Entry Barriers and Growth: The Role of Endogenous Market Structure [*]

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January 19, 2024

Abstract

We use China's growth experience as a laboratory to study how reductions in administrative and regulatory entry barriers contribute to growth. We develop a model

[*]Manuscript received May 2022; revised September 2023.

We thank the handling editor, Dirk Krueger, and four anonymous referees for their valuable comments and suggestions. We also gratefully acknowledge helpful comments from Sina Ates, Paco Buera, Wei Cui, Tuo Chen, Hanming Fang, Ying Feng, Chad Jones, Pete Klenow, Justin Yifu Lin, Rachel Ngai, Michael Song, Ping Wang, and Shangjin Wei as well as the seminar and conference participants at NASMES, ABFER Annual Meeting, CICM, ESEM, ESSIM, SAET, China Macro-Finance Study Group, Bristol, UCL, Essex, Jinan University, Fudan University, Hunan University and the 7th NSE International Conference. The paper was previously circulated under the title "Growing Through Competition: The Reduction of Entry Barriers in Chinese Manufacturing." All remaining errors are ours. Helu Jiang thanks research support sponsored by Shanghai Pujiang Program [21PJC053]. Lijun Zhu acknowledges financial support from the National Natural Science Foundation of China (72373005).

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of endogenous productivity and market structure with heterogeneous firms and frictional entry and calibrate it to Chinese manufacturing firms. We show that the reduction of entry barriers brings about 1.05 percentage points of productivity growth over the 1990-2004 period, accounting for 18.3% of the productivity growth in the 2004-2007 period. A decomposition exercise shows that entry mainly affects growth through promoting a more competitive market structure, which more than offsets the negative Schumeterian effect.

JEL classification: D22, D43, O11, O30, O47

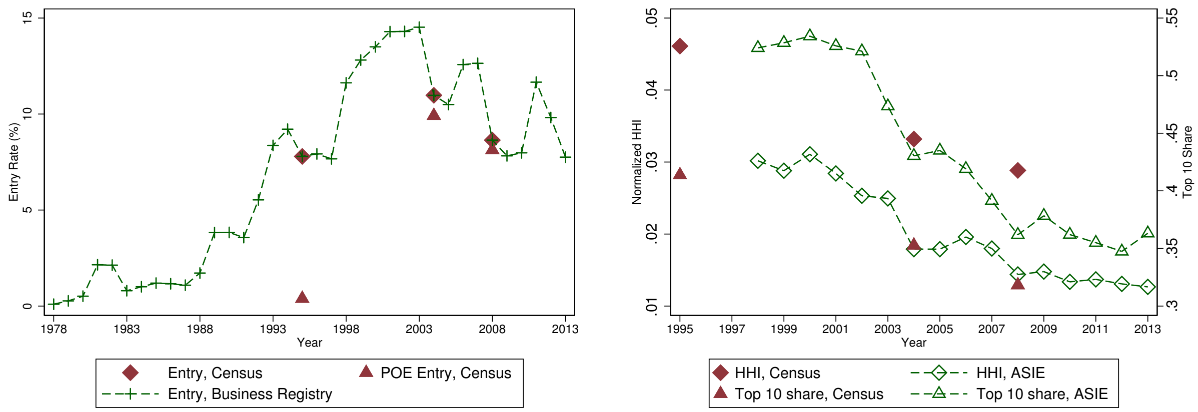
Keywords: Entry Barriers; Firm Dynamics; Market Structure; Endogenous Growth

1. Introduction

Growth in an economy might be stifled if entry is limited and incumbents, facing no competitive pressure, lack incentives to improve and grow. Writing on the rise of the Western world during 1500-1700, North and Thomas (1973) ascribe the stagnation of France to the industrial regulation and the guild system that granted monopoly to insiders and restricted entry of outsiders; In England, in contrast, new rules like the Statute of Monopolies introduced in the early 17th century stroke down monopolistic privileges and barriers to entry, which previously circumscribed profitable opportunities in trade and commerce, and eventually set the stage for the industrial revolution. This historical view is echoed by many observers of China's reforms and industrialization since the late 1970s when state monopoly was cut back, private firm entry permitted, and state-owned enterprises privatized. The force of incentives and competition released in the process is deemed to be a critical pillar underpinning the success of the reforms (McMillan and Naughton, 1992; Groves et al., 1994; Qian, 2002; Brandt et al., 2008; Zhu, 2012).

In this paper, we use China's growth experience as an example to study how reducing entry barriers contributes to economic growth through strengthening competition. While the output and productivity growth experienced since the start of the economic reforms is well documented, the accompanying changes in the market structure and level of competition are less recognized in the growth literature on China. The left panel in Figure 1.1 presents the entry rate, i.e. the new firms' share in total active firms, in China's industrial sector since 1978. Before the 1990s, entry of private firms was strictly prohibited. As shown, firm entry rate rose dramatically from 1% in the 1980s to above 10% in the late 1990s and early 2000s. Panel (b) shows the trends of two measures of competition: the normalized Herfindahl–Hirschman Index (HHI), which adjusts for the total number of firms, and the revenue share of the ten largest firms averaged across 4-digit industries, since 1995 when our firm-level data sets start. Both display a clear declining trend from

1995 to 2013. Over the same time period, the Chinese economy evolved from almost stagnation before the reforms to an average annual growth rate of GDP per capita of over 8% in the post-reform era (Zhu, 2012).



(a) Entry Rate

(b) HHI and Top 10 Share

Figure 1.1: Entry and Competition in the Chinese Industrial Sector, Since 1980

Note: This figure shows aggregate entry rates constructed from the Industrial Census and the Business Registry Records (Panel (a)), normalized HHI (left axis) and top 10 firms' revenue share (right axis) constructed from the Census and Annual Survey of Industrial Enterprises (ASIE) respectively (Panel(b)). The construction of the series is detailed in Online Appendix A.4.

To allow entry to affect competition as well as growth, we build on the endogenous growth model of step-by-step innovations (Aghion et al., 2001), which features endogenous productivity and market structure, and enrich it with frictional entry and ex-ante heterogeneous firms to study the entry-competition-growth nexus. The economy consists of a continuum of symmetric industries, where in each industry, a leader and a follower produce imperfectly substitutable goods, engage in Bertrand competition, and incur costs to advance on a quality ladder in order to expand their market shares. A key feature of the model is that the closer the quality gap between the leader and the follower is, the tighter the competition, and therefore both have a stronger incentive to advance on the ladder and expand their businesses. As the aggregate productivity growth is fueled by such expansion efforts, an economy with more competitive industries also achieves higher productivity growth. We introduce ex-ante firm heterogeneity in the model, whereby firms can have high or low cost of expansion, and frictional entry, whereby there is a potential entrant in each industry, who makes costly attempts to replace the follower subject to probabilistic entry approval, which we interpret as the entry barrier.

As the entry barrier is lowered, entrants, faced with easier access, increase their expansion effort, a positive *direct effect* on growth. On the other hand, incumbents, faced with higher threats, tend to decrease their expansion effort, resulting in a negative *Schumpeterian effect*. Both the direct and Schumpeterian effects on growth are essential in step-by-step models. The firm heterogeneity enacts a third channel whereby aggregate growth is affected by the type composition of the active firms. As young entrants replace old incumbents who may not be as efficient in expansion, the type distribution can be improved in the stationary equilibrium, leading to a potentially positive *replacement effect* on growth, reminiscent of the selection effect of entry emphasized in Hopenhayn or Melitz type of models reinterpreted in the words of endogenous growth. Lastly, in contrast to the Hopenhayn or Melitz framework, our model admits a fourth channel in which the composition of market structure affects growth. In our model, entrants have stronger incentives to grow than incumbents due to the familiar Arrow replacement effect. As entrants are allowed in, they bring about competition and dynamism, so that more industries become more competitive in the stationary equilibrium. And it is in those competitive industries where most expansion efforts take place. This positive *pro-competitive effect* on growth is the major innovation relative to the previous studies of entry on growth in the Chinese context in the literature. We will show this last channel is quantitatively the most important one driving the growth-enhancing impact of entry.

We calibrate the model to the Chinese manufacturing in 2004-7 and quantify how much of the productivity growth is generated by the increased entry associated with the reduction of entry barriers in the 1990s and early 2000s. To isolate the amount of entry that is induced by policy, we use an external measure of the regulatory cost of entry from World Bank (2020) as the measure of entry barrier and gauge the change in the entry barrier from 1990 to 2004. We find that the reform-induced entry generates 1.05 percentage points of productivity growth, accounting for about 18.3% of the 5.74 percentage points of productivity growth in the 2004-7 period. Of the gain in productivity growth, 8.52% stems from the direct effect, 17.19% from the replacement effect, and as much as 128.17% from the pro-competitive effect, more than off-setting the negative Schumpeterian effect which contributes -53.89%. These results underscore the importance of adopting a model which endogenizes market structures.

We go on to show our main finding that the pro-competitive effect drives the gain in productivity growth is robust to a host of alternative modeling assumptions and parameter values. In particular, it carries over to a two-sector extension of the model, where sectors are distinguished by the level of state presence. The sector that has a higher share of state-owned enterprises experiences lower productivity growth, smaller increase in entry, more severe product market distortion, but even there entry enhanced productivity growth mainly through its impact on the market structures. We close the paper by presenting suggestive empirical evidence in support of the key mechanism highlighted by our quantitative study.

Our paper is related to three strands of literature. The first related literature studies the role of entry barrier in explaining economic growth or the lack thereof and the economic inequality in development (Parente and Prescott, 1999; Aghion et al., 2005b; Herrendorf and Teixeira, 2011; Asturias et al., 2023). Our framework has the capacity to evaluate multiple channels which are previously studied in isolation: the entry's effect on growth through affecting the composition of the active firms with different levels of productivity emphasized by Asturias et al. (2023) for example and entry's effect on growth through its impact on competition emphasized by Parente and Prescott (1999) for example.

The second strand of related literature is the Schumpeterian growth models of creative destruction (Aghion et al., 2001, 2005a). This class of models, extended to having heterogeneous firms, is widely used to study general issues related to firm dynamics and aggregate growth (Klette and Kortum, 2004; Lentz and Mortensen, 2014; Akcigit and Ates, 2023; Ates and Saffie, 2021; Peters, 2020). Previous studies often find that entry has an ambiguous if not negative effect on growth. In contrast, we show in a version of the model adapted to the context of a growing developing country, China, reducing entry barriers has a significant effect on productivity growth through its impact on market structure.

The third strand of literature investigates the mechanisms behind China's economic growth. This includes, but is not limited to, the expansion of the non-state sector (Zhu, 2012; Hsieh and Song, 2015), the reduction of entry barriers (Brandt et al., 2012, 2020); the improved allocation of capital (Song et al., 2011); and more generally the reduction in inefficiencies in output and factor markets (Hsieh and Klenow, 2009; Cheremukhin et al., forthcoming). Brandt et al. (2012) finds that net entry accounts for about two-thirds of China's TFP growth from 1998 to 2007. We contribute to this literature by organizing and interpreting the facts through the lens of a new type of model with endogenous productivity and market structure and highlight the critical role entry plays in enhancing competition and generating growth.

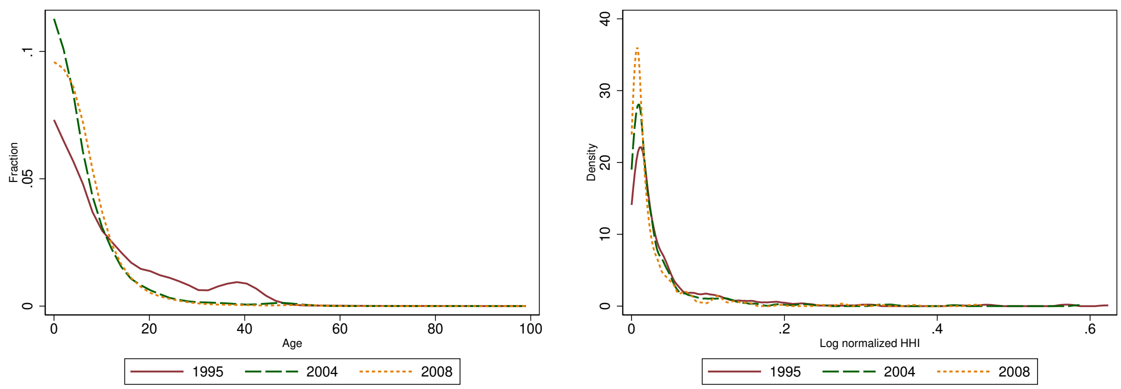
The rest of the paper is organized as follows. In Section 2, we provide some institutional background and motivating facts in the Chinese context. In Section 3, we present the theoretical framework. In Section 4, we calibrate the model to Chinese manufacturing in 2004-7 and quantify the impact on productivity growth from the reduction of entry barriers since 1990. We further decompose the growth impact to several channels to assess the relative importance of each and present our main quantitative findings. A number of robustness checks are then carried out, including an extension to a two-sector model. Section 5 provides some empirical evidence in support of our findings. Conclusion follows.

