiters and keep the others immune from counterfeiting. Counterfeit entry, however, is unlikely to be exogenous in practice because entry is more likely to occur for brands with larger sales or a looser trademark-management team. Although the fixed effects in panel econometric models capture unobserved time-invariant firm and product-line characteristics, they do not absorb unobserved time-variant characteristics, resulting in a correlation between counterfeit entry and the error term. A simple OLS would result in biased effect estimates. To account for endogeneity concerns, I located appropriate instruments that would identify the effects of the counterfeit-entry variable. While the IV strategy is similar to the one employed in Qian (2008), I explain the necessary institutional details here for completeness.

The Chinese shoe industry provides a convenient laboratory for studying counterfeit effects because of an unexpected enforcement change around 1995. The policy shift stems from shocks external to the shoe sector. In particular, there was an outburst of accidents in the food, drug, agriculture, cotton, and gas sectors due to sub-quality products. The Chinese General Administration of Quality Supervision, Inspection and Quarantine (AQSIQ, previously called the Quality and Technology Supervision Bureau, QTSB) soon issued two notifications to concentrate resources on enhancing quality quarantine and combating counterfeits in the main sectors prone to hazardous materials. This left loopholes in the fashion industry for massive counterfeiting. For instance, the AQSIQs devoted approximately 10-12% of their resources to monitoring footwear products in the early 1990s and only 2% after 1995 (AQSIQ Yearbooks). Data show that shoe brands experienced significant waves of counterfeit entry after the policy shift. The peak in entries came as early as 1996.

The authentic producers were caught by surprise by the influx of counterfeits of their brands. The victim brands quickly organized internal "brand-protection offices" to compensate for the loosened government monitoring. These internal offices were placed in charge of identifying counterfeits of their own brands in the marketplace, reporting to the AQSIQ, collaborating with them to trace and outlaw fake enterprises, etc. This is where the relationship between the branded company and the AQSIQ has played an important role. I used the number of workdays between a brand's ISO certification and application dates nationwide as the most suitable proxy. In addition, I matched the education and experience backgrounds of the brand and product-line managers with those of the AQSIQ officials based on their biographies to generate alternative IVs, and the results were robust.

There were two waves of ISO standards with which the sampled companies had to comply. The first wave was established in the year 1994 and the other in 2000. For each wave of ISO standards, I collected each company's first-application and final-grant dates for the corresponding certificate and calculated the number of workdays between these two dates (henceforth called "elapsed days"). I then constructed a variable that equaled the elapsed days for the ISO-1994 certificate for the years 1993-2000, and a variable that equaled the ISO-2000 elapsed days from 2001 onwards. The biographies are coded and matched based on a detailed codebook by myself and a political scientist (Qian and Shih 2011), posted as an online Appendix. I reverse-coded the experience-match variable in the end so that larger values correspond to a worse relationship, keeping the same direction as the ISO proxy.

The ISO-processing days were largely driven by relationships instead of brand or product characteristics. In particular, it is confirmed by correlating the ISO variable with the experience-match variables that the ISO certification time highly correlates with the preexisting relationship between the managers and QTSB officials because of their priorly overlapping schooling and work experiences (correlation coefficients are 0.79 with the brand-level experience-match variable and 0.63 with the product-line-level experience-match variable). When tabulating bivariate correlations between this relationship proxy and the key brand attributes (e.g., size, sales, product quality, or production costs) in my data, the biggest one was only 0.08. Similarly, the experience-match variables do not correlate with the company characteristics significantly. ISO and experience-matches are therefore unlikely to affect sales through other mechanism besides affecting counterfeit entry.[2]

Table 1 shows that a greater number of days spent by a branded company undergoing ISO application positively correlated with the average quantity of counterfeits of that company's brand after 1995. This correlation remains significant in company- and year-fixed-effects regressions. Section 4.1 reports the first-stage results to support IV validity. In robustness checks, I adopted alternative relationship proxies and received qualitatively similar results. Appendix B further documents these alternative relationship proxies.

Insert Table 1 about here

3 FIELD DATA

3.1 Data Collection and Description

The design of my research required obtaining data on each brand's product sales, as well as information on counterfeit infringements. Due to the underground nature of counterfeits, I gathered data through both secondary databases and primary research. The Chinese Industrial Census (CIC) conducted by the National Bureau of Statistics includes detailed financial data and basic firm characteristics (e.g., size, year of incorporation, etc.) for the entire population of Chinese manufacturing firms that have sales in excess of five million yuan (roughly US$600,000) for each of the census years. Several waves of data were available for the years 1995 and 1998-2005. While the CIC lists the company's main products, it has no further information on product-level details. Systematic data on counterfeits were not found in existing sources. It was absolutely necessary to conduct primary research to acquire brands' financial statements and counterfeit confiscations.

I gathered additional detailed information on sale quantities, transaction prices, and unit production costs at each quality tier for each general type of product, and on the corresponding counterfeits for each of the 31 branded companies sampled through stratified random sampling. The data were extracted from the brands' year-end financial statements as well as other internal records. I specifically

[2]The footwear sector has been privatized in China. All of the sampled companies are private, and sales are of market-equilibrium quantity.

requested brands' databases.[3] The company data corroborate those in the CIC for the shared variables and years. For instance, the sales, sales costs, profits, and export aggregates of my sample mirror the trends in the census of shoe companies (Table A1). My sample's price data also reflect the same shoe-price trends in the eBay dataset collected by researchers at the University of Chicago (Li et al. 2011).[4] While the eBay shoe-price data provide useful validation, I used the original company price records in the main analyses. Appendix B details all the data diagnostics and sampling methods.

The detailed sales quantity, price, and cost data were obtained next for finer categorization of products than in Qian (2008). For instance, if a company produces six types of products, including high-leg, medium-leg, and regular leather shoes for both women and men, and there are three quality/cost levels within each type, then data on sales were disaggregated to each of the 18 quality-type combinations. The data approach a product-level panel. The input and production costs for the products within each quality-type combination are very similar, although there are still variations in color and style (e.g., decorative button on the side or front) that the current data cannot fully capture. The life cycle of each style was one to two years; however, the product lines remained active over the sampled years. That is, the machinery and organization of each product line did not change for any existing quality tier, manufacturing various colors of the same shoe model. Brands offer a range of products, and each brand classifies their products into three quality tiers when reporting to the government. The low-tier product lines produce cheaper shoes with prices averaging around 17 USD (SD=8), the medium-tier lines produce shoes averaging 27 USD (SD=10), and the high-tier lines offer an average price of 43 USD (SD=19). New product lines added in later years were also clearly captured in the data and were analyzed separately from the existing product lines. Such fine-level aggregations are appropriate for the analyses at hand, as I am precisely interested in the differential sales impacts at the quality-tier level. As detailed in Section 4.4, I conduct additional cluster analyses where I form natural clusters of quality tiers based on the unit production costs in the full sample of existing product lines across brands.

I collected data on the year that counterfeits entered the market for *each quality tier of each brand*, whenever that existed, from each authentic firm's "brand-protection offices." Because these offices and the AQSIQ worked together to combat counterfeits, the AQSIQ offered feedback to each brand with statistics on its confiscated counterfeits. I therefore obtained records of the counterfeits

[3]The company contacts were very responsible, and they were cautious about not providing casual estimates in interviews. They would instead email or fax me after checking with their sources.

[4]The researchers collected transaction-level data on eBay for several product categories. For each transaction, the data include the shoe brand and type, final transaction price, shipping cost, seller and buyer IDs, product condition, starting bid, and number of bids.

that the brands had discovered and reported to the government as well as the counterfeits from the market and manufacturing sources that had been raided by the AQSIQ. The AQSIQ also kindly provided me with some of the internal financial records on the counterfeit entities and statistics on the characteristics of the counterfeit shoes they had confiscated. Data show that counterfeiters usually imitate all quality levels of authentic products, even though they use similarly inferior materials (e.g., synthetic leather or rubber) to produce shoes that mimic the different appearances of these products for the brand. They often play the low-price game and the price can be as low as a quarter of the authentic price.

Some descriptive statistics on the 31 companies over the 12-year panel are displayed in Table 1. The branded companies reported that their records represented the majority of their counterfeits. "There were probably other [counterfeits]," a representative brand commented, "but we did not feel threatened by them, so we didn't care too much to track them down." I created an indicator variable for noticeable counterfeiting equal to 1 if a branded product of a particular quality tier had been infringed upon and zero otherwise. I probed into the impacts of an unexpected and massive presence of counterfeiters on the sales of each quality tier within an authentic brand. I analyzed different quality tiers separately, so that brand-level and quality-tier-level variations upon counterfeit entry are more relevant than minor variations at the product level within a brand.

To control for the overarching macro-environment and consumption patterns, I obtained data on a common set of macro-indicators: GDP growth, GDP per capita PPP, the Consumer Price Index (CPI) from the World Development Indicator (WDI) database, and the economic inequality measures (Gini coefficients) from the UN Human Development Reports. All these data are available at annual levels in the sample period.

3.2 Descriptive Evidence: Sales Shares Shift to High Tiers

Table 2 tabulates the summary statistics of the analyzed variables before and after the new-policy year, 1995. As Table 1 shows, AQSIQ on average spent 11% of total resources in monitoring the shoe sector pre-1995 and only 2% afterward. This drop was accompanied by an influx of counterfeiting. While the median quantity of counterfeits across brands was zero before 1995, counterfeits surged to 857,100 pairs on average in the sampled years after 1995. The product costs and prices of counterfeits are on average only a fraction of those of authentic products.

