Protection versus Differentiation: Trademarks, Marketing, and Firm Performance*

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Abstract

This paper examines the rationale for trademark adoption and its impact on firm performance. We emphasize two functions of trademarks: protection and differentiation. Protection prevents competitors from using identical or confusingly similar brand names and logos. Differentiation helps consumers distinguish the owner's brand from others. An industry equilibrium model with endogenous marketing and trademark adoption rationalizes three facts we document in the data. First, most firms never apply for a trademark, although the application cost is negligible. Second, a firm's marketing generates positive spillovers to competitors' sales. These spillovers are stronger among firms with similar names, and arise only from firms without a trademark. Third, following a firm's first trademark application, the return to its own marketing rises while the spillover it receives from competitors' marketing disappears. We estimate the model using Chinese manufacturing firm data from 1998 to 2007. Counterfactual exercises show that stronger trademark protection and greater market transparency have large distributional effects. Both policies stimulate trademark adoption and marketing investment, but they benefit only the largest firms. Smaller firms earn lower profits even after adopting trademarks, because wider adoption intensifies marketing competition and reduces the marketing spillovers they rely on.

Keywords: trademarks, marketing spillovers, differentiation, intellectual property rights.

JEL Codes: D62, L11, L15, M37, O34.

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1 Introduction

Trademarks play a vital role in firms' operations. A trademark grants a firm exclusive legal rights to a unique identifier, such as a brand name or logo. This identifier helps consumers distinguish the firm's goods and services from those of its competitors, thereby supporting trust and brand recognition (Grossman and Shapiro, 1988a,b). A recent study based on a survey of 40,000 U.S. firms from 2008 to 2015 shows that firms, on average, regard trademarks, trade secrets, and copyrights as more important forms of intellectual property than patents (Mezzanotti and Simcoe, 2023). Although the existing literature has documented the effects of trademarks on firm production, quality choices, and innovation (Alfaro et al., 2024; Kuroishi, 2024; Heath and Mace, 2020), one fact remains puzzling. Only a small share of firms apply for trademarks, although registering a trademark is typically inexpensive. Take China as an example. The registration fee was about 1,000 RMB in 2002, yet only 26 percent of above-scale manufacturing firms had ever held a trademark.[1] Why do most firms not apply for trademarks, and how do trademarks affect firm performance and market outcomes?

In this paper, we show that in the presence of marketing externalities, having a trademark is not optimal for most firms. In addition to the business-stealing effect emphasized in the literature, marketing can generate positive spillovers to other firms in the same market. Such spillovers can arise from consumer confusion.[2] Some consumers informed by a firm's marketing may fail to recognize which firm informed them and may instead purchase from another firm offering a similar product. In this way, one firm's marketing can raise competitors' sales. These spillovers are stronger when firms are less differentiated.

A trademark changes this environment by helping consumers distinguish the trademarked firm from its competitors. This has two implications. First, a trademarked firm can retain a larger share of consumers informed by its own marketing. This raises the private return to marketing, giving the firm an incentive to adopt a trademark and to invest more in marketing afterward. Second, a trademarked firm is less likely to be mistaken for other firms. As a result, consumers informed by competitors' marketing are less likely to purchase from it out of confusion. This reduces the spillover the firm receives from competitors' marketing. The second force discourages trademark adoption,

[1] We match the universe of Chinese trademark registration records to the Annual Survey of Industrial Firms (ASIF), which covers all state-owned firms and all non-state firms with annual sales above 5 million RMB.

[2] Consumer confusion is a well-established concept in the marketing literature. It refers to a state in which consumers have difficulty forming confident purchase decisions. The literature identifies three main sources: similarity among products or brands, information overload, and ambiguity in product or marketing information; see Shahid et al. (2025) for a detailed review.

especially for less capable firms. These firms invest little in their own marketing and mainly rely on spillovers from others.

To test these conjectures, we document three empirical facts about marketing externalities and the role of trademarks. First, a firm's sales are positively correlated with both its own marketing and the average marketing of neighboring firms in the same market. The latter correlation captures positive marketing spillovers from other firms, net of business-stealing effects. Second, only the marketing investment of firms without trademarks generates this positive spillover. Third, after a firm files its first trademark application, the return to its own marketing increases by 12.3 percent, while the spillover it receives from competitors' marketing disappears. The point estimate turns slightly negative, consistent with a sharp decline in the positive spillover and a remaining business-stealing effect.

Motivated by these facts, we build a stylized industry equilibrium model with marketing externalities. Firms are heterogeneous in marginal cost and customer base, and compete monopolistically. Each firm makes three decisions. It chooses price, marketing investment, and whether to apply for a trademark by paying a fixed cost. A firm privatizes only part of the return to its marketing. The rest is shared by all firms in the same market. A trademark raises the private share of the firm's marketing return but lowers the firm's gain from competitors' marketing. Consumers allocate spending between the differentiated varieties and an outside good. Market size is therefore endogenous and depends on the aggregate demand that firms jointly build through marketing. The model is analogous to Melitz (2003) but adds one important feature: a firm's marketing partly benefits other firms in the same market. This externality creates an additional interaction among firms beyond the standard competition channel under CES demand, which changes firms' incentives to invest in marketing and apply for trademarks. In the model, trademark adoption follows a cutoff rule in a capability index that combines marginal cost and customer base.

We estimate the model parameters using the Simulated Method of Moments (SMM). The estimation proceeds in two stages. In the first stage, we use firm-level data on quantities, prices, and input expenditures to estimate production and demand functions, from which we recover firm-specific marginal costs and customer-base endowments. In the second stage, we use SMM to estimate the private return to a firm's own marketing and its gain from competitors' marketing, trademark effects, along with the marketing cost and the fixed cost of trademark adoption. We sample markets and

firms from the data, solve the equilibrium of each market, and run the same auxiliary regressions on the simulated panel as on the data. The parameters are chosen so that the simulated regression coefficients and other moments match their data counterparts. The estimates imply that a trademark raises a firm's private capture of its own marketing from 0.84 to 0.93, but halves its gain from competitors' marketing from 0.018 to 0.009. The estimated fixed cost of trademark adoption is 4,500 RMB.

Using the estimated model, we decompose each firm's customer base into two sources: its own marketing and spillovers from competitors' marketing. The relative importance of these two sources differs sharply across firms with different capabilities. For the least capable firms, own marketing contributes to only one-third of the customer base, while the remaining two-thirds come from marketing spillovers. By contrast, for the most capable firms, own investment accounts for almost the entire customer base.

The value of a trademark rises steeply with firm capability and is negative for most firms. Two forces drive this pattern. Protection raises the private return to a firm's own marketing, and this gain rises steeply with capability because capable firms invest more in marketing. Differentiation cuts the firm off from competitors' marketing spillovers, and this loss is nearly flat across firms. For firms in the top decile, the average net value of a trademark is 1.12 million RMB. For firms below the 60th percentile, holding a trademark lowers net profit by around 40,000 RMB on average. Both magnitudes far exceed the estimated fixed cost of adoption, suggesting that the cost is not a major driver of low trademark adoption.

We conduct two counterfactual experiments. In each exercise, we re-solve the equilibrium and compare it with the benchmark. The first experiment strengthens trademark protection by raising α_T by 20 percent. The trademark adoption rate rises from 0.28 to 0.43. Marketing investment also increases. The aggregate marketing cost rises by 4.1 percent, with both new adopters and incumbent holders spending more on marketing. The response is strongest among firms near the trademark adoption cutoff. Their adoption rate rises from 0.07 to 0.91, and their marketing cost increases by 24 percent. However, more investment does not translate into better performance. Aggregate sales increase by only 0.6 percent, and aggregate net profit decreases by 0.2 percent. The effects are heterogeneous across firms. Both sales and net profit rise for incumbent trademark holders. For those in the top decile, net profit rises by almost 0.6 percent. Sales also rise for new adopters because

they invest more in marketing, but the sales increase does not cover the additional marketing cost, leading to lower net profit. Less capable firms that remain unregistered lose most. Both their sales and net profit fall, because more trademark holders in the market reduce the marketing spillover they receive and intensify marketing competition. Stronger protection therefore has a limited aggregate effect but shifts profit toward the most capable firms.

The second experiment evaluates the effect of increased market transparency. Higher market transparency allows firms to capture a larger share of their own marketing regardless of trademark status, which reduces the spillover to competitors. A 5 percent increase in α_0 raises the trademark adoption rate from 0.28 to 0.91. Aggregate marketing cost increases by 15.6 percent. Marketing increases for all firms, with new trademark adopters experiencing the largest growth. Aggregate sales rise by 2.6 percent and the response is heterogeneous across firms. Sales rise only for firms with above-median capability, with firms in the top decile increasing the most, by more than 6 percent. Net profit follows the same pattern as in the first experiment. Aggregate profit decreases by 0.6 percent. Only the top firms convert the additional marketing into higher net profit. Other firms spend more on marketing, but their sales do not rise enough to cover the additional cost. Greater transparency therefore stimulates trademark adoption and marketing competition, and raises the dispersion within markets.

This study contributes to three strands of literature. First, it adds to the growing literature on trademarks. Theoretical work on the role of trademarks dates back to Grossman and Shapiro (1988a,b), while empirical evidence remains limited. Dinlersoz et al. (2023) and Heath and Mace (2020) examine how trademark protection affects firm performance and innovation decisions. Alfaro et al. (2024) and Kuroishi (2024) emphasize trademarks' role in reducing information asymmetry between firms and consumers. Desai et al. (2022) quantifies the value of trademarks using stock market reactions to new trademark registrations. Forte (2024) and Gao and Hitt (2012) use trademarks as a proxy for product variety. We contribute to this literature by modeling firms' trademark adoption decisions, highlighting the protective and differentiation roles of trademarks that jointly shape firms' trademark adoption decisions and marketing investments.

Second, our study contributes to the literature on how customer acquisition shapes firm dynamics and market outcomes. The literature highlights the importance of marketing investment for new exporters entering foreign markets (Jiang et al., 2026; Fitzgerald et al., 2024; Chen and Huang, 2022;

Arkolakis, 2010). Recently, another line of literature models and quantifies the role of marketing in customer acquisition in more general settings (Shen, 2026; Argente et al., 2025; Cavenaile et al., 2025, 2023; Jiang and Zhang, 2023; Bronnenberg et al., 2022; Gourio and Rudanko, 2014). We contribute to this literature in two ways. First, we document a positive externality of marketing investment. Top firms are the main contributors, while small firms are the main beneficiaries. Second, we show how trademarks reshape this interaction. By letting large firms privatize their marketing, trademarks cut off the externality that small firms rely on and thereby shape the firm distribution within markets.

Finally, this paper contributes to the literature on intellectual property rights (IPR) protection. Existing studies focus mainly on how IPR protection affects firm innovation and reach mixed conclusions. For instance, Fang et al. (2017) and Branstetter et al. (2006) find that stronger protection encourages innovation. In contrast, Heath and Mace (2020), Williams (2013) and Qian (2008) find that stronger protection can hinder innovation, as incumbent IPR holders may already extract sufficient rents and therefore have weaker incentives for subsequent innovation. We contribute to this literature by studying a different margin: how IPR protection shapes firms' endogenous trademark adoption decisions, which in turn affect their marketing incentives. We show that, beyond its limited aggregate effects, IPR protection has large distributional effects. New adopters respond the most to stronger protection. Firms that never adopt lose, and the gains are concentrated among top firms that already hold trademarks.

The rest of the paper is organized as follows. Section 2 describes the institutional background of China's trademark system and data. Section 3 presents stylized facts on firms' marketing investment and marketing spillovers following first trademark applications. Section 4 develops an industry equilibrium model with endogenous marketing investment, trademark adoption, and marketing spillovers. Section 5 details the estimation strategy and reports the main results. Section 6 performs two counterfactual exercises to evaluate the impact of strengthened trademark protection and improved market transparency. Section 7 concludes.

2 Institutional Background and Data

2.1 China's Trademark System

China's Trademark Law was enacted in 1982. The law established a national registration system administered by the Trademark Office of the State Administration for Industry and Commerce

(the Trademark Office, hereafter). By the end of our sample period, the law underwent two major amendments. The 1993 amendment adapted the trademark system to China's market-oriented reforms by extending protection to service marks, broadening the definition of infringement, and strengthening penalties. The 2001 amendment, adopted as part of China's WTO accession, was more substantial. It aligned China's trademark system with the TRIPS Agreement, strengthened protection for collective marks, certification marks, geographical indications, and well-known trademarks, and clarified infringement standards and damages. It also formalized opposition and appeal procedures, and allowed natural persons to apply for trademarks.[3]

Under China's Trademark Law, exclusive rights to a trademark arise from registration, not use. Using an unregistered trademark does not create legal rights, regardless of the length of use, and a competitor may still register the same trademark. The system follows a first-to-file rule: once a firm files an application with the Trademark Office, later applications for identical or similar trademarks on similar goods are rejected in favor of the earlier applicant. Filing therefore secures the applicant's claim even when the application is still pending for approval. Upon registration, the applicant obtains the exclusive right to the trademark. Because protection effectively begins at the application date, our baseline analysis uses the first trademark application as the key event and compares firm outcomes before and after the first filing.

Trademark application procedure. Figure 1 summarizes the application process. Trademark applications are processed at the national level by the Trademark Office. Each application first undergoes a formality check, which typically takes one to two months. This check verifies that all required documents, including the trademark image, are complete and properly formatted. After this check, the Trademark Office assigns an application number and announces receipt of the application. This announcement date is recorded in our data as the trademark "application date."

The application then enters substantive examination, which usually takes more than one year.[4] The Trademark Office evaluates the distinctiveness of the trademark and checks for conflicts with existing trademarks. Applications that pass this examination receive preliminary approval and are published for a three-month public opposition period, during which third parties may challenge the application.

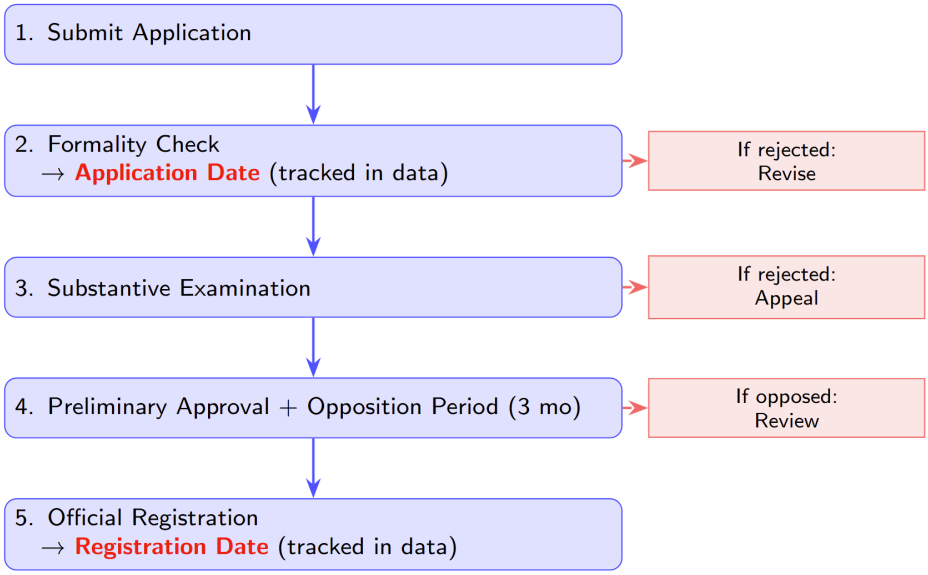
[3]Before 2001, only enterprises, institutions, and individual businesses could apply for a trademark. A trademark filed in the name of a firm's owner rather than the firm cannot be matched to the firm in our analysis sample. Because our firm data cover state-owned firms and non-state firms with annual sales above 5 million RMB, such cases are rare and have limited impact on our results.

[4]During the sample period, there was no statutory time limit for substantive examination, resulting in substantial variation in processing times.

If no one files an opposition, the trademark is officially registered. The registration announcement date is recorded in our data as the "registration date."

The standard procedure takes about fifteen months, but rejection or opposition at any stage can substantially prolong the process. Between 1998 and 2007, the average time from application acceptance to registration was 770 days. Review times increased sharply after 2002 as applications surged, rising from about 500 days before 2002 to more than 1,000 days between 2004 and 2006. Over the same period, the success rate declined from nearly 100 percent before 2001 to about 82 percent in 2007.

Figure 1: Trademark Application Procedure in China



Notes: This figure presents a simplified flowchart of the trademark application procedure in China. The procedure has three main stages: a formality check, a substantive examination, and a three-month opposition period after preliminary approval. The process usually takes more than one year, and rejection or opposition at any stage can substantially prolong it. Our data record two important dates for each application: the application date, when the application passes the formality check, and the registration date, when the trademark is officially registered.
Source: Authors' illustration based on the examination procedure of the Trademark Office (SAIC, now CNIPA).

Registering a trademark is inexpensive. Throughout our sample period, the official fee was 1,000 RMB per application per class. This fee was set in 1995 and remained unchanged until 2013.[5] A registered trademark is valid for ten years from the registration date and can be renewed for successive

[5]The fee schedule was set by the State Planning Commission and the Ministry of Finance (Ji Jia Ge [1995] No. 2404). Firms may file directly with the Trademark Office or through a trademark agency. Agency fees are of the same order of magnitude as the official fee, typically less than 1,000 RMB per application.

ten-year terms.[6] The registration fee is small relative to the scale of firms in our sample. For the median firm without a trademark, 1,000 RMB is less than 0.01 percent of sales. The direct cost of registration therefore cannot explain the low trademark adoption rate during the sample period.

2.2 Data

We combine four data sources for our empirical analysis. The first is China's trademark registration database, published by the State Administration for Industry and Commerce. For each application, the database records the applicant's name and address, trademark class, application and registration dates, expiration date, and descriptions of the mark and the goods it covers. We use all applications filed from 1982, when the Trademark Law was enacted, through 2007, the last year of our firm-level data. Starting in 1982 allows us to identify each firm's first application. We observe each application's status as of the end of 2022.

The second source is the Chinese Annual Survey of Industrial Firms (ASIF), collected by the National Bureau of Statistics of China from 1998 to 2007. The ASIF covers all state-owned enterprises and all non-state enterprises with annual sales above 5 million RMB. It reports sales, employment, capital stock, output, variable input costs, and selling expenses. We use selling expenses to measure firms' marketing investment. Following Brandt et al. (2012), we link firms across years to construct a panel. We then match trademark records to this panel by applicant name within each year, following Deng et al. (2020); Yu (2015), and use applicant addresses to improve match quality.