2. Institutional Background and Motivational Facts

Since the late 1970s, a sequence of economic reforms and opening-up policies were implemented to transform what was a centrally planned system with state ownership towards a market economy with diverse ownership types. Under the planned regime, the Chinese economy was dominated by state-owned enterprises (SOEs), with close-to-zero entry and exit, and private firms were not allowed to enter and operate. The first-stage reform implemented in the late 1970s and early 1980s mainly involved the de-collectivization of agriculture which initiated price and ownership incentives for farmers and the opening up to foreign investment in a few selected areas. However, many industries were still owned by the state.

The second-stage reform was launched in the late 1980s and continued throughout 1990s, gradually allowing the privatization of SOEs and encouraging the entry of private firms. In 1994, a new Company Law was adopted, which standardized the organization and activities of companies. In 1995, the policy "grasping the large and letting go of the small" (*zhuada fangxiao*) was adopted, improving efficiency of a small number of relatively large SOEs in selected sectors such as power and petrochemicals, railways, and telecommunications while allowing a large number of small SOEs to be privatized and encouraging firms to enter in non-strategic industries.

As a result of these reforms, from the 1990s to the 2000s the aggregate entry rate increased substantially and aggregate measures of competition improved for the entire industrial



(a) Firm Age

(b) Industry HHI

Figure 2.1: Distribution of Firm Age and Industry HHI, 1995, 2004, and 2008 Census Samples

Note: This figure shows the distribution of age across firms and normalized HHI across industries in the 1995, 2004, and 2008 Industrial Census respectively.

sector (Figure 1.1) . These changes are also reflected by how the cross-sectional distributions of firm age and industry concentration evolve over time. Figure 2.1(a) presents the distribution of firm age in 1995, 2004, and 2008.[1] In 1995, firms that had been established less than two years account for 15% of total firms. As the reduction in entry barriers enabled more firms to enter in late 1990s and early 2000s, this percentage rose to 24% in 2004 and 18% in 2008. With more entrants, the total number of active firms increased from 0.45 million in 1995 to 1.8 million in 2008. Over the same time period, the market structure experienced considerable changes too. Panel (b) of the same figure shows the distribution of the normalized HHI, which removes the effect on the index from a growing number of active firms, across industries in 1995, 2004, and 2008. The average industry HHI was 0.046 in 1995, and gradually decreased to 0.033 in 2004 and 0.029 in 2008.

Entry tends to bring in young firms which are more productive and grow faster than incumbent old firms. This selection channel through which entry affects growth is well

[1]Details on variable construction and sample selection are in Online Appendix A.

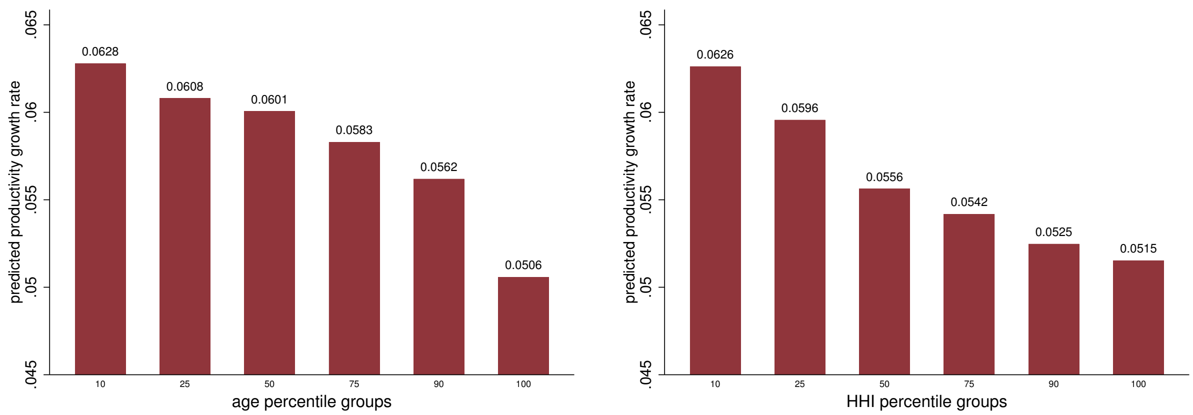
studied in the literature (Asturias et al., 2023; Brandt et al., 2020). In our sample of Chinese manufacturing firms, young firms also experience higher growth, similar to that documented for the US by Haltiwanger et al. (2016). In Figure 2.2(a), we show the predicted productivity growth by age groups for a panel of manufacturing firms from 2005 to 2007.[2] Firms less than 3 years old (the bottom 10% in the age distribution) grow 6.28% a year, while firms aged above 20 (the top 10% in the age distribution) grow 5.06% annually.

Moreover, we want to emphasize a new data pattern that growth tends to happen in industries that are more dynamic and less concentrated, as shown in Figure 2.2(b). In the least concentrated industries at the bottom 10% of the HHI distribution, the predicted productivity growth rate is 6.26%, while in the most concentrated 10%, this number is reduced to 5.15%. In addition to the aforementioned selection effect, the changing market structure can be another channel where entry affects growth.

In reality, productivity growth depends on both the distribution of firms' abilities to grow and the distribution of the market structure firms find themselves in, which affects their incentive to grow. Figure 2.2 merely portrays the joint outcomes of different forces. To decompose the contribution of the policy-induced entry to growth into various channels requires us to use a theoretical framework that allows both the type distribution of firms

[2] More specifically, we regress firm-level productivity growth on firm's age, controlling for 2-digit industry fixed effect, firm-level characteristics including log employment, log real capital, export, size dummy, and ownership types, and market-level characteristics including industry-level normalized HHI, total number of firms, total employment, and total real revenue in the ASIE 2005-7 panel, and then plot the average predicted productivity growth by age and HHI percentile groups in the figure. This pattern also holds when we use firm's employment, value added or revenue instead of productivity. Industry-level HHI is calculated using the 2004 Census sample.

and the market shares to endogenously respond to entry, which we turn to next.



(a) By Age Group

(b) By Industry HHI Group

Figure 2.2: Annual Firm Growth Rate by Age and industry HHI Groups

Note: This figures shows the predicted firm-level productivity growth by age percentile groups and by industry HHI percentile groups.

3. Model

In this section, we construct a theoretical model to study how entry affects productivity growth by enhancing competition. Building on the step-by-step quality ladder framework (Aghion et al., 2001; Akcigit and Ates, 2023), which captures how competition affects growth, we introduce 1) ex ante heterogeneity in firms' expansion costs and 2) barriers of entry, to study the impact of the reduction of entry barriers on industry competition and productivity growth. This will be the basis of the quantitative analysis on the Chinese manufacturing that follows in Section 4.

The representative household has the preference given by[3]

$$U = \int_0^\infty e^{-\rho t}[\ln Y(t) - L(t)]dt,$$

where $Y(t)$ is an aggregate consumption index defined as

$$\ln Y(t) = \int_0^1 \ln y_\nu(t) d\nu,$$

where $y_\nu(t)$ is the output of industry $\nu \in [0,1]$. Each industry consists of two firms. The final industry output is an aggregation of the outputs of the two firms,

$$y_\nu(t) = [y_{\nu,1}(t)^\delta + y_{\nu,2}(t)^\delta]^{1/\delta}.$$

The elasticity of substitution between outputs of the two firms in the same industry is governed by the parameter δ.

Use labor as numeraire and normalize wage to 1. Under the utility function, the total expenditure PY always equals 1.[4] As a result, the household optimally spends 1 on each of the intermediate goods. Furthermore, we can derive the demand functions of the two

[3] As in Aghion et al. (2001) we use a quasi-linear utility function to eliminate equilibrium effects through wage and focus on the effect of competition on growth. We consider this assumption appropriate for the Chinese historical context we study. From 1990 to the mid-2000s, China witnessed large-scale rural-to-urban migration which made the supply of labor to the urban sector relatively elastic. As documented in Imbert et al. (2022), there were 45 million rural-to-urban migrants from 2000 to 2005, accounting for 16% of the urban population in 2000. However, the growth-enhancing effect of entry in this model is sensitive to the assumption on labor supply elasticity.

[4] Note the Hamiltonian is $H = lnY - L + \lambda[rA + L - PY]$. From the two first order conditions, $1 = \lambda$ and $1/Y = \lambda P$, it follows that $PY = 1$.

firms in any industry, which are

$$y_1 = \frac{p_1^{1/(\delta-1)}}{p_1^{\delta/(\delta-1)} + p_2^{\delta/(\delta-1)}}, \qquad y_2 = \frac{p_2^{1/(\delta-1)}}{p_1^{\delta/(\delta-1)} + p_2^{\delta/(\delta-1)}}.$$

Firms use labor as the only input in production. There is a quality ladder. Denote n_1 and n_2 as the positions of firm 1 and firm 2 on the ladder and denote λ as the step size. Accordingly, their productivity levels are given by $z_1 = \lambda^{n_1}$ and $z_2 = \lambda^{n_2}$. It follows that $c_1 = \lambda^{-n_1}$ and $c_2 = \lambda^{-n_2}$ are the marginal costs of labor of firm 1 and firm 2, respectively.

The two firms in an industry engage in Bertrand competition.[5] Given the demand functions above, the optimal pricing rule follows $p_\iota = \frac{\epsilon_\iota}{\epsilon_\iota - 1} c_\iota$, where ϵ_ι is the price elasticity of demand for firm $\iota = 1,2$. It can be easily shown that this elasticity takes the form $\epsilon_\iota \equiv \frac{1-\delta\omega_\iota}{1-\delta}$, with $\omega_\iota \equiv p_\iota y_\iota = \frac{p_\iota^{\delta/(\delta-1)}}{p_1^{\delta/(\delta-1)} + p_2^{\delta/(\delta-1)}}$ being the revenue of firm $\iota = 1,2$. Correspondingly, the profit of firm ι is $\pi_\iota = \frac{\omega_\iota}{\epsilon_\iota}$, for $\iota = 1,2$. Note that as the revenue, ω_ι, is only determined by the price ratio, p_1/p_2, so is the elasticity of demand, ϵ_ι. From the optimal pricing rule, it follows that the price ratio, p_1/p_2, is entirely determined by the relative cost ratio, c_1/c_2, and ultimately it is the cost ratio that matters for the price ratio, the revenue, the elasticity of demand, and the profit.

Denote the quality gap n as the distance between the positions of the two firms, $|n_1 - n_2|$. Figure 3.1 presents firm's revenue as a logistic function of the quality gap; that is, it is convex initially and turns to concave eventually. The incremental revenue for a follower in an industry with a large gap is small; it increases as the follower catches up and it peaks when it is on par with the leader, and eventually decreases as it becomes the new leader and its quality advantage expands. To the extent that the incremental revenue measures

[5] We can alternatively assume Cournot competition, under which firm ι's optimal pricing rule is $p_\iota = \frac{1}{\delta(1-\omega_\iota)} c_\iota$. The key property that revenue and profit are logistic functions in technology gaps is unchanged.

the benefit of firms' efforts to move along the ladder, firms in industries with a smaller gap, i.e. less concentrated and more competitive industries, have a larger incentive to advance on the ladder either to escape competition or to leapfrog. An economy with a larger fraction of such industries hence tends to grow faster. We next introduce costly expansion whereby entrants and incumbents jointly determine the competitiveness of the industries they operate in.

