

Entry Barriers and Growth: The Role of Endogenous Market Structure

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Working Paper No. 956

June 2023

ISSN 1473-0278

School of Economics and Finance



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

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May 7, 2022

Abstract

We use China's growth experience as a laboratory to study how reductions in entry barrier contribute to economic growth by inducing a more competitive market structure. The removal of entry restrictions on private firms in the late 1990s and early 2000s made the Chinese economy more competitive and dynamic, propelling the growth acceleration from the early 1990s to late 2000s. We develop a model of endogenous productivity and market structure with heterogeneous firms and frictional entry and calibrate it to Chinese manufacturing from 2004-7. We show about 25% of the productivity growth in 2004-7 is contributed by the reduction of entry barriers during the reforms in the previous decade. While close to 40% of the gain in growth comes from entry bringing about younger firms with higher growth potential, over 60% of the gain in growth comes from entry enforcing tighter market competition which strengthens all active firms' incentive to grow. We also provide suggestive evidence that this mechanism may be at play in a wider economic context.

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

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

*We 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, China Macro-Finance Study Group, Bristol, UCL, Essex, Jinan University, Fudan 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.

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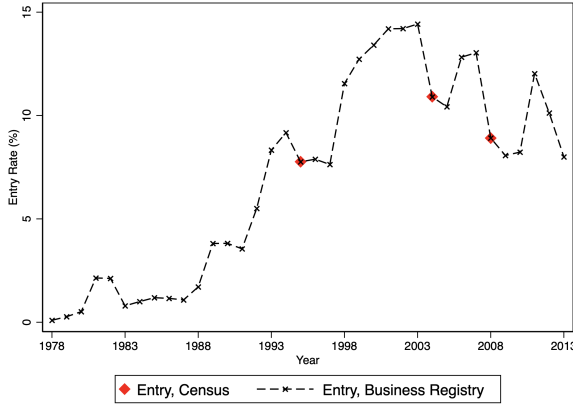
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1 Introduction

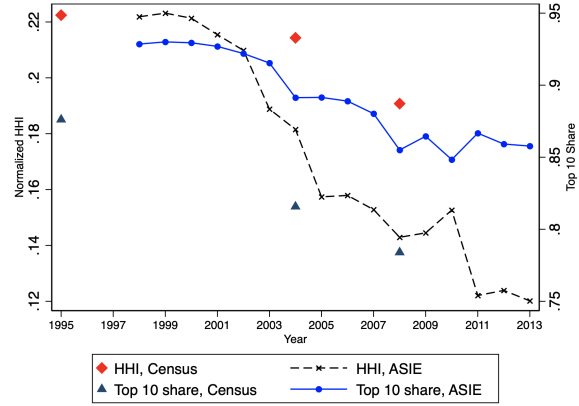
Growth in an economy might be stifled if entry is limited and incumbents, facing no competitive pressure, lack incentives to improve and growth. Writing on the rise of the western world during 1500-1700, [North and Thomas \(1973\)](#) ascribe the stagnation of France to the industrial regulation and 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 reform ([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 contribute 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 market structure or concentration measures: the normalized Herfindahl–Hirschman Index (HHI), which adjusts for the total number of firms, and the revenue share of the largest ten firms averaged across markets (defined as 4-digit industry and province cells), 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 in GDP per capita over 8% in the post-reform era ([Zhu, 2012](#)).

To allow entry to affect competition as well as growth, we develop a model that is built on the step-by-step quality ladder framework ([Aghion et al., 2001](#)), which features endogenous productivity and market structure, and enrich it with frictional entry and ex ante



(a) Entry Rate



(b) HHI and Top 10 Share

Figure 1.1: Entry and Market Structure 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 Appendix A.5.

heterogeneous firms to study the entry-competition-growth nexus. The economy consists of a continuum of symmetric industries. In each industry, there is a quality ladder which firms compete to climb. More specifically, there are two incumbent firms; the firm that is ahead on the quality ladder is the leader, and the one lagging behind is the follower. The leader and the follower, which produce goods that are imperfect substitutes, engage in Bertrand competition and incur costs to climb the ladder and expand their respective market shares. As is typical in this class of models, in industries where the quality gap between the leader and the follower is smaller and hence competition is tighter, growth incentives and expansion efforts by both the leader and the follower are stronger.

We introduce ex ante firm heterogeneity as follows: Firms can be one of two types—The high (low) growth potential type has lower (higher) cost of expansion; Over time, high types transition into low types, which is to capture that firms tend to grow slower as they age, a fact well known in the US data and we also document for China. There is a potential entrant in each industry at any point in time, who attempts to break into the market but is also subject to probabilistic approval, which we interpret as the entry barrier. Potential entrants who are successful in their expansion effort and obtain approval eventually enter to replace incumbents. Intuitively, when entry barrier is high and entry is severely limited, an industry is more likely to settle in a stale state where low-type follow-

ers do not pose meaningful challenges to low-type leaders. Without explicitly modelling state-owned enterprises, we view this state as a partial characterization of the pre-reform industries dominated by SOEs with low growth potential where market concentration is high, dynamism low, and growth stagnant.

As 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 typical in step-by-step quality ladder 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 are often inefficient in expansion, the type distribution is improved in the stationary equilibrium, leading to a 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. As entrants bring back competition and dynamism, more industries become more competitive in the stationary equilibrium and it is in those competitive industries where incentive to growth is the strongest and most expansion effort takes 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 important.

We calibrate the model to the Chinese manufacturing in 2004-7 and then conduct a counterfactual analysis to quantify how much of the 2004-7 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 which 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 then combine the change in the entry barrier with an elasticity of entry rate to the entry barrier estimated from a cross-sectional sample of Chinese provinces to construct a counterfactual entry rate in the pre-reform 1990s and recalibrate the model. We find that the reform-induced entry accounts for 24.7% of the productivity growth of the manufacturing sector from 2004-7. Of the policy-induced gain in growth, 37.60% stems from the replacement effect and 63.87% stems from the pro-competitive effect, while the direct and Schumpeterian effects roughly wash out. These results underscore the importance of adopting a model which endoge-

nizes market structures.

Last, we provide additional empirical evidence on the cross-sectional relationship between entry barriers, competition and growth, both from within and beyond China. Exploiting regional variations in the Starting a Business score from a special *Doing Business in China* Report from 2008 ([World Bank, 2008](#)), we document that within a 4-digit industry, in provinces where entry barrier is lower, measures of market competition and business dynamism are higher and firms achieve faster labor productivity growth in subsequent years. These correlations are robust to a host of region-year and firm-year controls, and consistent with the prediction of our model. Beyond China, in a panel of European countries for which we can aggregate micro-founded measures of competition and growth in a similar way, we also find entry barriers strongly and negatively correlate with measures of competition, business dynamism and productivity growth across countries and sectors. These results suggest the mechanism we formulate in this paper is not only at play along the growth path of China, but can also potentially be relevant in a much wider economic context.

The paper is related to three strands of literature. The first strand of literature examines 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., forthcoming](#)). In particular, [Asturias et al. \(forthcoming\)](#) study the role of entry in a Hopenhayn style model, in which the productivity distribution from which entrants draw grows at an exogenous rate. In contrast, we do not require successively more productive cohorts of entrants to generate growth. All cohorts of entrants in our model have the same type distribution and the transition between types is independent of cohort. More recently, [Peters \(2020\)](#) examines how the costs of entry and expansion can explain differences in firm size and misallocation between the US and Indonesia in a model of endogenous markup and productivity, and finds that the effect of the cost of entry on growth rate differences are muted. We obtain much larger effect on growth from reducing cost of entry in the Chinese context, because in our model old leading incumbents in the high entry barrier case tend to have low growth potential and their incentive to expand is limited by the escape competition concern. We think this is a plausible description of the state of affair in the pre-reform China, where, different than in the US, we do not observe highly productive old/large leaders.

The second strand of literature our paper relates to is Schumpeterian growth models with

step by step quality improvement (Aghion et al., 2001, 2005a). The class of Schumpeterian innovation-driven growth models, especially its extension into heterogeneous firms, are widely used to study general issues related to firm dynamics and aggregate growth (Lentz and Mortensen, 2014; Ates and Saffie, 2021; Peters, 2020). An example is Akcigit and Ates (2019), who uses this framework to study the declining business dynamism in the United States. It's worth pointing out that in versions of the Schumpeterian models where firms are ex-ante homogeneous, entry has ambiguous effect on growth and is often found to have limited effect on macroeconomic trends. We build on this class of models by introducing ex-ante heterogeneous firms and frictional entry to adapt to the context of a growing developing country and show in the case of China, reducing entry barriers has significant effect on 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., 2015). Brandt et al. (2012) finds that net entry accounts for about two thirds of China's TFP growth from 1998-2007. 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 market competition and generating growth.

The rest of the paper is organized as follows. In Section 2, we provide some institutional background of reforms targeting regulatory entry barriers and some motivating facts. In Section 3, we present the model of endogenous productivity and market structure with heterogeneous firms and frictional entry. In Section 4, we calibrate the model to the Chinese manufacturing in 2004-7 and quantify the contribution to growth from reducing the regulatory entry barriers in the preceding decade. We propose a growth rate decomposition to highlight the various channels through which entry affects growth. Section 5 provides further cross-sectional evidence that a lower entry barrier is associated with more competitive market structure and more rapid growth within and beyond China. 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, 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, i.e., four special economic zones. 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 state-owned firms and encouraging the entry of private firms. In 1994, a new Company Law was adopted, which standardizes 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 state-owned enterprises in selected sectors such as power and petrochemicals, railways, and telecommunications while allowing a large number of small state-owned enterprises to be privatized and encouraging firms to enter in non-strategic sectors and markets.