The third source is the Chinese Manufacturing Enterprises Product Output Quantity Survey (the Output Quantity Survey, hereafter), collected by the National Bureau of Statistics from 2000 to 2007. Compared with ASIF, the Output Quantity Survey covers relatively larger firms. The survey reports each firm's physical output by product, together with the product name and unit. We use this information to construct quantities and prices at the firm-year level. Because the Output Quantity Survey and the ASIF share the same firm identifier, we match them directly. We combine this survey with the ASIF to estimate firm-level physical productivity and demand shifters separately. In our analysis sample, 450,465 ASIF observations from 2000 to 2007 are matched to the Output Quantity Survey, accounting for about 30 percent of all ASIF observations in these years.

[6] The renewal fee was 2,000 RMB per class during our sample period. Our empirical variation comes from firms that file their first application in 1998 or later, and our sample covers ten years. These firms do not reach their first renewal date within the sample, so renewal decisions are beyond the scope of this paper.

The fourth source is gross output of industrial firms at the province × industry × year level, reported in provincial statistical yearbooks from 2001 to 2007. We use this information to proxy for market size in the structural estimation. Dividing total sales of our sample firms in each market by this output gives their market share; the remainder is the share of fringe firms outside our sample, which we model as the outside good.

We conduct the reduced-form analysis using the full ASIF panel matched to trademark records, which provides the broadest coverage. The structural estimation requires firm-level physical productivity and demand shifters, so we restrict that analysis to the subsample matched to the Output Quantity Survey. Table 1 reports summary statistics for the key variables in our analysis samples.

Table 1: Summary Statistics for the Key Variables

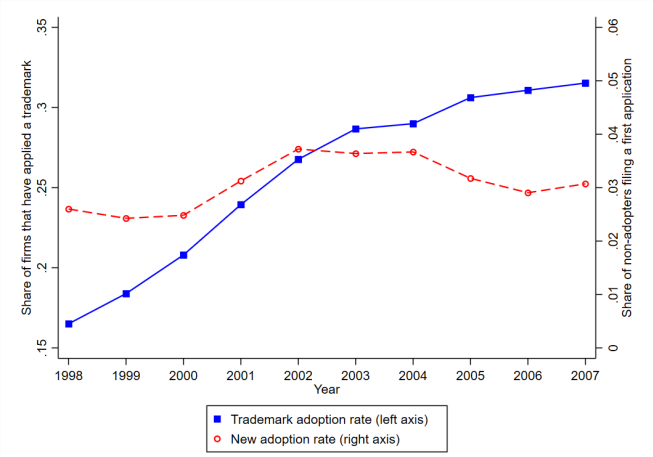
Variable	Mean	p25	p50	p75	SD	N
Panel A. Chinese Annual Survey of Industrial Firms, 1998–2007						
Sales value (mil RMB)	36.198	7.811	15.680	36.710	62.374	1,609,440
Capital stock (mil RMB)	10.655	1.251	3.326	9.204	23.579	1,609,440
Cost of goods sold (mil RMB)	31.204	6.592	13.406	31.533	54.872	1,609,440
Age	9.105	3.000	6.000	11.000	10.065	1,609,440
Selling Expenses (mil RMB)	0.963	0.044	0.246	0.829	2.326	1,609,440
Selling Expenses / Sales	0.031	0.003	0.016	0.041	0.041	1,609,440
Panel B. Trademark Registration Database, 1998–2007						
Dummy(First Trademark Application)	0.223	0.000	0.000	0.000	0.416	1,609,440
Number of registered trademarks (adopters only)	1.523	0.000	1.000	1.000	4.000	358,852
Panel C. Chinese Manufacturing Product Output Quantity Database, 2000–2007						
Quantity (log)	7.322	5.423	7.463	9.121	2.701	450,465
Price (log)	2.699	0.937	2.530	4.458	2.500	450,465

Notes: This table reports summary statistics of key variables for the analysis sample. Panel A reports firm-level variables from the ASIF in millions of RMB. In Panel B, Dummy(Trademark adoption) equals one once the firm has filed its first trademark application. The number of formally registered trademarks is reported for the subset of observations that have adopted trademarks. A firm that has adopted a trademark can have zero registered trademarks when its first application is still pending formal registration. Panel C reports log physical quantity of the firm's largest product and log unit price, defined as sales divided by quantity.

Measure of marketing investment. Following Jiang and Zhang (2026); Jiang et al. (2026), we measure marketing investment using selling expenses. Selling expenses include the operating costs of the sales department, such as salaries, materials, and utilities, as well as advertising and exhibition fees. Chinese accounting standards require firms to report selling expenses separately from general and administrative expenses, whereas North American standards combine them as SG&A. This separation allows us to distinguish demand-side investment from R&D and general administrative costs.[7]

[7] Under the Chinese accounting system in force during our sample period, firms report R&D expenditure under administrative expenses.

Figure 2: Trademark Adoption Rate: 1998–2007



Notes: This figure plots the trademark adoption rate by year for all firm-year observations in the ASIF sample from 1998 to 2007. The solid line (left axis) is the share of firms that have filed a first trademark application by the focal year. The dashed line (right axis) is the new adoption rate, defined as the share of non-adopters observed in both the previous and focal years that file a first application in the focal year. The adoption rate rises from 17 percent in 1998 to 32 percent in 2007. The new adoption rate rises through 2002 and declines afterward.

2.3 Trademark Adoption Patterns

Using the matched trademark and firm-level data, we document three patterns of trademark adoption.

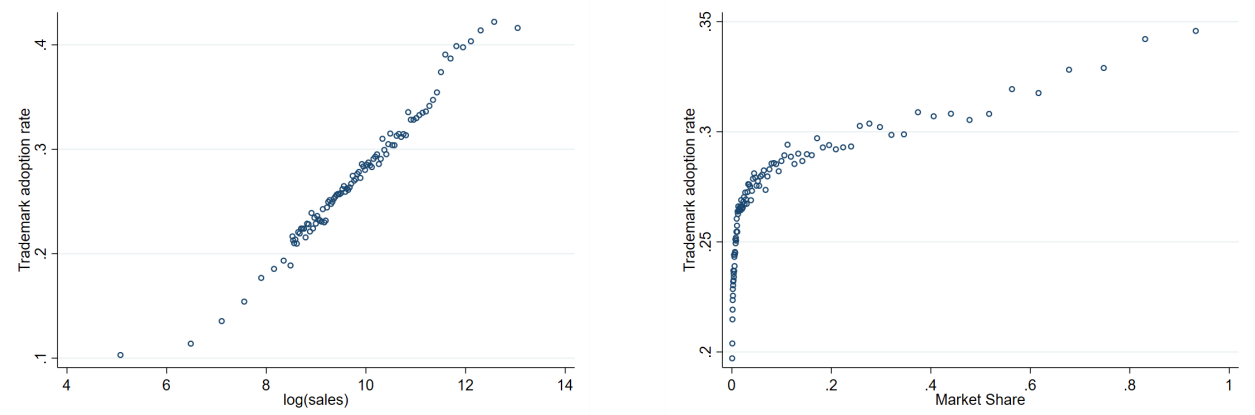
Pattern 1: Trademark adoption rate is low. Figure 2 plots trademark adoption rate over the sample period. The share of firms that have filed a first trademark application rises from 17 percent in 1998 to 32 percent in 2007. Growth is fastest between 2001 and 2004 and slows thereafter. The figure also plots the new adoption rate, defined as the share of non-adopters that file their first application in a given year. This rate is less volatile and remains around 3 percent per year. It rises from 2001 to 2004, likely reflecting the 2001 amendment to the Trademark Law, and returns after 2005 to a level slightly above the pre-amendment rate. Overall, trademark adoption is far from universal: more than two-thirds of firms still operate without a trademark by the end of 2007, and new adoption proceeds at a steady pace of about 3 percent per year.

Table 2: Summary Statistics by Trademark Status

	With Trademark			Without Trademark		
VARIABLES	Mean	SD	Median	Mean	SD	Median
Sales	45.169	71.846	20.105	33.624	59.127	14.656
Selling expenses	1.365	2.838	0.426	0.847	2.142	0.206
Selling expenses / sales	0.036	0.044	0.021	0.029	0.041	0.014
Employment	203.450	268.218	113.000	171.469	237.692	95.000
Capital stock	13.764	27.290	4.667	9.763	22.321	3.016
Age	8.770	9.139	6.000	9.201	10.313	6.000
Observations		358,852			1,250,588	

Notes: This table reports summary statistics for the ASIF sample from 1998 to 2007 for observations with trademarks and without trademark separately. Observations are at the firm-year level. An observation is classified as "with trademark" if the firm has filed its first trademark application by that year, and as "without trademark" otherwise. Sales, selling expenses, and capital stock are in millions of RMB. Employment refers to the number of workers. Firms with a trademark are larger, spend more on marketing both in levels and relative to sales.

Figure 3: Trademark Adoption Rate: by Firm Characteristics



(a) Log sales **(b)** Market share

Notes: This figure plots the trademark adoption rate against firm size and market share for all firm-year observations from 1998 to 2007. The adoption rate is the share of firms that have filed a first trademark application by the focal year. Each dot is the mean adoption rate in one of 100 equal-sized bins of the horizontal-axis variable. Panel (a) uses log sales. Panel (b) uses the firm's sales share in its city × 4-digit industry × year market, excluding single-firm markets. Adoption rises steadily with both measures.

Pattern 2: Trademark adopters are top firms. Trademark adoption is highly selective. Figure 3 plots adoption rates against firm size in log sales and market share. Adoption rises monotonically with log sales, from about 10 percent among the smallest group of firms to more than 40 percent among the largest. We measure market share as a firm's sales share in a city × 4-digit SIC industry ×

year cell. The market-share distribution is highly right-skewed, with most firms below 0.2. Adoption also rises with market share, from about 20 percent among firms with negligible shares to about 35 percent among firms that dominate their markets. Large firms and market leaders are therefore more likely to hold a trademark.

Table 2 compares trademark holders' characteristics with those of non-holders. Firms with a trademark have 34 percent higher sales and spend substantially more on marketing. Their selling expenses are 61 percent higher, and their selling-expense-to-sales ratio is 3.6 percent, compared with 2.9 percent for firms without a trademark. Trademarked firms are also slightly younger.

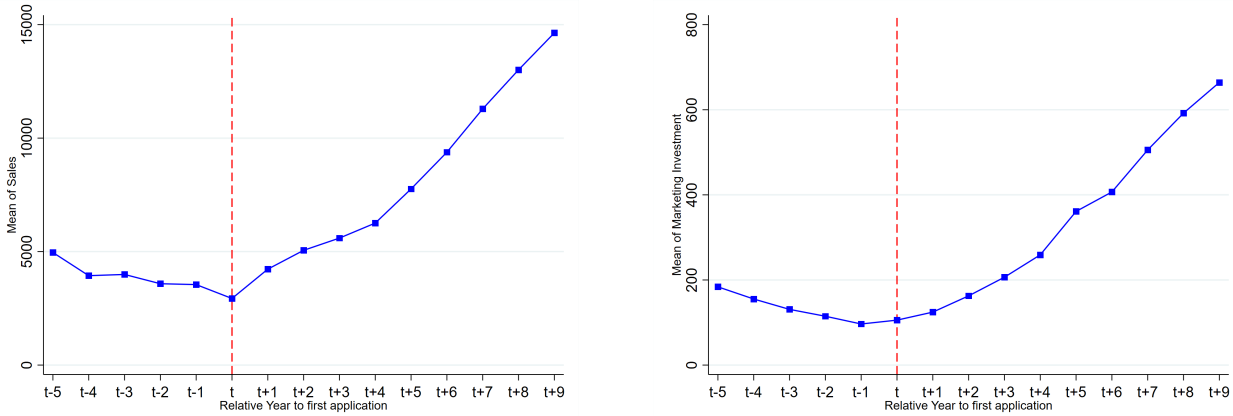
Pattern 3: Sales and marketing investment grow after the first trademark application. The relationship among trademark adoption, marketing investment, and sales is central to our analysis. Figure 4 plots average sales and marketing investment around firms' first trademark applications. Each observation is demeaned by its 4-digit SIC industry $\times$ year average to remove any industry-year-specific shocks. Two patterns stand out. First, applicants are larger and spend more on marketing than the average firm in their industry throughout the event window, as shown by the positive sales and marketing throughout the periods. Second, both sales and marketing investment rise sharply after the first application. In Appendix B.1, we use propensity score matching to pair each trademark applicant with a similar firm that has not applied for a trademark. Relative to matched controls, applicants' sales increase by 7.9 percent and their marketing investment increases by 24.6 percent after the first application.

3 Evidence on Marketing Spillovers and the Role of Trademarks

Section 2 shows that trademark adoption is selective and that firms expand sales and marketing investment after their first application. We now examine how a firm benefits from other firms' marketing investment through marketing externalities, and how trademarks influence the degree of such marketing externalities. The evidence highlights the central trade-off in trademark adoption: a trademark helps a firm appropriate greater returns to its own marketing investment, but it also limits the firm's ability to benefit from rivals' marketing externalities.

We define a market as a city $\times$ 4-digit SIC industry cell and index it by s. For firm i in market s and year t, let MKT_{it} denote the firm's own marketing investment and let $\overline{MKT}_{-i,st}$ denote the

Figure 4: Firm Performance Following First Trademark Application



(a) Sales **(b)** Marketing investment

Notes: This figure plots average sales and marketing investment around firms' first trademark applications. Panel (a) plots sales. Panel (b) plots selling expenses, our measure of marketing investment. Year t is the year of the first application, marked by the dashed vertical line. Each observation is demeaned by its 4-digit industry $\times$ year average. Both sales and marketing investment rise sharply afterward.

average marketing investment of all other firms in the same market. We estimate

$$y_{it} = \alpha \ln MKT_{it} + \beta \ln \overline{MKT}_{-i,st} + X_{it}'\Gamma + \nu_i + \eta_{jt} + \tau_{\ell t} + \varepsilon_{it}, \tag{3.1}$$

where y_{it} is either the firm's log sales or market share. Our parameter of interest α measures the return to a firm's own marketing investment, while β captures the association between the firm's performance and competitors' marketing investment. The vector X_{it} includes firm age, ownership type, employment, TFP, an indicator for having filed a first trademark application, and the number of firms in the market. We include firm fixed effects ν_i, industry $\times$ year fixed effects η_{jt}, and city $\times$ year fixed effects $\tau_{\ell t}$. Including firm fixed effects and a series of firm characteristics mitigates the potential impact of endogeneity on the estimates. Standard errors are clustered at the firm level.

Fact 1: Marketing generates positive spillovers to competitors' sales. Columns (1) and (2) of Table 3 report estimates of equation (3.1). The estimation result shows that a firm's marketing investment increases its sales, with an elasticity of 0.074. It also increases the firm's market share: a 10 percent increase in marketing investment raises the firm's market share by 0.052 percentage points.

More interestingly, Table 3 shows that besides competition, marketing generates positive spillovers. A one-percent increase in competitors' average marketing investment raises the focal firm's sales by

0.0024 percent. At the same time, it lowers the focal firm's market share. Competitors' marketing not only shifts market share away from the focal firm but also expands the total market, which raises the focal firm's sales. The positive coefficient on competitors' marketing captures the net of two effects on the focal firm: a negative business-stealing effect and a positive marketing spillover. The second effect has received limited attention in the literature.

A potential concern is that market-level demand shocks may simultaneously raise marketing and sales for all firms in the same market, generating a positive correlation between a firm's sales and its competitors' marketing. To address this concern, in Appendix B.2, we further add city × 4-digit industry × year fixed effects to absorb such shocks. Table 15 shows that the estimated spillover on sales remains robust.

Table 3: Marketing and Marketing Spillover

VARIABLES	log(sales)	Market Share	log(sales)	Market Share
	(1)	(2)	(3)	(4)
log(MKT_i)	0.0739***	0.00520***	0.0688***	0.00296***
	(0.000487)	(8.12e-05)	(0.000535)	(5.65e-05)
log(Average MKT_{-i})	0.00242***	-0.0456***		
	(0.000677)	(0.000271)		
log(Average MKT_{-i}:Tmark)			0.000277	-0.00790***
			(0.000576)	(0.000119)
log(Average MKT_{-i}:NonTmark)			0.00231**	-0.0185***
			(0.000899)	(0.000232)
Observations	1,246,904	1,246,904	919,919	919,919
R-squared	0.911	0.854	0.911	0.855
Control	Age, Ownership, Employment, TFP, D(First Trademark), Number of Firms			
FE	Firm + 4-digit SIC Industry × Year + City × Year			
Cluster	Firm			

Notes: This table shows the correlation between a firm's sales and market share and the marketing of the other firms in its market. Markets are 4-digit SIC industry×city×year cells, and Average MKT_{-i} is the mean marketing investment of all firms in the market other than firm i. Columns (3) and (4) compute this average separately over the other firms with a trademark (Tmark) and without one (NonTmark), using markets with both types. Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Competitors' marketing raises a firm's sales even though it lowers the firm's market share, and this positive spillover comes only from firms without a trademark.

The positive spillover implies that part of the demand created by a firm's marketing reaches its competitors. We attribute this leakage to consumer confusion. Consumer confusion is a well-established concept in the marketing literature. It refers to situations in which consumers have difficulty making confident purchase decisions. The literature identifies three main sources of confusion: similarity among products or brands, information overload, and ambiguity in product or marketing information (see Shahid et al., 2025, for a detailed review). When consumers receive marketing from firm i in market m, the message attracts them to market m from other markets. However, with

consumer confusion, consumers cannot perfectly identify or locate the advertised firm. Some of them end up buying from other firms in the same market. As a result, one firm's marketing spills over to its competitors.

We test this mechanism by examining how the strength of the spillover varies with the similarity of firm names. Consumers find it harder to tell apart firms with similar names. If consumer confusion drives the spillover, a firm should benefit more from the marketing of competitors with similar names than from the marketing of other competitors. For each firm, we measure the similarity between its name and the name of each competitor in the same market.[8] We then split competitors into a high-similarity group and a low-similarity group and compute average marketing investment for each group. Columns (1) and (3) of Table 4 report estimates of equation (3.1) with the two group averages replacing $\overline{MKT}_{-i,st}$. The spillover comes mainly from competitors with similar names. A one-percent increase in their average marketing investment raises the focal firm's sales by 0.0029 percent. The effect of competitors with dissimilar names is much smaller and statistically insignificant. We also compute the average name similarity in each market and interact competitors' average marketing with an indicator for high-similarity markets. Columns (2) and (4) show that the spillover is larger in high-similarity markets.