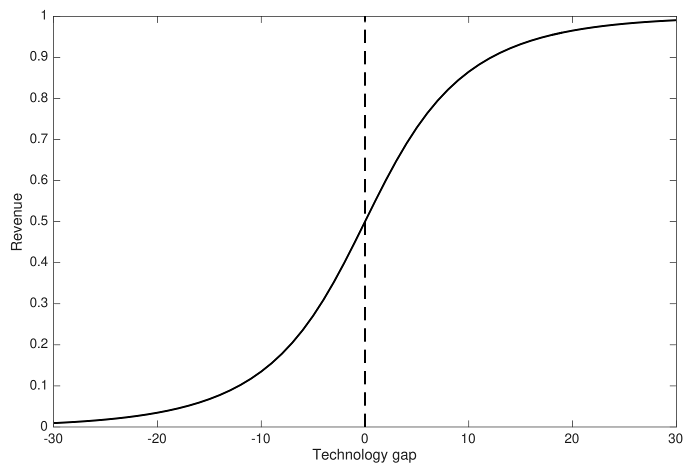


Figure 3.1: Revenue Function, Model

Note: This figure shows the revenue of a firm as a function of its quality gap relative to its opponent in the model.

Expansion Technology and Costs In each industry, there exists a leader, a follower, and a potential entrant. Define $\pi(n)$ and $\bar{\pi}(n)$ as the profit for the leader and follower in an industry with quality gap n, respectively. We label an industry where $n = 0$ a neck-and-neck industry. When a leader's expansion effort succeeds, its advantage increases from n to $n+1$. When a follower succeeds, with probability ϕ it closes the technological gap completely and with the complementary probability it cuts the gap by one step from n to $n-1$.[6] If a potential entrant successfully enters, it replaces the follower in an industry

[6]There are different ways to interpret follower's catch-up process. One interpretation is that ϕ measures the likelihood of a drastic innovation which spans a number of technological steps. Another interpretation

with positive gap, i.e. $n \geq 1$, and replaces either incumbent with equal probability in a neck-and-neck industry, similar to Akcigit and Ates (2023).

Firms are heterogeneous and have two types: High and Low growth potential. The high (low) growth potential type has low (high) cost of expansion summarized by the parameter β_i and $\beta_h < \beta_l$. To achieve an arrival rate of x of successful expansion, a firm needs to hire $\beta_i \frac{x^\alpha}{\alpha}$ units of labor and pay a cost equal to that amount. A high (low) type firm transits to become a low (high) type at Poisson rate σ_h (σ_l). An industry therefore is fully characterized by (i, j, n), where i and j are the types of the leader and the follower respectively, and n is the quality gap. Use X and $\overline{X}$ to differentiate objects for the leader and the follower. In a neck-and-neck industry $(i, j, 0)$, we use X^i and X^j to differentiate from the two incumbent firms.

There is a potential entrant in each industry at any point in time. With an exogenous probability θ, the entrant is of high type, and with probability $1 - \theta$, it is of low type. After realizing its type, the entrant spends to attempt a product which is better than that offered by the existing follower. Similar to the follower, With probability ϕ, the entrant becomes neck-and-neck with the leader; with probability $1 - \phi$, the existing quality gap is cut by 1 step. However, even if the expansion effort is successful, its entry is subject to an administrative review: only with probability τ is its application approved and only then can it enter the market with the new product to replace the follower. Entrants whose application is not approved exit the market and obtain a value normalized to 0.

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is that ϕ measures the ease of costly imitation. After spending resources to study the leading technology, followers either must invent a new way of producing leaders' goods and proceed one step at a time or can copy the leaders' technologies to catch up completely due to imperfect IP protection.

For an industry characterized by (i, j, n), where $i, j \in \{h, l\}$ and $n \geq 1$, denote $V_{ij}(n)$, $\overline{V}_{ij}(n)$, and $V^e_{ij}(n)$ the value functions of the leader, the follower and the potential entrant. The value function for the leader satisfies

$$\begin{aligned}
rV_{ij}(n) = \max_{x_{ij}(n)} \underbrace{\pi(n)}_{\textit{profit}} - \underbrace{\beta_i \frac{x_{ij}(n)^\alpha}{\alpha}}_{\textit{exp. cost}} + \underbrace{x_{ij}(n)[V_{ij}(n+1) - V_{ij}(n)]}_{\textit{successful expansion}} + \underbrace{\sigma_i[V_{-ij}(n) - V_{ij}(n)]}_{\textit{change of own type}} \\
+ \underbrace{\sigma_j[V_{i-j}(n) - V_{ij}(n)]}_{\textit{change of follower's type}} + \underbrace{\overline{x}_{ij}(n)\{\phi[V^i_{ij}(0) - V_{ij}(n)] + (1-\phi)[V_{ij}(n-1) - V_{ij}(n)]\}}_{\textit{successful expansion by the follower}} \\
+ \underbrace{\tau\theta {x^{eh}}_{ij}(n)\{\phi[V^i_{ih}(0) - V_{ij}(n)] + (1-\phi)[V_{ih}(n-1) - V_{ij}(n)]\}}_{\textit{successful entry by a high-type entrant}} \\
+ \underbrace{\tau(1-\theta) {x^{el}}_{ij}(n)\{\phi[V^i_{il}(0) - V_{ij}(n)] + (1-\phi)[V_{il}(n-1) - V_{ij}(n)]\}}_{\textit{successful entry by a low-type entrant}}.
\end{aligned}$$

The leader optimally chooses its expansion intensity, $x_{ij}(n)$. The flow value of a leader consists of: static profit minus expansion cost; gains in value upon a successful expansion; changes in value due to an exogenous change of own type or that of the follower; and changes in value due to successful expansion by the follower or successful entry of an entrant.

The value function for the follower in industry (i, j, n) can be defined analogously as

$$\begin{aligned}
r\overline{V}_{ij}(n) = \max_{\overline{x}_{ij}(n)} \overline{\pi}(n) - \beta_j \frac{\overline{x}_{ij}(n)^\alpha}{\alpha} + \overline{x}_{ij}(n)\{\phi[V^j_{ji}(0) - \overline{V}_{ij}(n)] + (1-\phi)[\overline{V}_{ij}(n-1) - \overline{V}_{ij}(n)]\} \\
+ \sigma_i[\overline{V}_{-ij}(n) - \overline{V}_{ij}(n)] + \sigma_j[\overline{V}_{i-j}(n) - \overline{V}_{ij}(n)] + x_{ij}(n)[\overline{V}_{ij}(n+1) - \overline{V}_{ij}(n)] \\
+ \tau[\theta {x^{eh}}_{ij}(n) + (1-\theta){x^{el}}_{ij}(n)][0 - \overline{V}_{ij}(n)],
\end{aligned}$$

and the value function of the potential entrant in industry (i, j, n) is

$$V^e_{ij}(n) = \theta {V^{eh}}_{ij}(n) + (1-\theta){V^{el}}_{ij}(n),$$

with

$$V^{ek}_{ij}(n) = \max_{x^{ek}_{ij}(n)} \; -\beta_k \frac{x^{ek}_{ij}(n)^{\alpha}}{\alpha} + \tau * x^{ek}_{ij}(n)[\phi V^k_{ki}(0) + (1-\phi)\overline{V}_{ik}(n-1)], \quad k = h, l.$$

The parameter τ stands for the entry barrier. A smaller τ implies a lower probability of the entrant's application being approved, which represents a higher entry barrier. We relegate the value functions for firms in a neck-and-neck industry, the inflow-outflow tables across states and the derivation of the aggregate growth in Online Appendix B.

Balanced Growth Path and Aggregate Growth We focus on the balanced growth path (BGP) of the model economy. On the BGP, the aggregate growth is solely driven by productivity growth and the distribution over industry gaps and type configurations is stationary. Denote $\mu_{ij}(n)$ as the fraction of industries of (i, j, n) in the stationary distribution. It can be shown that the aggregate growth rate has the following form:

$$g \equiv \frac{d \ln Y}{dt} = \left[\sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) x_{ij}(n) + \mu(0) x(0) \right] * \ln \lambda,$$

where

$$\mu(0)x(0) \equiv \sum_{i=h,l} \mu_{ii}(0) \left(2x^i_{ii}(0) + \tau x^e_{ii}(0) \right) + \mu_{hl}(0) \left(x^h_{hl}(0) + x^l_{hl}(0) + \tau x^e_{hl}(0) \right)$$

is the share of neck-and-neck industries times all three firms' expansion intensities in these industries. The aggregate growth rate is equal to the average of the leader's productivity growth rates for all industries with a positive gap, plus average productivity growth rates for all firms in neck-and-neck industries.

4. Quantitative Analysis

We solve the model numerically. To do that, we set a limit to the number of steps a leader can possibly be ahead of its follower and denote it by $\overline{n}$. At $n = \overline{n}$, a leading firm simply stops expansion. We verify that firms' expansion intensity in an industry with gap $\overline{n}-1$ is indeed very close to 0. We calibrate the stationary equilibrium of the model to data moments from 2004 to 2007. The calibrated baseline represents a quantitative theory of the productivity growth of the Chinese manufacturing sector in the mid-2000s. We then conduct a counterfactual exercise, asking what would happen to productivity growth if the entry barrier in the baseline was instead as high as that in the early 1990s. To understand the effect of the entry barrier on productivity growth, we then decompose the difference in the growth rates between the baseline and the counterfactual economies into several channels. At the end of the section, we extend the model to a two-sector model to speak to the cross-industry heterogeneity in the presence of SOEs.

4.1. Calibration

Data and Sample Selection Our two main data sources for constructing data moments are the Annual Survey of Industrial Enterprises (ASIE) 2005-7 and the Industrial Census 2004. The ASIE is a panel of "above scale" industrial firms, i.e. firms with annual sales above 5 million RMB which account for around 90% of the total industrial output and 70% of the total industrial employment (Brandt et al., 2012). It provides us with detailed information on firm-level accounting variables, which we use to construct targets related to firm dynamics and productivity growth.[7] The Industrial Census, on the other hand, surveys all active firms in the economy in a cross-section, which we use to construct entry rates. In both datasets, we restrict the sample to the manufacturing sector. The sample selection and variable construction follow the standard practice in the literature, which we report together with the summary statistics in Online Appendices A.1 and A.2.

[7] We skip the 2004 wave of ASIE because information on value added is missing for that wave from the source data. For more details on ASIE, see Online Appendix A.1.

Calibration Strategy There are 11 parameters $\{\rho, \alpha, \beta_h, \beta_l, \tau, \theta, \sigma_h, \sigma_l, \delta, \phi, \lambda\}$ in the baseline model. The subjective discount rate ρ is set to 0.03 such that the annual discount rate is about 3%. The inverse of the cost elasticity of success α is set to 2, a value commonly adopted in the Schumpeterian growth literature (e.g. Acemoglu et al. (2018)). We jointly calibrate the remaining nine parameters by minimizing the weighted sum of percentage deviations of selected model moments from their data counterparts. As the model is set up in continuous time, we map one year in the data to 20 periods in the model. We simulate $10,000$ industries for $4,000$ periods and construct the model moments using the last 500 periods of data. The moments are selected to inform the parameters and we explain the selection logic as follows.

The transition probabilities σ_h and σ_l between high and low types are chosen to match the transition probabilities between high-growth firms whose growth rates are above the industry median and low-growth firms whose growth rates are below the industry median, controlling for firm size and the industry concentration. A firm can grow at a high rate either because its marginal cost of expansion is low (i.e. of the high type) or because it has strong incentive to grow (i.e. in a less concentrated industry). To control for the latter in the data, we use a probit regression to predict the probability of a high-growth (low-growth) firms remaining high-growth (low-growth) in the next year, controlling for observable firm characteristics (such as age, revenue, employment, ownership types and industries) and industry characteristics (such as HHI, number of firms, market employment and revenue), and use the predicted transition probabilities as targets. In the model, after controlling for firm size and industry characteristics, a firm's residual growth is determined by its type. This means, if in the equilibrium more than half of the firms are of the high type, then the median firm in the two-point residual growth distribution has the high type and the group of low-growth firms consists of a mixture of high and low types. To be consistent with the data moments, we calculate the transition over a 20-period window between having above-median and having below-median residual growth rates by combining the σ's with the endogenous shares of the two types.