Insert Table 2 about here

Figure 1a plots the sales of shoes at the three broad quality tiers, which the companies classify, as percentages of total domestic sales. It is interesting to note that the quality lines moved upward after entry by counterfeiters. That is, the higher-end shoes occupied larger shares in total sales post entry and the low-end shoes saw their shares decline dramatically. While I will present more-rigorous analyses in the next sections, these summary statistics paint a general picture of the differential effects of counterfeit entry on authentic sales of different quality levels.

Part of the increase in sales was due to the introduction of new products. I therefore separately compiled the sales shares for products of fixed quality pre- and post-entry by counterfeiters and those for the new products introduced after the infringements in Figure 1b. Among the fixed quality tiers, the percentage of sales of high-end shoes increased post entry, but that of medium-quality and low-end shoes declined. However, the decline in the sales of medium-quality shoes tended to be overcompensated by the new products in the same quality tier, whereas the sales of the new products in the low-end tier were not sufficient to make up for the category percentage drop.

Insert Figures 1a and 1b about here

3.3 OLS

The increases in the sales share of high-end products in Figure 1 could in part be due to the spillover effects of counterfeiting and in part be a direct consequence of new-product introduction after entry, as documented in Qian (2008). To disentangle these two parts, I matched products of similar quality tiers before and after entry by counterfeiters throughout the sample period, based on a similar price and costs. I compiled this sample of existing product lines separately from the rest of the sample of new product lines. I then investigated entry effects on the sales of these existing product lines according to three quality tiers: low, medium, and high.

$$\begin{aligned}\ln(Sales_{ajt}) &= \beta_0 + \beta_1^T \text{Entry}_{ajt} * \text{Tier}_{ajt} + \beta_2 lnP_{ajt} + \beta_3^T \text{TierDum}_{aj} + \beta_4^T \text{BrandDum}_a \\ &+ \beta_5^T X_{ajt} + \beta_6^T \text{YearDum}_t + \beta_7^T \text{ProdDum}_{aj} + \beta_8^T \text{YearDum}_t \text{TierDum}_{aj} + \epsilon_{ajt}, \quad (1)\end{aligned}$$

where Entry_{ajt} is an indicator variable that takes on value 1 if there is a positive presence of counterfeits in the market for brand a's product type j in year t. Tier_{ajt} is a vector of dummies indicating the three levels of quality. With this parametrization, β_1 is a vector of parameters denoting the tier-specific entry effects. lnP_{ajt} is the log price of the product, and X_{ajt} is a vector of control characteristics, such as company a's age and size and product j's shoe orientation (male or female) or usage (winter boots, sandals, dress shoes, etc.) in year t. The fixed effects for the panel year (12 years) and product lines within the quality tier of the 31 brands control for year-specific factors and time-invariant product-line characteristics.

A simple OLS regression shows that counterfeit entry has a very significant correlation with authentic sales, implying that after entry, authentic sales went up by 35%. This effect is partly an artifact of the endogeneous counterfeiting treatment. The omitted variable bias potentially enters OLS in two directions: an upward bias since brands with larger sales are more likely to experience counterfeiting, and a downward bias due to internal management effects, which are positively correlated with the sales outcome but negatively correlated with the brand's counterfeit entry. In particular, a brand with good internal management may effectively ward off counterfeits as well as maintain high sales. In fact, when simply regressing log sales quantities on the fake entry dummy and a year trend, the entry coefficient is very large. While the company-fixed effects help control for the omitted brand effects, they do not control for the time-variant management effects, resulting in a downward bias in the OLS estimates. I therefore adopt IV to address this endogeneity concern in Section 4.

3.4 Institutional Data to Preclude Alternative Explanations

The econometric model presented in the next section formally addresses the endogeneity concerns. As explained in Section 2.1, confounding factors will not lead to bias in the treatment-effect estimate as long as they are orthogonal to the treatment variable. The natural experiment and the instrumental-variable approach therefore would identify the effects of entry by counterfeiters. Nonetheless, I discuss a few more institutional details here to preclude alternative explanations for the interested reader before moving on to the formal models.

China entered an incredible boom in the late 1980s, which continued through the 1990s. Easy credit conditions prevailed in China primarily in the 1980s (Naughton 2002). An unsustainable credit expansion drove demand well beyond supply, and prices began to rise rapidly. At the peak, the CPI was growing at around 25% per year, and China was taking in a massive quantity of imports, running a substantial current-account deficit. China had to tighten credit conditions in the early 1990s in the hope of slowing the acceleration of non-performing loans (Gabriel 1998). Zhu Rongji took strong steps to slow down the growth. Investments and growth dropped sharply, as did the rate of price increases. By the late 1990s, there was deflation in China. Given the negative macro trends in the mid- to late-1990s, the positive coefficients on instrumented counterfeit entry (controlling for year and company dummies), as reported in Section 3, provide rather convincing evidence that the higher authentic sales were due to counterfeits rather than macro factors.

The regional-level macroeconomic environment data exhibit a drastic increase in inequality in the late 1980s and early 1990s, instead of the late 1990s, when the spikes in the high-end authentic sales were most pronounced. Thus, the increases in high-end shoe sales are not likely to be attributable to inequality. I also gathered data on CPI specifically for the shoes and garments sector from the Yearbooks, and found this price index to follow the overall CPI quite closely (correlation coefficient = 0.89). These macroeconomic variables are all controlled for in my analyses. The sales increase is not an artifact of inflation either.

Chinese laws granted import licenses only to the registered companies. The counterfeiters had no access to advanced shoe-making technology, which was primarily imported from Italy. It is possible that China's accession to the WTO broadened technology imports to enable high-quality counterfeits. Yet this aftermath of WTO did not take place until the mid-to-late 2000s (Cogitamus Consulting, 2009), which is at the tail end of the time period I examine. The jumps in my sales data took place immediately upon entry by the counterfeiters of the their brands. Nonetheless, I controlled for this timeline in regressions, and the results were robust. Additional institutional research and data analyses were performed to rule out confounding factors. They are detailed in Appendix B, along with other robustness checks.

4 EMPIRICAL IDENTIFICATIONS

An even richer database than that of Qian (2008) results in more identification power at the product-quality level. In particular, each brand has several quality levels, with different sales quantities and values of products at each level. Therefore, the loosening of the government enforcement for footwear essentially created dozens of "mini-experiments," which I exploited to identify the entry effects of counterfeiters on authentic sales of these products.

4.1 *First Stage IV Estimations*

I instrumented for the entry of counterfeiters using the plausibly exogenous enforcement shift away from the footwear industry and its interactions with the relationship between each brand and the AQSIQ. I constructed an indicator variable, Loose, to benchmark the years with loosened public enforcement for shoes (Loose=0 before 1995 and 1 since 1995). This enforcement diversion and its interaction with the relationship between a brand and the AQSIQ served as the main instrumental variables for counterfeit entry. Because the enforcement diversion arose from a series of accidents that took place in other industries, it is plausibly exogenous to the shoe sector. This IV also satisfies the exclusion restriction, because tightened public enforcement in other sectors is not supposed to affect shoe sales directly. Since the number of workdays it took each brand to obtain ISO certification from the AQSIQ (averaged across its subsidiaries in various regions) proxies for the brand's acquaintance only with the AQSIQ, this ISO proxy does not affect sales directly.

The entry by counterfeiters is identified with the equation below:

$$\begin{aligned} \text{Entry}_{ajt} &= \alpha_0 + \alpha_1(\text{Relation*Loose})_{at} + \alpha_2\text{Loose}_t + \alpha_3\text{Relation}_{at} + \alpha_4\text{BioMatch}_{ajt} \\ &\quad +\alpha_5(\text{Biomatch*Loose})_{ajt} + \alpha_6^T\text{Year Dummies}_t + \alpha_7^T\text{Firm Dummies}_a + \psi_{ajt} \qquad (2) \end{aligned}$$

where Entry_{ajt} is an indicator variable for the existence of counterfeits of brand a's product type j in the market at time t, and it equals 1 if there are counterfeit infringements for brand a in year t. Relation_{at} is the ISO time proxying for the relationship between brand a and the AQSIQ, and $(\text{Relation*Loose})_{at}$ is the interaction variable between this ISO proxy and the legislation dummy. BioMatch_{ajt} is the variable based on matching the education and experience background of the manager of brand a's product-line j and that of the AQSIQ officials, and $(\text{Biomatch*Loose})_{ajt}$ is its interaction variable with the policy shift dummy.

I bring in additional product-line-level exogenous variations in relationships by compiling the product managers' experience matches with AQSIQ officials. With an additional level of random variation due to this alternative IV, the rationale for the additional effort is to increase the amount of random variation in counterfeit sales and therefore increase the efficiency of the IV estimation. About a third of the bios cannot be found or matched. This creates a missing-data problem. I therefore use the nonparametric approach of Qian and Xie (2011) to impute these unobserved missing values. An important assumption in a missing-data approach is the missing at random (MAR) assumption, which requires the missingness to be independent of unobserved values, given other observables. Even though this is a plausible assumption when a rich set of observables (e.g., observables at the firm level, counterfeit sales, cost, price, etc.) is conditioned on, it is typically an untestable assumption. I therefore report this analysis as a robustness check and use the brand-level relationship for the main specifications. Combating counterfeits primarily involves brand-level collaboration with the AQSIQ, so the brand-level relationship is the most relevant in any case.