An alternative mechanism for the positive marketing spillover is collective reputation (e.g., Bai et al., 2022; Wang and Xing, 2023). Firms in the same market share a common reputation among consumers. When one firm invests in marketing, consumers may update their valuation of the whole market rather than of the firm alone, so the marketing raises demand for all firms in the market. Fact 2 below shows that this mechanism is not supported by our data.

Fact 2: Firms with trademarks generate smaller marketing spillovers to other firms than firms without trademarks. Columns (3) and (4) of Table 3 compare the spillover from competitors with trademarks and from competitors without them. We extend equation (3.1) to allow the spillover to differ between the two groups of competitors. The sample is restricted to markets with both types of competitors, leaving 919,919 observations. Although marketing by both groups lowers the focal firm's market share, the effect on sales differs. Marketing by competitors without trademarks generates a positive and statistically significant spillover to the focal firm's sales, while marketing by

[8] We remove region names and organization-form words from each firm name and compute the cosine similarity between the character vectors of the remaining names. Characters that are common within a industry receive lower weights.

Table 4: Marketing Spillover: Heterogeneity by Firm Name Similarity

VARIABLES	log(sales)	Market Share	log(sales)	Market Share
	(1)	(2)	(3)	(4)
log(MKT_i)	0.0734***	0.00508***	0.0720***	0.00460***
	(0.000485)	(8.09e-05)	(0.000489)	(7.33e-05)
log(Average MKT_{-i}: High Similarity)	0.00292***	-0.0198***		
	(0.000561)	(0.000188)		
log(Average MKT_{-i}: Low Similarity)	0.000262	-0.0161***		
	(0.000496)	(0.000158)		
log(Average MKT_{-i})			0.00122	-0.0465***
			(0.000873)	(0.000348)
log(Average MKT_{-i}) × High Similarity Market			0.00333***	0.0136***
			(0.00129)	(0.000405)
Observations	1,241,150	1,241,150	1,241,150	1,241,150
R-squared	0.918	0.873	0.909	0.860
Control	Age, Ownership, Employment, TFP, Number of Firms			
FE	Firm + 4-digit SIC Industry × Year + City × Year			
Cluster	Firm			

Notes: This table reports estimates of equation (3.1) with competitors' marketing split by the similarity of firm names. Name similarity is the cosine similarity between the character vectors of two firm names after removing region names and organization-form words. Columns (1) and (2) compute Average MKT_{-i} separately over competitors with high and low similarity to the focal firm. Columns (3) and (4) interact Average MKT_{-i} with an indicator for markets whose average pairwise similarity is above the median of their 2-digit industry. Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The sales spillover comes mainly from competitors with similar names.

competitors with trademarks generates no statistically significant spillover. This pattern is consistent with the consumer confusion mechanism. A trademark grants a firm exclusive rights to its brand identifiers and prevents competitors from using identical or confusingly similar marks. Consumers can then recognize and locate the advertised firms, which eliminates the spillover to competitors. The pattern does not support collective reputation as the main mechanism. If collective reputation were at work, marketing by competitors with and without trademarks should generate similar spillovers.

Fact 3: Firms with trademarks benefit less from marketing spillovers, although trademarks raise the return to own marketing investment. Define the dummy D_{it} equal to one from the year of firm i's first trademark application onward. To examine how a firm's own trademark status changes both the return to its own marketing and the spillover it receives from its competitors, we interact both marketing terms in equation (3.1) with firm $i's$ trademark status D_{it}:

$$y_{it} = (\alpha + \alpha_D D_{it}) \ln MKT_{it} + (\beta + \beta_D D_{it}) \ln \overline{MKT}_{-i,st} + \rho D_{it} + X'_{it}\Gamma + \nu_i + \eta_{jt} + \tau_{\ell t} + \varepsilon_{it}. \quad (3.2)$$

The coefficients α_D and β_D measure the impact of the focal firm's trademark status on the return to

its own marketing investment and the marketing spillover it receives from competitors.

Table 5 reports the results. As shown in column (1), the first trademark application raises the sales elasticity of marketing by 0.009, an increase of 12 percent from its benchmark (0.0727) before applying for trademarks. This suggests that the trademark increases the firm's private gains from its own marketing investment. However, applying for a trademark also prevents the firm from benefiting from other firms' marketing investment. As shown in the table, applying for a trademark reduces the sales elasticity of competitors' average marketing (the marketing spillover effect) by 0.00337, which offsets the spillover effect (0.00296) before the trademark application. The spillover effect falls to zero after the firm applies for a trademark.

The market-share estimates in column (2) show the same pattern: the effect of competitors' marketing on a firm's market share becomes more negative after the firm applies for a trademark, changing from -0.045 to -0.049.

These results highlight the trade-off behind trademark adoption. A trademark protects a firm's customer base and raises the return to its own marketing. At the same time, the differentiation created by the trademark reduces the firm's ability to benefit from competitors' marketing. Firms that invest heavily in marketing gain from the first effect. Firms that invest little and rely more on competitors' marketing lose from the second. This trade-off helps explain why most firms do not apply for trademarks despite the low registration fee.

4 Model

Motivated by the empirical facts in Section 3, we develop a static industry equilibrium model in which firms make endogenous marketing investment and adopt trademarks to build a customer base. The model serves three purposes. First, it clarifies the mechanisms through which trademarks affect firm behavior and market outcomes. Second, it quantifies the effects of trademarks on marketing decisions by separately identifying their protection and differentiation effects. Third, it predicts how trademark-related policies affect firm performance and market outcomes.

The model formalizes the trade-off highlighted by the reduced-form evidence. Marketing helps a firm build demand, but the firm cannot fully appropriate the return to its own marketing: some consumers informed by its marketing may purchase from other firms in the same market. A trademark has two

Table 5: Trademark Adoption, Private Return of Marketing and Marketing Spillover

VARIABLES	log(sales)	Market Share
	(1)	(2)
$\log(MKT_i)$	0.0727***	0.00518***
	(0.000508)	(8.60e-05)
$\log(MKT_i)$ × D(First Trademark)	0.00893***	0.000180
	(0.00113)	(0.000214)
log(Average MKT_{-i})	0.00296***	-0.0451***
	(0.000736)	(0.000288)
log(Average MKT_{-i}) × D(First Trademark)	-0.00337**	-0.00379***
	(0.00157)	(0.000635)
D(First Trademark)	0.0174	0.0235***
	(0.0125)	(0.00435)
Observations	1,246,904	1,246,904
R-squared	0.911	0.854
Control	Age, Ownership, Employment, TFP, Number of Firms	
FE	Firm + 4-digit SIC Industry × Year + City × Year	
Cluster	Firm	

Notes: This table interacts the specification in Table 3 with D(First Trademark), an indicator equal to one from the year of the firm's first trademark application onward. Markets and Average MKT_{-i} are defined as in Table 3. Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. After the first application, the elasticity of sales with respect to own marketing rises by 12 percent, from 0.073 to 0.082, and the spillover from competitors' marketing falls from 0.003 to zero.

opposing effects. It raises the effectiveness of the firm's own marketing investment, reflecting the protection role of trademarks. At the same time, it differentiates the firm's brand from others and therefore reduces the firm's ability to benefit from the marketing spillovers generated by competitors. We embed this mechanism in a monopolistic competition model with a two-tier demand system and an outside option. The outside option allows the size of the differentiated market to respond to the aggregate demand that firms build through marketing.

4.1 Model Setup

Environment. A market consists of a continuum of firms of mass one. Each firm produces one differentiated variety and competes monopolistically. Firm $i \in \Omega$ draws a pair of states (ω_i, ξ_i) from a joint distribution G, where ω_i is the productivity that determines the firm's marginal cost and $\xi_i > 0$ is an exogenous demand attribute, which we call *product appeal*. Firms observe their types and choose prices, marketing investment, and trademark status to maximize their profit, taking market aggregates as given. Because firms are atomless, an individual firm's decisions do not affect these aggregates.

A representative consumer has total expenditure E and allocates it between the differentiated varieties and a homogeneous outside option. The outside option is supplied competitively at a constant price normalized to one, $p_o = 1$. Firm-level objects carry the subscript i; unsubscripted objects denote aggregates or primitives.

Consumer preferences. A representative consumer has a nested CES preference. In the upper layer, the consumer chooses between the differentiated composite good Q and the outside option q_o:

$$U = \left[Q^{(\varepsilon-1)/\varepsilon} + \zeta^{1/\varepsilon} q_o^{(\varepsilon-1)/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)}, \tag{4.1}$$

where $\varepsilon > 0$ is the elasticity of substitution between the differentiated composite good and the outside option, and $\zeta \geq 0$ is the taste weight on the outside option. In the lower layer, the differentiated composite good aggregates the continuum of varieties:

$$Q = \left[\int_\Omega \phi_i^{1/\sigma} q_i^{(\sigma-1)/\sigma} \, di \right]^{\sigma/(\sigma-1)}, \tag{4.2}$$

where q_i is the quantity of variety i, $\sigma > 1$ is the elasticity of substitution across varieties, and ϕ_i is a firm-specific demand shifter. It may arise from more customers, or higher product quality that attracts more purchases. A larger customer base means that, at a given relative price and market size, the firm sells more. Below, we specify how firms build this customer base through their own marketing and through spillovers from competitors' marketing.

The consumer takes prices p_i and demand shifters ϕ_i as given and faces the budget constraint

$$\int_\Omega p_i q_i \, di + q_o = E. \tag{4.3}$$

Throughout, we maintain $1 < \varepsilon \leq \sigma$. Thus, substitution between the differentiated composite good and the outside option is no stronger than substitution across varieties. This assumption implies that market size expands when firms collectively build demand, and it delivers a unique inner equilibrium as described in Section 4.3.

Demand function. Because preferences are homothetic within each layer, the consumer's problem can be solved by two-stage budgeting. The lower layer allocates expenditure on the differentiated

composite good across varieties and defines the customer-base-adjusted price index

$$P = \left[\int_{\Omega} \phi_i p_i^{1-\sigma}\, di\right]^{1/(1-\sigma)}. \tag{4.4}$$

The upper layer allocates total expenditure between the differentiated composite good and the outside option. Let E_Q denote total expenditure on the differentiated varieties. Then

$$E_Q = s_Q(P)E, \qquad s_Q(P) \equiv \frac{P^{1-\varepsilon}}{P^{1-\varepsilon} + \zeta} \in (0,1). \tag{4.5}$$

Combining the two layers, firm i faces demand

$$q_i = \underbrace{\phi_i \left(\frac{p_i}{P}\right)^{-\sigma}}_{\text{within-market demand}} \times \underbrace{\frac{E_Q}{P}}_{\text{market size}}, \tag{4.6}$$

or equivalently $q_i = \phi_i p_i^{-\sigma} P^{\sigma-1} E_Q$. Demand therefore has two components. The first captures competition within the differentiated market: a firm sells more when it has a larger customer base or charges a lower price relative to the market price index. The second captures the size of the market: the expenditure share $s_Q(P)$ determines how much of the total budget E is attracted away from the outside option.[9]

Formation of customer base. The firm's customer base combines exogenous product appeal and an endogenous component built through marketing and marketing spillovers. Given product appeal ξ_i, the customer base is

$$\phi_i = \xi_i \left[\phi_0 + \alpha_i m_i + \beta_i \Lambda\right], \qquad \Lambda = \int_{\Omega} (1-\alpha_j) m_j\, dj, \tag{4.7}$$

where $\phi_0 > 0$ is the baseline customer base, $m_i \geq 0$ is firm i's marketing investment, and Λ is the public pool of consumers generated by marketing spillovers in the market.

The interpretation is as follows. Each unit of marketing reaches a mass of potential consumers. Firm i privately captures a fraction α_i of these consumers: they correctly identify the firm and purchase from it. The remaining fraction $1-\alpha_i$ are informed by marketing but may be confused about the

[9]The upper layer makes the market boundary endogenous. When firms build larger customer bases, the price index P falls. If $\varepsilon > 1$, a lower P raises $s_Q(P)$ and attracts expenditure from the outside option. Scaling all demand shifters by a common factor t gives $d\ln E_Q / d\ln t = (\varepsilon-1)[1-s_Q(P)]/(\sigma-1)$ (Appendix C.1). The response is bounded because $E_Q < E$. As $\zeta \to 0$, the model converges to the fixed-expenditure benchmark.

source of the message or may purchase from a similar firm. These confused consumers enter the public pool Λ, which forms the source of marketing spillover to other firms. Each firm then receives a share β_i of the confused consumers in the market. The term $\beta_i\Lambda$ measures the benefits firm i receives from marketing spillovers from its competitors. If $\beta_i\Lambda > (1-\alpha_i)m_i$, firm i gains net benefit from marketing spillovers in the market; otherwise, it is a net contributor of marketing spillover. Thus, a firm's customer base increases with its own marketing, $\alpha_i m_i$, and with the spillovers it receives from other firms' marketing, $\beta_i\Lambda$.[10]

Trademark status affects both the private return to own marketing investment and firms' gains from marketing spillover, as characterized below:

$$\alpha_i \equiv \alpha_0 + \alpha_T T_i, \qquad \beta_i \equiv \beta_0 + \beta_T T_i, \tag{4.8}$$

where the dummy $T_i \in \{0,1\}$ indicates whether firm i holds a trademark. We impose

$$0 < \alpha_0 < \alpha_0 + \alpha_T < 1, \qquad 0 \leq \beta_0 + \beta_T < \beta_0 \leq 1. \tag{4.9}$$

These restrictions encode the two roles of trademarks. First, a trademark raises the private returns to the firm's own marketing investment, $\alpha_T > 0$. Intuitively, consumers reached by a trademarked firm's marketing are more likely to identify and purchase from this firm. This is the protection channel. Second, a trademark lowers the firm's gain from marketing spillover, $\beta_T < 0$. Because the trademarked firm is more differentiated from other firms, consumers drawn in by competitors' marketing are less likely to have confusion and purchase from the trademarked firm. This is the differentiation channel. The term $\alpha_0 + \alpha_T < 1$ ensures that trademark holders still contribute positively to marketing spillover, and $\beta_0 + \beta_T \geq 0$ ensures that trademark holders still have non-negative benefits from other firms' marketing spillover.

Product appeal ξ_i scales the demand value of the baseline customer base, own marketing effect, and marketing spillover effect. It is exogenously given when the firms are making the production, marketing, and trademark decisions. We introduce this demand-side heterogeneity to match the fact that in the data firms with similar productivity differ substantially in marketing behavior and trademark adoption. Conditional on cost, firms with higher product appeal have stronger incentives

[10] Because firms are atomless, a firm's own contribution to Λ has no effect on the pool it takes as given when choosing marketing.

to invest in marketing and to adopt a trademark. Thus, adoption sorts on a capability index that combines cost and demand appeal, rather than on productivity alone, as we detail later.

Production. Each firm produces at a constant marginal cost c_i, which varies across firms. We summarize firm heterogeneity by the joint draw $(\omega_i, \xi_i) \sim G$. In estimation, we recover c_i from an estimated production function using data on output quantity, variable input costs, and capital stock. Section 5 details the estimation strategy.

4.2 Firm's Problem

Each firm chooses its trademark status, marketing investment, and price to maximize profits. Marketing investment m_i costs Bm_i^γ, where $B > 0$ and $\gamma > 1$. The convex cost captures increasing marginal costs of acquiring customers, as in Arkolakis (2010). Applying for a trademark requires paying a fixed cost $F > 0$. The firm's optimization problem is

$$\max_{T_i \in \{0,1\},\, m_i \geq 0,\, p_i} \quad (p_i - c_i)q_i - Bm_i^\gamma - FT_i \qquad \text{s.t. (4.6) and (4.7)}, \tag{4.10}$$

taking the aggregate state variables (P, E_Q, Λ) as given.

We solve the firm's problem by backward induction. The firm first decides whether to adopt a trademark, then chooses marketing given its trademark status, and finally sets its price given its customer base. We characterize the three decisions in reverse order.

Optimal pricing. Given customer base and marginal cost, monopolistic competition and constant-elasticity demand imply the standard constant markup,

$$p_i^* = \mu c_i, \qquad \mu \equiv \frac{\sigma}{\sigma - 1}. \tag{4.11}$$

With a constant markup, operating profit is a fixed share $1/\sigma$ of sales. Substituting the demand function (4.6) and the customer base (4.7), operating profit is

$$\pi_i^{\text{op}}(T_i, m_i) = \kappa_i \left(\phi_0 + \alpha_i m_i + \beta_i \Lambda\right), \qquad \kappa_i \equiv \kappa(c_i, \xi_i) \equiv \frac{\mu^{1-\sigma}}{\sigma} P^{\sigma-1} E_Q \, \xi_i c_i^{1-\sigma}, \tag{4.12}$$

where κ_i is the operating profit generated by one unit of endogenous customer base. It consists of three parts. The constant term $\mu^{1-\sigma}/\sigma$ reflects the markup. The market-specific term $P^{\sigma-1}E_Q$ is the

demand scale: a larger market-level expenditure or a higher price index raises the profit from each customer, and every firm in the market takes this term as given. The firm-specific term $x_i \equiv \xi_i c_i^{1-\sigma}$ combines the firm's cost advantage and demand advantage. We refer to x_i as the firm's capability index. It ranks firms within a market, and all firm-level outcomes below are monotone in it.

A firm's total profit conditional on trademark status T_i and marketing m_i is then

$$\pi_i(T_i, m_i) = \kappa_i \left[\phi_0 + (\alpha_0 + \alpha_T T_i) m_i + (\beta_0 + \beta_T T_i)\Lambda\right] - B m_i^{\gamma} - F T_i. \tag{4.13}$$

Marketing. Because the firm takes the public pool Λ as given, the marginal return to its own marketing depends on the private return rate α_i, but not on the marketing spillover rate β_i. Marketing spillover affects the level of the customer base and hence profits, but it does not affect the marginal product of the firm's own marketing investment.