The moments that inform the expansion cost parameters of high- and low-type firms, β_h and β_l, are chosen to be the average productivity growth of old and large firms and that of young and large firms. In ASIE 2005-7, we label firms whose revenue is above (below) the 4-digit industry median as large (small) firms and whose age is above (below) the industry median as old (young) firms. The fact that older firms grow more slowly may reflect that they tend to be low type or that they tend to be bigger and bigger firms naturally have lower incentive to grow due to the diminishing return from expansion (recall Figure 3.1). Only after controlling for size, the growth margin between the young and the old is informative about the type-specific expansion costs. We choose to condition on the large size as it excludes the entrants from the comparison, whose type distribution is determined by θ rather than the σ's.

The elasticity of substitution between firms within the same industry, δ, determines the dispersion of market power for a given technology gap: the higher the substitutability, the more mark power a given technological advantage rewards the leader.[8] In the model, the labor cost share (or one minus the profit share) of a firm is inversely related to its market power. The value of δ is set to match the economy wide 75-to-25 ratio of labor cost share in model and data.[9]

[8] This parameter measures the level of "product market competition" in Aghion et al. (2001). This is conceptually different from what we refer to as competition in this paper. We describe an industry with a smaller gap as a more competitive industry and describe an economy with a distribution of gaps that favors smaller gaps as a more competitive economy.

[9] Note that in the model, the labor income includes income of the labor used for both production and

The probability of high-type entrants, θ, and the probability of fast catch-up, ϕ jointly affect the relative size of the entrants and their initial growth. The higher the θ, the faster on average entrants grow. We choose θ to target the entrants' share of industry revenue by the end of their first year in the ASIE panel. In the model, we simulate the same statistics for entrants by the end of the 20th period. On the other hand, ϕ determines the probability of the relatively rare event of an entrant or follower closing a large technological gap abruptly. We therefore select the complementary probability, which is the probability of an entrant remaining a follower by the end of its first year (or by the end of the 20th period in the model), as the relevant moment.

Lastly, the entry barrier parameter τ directly affects the entry rate and hence we target the average entry rate in 2004 Census. And the quality step parameter λ is set to match the average annual productivity growth from ASIE 2005-7. In sum, all these calibrated parameters capture, some in a reduced-form way, how the existing institutions and technology in 2004-7 support productivity growth.

After constructing the model and data moments, we choose parameter values to minimize the following loss function, which is a weighted average of the distances, in percentage

expansion. However, the exact data counterpart of this labor income is elusive as remuneration for labor in expansion may not be captured by the wage bill (Koh et al., 2020; Eisfeldt et al., 2023). We find in the ASIE panel, our preferred measure of the expansion cost, the sum of sales and management cost (see Section 5.1), is a better predictor of productivity growth than the wage bill. Therefore, we construct in the model the production labor cost share, i.e. the production labor cost divided by the sum of the production labor cost and profit, to be mapped to the data wage bill divided by the sum of the wage bill and profit.

Table 4.1: Calibrated Parameters and Targeted Moments

Para.	Description	Value	Moment	Data	Model
externally set					
ρ	discount rate	0.030	–	–	–
α	inverse of elasticity	2.000	–	–	–
internally calibrated					
σ_h	H to L trans. prob.	0.1909	high- to high-gr trans.	0.7833	0.7834
σ_l	L to H trans. prob.	0.0927	low- to low-gr trans.	0.8353	0.8350
β_h	exp. cost of H firms	1.2342	old and large firms' gr	0.0406	0.0406
β_l	exp. cost of L firms	2.4632	young and large firms' gr	0.0744	0.0768
δ	E.o.S. within industry	0.7053	labor share's 75/25 ratio	2.1961	2.1990
ϕ	prob. of catch-up	0.0846	pr. entrants staying small	0.6769	0.7224
θ	prob. of H entrants	0.7747	entrants' rev share	0.0556	0.0614
τ	entry barrier	0.9317	average entry rate	0.1098	0.0985
λ	quality step	1.2066	aggregate gr	0.0574	0.0574

Note: This table lists the externally set parameter values and the internally calibrated parameter values.

terms, between the model and data moments:

$$\sum_{k=1}^{9} \iota_k \frac{|\text{model}(k) - \text{data}(k)|}{0.5 * |\text{model}(k)| + 0.5 * |\text{data}(k)|}.$$

To match well at the macro level, the moments of aggregate productivity growth rate is assigned a weight (ι_k) 5 times the weight of others. Table 4.1 summarizes the calibrated parameter values and the moments used in the calibration.

Parameter Identification While the nine internally calibrated parameters are jointly optimized, we can still examine whether some moment conditions are particularly informative about some parameters as intended by our calibration strategy. The answer is affirmative. Varying a parameter around its baseline value while keeping others at their baseline values induces significant variation in the value of the associated moment in the model, reassuring us that the moments are indeed informative about the underlying model parameters as we expect. These results together with the response of the loss function to local variations of the calibrated parameters are reported in Online Appendix

C.1.

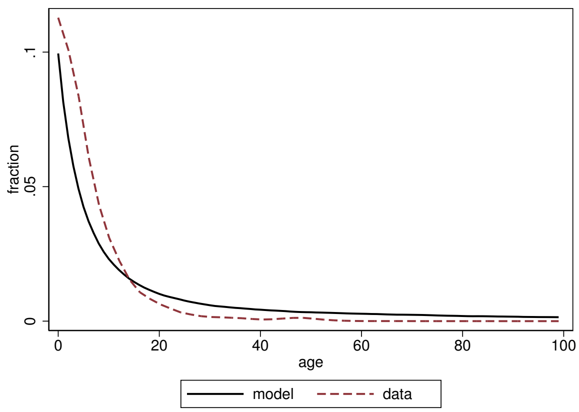
4.2. Results

Table 4.1 reports the values of the parameters together with their associated data and model moments in the baseline model. A high-type firm faces 19.09% chance of transitioning to low-type, while a low-type firm faces 9.27% chance of transitioning to high-type. This means that there are substantial type conversions in both directions, though on average as a firm ages, it is more likely to be a low type. The low-type firms face almost twice as high marginal expansion cost than the high-type firms, and as many as 77.47% of all entrants are of high type. These parameters suggest that, consistent with previous literature, we should expect a positive replacement effect whereby more entry brings in more high type firms improving aggregate productivity. The elasticity of substitution between leader's and follower's outputs within an industry is $1/(1-\delta) = 3.39$, within the range commonly found in the literature. The elasticity determines how the size of the technological lead affects leader's and follower's market shares and therefore their incentive to climb the ladder. The probability of immediate catch-up is relatively low at 8.46%, while the entry barrier is relatively low with a success rate of 93.17% of all entry applications by 2004. Taken together, the baseline describes the state of the economy in mid-2000s. In what follows, we examine how our baseline model performs with respect to a number of non-targeted moments, ranging from the joint distribution of productivity, age, and size to various measures of competition.[10]

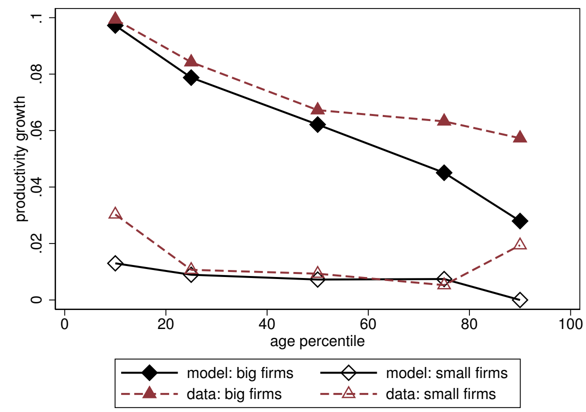
Non-Targeted Moments: Age, Size, and Productivity Growth Although we do not target the age distribution, our model replicates reasonably well the empirical distribution of firm age (Figure 4.1(a)). Both distributions peak at small ages and exhibit a thick right

[10]In Online Appendix C.2, we report all the numbers underlying Figure 4.1 in tables. In addition, we also report the model's prediction of labor shares at various percentiles against the data.

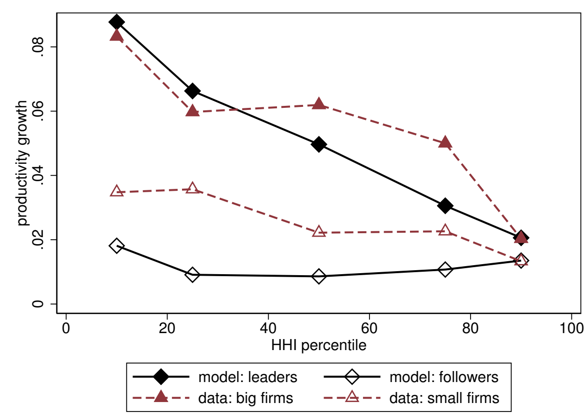
tail. As our model only admits duopoly in an industry, we necessarily fail to match the firm size distribution in the data. However, when we structure the data loosely according to large and small firms in an industry, conceptually corresponding to leaders and followers in an industry, our model replicates relatively well the conditional distribution of productivity growth by age percentile, for large and small firms separately (Figure 4.1(b)). This means, although the model misses the dispersion of sizes within the groups of large and small firms, the two groups of firms on average behave in a similar way as captured by the leaders and followers in the model.



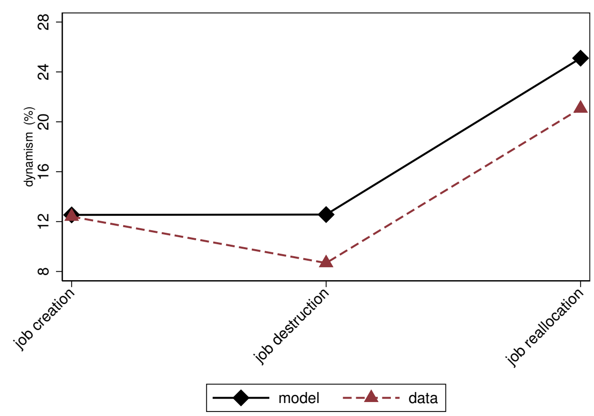
(a) Age Distribution



(b) Productivity Growth by Size and Age



(c) Productivity Growth by Size and HHI



(d) Business Dynamism

Figure 4.1: Age, Conditional Productivity Growth, Dynamism, Model vs. Data

Note: This figure shows some non-targeted moments in model and in data.

Non-Targeted Moments: Concentration and Dynamism Although the duopoly assumption implies that we cannot match the empirical distribution of HHI across industries, the model can reproduce the key data feature that productivity growth declines in industry concentration, which lies at the heart of the paper. In Figure 4.1(c), we show the average productivity growth by HHI percentiles for leaders and followers separately in the model and their data counterparts. The model does a very good job replicating the declining pattern especially for leaders, whose expansion efforts directly contribute to aggregate productivity growth. The correlation between the leader's productivity growth and HHI is -0.0664 in the model, and that between the large firms' productivity growth and HHI is -0.0610 in the data. Finally, with new firms entering and incumbents expanding and contracting, we can track the labor employed for production and expansion of a firm upon entry in the model simulation and compute the job creation, destruction, and reallocation rates à la Decker et al. (2016). Figure 4.1(d) compares these measures of business dynamism in the model with their data counterparts. The model generates a realistic rate of job creation, but over-predicts the job destruction rate. As in the model entrants replace incumbents one for one and in the data we have positive net entry, this over-prediction is unsurprising.

In sum, the model does a reasonably good job in reproducing a number of non-targeted moments, which are nevertheless highly relevant facts for our study. With the baseline model validated, we now move on to the counterfactual analysis.

4.3. Counterfactual Analysis

Entry cost can stem from different sources. Technological progress in transportation, information and communications, and finance can all lower the cost of entry in all sectors. As we are interested in quantifying the effects of lowering the administrative and regulatory cost of entry, we need to isolate the part of the increase in observed entry that is attributed to the reduction in such entry barrier to construct a counterfactual entry rate in 1990, and then recalibrate the model targeting that counterfactual entry rate. In other words, we take the baseline calibrated to the 2004-7 Chinese manufacturing sector and assess counterfactually what the growth rate would be if the entry barriers in 2004-7 were as high as those in 1990.

4.3.1. Calibrating the Counterfactual Entry Barrier in 1990

To construct the counterfactual entry rate in 1990, we need two ingredients: an estimate of the change in a measure of entry barrier in the country from 1990 to 2004 and an estimate of the elasticity of observed entry rates to the measured entry barrier. We proceed as follows.