As a result of these reforms, from 1990s to 2000s the aggregate entry rate increased substantially and aggregate measures of competition improved for the entire industrial sector (Figure 1.1). These changes are also reflected by how the cross-sectional distributions of firm age and market-level concentration evolve over time. Panel (a) of Figure 2.1 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 the 1995 Census to 1.8 million in the 2008 Census. 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 markets (defined as 4-digit industry cross province cells) in 1995, 2004, and 2008. In 1995, 33.3% of markets

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

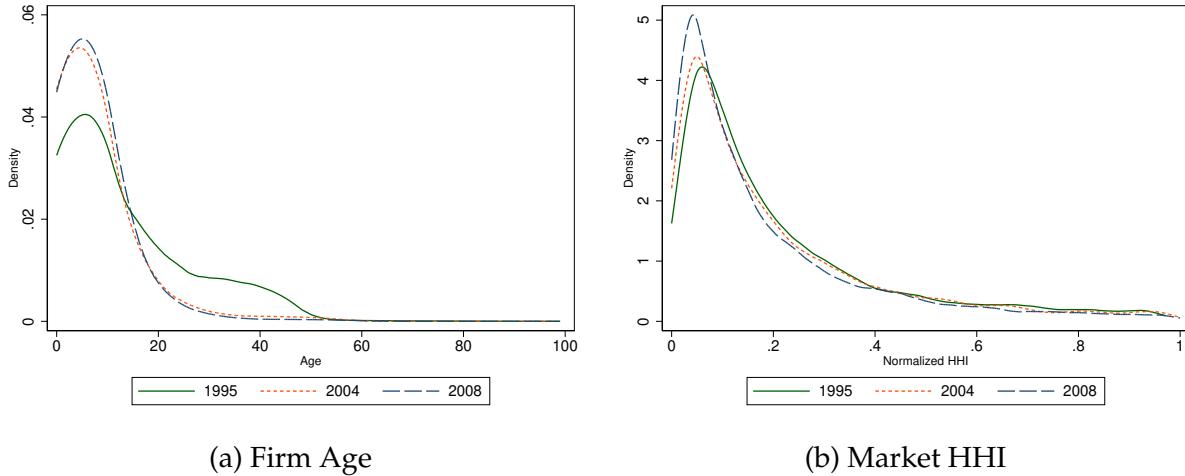


Figure 2.1: Distribution of Firm Age and Market HHI, 1995, 2004, and 2008 Census Samples

Note: This figure shows the distribution of age across firms and normalized HHI across markets in the 1995, 2004, and 2008 Industrial Census respectively. Details on variable construction and sample selection are in Appendix A.

had a normalized HHI greater than 0.5, while this fraction decreased sharply to 26.2% in 2004 and further to 22.6% in 2008.

Entry tends to bring in young firms which are more productive and grow faster than incumbent old firms. This is a selection channel through which entry affects growth, which is well studied in the literature (Asturias et al., forthcoming; Brandt et al., 2020). We confirm that 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 Panel (a) of Figure 2.2, we show the predicted employment growth by age groups for a panel of manufacturing firms from 2005-7.² Firms less than 2 years old (the bottom 5% in the age distribution) grow 9.3% a year, while firms aged above 22 (the top 5% in the age distribution) grow 2.65% annually. Moreover, in this paper we want to emphasize a new pattern in the data where growth tends to happen in markets that are more competitive and less concentrated, as shown in Panel (b) of Figure 2.2. In addition to the aforementioned selection effect, the changing market structure can be another channel where entry affects growth. In a world where entry changes both the productivity of growth potential

²More specifically, using employment as the measure of firm size, we regress firm-level annual employment growth on firm's age, controlling for 4-digit industry fixed effect, firm-level characteristics and market-level characteristics in the ASIE 2005-7 panel, and then plot the average predicted employment growth by age and HHI percentile groups in the figure. This pattern also holds when we use firm's revenue, value added or productivity instead of employment.

distribution of the active firms (and therefore the active firms' abilities to grow) and the market structure in which those firms operate (and therefore the active firms' incentive to grow), these figures merely portray the joint outcome of those forces from different angles. 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 and the market structures to endogenously respond to entry, which we turn to next.

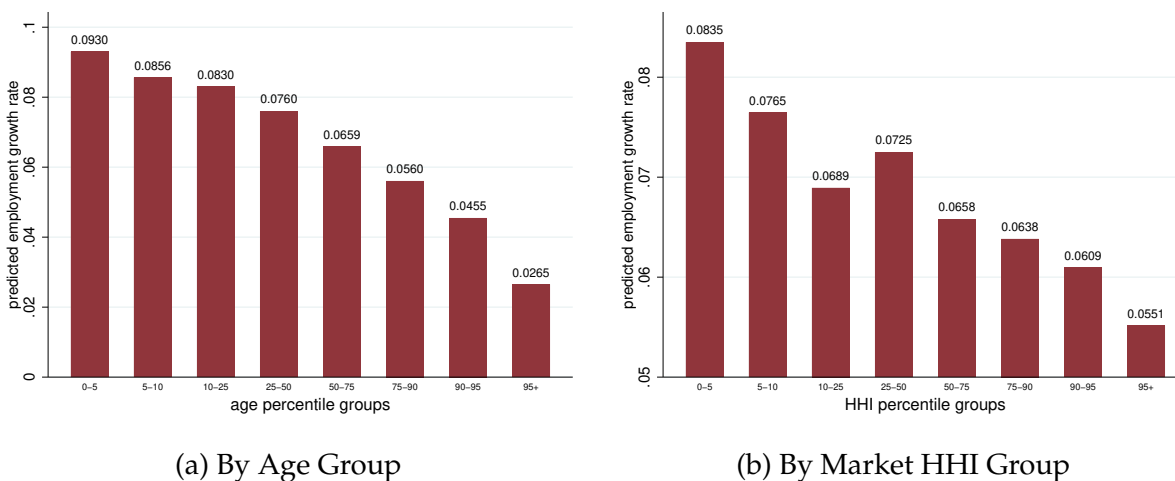


Figure 2.2: Annual Firm Growth Rate by Age and HHI Groups

Note: This figures shows the predicted annual firm employment growth by age percentile groups and by HHI percentile groups. Firm's employment growth is calculated as the average of annual growth rates over 2005-7. We regress firm-level employment growth rate on firm's age, controlling for employment, capital, ownership types, 4-digit industry fixed effects and market characteristics such as market-level HHI, total number of firms, total employment, and total real revenue.

3 Model

In this section, we construct a theoretical model to study how entry affects economic growth by inducing a more competitive market structure. Building on the step-by-step quality ladder framework (Aghion et al., 2001; Akcigit and Ates, 2019), 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 barrier on market structure and aggregate 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 by³

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

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 over 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 firms in any industry, which are

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

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 $p_i = \frac{\epsilon_i}{\epsilon_i - 1} c_i$, where ϵ_i is the price elasticity

³As in [Aghion et al. \(2001\)](#) we use a log-linear utility function to eliminate equilibrium effects through wage, and focus on the competition effect.

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

⁵We can alternatively assume Cournot competition, under which firm i 's optimal pricing rule is $p_i = \frac{1}{\delta(1-\omega_i)} c_i$. The key property that revenue and profit are logistic functions in technology gaps is unchanged.

of demand for firm $i = 1, 2$. It can be easily shown that this elasticity takes the form $\epsilon_i \equiv \frac{1-\delta\omega_i}{1-\delta}$, with $\omega_i \equiv p_i y_i = \frac{p_i^{\delta/(\delta-1)}}{p_1^{\delta/(\delta-1)} + p_2^{\delta/(\delta-1)}}$ being the revenue of firm $i = 1, 2$. Correspondingly, the profit of firm i is $\pi_i = \frac{\omega_i}{\epsilon_i}$, for $i = 1, 2$. Note that as the revenue, ω_i , is only determined by the price ratio, p_1/p_2 , so is the elasticity of demand, ϵ_i . 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.

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.⁶ 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 the benefit of firms' efforts to move along the ladder, firms in industries with a smaller gap, i.e. more competitive industries, have a larger incentive to advance on the ladder either to escape competition or to leapfrog.

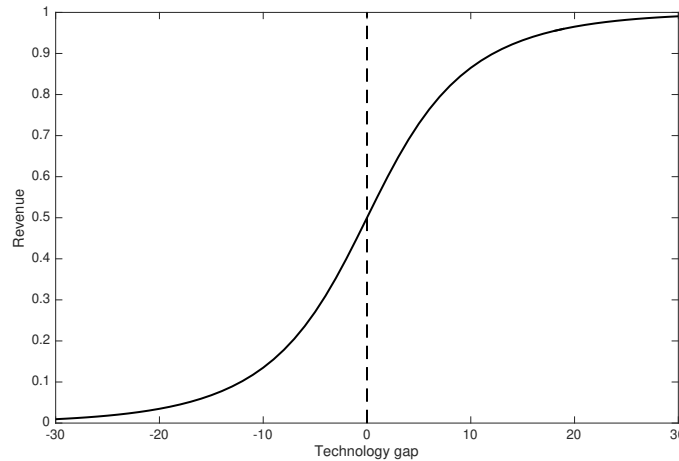


Figure 3.1: Revenue Function, Model

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

Investment and Expansion In each industry, there exists a leader, a follower, and a potential entrant. Denote n the quality gap between the current leader and follower in an

⁶Profit, which determines firm's innovating incentives, follows a similar functional form.

industry, and $\pi(n)$ and $\bar{\pi}(n)$ the associated profit for the leader and follower, respectively. We label an industry where $n = 0$ a neck-and-neck industry. When a leader invests and succeeds, it expands its advantage from n to $n + 1$. Upon a successful investment of a follower, with probability ϕ , it immediately catches up with the leader and closes completely the quality gap, i.e. from n to 0; with probability $1 - \phi$, it cuts the quality gap by 1 step, from n to $n - 1$. If a potential entrant invests and succeeds, it replaces the follower in an industry with positive gap, i.e. $n \geq 1$, and replaces each incumbent firm with equal probability in a neck-and-neck industry.⁷

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 we have $\beta_h < \beta_l$. To achieve an arrival rate of x of successful expansion, a firm needs to pay a cost of $\beta_i \frac{x^\alpha}{\alpha}$. Overtime, a high-type firm may transit to become a low type at Poisson rate σ , while a low type is an absorbing state. This captures the fact that some firms become less productive at expansion as they grow old over time.^{8,9} Depending on the types of the leader and follower pair, we can divide industries into four categories: hh, hl, lh , and ll . The first letter stands for the leader's type and the second the follower's type. For example, in an hh industry, both leader and follower are of the high type. An industry 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 \bar{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. Given our assumption of the type transition, the Poisson rate of type transition for a type- i firm is

$$\sigma_i = \begin{cases} \sigma, & \text{if } i = h; \\ 0, & \text{if } i = l. \end{cases}$$

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 invests to attempt a product which is better than that offered by the existing follower. With probability ϕ , the quality of its product is on par

⁷This setting for entrants is the same as [Akcigit and Ates \(2019\)](#).

⁸[Acemoglu et al. \(2018\)](#) make a similar assumption.

⁹The model abstract away from capital and labor market frictions, which can impact the rate at which a firm grows. In other words, the effects of such frictions are captured in a reduced form by parameters such as the quality step size, λ , and the cost of expansion parameters, $\beta_i, i = h, l$.

with that of the current leader; with probability $1 - \phi$, it cuts the existing quality gap by 1 step. However, even if the investment is successful, its entry is subject to an administrative review: with probability τ , its application is approved, and with probability $1 - \tau$, it is not. Only when the application is approved, the firm can 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.