Proposition 1 (Optimal marketing investment)**.** *Conditional on trademark status T_i, the optimal marketing investment is uniquely given by*

$$m_i^*(T_i) = \left[\frac{\kappa_i(\alpha_0 + \alpha_T T_i)}{B\gamma}\right]^{1/(\gamma-1)}. \tag{4.14}$$

Equation (4.14) implies that marketing is strictly increasing in the capability index x_i. Holding (c_i, ξ_i) fixed, trademark status raises marketing at a rate given by

$$\ln \frac{m_i^*(1)}{m_i^*(0)} = \frac{1}{\gamma - 1} \ln \frac{\alpha_0 + \alpha_T}{\alpha_0} > 0. \tag{4.15}$$

Proof. The first-order condition of equation (4.13) with respect to m_i is

$$\kappa_i(\alpha_0 + \alpha_T T_i) = B\gamma m_i^{\gamma - 1}.$$

Since $\gamma > 1$, the objective is strictly concave in m_i, and the solution is unique and interior. Monotonicity in x_i follows from $\kappa_i \propto x_i$. Equation (4.15) follows by taking the ratio of the marketing policies under $T_i = 1$ and $T_i = 0$. □

Proposition 1 connects directly to the empirical facts. First, more capable firms invest more in marketing. Second, a trademark raises marketing investment by increasing the private return to own

marketing. This implication is consistent with the increase in marketing investment following the first trademark application documented in Section 2. In estimation, these margins help discipline the curvature of the marketing cost function, γ, and the protection effect of trademarks, α_T.[11]

Trademark adoption. Substituting the optimal marketing policy into equation (4.13), the optimized surplus from private marketing is

$$S_i(T_i) = B(\gamma - 1)\left[\frac{\kappa_i(\alpha_0 + \alpha_T T_i)}{B\gamma}\right]^{\gamma/(\gamma-1)}. \tag{4.16}$$

The value of trademark status T_i is therefore

$$V_i(T_i) = \kappa_i\left[\phi_0 + (\beta_0 + \beta_T T_i)\Lambda\right] + S_i(T_i) - FT_i. \tag{4.17}$$

Let $\alpha_1 = \alpha_0 + \alpha_T$, $\beta_1 = \beta_0 + \beta_T$. The net gain from adopting a trademark, $\Delta V_i \equiv V_i(1) - V_i(0)$, is thus

$$\Delta V_i = \underbrace{B(\gamma-1)\left[\frac{\kappa_i}{B\gamma}\right]^{\gamma/(\gamma-1)}\left[\alpha_1^{\gamma/(\gamma-1)} - \alpha_0^{\gamma/(\gamma-1)}\right]}_{\text{gain from higher private return to own marketing}} + \underbrace{\kappa_i\beta_T\Lambda}_{\text{loss of spillover access}} - F. \tag{4.18}$$

The first term is the gain in private marketing surplus. It is positive because $\alpha_T > 0$: a trademark raises the private return to marketing, which increases the optimized marketing surplus. The second term is the firm's loss from marketing spillover after adopting a trademark. It is negative because $\beta_T < 0$: a trademark reduces the firm's ability to benefit from the marketing spillover generated by competitors' marketing investments. The fixed cost F is the direct cost of trademark adoption.

This equation summarizes the central trade-off of the paper. Firms with high capability invest heavily in their own marketing and gain more from the protection channel. Firms with low capability invest little and rely more on spillovers, making the differentiation channel more costly. Because κ_i is proportional to firm capability x_i, the adoption gain depends on firm fundamentals only through this capability index. The private gains from trademark dominate for high capability firms, while the market spillover benefits dominate for low capability firms.

[11] Observed selling expenses $SE_i = B[m_i^*]^\gamma$ satisfy

$$SE_i/r_i = \frac{(\alpha_0 + \alpha_T T_i)m_i^*}{\sigma\gamma\,\tilde{\phi}_i},$$

where $r_i = \sigma\kappa_i\tilde{\phi}_i$ is revenue and $\tilde{\phi}_i = \phi_0 + (\alpha_0 + \alpha_T T_i)m_i^* + (\beta_0 + \beta_T T_i)\Lambda$. The slope κ_i cancels from this ratio, and we use this identity in identification.

Proposition 2 (Trademark adoption cutoff)**.** *Under the restrictions in equation (4.9), the trademark adoption set is an upper interval in the capability index x_i. It is either empty, full, or characterized by a unique threshold x^* such that*

$$T_i = \mathbf{1}\{x_i \geq x^*\}, \tag{4.19}$$

with the marginal firm, $x_i = x^*$, satisfying $\Delta V_i = 0$.

Proof. See Appendix C.2. □

Proposition 2 provides a characterization of the patterns of trademark adoption documented in Section 2. Trademark adoption is concentrated among firms with high capability, but capability is not productivity alone. Conditional on marginal cost, firms with higher product appeal have stronger incentives to market and to adopt. As a result, firms with similar productivity may differ in both marketing investment and trademark status, consistent with the heterogeneity observed in the data.

4.3 Industry Equilibrium

We index firm types by (c, ξ) and the corresponding capability index by $x = \xi c^{1-\sigma}$. In equilibrium, the aggregates that firms take as given must be generated by the firms' own decisions.

An industry equilibrium consists of firm policies $\{p(c,\xi), m(c,\xi), T(c,\xi)\}$ and aggregates (Λ, P, E_Q) such that:

1. **Firm optimization.** Given (P, E_Q, Λ), firms solve problem (4.10). In particular,

$$p(c,\xi) = \mu c, \qquad m(c,\xi) = m^*(c,\xi,T), \qquad T(c,\xi) = T(x),$$

   where $m^*(c,\xi,T)$ is given by Proposition 1 and $T(x)$ is characterized by Proposition 2.

2. **Aggregate consistency.** The public pool, price index, and composite expenditure satisfy

$$\Lambda = \int (1 - \alpha_0 - \alpha_T T(x))\, m^*(c,\xi,T(x))\, dG, \tag{4.20}$$

$$P^{1-\sigma} = \mu^{1-\sigma} \int \phi(c,\xi) c^{1-\sigma}\, dG, \tag{4.21}$$

$$E_Q = s_Q(P) E, \tag{4.22}$$

where $\phi(c, \xi)$ is given by equation (4.7) evaluated at the equilibrium policies.

3. **Market clearing.** Each variety is produced to meet demand, and the outside option absorbs residual expenditure, so $q_o = E - E_Q$.

The equilibrium system has a useful recursive structure. Firms respond to market conditions only through the demand scale $A \equiv P^{\sigma-1} E_Q$, the market-specific term in equation (4.12). Given a candidate trademark adoption cutoff x^*, firm policies are functions of A and x^*. The consistency conditions then reduce to a single equation in A.

Proposition 3 (Inner equilibrium)**.** *Fix a cutoff x^*. For $1 < \varepsilon \leq \sigma$, the aggregates consistent with firm optimization are characterized by the unique root $A > 0$ of the one-dimensional equation*

$$A\, P^{1-\sigma}(A; x^*) \left[1 + \zeta\, P(A; x^*)^{\varepsilon-1}\right] = E, \tag{4.23}$$

where $P^{1-\sigma}(A; x^*)$ is the price index implied by firm policies at demand scale A. For a fixed cutoff x^*, $P^{1-\sigma}(A; x^*)$ is a strictly increasing affine function of $A^{1/(\gamma-1)}$.

Proof. See Appendix C.3. □

The equilibrium cutoff must also be consistent with the aggregates it induces. In an interior equilibrium, the marginal firm is indifferent between adopting and not adopting:

$$\Delta V(x^*) = 0,$$

where ΔV is evaluated at the inner equilibrium associated with x^*. The no-adoption corner obtains when the adoption gain of the highest-x firm is below zero. The full-adoption corner obtains when the adoption gain of the lowest-x firm is above zero.

Computing the equilibrium therefore requires a one-dimensional root find in A nested inside a one-dimensional search over the cutoff x^*. The two-dimensional heterogeneity in cost and appeal does not create additional computational burden because firm decisions depend on fundamentals through the scalar capability index x. As $\zeta \to 0$, equation (4.23) reduces to $AP^{1-\sigma}(A) = E$, the standard monopolistic competition equilibrium with fixed industry expenditure. The outside option generalizes this benchmark by allowing the market size to respond to the demand that firms jointly

build through marketing.

5 Model Estimation

5.1 Estimation Strategy

We estimate the model in two stages. In the first stage, we recover firm-level fundamentals: marginal cost c_i and demand shifter ϕ_i. This step uses firm-level data on quantities, prices, and input expenditures from the ASIF matched to the Output Quantity Survey. In the second stage, we take these recovered fundamentals as given, solve the model equilibrium in each market, and estimate the remaining parameters using the Simulated Method of Moments (SMM). The moments are chosen to discipline the protection effect of trademarks, the differentiation effect of trademarks, the marketing cost function, and the fixed cost of trademark adoption.

First stage: marginal cost. We assume that each firm produces with quasi-fixed capital k_i and a bundle of variable inputs:

$$y_i = e^{\omega_i} k_i^{\alpha_k} v_i, \tag{5.1}$$

where v_i is a constant-returns bundle of labor and materials with unit cost h, and ω_i is firm-level log physical productivity (TFPQ). Capital is fixed within the period, while variable inputs adjust to meet demand. Because production has constant returns in variable inputs conditional on capital, marginal cost is constant:

$$c_i = \frac{h}{e^{\omega_i} k_i^{\alpha_k}}. \tag{5.2}$$

This equation shows that marginal cost is decreasing in productivity and in capital stock.

To recover marginal cost, we estimate the production function in equation (5.1) with the control function approach of Ackerberg et al. (2015) and recover ω_i as the estimated physical productivity.[12] We assume that the unit cost of the input bundle h is common to all firms within a market. Since the model focuses on firm heterogeneity within a market, we normalize marginal cost by its market average, which removes h. Therefore, the within-market variation in marginal cost is driven entirely by differences in physical productivity and capital stock. Table 17 reports the estimated input elasticities and the parameters of the productivity process.

[12] To perform the control function approach, we assume that ω_i follows a first-order Markov process, $\omega_{it} = \rho_0 + \rho_1 \omega_{it-1} + \epsilon_{it}$, where ϵ_{it} is a transitory shock. This assumption serves only to identify the production function; the model itself is static and takes ω_i as given within the period.

First stage: demand shifter. We then recover the demand shifter from the demand equation. Taking logs of equation (4.6) gives

$$\ln q_i = -\sigma \ln p_i + \ln \phi_i + \ln \left(P^{\sigma-1} E_Q \right). \tag{5.3}$$

Firm demand depends on price p_i, the elasticity of substitution σ, the firm-specific demand shifter ϕ_i, and the market-level demand scale $P^{\sigma-1}E_Q$. In the baseline estimation, we set $\sigma = 4$ following the literature (Melitz and Redding, 2015; Chen et al., 2025). This value implies a markup of 1.33, close to the estimates for Chinese manufacturing in Brandt et al. (2017).[13] With quantity and price data, we recover $\ln \phi_i$ as the residual of equation (5.3). We then demean $\ln \phi_i$ within each market, which removes market-level demand variation.

Equation (4.7) shows that the demand shifter combines an exogenous product appeal ξ_i, which is fixed over time, with an endogenous customer base, which firms can build through marketing in the short run. We do not separate the two components in the first stage. Instead, we feed (c_i, ϕ_i) into the second stage, which recovers product appeal inside the estimation loop.

Second stage: SMM estimation. Given the recovered fundamentals (c_i, ϕ_i), we estimate the remaining parameters

$$\Theta = [\alpha_0, \alpha_T, \beta_0, \beta_T, B, \gamma, F, \sigma_r]. \tag{5.4}$$

The parameters α_0 and α_T govern the private return to own marketing for firms without and with trademarks. The parameters β_0 and β_T govern firms' access to the public pool of marketing spillovers. Thus, α_T captures the protection effect of trademarks, while β_T captures the differentiation effect. The parameters B and γ determine the level and curvature of the marketing cost function. The parameter F is the fixed cost of trademark adoption. Finally, σ_r is the standard deviation of observation noise in log sales.

We estimate these parameters using SMM. Rather than simulating firms from an estimated distribution of fundamentals, we sample firms directly from the data. For the structural estimation, a market is defined at the province $\times$ two-digit SIC industry $\times$ year level. We randomly select 50 markets with at least 100 firms each and sample 100 firms from each selected market. For each sampled firm,

[13] In a static framework we do not estimate the demand elasticity directly. With a dynamic demand evolution process, the elasticity can be estimated by GMM using productivity and capital stock as instruments (Jiang et al., 2026).

the first stage provides (c_i, ϕ_i). Given a candidate parameter vector Θ, we solve the equilibrium in each market and obtain model-implied sales, marketing investment, and trademark status for every sampled firm. We then choose Θ to minimize the distance between the empirical moments and their model-implied counterparts.

Table 6 reports the eight targeted moments and the parameters that they primarily discipline. Because we estimate eight parameters using eight moments, the model is just identified. The first four moments are regression coefficients from log-sales regressions that relate firm sales to own marketing and competitors' average marketing, estimated separately for trademark holders and non-holders. Equation (4.7) implies that own marketing affects demand through α_i, whereas competitors' marketing affects demand through the public pool and the firm's access parameter β_i. Therefore, the coefficients for non-holders discipline α_0 and β_0, while the differences between holders and non-holders discipline α_T and β_T.

The average selling-expense-to-sales ratio, SE/r, disciplines the level of marketing costs, B. The difference in the selling-expense-to-sales ratio between firms in the top and bottom productivity deciles disciplines the curvature parameter γ, because γ determines how rapidly marketing investment rises with firm capability, as shown in Proposition 1. The slope of the market-level trademark adoption rate on log market size disciplines the fixed cost F. A positive fixed cost in RMB is easier to cover in larger markets, where the private gain from protection is larger for a firm at any given rank of x. The adoption rate therefore rises with market size. Finally, the variance of log sales disciplines σ_r, because the model without observation noise generates less sales dispersion than observed in the data.

Table 6: Targeted Moments and Parameters

Moment	Identifies
Elasticity of sales with respect to own selling expenses, non-trademark firms	α_0
Elasticity of sales with respect to own selling expenses, trademark firms	α_T
Elasticity of sales with respect to market-average selling expenses (leave-one-out), non-trademark firms	β_0
Elasticity of sales with respect to market-average selling expenses (leave-one-out), trademark firms	β_T
Mean marketing intensity $SE_i/Sales_i$	B
Marketing intensity gap between the top and bottom productivity deciles	γ
Slope of the market adoption rate on log market size	F
Variance of log sales	σ_r

Notes: This table summarizes the targeted moments and the parameter that each moment primarily disciplines. Data and model moments are computed with the same regressions, the same split by trademark status, and the same fixed effects. The four elasticities are slopes of log sales on log selling expenses with industry, province, and year effects, and the market average excludes the firm itself. Deciles are of the productivity within each market. The market size slope is the regression coefficient of the share of trademark holders in a market on the log of market expenditure E_s across the sampled markets. See Section 5 for the identification details.

Parameters set outside the SMM. Two upper-tier demand parameters remain to be specified: the elasticity of substitution between the differentiated composite good and the outside option, ε, and the taste weight on the outside option, ζ_s. These parameters are not separately identified by the firm-level moments used in the SMM. Within a market, firm decisions depend on the upper tier only through the composite demand scale $A_s = P_s^{\sigma-1} E_{Qs}$. Any upper-tier parameterization that delivers the same A_s generates the same inner-tier equilibrium.

We interpret the outside option as the competitive fringe in the same industry, consisting primarily of firms below the ASIF reporting threshold. Because substitution between sampled firms and fringe firms occurs within the same broad industry, we set the upper-tier elasticity equal to the within-industry elasticity across varieties, $\varepsilon = \sigma$. To recover ζ_s, we follow the standard practice of using external data to proxy for total market size (Berry et al., 1995; Nevo, 2001). Specifically, we use annual gross output for each province $\times$ industry cell from provincial statistical yearbooks. This gives the market share of sampled firms and the residual share of fringe firms. Given the model-implied composite expenditure and the observed market share of sampled firms, we invert equation (4.5) to recover ζ_s for each market. By construction, this calibration reproduces the estimated inner-tier equilibrium.

The upper-tier demand system does not affect the baseline parameter estimates. It matters for the counterfactual exercises because policies that change firms' marketing and trademark decisions also change the demand shifters of sampled firms, which can shift expenditure between sampled firms and the competitive fringe.

Table 7 summarizes the parameters and variables set outside the SMM. We set the elasticity of substitution across varieties to $\sigma = 4$, following the literature (Melitz and Redding, 2015; Chen et al., 2025). This value implies a markup of 1.33, close to estimates using Chinese manufacturing data in Brandt et al. (2017). We normalize the baseline customer base to $\phi_0 = 1$. Firm fundamentals (c_i, ϕ_i) are recovered in the first stage, and product appeal ξ_i is backed out inside the second-stage estimation loop. The upper-tier demand parameters (E_s, ζ_s) are calibrated using external market-size data.

5.2 Estimation Results

Table 8 reports the estimates of the key remaining parameters, and Table 9 reports the fit of the targeted moments and two untargeted moments. The estimation results show that a trademark

Table 7: Externally Set Parameters and Measured States

Parameter	Value/Source
Elasticity of substitution across varieties	$\sigma = 4$
Elasticity of substitution between the composite good and the outside good	$\varepsilon = 4$
Baseline level of the customer base	$\phi_0 = 1$, normalization
Marginal cost c_i	Recovered in the first stage
Demand shifter ϕ_i	Recovered in the first stage
Potential market expenditure E_s	Implied by province $\times$ 2-digit industry annual output
Taste on the outside good ζ_s	Inverted to rationalize the observed market share

Notes: This table lists the parameters that are fixed before the second-stage estimation. σ is borrowed from the literature. ε is set equal to σ. c_i and ϕ_i are recovered using firm-level data in the first stage. E_s and ζ_s are calibrated from external market-level annual output, where s indexes province $\times$ two-digit industry $\times$ year cells.

raises the private capture rate of a firm's own marketing from 0.84 to 0.93. At the same time, it roughly halves the firm's benefit from marketing spillover due to other firms' marketing investment, from 0.018 to 0.009. These estimates quantify the trade-off of the two opposing forces that govern firms' trademark decisions: trademarks protect the return to a firm's own marketing, but they also differentiate the firm from others and reduce the spillovers it receives from competitors' marketing investments.

The estimated marketing cost function is mildly convex, with $\gamma = 1.43$. As a result, marketing effort responds strongly to the capability index $x = \xi c^{1-\sigma}$: the elasticity of marketing effort with respect to x is $1/(\gamma - 1) = 2.4$, and the elasticity of marketing expenditure is $\gamma/(\gamma - 1) = 3.4$. Because trademark adoption raises the private return to marketing, the gains from adopting a trademark increase sharply with firm capability.

The estimated fixed cost of trademark adoption is RMB 4,530 per period. This value is of the same order of magnitude as the official fee for filing a trademark application in China during our sample period.[14] The two costs are not directly comparable: in the static model, F is paid each period, whereas the official fee is paid once and covers a ten-year registration term. We therefore interpret F more broadly as including the official fee, agency fees, and the time and administrative costs associated with preparing and filing an application. The small estimate of F is consistent with the main message of the paper: direct application costs are not the primary reason why most firms do not apply for trademarks.