In addition to the potential endogeneity of the entry variable, product price may be endogenous to sales. In robustness analyses, I adopted the traditional IV of product cost for that, and the results on counterfeiting effects remain qualitatively unchanged (Tables A2-A6). The model is as follows:

$$\ln P_{ajt} = \gamma_0 + \gamma_1 * \ln C_{ajt} + \zeta_{ajt} \qquad (3)$$

where $\ln P_{ajt}$ denotes the log price of brand a's product j at the year t, and $\ln C_{ajt}$ similarly denotes the corresponding product cost in logs.

Table 3 exhibits the estimates from alternative first-stage specifications. As shown in Columns 1 and 2, the loose-policy indicator and the interaction IV significantly predict counterfeit entry, statistically significant at the 1% level. These robust estimation results across alternative specifications tell a consistent and clear story: the public enforcement diversion encouraged counterfeit entry (positive and significant coefficient on "Loose"), and its encouragement was stronger for counterfeiters of brands that had a worse relationship with the AQSIQ than the other brands (positive and significant coefficient on "Relation*Loose", using two alternative proxies for relationship). Column 3 illustrates the relevance of the experience-match variable and counterfeiter entry. Column 4 shows a specification where all instruments are employed with year- and brand-fixed effects, as in the estimations underlying the results in Column 5 of Table 5.

Insert Table 3 about here

4.2 IV Regressions for Sales of Fixed Quality Levels

To test the counterfeiting effect on the branded product sales of the three existing quality tiers (low, medium, and high), I estimated equations (1) and (2) simultaneously. Using the log sales quantity and values as alternative dependent variables, I arrived at robust results. For brevity, I report the specifications with the log sale quantity as dependent variables and report the others in the online Appendix. Table 4 presents the results and reveals interesting patterns. Results show that the entry of counterfeiters has a positive effect on high-end shoe sales but a negative one on low-end sales, statistically significant at the 5% level (Column 2 in Table 4). The magnitudes of the entry coefficients are larger than the OLS estimates, as discussed in Section 3.3 (coefficient = 0.49 for the high-end sales and -0.75 for the low-end sales), implying that counterfeiter entry increased high-end authentic sales by 63.23% and decreased low-end sales by 52.76%. I also executed the IV regression within each quality-tier stratum of shoes separately. Results are robust (Columns 3-5 in Table 4).

Counterfeit entry hurts low-end products but helps high-end ones. This is because counterfeits are closer substitutes to low-end shoes than to high-end ones. Counterfeiters entered for different quality tiers for each infringed brand, yet it is harder and more costly to imitate the high-tiered products due to technology as well as incentive constraints. It is intuitive that the low-end product lines suffered more business-stealing effects due to counterfeits. The sales of the high-end authentic products increased significantly after counterfeiters entered, controlling for year- and product-line fixed effects and other time-varying company and shoe characteristics, such as company age and size. This reflects the potential advertising effect of counterfeits on the brand. Counterfeits could serve as a form of mass advertising, increasing brand awareness, especially for customers who would not have been captured by the brand otherwise. Qian and Xie (2013) provide survey results in which Chinese consumers learned about their favorite brands initially through counterfeits.[5] In China, brand awareness has definitely been an increasing function in the number of people using the brand.

This relates to the "diseconomies of scope" theory proposed by Bresnahan et al. (2010) and to the finding in Godes and Mayzlin (2009) that the word of mouth that is most effective at driving sales is created by less-loyal customers. Counterfeits could in that sense serve as "buzz agents" by providing "independent" affirmations of the brand. The advertising effect is more pronounced when the new customers who learn the brand name, and who value quality and authenticity, subsequently choose the high-end authentic products. These new customers recruited by the counterfeits are then gained by the authentic company. The potential spillover effect of counterfeits may be considered an "externality" to the branded firm. Since the authentic branded companies do not internalize such advertising costs in their own optimizations, the advertising hype can lead to heterogeneous sales impacts for authentic products of different quality tiers. It can both shift and rotate demand functions for products of different quality levels. Notably, because counterfeits impose less competitive pressure on a high-end authentic product with a wider quality gap, the equilibrium sale quantity of the high-end authentic product primarily increases when counterfeits enter the market and boost brand awareness. The equilibrium sales quantity of the low-end authentic product declines in net as the business-stealing effect of counterfeits outweighs the advertising effect.

Benchmarking against the overall observed change in sales (Figure 1), the point estimate of the entry coefficient in the high-end sales sample (Table A2) implies that 29% of the increases in the sales of high-quality-tier shoes can be attributed to the net positive spillover effects of counterfeits.[6] The medium-quality authentic products did not witness significant changes in sales due to counterfeiting, although the sign of the coefficient on the instrumented entry variable was negative. However, the sales of the low-end authentic products dipped significantly upon the entry of counterfeits, both in quantity and values. The coefficients on the instrumented entry dummy are -0.75 in the pooled regression (Column 2 of Table 4) for low-end sales quantity and values (Table A2), implying a 53% drop in sales

[5]Since the cultural revolution in 1976 and the opening up of the market economy, there has been unleashed energy from both the supply and demand sides. Chinese consumers have been delighted as well as overwhelmed by the booming brand and product varieties. The general lack of information about different brands does not match the consumers' eagerness to use and associate with brands. Therefore, they often look to others or look for marketplace "trends" to learn about popular brands (Lin 2011).

[6]The coefficients translate to a 63.23% increase in quantity and 50% increase in values of high-end sales, converting from the log scale. Drawing relevant summary statistics on the sale quantities, prices, and percentages of total sales pre- and post-entry by counterfeiters in Figure 1, the overall observed percentage change in sales is $\frac{558.28*32.24*17.0\%-309.38*26.21*13.9\%}{558.28*32.24*17.0\%} = 172\%$. Similarly, the fraction of change due to the spillover effect of counterfeits is $\frac{50\%}{172\%} = 29\%$.

for the low-end shoes. A similar back-of-the-envelope calculation reveals that 86% of the decline in low-end sales after counterfeiters entry comes from the net negative substitution effect.[7] This is indicative of the moderate advertising and fierce competitive effects of counterfeits; in net, the counterfeiting effect on the high-end sales is positive and of moderate magnitude while that on the low-end sales is largely negative.

In robustness checks, I repeated the simultaneous equations model estimations by adding a control for the log average price of counterfeits of each quality tier, as instrumented by the log unit production cost of counterfeits. The estimation results do not change qualitatively. That is, the entry coefficients remain positive and significant for the high-end sales quantity and values, and negative and significant for the low-end sales quantity and values. Since the data for counterfeit prices are less systematic, I kept my main specifications as described earlier. I further conducted robustness analyses with controls for the time-variant brand-advertising expenditure and the number of company stores of the brand in alternative specifications. The results are qualitatively similar. Qian (2008) shows that the authentic brands' advertising expenditure did not change significantly after entry by counterfeits, so this control is not collinear with the main treatment variable. I controlled for advertisement (Tables 4-6). However, because the number of stores is endogenous to sales and counterfeiter entry, I did not include it in the main regression specifications. To the extent that the IV teases out the plausibly exogenous parts of counterfeit entry, the sales responses are less susceptible to omitted variable bias, especially in the time period immediately following entry.

Insert Table 4 about here

4.3 Robustness Analyses

In addition to the manufacturer's own classifications of the three quality levels, I conducted a cluster analysis of all the fixed-quality (from existing product lines) shoe products in the sample based on the unit production costs of the products. Notably, it is not meaningful to examine the distribution of raw unit cost across different quality tiers because the cost is also related to the product type and therefore it is not meaningful to compare the cost across product lines from different quality tiers. Similar to the other analyses in this study, the product lines (types) need to be controlled for in this comparison. I therefore regress the deflated unit production cost on the product line dummies and obtain the regression residuals. Boxplots of the cost residuals of the three quality tiers show that the manufacturers' classifications of quality tiers are rather clear in that the majority of the sampled data

[7] The overall percentage drop in low-end sales is $\frac{558.28*32.24*32.1\%-309.38*26.21*5.6\%}{558.28*32.24*32.1\%} = -61\%$, of which the counterfeiting effect accounts for $\frac{-53\%}{-61\%} = 86\%$.

across quality tiers do not overlap across the three quality tiers (Figure 2a). In particular, the high-end and low-end shoe distributions include completely distinct unit production costs since the minimum line of the high-end distribution is above the maximum line of the low-end distribution.

Insert Figure 2 about here

I then apply the standard cluster analysis using the kmeans method on the unit production cost residuals. This procedure formed three natural clusters. Figure 2b plots the distributions of quality (proxied by the unit production cost residuals) of the three quality clusters. It appears that the three clusters are further separated from each other as compared to those defined by the manufacturers. I then repeated the simultaneous equation estimations on these three natural clusters instead of the three tiers by the manufacturers' classifications (Column 1 of Table 5). I also repeated the IV regressions on the three clusters separately (Columns 2-4 of Table 5). The formal regression results on these sets of products are reported in Table 5. Results are again consistent and robust: the entry effect for the sale quantity of the cluster of high-quality shoes remains positive and significant, implying a 51% increase in sale quantity. However, the effect is estimated to be negative for the cluster with the lowest quality shoes, and statistically significant at the 1% level. The coefficient magnitudes become larger because the natural clustering results in more distinct quality tiers, hence revealing the net positive effects on the high-end sales and negative effects on the low-end sales as more salient.

As a final robustness check with this naturally clustered data based on costs, I estimated Equations (1)-(2) with additional interaction variables between the year trend and each of the brand dummies. This allows for a different time trend for each brand in the sample. Results are qualitatively unchanged. I also employed the full set of IVs, as listed in Column 4 of Table 3, including the main ISO relationship proxy as well as the variable based on experience-matches between the product-line managers and the AQSIQ officials. Results are again robust (Column 5 of Table 5).