There are two sets of value functions. The first set describes the values of the leader, the follower and the potential entrant in an industry with a quality gap of $n \geq 1$: $V_{ij}(n)$, $\bar{V}_{ij}(n)$, and $V_{ij}^e(n)$. The second set of value functions describes the values of the two incumbents and the potential entrant in a neck-and-neck industry: $V_{hi}^h(0)$, $V_{li}^l(0)$, and $V_{ij}^e(0)$. Since there is no notion of leader or follower in the neck-and-neck state, the bar notation no longer applies and the order of the types in the subscripts has no meaning. Instead, $V_{hi}^h(0)$ (or $V_{li}^l(0)$), for $i = h, l$, simply denotes the high-type (or low-type) incumbent in the neck-and-neck industry with composition $\{h, i\}$ (or $\{l, i\}$). Since $V_{hl}^h(0) = V_{lh}^h(0)$ and $V_{hl}^l(0) = V_{lh}^l(0)$, for convenience we use $V_{hi}^h(0)$ and $V_{li}^l(0)$ in these cases. We outline the value functions as follows.

Start with the first set of value functions for an industry characterized by (i, j, n) , where $i, j \in \{h, l\}$ and $n \geq 1$. The value function for the leader is

$$\begin{aligned}
rV_{ij}(n) = \max_{x_{ij}(n)} & \underbrace{\pi(n)}_{\text{profit}} - \underbrace{\beta_i \frac{x_{ij}(n)^\alpha}{\alpha}}_{\text{exp. cost}} + \underbrace{x_{ij}(n)[V_{ij}(n+1) - V_{ij}(n)]}_{\text{successful expansion}} + \underbrace{\sigma_i[V_{lj}(n) - V_{ij}(n)]}_{\text{change of self-type}} \\
& + \underbrace{\sigma_j[V_{il}(n) - V_{ij}(n)]}_{\text{change of follower type}} + \underbrace{\bar{x}_{ij}(n)\{\phi[V_{ij}^i(0) - V_{ij}(n)] + (1 - \phi)[V_{ij}(n-1) - V_{ij}(n)]\}}_{\text{successful expansion by follower}} \\
& + \underbrace{\tau\theta x_{ij}^{eh}(n)\{\phi[V_{ih}^i(0) - V_{ij}(n)] + (1 - \phi)[V_{ih}(n-1) - V_{ij}(n)]\}}_{\text{successful entry by high type entrant}} \\
& + \underbrace{\tau(1 - \theta)x_{ij}^{el}(n)\{\phi[V_{il}^i(0) - V_{ij}(n)] + (1 - \phi)[V_{il}(n-1) - V_{ij}(n)]\}}_{\text{successful entry by low type entrant}}
\end{aligned}$$

The leader optimally chooses its investment intensity, $x_{ij}(t)$, at the associated cost. 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 the entrant.

The value function for the follower in industry (i, j, n) is

$$\begin{aligned} r\bar{V}_{ij}(n) = \max_{\bar{x}_{ij}(n)} & \bar{\pi}(n) - \beta_j \frac{\bar{x}_{ij}(n)^\alpha}{\alpha} + \bar{x}_{ij}(n) \{ \phi [V_{ji}^j(0) - \bar{V}_{ij}(n)] + (1 - \phi) [\bar{V}_{ij}(n-1) - \bar{V}_{ij}(n)] \} \\ & + \sigma_i [\bar{V}_{lj}(n) - \bar{V}_{ij}(n)] + \sigma_j [\bar{V}_{il}(n) - \bar{V}_{ij}(n)] + x_{ij}(n) [\bar{V}_{ij}(n+1) - \bar{V}_{ij}(n)] \\ & + \tau [\theta x_{ij}^{eh}(n) + (1 - \theta) x_{ij}^{el}(n)] [0 - \bar{V}_{ij}(n)]. \end{aligned}$$

Symmetrically, the flow value of a follower 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 leader; and changes in value due to successful expansion by the leader or successful entry of the entrant.

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

$$V_{ij}^e(n) = \theta V_{ij}^{eh}(n) + (1 - \theta) V_{ij}^{el}(n)$$

with

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

The parameter τ stands for the entry barrier. A smaller τ implies a smaller probability of entrant application being approved, which represents a higher entry barrier.

Similarly, we can write down the second set of value functions for firms in a neck-and-neck industry. In a neck-and-neck industry, the two incumbents obtain the same profit, denoted by $\pi(0)$. For an incumbent firm of type i , the value function is

$$\begin{aligned} rV_{ij}^i(0) = \max_{x_{ij}^i(0)} & \pi(0) - \beta_i \frac{x_{ij}^i(0)^\alpha}{\alpha} + x_{ij}^i(0) [V_{ij}(1) - V_{ij}^i(0)] + \sigma_i [V_{lj}^l(0) - V_{ij}^i(0)] \\ & + \sigma_j [V_{il}^i(0) - V_{ij}^i(0)] + x_{ji}^j(0) [\bar{V}_{ji}(1) - V_{ij}^i(0)] \\ & + \tau \theta x_{ij}^{eh}(0) \left\{ \frac{1}{2} [0 - V_{ij}^i(0)] + \frac{1}{2} [\bar{V}_{hi}(1) - V_{ij}^i(0)] \right\} \\ & + \tau (1 - \theta) x_{ij}^{el}(0) \left\{ \frac{1}{2} [0 - V_{ij}^i(0)] + \frac{1}{2} [\bar{V}_{li}(1) - V_{ij}^i(0)] \right\}. \end{aligned}$$

The value function for firm j can be expressed in a symmetric way.

In a neck-and-neck industry, when an entrant successfully enters, it replaces either of the two incumbents with equal probability and becomes a leader with one step ahead of the opponent. For an entrant in a neck-and-neck industry, the value is

$$V_{ij}^e(0) = \theta V_{ij}^{eh}(0) + (1 - \theta) V_{ij}^{el}(0),$$

where

$$V_{ij}^{ek}(0) = \max_{x_{ij}^{ek}(0)} -\beta_k \frac{x_{ij}^{ek}(0)^\alpha}{\alpha} + \tau * x_{ij}^{ek}(0) \left[\frac{1}{2} V_{ki}(1) + \frac{1}{2} V_{kj}(1) \right], \quad k = h, l.$$

Stationary Distribution We focus on the balanced growth path (BGP) of the model economy. On the BGP, the distribution over industry types is stationary, Denote $\mu_{ij}(n)$ the fraction of industries of (i, j, n) , $i, j \in \{h, l\}$ and $n \geq 0$, in stationary distribution. Naturally

$$\sum_i \sum_j \sum_n \mu_{ij}(n) = 1.$$

Table 3.1 lists the inflow into and outflow from an industry where both the leader and the follower are of high type, i.e. $(i = h, j = h)$, as a function of the quality gap, n . For notational convenience, we define $x_{ij}^e(n) \equiv \theta x_{ij}^{eh}(n) + (1 - \theta) x_{ij}^{el}(n)$ to note the aggregate entry intensity in industry (i, j, n) . For $n = 0$, the inflow is contributed by high-type firms which were previously a follower or an entrant in an industry with gap n and successfully caught up with the then high-type leader. For $n = 1$, the inflow is contributed by high-type firms which were previously an incumbent or an entrant in a neck-and-neck industry and successfully got ahead. For $n \geq 2$, the inflow comes from previously high-type leaders in the industry with gap $n - 1$ who successfully advanced. On the other hand, for all $n \geq 0$, the outflow consists of successful investment by either incumbents or entrant, and exogenous changes in the type of the incumbents. In a stationary distribution, *inflow* is equal to *outflow* for all states. We relegate the analogous tables for industries with $(i = h, j = l)$, $(i = l, j = h)$ and $(i = l, j = l)$ to Tables B.1, B.2, and B.3 in Appendix B.1.

Table 3.1: Inflow and Outflow in Industry ($i = h, j = h$)

State	Inflow	Outflow
n=0:	$\sum_{n \geq 2} [\mu_{hh}(n)\bar{x}_{hh}(n) + \mu_{hh}(n)\tau\theta x_{hh}^{eh}(n) + \mu_{hl}(n)\tau\theta x_{hl}^{eh}(n)]\phi +$ $\mu_{hh}(1)\bar{x}_{hh}(1) + \mu_{hh}(1)\tau\theta x_{hh}^{eh}(1) + \mu_{hl}(1)\tau\theta x_{hl}^{eh}(1)$	$= \mu_{hh}(0) [2x_{hh}^h(0) + \tau x_{hh}^e(0) + 2\sigma]$
n= 1:	$\mu_{hh}(0) [2x_{hh}^h(0) + \tau\theta x_{hh}^{eh}(0)] + \mu_{hl}(0)\tau\theta x_{hl}^{eh}(0)/2 +$ $\mu_{hh}(2)[\bar{x}_{hh}(2) + \tau\theta x_{hh}^{eh}(2)](1 - \phi) + \mu_{hl}(2)\tau\theta x_{hl}^{eh}(2)(1 - \phi)$	$= \mu_{hh}(1) [x_{hh}(1) + \bar{x}_{hh}(1) + \tau x_{hh}^e(1) + 2\sigma]$
n ≥ 2 :	$\mu_{hh}(n-1)x_{hh}(n-1) + \mu_{hl}(n+1)\tau\theta x_{hl}^{eh}(n+1)(1 - \phi) +$ $\mu_{hh}(n+1)[\bar{x}_{hh}(n+1) + \tau\theta x_{hh}^{eh}(n+1)](1 - \phi)$	$= \mu_{hh}(n) [x_{hh}(n) + \bar{x}_{hh}(n) + \tau x_{hh}^e(n) + 2\sigma]$

Note: This table lists the inflow to and outflow from all possible states (i.e. gap sizes) given a (h, h) leader-follower configuration.

Aggregate Growth As shown in Appendix B.2, the aggregate growth rate is

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

where

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

is the share of neck-and-neck industries times firm's investment intensities in these industries. Here again μ and x refer to the mass of industries in a given state and the investment intensity. The aggregate growth rate is equal to the average of 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

To numerically solve the model, we set a limit to the number of steps a leader can possibly be ahead of its follower and denote it by \bar{n} . At $n = \bar{n}$, a leading firm simply stops expansion. We verify that firms' expansion intensity in an industry with gap $\bar{n} - 1$ is indeed very close to 0.

4.1 Calibration

We calibrate the stationary equilibrium of the model to data moments from 2004 to 2007. We construct our main data targets from two data sources: 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 from 2005 to 2007, which we use to construct targets related to firm dynamics.¹⁰ 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. The variable definitions and panel constructions follow the standard practice in the literature and we report the details of sample selection and the summary statistics in Appendix A.

There are 10 parameters: $\{\rho, \alpha, \beta_h, \beta_l, \tau, \theta, \sigma, \delta, \phi, \lambda\}$. We set $\rho = 0.03$ to match an annual interest rate of 3%. For the parameter α , which is the inverse of the cost elasticity of investment, we choose $\alpha = 2$, a value commonly adopted in the Schumpeterian growth literature (e.g. Acemoglu et al. (2018)). The remaining eight parameters are chosen to match model moments with those in data. All moments are constructed from ASIE 2005-7 except the entry rate, which we construct from 2004 Census, and the labor share, which we take from the literature. We select moments based on observable firm characteristics such as firm size and age, which are informative about the underlying parameters. We label firms in the ASIE 2005-7 panel whose revenue is above (below) the 4-digit industry median as large (small) firms and firms whose age is above (below) the industry median as old (young) firms.