Table 9 shows that the model matches the marketing intensity moments, the market size slope, and the spillover slope for holders very well. It overstates the own-marketing slopes and understates the

[14]The official registration fee was RMB 1,000 per class in 2002.

Table 8: Parameter Estimates

	Parameters	Estimates	s.e.
Private capture of own marketing, non-holder	α_0	0.842	0.017
trademark effect	α_T	0.086	0.009
holder	$\alpha_1 = \alpha_0 + \alpha_T$	0.928	0.008
Public-pool access, non-holder	β_0	0.0185	0.0015
trademark effect	β_T	−0.0092	0.0008
holder	$\beta_1 = \beta_0 + \beta_T$	0.0093	0.0008
Marketing cost scale	B	15,275	387
Marketing cost curvature	γ	1.425	0.010
Trademark adoption fixed cost	F	4.53	1.72
Measurement error in sales	σ_r	1.056	0.008

Notes: This table reports the second-stage SMM estimates. Markets are defined at province × 2-digit industry × year level. The regressions control for industry, province, and year fixed effects for both data and model moments. $\sigma = 4$ and $\phi_0 = 1$ are externally selected. B and F are in thousand RMB. Standard errors come from a bootstrap with 200 replications. Each replication redraws the data moments from a firm-clustered bootstrap, redraws firms within the simulated markets, and re-estimates the model. A trademark raises the private capture of own marketing from 0.84 to 0.93 and halves access to the public pool.

spillover slope for non-holders. These gaps reflect a restriction of the model. All four sales elasticities are anchored by the common term $(\gamma - 1)/\gamma$, which bounds the own-marketing slopes from below.[15] The curvature γ is pinned down by the marketing intensity moments, and the common term equals 0.30 at the estimate, above the data values of 0.20 and 0.23. With γ fixed, the four slopes cannot move independently, and the estimate balances the gaps across them. In future work, we will relax this restriction by allowing the marketing cost to vary across firms. Among the untargeted moments, the model matches the sales increase after the first trademark application, 0.065 against 0.055 in the data, and generates an adoption rate of 27.6 percent against 25.8 percent.

5.3 Building Customer Base: Own Investment Versus Spillover

We next use the estimated model to decompose each firm's customer base into its private and spillover components. This exercise addresses two questions. How is a firm's customer base formed? And how does this composition vary with firm capability?

For firm i, define the endogenous component of the demand shifter (customer base) as

$$\tilde{\phi}_i = \phi_0 + \alpha_i m_i^* + \beta_i \Lambda. \tag{5.5}$$

[15] Proposition 1 gives $m_i \propto (A x_i \alpha_i)^{1/(\gamma-1)}$, so $\ln x_i = \frac{\gamma-1}{\gamma} \ln SE_i$ up to a constant. The elasticity of sales with respect to selling expenses is this term plus the contribution of the firm's customer base.

Table 9: Moment Fitness

Moment	Description	Data	Model
Targeted Moments			
mean SE/r	Marketing intensity	0.0282	0.0267
γ-gap	Marketing intensity gap, top vs. bottom deciles	0.279	0.274
Size slope	Slope of adoption rate on log market size	0.062	0.062
s_1	Own marketing slope, non-holders	0.197	0.327
s_2	Own marketing slope, holders	0.228	0.541
s_3	Marketing spillover slope, non-holders	0.420	0.248
s_4	Marketing spillover slope, holders	0.239	0.254
variance $\ln r$	Dispersion of log sales	1.444	1.677
Objective function			0.170
Untargeted Moments			
TM share	Trademark adoption rate	0.258	0.276
$\Delta \ln$ sales	Sales increase after the first application	0.055	0.065

Notes: This table compares the eight targeted moments and two untargeted moments in the data and in the model at the estimated parameters. s_1 to s_4 are the four sales elasticities listed in Table 6. The objective function is the identity-weighted sum of squared moment gaps at the estimate.

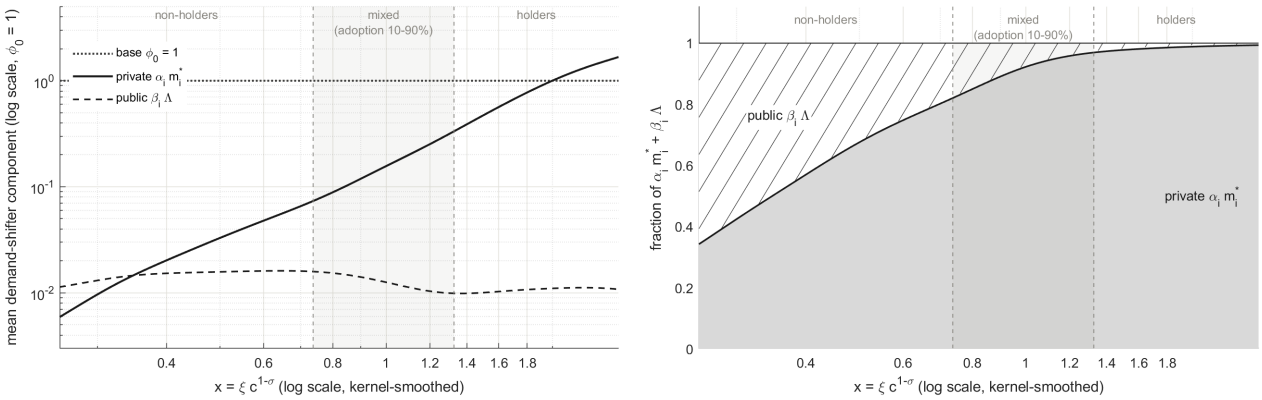
It has three parts. The first is the baseline component ϕ_0, which captures demand not explained by current-period marketing. In a dynamic interpretation, this term corresponds to the inherited stock of customers or brand awareness. The second component, $\alpha_i m_i^*$, is the private contribution of the firm's own marketing. The third component, $\beta_i \Lambda$, is the spillover contribution from the public pool generated by other firms' marketing.

Figure 5 Panel (a) decomposes the customer base along the capability index $x = \xi c^{1-\sigma}$. For most firms, the baseline component is the largest part of the customer base, while own marketing accounts for a smaller share. Own marketing becomes quantitatively important only among the most capable firms. This pattern is consistent with the literature showing that demand endowments account for much of cross-sectional demand heterogeneity and that firms adjust demand only gradually (Jiang and Zhang, 2026; Jiang et al., 2026; Sterk et al., 2021). Nevertheless, the relative importance of own marketing and spillovers varies systematically with firm capability. Less capable firms rely more on the public pool, whereas more capable firms rely increasingly on their own marketing.

Figure 5 Panel (b) focuses on the marketing-related component of the customer base and decomposes it into the private component, $\alpha_i m_i^*$, and the spillover component, $\beta_i \Lambda$. For the least capable firms, the public pool accounts for roughly two-thirds of marketing-related demand. For the most capable firms, almost all marketing-related demand comes from their own marketing. The profile also reflects the cutoff structure of trademark adoption: firms above the adoption threshold hold trademarks,

which increases their private capture of own marketing but reduces their access to the public pool.

Figure 5: Customer Base Decomposition: by Firm Capability



(a) Customer base decomposition

(b) Private versus spillover contribution

Notes: This figure decomposes the firm's customer base $\tilde{\phi}_i = \phi_0 + \alpha_i m_i^* + \beta_i \Lambda$ using the estimated parameters, with each firm evaluated at its equilibrium trademark status. Panel (a) plots the three components against the capability index $x = \xi c^{1-\sigma}$. Both the customer base and the capability index are on a log scale, and ϕ_0 is normalized to one. Panel (b) compares the private and spillover contributions to marketing-related demand. The solid line is the private share, $\alpha_i m_i^* / (\alpha_i m_i^* + \beta_i \Lambda)$, and the hatched area above it is the spillover share. Curves are kernel-smoothed across firms. Vertical dashed lines mark where the adoption rate crosses 10 and 90 percent. The baseline component dominates for most firms. The public pool supplies about two-thirds of marketing-related demand for the least capable firms and almost none for the most capable firms.

5.4 Value of the First Trademark

Finally, we quantify the value of a first trademark to the firm. For each firm, we conduct a partial-equilibrium accounting exercise. We hold market aggregates and all other firms' decisions fixed at their equilibrium values, but set the focal firm's trademark status exogenously to either zero or one. We then compute the differences in sales, marketing investment, and net profit between the trademarked and non-trademarked scenarios. Table 10 reports summary statistics for these gaps.

This exercise isolates the firm-level trade-off emphasized by the model. On the one hand, a trademark raises the private return to own marketing. This gain is increasing in firm capability because more capable firms invest more in marketing and earn larger returns from protecting their marketing investment. On the other hand, a trademark reduces the firm's access to the public pool. This loss is especially important for less capable firms, which rely more heavily on spillovers from competitors' marketing.

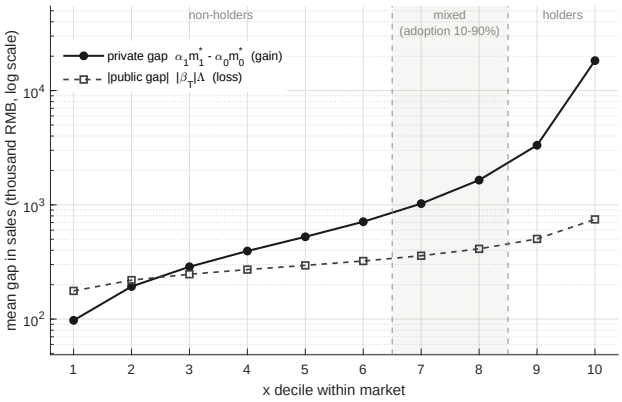
Table 10: Value of the First Trademark: by Firm Capability

	Δ Sales			Δ Marketing Cost	Δ Net Profit	Net Profit/Sales (%)
Decile	Δ Total	Δ Private	Δ Public			
1	−79	97	−176	17	−41.6	−0.188
2	−26	193	−219	34	−45.4	−0.160
3	40	287	−247	51	−45.6	−0.141
4	123	394	−271	70	−44.0	−0.122
5	230	525	−295	94	−40.6	−0.102
6	389	711	−322	127	−34.0	−0.077
7	666	1,025	−358	183	−20.5	−0.042
8	1,234	1,645	−412	293	10.8	+0.015
9	2,820	3,323	−503	592	108.5	+0.108
10	17,544	18,290	−745	3,258	1,123.1	+0.363

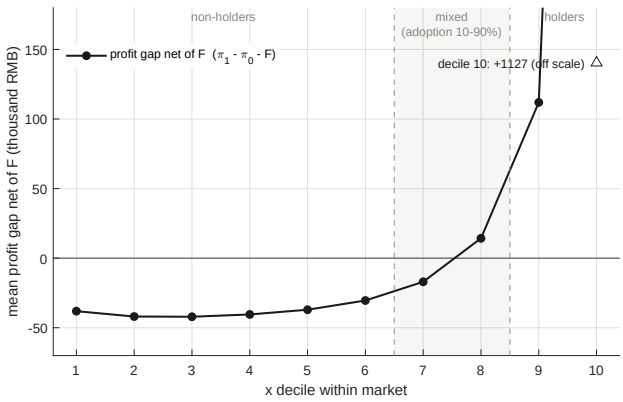
Notes: This table reports the value of a first trademark by decile of the capability index x within each market. For each firm we compare outcomes with and without a trademark at fixed market aggregates, with marketing re-optimized in both states, and report decile means in thousand RMB. Δ Sales is the sum of a private gain, proportional to $\alpha_1 m_1^* - \alpha_0 m_0^*$, and a public loss, proportional to $\beta_T \Lambda$. Δ Net Profit equals Δ Sales/σ minus Δ Marketing Cost minus the fee $F = 4.53$. Net Profit/Sales expresses Δ Net Profit as a percent of the firm's sales. The net payoff turns positive only in the eighth decile and reaches 1.12 million RMB in the top decile.

Figure 6 Panel (a) decomposes the sales effect of trademark ownership into the private gain from own marketing and the loss from reduced access to the public pool. The private gain rises steeply with firm capability, while the public-pool loss is much flatter. As a result, the net sales effect is negative for less capable firms and becomes positive only higher in the capability distribution.

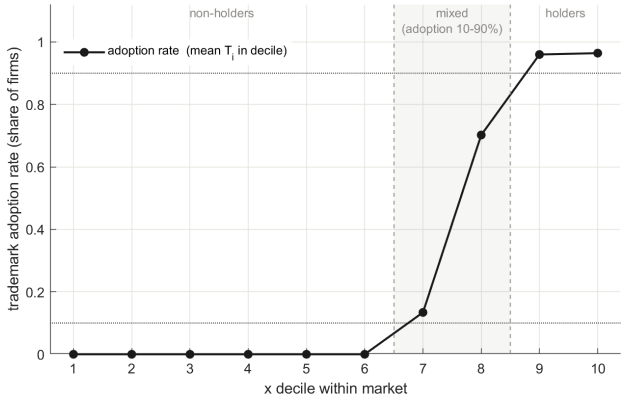
Figure 6: Value of the First Trademark and Adoption: by Firm Capability



(a) Private gain versus spillover loss in sales



(b) Net payoff in profit with trademark



(c) Trademark adoption rate

Notes: This figure plots the value of a first trademark by decile of the capability index $x = \xi c^{1-\sigma}$ within each market, computed as in Table 10. Panel (a) plots the two components of the sales gap on a log scale: the private gain from higher capture of own marketing and the absolute value of the loss from reduced access to the public pool. Panel (b) plots the profit gap net of the fixed adoption cost F. Panel (c) plots the trademark adoption rate, the share of firms holding a trademark in equilibrium, by the same deciles. Dashed lines mark where the adoption rate crosses 10 and 90 percent. The private gain rises steeply with capability while the spillover loss is relatively flat, so the net payoff turns positive only for more capable firms.

Trademark ownership also induces firms to increase marketing investment. This additional spending is necessary to take advantage of the higher private return to marketing, but it reduces net profit. Panel (b) reports the net payoff from trademark ownership after accounting for the change in marketing costs and the fixed adoption cost. The payoff is negative for a large share of firms and rises sharply only in the upper tail of the capability distribution. For firms in the top decile, the average net benefit of holding a trademark is about RMB 1.12 million, far above the estimated application cost. By contrast, for less capable firms the loss of spillover access and the additional marketing cost

outweigh the private marketing gain. This explains why trademark adoption is concentrated among more capable firms despite the low direct cost of filing.

Because the model is static, these estimates should be interpreted as the current-period value of trademark ownership. They likely understate the full value of a trademark for firms that benefit from adoption. A registered trademark is a durable asset, and the relevant long-run value includes the discounted stream of future gains. In addition, marketing may have persistent effects on demand, and trademarks may accumulate reputation and brand capital over time. These dynamic forces are outside the model, but they would amplify the value of trademark ownership for firms that can profitably use trademarks to protect their own marketing investments.

6 Counterfactual Policy Experiments

We use the estimated model to evaluate two counterfactual policies. The first experiment strengthens trademark protection. We increase the effect of a trademark on the private return to own marketing, α_T, holding all other parameters fixed. This captures policies that strengthen trademark protection and help firms appropriate more of the demand generated by their own marketing. The second experiment improves market transparency. We raise the baseline private capture of marketing, α_0, which applies to all firms regardless of trademark status. This captures changes that help consumers better distinguish products in the market, such as digitization, better search technologies, or more transparent retail environments.

In each experiment, we change one policy-relevant parameter, re-solve firms' optimal trademark and marketing decisions in all sampled markets, and compare the new equilibrium with the baseline. We report both aggregate outcomes and firm responses across the capability distribution. The heterogeneous responses matter. Policies that encourage trademark adoption often raise marketing investment and shift demand toward more capable firms, but they also reduce the marketing spillovers on which less capable firms rely.

6.1 Strengthening Trademark Protection

We first examine policies that strengthen trademark protection. Specifically, we scale the trademark protection effect α_T by factors of 0, 0.8, 1.2, and the feasibility cap of 1.84, holding all other

parameters fixed.[16] We then re-solve the equilibrium in all sampled markets. Table 11 reports the effects on aggregate sales, aggregate marketing investment, aggregate net profit, the trademark adoption rate, the sales gap between firms in the top and bottom capability deciles, and within-market sales dispersion.

Stronger trademark protection has a large effect on trademark adoption and marketing investment. A 20 percent increase in α_T raises the trademark adoption rate by 15 percentage points, from 0.28 to 0.43. It also raises aggregate marketing investment by 4.1 percent and the marketing-to-sales ratio by 3.5 percent. Lowering trademark protection has the opposite effect. It substantially reduces trademark adoption and marketing investment. These results confirm that trademark protection has a large effect on firms' trademark adoption and marketing decisions.

However, the effects on aggregate sales and profits are much smaller. A 20 percent increase in α_T raises aggregate sales by only 0.6 percent. Even the extreme scenarios generate limited sales effects: raising α_T to the feasibility cap increases aggregate sales by 2.9 percent, and eliminating the protection effect reduces them by 2.3 percent. Moreover, stronger protection lowers aggregate profit. A 20 percent increase in α_T reduces aggregate net profit by 0.2 percent. This is because stronger protection intensifies competition in marketing, which increases the firms' marketing expenditure. Much of the sales gain is offset by the higher marketing costs.