I performed alternative clustering based on the unit production price instead of cost, repeating the same steps as described in the cost case, and the results are qualitatively similar (Column 6 of Table 5). However, price may be an inferior proxy for quality because pricing can be partly based on brand premium, which has little to do with the actual quality that went into producing a particular pair of shoes.

The IVs provide exogenous identification of the counterfeiting effects such that the effect estimates do not suffer from omitted variable bias due to confounding trends. In addition, the panel structure and the presence of the control group of brands that were never infringed by counterfeits serve as solid benchmarks for comparison which helps net out the macro trends. I further conduct robustness analyses including the interaction variables between the year trend and brand- and tier-fixed effects. The results are again robust with this model, which thoroughly controls for potential confounding trends that may be heterogeneous to different brands and quality tiers.

Insert Table 5 about here

4.4 Effects of Counterfeits on Product-Level Sales Over Time

While Section 4.2 tests the overall impacts of counterfeit entry, this section attempts to trace the sales effects over a longer time horizon. For the samples of shoes at each quality tier, I regressed the log sales quantity on the set of dummies indicating different years relative to counterfeiter entry, controlling for the time-varying company attributes, macro conditions, and company-fixed effects.

$$\begin{aligned}\ln(Sales_{ajt}) \quad &= \quad \beta_0 + \sum_{k=-5}^{5} \beta_{1k} * \text{YearToEntry}_{a,j,k} + \beta_2 * ln\hat{P}_{ajt} \\ &\quad + \beta_3^T * X_{ajt} + \beta_4^T * \text{YearDum}_t + \beta_5^T * \text{ProdDum}_{aj} + \epsilon_{ajt}\end{aligned}$$

where I regressed the log sales quantity of brand a, product j in year t on the set of dummies indicating years (k) relative to entry from five years pre-entry to five years post entry, controlling for the instrumented log product price and other characteristics. I plotted the regression coefficients on the year indicators against the corresponding years relative to entry for the sample of existing product lines and the sample of new product lines in Figures 3 and 4, respectively. Because the new products were introduced only after facing competition from counterfeiting, the coefficients for the years prior to the infringements were not plotted in Figure 4.

Figure 4 demonstrates the positive effects of counterfeits on the high-end shoes. Such an advertising effect was felt immediately upon the entry of counterfeits and lasted for a few years before it dwindled. It is possible that counterfeits first served to improve consumer awarenesses of the brand and later contributed negatively to brand equity because some consumers could misattribute the inferior counterfeit quality to the brand itself. The negative impacts on the other two quality tiers are quite large and long lasting. Some of the dips in these sales are offset by the sales of new products in these two tiers, as indicated in Figure 4. The regression underlying Figure 3 uses the year of entry by counterfeits as the benchmark, so all the coefficients plotted indicate the relative change in the log sales quantity of a particular quality tier in the respective year relative to entry. Because almost all the new products were introduced at least a year after the counterfeits entered the market, Figure 4 uses the first year of observation, one year after entry, as the benchmark for comparison. These two figures are most suitable for demonstrating the changes in the log sales quantity in the years relative to entry within each quality tier.

The trend that the positive effect on the high-end shoes was largest in the year immediately following the massive entry of counterfeits again rules out the alternative explanation that the authentic companies' own self-enforcement was the driving force. Authentic firms invested in self-enforcement with some lags and the number of company stores grew in the later years of the sample period, which is the opposite of the trend of the high-end sales increases.

Insert Figures 3 and 4 about here

4.5 Mechanisms of the Spillover Effect of Counterfeits

While the negative effect of entry by counterfeiters on the sales of low-end shoes is consistent with traditional business-stealing intuitions, the positive effect on the sales of high-end shoes was at first surprising. Yet positive effects of IPR infringement have been termed the "piracy paradox" in a paper by Raustiala and Sprigman (2009), who study historical incidences of fashion innovation and find that imitation could turn a formerly innovative design into a nonexclusive feature and stimulate further product differentiations. The positive effect of counterfeiting on authentic product innovations is also identified in Qian (2008).

A strand of literature proposes that copyists create barriers to entry for competitors (Givon and Muller 1995) and help the originator establish its own technology as an industry standard, with switching costs further cementing the originator's competitive position (Katz and Shapiro 1994). Unlike software and other high-tech industries, there is very little standard-claiming behavior in the Chinese shoe sector. In addition, the shoe-industry size has been stabilized since the late 1980s, and national statistics show that the number of employees in the footwear and garment industry was approximately 1,750,000 throughout the 1990s (Tables 12-2 and 13-2 in each YearBook, Chinese National Bureau of Statistics). According to the Basic Unit Census of China (National Bureau of Statistics 1996), most legal shoe companies were established in the late 1980s. The 1990s witnessed a rather steady industry size. This evidence suggests that the positive spillover effect of counterfeits is not likely to work through the entry-barriers argument in this context.

In this subsection, I present a set of analyses that demonstrate the potential advertising effect of counterfeiting mainly due to increased brand awareness. In particular, I implement a difference-in-difference-in-difference model with simultaneous equation estimations:

$$\begin{aligned}\ln(Sales_{ajt}) \quad = \quad & \beta_0 + \beta_1^T \text{Entry}_{ajt} * M_{ajt} * \text{Tier}_{ajt} + \beta_2^T \text{Entry}_{ajt} * \text{Tier}_{ajt} \\ & + \beta_3 M_{ajt} * \text{Tier}_{ajt} + \beta_4^T X_{ajt} + \beta_5 lnP_{ajt} \\ & + \beta_6^T \text{TierDum}_{aj} + \beta_7^T \text{YearDum}_t + \beta_8^T \text{ProdDum}_{aj} + \epsilon_{ajt} \qquad (4)\end{aligned}$$

where M_{ajt} is a set of moderating factors as detailed in the following paragraphs, M_{ajt} ={High fashion, non-renowned, single-brand, non-famous, young brand, young cohort}. All the other variables are defined as before. The model is equivalent to a model that includes the first-order terms of M_{ajt}, one at a time, as well as the two-way and three-way interactions with the entry dummy and the set of dummies on quality tiers. A benefit of the current model setup is that it is easily interpretable: β_1, β_2 and β_3 all correspond to the tier-specific effects. IVs are again implemented to address the endogeneity concerns. Results are compiled in Table 6.

The first piece of evidence in the data that points to the advertising effect is that the positive sales impact of counterfeits is most pronounced in the product lines for dress shoes and women's high-leg boots (henceforth "high fashion"). This is expected because people buy them not just out of necessity but to keep up with the latest style. Column 1 of Table 6 reports the IV regression results on the log sales quantities of the three quality tiers of these fashion boots, and the entry effects on the high-end fashion boots are estimated to be as high as 0.76 (0.37+0.39 in Column 1 of Table 6) for the log sales quantities, statistically significant at the 1% level. The demand-enlarging effects for the less-fashionable products are much more moderate (coefficients are estimated to be 0.39 in the same Column 1). I further conducted the IV regression on the stratified sample of "high fashion" shoes and the rest of the sample separately, with log sale quantities and values as alternative outcomes, respectively. The complete tabulations of the coefficients in these estimations are displayed in Tables A3-A4 and results are robust.

Insert Table 6 about here

The second piece of evidence that speaks to the advertising effect is that the sales impact of counterfeits is more positive for the high-end shoes of brands that were less famous at the time of infringement. The Chinese Trademark Office grants the "well-known (renowned) brands" designation to national and international brands according to the Chinese Trademark Law and the Paris Convention.[8] I repeated the IV regression estimations for the three tiers of shoes among the set of brands that were not listed as "renowned" at the time of infringement by counterfeits. As shown in Column 2 of Table 6, the average effect of counterfeiting on the sales quantities of high-end shoes of renowned brands is 0.23, and that of the non-renowned brands is 0.69 (0.23+0.46), and statistically significant at the 5% level. The positive effects on the non-renowned brands is apparently much higher than the corresponding effect sizes for the renowned brands. For these non-famous brands, the entry effect on medium-tiered

[8]The modern concept of the "renowned" trademark is codified in Article 6bis of the International Convention for the Protection of Intellectual Property (the Paris Convention). It uses the French expression "notoirement connue," literally "notoriously known" or, in better English, "well known."

shoe sales was also positive. While the effect on low-tiered shoes was still negative and statistically significant, the point estimates were less negative than those in the renowned-brands sample. Results are again robust to executing the regressions separately for the samples of renowned and non-renowned brands. The demand-enlarging effects for the renowned brands were much smaller, with 12% of the increase in sales for the high-tiered shoes attributable to the spillover effects (Table A6). The effect on the low-tiered shoes was again significantly negative.

Along the same line of thought, I use three other indicators for how established the brands are and stratify accordingly. First, I stratify based on whether the brand was authenticated as "Famous Brands in China" at the time of infringement. The positive effect is again larger for the brands that were not "famous" at the time of infringement by 0.33, as compared to the domestically famous ones (Column 3 of Table 6).

Second, I stratify by the age of the brands. If counterfeits serve as mass advertisement, then infringement surely has a larger impact when information about the brand has not yet been widely disseminated. This suggests that the positive effects of counterfeiting would be larger for newer brands than for more-established brands. Such is the case empirically (Column 4 of Table 6). I defined "new brands" as those whose age is below the median level. It is interesting to note that the impacts on the low-end authentic sales is highly negative here, demonstrating the severe double-edged effects of counterfeiting. While spreading the word is especially helpful for the new brand's high-end products, the low-end sales are much hurt since counterfeits serve as such close substitutes for an unknown brand without a loyal customer base.