In order to alleviate the concern that in the data, at least a part of the actual growth is driven by capital accumulation which is absent in the model, we construct firm-level growth rates in the ASIE panel that are purged from capital accumulation. Specifically, we first run a regression of the firm-level growth rate in real value added against the growth rate in real capital stock, and interpret the coefficient as capital expansion’s contribution to output growth. Then we subtract from real value added growth rate the capital growth rate times this coefficient for each firm, and use the residual growth rate to construct growth rate moments in our calibration.

¹⁰We 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 Appendix A.1.

Following [Acemoglu et al. \(2018\)](#), we simulate 10,000 industries for 4,000 periods and calibrate β_h and β_l such that the average output growth rates of young and old firms in the model are consistent with the average annual output growth rates of young and old firms in data from 2005 to 2007. Intuitively, due to the assumption on the type transition process, old (young) incumbents tend to have a low (high) type, therefore the growth margin between the two is informative about the type-specific expansion costs. The entry barrier parameter τ determines the quantity of entrants, and is chosen to match the entry rate in model with the entry rates in Industrial Census 2004.

Table 4.1: Parameter Values

Parameter	Description	Value
<i>externally calibrated</i>		
ρ	discount rate	0.030
α	inverse of investment elasticity	2.000
<i>internally calibrated</i>		
β_h	expansion cost of high type firms	1.248
β_l	expansion cost of low type firms	2.336
τ	entry barrier	0.844
σ	high-to-low type transition rate	0.145
δ	elasticity of substitution within industry	0.706
θ	probability of high type entrants	0.803
ϕ	probability of immediate catchup	0.099
λ	quality step	1.216

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

The parameter σ , which governs the transition rate from high to low type, is chosen such that the model simulated probability of transiting from large to small firms within one year matches its counterpart in the ASIE 2005-7 panel. The elasticity of substitution between firms within the same industry, δ , determines the division of total revenue between profit and wage, and is chosen to match the average labor share ([Song et al., 2011](#)).¹¹ The

¹¹The calibrated value of δ , 0.706, implies a within-industry elasticity of substitution between leader and follower of $\frac{1}{1-\delta} = 3.40$. We have tried larger values e.g. $\delta = 0.85$ and 0.9. The effect of δ , while keeping all other parameters unchanged, on the aggregate growth rate in our model is nonlinear. A larger value of δ

probability of high type entrants, θ , and the probability of immediate catchup, ϕ , jointly affects the size of entrants and their initial growth. We choose the values of θ and ϕ to match the model simulated fraction of total revenue accounted by firms of 1 year old or less and the probability of remaining small for entrants after 1 year with their ASIE counterparts. Last, the quality step parameter λ is set to match the average annual growth rate of output (absent capital accumulation) with its ASIE counterpart. In sum, all these calibrated parameters capture, in a reduced-form way, how the existing institutions in 2004-7 (e.g. capital and labor market institutions and the legal environment) support economic growth.

Table 4.2: Data and Model Moments

Moment	Data	Model
growth rate of young firms	0.083	0.067
growth rate of old firms	0.039	0.032
1 year entry rate	0.109	0.097
large-to-small transition probability	0.066	0.044
labor share	0.500	0.504
probability of small for entrants	0.625	0.659
rev. share of entrants	0.058	0.076
aggregate growth rate	0.058	0.059

Note: This table lists the targeted moments in the data and their counterparts produced by the calibrated model.

We have a total of nine moments to calibrate the nine parameters internally. After computing the model moments from simulated data, we choose parameter values to minimize a weighted sum of the distance between 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 growth rate is assigned a weight (ι_k) 5 times the weight of others. Table 4.1 summarizes the calibrated parameter values and Table 4.2 lists the moments used in the calibration.

increases leader's profits and investment intensity, but also dampens entry. However, the counterfactual analysis presented in the next section is robust to different values of δ .

4.2 Counterfactual Analysis

Entry cost can stem from different sources. Over the past decades, technological progress in transportation, information and communications, and financial technology can naturally lower the cost of entry in all sectors. This technological component of entry cost differs from what we consider as entry barriers which are imposed by policy. As we discuss in Section 2, we are interested in evaluating the consequence of the series of reforms that aimed to lower the administrative and regulatory cost of entry. To do so, we need first 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, which differs from the observed entry rate in 1990, and then recalibrate the model targeting the counterfactual entry rate. In other words, we take the model calibrated to the 2004-7 Chinese manufacturing sector in the previous section and assess counterfactually what the growth rate would be if the entry barriers in 2004-7 were as high as those in 1990.

Counterfactual entry rate in 1990 To construct the counterfactual entry rate in 1990, we need two ingredients: an estimate of the change in some 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 construct such counterfactual rates 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. Using the measure of entry barrier that is closest in spirit to our model, “Time (Days) to Start a Business,” we estimate the elasticity of entry rates with respect to days to start a business from the merged sample of the 2008 Census and the province-level measure of entry barrier. 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.¹² We find one additional day spent getting the approval for a new business lowers the entry rate by 0.15 percentage points. Then using the longest time series available for this measure of entry barrier, i.e. for Shanghai 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 observed level of 46 in 2004. This implies a counterfactual reduction of 28.72×0.1580 or 4.54 percentage points in entry rates from the 2004 level.

¹²The result of the estimation are reported in Table C.2 in Appendix C.

Results and Discussion We recalibrate the model keeping all other parameters as in the baseline except τ and recalibrate τ to match a counterfactual entry rate of 5.16%.¹³ This leads to a decrease in the value of τ from 0.844 in the baseline to 0.546. The aggregate growth rate consequently decreases from 5.87% in the baseline to 4.42%, a reduction of 1.45 percentage points which amounts to a 24.7% reduction of baseline growth.

One way to understand the lower aggregate growth in the counterfactual economy is to compare the properties of the observables in the two economies. In particular, we can examine how the distribution of firm age and the distribution of industry concentration change from the baseline to the counterfactual with higher entry barrier. Take HHI as measuring concentration in an industry. Recall that ω_1 and ω_2 are both the revenue and revenue share of the two firms in an industry. As a result, the industry normalized HHI is

$$HHI = \frac{\omega_1^2 + \omega_2^2 - 1/2}{1 - 1/2}.$$

We simulate a large sample of industries and firms for long enough to reach the BGP with a stationary distribution of firms' age and industry attributes and plot the distribution of age across firms and the distribution of HHI across industries in the two economies in Figure 4.1.

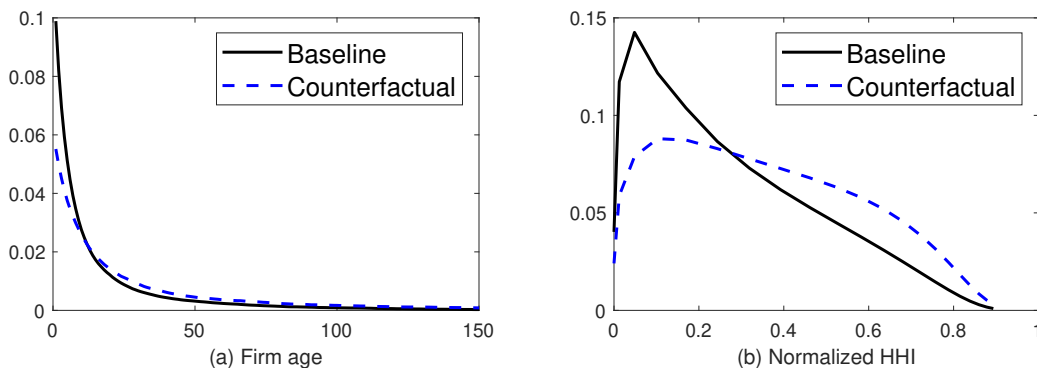


Figure 4.1: Distribution of Firm Age and HHI, Baseline and Counterfactual

Note: This figure shows the distribution of firm age in the baseline and counterfactual economy respectively (Panel (a)) and the distribution of industry-level normalized HHI in the baseline and counterfactual economy respectively (Panel (b)) from the model simulated data.

Compared to the baseline (i.e. the 2004-7 economy), the counterfactual economy has less

¹³We start from model predicted 9.7% entry rate and subtract from it the counterfactual reduction of 4.54%.

entry and since young entrants replace old incumbents in the model, the counterfactual economy consequently has an age distribution that is more skewed to the right (Figure 4.1(a)). Moreover, compared to the baseline, the counterfactual economy ends up having more industries in which the leader becomes dominant and faces little challenge from either the follower or an entrant, resulting in the distribution of HHI having a thicker right tail (Figure 4.1(b)). Even though we do not directly require these endogenous distributions to match those in the data, the model produces a very similar pattern as data counterparts (1995 vs 2008) portrayed in Figure 2.1. As leaders in industries with more concentration invest less, this has a rather negative effect on aggregate growth in the counterfactual economy, which will be clear in the formal model-based decomposition we present next.

Growth Decomposition Lowering entry barrier affects growth along four margins. One, it induces more expansion efforts from potential entrants across industries, leading to a direct positive effect on growth. Two, it discourages incumbents from costly expansion in a given market structure 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. Four, it changes the endogenous distribution of firms over different market structures, essentially relocating firms towards more competitive markets with closer quality gaps between the leader and follower. This last 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 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. $\psi = (h, h), (h, l), (l, h), (h, h)$; and keep $n \in \{0, 1, \dots, \bar{n}\}$ to denote industry's quality gap. We rewrite the growth rate formula as

$$g = \sum_{\psi} \mu(\psi, 0) x^e(\psi, 0) \ln \lambda + \sum_{\psi} \sum_n \mu(\psi, n) x(\psi, n) \ln \lambda.$$

where the first component denotes all terms associated with the entrant's investment intensity in the growth rate formula, and the second component denotes all remaining terms in the growth rate formula.

Note that the baseline economy has a lower entry barrier and a higher growth rate. We

can decompose the effect of a lower entry barrier on the gain in aggregate growth in the baseline economy as follows¹⁴

$$\begin{aligned}
g_b - g_c \approx & \underbrace{\sum_{\psi} \mu_c(\psi, 0) [x_b^e(\psi, 0) - x_c^e(\psi, 0)] \ln \lambda}_{\text{direct effect}} + \underbrace{\sum_{\psi} \sum_n \mu_c(\psi, n) [x_b(\psi, n) - x_c(\psi, n)] \ln \lambda}_{\text{Schumpeterian effect}} \\
& + \underbrace{\sum_{\psi} \sum_n x_b(\psi, n) [f_b(\psi|n) - f_c(\psi|n)] \tilde{\mu}_c(n) \ln \lambda}_{\text{replacement effect}} \\
& + \underbrace{\sum_{\psi} \sum_n x_b(\psi, n) [\tilde{\mu}_b(n) - \tilde{\mu}_c(n)] f_b(\psi|n) \ln \lambda}_{\text{pro-competitive effect}}.
\end{aligned}$$

where subscripts b and c denote the baseline and the counterfactual economy, respectively. $f_s(\psi|n), s = b, c$ denotes the distribution of ψ conditional on a given value of n , and $\tilde{\mu}_s(n) \equiv \sum_{\psi} \mu_s(\psi, n)$ is the (unnormalized) marginal distribution of n .