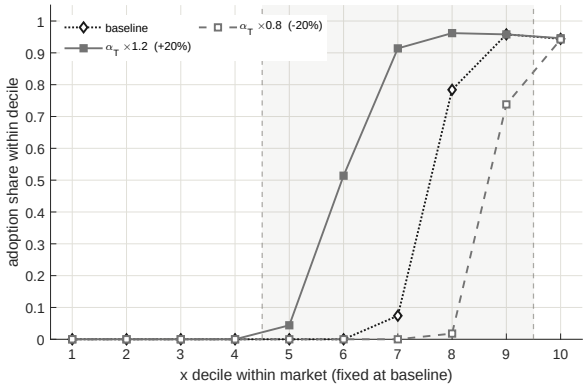
Table 11: Aggregate Effects of Trademark Protection

	Trademark effect on private capture α_T ×				
	0	0.8	1 (baseline)	1.2	1.84 (cap)
Aggregate sales (bn RMB)	−2.3%	−0.6%	243.8	+0.6%	+2.9%
Aggregate marketing cost (bn RMB)	−14.3%	−3.9%	11.91	+4.1%	+17.4%
Aggregate net profit (bn RMB)	+0.7%	+0.2%	49.04	−0.2%	−0.6%
Sales gap, top vs bottom decile (log points)	−2.9%	−0.7%	2.181	+0.7%	+2.7%
Sales dispersion (s.d. of $\ln r$)	−1.6%	−0.5%	0.754	+0.5%	+1.9%
Trademark adoption rate	−27.6pp	−10.6pp	27.6%	+15.8pp	+68.3pp
Marketing cost-to-sales ratio (sales weighted)	−12.3%	−3.3%	0.0489	+3.5%	+14.1%
Mean inside share s_Q	−1.1%	−0.3%	0.341	+0.3%	+1.5%

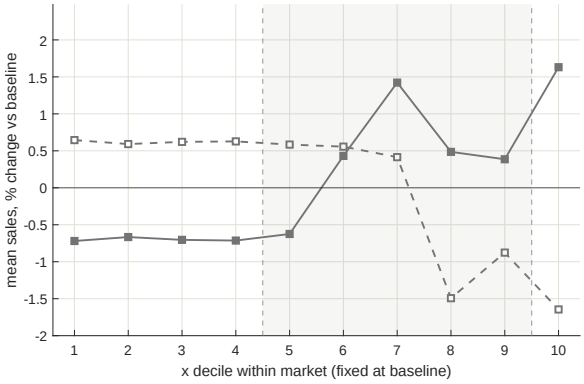
Notes: This table reports aggregate outcomes when α_T is scaled by the multiplier in the column header and the equilibrium of every market is re-solved. The baseline column reports levels, and the other columns report percent changes relative to the baseline, except for the adoption rate, which is reported as changes in percentage points. The multiplier 1.84 is the largest value that keeps $\alpha_0 + \alpha_T$ below one. The sales gap is the difference in mean log sales between the top and bottom deciles of x pooled across markets, dispersion is the pooled standard deviation of log sales, the marketing cost-to-sales ratio is the sales weighted firm average, and s_Q is the mean share of the analysis sample in province-level output. Net profit is $r_i/\sigma - \mathrm{SE}_i - FT_i$. Stronger protection raises marketing investment far more than sales and widens sales dispersion within markets.

[16] The feasibility cap is the largest scaling factor that preserves the restriction $\alpha_0 + \alpha_T < 1$.

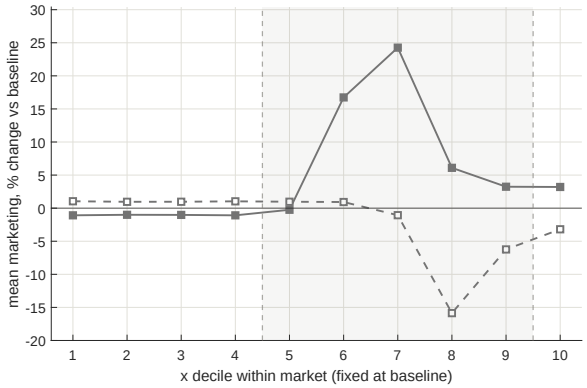
Figure 7: Heterogeneous Response to a ±20 Percent Change in Trademark Protection



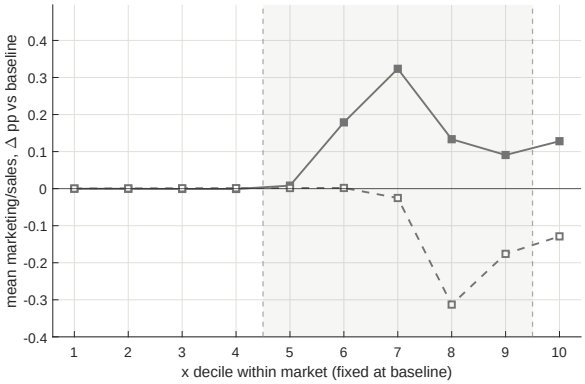
(a) Adoption share



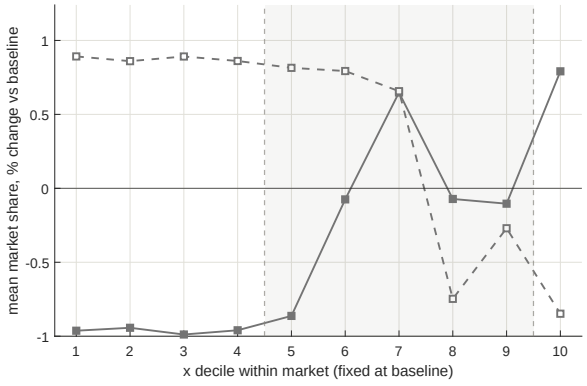
(b) Sales



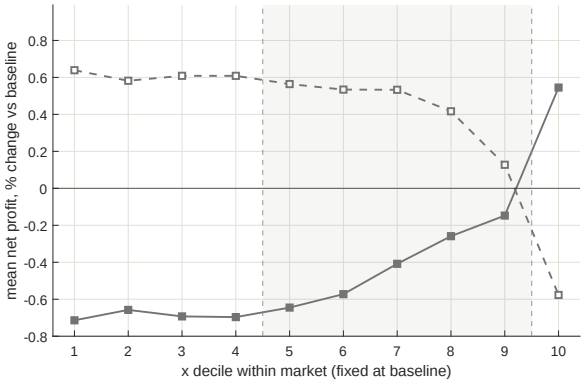
(c) Marketing cost



(d) Marketing cost-to-sales ratio



(e) Market share



(f) Net profit

Notes: This figure plots firm responses to a 20 percent increase (solid lines) and a 20 percent decrease (dashed lines) in α_T by decile of the capability index $x = \xi c^{1-\sigma}$. Deciles are formed within each market at the baseline and held fixed across scenarios. Panel (a) plots the adoption share in each decile, with the baseline shown by the dotted line. Panels (b), (c), (e), and (f) plot mean percent changes relative to the baseline. Panel (d) plots changes in percentage points. Net profit is $\pi_i = r_i/\sigma - \mathrm{SE}_i - F\,T_i$. The shaded band marks the deciles over which adoption changes most between the two scenarios. Firms around the seventh decile respond most strongly, but only the top decile experiences higher net profit.

The muted aggregate effects on sales and profits reflect strong heterogeneity across firms, with major gains for high-capability firms and substantial losses for low-capability ones. Figure 7 shows responses to a 20 percent change in trademark protection effect, α_T, by decile of firms' capability index. Panel (a) shows that stronger protection substantially increases trademark adoption. Two forces in the model drive this response. First, stronger protection directly raises the value of a trademark by increasing the private return to protected marketing. Second, as more firms adopt trademarks, the public pool becomes thinner. This lowers the value of remaining without a trademark and further encourages adoption.

The largest response occurs among firms near the baseline adoption cutoff. In the seventh decile, the adoption share rises from around 10 percent to 91 percent. These firms also show the largest increases in marketing investment (24 percent) and sales (1.5 percent). Panels (b) and (e) show that their sales and market share rise by about 1.5 and 0.7 percent. However, their net profit declines substantially. Stronger protection raises the private return of marketing and intensifies marketing competition. Both forces make these firms raise marketing investment sharply, and the extra cost outweighs their gain in sales. Trademark adoption also rises among firms in nearby deciles, with smaller effects.

Firms in the top decile of the capability index gain most in sales and profits, although their trademark status does not change. Their sales rise by about 1.6 percent and their net profit by almost 0.6 percent. These firms already hold trademarks and invest heavily in marketing, so they benefit most from the higher private return induced by the stronger protection.

By contrast, firms that remain without trademarks lose sales and profits substantially when protection becomes stronger. Following a 20 percent increase in α_T, firms in the bottom five capability deciles lose almost 1 percent of their market share on average, and their net profit falls by about 0.7 percent. This is because their competitors adopt more trademarks and invest more in marketing, which intensifies competition and shrinks the marketing spillovers available in the market. Stronger protection therefore generates large distributional effects. A 20 percent increase in α_T raises the sales gap between the top and bottom capability deciles by 0.7 percent and the standard deviation of log sales by 0.5 percent.

6.2 Improving Market Transparency

The second experiment examines market transparency. In a more transparent market, consumers can better identify the firm that sends a marketing message. This increases private capture of marketing for all firms regardless of trademark status and reduces the marketing externality. We implement this experiment by scaling the benchmark private capture of marketing α_0 by 0.95 and 1.05, while holding all other parameters fixed. We then re-solve the firms' decisions and equilibrium in all sampled markets. Table 12 reports the effects on aggregate sales, aggregate marketing investment, aggregate net profit, the trademark adoption rate, the sales gap between firms in the top and bottom capability deciles, as well as the within-market sales dispersion.

Market transparency has an even larger effect on trademark adoption and marketing investment than trademark protection. A 5 percent increase in α_0 shrinks the equilibrium public pool by 89 percent and raises the trademark adoption rate by 63 percentage points, from 0.28 to 0.91.[17] It also raises aggregate marketing investment by 15.6 percent and the marketing-to-sales ratio by 12.7 percent. A 5 percent decrease in α_0 has the opposite effect. It lowers the adoption rate to 0.14 and reduces aggregate marketing investment by 14.1 percent.

Consistent with the first experiment, the effects of market transparency on aggregate sales and profit are much smaller. A 5 percent increase in α_0 raises aggregate sales by only 2.6 percent. The additional marketing cost exceeds the gain in production profit, so aggregate net profit falls by 0.6 percent. Decreasing market transparency has the opposite effect. It discourages marketing investment, which lowers aggregate sales but raises aggregate net profit.

Although higher market transparency induces more than 90 percent of firms to adopt trademarks, firm performance in different capability deciles responds very differently. Figure 8 shows responses to a 5 percent change in α_0 by decile of the capability index. New adopters raise marketing investment by about 40 percent, and incumbent holders by about 13 percent. Sales fall in the bottom five deciles and rise from the sixth decile upward. The sales response rises with capability, from a 2.3 percent loss in the bottom decile to a 6.5 percent gain in the top decile. The decomposition in Section 5.3 rationalizes this pattern. Firms' reliance on their own marketing increases with capability. Higher market transparency raises the private return to marketing and at the same time shrinks the public

[17] The averaged public pool Λ_s across sampled markets equals 1.11 at the baseline, falls to 0.12 when α_0 rises by 5 percent, and rises to 1.79 when α_0 falls by 5 percent. Two forces drive the large response. Higher private capture directly lowers the share of marketing that flows into the pool. The resulting trademark adoption then moves more marketing under trademark protection and thins the pool further.

Table 12: Aggregate Effects of Market Transparency

	Market transparency α_0 ×		
	0.95	1 (baseline)	1.05
Aggregate sales (bn RMB)	−2.3%	243.8	+2.6%
Aggregate marketing cost(bn RMB)	−14.1%	11.91	+15.6%
Aggregate net profit (bn RMB)	+0.5%	49.04	−0.6%
Sales gap, top vs bottom decile (log points)	−2.5%	2.181	+2.5%
Sales dispersion (s.d. of $\ln r$)	−1.7%	0.754	+1.7%
Trademark adoption rate	−13.6pp	27.6%	+63.2pp
Marketing cost-to-sales ratio (sales weighted)	−12.0%	0.0489	+12.7%
Mean inside share s_Q	−1.2%	0.341	+1.3%

Notes: This table reports aggregate outcomes when the private capture parameter α_0 is scaled relative to its baseline value, holding other parameters fixed. The equilibrium of every market is re-solved. The multiplier cannot exceed 1.086, above which $\alpha_0 + \alpha_T$ would exceed one. The baseline column reports levels, and the other columns report percent changes relative to the baseline, except for the adoption rate, which is reported as changes in percentage points. Net profit is $r_i/\sigma - \mathrm{SE}_i - F\,T_i$. A 5 percent increase in transparency more than triples the adoption rate and raises marketing investment six times as much as sales.

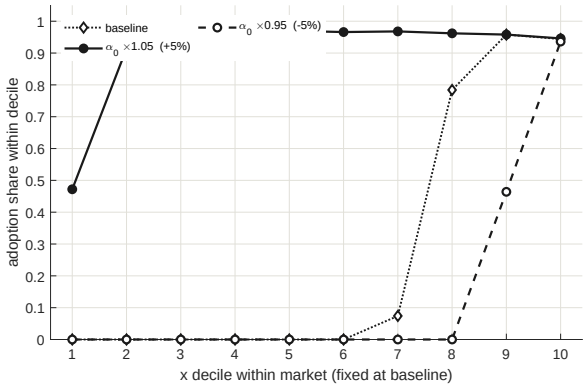
pool. As a result, firms that rely mainly on their own marketing benefit from the higher private capture, while less capable firms that rely mainly on the spillover suffer.

The increase in marketing cost induced by higher market transparency offsets the gain in sales, so net profit falls for most firms in the market. Firms in the top decile are the exception. These firms already hold trademarks and invest heavily in marketing, so they benefit most from the higher private return induced by market transparency. Their increase in sales is large enough to cover the additional marketing cost, raising their net profit by about 2.2 percent.

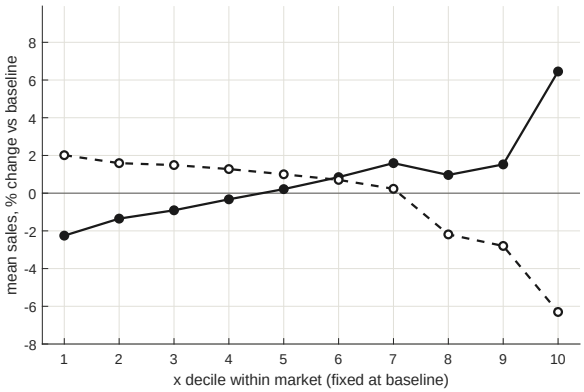
Greater market transparency shifts the return to marketing from the spillover to private capture. This shift favors more capable firms and has a large distributional effect. Increasing α_0 by 5 percent widens the sales gap between firms in the top and bottom capability deciles by 2.5 percent and increases the standard deviation of log sales by 1.7 percent.

Lower transparency has the opposite effect. A 5 percent decrease in α_0 raises sales for firms in the bottom seven deciles even though they spend less on marketing. More capable firms lose more, and sales in the top decile fall by more than 6 percent. Net profit rises for all firms in the bottom nine deciles for two reasons: marketing competition from top firms weakens, and the lower private return leads firms to cut their own marketing investment. For firms in the top decile, the net profit falls by more than 2 percent.

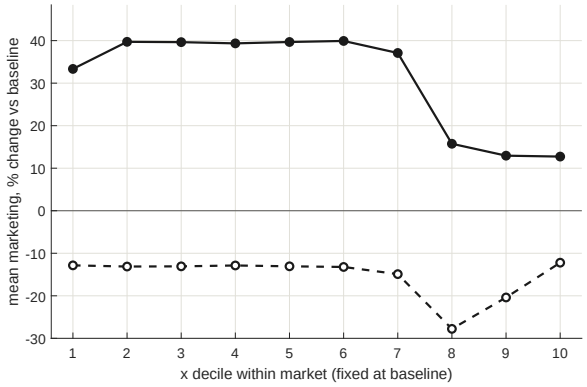
Figure 8: Heterogeneous Response to a ±5 Percent Change in Market Transparency



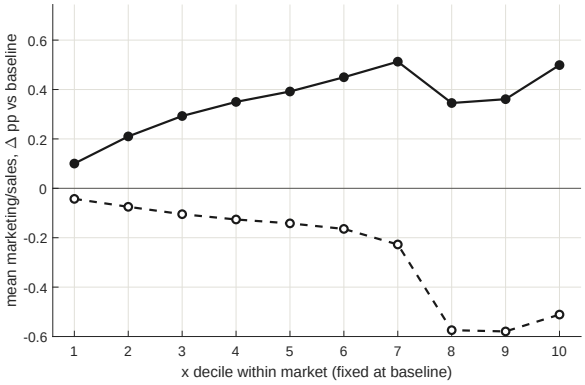
(a) Adoption share



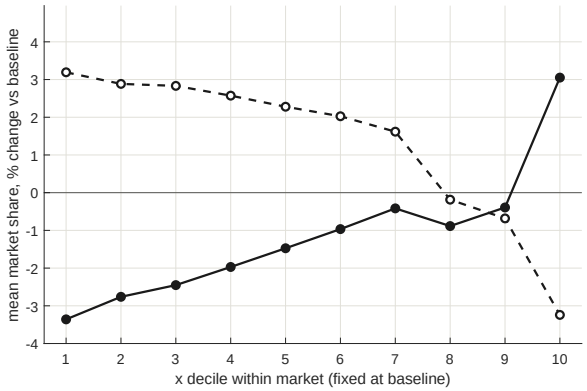
(b) Sales



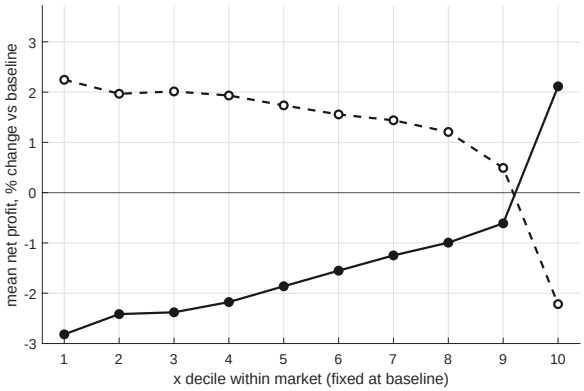
(c) Marketing cost



(d) Marketing cost-to-sales ratio



(e) Market share



(f) Net profit

Notes: This figure plots firm responses to a 5 percent increase (solid lines) and a 5 percent decrease (dashed lines) in α_0 by decile of the capability index $x = \xi c^{1-\sigma}$. Deciles are formed within each market at the baseline and held fixed across scenarios. Panel (a) plots the adoption share in each decile, with the baseline shown by the dotted line. Panels (b), (c), (e), and (f) plot mean percent changes relative to the baseline. Panel (d) plots changes in percentage points. Net profit is $\pi_i = r_i/\sigma - \mathrm{SE}_i - F T_i$. Higher transparency induces almost all firms to adopt and raises marketing across the distribution, but sales and net profit rise only near the top. Lower transparency reverses the pattern and shifts sales and profit toward less capable firms.

7 Conclusion

A trademark both protects a firm's unique identifier and differentiates the firm from its competitors. In China, trademark registration is inexpensive, yet adoption is far from universal. The official application fee was about RMB 1,000 in 2002, but only around 26 percent of above-scale manufacturing firms held a trademark during our sample period. This paper asks why most firms do not apply for trademarks and how trademark adoption affects firm performance and market outcomes.

We answer these questions by focusing on marketing spillovers. Using matched Chinese trademark records and firm-level data, we document three facts. First, a firm's marketing investment generates positive spillovers to competitors' sales. Second, these spillovers are generated mainly by firms without trademarks. Third, after a firm files its first trademark application, the return to its own marketing rises, while the spillover it receives from competitors' marketing disappears.