In 2008, the World Bank published a special *Doing Business in China* report, which contains measures of administrative and regulatory costs of starting a business in 26 provinces and 4 centrally-administered municipalities based on a survey investigating the procedures that a standard small to medium-sized company needs to complete to start operations formally. The measure of entry barrier that is closest in spirit to our model is "Time (Days) to Start a Business", which is the total time required to obtain all necessary permits and licenses and complete all required inscriptions, verifications and notifications with the relevant authorities. We estimate the elasticity of entry rates with respect to this measure in a cross-province regression and obtain an elasticity of 0.1580. That is, one additional day spent getting the approval lowers the entry rate by 0.1580 percentage points.[11] Then using the longest time series available for this measure of entry barrier, i.e. for Shanghai

[11] We regress 4-digit industry cross province-level entry rates on province-level "Time (Days) to Start a Business" controlling for industry-province characteristics, province-level characteristics and 4-digit industry fixed effects with standard errors clustered at 4-digit industry level. The results are reported in Online Appendix C.4.1.

from 2004 to 2020, we extrapolate linearly backwards in time to arrive at 74.74 days in 1990, an increase of 28.72 days from the 2004 level. This implies a counterfactual reduction of 28.72×0.1580 or 4.54 percentage points in entry rates from the 2004 level, which accounts for 63.52% of the difference in observed entry rates between 1990 and 2004.

Since the baseline entry rate is 9.85%, we recalibrate τ, while keeping all other parameters unchanged, to match the counterfactual entry rate of 9.85%-4.54%=5.31%. This leads to a decrease in the value of τ from 0.9317 in the baseline to 0.6710. The aggregate growth rate consequently decreases from 5.74% in the baseline to 4.69%, a reduction of 1.05 percentage points which amounts to a 18.29% reduction of baseline productivity growth.

4.3.2. Growth Decomposition

By comparing the steady states of the baseline and the counterfactual economy, we identify four channels through which lowering entry barrier affects productivity growth. One, it induces more expansion efforts from potential entrants across industries, leading to a positive *direct effect* on growth. Two, it discourages incumbents from costly expansion in a given industry because of heightened threat of entry, i.e. a negative *Schumpeterian effect* on growth. Three, it improves the endogenous distribution of firms' types, since entrants who tend to be of high growth potential replace incumbents who tend to be of low growth potential, leading to a positive *replacement effect*. Four, it changes the endogenous distribution of firms over technological gaps, relocating firms towards more industries that have smaller gaps, are less concentrated and thus more competitive. This last effect, which we term the *pro-competitive effect*, is a growth-enhancing effect and, as our growth decomposition exercise shows, turns out to be the most important channel through which entry promotes growth.

Start from the formula for the aggregate growth rate of the economy we have derived in Section 3. To conserve notation, use ψ to denote the type configuration of a leader-follower pair, i.e. $\psi \in \{(h,h),(h,l),(l,h),(h,h)\}$, and rewrite the growth rate formula as

$$\begin{aligned} g &= \sum_{\psi} \mu(\psi,0)\tau x^e(\psi,0)\ln\lambda + \sum_{\psi}\sum_{n\geq 0} \mu(\psi,n)x(\psi,n)\ln\lambda \\ &= \sum_{\psi} \tilde{\mu}(\psi)f(0|\psi)\tau x^e(\psi,0)\ln\lambda + \sum_{\psi}\sum_{n\geq 0} \tilde{\mu}(\psi)f(n|\psi)x(\psi,n)\ln\lambda, \end{aligned}$$

where with a slight abuse of notation, $x(\phi,0)$ is taken to mean not just the leader's expansion effort but the sum of both incumbents'. The second line follows from the law of total probability, where $\tilde{\mu}(\psi) \equiv \sum_n \mu(\psi,n)$ is the marginal distribution of ψ and $f(n|\psi)$ denotes the distribution of n conditional on ψ. It is noteworthy that there is an equally valid and symmetric way of expressing the joint distribution $\mu(\psi,n)$ as the product of the marginal distribution of n and the conditional distribution of ψ conditional on n. The decomposition exercise following this alternative representation is conducted in Online Appendix C.3.[12]

Taking the difference between baseline and counterfactual growth, we can express the growth difference as the sum of the effects from successively changing the entrant's expansion intensities, the incumbents' expansion intensities, the distribution of types, and the conditional distribution of gaps from the counterfactual to the baseline level, which correspond exactly to the aforementioned direct, Schumpeterian, replacement, and pro-

[12]Under this alternative, we obtain a slightly smaller replacement effect and an even larger pro-competitive effect. To the extent that our main focus is on this new pro-competitive effect, we choose the relatively conservative estimate as our main finding.

competitive effects:

$$
\begin{aligned}
g_b - g_c = & \underbrace{\sum_{\psi} \mu_c(\psi,0)\left[\tau_b x_b^e(\psi,0) - \tau_c x_c^e(\psi,0)\right] \ln \lambda}_{\textit{direct effect}} + \underbrace{\sum_{\psi}\sum_{n\geq 0} \mu_c(\psi,n)\left[x_b(\psi,n) - x_c(\psi,n)\right] \ln \lambda}_{\textit{Schumpeterian effect}} \\
& \underbrace{+ \sum_{\psi}\left[\tilde{\mu}_b(\psi) - \tilde{\mu}_c(\psi)\right] f_c(0|\psi) \tau_b x_b^e(\psi,0) \ln \lambda + \sum_{\psi}\sum_{n\geq 0}\left[\tilde{\mu}_b(\psi) - \tilde{\mu}_c(\psi)\right] f_c(n|\psi) x_b(\phi,n) \ln \lambda}_{\textit{replacement effect}} \\
& \underbrace{+ \sum_{\psi} \tilde{\mu}_b(\psi)\left[f_b(0|\psi) - f_c(0|\psi)\right] \tau_b x_b^e(\psi,0) \ln \lambda + \sum_{\psi}\sum_{n\geq 0} \tilde{\mu}_b(\psi)\left[f_b(n|\psi) - f_c(n|\psi)\right] x_b(\psi,n) \ln \lambda}_{\textit{pro-competitive effect}}
\end{aligned}
$$

where subscripts b and c denote the baseline and the counterfactual economy, respectively. As is in many decomposition exercises in quantitative models, the order of introducing the baseline counterparts to the counterfactual components of aggregate growth matters for the quantitative magnitude of each effect. Following Ozkan et al. (2023), we report the Shapley-Owen decomposition results, which is essentially the simple average decomposition result of all possible orderings of evaluating the four effects.[13] The result is in Table 4.2.

Table 4.2: Shapley-Owen Decomposition of Growth Rate Differences between the Baseline and the Counterfactual Economy

Growth Rate Diff.	Direct	Schumpeterian	Replacement	Pro-Competitive
0.0105	0.0009	-0.0057	0.0018	0.0135
	8.52%	-53.89%	17.19%	128.17%

Note: This table shows the decomposition of the growth difference between the baseline and counterfactual economy into the direct, Schumpeterian, replacement, and pro-competitive effects.

Under the calibrated parameters, the four effects all have the expected signs, but their quantitative magnitudes vary greatly. The direct effect from entrants is modest, account-

[13]Online Appendix C.3 contains an introduction to the Shapley-Owen decomposition.

ing for 8.52% of the gain in aggregate growth in the baseline relative to the counterfactual. Similarly, the replacement effect, stemming from a better type distribution following the entry of high-growth type firms, is also moderate, accounting for 17.19% of the growth difference. The dominant force driving the gain in aggregate growth is the pro-competitive effect, which accounts for 128.17% of the growth difference, more than offsetting the negative Schumpeterian effect of -53.89%. These results point to the quantitative significance of allowing for the market structure to endogenously respond to entry in accounting for its impact on growth.

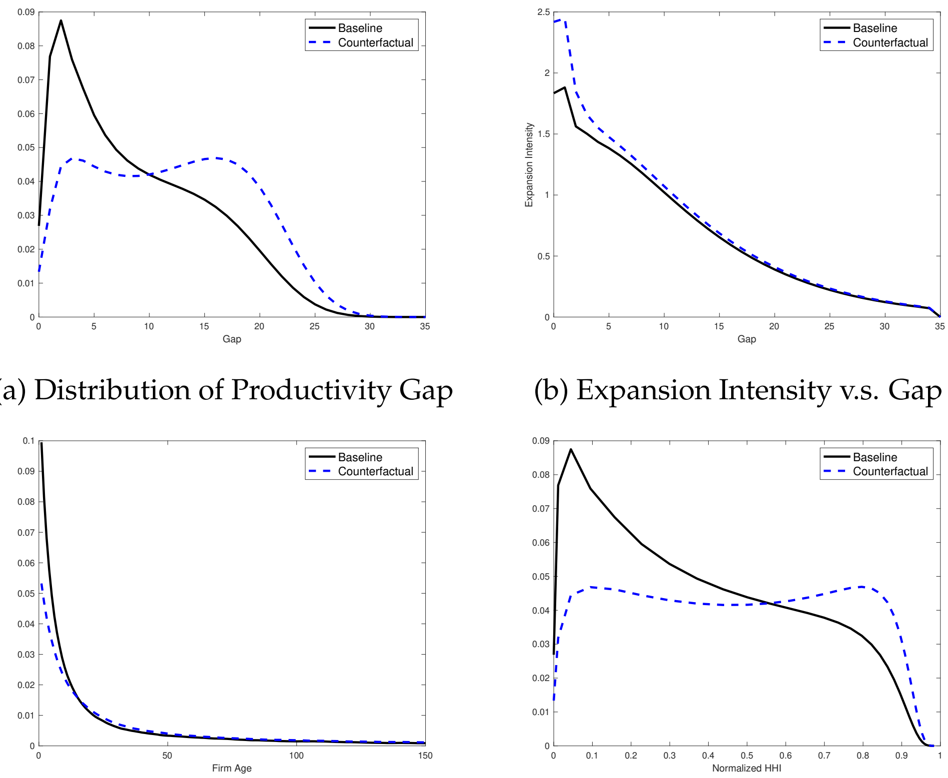
4.3.3. Discussions

The decomposition highlights two main countervailing forces more entry brings to the economy, a strong and growth-enhancing movement of industries towards more competitive industries and a sizeable reduction in the expansion incentives among incumbent leaders. To see these points, we plot the distribution of industries over the gap n and the leaders' expansion effort as a function of n in the baseline and counterfactual in Figure 4.2.[14]

Compared to the counterfactual with high entry barriers, the baseline produces a much larger mass of industries at small n as shown in Figure 4.2(a). It is in these highly competitive industries where the escape competition force is the strongest, as is typical in

[14] To be more precise, $\mu(n)$ is the marginal distribution of industry gaps and $x(n)$ is the average of leaders' expansion effects at gap n across all four type configurations. We show these two figures instead of $\mu(n|\psi)$ and $x(\psi, n)$ for brevity, but also because the decomposition shows that the replacement effect is relatively small, meaning that the type distributions in the counterfactual and the baseline are relatively similar. To illustrate, in the counterfactual model 36.23% of the leaders and 44.64% of the followers are of high type, and these numbers are slightly higher at 39.25% and 50.18% in the baseline (Table C.6). For more details and a discussion of the replacement effect, see Online Appendix C.3.

models of step-by-step innovation (Aghion et al., 2001) and evident from the downward sloping shape of the expansion effort function in Figure 4.2(b). As the baseline model produces a larger fraction of industries where leaders are most motivated to expand their businesses, the pro-competitive effect is strongly growth-enhancing. At the same time, Figure 4.2(b) also shows that relative to the counterfactual, leaders in the baseline spend less on expansion at every n, consistent with the sizeable negative Schumpeterian effect in the decomposition.



(a) Distribution of Productivity Gap

(b) Expansion Intensity v.s. Gap

(c) Distribution of Firm Age

(d) Distribution of Normalized HHI

Figure 4.2: Key Model Predictions, Baseline and Counterfactual

Note: This figure shows the distribution of productivity gap, expansion intensity as a function of the productivity gap, distribution of firm age and of normalized HHI in the baseline and the counterfactual.