We can decompose the effect of higher entry on aggregate output growth into four components: a direct effect, a Schumpeterian effect, a replacement effect and a pro-competitive effect. As entrants' investment intensity in neck-and-neck industries directly enters the growth rate formula, a lower entry cost directly increases this intensity and therefore promotes aggregate growth. When the entry rate is high, incumbent leaders are more likely to face a high type challenger and consequently face a higher probability of being overtaken, which discourages the incumbent leader to invest in expansion. This is the Schumpeterian effect, typical in models of creative destruction, and it dampens growth.¹⁵ Both the direct effect and the Schumpeterian effect work through the x terms in the growth rate formula.

A higher entry rate also changes the industry composition, i.e. the μ terms. Firms become less expansive stochastically over their lifetime. When there are more entrants, more young firms with higher growth potential enter and replace old incumbents with

¹⁴As detailed in Appendix C.1, there are two symmetric approaches to decompose the changes in μ/s into the replacement effect and the pro-competitive effect. The relative magnitude of the two effects differ non-trivially under the two approaches. In the text, we report the average from these two approaches.

¹⁵A closer look at the difference, $x_b(n) - x_c(n)$, at various levels of n reveals that there is also a secondary effect, whereby for an incumbent leader who is having an intermediate value of lead n over the follower, its expansion effort can be higher in the baseline than in the counterfactual. This happens because the Schumpeterian effect is especially strong when n is small and diminishes as n gets larger, so that, faced with the threat of higher entry, the incumbent leader invests more to escape future competition.

lower growth potential. In other words, the distribution of the four type configurations of leader-follower pairs, ψ , given any quality gap n , or $f(\psi|n)$, evolves in such a way that relocates industries away from (l,l) and towards (h,h) . This is the replacement effect, which tends to increase aggregate growth. Lastly, when the entry barrier is lower, it is more difficult for an incumbent firm to accumulate and build up advantage. The economy thus have more industries in which the quality distance between firms are close and competition is fierce. Since both firms in more competitive industries have more incentive to expand and a lower entry barrier shifts more masses to such competitive industries, we refer to this last effect the pro-competitive effect and it is growth-enhancing.

The result of the decomposition is found in Table 4.3.¹⁶ Under the calibrated parameters, the negative Schumpeterian effect almost exactly cancels out the positive direct effect associated with higher entrants' investment intensity in neck-and-neck industries. This means the gain in growth in the baseline economy comes entirely from the compositional change of industry distribution over types and quality gaps (or competitiveness), namely the replacement effect and the pro-competitive effect. More specifically, of the 1.45 percentage point difference in the growth rates between the baseline and counterfactual economy—25% of the 5.87 percentage point growth rate in the baseline—a little under 40% is due to the replacement effect and more than 60% is due to the pro-competitive effect.

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

growth rate diff.	direct	Schumpeterian	replacement	pro-competitive
0.0145	0.0005	-0.0007	0.0056	0.0096
	3.14%	-4.60%	37.60%	63.87%

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. The decomposition is not exact. We adjust the raw values such that sub-entries sum to 100%.

The replacement effect can be discerned from Table 4.4, where we show the distribution of industries over the four type configurations of leader-follower pairs for the two

¹⁶It should be pointed out that this decomposition results are not driven by weights chosen in the decomposition formula. Using $\frac{\mu_b(n)+\mu_c(n)}{2}$ instead of $\mu_c(n)$ as the weights in the direct and Schumpeterian effects and $\frac{x_b(n)+x_c(n)}{2}$ instead of $x_b(n)$ as the weights in the replacement and pro-competitive effects, we obtained effects that are quite similar to those in Table 4.3.

economies. In the baseline economy, 24.3% of industries have a high-type leader and 41.5% of industries have a high-type follower; these two numbers are lower at 14.6% and 28.7% in the counterfactual economy with high entry barrier. The higher prevalence of the high type means that the baseline economy has higher shares of industries with (h,h) , (h,l) and (l,h) configurations and a lower share of industries with (l,l) compared to the counterfactual economy. To the extent that firm’s age is closely linked to its type, Figure 4.1 (a), which shows the distribution of age in the two economies, confirms this patterns as well.

Table 4.4: Distribution of Industry Types, Model

	(h,h)	(h,l)	(l,h)	(l,l)	h Leader	h Follower
Baseline	10.3%	14.0%	31.5%	44.2%	24.3%	41.5%
Counterfactual	4.3%	10.3%	24.4%	61.0%	14.6%	28.7%

Note: This table shows the composition of the four types of leader-follower configurations in the Baseline and Counterfactual Economy.

The pro-competitive effect, which shifts masses of industries from large quality gaps towards small quality gaps, is demonstrated in the right panel of Figure 4.1. The HHI is simply an increasing transformation of quality gap n . The fact that the pro-competitive effect is growth-enhancing is shaped by the escape competition force in models with step-by-step quality improvement (e.g. Aghion et al. (2001)). The escape competition force is at its strongest when the distance between the leader and the follower is close. In such an industry, the follower has strong incentive to grow to leapfrog the leader and as a consequence the leader has strong incentive to grow to escape from competition. This negative relationship between leader’s incentive to grow and its advantage is depicted in Figure 4.2 for the case of (h,h) industries in the counterfactual economy. Since most of the investment in an economy happens in relatively competitive industries, it then naturally follows that the pro-competitive effect of entry boosts aggregate investment and promotes growth.

Robustness of the Counterfactual In the baseline counterfactual exercise, we linearly extrapolate the change in “days to start a business” in Shanghai from 2004-2020 backwards to 1990 to obtain the counterfactual entry barrier index in 1990. This might raise some concerns. On one hand, due to data availability, the choice to focus on Shanghai,

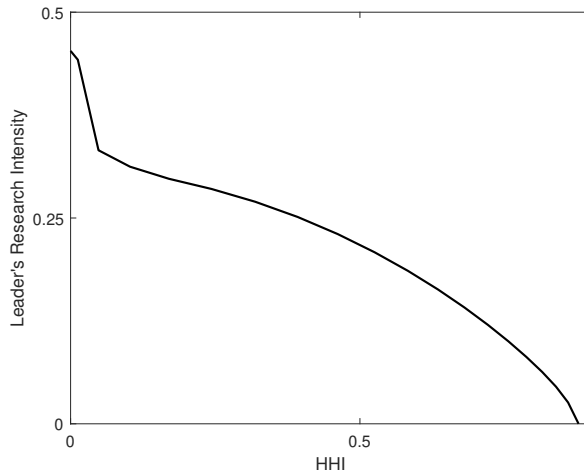


Figure 4.2: HHI and Leader's Investment Intensity in a (h, h) Industry

Note: This figure shows the leader's investment intensity as a function of HHI.

one of the most prosperous regions in China, may bias the extent of entry barrier reduction downwards, as it may already have achieved lower entry barrier in 2004 relative to other regions and therefore the observed slope of the trend of measured entry barrier is flatter. On the other hand, there are monetary costs in addition to time cost in starting a business and therefore a well-rounded measure of entry barrier may be preferred.

To address these concerns, we consider several alternatives, each with its own compromise. To address the issue of the particular measure of entry barrier, we consider alternatively the overall Starting a Business score from World Bank's flagship *Doing Business* survey, which is available at the level of country and selected cities (i.e. Shanghai and Beijing for China). For Shanghai, we linearly extrapolate from the observed 2004-2020 series backwards to 1990. The caveat of using this measure is that the special 2008 *Doing Business in China* survey does not report this score at the province level. Instead, we rely on a cross-country regression of entry rates on this score from a European sample to estimate the elasticity. Following this approach yields a counterfactual reduction in entry rates of 4.22 from 1990 to 2004, slightly lower than our baseline counterfactual of 4.54.

To address the non-representativeness of Shanghai, we repeat the above exercises for China instead of Shanghai, with the caveat that the Starting a Business score series is available for China as a whole country only from 2014 to 2020. Combining the linear extrapolation of the score for China with the elasticity of entry rate to the score from the cross-country sample, we arrive at a counterfactual reduction in entry rates of 5.44 from

1990 to 2004.

In light of these results, as a robustness check, we allow the change in the counterfactual entry rate associated with the reduction in entry barriers to vary from 20% less to 20% more than the baseline 4.54, which will cover both cases of the alternatives above. Throughout this range, the growth rate differential decomposition produces very similar results to that in our baseline counterfactual, with the replacement effect accounting for close to 40% and the pro-competitive effect accounting for over 60%.¹⁷

To sum up, in this section, we have shown how entry affects aggregate growth through the different channels in our model. In the case of China, when we compare the pre-reform, high entry barrier counterfactual to the post-reform, low entry barrier baseline, the gain in output growth is entirely driven by compositional changes in how industries are distributed over types and quality gaps. Of the two types of compositional changes, the replacement effect, similar to selection in the literature, accounts for about 40%, and the pro-competitive effect, the new effect coming from allowing endogenous market structures, accounts for over 60% of the impact on aggregate growth.

5 Supportive Cross-Section Evidence

We have so far focused on the relationships and interactions between entry barriers, competition (or market structure), and growth along the growth path of Chinese manufacturing. We highlight the mechanism whereby policy induced increase in entry promoted economic growth over time through improving the type distribution of the firms and improving the market structure in which these firms compete. In this section, we document additional empirical support for *cross-sectional* patterns among entry barriers, competition, and growth, both within and beyond China, suggesting the same mechanism could be at play in a much wider context.

¹⁷Appendix C.2 details how we construct the counterfactual reduction in entry rates using the alternative methods and Appendix C.3 details the result of the robustness checks on the growth differential decomposition.