Motivated by these facts, we develop and estimate an industry equilibrium model with endogenous marketing investment and trademark adoption. In the model, marketing is only partially appropriable: some consumers reached by a firm's marketing enter a public pool and may purchase from other firms. A trademark raises the share of own marketing that the firm captures privately, but it reduces the firm's access to the public pool. The estimates quantify this trade-off. A trademark raises the private capture of own marketing from 0.84 to 0.93, but it roughly halves access to the public demand pool.

The model explains why low application costs do not imply universal adoption. The estimated fixed cost of adoption is about RMB 4,500 per period. This cost is comparable to the official registration fee, and small relative to the gains that capable firms earn from a trademark. The main deterrent is not the direct cost of filing. Instead, adopting a trademark reduces access to marketing spillovers and induces additional marketing investment. Because the private gain from protection increases sharply with firm capability, while the loss of spillover access is relatively flat, trademark adoption follows a cutoff rule. Only sufficiently capable firms profit from adoption. For many smaller firms, not applying for a trademark is an optimal response to their reliance on competitors' marketing spillovers.

The counterfactual exercises show that policies encouraging trademark adoption have limited aggregate effects but large redistributive consequences. Both stronger trademark protection and greater market transparency stimulate adoption and marketing investment. However, aggregate sales change by only a few percent, while marketing expenditures respond much more strongly. The gains are concentrated

among the most capable firms. Firms that remain without trademarks are hurt by a thinner public pool and intensified marketing competition. Even many new adopters spend more on marketing without earning enough additional sales to raise net profit.

Overall, trademarks are not simply a low-cost legal tool that all firms should adopt. They change the allocation of marketing returns within a market. By protecting a firm's own marketing and differentiating it from others, trademarks benefit firms that can profitably build their own customer base, but they can harm firms that depend on spillovers. This trade-off is central for understanding trademark adoption and for evaluating trademark-related policies.

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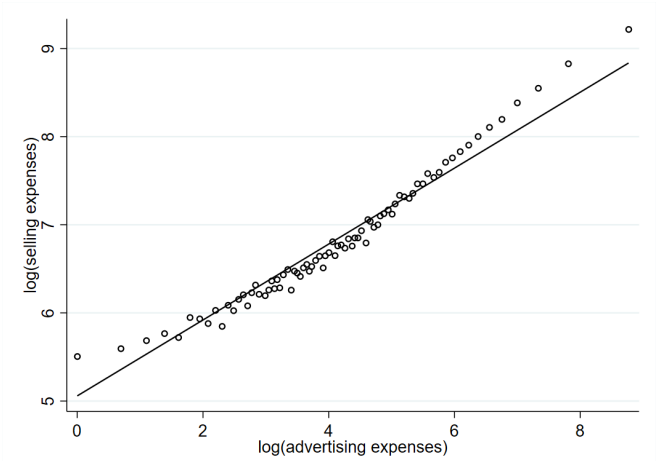
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A Data Appendix

A.1 Measuring Marketing Investment

Figure 9: Selling Expenses versus Advertising Expenses Correlation



Notes: This figure plots log selling expenses against log advertising expenses. The ASIF reports advertising expenses in 2001 and 2004 to 2007. Each circle is the mean of the two variables within a quantile bin of log advertising expenses, and the line is the linear fit on the underlying firm-year data. The sample contains 146,319 firm-year observations. The slope is 0.43 and the correlation is 0.48. At the median, advertising accounts for 5 percent of selling expenses.

B Additional Empirical Results

B.1 Firm Performance around the First Trademark Application

We study how trademarks affect firms by tracking firm performance after their first trademark application. Section 2 shows that firms that apply for trademarks are younger, larger, and spend more on marketing than firms that do not apply. As a result, a direct comparison between applicants and all other firms would confound the effect of the trademark with selection into applying. To address this selection, we use propensity score matching (PSM) to match each new applicant with one control firm that has similar pre-application characteristics. We then compare applicants with their matched controls after the application to isolate the effect of the trademark application.

We conduct the match in two steps. First, we require each treated firm and its control to have the same 4-digit industry, province, age group, and ownership type in the year before the application. Second, we estimate the probability of applying for a first trademark (the propensity score) as

a function of capital stock, employment, and pre-application level and growth of marketing cost. Among the candidate controls that meet the criteria in the first step, we select the one with the closest propensity score. In the baseline, the controls are firms that have not applied for a trademark within three years after the treated firm's application. As a robustness check, we restrict the controls to firms that never apply for trademarks during the sample period.

To track firm performance before and after the application, we restrict the treatment group to firms that file their first trademark application between 2001 and 2004 and are observed in three consecutive years starting two years before the application. This requirement is the main source of sample loss. About half of the first applicants in 2001 to 2004 are not observed in all three years, which leaves 7,009 treated firms. Of these firms, 4,931 have at least one candidate control after the first-step matching, and 2,150 are matched successfully in the second step.[18] Table 13 reports pre-treatment firm characteristics for treated and non-treated groups before and after matching. Before matching, the standardized bias is 21 percent for log(sales) and 31 percent for log(marketing). After matching, the standardized bias is about 5 percent or less for every matching variable and zero for ownership. Sales is not a targeted matching variable. The matching narrows the standardized bias in log(sales) from 21 to 8 percent.

Using the matched sample, we estimate the effect of first trademark application using the following regression

$$y_{ict} = \delta \, \text{Treat}_i \times \text{Post}_{ct} + X'_{it}\gamma + \mu_{ic} + \eta_{jct} + \varepsilon_{ict}, \tag{B.1}$$

where y_{ict} is an outcome of firm i in year t, and c is the first application year of the treated firm in its matched pair. Treat_i equals one for treated firms, and Post_{ct} equals one from year c onward. We stack the matched samples for the four first application years, 2001 to 2004. The fixed effects μ_{ic} are specific to each firm and first application year. The fixed effects η_{jct} are specific to each industry, calendar year, and first application year. With these fixed effects, we compare each treated firm only with controls in the same industry and calendar year that are matched to the same first application year. X_{it} contains firm age, ownership type, log capital, and TFP. We cluster standard errors at the firm level.

Panel A of Table 14 shows that sales rise by 7.9 percent and marketing expenses rise by 24.6 percent

[18] We match without replacement, so each control firm is used once. A treated firm is left unmatched if its closest remaining candidate control differs by more than 0.2 standard deviations of the logit of the propensity score.

after the first application, relative to matched controls. The marketing to sales ratio rises by 0.3 percentage points, or 11 percent of its mean of 2.8 percent. We find no change in market share or in the ratio of sales to the cost of goods sold, our proxy for the markup. Panel B shows similar estimates when the controls are restricted to firms that never apply.

Table 13: Balance Test Before and After Matching

VARIABLES	Before matching				After matching			
	Treated	Control	Std. bias	p-value	Treated	Control	Std. bias	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controls: not applied by $t+3$								
log(sales)	10.025	9.813	20.6	0.000	9.944	9.865	7.7	0.007
log(marketing)	5.456	4.698	30.7	0.000	5.292	5.373	-3.3	0.212
Δ log(marketing)	0.231	0.114	7.6	0.000	0.230	0.206	1.6	0.576
log(capital stock)	8.565	8.175	27.3	0.000	8.423	8.363	4.2	0.136
log(employment)	5.036	4.877	16.8	0.000	4.955	4.907	5.1	0.076
Age	10.688	10.030	6.3	0.000	9.702	9.812	-1.1	0.715
State-owned	0.293	0.247	10.2	0.000	0.236	0.236	0.0	1.000
Foreign-owned	0.149	0.188	-10.2	0.000	0.164	0.164	0.0	1.000
Private	0.558	0.565	-1.5	0.340	0.600	0.600	0.0	1.000
# Firms	4,931	28,110			2,150	2,150		
Panel B. Controls: never applied								
log(sales)	10.027	9.810	20.9	0.000	9.941	9.865	7.4	0.010
log(marketing)	5.454	4.689	30.9	0.000	5.288	5.352	-2.6	0.329
Δ log(marketing)	0.231	0.111	7.8	0.000	0.226	0.223	0.2	0.947
log(capital stock)	8.563	8.172	27.4	0.000	8.414	8.367	3.3	0.239
log(employment)	5.037	4.875	17.2	0.000	4.953	4.908	4.8	0.098
Age	10.675	10.059	5.9	0.000	9.733	9.844	-1.1	0.712
State-owned	0.292	0.249	9.7	0.000	0.237	0.237	0.0	1.000
Foreign-owned	0.150	0.188	-10.3	0.000	0.163	0.163	0.0	1.000
Private	0.558	0.563	-0.9	0.549	0.600	0.600	0.0	1.000
# Firms	4,900	27,439			2,123	2,123		

Notes: This table reports firm characteristics in year $t-1$, the year before the first trademark application, pooled over the 2001–2004 cohorts. Columns (1)–(4) compare treated firms with candidate controls in the same 4-digit industry, province, age group, and ownership type. Columns (5)–(8) use controls matched on log(capital stock), log(employment), log(marketing), and Δ log(marketing). Std. bias is the difference in means in percent of the pooled pre-matching standard deviation, and the p-value is from a t test of equal means. After matching, Std. bias is about 5 percent or less for the matching variables in both panels.

We track the dynamics of firm performance around the first trademark application. We replace $\text{Treat}_i \times \text{Post}_{ct}$ in equation (B.1) with interactions between Treat_i and indicators for each year relative to the application. We omit year $c-1$ and bin the years before $c-3$ and the years after $c+3$. Figure 10 plots the coefficients for log sales in Panel (a) and for log marketing in Panel (b). The matching targets the level of marketing expenses in $c-1$ and their growth from $c-2$ to $c-1$. Marketing expenses in $c-3$ and earlier are untargeted, and so are sales in all pre-application years. These untargeted coefficients provide a validation test of pre-trends. The figure shows no significant pre-trend in either panel. Both sales and marketing expenses rise in the year of the first application

Table 14: Firm Performance Following First Trademark Application: PSM

VARIABLES	log(sales)	log(marketing)	Marketing/Sales	Sales/COGS	Market Share
	(1)	(2)	(3)	(4)	(5)
Panel A. Controls: not applied by $t+3$					
Dummy(First Trademark)	0.079***	0.246***	0.003***	0.025	-0.004
	(0.016)	(0.052)	(0.001)	(0.027)	(0.004)
Observations	28,835	28,835	28,835	28,835	28,835
R-squared	0.899	0.765	0.740	0.252	0.875
Panel B. Controls: never applied					
Dummy(First Trademark)	0.075***	0.223***	0.003***	0.028	-0.004
	(0.016)	(0.054)	(0.001)	(0.028)	(0.004)
Observations	28,488	28,488	28,488	28,488	28,488
R-squared	0.898	0.764	0.739	0.251	0.876
Control	Age, ownership, capital stock, TFP				
FE	Firm × First Application Year, 4-digit SIC Industry × Year × First Application Year				
Cluster	Firm				

Notes: This table reports estimates of equation (B.1) on the sample matched by PSM. Dummy(First Application) equals one from the year of a firm's first trademark application onward. Treated firms are matched 1:1 to controls in the year before the application. Each control has the same age group, ownership type, 4-digit industry, and province as the treated firm and the closest propensity score, estimated from capital stock, employment, and the level and growth of marketing. The matched samples are stacked by first application year. Panel A uses controls with no application through $t+3$; Panel B uses controls that never apply. Standard errors clustered at the firm level are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. After the first application, both sales and marketing investment rise; market share and the raw markup do not change significantly.

and continue to rise thereafter.

B.2 Robustness: Marketing Spillover

A concern with Table 3 is that market-level shocks drive both marketing and sales. If a positive demand shock raises the marketing and sales of every firm in a market, rivals' marketing is positively correlated with firm i's sales even without any spillover. The industry × year and city × year fixed effects in Table 3 do not absorb shocks specific to a city × 4-digit industry × year. In Table 15, we address this concern by controlling for firm and city × 4-digit industry × year fixed effects, which absorb market-year shocks. The spillover is then identified from within-market variation in the leave-one-out average of rivals' marketing. For a firm with a very small share of the market's marketing, this average is almost equal to the market average and provides almost no within-market variation. We therefore keep firm-years whose selling expenses exceed 1 percent of the market total. Average MKT_{-i} is still computed over all other firms in the market, including the dropped ones.

Including market-year fixed effects also creates a mechanical relation between own and rivals' marketing. With equal weights, the fixed effects absorb total marketing in the market. As a result, the leave-one-out average is a decreasing function of the firm's own marketing within a market-year. Following Bloom et al. (2013), we weight each rival's marketing by $\exp(-d_{ij}/10)$, where d_{ij} is the

Table 15: Marketing Spillover with Market Fixed Effects

VARIABLES	log(sales)	Market Share	log(sales)	Market Share
	(1)	(2)	(3)	(4)
Panel A. Equal-weighted rivals				
log(MKT_i)	0.230***	0.00236***	0.239***	0.0167***
	(0.00157)	(0.000243)	(0.00172)	(0.000237)
log(Average MKT_{-i})	0.00680**	-0.0999***		
	(0.00271)	(0.000844)		
log(Average MKT_{-i}) (Tmark)			-0.00135	-0.00953***
			(0.00189)	(0.000422)
log(Average MKT_{-i}) (NonTmark)			0.00509**	-0.0232***
			(0.00258)	(0.000729)
Observations	660,408	660,408	429,789	429,789
R-squared	0.957	0.944	0.954	0.930
Panel B. Distance-weighted rivals				
log(MKT_i)	0.227***	0.0254***	0.238***	0.0204***
	(0.00136)	(0.000245)	(0.00167)	(0.000226)
log(Average MKT_{-i})	0.00206*	-0.0179***		
	(0.00117)	(0.000286)		
log(Average MKT_{-i}) (Tmark)			-0.000372	-0.00305***
			(0.00122)	(0.000200)
log(Average MKT_{-i}) (NonTmark)			0.00275**	-0.00495***
			(0.00132)	(0.000230)
Observations	640,419	640,419	417,366	417,366
R-squared	0.957	0.939	0.954	0.930
Control	Age, Ownership, Employment, TFP, D(First Trademark)			
FE	Firm + City × 4-digit Industry × Year			
Cluster	Firm			

Notes: This table re-estimates Table 3 with city × 4-digit industry × year fixed effects on firm-years whose selling expenses exceed 1 percent of their market total. In Panel A, Average MKT_{-i} is the equal-weighted average over all other firms in the market, including those dropped by this restriction. In Panel B, it weights each other firm by $\exp(-d_{ij}/10)$, where d_{ij} is the great-circle distance in kilometers. The sales spillover remains positive in both panels and comes from rivals without trademarks. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

distance between firms i and j in kilometers. Two firms in the same market then face different exposure to rivals' marketing depending on their locations, which breaks this deterministic link.

Panel B reproduces the pattern in Table 3. Own marketing raises sales and market share. Rivals' marketing raises firm i's sales and lowers its market share. The sales coefficient is 0.0068 in Panel A and 0.0021 in Panel B. Columns 3 and 4 split rivals by trademark status. The sales spillover comes from rivals without trademarks, with coefficients of 0.0051 in Panel A and 0.0028 in Panel B. The coefficient on rivals with trademarks is close to zero in both panels. These results show that market-year shocks do not explain the positive spillover. The smaller spillover from rivals with trademarks also holds within markets.

B.3 Heterogeneity: Marketing Spillover by Sector

We split industries into consumption goods and intermediate goods. Firms in consumption goods industries sell to households or retailers, such as food, apparel, furniture, household appliances, and whole vehicles. They account for 28 percent of firm-years in our sample. Intermediate goods industries include textiles, chemicals, metals, machinery, and electronic components. We interact own and competitors' marketing in equation (3.1) with a consumption goods indicator.

Table 16: Marketing Spillover: Heterogeneity by Sector

VARIABLES	log(sales)	Market Share	log(sales)	Market Share
	(1)	(2)	(3)	(4)
log(MKT_i)	0.0716***	0.00510***	0.0665***	0.00292***
	(0.000547)	(9.59e-05)	(0.000608)	(6.84e-05)
log(MKT_i) × Consumption	0.00902***	0.000394**	0.00820***	0.000167
	(0.00103)	(0.000188)	(0.00113)	(0.000135)
log(Average MKT_{-i})	0.00168**	-0.0453***		
	(0.000762)	(0.000310)		
log(Average MKT_{-i}) × Consumption	0.00289*	-0.00150**		
	(0.00161)	(0.000620)		
log(Average MKT_{-i}:Tmark)			4.19e-05	-0.00761***
			(0.000650)	(0.000133)
log(Average MKT_{-i}:Tmark) × Consumption			0.000986	-0.00123***
			(0.00138)	(0.000285)
log(Average MKT_{-i}:NonTmark)			0.000754	-0.0190***
			(0.00104)	(0.000270)
log(Average MKT_{-i}:NonTmark) × Consumption			0.00560***	0.00162***
			(0.00200)	(0.000504)
Observations	1,246,904	1,246,904	919,919	919,919
R-squared	0.911	0.854	0.911	0.855
Control	Age, Ownership, Employment, TFP, D(First Trademark), Number of Firms			
FE	Firm + 4-digit SIC Industry × Year + City × Year			
Cluster	Firm			

Notes: This table reports estimates of equation (3.1) with own and competitors' marketing interacted with an indicator for consumption-goods industries. Consumption goods are industries whose downstream users are households or retailers, classified at the 2-digit SIC level and refined at the 3- or 4-digit level for mixed industries; they account for 28 percent of firm-years. Columns (3) and (4) split competitors by trademark status and use markets with both types. Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The sales spillover is concentrated in consumption-goods industries and comes from competitors without trademarks.

Table 16 reports the results. Competitors' marketing raises a firm's sales in both sectors, but the magnitude is larger in consumption goods industries. In column (1), the elasticity of a firm's sales with respect to competitors' marketing is 0.0017 in intermediate goods industries and 0.0046 in consumption goods industries. Column (3) shows that firms without trademarks generate a larger spillover in consumption goods industries than in intermediate goods industries, while firms with trademarks generate no spillover in either sector. The market-share effects in columns (2) and (4) are similar across sectors.