In addition, I stratify based on the number of sub-brands the branded company owns. Results again show that the positive effect is larger for brands that have only a single brand compared with more-established brands with multiple sub-brands (Column 5 of Table 6). The net positive effect for the high-end shoes is 31% higher for the brands with just a single brand than those with multiple sub-brands, based on the coefficients (0.48+0.27 vs. 0.27).

Finally, I stratify by the types of shoes tailored to customers of different age groups. Although the classification may not be perfect because some shoes can be purchased across age groups, I worked with the companies to classify the shoes to the best of our ability based on their design intentions and their records of customer demographics. For instance, medium-leg men workboots are primarily worn by customers aged 20-45, and "oldman's shoes" (a type of shoes with thick cotton insides) are designed for old people. I found that the positive spillover effects of counterfeiting are larger for shoes that are made for young people than for the older generations (Column 6 of Table 6). If the effect were not due to an advertising mechanism, then we would expect to find the effect to be similar across the different types of shoes across age groups.

In sum, these stratification analyses show that the positive marginal effects of entry by counterfeiters on the sales of authentic shoes are largest among the high-fashion boots and high-tier shoes of the less-established brands. The effects are also larger for shoes made for young people than for the older generation. These are exactly the products and brands that are expected to benefit most from mass advertising. Counterfeits and imitations help establish "trends," and trends are key drivers of sales (Raustiala and Sprigman 2010). The results, therefore, provide notable evidence of the advertising effects of counterfeits. The positive effect extends beyond the fashion industry. In an interview with the *New York Times*, the chief executive of LogMeIn (Michael Simon), a company whose software is used in smartphones and tablets, commented, "If people are going to steal something, we sure as hell want them to steal our stuff. When you have a saturated market like Microsoft and have no growth in these devices, then it might be different"(Schmidle 2010).

4.6 Discussions of Results from the Field Data

The findings presented so far further enhance those in Qian (2008), which indicate that the authentic producer upgrades quality in response to counterfeit infringements. In particular, among the set of branded companies whose products started at similar price and quality levels, only those that experienced counterfeit infringements strove to innovate after being counterfeited massively. The companies that were better acquainted with the AQSIQ and did not experience massive counterfeiting threats did not witness internal quality upgrades. Such effects encounter interesting developments here: not only did firms innovate to alleviate competition from counterfeits, we also see that their percentages of sales concentrated more toward the higher-end shoes over time. The findings in this study that counterfeits have positive effects on high-end products and a negative substitution effect on low-end products explain the incentives for the aforementioned business strategies as observed.

These strategies had positive effects for consumers, since the quantity demand increased, the product variety increased, and the deflated price associated with the basic characteristics remained stable. I have also replicated these results in the lab. Lab experiments further enrich the evidence for the advertising mechanism based on the respondents' stated preferences and purchase motivations.[9]

[9]Please see online appendix through http://www.nber.org/ỹiqian for more details.

5 CONCLUSION

The sales impacts of counterfeits represent an urgent concern for business managers and policy makers. New York's senior senator, Charles E. Schumer, introduced legislation at the beginning of August 2010 that would rewrite copyright law to cover fashion design (Raustiala and Sprigman, 2010), but he may not have had the positive effect of imitations in mind. This paper collects product-line-level panel data on Chinese shoe companies to investigate the sales impact of counterfeiting. I identified an exogenous loosening of public enforcement in monitoring footwear trademarks and its differential consequences in counterfeit infringements for brands with heterogeneous degrees of acquaintance with the government agency in charge of counterfeit enforcement. This difference-in-difference approach is operationalized by the interaction between enforcement diversion and the relationship proxy to instrument for counterfeiters entry. I obtained empirical results robust across specifications and consistent with theory. In addition, the causal relationship between counterfeiting and the purchase intent for authentic products was established in experiments where exposure to counterfeit shoe stimuli was randomly assigned across a sample of respondents.

The study uncovers heterogeneous effects that counterfeits can have on the sales of branded products of three quality tiers among existing product lines. In particular, counterfeits have both advertising effects for the brand and substitution effects for the authentic products. The advertising effect likely dominates the substitution effect for high-end authentic product sales, as reflected in the net positive effect of counterfeiting on high-end authentic sales. The substitution effect outweighs the advertising effect for low-end product sales, resulting in a net negative effect as analyzed. The effects last for a few years before leveling off. Such differential effects reinforce incentives for authentic producers to innovate. Data show that the market shares for the higher-quality products increased post entry and those of the lower-end products declined. There is also evidence for product-line proliferation after entry.

Similar heterogeneous effects on the purchase intent of high-, medium-, and low-tier branded products were replicated in experimental settings. Responses in the experiments suggest that counterfeits signal brand popularity to at least some consumers and a large number of consumers prefer to enjoy a variety of quality levels. Counterfeits therefore steal demand from the low-end authentic products while having positive spillover effects for high-end authentic products. These findings substantiate and enrich the discovery in prior research (Qian 2008, 2011) that authentic firms' average prices and quality increase after entry by counterfeits. Combining these studies gives a deeper understanding of how counterfeit entry under weak intellectual property protection affects innovation incentives of firms and markets.

I also identify heterogeneous effects of counterfeiting along other dimensions of brand and product attributes. Notably, the positive spillover effects are larger for newer brands, less established brands, and brands that are less famous at the time of the infringement. The effects are also larger for products that are more fashion-driven in nature and are tailored to young customers. All these findings hint at the advertising effects of counterfeiting for the brand and product being infringed. It is worth noting that this study disentangles the separate effects of the life stage of a brand and the quality tier within a brand portfolio. Within each type of brands and each class of products, the counterfeiting effects are again identified at the quality-tier level through the difference-in-difference-in-difference simultaneous equation estimations.

In sum, this paper identifies the heterogeneous effects of counterfeits on authentic product sales through a combination of field data and lab experiments. The findings have important policy implications. Since counterfeits hurt primarily low-end authentic products and have positive net effects on high-end ones, the focus of enforcement against counterfeits should be directed toward low-quality counterfeits or counterfeits that directly steal business from authentic producers. It seems not only socially beneficial to weed out low-quality counterfeits and to keep certain levels of higher-quality competition, but also privately efficient to the branded companies.

In addition, the findings that the positive sales impact of counterfeiting is more pronounced for brands that were not yet well known at the time of infringement could imply that trademarks and IPR may be optimally enforced at different stages of brand or product adoption cycles. This is exactly what Microsoft did in China. It fiercely enforced measures against piracy only after the majority of the Chinese users had adopted its products (in either authentic form or pirated copies).

The positive spillover effect of a low-quality entrant on the original brand is also identified in Qian et al. (2011), using the comprehensive scanner database by an American apparel company. Kuksov and Xie (2011) also theorize about the positive competition effect in the status goods market. The findings here, therefore, have applications beyond counterfeiting. Together, this body of research suggests that there is an optimal level of IPR protection, and the optimum varies from country to country (Qian 2007 and 2009), sector to sector (Qian 2008, Qian et al. 2012), brand to brand, and even product to product. The optimum could also have a time dimension in light of the longer-term effects discussed in this study. After all, counterfeiters can be both foes and friends.

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Table 1. Political Connections and Average Counterfeiting Occurrences By Brand

Notes: This table tabulates the average number of ISO certification days and the average sales quantities of counterfeits for each of the 31 brands in the sample.

Brand	# ISO Days	The Sales Quantity of Counterfeits
1	31	0
2	31	14
3	31	51
4	46	0
5	49	126
6	65	27
7	65	75
8	78	0
9	86	14
10	95	75
11	102	27
12	107	0
13	114	146
14	115	60
15	120	0
16	144	0
17	146	96
18	169	62
19	172	184
20	172	135
21	199	96
22	204	41
23	214	197
24	214	145
25	224	40
26	249	161
27	259	111
28	264	160
29	276	220
30	289	146
31	303	221

Table 2: Summary Statistics Before and After the Policy Change

Variable:	**Pre-1995**	**Post-1995**
Percentage of Government Resources in	.11	.02
Monitoring Footwear Trademarks	(.004)	(.001)
Workdays Authentic Company Took to Pass ISO	142	149
(Relationship Proxy)	(116.5)	(112.6)
Experience matches between brand managers	3.11	3.36
and AQSIQ Officials	(3.79)	(3.83)
Experience matches between product managers	4.98	5.11
and AQSIQ Officials	(2.16)	(2.14)
Incorporation Year of Authentic Brands	1985	1985
	(11)	(11)
Number of Company Stores	0	684
	(0)	(533.5)
Authentic Brand-Protection Office Personnel	.17	4.0
(Head count)	(.46)	(2.23)
Quantity (in 10,000 pairs)		
Fake Sale Quantity	Median 0	85.71
		(75.85)
Authentic Sale Quantity	309.38	558.28
	(725.76)	(995.82)
Prices, Costs, and other Numerairs (Deflated, in USD)		
Fake Shoe Price	Median 0	7.32
	(8.33 to 10.4)	(4.2)
Fake Shoe Costs	Median 0	2.66
	(2.2 to 3.56)	(1.56)
Average Authentic Price of Existing Product Lines	26.21	32.24
	(13.64)	(20.45)
Average Authentic Costs of Existing Product Lines	22.61	25.18
	(12.90)	(18.43)
Average Authentic Price of New Product Lines		45.37
		(26.06)
Average Authentic Costs of New Product Lines		35.47
		(24.37)
Self-enforcement Costs of Authentic Brands	520	81380
	(1550)	(83140)
Advertising Expenditure	1496700	2381500
	(2724200)	(3329300)
Real GDP per capita PPP	310.25	488.13
	(5.57)	(2.83)
No. of Obs.	62	310

This table presents the summary statistics of the brand-level dataset, slicing it into two parts: data prior to the year 1995, when the Chinese government reallocated enforcement resources away from the footwear sector to fill in the needs of the safety sectors, and data after 1995. Each row reports the means and standard deviations (in parentheses) of a variable in the two time lines. The range statistics for the counterfeit shoe prices and costs report the ranges of the corresponding values when counterfeits existed for some brands. It was rather sparse before the policy shift. The percentage of government resources devoted to monitoring the shoe sector is obtained from the Quality and Technology Supervision Bureau. Real GDP per capita PPP is obtained from the World Bank *World Development Indicators (WDI)*. Prices and costs are deflated using the Consumer Price Index published in the WDI (Year 1995 was set as the base year in the database).