Lastly, in Figure 2.1 of Section 2, we show how the distributions of firm age and industry normalized HHI evolve over time in the census sample. Although the observed distributions from 1995 Census cannot be directly compared to those generated from our counterfactual exercise, we can still examine whether the way the distributions shift from the counterfactual to the baseline is consistent with their evolution in the data (Figure 4.2(c) and (d)). Relative to the counterfactual, the distributions of firm age and normalized HHI are both shifted to the left, indicating more young firms and more competitive industries in the baseline, which is consistent with the empirical evolution of these distributions from 1995 to 2004.

4.3.4. Robustness Checks

From here on, we refer to the set of results from the baseline calibration, the counterfactual simulation and the associated decomposition that we have presented so far as the benchmark. To assess the robustness of the findings from the benchmark, we vary different aspects of the benchmark model one at a time to establish a new baseline, repeat the counterfactual analysis and compare the resulting decomposition result with the benchmark result. In the first robustness check, we shut down type transition entirely by letting $\sigma_h = \sigma_l = 0$. In the second, we let entrants enjoy a higher probability of immediate catch-up than incumbent followers. In the last, we add costless imitation along the lines of Aghion et al. (2001). The decomposition results from these three robustness checks are summarized and contrasted with the benchmark result in Table 4.3.[15]

[15] In addition to the three robustness checks presented here, we also report results in Online Appendix C.4 where 1) we vary the entry barrier τ differently than in the benchmark counterfactual, motivated by alternative ways to construct the counterfactual entry rate target (Online Appendix C.4.1); 2) we vary the value of the within-industry elasticity of substitution δ (Online Appendix C.4.2); 3) we vary the probability of fast catch-up ϕ (Online Appendix C.4.3); 4) we vary the probability of the high type among entrants θ (Online Appendix C.4.4). In all cases, the decomposition results share the same qualitative features as our benchmark result that pro-competitive effect is the strongest contributor to the productivity growth difference.

Table 4.3: Decomposition of Growth Rate Differences between the Baseline and Counterfactual Economy, Robustness Checks

Baseline Growth	Growth Rate Difference	Direct	Schumpeterian	Replacement	Pro-Competitive
Benchmark					
0.0574	0.0105	0.0009	-0.0057	0.0018	0.0135
		8.52%	-53.89%	17.19%	128.17%
Exercise 1. Permanent Types: $\sigma_h = \sigma_l = 0$					
0.0575	0.0066	0.0007	-0.0020	-0.0000	0.0079
		10.00%	-29.77%	-0.50%	120.28%
Exercise 2. Entrants' Faster Catch-Up: $\phi = 0.8 * \phi_e$					
0.0547	0.0115	0.0007	-0.0061	0.0017	0.0153
		6.01%	-53.36%	14.55%	132.80%
Exercise 3. Costless Imitation: $h = 0.0118$					
0.0612	0.0110	0.0012	-0.0065	0.0023	0.0141
		10.47%	-59.02%	20.90%	127.64%

Note: This table shows the decomposition of the growth difference between the baseline and counterfactual economy into the direct, Schumpeterian, replacement, and pro-competitive effects under alternative model assumptions.

Permanent Types Lentz and Mortensen (2014) show in a model of product innovation along the lines of Klette and Kortum (2004) that the stochastic transition of the creative types (similar to the high and low types in this model) matters for the desirability of entry. In their setting, when types are permanent, barring entry is actually good for growth due to the negative Schumpeterian effect of entry. We therefore simulate the model where $\sigma_h = \sigma_l = 0$ and all other parameters are kept as in the benchmark baseline, resulting in a new baseline growth of 5.75 percentage points. Then we increase the entry barrier by reducing τ to 0.6710 as in the benchmark and find that the aggregate growth is lowered by 0.66 percentage points (see Exercise 1 in Table 4.3). That is, reducing entry barriers is growth-enhancing even under permanent types. Two main points set the two papers apart: 1) While in Klette-Kortum type of models, the reward from entry is the same as the reward from product line expansion by an incumbent, in our model entrants have a stronger incentive to expand than the followers they replace due to the Arrow replacement effect.[16] 2) While in Klette-Kortum type of models, every industry is dominated by a monopolist, in our model entry shifts firms towards more competitive industries. The combination of entrants' strong incentive to expand and a positive impact on competition overwhelms the Schumpeterian effect independent of the assumption on type transition.

That said, the growth difference of 0.66 percentage points is much smaller than the 1.05 in the benchmark. This suggests that the type transition in the benchmark interacts and amplifies entry's contribution to growth. When entry is restrictive, the benchmark assumption of $\sigma_h > \sigma_l$ leads to a counterfactual steady state dominated by low types and less competitive industries relative to that under permanent types, which gives entry a bigger role to play, as evidenced by higher growth generated from direct, replacement, and pro-competitive channels under the benchmark. When examining the relative contributions of the four channels, we find in either case the relative importance of the pro-competitive effect is similar and is clearly the driving force behind the gain in growth.

Entrants' Faster Catch-Up In the benchmark calibration, entrants and followers face the same probability of fast catch-up: $\phi = \phi_e$ as in Akcigit and Ates (2023). Motivated by the result in prior literature that entrants are more likely to pursue radical innovations than incumbents (Akcigit and Kerr, 2018), we keep entrants' probability ϕ_e at the benchmark value and lower the followers' probability to $\phi = 0.8\phi_e$. This change reduces the baseline growth rate slightly to 5.47 percentage points but leads to a slightly larger growth differ-

[16] In an industry with technology gap n, the incremental value associated with successful expansion for a follower is $V(n-1) - V(n)$, which is smaller than the incremental value for an entrant, $V(n-1) - 0$. Such difference is not featured in Klette-Kortum type of models as adding a new product line brings the same incremental value for both entrants and incumbents.

ence compared to the counterfactual (see Exercise 2 in Table 4.3). This suggests that in the counterfactual where followers catch up more slowly, the industries tend to appear less competitive, which gives entry a bigger role to play. The decomposition of the growth difference is however similar to our benchmark result.

Costless Imitation In the literature, imitation is often modeled as a costless Poisson arrival rate on top of the expansion effort (e.g. Aghion et al. (2001)). We incorporate such costless imitation by assuming that the success of expansion arrives at the rate $x + h$, with the parameter h governing the importance of imitation, while keeping all other model aspects and parameters as in the benchmark. We set h to be a third of the baseline level of the follower's expansion intensity 0.0355 in the benchmark so that roughly a quarter of follower's catch-up is realized through free imitation. Unsurprisingly, the new baseline growth is higher at 6.12 percentage points (see Exercise 3 in Table 4.3). However, the growth difference between the baseline and counterfactual and its decomposition is similar to the benchmark results.

In all three robustness checks, the main message from the decomposition exercises remains the same. The dominant force to deliver higher productivity growth from a reduction of entry barriers is through promoting more competitive and dynamic industries.

4.4. A Two-Sector Extension with Input Wedges

So far we have abstracted away ex-ante heterogeneity across industries. However, prior research documents substantial cross-sectional variations in entry barriers, which are closely associated with the size of the state sector in an industry (Brandt et al., 2020). Moreover, the presence of SOEs are often suggestive of resource misallocation, which can have a large negative impact on aggregate total factor productivity (Hsieh and Klenow, 2009). In this section, we extend the benchmark model to having two sectors: a private firm dominated sector (Sector 1) and an SOE dominated sector (Sector 2). Suppose industries over the interval $[0,\zeta]$ are in Sector 1 and industries over $[\zeta,1]$ are in Sector 2.

The two sectors differ along three dimensions. First, the two sectors have their sector-specific expansion costs, β_h^i and β_l^i, where $i = 1,2$. These differences can reflect dynamic distortions that impede business expansion among the SOEs relative to private firms. Second, they have sector-specific entry barriers, τ_1 and τ_2, and in particular the reduction in τ is allowed to differ between the two sectors. Third, firms in Sector 2 face two sources of distortions: a distortion in the product market in the form of a static input wedge parametrized by ξ_2 and a distortion on the entry margin parametrized by ν_2.[17]

Distortions in Sector 2 Suppose that the two firms in an industry in Sector 2, with their unit cost of production given by c_1 and c_2, face an input wedge, $1+\chi_i$, $i = 1,2$. It is easy to show that the profit and revenue are functions of p_1/p_2 as before, while the relative price is affected by input distortions as well as technological gap (see Online Appendix C.5):

$$\frac{p_1}{p_2} = \frac{1+\chi_1}{1+\chi_2}\frac{\epsilon_1}{\epsilon_1 - 1}\frac{\epsilon_2 - 1}{\epsilon_2}\frac{c_1}{c_2} = \frac{1+\chi_1}{1+\chi_2}\frac{\epsilon_1}{\epsilon_1 - 1}\frac{\epsilon_2 - 1}{\epsilon_2}\lambda^{-n}.$$

To capture the wedges in the simplest possible form, we assume the relative wedges within a sector, $\frac{1+\chi_1}{1+\chi_2}$, is a function of the technology gap n, and parameterize this function as $(1+\xi_2)^{-n}$. When $\xi_2 > 0$, then $\chi_1 < \chi_2$ gives the leader (firm 1) an advantage relative to what their cost difference suggests. When $\xi_2 < 0$, the opposite is true and the follower

[17] We assume Sector 1 is free of distortions as we focus on the difference in the misallocation of resources between industries with a large state presence and the rest. To model the static distortion in production, assuming an input wedge instead of an output wedge is without loss of generality as there is one single input in the production.

(firm 2) captures a market share larger than what the cost advantage suggests. In addition, we also include an entry cost wedge (subsidy) in Sector 2, ν_2, such that the cost of entry becomes $\frac{\beta}{\nu_2}\frac{(x^e)^\alpha}{\alpha}$. For $\nu_2 > 1$, entry is subsidized and cost reduced. This allows for the possibility that the entry margin to the state-dominated sector can be distorted beyond the administrative and regulatory entry barrier we recognize.

Calibration We fix the parameters that are common to the two sectors at the benchmark level, $\{\rho, \alpha, \sigma_h, \sigma_l, \delta, \phi, \theta, \lambda\}$ and jointly calibrate the remaining parameters by minimizing a new set of model and data moments: $\{\zeta, \beta_h^1, \beta_l^1, \beta_h^2, \beta_l^2, \tau_1, \tau_2, \nu_2, \xi_2\}$. In the ASIE 2005-7 panel, we classify industries with SOE share larger than the economy-wide median SOE share as Sector 2 and industries below the median as Sector 1. As a result the SOE share in Sector 2 is 42.07% whereas in Sector 1 it is only 10.29% (Table 4.4). The sizes of the two sectors are similar, with Sector 1 slightly bigger, commanding almost 60% of total revenues in the economy. Notably, industries in Sector 1 appear more competitive by having more firms, lower HHI and more entry. The productivity growth rate is higher at 6.30% in Sector 1, as compared to 4.88% in Sector 2.

Table 4.4: Comparison of Sector 1 and Sector 2 in the Data

Moments	Sector 1	Sector 2
SOE share	10.29%	42.07%
Revenue share of total economy	53.83%	46.14%
Number of industries	212	211
Number of firms per industry	3241	2811
Average HHI per industry	0.0307	0.0358
Entry rates	12%	9.78%
Aggregate productivity growth	6.30%	4.88%

Note: This table shows summary statistics for the two sectors in 2004 Census.

The parameter that governs the relative sizes of the two sectors, ζ, is chosen to match the value added share of industries classified as Sector 1 in the data. The expansion costs in the two sectors target the productivity growth rate of the old and large firms and that of the young and large firms in the two sectors in the data.

The entry barrier of Sector 1 is directly calibrated to the average entry rate in Sector 1 in the 2004 Census. Using the benchmark value of τ and size of Sector 2, ζ, the entry barrier in Sector 2, τ_2, is inferred from $\zeta\tau_1 + (1-\zeta)\tau_2 = \tau$, with τ the level of entry barriers at the baseline of the one sector benchmark model. However, the inferred τ_2 may not imply the actual entry rate in Sector 2 in the 2004 Census, so the entry wedge ν_2 is chosen to bring the model entry rate in Sector 2 close to the data counterpart.