5.1 Cross-Province Evidence within China

In this section, 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 principle component analysis to construct an index of entry barrier that summarizes measures of various regulations of starting a business, and merge it with the firm-level micro data from the 2008 Census and ASIE 2008-2013 panel (skipping 2010). From the Census sample, we construct measures of market structure such as the normalized HHI and the revenue share of the top 10 firms in a market. We define a market at 4-digit CIC industry and province level, as the variation of entry barrier comes at the province level. From the ASIE panel, we construct outcome variables such as firm-level job reallocation rates, which are then aggregated to the market level as a measure of business dynamism of a market (Decker et al., 2016), and firm-level labor productivity growth rates.¹⁸

We relate the market-level measures of competition and business dynamism and the firm-level measure of labor productivity growth from 2008 to 2013 to our province-level Entry Barrier Index of 2008. In all regressions, to recognise the potentially different stages of transitional growth different provinces are at, we control for provincial characteristics such as GDP per capita, industrial output share and population in 2008. In regressions of market-level outcomes, we control for market size in 2008 in terms of total number of firms, total employment and revenue as well as the state presence proxied by employment weighted SOE shares. In the regressions of firm-level outcomes, we control for firm characteristics such as age, employment, sales, ownership types and export-to-output ratio in 2008. All regressions include 4-digit industry fixed effects and standard errors are clustered at the 4-digit industry level. The results are in Table 5.1.¹⁹

¹⁸We focus on labor productivity, which is revenue over employment, as in ASIE 2008-2013 firm-level information on value added, capital stock and intermediate inputs are missing. For details of the World Bank data and the construction of entry barrier index, see Appendix A.3. For details of the variable construction, sample selection and summary statistics of the ASIE and the Census samples, see Appendix A.1 and A.2.

¹⁹In addition to the baseline results, we consider several robustness checks. In Appendix D.1, we report results when we use the rank of Starting a Business given in the World Bank's special report instead of the Index we construct. In Appendix D.2, we report results using employment-based measures of market concentration (HHI and top 10 firm's market share) instead of revenue-based measures of concentration. Neither changes our main results reported here. In Appendix D.3, we further look into the firm-level out-

Table 5.1: 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
Entry Barrier Index (PF)	0.155*** (9.38)	0.0269*** (12.65)	-0.0257*** (-6.29)	-0.0125*** (-3.84)	-0.0344*** (-2.60)	-0.0288*** (-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	10,842	10,842	7,260	7,260	88,871	88,871

t statistics in parentheses

Province controls include GDP per capita, 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, controlling for 4-digit CIC industry fixed effects, with standard errors clustered at 4-digit CIC industry level. Province controls include GDP per capita, the industrial GDP share, and total population in 2008. Market controls include total employment, total revenue, and employment weighted SOE share in 2008. Firm controls include firm age, employment, sales, ownership types, and export to output ratio in 2008.

We start by showing markets in provinces with one standard deviation lower entry barrier appear to be less concentrated, enjoying a 15.5% reduction of HHI and 2.69 percentage points lower 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% reduction in top concentration. When we look at the level of turnover in the labor market, the same reduction in entry barriers correlates with 2.57 percentage points increase in job reallocation rates in 2008-9 and 1.25 percentage points increase three years later in 2011-3 ((Column [3] and [4])). These amount to a 11% increase from the average job reallocation rate in 2008-9 and 4% increase from the average in 2011-13.

Turning to direct firm-level evidence from the ASIE panel, we find that in markets with _____ comes for firms of different ownership types separately and firms of different exporting status separately, and show the empirical patterns are driven by private and domestic firms.

lower entry barriers firms achieve higher labor productivity growth rates (Columns [5] and [6]). One standard deviation lower entry barrier coincides with about 3 percentage points higher labor productivity growth in 2008-9 and in 2011-3. As the average labor productivity growth in those two periods is 31.3%, this amounts to an increase of about 10% of the mean.

5.2 Cross-Country Evidence beyond China

We combine the Starting a Business scores reported at the country level from the World Bank with the *CompNet* data to construct a panel of 15 European countries from 2009 to 2016. *CompNet* is a data initiative founded by the European System of Central Banks and provides high-standard micro-founded datasets of distributional statistics of competition and productivity by 2-digit industry or sector for a number of European countries. The advantage of using *CompNet* is that we can construct outcome variables such as HHI, top 10 firm's revenue share, job reallocation rates at the sector level in a way similar to what we did with the Chinese micro data.²⁰

Following a similar empirical design as in the last section, we relate outcomes in terms of market structure, business dynamism and productivity growth to the measure of entry barrier, the Starting a Business Score in this case, with country-sector and year fixed effects, controlling for various country and sector level time-varying characteristics. Table 5.2 shows the result. We find a robust and significant negative correlation between entry barriers and measures of competition, business dynamism, and productivity growth. In other words, this pattern of empirical correlations extends beyond the Chinese context to the panel of European countries as well. This naturally calls for a more systematic examination of the role entry plays in growth when allowing the market structure to be endogenous to entry for countries at different stages of development, an avenue of research we leave for the future.

6 Conclusion

In this paper, we revisit the narrative that the economic reforms removed hurdles to enter previously state-dominated industries, unleashed unprecedented competition, and

²⁰See Appendix A.4 for details of the *CompNet* sample.

Table 5.2: Entry Barrier, Market Structure, and Growth, Cross-Country European Panel 2009-2016

	Top 10 Revenue Share	HHI	Job Reallocation	Productivity growth
	(1)	(2)	(3)	(4)
World Bank Starting a Business Score	-0.00251*** (-2.95)	-0.000177** (-2.39)	0.00261*** (4.60)	0.00184** (2.29)
R^2	0.976	0.974	0.566	0.204
Country-Sector F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Sector controls	Yes	Yes	Yes	Yes
Economy controls	Yes	Yes	Yes	Yes
Observations	1520	513	1613	1672

t statistics in parentheses

Sector controls include sector (2-digit industry) level employment and capital.

Economy controls include output share of manufacturing out of the non-financial business sector and share of export in manufacturing.

Standard errors are clustered at country-sector level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the results from regressing economic outcomes such as productivity growth, top 10 revenue share, HHI and job reallocation rate on starting a business score in a panel of European countries from *CompNet*. Details of sample construction are in Appendix A.4.

achieved remarkable aggregate 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 growth in China.

We calibrate the model to the Chinese manufacturing sector in 2004-7 and use it to assess quantitatively the contribution to aggregate growth from the reduction in administrative and regulatory entry barriers throughout the 1990s and early 2000s. We find that the policy-induced entry accounts for 24.7% of the 5.87 percentage point aggregate productivity growth achieved in 2004-7. The gain in growth from the reduction of entry barriers is almost entirely driven by compositional changes in firm types and market competitiveness. The replacement effect, which reflects the higher prevalence of the high growth potential type as a result of entry, explains close to 40% of the growth difference. The pro-competitive effect, which can only be identified in our model with endogenous market structure, explains over 60% of the growth difference. By focusing on entry, we inevitably abstract away from reforms in other spheres of the economy such as trade and urbanization.

While our framework permits growth to respond endogenously to changing market struc-

ture, it has limitations. For instance, it cannot generate bouts of growth of the capital deepening type that occur in the transitional dynamics of a neoclassical growth model. In other words, the framework does not feature an endogenous mechanism that can produce non-monotone growth trajectories. As a result, when calibrating the model, we try to purge the component of growth which comes from neoclassical-style capital deepening from the data moments we use as targets. By calibrating the model to the 2004-7 period, we take a snapshot of the economy and interpret parameters such as the step size and costs of expansion as, in a reduced-form way, how the existing institution supports growth beyond the mechanisms explicitly modeled in the paper. Nevertheless, the counterfactual exercises are informative about the contribution of the reduction of entry barriers to the observed level of growth in 2004-7. 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.

More generally, how entry can affect growth through affecting the market structure in which active firms operate can differ along different stages of development. We provide preliminary empirical evidence that the negative correlation between entry barrier and competition/growth exists not only in the Chinese context across time and across space but also across a panel of more advanced European economies. Answers to this question will have policy implications in a much wider economic context, which deserves further research.

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Online Appendix of “Entry Barriers and Growth: The Role of Endogenous Market Structure”

Appendix A Data and Sample Construction

A.1 Annual Survey of Industrial Enterprises

The Annual Survey of Industrial Enterprises (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, including for example revenue, value added, intermediate inputs, employment, capital stock, from 1998 to 2007, except 2004 for which value added is missing. From 2008 to 2013, the firm-level source data no longer contain information about value added, intermediate input, and capital stock. For this reason, we use the 2005-7 panel to construct calibration targets, for which we need more detailed information, and use the 2008-13 panel (skipping 2010) only in the cross-sectional empirical study to provide additional support for the mechanisms of the paper.

A.1.1 ASIE Sample Construction

ASIE Panel Construction. Following Brandt et al. (2012), we create an unbalanced panel of firms between 1998 and 2013, using the unique firm IDs to link firm over time. For those that cannot be matched by IDs, we use additional information such as firm name, name of legal person representative, address, industry, and etc. to create a match. Since it’s possible that firms exit the sample and reenter later, according to their methodology, we first match the samples of two consecutive years, then three consecutive years, and finally create a 16-year-panel sample.²¹

²¹The ASIE samples branches and subsidiaries of a multi-plant firm separately, which may produce a potential downward bias on the measure of market concentration, or an upward bias on the measure of market competition. To address this issue, we isolate from the name of the company the core component of the name (e.g. dropping the references to branches or subsidiaries) and use fuzzy string match to identify observations which potential belong to the same firm. The number of observations which are potentially plants of multi-plant firms identified this way account for less than 1% of the total number of observations. Either dropping these observations or keeping the plant with the largest revenue does not change the results in any material way. For the sake of simplicity, we refer to the sample as a firm-level sample.

Industry Code. Firms in the ASIE are classified into an industry by the 4-digit Chinese Industry Classification (CIC) system. CIC 1994 codes and 2002 codes are used in different years of our sample, and there was a revision of the classification system in 2003. In order to harmonise the CIC code and make it comparable over time, we follow [Brandt et al. \(2012\)](#) and implement the same industry concordance. For the industries that cannot be converted using their methods in Industrial Census, we manually match them using their Chinese names.

State Ownership. To define state ownership in ASIE, we adopt two approaches. First, we follow the approach as in [Hsieh and Song \(2015\)](#) to define a state-owned firm when the share of registered capital held directly by the state is more than 50 percent of when the controlling shareholder is reported as the state. We have verified that we can replicate the main facts documented in their paper using our sample. We also define state ownership using firms' "registered ownership type". Specifically, the state-owned enterprises (SOE) are those with register types equal to 110 and 151, foreign-owned enterprises (FOE) are those with register types range between 210 and 390, and the rest of firms are defined as private-owned enterprises (POE). Notice that due to the availability of data, constructing ownership types using the first approach is infeasible in sample years after 2008.

Firm's Age. We use firm's birth year to construct the age of a firm in ASIE. We first clean the reported birth year *bdat*, by adding 1900 to reports which are between 50 and 100, then we replace those which are smaller than 1900. We then compare, by firm, the smallest value in the reported birth year and the earliest year of wave that the firm appears in the sample. If the former is greater than the latter, then we replace the birth year by missing. Instances like this occur when firms go through a slight change in name and the original firm ID, which are nevertheless matched through the panel construction algorithm for sharing the same address, telephone number and legal person for example. The birth year reported is then for the restructured firm, while we have no information when the original firm is established. The age of a firm is then the survey year minus the birth year plus one, so the smallest age is 1.