Table 3: First-stage IV Regression

Dependent Variable:	Fake Entry			
	(1)	(2)	(3)	(4)
Loose	.72**			
	(.04)			
Relation proxied by ISO		.11		.11
(scaled by dividing 100)		(.13)		(.12)
Relation proxied by Biographic Match			.08	.09
			(.06)	(.08)
Loose*ISO		.24**		.33**
		(.01)		(.06)
Loose*Bio-match			.13**	.14**
			(.03)	(.03)
Year trend	-.0001			
	(.0002)			
Year Fixed Effects	No	Yes	Yes	Yes
No. of Obs.	372	372	5833	5833
p-values	.00	.00	.00	.00

This table reports the first stage of IV estimations. All models use brand-fixed effects. The counterfeit entry dummy (equals one if counterfeits are discovered for a brand) and log of deflated authentic product prices are regressed on the set of I.V., with the 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: *–5%; **–1%. Columns 1 to 4 present alternative first-stage IV specifications to show robust significant relationship between the set of IVs and the entry of counterfeits. The variables are: Loose – a dummy indicating enforcement legislation change, which equals 1 in 1995 onwards; ISO – relationship between the brand and the QTSB, as proxied by the number of work days between the application and grant dates of ISO certificate for an authentic company; Loose*ISO – interaction between legislation change and a company's relationship with the government; Biographic matches – an 1-10 scaled variable that is constructed based on the education and experience matches between the brand and product-line managers and that of the AQSIQ officials; Loose*Bio-match – interaction between legislation change and the biographic-match variable.

Table 4. IV Regression Results for Log Sale Quantity of Three Fixed Quality Tiers

Notes: This table reports five regression specifications. Point estimates (standard errors) are reported in the first (second) row aligning with the corresponding independent variable. Standard Errors are clustered at the product-line level. Year trend is used in order to obtain the estimates on the macroeconomic variables. "*" and "**" denote statistical significance at the 0.05 and 0.01 levels, respectively.

Variable	OLS pooled	IV pooled	High-end	Medium-end	Low-end
	(1)	(2)	(3)	(4)	(5)
Entry			0.46*	-0.23	-0.57*
			(0.22)	(0.18)	(0.23)
High-end	0.31*	0.49*			
	(0.13)	(0.18)			
Medium-end	-0.27*	-0.16			
	(0.12)	(0.15)			
Low-end	-0.94**	-0.75**			
	(0.15)	(0.20)			
ln(price)	-0.19*	-0.19*	-0.11	-0.18	-0.26
	(0.09)	(0.10)	(0.19)	(0.15)	(0.16)
ln(Ads)	0.22*	0.23*	0.27*	0.21	0.13
	(0.11)	(0.12)	(0.14)	(0.17)	(0.19)
Age	0.01	0.01	0.01	0.00	0.00
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
ln(household	3.66	4.26	0.45	3.11*	5.87**
consumption)	(2.38)	(2.27)	(0.67)	(1.45)	(1.12)
Economic growth	0.02	-0.01	0.08*	-0.06	-0.15**
	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
Consumption per	-0.02	-0.03*	0.05	-0.05	-0.18**
GDP	(0.01)	(0.01)	(0.03)	(0.04)	(0.04)
Gini coefficient	0.01	0.08	0.06	0.23**	0.39**
	(0.04)	(0.06)	(0.07)	(0.08)	(0.10)
Female shoes	0.52**	0.42**	0.18*	0.56**	0.47**
	(0.03)	(0.05)	(0.08)	(0.09)	(0.10)
High-leg boots	-1.41**	-1.43**	-1.38**	-1.52**	-1.62**
	(0.05)	(0.05)	(0.11)	(0.14)	(0.16)
Medium-leg boots	-0.98**	-0.99**	-0.96**	-1.03**	-1.08**
	(0.04)	(0.03)	(0.05)	(0.06)	(0.09)
Slippers	-1.55**	-1.54**	-1.51**	-1.47**	-1.61**
	(0.05)	(0.05)	(0.08)	(0.07)	(0.09)
Sport shoes	1.27**	1.53**	0.81**	1.32**	1.56**
	(0.26)	(0.22)	(0.31)	(0.30)	(0.33)
Constant	-11.67*	-10.98*	15.28*	-7.21	-12.39*
	(4.95)	(4.87)	(6.92)	(7.82)	(5.52)
Year Trend	Y	Y	Y	Y	Y
Brand and product-line FE	Y	Y	Y	Y	Y
Tier FE	Y	Y	N	N	N
Year Trend*Tier	Y	Y	N	N	N
N	5833	5833	1944	1945	1944

Table 5. Robustness Analyses with More Control Covariates and Natural Clusters of Quality Tiers

Notes: This table reports six regression specifications based on data resulting from natural clustering. Point estimates (standard errors) are reported in the first (second) row aligning with the corresponding independent variable. Standard Errors are clustered at the product-line level. Year trend is used in order to obtain the estimates on the macroeconomic variables. "*" and "**" denote statistical significance at the 0.05 and 0.01 levels, respectively.

Variable	Cluster C	High-end	Medium	Low-end	Interact C	Cluster P
	(1)	(2)	(3)	(4)	(5)	(6)
Entry		0.51**	-0.12	-0.71**		
		(0.19)	(0.21)	(0.28)		
High-end	0.58**				0.40**	0.56**
	(0.16)				(0.13)	(0.18)
Medium-end	-0.01				0.01	0.37
	(0.15)				(0.14)	(0.29)
Low-end	-0.48**				-0.57**	-0.65**
	(0.18)				(0.14)	(0.23)
ln(price)	-0.23*	-0.17	-0.20	-0.28	-0.32*	-0.26**
	(0.11)	(0.21)	(0.19)	(0.19)	(0.12)	(0.10)
ln(Ads)	0.21	0.28	0.22	0.18	0.26*	0.22
	(0.12)	(0.15)	(0.17)	(0.17)	(0.12)	(0.12)
Age	0.00	0.01	0.00	0.01	0.00	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)
ln(household	3.17	0.24	3.56*	4.27*		2.98
consumption)	(1.82)	(0.87)	(1.38)	(2.12)		(1.76)
Economic growth	-0.03	0.08*	-0.08**	-0.11*		0.02
	(0.03)	(0.03)	(0.03)	(0.04)		(0.02)
Consumption per	-0.02	-0.06	0.04	-0.03		-0.01
GDP	(0.02)	(0.04)	(0.05)	(0.04)		(0.03)
WTO Accession	-0.04	-0.02	-0.07	-0.14*		-0.05
	(0.04)	(0.05)	(0.06)	(0.07)		(0.04)
Gini coefficient	0.05	-0.08	0.13	0.43**		0.07
	(0.04)	(0.08)	(0.09)	(0.14)		(0.06)
Female shoes	0.47**	0.36**	0.36**	0.35**	0.48**	0.52**
	(0.04)	(0.07)	(0.06)	(0.08)	(0.10)	(0.06)
High-leg boots	-1.51**	-1.51**	-1.44**	-1.4**	-1.51**	-1.40**
	(0.08)	(0.12)	(0.14)	(0.12)	(0.07)	(0.07)
Medium-leg boots	-0.98**	-1.13**	-1.02**	-1.0**	-0.98**	-0.96**
	(0.03)	(0.04)	(0.04)	(0.06)	(0.04)	(0.03)
Slippers	-1.46**	-1.57**	-1.53**	-1.6**	-1.46**	-1.53**
	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)
Sport shoes	1.52**	1.37**	1.98**	1.11**	1.52**	1.46**
	(0.13)	(0.28)	(0.19)	(0.21)	(0.11)	(0.23)
Constant	-8.67	14.71**	-4.41	-10.79	4.98*	-7.58
	(5.12)	(6.45)	(6.53)	(8.43)	(2.12)	(4.73)
Year Trend	Y	Y	Y	Y	Y	Y
Brand and line FE	Y	Y	Y	Y	Y	Y
Tier FE	Y	N	N	N	Y	Y
YearTrend*Tier	Y	N	N	N	N	Y
YearTrend*Brand*Tier	N	N	N	N	Y	N
N	5833	1518	2099	2216	5833	5833

Table 6. Stratification Analyses on the Mechanisms of the Positive Spillover Effects

Notes: This table reports six regression specifications to test the mechanism of the positive spillover effects of counterfeiting. The moderating factors are: 1. Whether the product is highly fashionable (dress shoes and tall-leg women boots) or not; 2. Whether the brand was not classified as a "renowned brand" at the time of infringement; 3. Whether the brand was not listed as "China Famous Brands" at the time of the infringement; 4. Whether the brand is relatively new, whose age is below the median; 5. Whether the brand has a single brand; 6. Whether the products were designed more for younger customers. Point estimates (standard errors) are reported in the first (second) row aligning with the corresponding independent variable. Standard Errors are clustered at the product-line level. Year trend is used in order to obtain the estimates on the macroeconomic variables. "*" and "**" denote statistical significance at the 0.05 and 0.01 levels, respectively.