To calibrate the parameter that governs the severity of input wedges in Sector 2, we construct a measure of relative misallocation between the two sectors from the ASIE 2005-2007. As the model only has predictions on market shares, we regress the market share of a firm in the 4-digit industry to its logged productivity, controlling for the 4-digit industry fixed effects in Sector 1 and in Sector 2 separately. We take the ratio of the Sector 2 coefficient of log productivity to the Sector 1 coefficient, which gives us the targeted moment associated with ξ_2. This moment is 1.25 in the data, meaning market shares are more sensitive to productivity in Sector 2 than in Sector 1, suggesting relative to Sector 1, the leading firms in Sector 2 tend to have even larger market shares. We run analogous regressions in the two sectors in the model and compute the ratio of the coefficients to be matched to the data moment.

Results The calibration results are in Table 4.5. The marginal expansion costs of both types of firms are higher in Sector 2, rationalizing the lower productivity growth rates among both young and old (conditional on being large) firms. The input wedge parameter ξ_2 is positive, indicating that the input distortion favors the leaders in Sector 2, rationalizing the higher concentration given productivity differences observed in Sector 2.[18] The calibrated entry barrier in Sector 1 is 98.02% and in Sector 2 is 86.15%. However, given the higher entry barrier, the high expansion costs, and the disadvantage the input wedge imposes on followers in Sector 2, the model implied entry is much lower than in the data. The difference justifies an entry subsidy $\nu_2 > 1$, which means that the entrants to Sector 2, possibly firms owned by or connected to the state, are encouraged to enter despite the rather limited growth potential.

Table 4.5: Re-calibrated Parameters and Moments in the Two-Sector Model

Para.	Description	Value	Moment	Data	Model
ζ	size of S1	0.5914	value added share of S1	0.5914	0.5914
β_h^1	exp. cost of H firms in S1	1.1742	old and large firms' gr in S1	0.0449	0.0401
β_l^1	exp. cost of L firms in S1	3.6128	young and large firms' gr in S1	0.0750	0.0750
β_h^2	exp. cost of H firms in S2	1.6489	old and large firms' gr in S2	0.0386	0.0378
β_l^2	exp. cost of L firms in S2	2.7802	young and large firms' gr in S2	0.0675	0.0674
τ_1	entry barrier in S1	0.9802	entry rate in S1	0.1200	0.1203
ν_2	entry distortion in S2	1.4703	entry rate in S2	0.0978	0.0977
ξ_2	input wedge in S2	0.0212	ratios of TFP-size elast. S2 to S1	1.2500	1.2502

Note: $S1$ and $S2$ stand for sector 1 and 2, respectively.

As a validity check, we examine the sector-specific productivity growth rates in the model and in the data, which are not used as targets. The model predicts an aggregate productivity growth of 6.13% in Sector 1 as compared to 6.30% in the data and an aggregate productivity growth of 5.24% in Sector 2 as compared to 4.88% in the data.

Counterfactual and Decomposition In the counterfactual exercise, we recalibrate the two entry barrier parameters to target two counterfactual entry rates in the two sectors. Given the counterfactual reduction of economy-wide entry rate of 4.54 percentage points in the benchmark, we assume the counterfactual reduction in a sector to be in proportion

[18] For a precise proof of the effect of ξ_2 on the revenue share of the leader ω_1, see Online Appendix C.5.

to the change in observed entry rate from 1995 to 2004 in that sector, leading to 4.86 and 3.84 percentage points of counterfactual entry rate reduction in Sector 1 and Sector 2.[19] We re-calibrate the τ's in the two sector accordingly and find that the aggregate growth drops to 4.77 percentage points in the counterfactual, which is 1 percentage point lower than the baseline.

Table 4.6 shows the decomposition results for the two-sector model. In the sector that experiences a larger reduction in entry barriers, Sector 1, the gain in productivity growth is slightly higher. More importantly, across two sectors, the main driver of productivity gain is invariably through the pro-competitive effect. In fact, in the sector dominated by SOEs, the pro-competitive effect makes a slightly larger contribution to the growth differential than in the other sector. It is intuitive. As industries in Sector 2 are more concentrated than those in Sector 1, the increase in entry first and foremost changes the market structures across industries towards less concentration and more competition in that sector. To put it in other words, when the market structures are highly concentrated, the additional potential entrants allowed into the economy will not have much incentive to expand (i.e. smaller contribution from the direct effect), the incumbents will not find them as threatening (i.e. smaller contribution from the lower Schumpeterian effect), and even if the entrants bring in more high types into the sector, their incentive to expand will be hampered by the large gap they often find themselves in as a follower (i.e. smaller contribution from the lower replacement effect). As the relative importance of the chan-

[19]Since the observed changes in entry rates are 3.41, 2.69, and 3.18 percentage points for Sector 1, Sector 2, and the whole manufacturing, the counterfactual reductions in entry rates are then $4.54 \times \frac{3.41}{3.18} = 4.86$, $4.54 \times \frac{2.69}{3.18} = 3.84$, and 4.54 percentage points in Sector 1, Sector 2, and the whole manufacturing. This is consistent with the fact that SOE shares are negatively correlated with both contemporaneous entry rates but also subsequent entry growth (Online Appendix D.8).

nels adds up to one, it must imply that the relative contribution from the pro-competitive effect is larger in Sector 2. The last row in the table reports the weighted average of the growth differential and the four effects across the two sectors. Reassuringly, the overall picture remain similar to what we find from the benchmark one-sector model.[20]

Table 4.6: Decomposition of Growth Rate Differences between the Baseline and Counterfactual Economy in the Two-Sector Model

Growth Rate Diff.	Direct	Schumpeterian	Replacement	Pro-Competitive
Sector 1				
0.0108	0.0009	-0.0069	0.0036	0.0131
	8.59%	-63.71%	33.61%	121.51%
Sector 2				
0.0097	0.0006	-0.0053	0.0010	0.0134
	6.27%	-54.88%	10.80%	137.81%
Aggregate				
0.0104	0.0008	-0.0062	0.0026	0.0132
	7.69%	-59.61%	25.00%	126.92%

Note: This table shows the decomposition results for the two-sector model. The decomposition result for the aggregate economy is the weighted sum of those in Sector 1 and in Sector 2, with ζ as the weight for Sector 1.

5. Supportive Empirical Evidence

In this section, we delve into the empirical content of expansion costs and document additional empirical support for cross-sectional patterns among entry barriers, competition,

[20] An interesting counterfactual exercise which we cannot conduct due to data limitations is to calibrate the model to the 1990 economy and ask what is the effect on productivity growth from reducing entry barriers while keeping all other parameters constant. The insight from the two-sector model suggests that we would get a smaller positive impact on growth from the entry barrier reduction, but the impact may well be mostly driven by the pro-competitive effect (comparing the counterfactual and decomposition results for Sector 2 to Sector 1).

and growth in Chinese manufacturing.

5.1. Empirical Counterpart of Expansion Efforts

The aggregate productivity growth in this model is fueled by costly expansion efforts incumbents and entrants make to climb the quality ladder. The empirical content of the expansion efforts is therefore any costly activities to increase a firm's operational efficiency, reach new markets, streamline supply chains etc, which during the time period we examine are probably more relevant than R&D.[21] We therefore map the expansion cost to the sum of the sales and management expenses to arrive at a measure similar to the selling, general and administrative expenses following Eisfeldt and Papanikolaou (2014). This measure includes advertizing and marketing costs, R&D, administrative expenses and training costs, and we deflate it by the GDP deflator. Measured in this way, the employment-weighted firm-level expansion cost grows at 3.93% annually and the aggregate expansion cost per worker grows at 9.72% annually in our ASIE 1998-2007 panel.[22]

For this measure to be fit for purpose, we first verify that it predicts higher productivity growth in firm-level panel regressions. More specifically, we regress productivity growth of a firm on log expansion cost, controlling for firm fixed effect and year fixed effect, with or without further firm-level controls consisting of firm's log employment and last year's log capital stock (Column [1] and [2] of Table 5.1). Moreover, consistent with our model prediction, we find in less concentrated and more competitive industries, industry leaders spend more on expansion. We regress the log average expansion cost of the top

[21] Even today the efficiency of the R&D investments in China is uninspiring despite the central government's aggressive indigenous innovation policies (Wei et al., 2017; König et al., 2022; Cao et al., 2023).

[22] We plot the figure of these time series in Online Appendix D.1, where details of the following regressions can also be found.

10 firms in terms of revenue in a 4-digit industry from 2005 to 2007 on standardized HHI in 2004, controlling for 2-digit industry fixed effect and year fixed effect, with or without further 4-digit industry controls consisting of total number of firms, total employment, total revenue, and employment weighted SOE share all measured in 2004. The results are in Column [3] and [4] of the same table. In industries whose HHI is one standard deviation higher, the average expansion cost of the leading firms is 15 to 17% lower.

Table 5.1: Expansion Cost, Productivity Growth, and Market Structure

	Firm Productivity Growth		Top 10 Expansion Cost	
	(1)	(2)	(3)	(4)
	1999-2007	1999-2007	2005-2007	2005-2007
lnintan	0.0130***	0.0186***		
	(12.26)	(17.13)		
HHI in 2004			-0.169**	-0.148**
			(-2.69)	(-2.61)
R^2	0.239	0.262	0.366	0.413
Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	-	-
Firm controls	No	Yes	-	-
2-digit Industry F.E.	-	-	Yes	Yes
4-digit Industry controls	-	-	No	Yes
Observations	579819	579819	1278	1278

t statistics in parentheses
Firm controls include firm-level employment and lagged capital stock.
Industry controls include total number of firms, total employment and revenue, and employment weighted SOE share in 2004.
Standard errors are clustered at firm-level in firm productivity growth regressions.
Standard errors are clustered at 2-digit industry level in top 10 expansion cost regressions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results of regressing the firm-level productivity growth on expansion cost (column [1]-[2]) from 1999 to 2007 and the results of regressing the industry-level top 10 firms' average expansion cost between 2005 and 2007 on the industry's normalized HHI in 2004 (column [3]-[4]). See paper for detailed description of regression specifications.

5.2. Cross-Sectional Relationship Between Entry Barrier, Competition, and Growth

We exploit regional heterogeneity in China, albeit from a later period 2008-2013, to provide further supportive evidence on the relationships between entry barriers, competition and growth. In 2008, World Bank published a special report *Doing Business in China*, providing measures of the ease of starting a business in 26 provinces and 4 centrally administered municipalities in China. We use principal component analysis to construct an index of entry barrier that summarizes measures of various regulations of starting a business at the province level, and examine how this index of entry barrier correlates with outcomes in competition and growth across markets (defined as province-industry cells).

We examine two hypotheses: whether at the market level, measures of concentration and business dynamism correlate with the entry barrier index and whether at the firm level, firm's productivity correlates with the entry barrier index. At the market level, we use the log normalized HHI and the top 10 revenue share from 2008 Census as measures of concentration and the job reallocation rates in 2008-9 and in 2011-3 aggregated to the market level from ASIE as measures of business dynamism. To evaluate the first hypothesis, we regress each of these outcomes on the entry barrier index measured in 2008, controlling for province characteristics such as GDP per capita, industrial GDP share, and total population all measured in 2008, market characteristics such as total number of firms, total employment, total revenue, and employment weighted SOE shares all measured in 2008, and industry fixed effects. To evaluate the second hypothesis, we regress firm-level labor productivity growth over 2008-9 period and over 2011-3 period on the entry barrier index, controlling for province characteristics and firm characteristics such as age, employment, sales, ownership type, and export to output ratio all measured in 2008, and industry fixed effects.[23]

[23]We focus on labor productivity, which is revenue over employment, in this exercise, as in ASIE 2008-2013 firm-level information on value added, capital stock and intermediate inputs are missing. We skip the year 2010 in ASIE due to various irregularities displayed in 2010, a well-known problem in the literature (Chen et al., 2021). For details of the variable construction, sample selection and summary statistics of the ASIE and the Census samples, see Online Appendix A.1 and A.2. For details of the World Bank data and the construction of entry barrier index, see Online Appendix A.3. For details of the regressions, see Online Appendix D.2.