Firm's Location. We use the first two digits of the region code to construct firms' location (province). For those firms with missing value of county code, we use the first two digits of postcode.

Real Output and Input Values. For 2005 to 2007, we deflate all nominal values, including gross output, value added, intermediate inputs and wages, to real values.²² To obtain real values of output, value added and revenue, we deflate the nominal variables using the output deflator supplied by [Brandt et al. \(2012\)](#). Similarly, we deflate the intermediate input with the input deflator supplied by their paper. The construction of real capital stock also follows them. All economic values are therefore in 1998 Chinese *yuan*.

Business Dynamism. In the cross-sectional empirical analysis in Section 5, business dynamism is measured by firm-level job reallocation rates constructed following [Decker et al. \(2016\)](#) for ASIE 2008-2013 (skipping 2010) and then aggregated up to the market level. We drop the year 2010 in ASIE sample due to various irregularities displayed in 2010, a well-known problem in the literature ([Chen et al., 2021](#)).

Labor Productivity. In the cross-sectional empirical analysis in Section 5, firm-level labor productivity is constructed as the annual growth rate of the ratio of revenue to employment for ASIE 2008-2013 (skipping 2010).

A.1.2 Sample Selection in ASIE

We restrict the ASIE sample to the manufacturing industries, that all 4-digit CIC codes between 1300 and 4400. We drop all firms with missing firm identification numbers, province, industry, age, or employment, and drop those with negative values of age or revenue. And then we trim the top and bottom 1% of revenue, employment and labor productivity by year. The following table [A.1](#) shows the detailed sample selection process.

A.1.3 Summary Statistics, ASIE

We report the summary statistics of the key variables in the ASIE 2005-2007 subsample, from which we construct the calibration targets in Section 4, and the summary statistics of the relevant variables in the ASIE 2008-2013 subsample, which we use in the cross-sectional empirical analysis in Section 5, in the following table [A.2](#).

²²Information of output and value added is missing in the 2004 ASIE survey. For this reason, we leave 2004 out of the data used for calibration target construction and use 2005-7 only.

Table A.1: 1998-2013 ASIE Sample Selection

	Observations
Raw Data	4,350,844
Drop missing identification	4,350,844
Keep manufacturing industries	4,037,868
Drop missing province	4,037,866
Drop missing industry	3,888,837
Drop missing age	3,886,408
Drop missing employment	3,847,413
Drop negative revenue	3,847,413
Drop negative age	3,847,382
Trim revenue, employment and labor productivity	3,696,426
Final analysis sample	3,696,426

Note: This table reports the change of the number of observations at each step of the sample selection process in the construction of the 1998-2013 ASIE analysis sample.

A.2 Industrial Census

A.2.1 Census Sample Construction

We define industry, firm's age, and location using the same approach as those used in constructing ASIE sample. For the ownership types, since the share of registered capital held by the state is not reported in Census, we construct state ownership only based on firm's "registered ownership type" (same as the second approach used in the ASIE sample). Similarly, the state-owned enterprises (SOE) are those with register types equal to 110 and 151, foreign-owned enterprises (FOE) are those with register types range between 210 and 390, and the rest of firms are defined as private-owned enterprises (POE).

Entry We construct entry rate from the census sample, which includes all firms. In order to alleviate the issue of reporting errors, we use 2-year averages to construct new entrants. For example, from the 2004 Census sample, we define the entry rate as the ratio of average number of new entrants in 2003 and 2004 to total number of firms in 2004.

Competition and Concentration In the cross-sectional empirical analysis in Section 5, we define a market at 4-digit CIC industry and province level. HHI is defined as the sum of squared revenue or employment shares of all firms within a market, normalized by the total number of firms. In addition, we measure concentration by the top 10 firms' revenue

Table A.2: Summary Statistics, ASIE

	2005	2006	2007
Age	11.07 (10.56)	10.85 (10.22)	10.53 (9.81)
Age	11.07 (10.56)	10.85 (10.22)	10.53 (9.81)
SOE (%)	5.12 (22.04)	4.41 (20.52)	3.44 (18.23)
Value added	11863.37 (25179.56)	13268.23 (28490.72)	14804.44 (31296.14)
Employment	177.55 (265.87)	169.77 (259.45)	161.50 (246.32)
Capital	13242.06 (36517.08)	13549.35 (38773.11)	13827.01 (39331.85)
Number of firms per market-year		193.91 (299.82)	
Number of markets		8808	
Number of market-year observations		23754	
		ASIE, 2008-2013	
	2008-09		2011-13
Job reallocation rate	0.2342 (0.1924)		0.3168 (0.1918)
Labor productivity growth	0.4494 (1.6109)		0.1765 (1.1479)
Number of firms per market-year		353.36 (564.61)	
Number of markets		10394	
Number of market-year observations		32231	

Means and standard deviations (in parentheses).

Note: This table reports the mean and standard deviations (in parentheses) of the key variables for the ASIE sample.

or employment share within a market.

A.2.2 Sample Selection in Census

We restrict the Industrial Census sample to the manufacturing industries, that all 4-digit CIC codes between 1300 and 4400. We drop all firms with missing province, industry, age, or employment, and drop those with negative values of age and revenue. The following table A.3 details the sample selection process in Industrial Census.

A.2.3 Summary Statistics, Census

Our census sample is three repeated cross-sections of firms in 33 two-digit industries consisting of over 10,000 markets. The summary statistics of key variables are in table A.4.

Table A.3: Census Sample Selection

	1995	2004	2008
Raw Data	687,478	1,328,891	1,823,848
Keep manufacturing industries	684,261	1,328,891	1,823,848
Drop missing province	684,261	1,328,890	1,823,848
Drop missing industry	684,254	1,328,890	1,823,847
Drop missing age	449,292	1,280,683	1,810,000
Drop missing employment	448,030	1,280,683	1,810,000
Drop negative revenue	448,030	1,280,682	1,810,000
Drop negative age	448,030	1,280,682	1,810,000
Final analysis sample	448,030	1,280,682	1,810,000

Note: This table reports the change of the number of observations at each step of the sample selection process in the construction of the 1995, 2004, and 2008 Census sample.

Comparing the 1995 Census to 2004 Census, there is a clear increase in entry rate and a clear decrease in HHI and top 10 concentration. The relatively low entry rate from the 2008 Census may be due to the exceptional economic condition following the global financial crisis in 2008. Yet despite of an entry slow-down, the HHI and top 10 revenue share continue to decline from 2004.

Table A.4: Summary Statistics, Industrial Census

	Census Sample		
	1995	2004	2008
Entry Rate	0.0780 (0.0817)	0.1098 (0.0773)	0.0864 (0.0649)
HHI	0.2224 (0.2230)	0.2143 (0.2260)	0.1908 (0.2114)
Top 10 rev. share	0.8761 (0.1856)	0.8157 (0.2277)	0.7840 (0.2370)

Note: This table reports the mean and standard deviations (in parentheses) of the key variables for the Industrial Census.

A.3 World Bank’s *Doing Business* Survey and *Doing Business in China* 2008 Special Survey

The World Bank publishes its flagship *Doing Business* Survey since 2004, which provides objective measures of business regulations and their enforcement across economies and selected cities at the subnational and regional level. For our purpose, we extract the Starting a Business score and its subcomponents for China and Shanghai in the construction of counterfactual entry rates in our counterfactual exercise. We also extract the Starting a Business scores from 15 European countries in the construction of a cross-country panel to evaluate the cross-sectional relationship between entry barrier, competition and growth (see Section A.4).

We plot here the Starting a Business score series for China and Shanghai as well as the “time (days) to start a business” from the *Doing Business* Survey in Figure A.1. These times series look remarkably linear, which motivates our decision to extrapolate linearly back to earlier years in the counterfactual exercise.

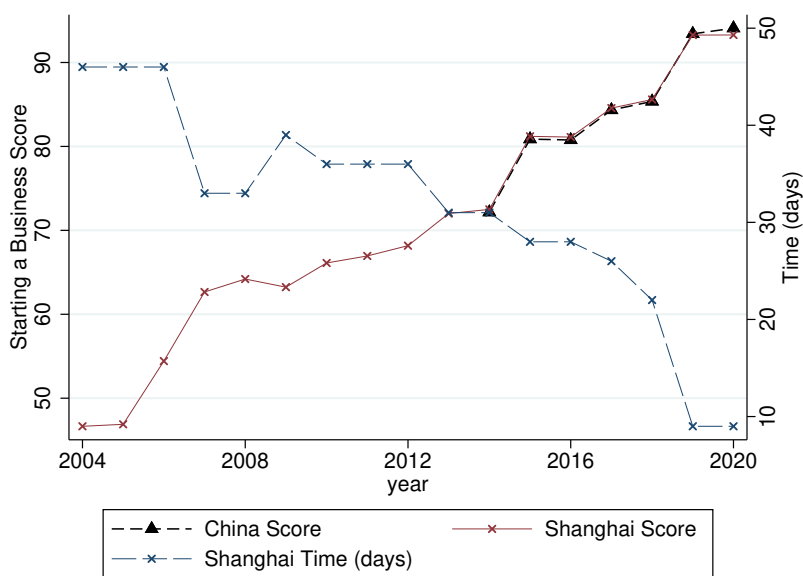


Figure A.1: Trend of Starting a Business Score and Time (days) to Start a Business

Note: This figure shows the Starting a Business Score for China and Shanghai (left axis) and Time (days) to Start a Business for China (right axis) over time.

In 2008, the World Bank published a special *Doing Business in China* providing indicators of ease of starting a business in 26 provinces and 4 centrally administered municipalities.

We make use of this data in the cross-sectional empirical analysis in Section 5. The indicators which measure the ease of starting a business include (1) Time (days) to start a business, (2) Number of procedures involved, (3) Cost of the procedures (% of income per capita), and (4) Minimum paid-in capital (% of income per capita), reflecting the main aspects of the time and monetary costs of starting a business. The survey, however, does not report an overall Starting a Business score for each province, as the flagship *Doing Business* surveys do at the country level. It does contain a ranking of the provinces in terms of the overall ease of doing business. Consequently, we construct an index of entry barrier based on principal component analysis on the four indicators and standardize it to have a mean of zero and a standard deviation of one. The higher our index, the higher entry barriers. This index, unlike entry rates that might have captured firms' strategic entry decisions in response to changes in demand or regulation, serves as a cleaner proxy for policy-induced entry barriers across regions in China. Table A.5 shows that our index is not only closely correlated with the four underlying indicators, but also has a high correlation with the reported ranking. Other province-level controls such as GDP per capita, the industrial GDP share and total population used in the empirical analysis are obtained from National Bureau of Statistics of China.