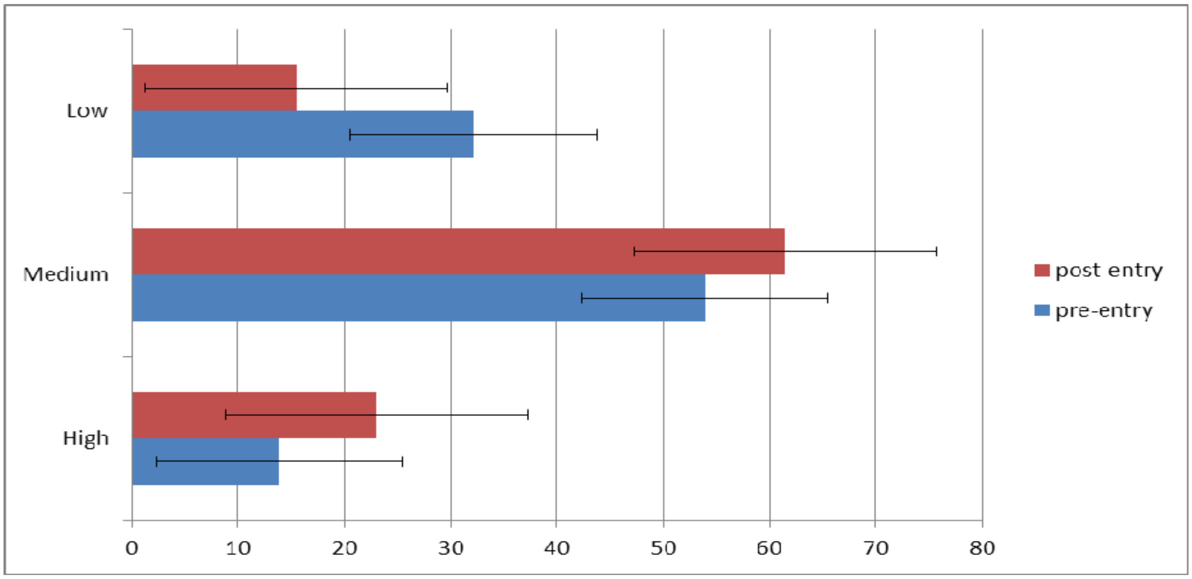
Variable	fashion	nonrenown	nonfamous	newbrand	onebrand	user-age
	(1)	(2)	(3)	(4)	(5)	(6)
E*M						
High-end	0.37*	0.46*	0.33*	0.51*	0.48*	0.37*
	(0.17)	(0.21)	(0.16)	(0.24)	(0.22)	(0.15)
Medium-end	0.46	0.39	0.21	-0.29	-0.36*	-0.35
	(0.19)	(0.19)	(0.20)	(0.18)	(0.17)	(0.18)
Low-end	0.12	0.21	0.16	-0.85**	0.63*	0.46*
	(0.24)	(0.25)	(0.19)	(0.27)	(0.23)	(0.18)
Entry (E)						
High-end	0.39*	0.23*	0.35*	0.16	0.27	0.29*
	(0.16)	(0.12)	(0.13)	(0.13)	(0.17)	(0.13)
Medium-end	-0.33*	-0.24	-0.22	-0.04	0.19	-0.13
	(0.17)	(0.16)	(0.19)	(0.15)	(0.14)	(0.18)
Low-end	-0.78**	-0.89**	-0.82**	-0.38*	-1.01**	-1.09**
	(0.21)	(0.21)	(0.17)	(0.16)	(0.18)	(0.26)
Moderator (M)						
High-end	0.14*	-0.23	-0.45	-0.54*	-1.22*	0.42
	(0.06)	(0.81)	(0.33)	(0.23)	(0.47)	(0.22)
Medium-end	0.02	0.98**	-0.37	-0.14	-0.53	0.06
	(0.19)	(0.20)	(0.36)	(0.37)	(0.52)	(0.09)
Low-end	-0.72	-0.17	-4.67*	2.13**	-2.35**	-0.62
	(1.28)	(1.07)	(1.19)	(0.81)	(0.82)	(1.01)
ln(price)	-0.21*	-0.19*	-0.18*	-0.18	-0.20*	-0.19*
	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)
ln(Ads)	0.21	0.22*	0.25*	0.20	0.20	0.24*
	(0.12)	(0.11)	(0.12)	(0.13)	(0.13)	(0.12)
age	0.01	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Economic growth	0.03	0.03	0.02	0.02	0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
log(household	2.67	2.85	2.75	2.66	2.69	2.71
consumption)	(1.73)	(1.58)	(1.58)	(1.63)	(1.52)	(1.71)
Consumption per GDP	-0.03	-0.02	0.01	-0.03	-0.04*	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Gini coefficient	0.07**	0.06**	0.07**	0.06**	0.04**	0.08**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)

Female shoes	0.51**	0.50**	0.51**	0.48**	0.51**	0.51**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
High-leg boots	-1.46**	-1.44**	-1.47**	-1.44**	-1.46**	-1.46**
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Medium-leg boots	-0.86**	-0.86**	-0.95**	-0.91**	-0.90**	-0.99**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Slippers	-1.53**	-1.53**	-1.52**	-1.53**	-1.52**	-1.47**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Sport shoes	1.49**	1.48**	1.51**	1.48**	1.60**	1.55**
	(0.20)	(0.20)	(0.19)	(0.20)	(0.21)	(0.21)
Year Trend	Y	Y	Y	Y	Y	Y
Brand- and line-FE	Y	Y	Y	Y	Y	Y
Tier FE	Y	Y	Y	Y	Y	Y
YearTrend*Tier	Y	Y	Y	Y	Y	Y
N	5833	5833	5833	5833	5833	5833

Figure 1. Bar Chart of the Percentage Sales Pre- and Post-Entry by Quality Tiers

Note: This figure presents the percentage sales breakdown of the product-line level dataset, slicing it into two parts: data prior to the year that the corresponding brand was infringed by its counterfeits and the data after that. All company-level data are gathered through original interviews and surveys. Existing product lines refer to those that existed throughout the sample period, while new product lines refer to those that were added one to three years after the brands were infringed by counterfeits.

a. Overall Breakdowns of Three Quality Tiers



b. Breakdown by Existing Product Lines and New Product Lines, Each of Three Quality Tiers

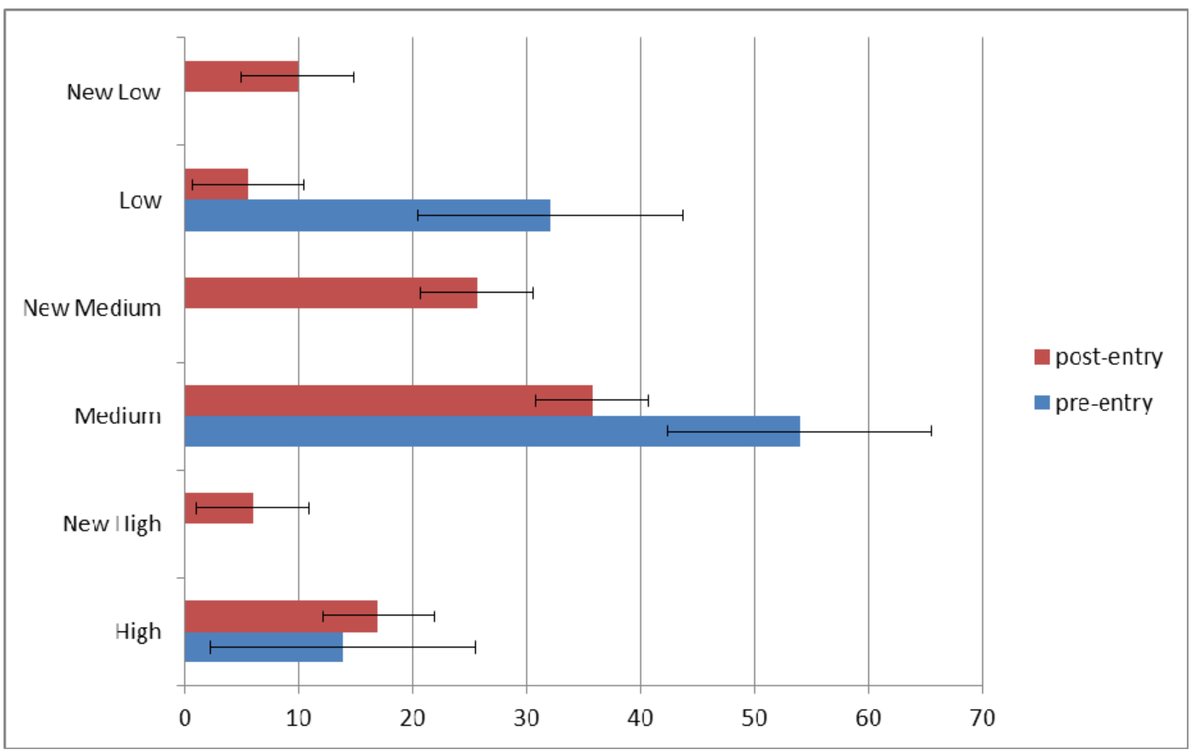


Figure 2a. Box Plots of the Distributions of the Product-type-adjusted Deflated Unit Production Cost Across Manufacturers' Quality Tiers