The results are in Table 5.2. Markets in provinces with one standard deviation higher entry barrier appear to be more concentrated, with a 15.5% higher HHI index and 2.69 percentage points higher revenue share of the top 10 firms (Column [1] and [2]). As the average revenue share of the top 10 firms is 78.4% in 2008, this amounts to a 3.4% increase in top concentration. When we look at the speed of job turnover, the same increase in entry barriers correlates with 2.57 percentage points reduction in job reallocation rates in 2008-9 and 1.25 percentage points reduction three years later in 2011-3 ((Column [3] and [4])). These amount to a 11% reduction from the average job reallocation rate in 2008-9 and 4% reduction from the average in 2011-13. At the firm-level, one standard deviation higher entry barrier coincides with about 3 percentage points lower labor productivity growth in 2008-9 and in 2011-3, or about 10% of the mean.

Table 5.2: Entry Barrier, Market Structure, and Growth, Cross-Section within China in 2008

	Market Structure		Business Dynamism		Firm Labor Productivity Growth	
	(1) log normalized HHI	(2) top 10 Share	(3) 2008-2009	(4) 2011-2013	(5) 2008-2009	(6) 2011-2013
Standardized values of (rank_hat_PF_raw)	0.155***	0.0269***	-0.0257***	-0.0125***	-0.0344***	-0.0288***
	(9.38)	(12.65)	(-6.29)	(-3.84)	(-2.60)	(-4.42)
R^2	0.407	0.635	0.098	0.183	0.039	0.023
4-digit Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes	Yes	Yes
Market controls	Yes	Yes	Yes	Yes	-	-
Firm controls	-	-	-	-	Yes	Yes
Observations	10842	10842	7260	7260	88871	88871

t statistics in parentheses
Province controls include GDP per cpaita, industrial GDP share, and total population in 2008.
Market controls include total number of firms, total employment, total revenue, and employment weighted SOE share in 2008.
Firm controls include age, employment, sales, ownership types and export to output ratio in 2008.
Standard errors are clustered at 4-digit industry level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the results of regressing the market-level normalized HHI and top 10 revenue share (column [1]-[2]), job reallocation rates in 2008-09 and 2011-13 (column [3]-[4]), and firm-level labor productivity growth in 2008-09 and 2011-13 (column [5]-[6]) on the Entry Barrier Index respectively. See paper for detailed descriptions of regression specifications.

In sum, we observe a clear pattern in the data that markets tend to be more concentrated and less dynamic and firm's productivity growth tend to slow down where entry barriers are higher. In Online Appendix D.6, following the same methodology, we report similar relationships between entry barriers, concentration, and productivity growth in a panel of European countries, which suggests that the mechanism we emphasize in this paper may deserve study in other economic contexts too.[24]

6. Conclusion

In this paper, we revisit the narrative that the economic reforms removed hurdles to entering previously state-dominated industries, unleashed unprecedented competition, and achieved remarkable productivity growth in the economic history of the People's Republic of China. We examine this process through the lens of a model of endogenous productivity and market structure with heterogeneous firms and frictional entry. To the best of our knowledge, we are the first to adopt such a theoretical framework to understand the effect of the reduction of entry barriers on TFP growth in China.

We calibrate the model to the Chinese manufacturing sector in 2004-7 and ask counterfactually what the productivity growth would be if the regulatory and administrative entry

[24] In Online Appendix D, we conduct a series of additional empirical analyses. We report the results using alternative measures of entry barriers (in Online Appendix D.3); using employment-based measures of market concentration (in Online Appendix D.4); focusing on the subsamples of privately owned firms and of firms serving mainly the domestic markets respectively (in Online Appendix D.5). Furthermore, the World Bank's measure of the entry barriers captures the variation across provinces in the formal institution but does not reflect potential differences in business culture or informal institutions, which nevertheless can be important (Bai et al., 2020). Admittedly these measures can also correlate with other formal institutions that affect our outcome variables, leading to an omitted variable bias. Therefore we interpret our empirical results as only suggestive. We show in Online Appendix D.7 that if we replace the entry barrier measure with the observed entry rate, the same correlation patterns emerge.

barriers remained as high as in 1990. We find that the reduction in entry barriers accounts for 1.05 percentage points of aggregate productivity growth, or 18.3% of the level achieved in 2004-7. The gain in growth is predominantly driven by a pro-competitive effect whereby increased entry induces more industries to be less concentrated and more competitive. This pro-competitive effect more than offsets the negative Schumpeterian effect, which discourages incumbents to grow faced with heightened threat from entry. In comparison, the entry induced replacement effect is relatively moderate. These main findings are robust to extending the model to having two sectors, a private firm dominated sector and an SOE dominated sector, and allowing for additional sources of misallocation associated with the SOE dominated sector.

While our paper focuses on the regulatory and administrative burden a potential entrant must overcome, these entry barriers may reflect one of many facets of a higher-level economic strategic plan, be it industrial policy or local government fiscal policy. Our results highlight the vital importance of allowing for endogenous market structure in the evaluation of those policies. More generally, we recognise that entry barrier is only one form of anti-competitive measures. Unequal access to credit and financial markets, preferential treatment in tax/subsidies, political interference in commercial activities or biased courts can all hinder competition and prevent the economy from achieving its growth potential. We leave each of these topics for future research.

Data Availability Statement

We use two main sources of data for our paper: (1) Annual Surveys of Industrial Enterprises (ASIE) from 1998 to 2013 and (2) Industrial Census 1995, 2004 and 2008, both of which are from the National Bureau of Statistics of China. Both data are widely used in the literature.

We obtained access to the ASIE through Peking University Library, who purchased the data from the following vendor:
Beijing Sou Zhi Data Science Ltd
Tel: 010-85786020
Email: sales@sozdata.com
Address: 303, 3/F, Kunxun Building, no. 9 Zhichun Road, Haidian District, Beijing 100083, China

We obtained access to the Census data from Shanghai University of Finance and Economics Library, who purchased the data from a vendor no longer in operation. However the data can also be purchased from EPSDATA:
https://www.epsnet.com.cn/index.html#/Index (accessed last 12/31/2023).

We note that the raw data from the above two sources are not available for public download. But some research universities in mainland China have access to both of them, for example the Experiment and Data Center of Shanghai Jiaotong University's Antai College of Economics and Management. We however provide replication codes, which will help anyone who has access to these data to replicate our main results in the paper.

We also use the World Bank's data on Starting a Business in the Doing Business Survey. This data is publicly available, which we also provide in the replication package. The

replication package is available for download at the following repository:
https://qmro.qmul.ac.uk/xmlui/handle/123456789/94013.

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr, "Innovation, Reallocation, and Growth," *American Economic Review*, 2018, *108* (11), 3450–91.

Aghion, Philippe, Christopher Harris, Peter Howitt, and John Vickers, "Competition, Imitation and Growth with Step-by-Step Innovation," *Review of Economic Studies*, 2001, *68* (3), 467–492.

_ , Nick Bloom, Rchard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: An Inverted-U Relationship," *Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

_ , Robin Burgess, Stephen Redding, and Fabrizio Zilibotti, "Entry Liberalization and Inequality in Industrial Performance," *Journal of the European Economic Association*, 2005, *3*, 291–302.

Akcigit, Ufuk and Sina T. Ates, "What Happened to U.S. Business Dynamism," *Journal of Political Economy*, 2023, *131* (8), 2059–2124.

_ and William R Kerr, "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 2018, *126* (4), 1374–1443.

Asturias, Jose, Sewon Hur, Timothy J. Kehoe, and Kim J. Ruhl, "Firm Entry and Exit and Aggregate Growth," *American Economic Journal: Macroeconomics*, 2023, *15* (1), 48–105.

Ates, Sina T. and Felipe E. Saffie, "Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 304–356.

Bai, Chong-En, Chang-Tai Hsieh, and Zheng Song, "Special deals with Chinese characteristics," *NBER Macroeconomics Annual*, 2020, *34* (1), 341–379.

Brandt, Loren, Gueorgui Kambourov, and Kjetil Storesletten, "Barriers to Entry and Regional Economic Growth in China," *CEPR Discussion Papers*, 2020.

__ **, Johannes Van Biesebroeck, and Yifan Zhang**, "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 2012, *97* (2), 339–351.

__ **, Thomas G. Rawski, and John Sutton**, "China's Industrial Development," in Loren Brandt and Thomas G. Rawski, eds., *China's Great Economic Transformation*, Cambridge University Press, 2008, p. 569–632.

Cao, Linyi, Helu Jiang, Guangwei Li, and Lijun Zhu, "Haste Makes Waste? Quantity-Based Subsidies Under Heterogeneous Innovations," *Journal of Monetary Economics*, 2023.

Chen, Qiaoyi, Zhao Chen, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Xu, "Regulating Conglomerates in China: Evidence from an Energy Conservation Program," *NBER Working Paper No. 29066*, 2021.

Cheremukhin, Anton, Mikhail Golosov, Sergei Guriev, and Aleh Tsyvinski, "The Political Development Cycle: the Right and the Left in People's Republic of China from 1953," *American Economic Review*, forthcoming.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Declining Business Dynamism: Implications for Productivity," *Brookings Institution, Hutchins Center Working Paper*, 2016.

Eisfeldt, Andrea L. and Dimitris Papanikolaou, "The Value and Ownership of Intangible Capital," *American Economic Review*, 2014, *104* (5), 189–194.

__ **, Antonio Falato, and Mindy Z. Xiaolan**, "Human Capitalists," *NBER Macroeconomic Annual*, 2023, *23.*

Groves, Theodore, Yongmiao Hong, John McMillan, and Barry Naughton, "Autonomy and Incentives in Chinese State Enterprises," *Quarterly Journal of Economics*, 1994, *109* (1), 183–209.

Haltiwanger, John, Ron S. Jarmin, Robert Kulick, and Javier Miranda, "High Growth Young Firms: Contribution to Job, Output, and Productivity Growth," in John Haltiwanger, Erik Hurst, Javier Miranda, and Antoinette Schoar, eds., *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, University of Chicago Press, 2016, pp. 11–62.

Herrendorf, Berthold and Arilton Teixeira, "Barriers to Entry and Development," *International Economic Review*, 2011, *52* (2), 573–602.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

— **and Zheng Michael Song**, "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," *Brookings Papers on Economic Activity*, 2015, pp. 295–346.

Imbert, Clement, Marlon Seror, Yifan Zhang, and Yanos Zylberberg, "Migrants and Firms: Evidence from China," *American Economic Review*, 2022, *112* (6), 1885–1914.

Klette, To Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

Koh, Dongya, Raul Santaeulalia-Llopis, and Yu Zheng, "Labor Share Decline and Intellectual Property Products Capital," *Econometrica*, 2020, *88* (6), 2609–2628.

König, Michael, Kjetil Storesletten, Zheng Song, and Fabrizio Zilibotti, "From Imitation to Innovation: Where is All That Chinese R&D Going?," *Econometrica*, 2022, *90* (4), 1615–1654.

Lentz, Rasmus and Dale T. Mortensen, "An Empirical Model of Growth Through Product Innovation," *Econometrica*, 2014, *76* (6), 1317–1373.

McMillan, John and Barry Naughton, "How to Reform a Planned Economy: Lessons from China," *Oxford Review of Economic Policy*, 1992, *8* (1), 130–143.

North, Douglass C. and Robert Paul Thomas, *The Rise of The Western World: A New Economic Histroy*, Cambridge University Press, 1973.

Ozkan, Serdar, Joachim Hubmer, Sergio Salgado, and Elin Halvorsen, "Why Are the Wealthiest So Wealthy? A Longitudinal Empirical Investigation," 2023. CESifo Working Paper No. 10324.

Parente, Stephen L. and Edward C. Prescott, "Monopoly Rights: A Barrier to Riches," *American Economic Review*, 1999, *89* (5), 1216–1233.

Peters, Michael, "Heterogeneous Markups, Growth and Endogenous Misallocation," *Econometrica*, 2020, *88* (5), 2037–2073.

Qian, Yingyi, "How Reform Worked in China," *William Davidson Institute Working Paper 473*, 2002.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing Like China," *American Economic Review*, 2011, *101* (1), 196–233.

Wei, Shang-Jin, Zhuan Xie, and Xiaobo Zhang, "From "Made in China" to "Innovated in China": Necessity, Prospect, and Challenges," *Journal of Economic Perspectives*, 2017, *31* (1), 49–70.

World Bank, *Doing Business 2020*, Washington, DC: The World Bank, 2020.

Zhu, Xiaodong, "Understanding China's Growth: Past, Present, and Future," *Journal of Economic Perspectives*, 2012, *26*, 103–124.