C Model Appendix

C.1 Firm's Demand Function

Conditional on composite expenditure $E_Q \equiv \int_\Omega p_i q_i \, di$, the inner allocation solves

$$\max_{\{q_i\}} \left[\int_\Omega \phi_i^{1/\sigma} q_i^{(\sigma-1)/\sigma} \, di \right]^{\sigma/(\sigma-1)} \qquad \text{s.t.} \qquad \int_\Omega p_i q_i \, di = E_Q. \tag{C.1}$$

The first-order condition $Q^{1/\sigma} \phi_i^{1/\sigma} q_i^{-1/\sigma} = \lambda p_i$, substituted into the budget constraint, delivers the price index (4.4), $Q = E_Q/P$, and the conditional demand

$$q_i = \phi_i \left(\frac{p_i}{P} \right)^{-\sigma} \frac{E_Q}{P}. \tag{C.2}$$

Given P, the upper allocation solves

$$\max_{Q \geq 0,\, q_o \geq 0} \left[Q^{(\varepsilon-1)/\varepsilon} + \zeta^{1/\varepsilon} q_o^{(\varepsilon-1)/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)} \qquad \text{s.t.} \qquad PQ + q_o = E. \tag{C.3}$$

The first-order conditions give $q_o = \zeta P^\varepsilon Q$. With the overall price index $\mathcal{P} = \left[P^{1-\varepsilon} + \zeta \right]^{1/(1-\varepsilon)}$, the upper-stage demands are $Q = (P/\mathcal{P})^{-\varepsilon} E/\mathcal{P}$ and $q_o = \zeta \mathcal{P}^\varepsilon E/\mathcal{P}$, and composite expenditure is $E_Q = PQ = s_Q(P)E$ with $s_Q(P) = P^{1-\varepsilon}/(P^{1-\varepsilon} + \zeta)$. Substituting into equation (C.2) yields equation (4.6). Scaling all shifters by t scales $P^{1-\sigma}$ by t; differentiating $\ln E_Q = \ln s_Q(P) + \ln E$ with respect to $\ln t$ gives the local market-size elasticity

$$\frac{d \ln E_Q}{d \ln t} = \frac{(\varepsilon - 1)\left[1 - s_Q(P)\right]}{\sigma - 1}. \tag{C.4}$$

C.2 Proof of Proposition 2

Let $y = \kappa(c, \xi) > 0$, $a = \gamma/(\gamma - 1) > 1$, and

$$C = B(\gamma - 1)(B\gamma)^{-a} \left(\alpha_1^a - \alpha_0^a \right) > 0.$$

The gross adoption benefit in equation (4.18) is $g(y) = Cy^a + \beta_T \Lambda y$. It is strictly convex with $g(0) = 0$ and $g(y) \to \infty$ as $y \to \infty$. Since $F > 0$, the net gain $g(y) - F$ starts below zero and can cross zero only once, on the increasing branch of g: at any root, $Cy^{a-1} + \beta_T \Lambda = F/y > 0$, hence

$g'(y) = aCy^{a-1} + \beta_T \Lambda > (a-1)Cy^{a-1} > 0$. Finally, $\kappa(c, \xi) = (\mu^{1-\sigma}/\sigma)Ax$ is strictly increasing in x, so the adoption set $\{x : \Delta V(x) \geq 0\}$ is an upper interval, with unique interior threshold x^* whenever it is neither empty nor full. □

C.3 Proof of Proposition 3

Define $D \equiv \left(\mu^{1-\sigma}/(\sigma B\gamma)\right)^{1/(\gamma-1)}$. Equations (4.12) and (4.14) give the policy $m(x, T) = D\left[Ax\left(\alpha_0 + \alpha_T T\right)\right]^{1/(\gamma-1)}$, so the consistency conditions (4.20) and (4.21) become

$$\Lambda = DA^{1/(\gamma-1)}\left[(1-\alpha_1)\alpha_1^{1/(\gamma-1)}\int_{x\geq x^*} x^{1/(\gamma-1)}dG + (1-\alpha_0)\alpha_0^{1/(\gamma-1)}\int_{x<x^*} x^{1/(\gamma-1)}dG\right], \quad \text{(C.5)}$$

$$P^{1-\sigma} = \mu^{1-\sigma}\Big\{\phi_0\mathbb{E}[x] + DA^{1/(\gamma-1)}\left[\alpha_1^{\gamma/(\gamma-1)}\int_{x\geq x^*} x^{\gamma/(\gamma-1)}dG + \alpha_0^{\gamma/(\gamma-1)}\int_{x<x^*} x^{\gamma/(\gamma-1)}dG\right] + \Lambda\left[\beta_1\int_{x\geq x^*} x\,dG + \beta_0\int_{x<x^*} x\,dG\right]\Big\}, \quad \text{(C.6)}$$

using $\phi\, c^{1-\sigma} = \tilde{\phi}\, x$. Substituting equation (C.5) into equation (C.6) yields the affine form

$$P^{1-\sigma}(A; x^*) = \mu^{1-\sigma}\left(X_0 + X_1 A^{1/(\gamma-1)}\right), \qquad X_0 = \phi_0\mathbb{E}[x] > 0, \quad X_1 > 0, \quad \text{(C.7)}$$

where X_1 collects the α- and β-terms, all positive under equation (4.9). Combining $A\,P^{1-\sigma} = E_Q$ with the boundary condition (4.22) gives equation (4.23). Write $z \equiv P^{1-\sigma}(A; x^*)$ and $\theta \equiv (\varepsilon-1)/(\sigma-1) \in (0, 1]$, so that $P^{\varepsilon-1} = z^{-\theta}$ and the left side of equation (4.23) is $Az + \zeta Az^{1-\theta}$. Since z is strictly increasing in A with $z(0) = \mu^{1-\sigma}X_0 > 0$, both terms are strictly increasing and unbounded in A for $\theta \leq 1$, and the left side tends to 0 as $A \to 0$. A root therefore exists and is unique. □

D First Stage Estimation Results

D.1 First Stage Estimates and the Distribution of Firm Fundamentals

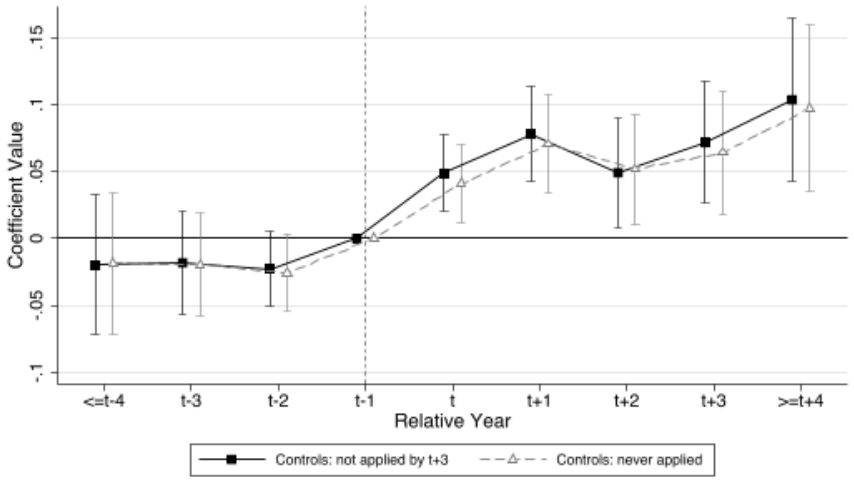
Table 17: First Stage Estimation: Production Function

Parameter	Economic Interpretation	Estimate	Std. Error
α_m	Material Elasticity	0.626	(0.010)
α_l	Labor Elasticity	0.374	(0.010)
α_k	Capital Elasticity	0.015	(0.001)
ρ_0	Productivity Intercept	0.066	(0.0108)
ρ_1	Productivity Persistence	0.723	(0.0071)

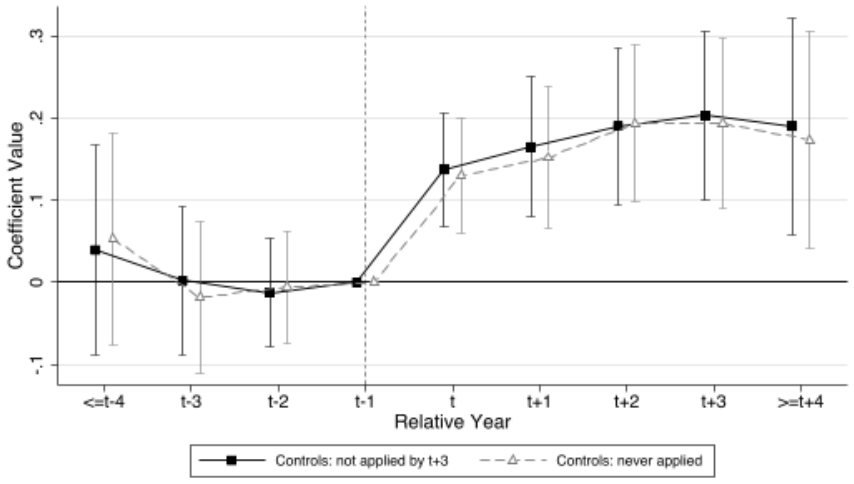
Notes: This table reports the first-stage estimates of the Cobb-Douglas production function and the AR(1) process of productivity. We impose constant returns to scale in materials and labor, so $\alpha_l = 1 - \alpha_m$. Standard errors are from a firm-clustered bootstrap with 200 replications.

D.2 Firm Fundamentals, Marketing Intensity, and Trademark Adoption

Figure 10: Sales and Marketing around the First Trademark Application



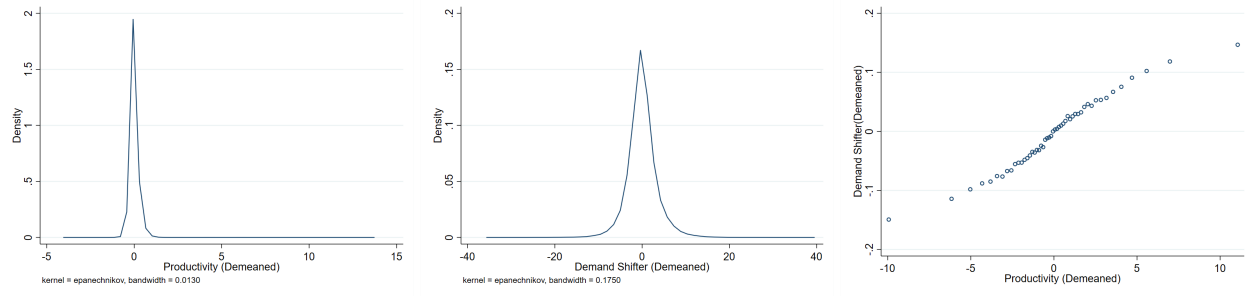
(a) log(sales)



(b) log(marketing investment)

Notes: This figure plots event study estimates of the effect of the first trademark application, from equation (B.1) with the treatment term replaced by interactions of Treat_i with relative-year indicators. Panel (a) plots log sales and Panel (b) log marketing investment. The reference year $t-1$ is omitted; years before $t-3$ and after $t+3$ are binned. Solid squares use the baseline controls, which have not applied by $t+3$; hollow triangles use controls that never apply. Vertical bars are 95 percent confidence intervals, with standard errors clustered at the firm level. Neither outcome shows a pre-trend, and both rise from the application year onward.

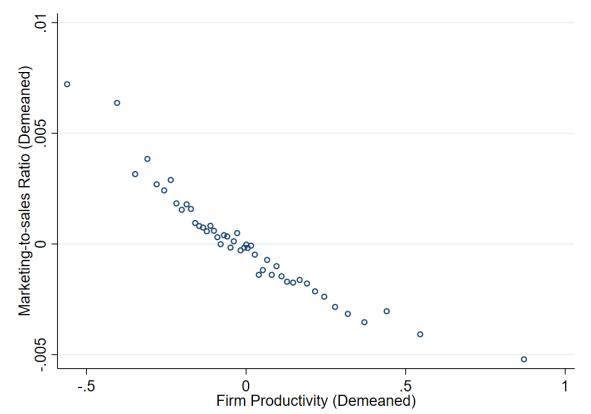
Figure 11: Distribution of Productivity and Demand Shifter



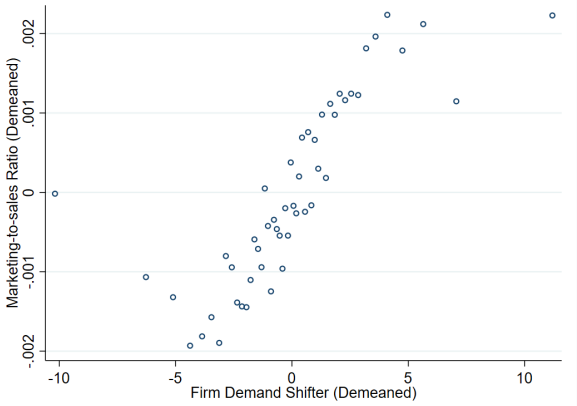
(a) Productivity ω **(b)** Demand shifter $\ln \phi$ **(c)** Correlation: ω and $\ln \phi$

Notes: This figure plots the distribution of the two firm-level primitives recovered in the first stage. Productivity is ω_i from the production function estimates in Table 17. The demand shifter is $\ln \phi_i = \ln q_i + \sigma \ln p_i$ with $\sigma = 4$. Both are demeaned by their unit $\times$ province $\times$ industry $\times$ year cell. Panels (a) and (b) plot kernel densities. Panel (c) plots the mean demand shifter in 50 equal-sized bins of productivity. The demand shifter is far more dispersed than productivity, and the two are positively and almost linearly related.

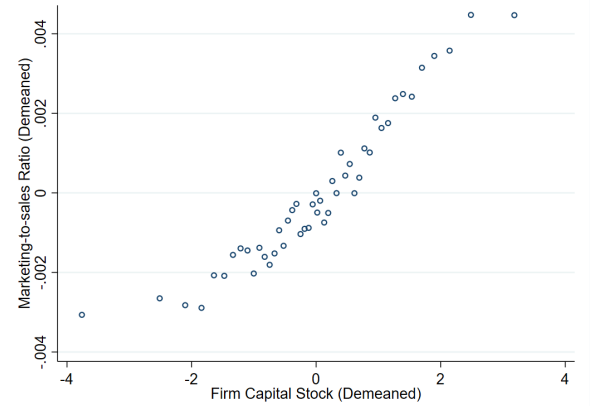
Figure 12: Marketing Intensity by Firm Fundamentals



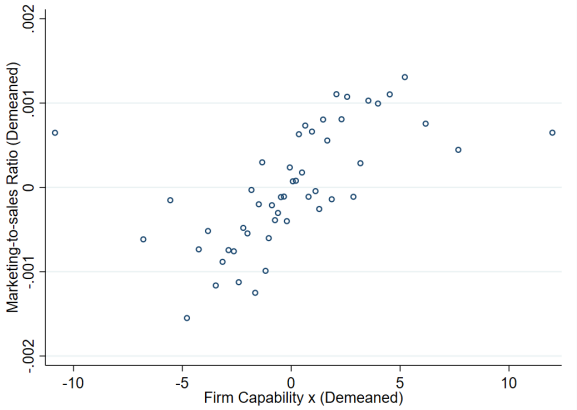
(a) Productivity ω



(b) Demand shifter $\ln \phi$



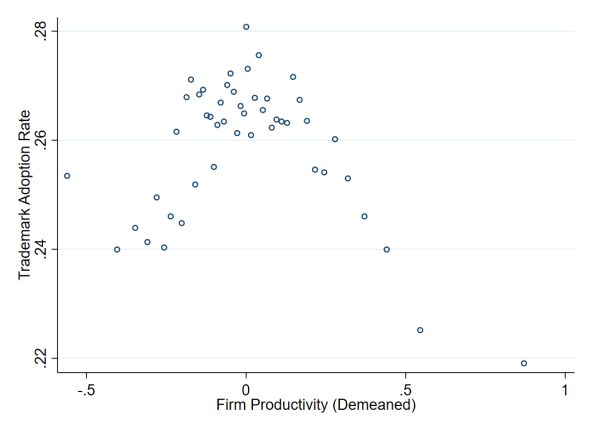
(c) Capital $\ln k$



(d) Ex-Post Capability index $\ln x'$

Notes: This figure plots marketing intensity against firm fundamentals recovered in the first stage, for the structural estimation sample described in Section 5.1. Marketing intensity is selling expenses over sales. Each fundamental is demeaned within a province × industry × year market. Panel (a) uses log physical productivity, Panel (b) the log demand shifter, Panel (c) log capital, and Panel (d) the log ex-post capability index $x' = \phi c^{1-\sigma}$. Each dot is the mean marketing intensity in one of 50 equal-sized bins of the horizontal-axis variable. Marketing intensity rises with each fundamental and most steeply with the capability index.

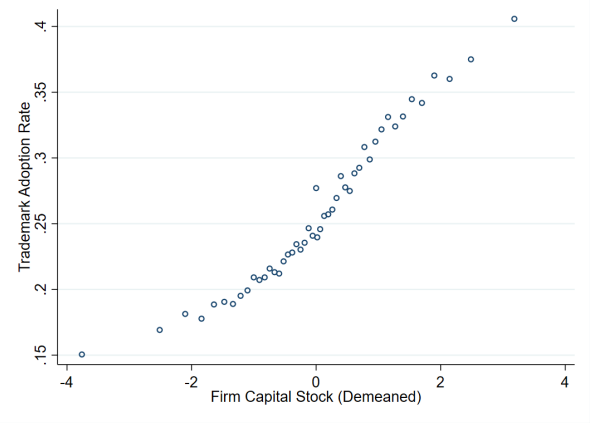
Figure 13: Trademark Adoption Rate by Firm Fundamentals



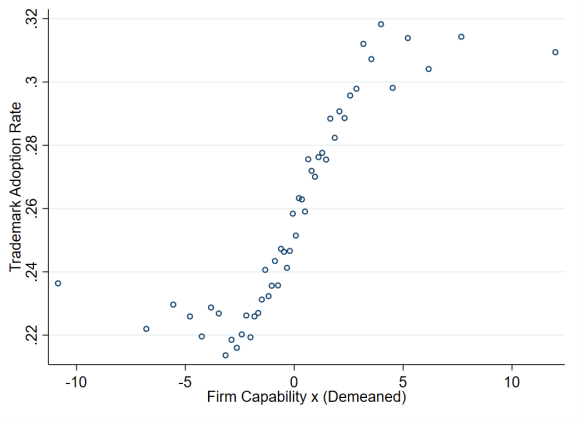
(a) Productivity ω



(b) Demand shifter $\ln \phi$



(c) Capital $\ln k$



(d) Capability index $\ln x$

Notes: This figure plots the trademark adoption rate against the firm fundamentals as in Figure 12. The adoption rate is the share of firms that have filed a first trademark application by the focal year. Each fundamental is demeaned within a province × industry × year market. Each dot is the mean adoption rate in one of 50 equal-sized bins of the horizontal-axis variable. Adoption rises with productivity and with the demand shifter, and the relation is steepest for the capability index, consistent with the sorting on x in Proposition 2.