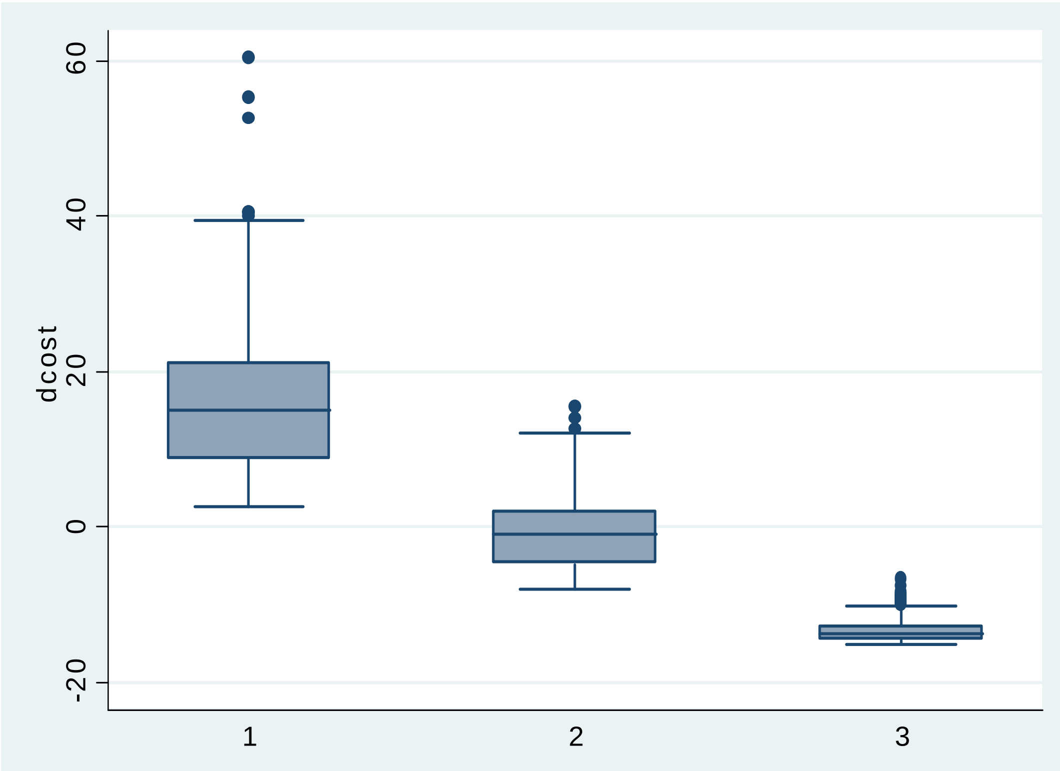


Figure 2b. Box Plots of the Distributions of the Product-type-adjusted Deflated Unit Production Cost Across Quality Tiers by Natural Clustering

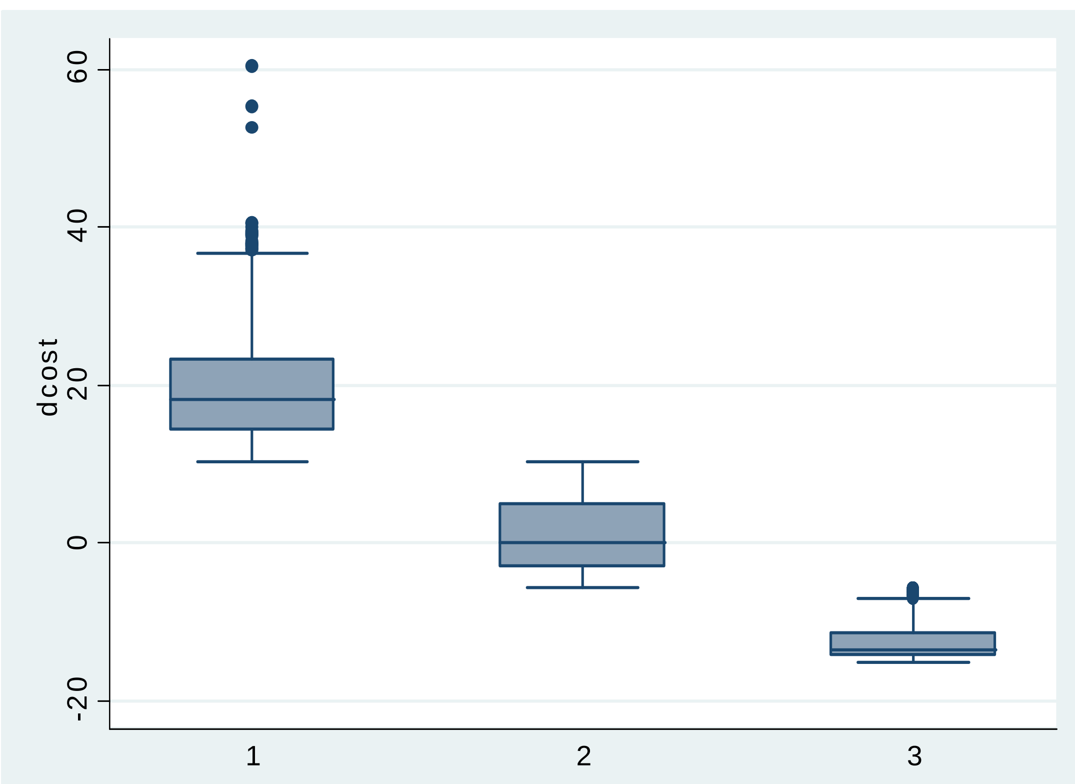


Figure 3: Coefficient Trend of Log Sale Quantity against Years Relative to Entry for the Existing Product Lines

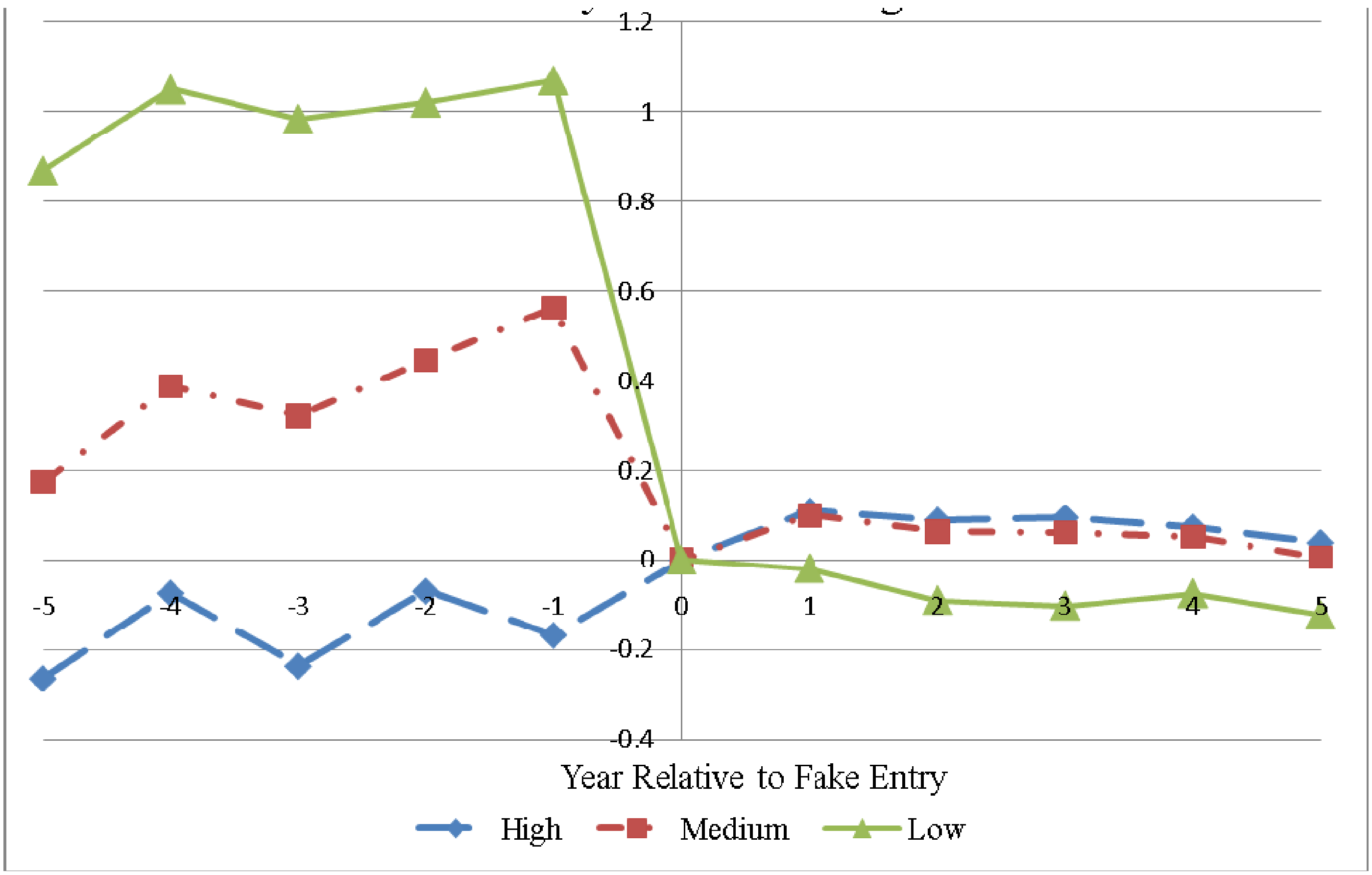


Figure 4: Coefficient Trend of Log Sale Quantity Against Years Relative to Entry for the New Product Lines