Table A.5: Summary Statistics, *Doing Business in China 2008*

	Mean (Std. dev)	Correlation with Entry Barrier Index (PF)
Starting a Business rank	15.47 (8.77)	0.920***
Time (days)	41.07 (6.64)	0.624***
Procedures (number)	13.57 (0.68)	0.501**
Cost (% of income per capita)	11.01 (5.26)	0.929***
Paid in min. capital (% of income per capita)	273.75 (89.88)	0.951***
Observations	30	

standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table shows the mean and standard deviation of the Starting a Business ranking and the four Indicators reported by [World Bank \(2008\)](#), and their correlations with the Entry Barrier Index (PF), which we construct from the principal factor of the four indicators.

A.4 CompNet

In the construction of the counterfactual entry rate in 1990 in the absence of the policies that facilitated entry, we merge a panel of European countries from *CompNet* with World Bank's Starting a Business Score from its flagship *Doing Business* Survey to estimate the elasticity of entry rate with respect to the Starting a Business Score. In addition, we also document cross-country patterns of correlation between entry barriers, competition and growth from this sample in Section 5.2. We report the summary statistics from this European sample here.

CompNet is a data initiative founded by the European System of Central Banks and currently hosted at the Halle Institute for Economic Research, Germany. It provides high-standard micro-founded datasets of distributional statistics of competition and productivity for about 20 European countries. All of the outcome variables we use are from the unconditional descriptive statistics for the weighted sample including all firms at the 2-digit sector level from the latest 7th Vintage data. We focus on the manufacturing sector, which are all sectors with codes less than or equal to 33 and next we detail the variables of interest. We also restrict the sample to 2009-2016, for which we have a balanced sample of 15 countries. This is the largest balanced sample we can construct from the available data.

We use sector-level weighted average log TFP (*PE37_Intfp_vcd_wd_S_mn*) as the productivity measure. The underlying firm-level TFP is estimated from a value-added Cobb-Douglas production function following a control function approach with Wooldridge correction. We use first difference at the sector level to construct sector-average productivity growth.

The two measures for concentration are both at the sector level. The top 10 firms' revenue share in the sample is available from the variable *CR02_top_rev_sam_S_tot* and the estimated population is *CV03_hhi_rev_pop_S_tot*. We further obtain the sector-level average job reallocation rate from *LG01_firm_1y_mn*, which has the underlying firm-level job reallocation rates calculated in the same way as we do in the ASIE sample. Finally the entry rate at the sector-level is taken to be the share of new firm available from *OD02_firm_age_new_mn*. We then merge the economic outcomes with the World Bank's Starting a Business scores (World Bank, 2020). In Table A.6, we report the average of the key variables by country.

Table A.6: Summary Statistics, *CompNet* 2009-2016

Country	Starting a Business score	Productivity growth	Top 10 revenue share	HHI	Job reallocation	Entry rate
Belgium	91.27	0.03	0.62	.	-0.01	0.05
Croatia	82.54	-0.01	0.60	0.03	-0.02	0.16
Denmark	91.16	0.02	0.58	0.03	-0.02	0.12
Finland	92.35	-0.00	0.63	0.02	-0.02	.
France	92.64	0.01	0.31	0.01	-0.01	0.00
Germany	81.51	-0.00	0.40	0.00	-0.00	0.00
Italy	84.78	-0.01	0.25	0.01	-0.00	0.14
Lithuania	86.72	0.03	0.67	0.03	-0.02	0.25
Netherlands	89.91	0.01	.	0.03	0.00	0.11
Portugal	90.01	0.01	0.40	0.03	-0.01	.
Romania	89.87	0.03	.	0.01	-0.04	0.15
Slovenia	92.83	0.00	0.66	.	-0.00	0.13
Spain	76.77	0.00	0.39	0.01	-0.03	0.08
Sweden	92.29	-0.01	0.57	0.02	-0.01	0.08
Switzerland	86.82	-0.01	0.61	0.01	-0.04	.

Note: This table reports the average of the key variables by country from the analysis sample of *CompNet* 2009-2016. Some variables are missing for a small number of countries due to data limitations.

A.5 Supplementary Information of the Figures and Tables

Figure 1.1 In Panel (a), two measures of aggregate entry rates are reported from two different sources. The entry rates constructed from the 1995, 2004 and 2008 Industrial Census follow the definition in Section A.2. To be consistent with the definition of entry rates we adopt for the census data, the entry rate for a year from the Business Registry and NBS data are calculated as the average of the number of newly registered firms in the Business Registry Record from that year and the preceding year divided by the total number of active firms in that year for the industrial sector. Further adjustments are needed on the raw entry rates constructed from Business Registry Records and NBS, because the NBS made two structural changes in its reporting of the total number of active firms in 1998 and in 2004. To the extent that the Industrial Census is the most accurate data source for the purpose of computing entry rates, we adjust the level of the raw entry rates computed from the Business Registry and NBS over the period 1960-1998 up so that the entry rate in the 1995 matches that from the 1995 Industrial Census. We apply the same adjustment to 1999-2004 and 2005-2008, benchmarking the levels of those from the Business Registry and NBS data to those in the 2004 and 2008 Industrial Census.

In Panel (b), we plot measures of market concentration (HHI and top 10 firms' revenue share) averaged across markets from both Census and ASIE. As ASIE only includes above-scale firms while Census includes all operating firms, ASIE necessarily biases the HHI down and biases the top 10 revenue share up. However, regardless of the data source, the broad picture of declining concentration over the sample period of 1995-2013 is clear.

Appendix B Model Derivations

B.1 Inflow and Outflow Tables

In this section, we present the inflow to and outflow from an industry with a given n for the other three type categories of the leader-follower pair: (h,l) , (l,h) and (l,l) , in Tables B.1-B.3. The table for the (h,h) configuration is Table 3.1 in the paper.

Table B.1: Inflow and Outflow in Industry ($i = h, j = l$)

State	Inflow	Outflow
n=0:	$2\mu_{hh}(0)\sigma + \sum_{n \geq 2} \mu_{hh}(n)\tau(1-\theta)x_{hh}^e(n)\phi + \sum_{n \geq 2} \mu_{hl}(n)[\bar{x}_{hl}(n) + \tau(1-\theta)x_{hl}^e(n)]\phi +$ $\sum_{n \geq 2} \mu_{lh}(n)[\bar{x}_{lh}(n) + \tau\theta x_{lh}^e(n)]\phi + \sum_{n \geq 2} \mu_{ll}(n)\tau\theta x_{ll}^e(n)\phi + \mu_{hh}(1)\tau(1-\theta)x_{hh}^e(1) +$ $\mu_{hl}(1)[\bar{x}_{hl}(1) + \tau(1-\theta)x_{hl}^e(1)] + \mu_{lh}(1)[\bar{x}_{lh}(1) + \tau\theta x_{lh}^e(1)] + \mu_{ll}(1)\tau\theta x_{ll}^e(1)$	$= \mu_{hl}(0)[x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0) + \sigma]$
n=1:	$\mu_{hl}(0)[x_{hl}^h(0) + \tau\theta x_{hl}^e(0)/2] + \mu_{ll}(0)\tau\theta x_{ll}^e(0) + \mu_{hh}(1)\sigma +$ $\mu_{hh}(2)\tau(1-\theta)x_{hh}^e(2)(1-\phi) + \mu_{hl}(2)[\bar{x}_{hl}(2) + \tau(1-\theta)x_{hl}^e(2)](1-\phi)$	$= \mu_{hl}(1)[x_{hl}^h(1) + \bar{x}_{hl}(1) + \tau x_{hl}^e(1) + \sigma]$
n ≥ 2:	$\mu_{hl}(n-1)x_{hl}(n-1) + \mu_{hh}(n)\sigma + \mu_{hh}(n+1)\tau(1-\theta)x_{hh}^e(n+1)(1-\phi)$ $\mu_{hl}(n+1)[\bar{x}_{hl}(n+1) + \tau(1-\theta)x_{hl}^e(n+1)](1-\phi)$	$= \mu_{hl}(n)[x_{hl}(n) + \bar{x}_{hl}(n) + \tau x_{hl}^e(n) + \sigma]$

Note: This table lists the inflow to and outflow from all possible states (i.e. gap sizes) given a (h,l) leader-follower configuration.

B.2 Derivation of Aggregate Output Growth

Define

$$g \equiv \frac{d \ln Y(t)}{dt} = \int_0^1 \frac{d \ln y_v(t)}{dt} dv,$$

Table B.2: Inflow and Outflow in Industry ($i = l, j = h$)

State	Inflow	Outflow
n=0:	$2\mu_{hh}(0)\sigma + \sum_{n \geq 2} \mu_{hh}(n)\tau(1-\theta)x_{hh}^e(n)\phi + \sum_{n \geq 2} \mu_{hl}(n)[\bar{x}_{hl}(n) + \tau(1-\theta)x_{hl}^e(n)]\phi +$ $\sum_{n \geq 2} \mu_{lh}(n)[\bar{x}_{lh}(n) + \tau\theta x_{lh}^e(n)]\phi + \sum_{n \geq 2} \mu_{ll}(n)\tau\theta x_{ll}^e(n)\phi + \mu_{hh}(1)\tau(1-\theta)x_{hh}^e(1) +$ $\mu_{hl}(1)[\bar{x}_{hl}(1) + \tau(1-\theta)x_{hl}^e(1)] + \mu_{lh}(1)[\bar{x}_{lh}(1) + \tau\theta x_{lh}^e(1)] + \mu_{ll}(1)\tau\theta x_{ll}^e(1)$	$= \mu_{hl}(0)[x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0) + \sigma]$
n=1:	$\mu_{hh}(0)\tau(1-\theta)x_{hh}^e(0) + \mu_{hl}(0)[x_{hl}^l(0) + \tau(1-\theta)x_{hl}^e(0)/2] + \mu_{hh}(1)\sigma +$ $\mu_{lh}(2)[\bar{x}_{lh}(2) + \tau\theta x_{lh}^e(2)](1-\phi) + \mu_{ll}(2)\tau\theta x_{ll}^e(2)(1-\phi)$	$= \mu_{lh}(1)[x_{lh}(1) + \bar{x}_{lh}(1) + \tau x_{lh}^e(1) + \sigma]$
n ≥ 2:	$\mu_{lh}(n-1)x_{lh}(n-1) + \mu_{hh}(n)\sigma + \mu_{ll}(n+1)\tau\theta x_{ll}^e(n+1)(1-\phi) +$ $\mu_{lh}(n+1)[\bar{x}_{lh}(n+1) + \tau\theta x_{lh}^e(n+1)](1-\phi)$	$= \mu_{lh}(n)[x_{lh}(n) + \bar{x}_{lh}(n) + \tau x_{lh}^e(n) + \sigma]$

Note: This table lists the inflow to and outflow from all possible states (i.e. gap sizes) given a (l, h) leader-follower configuration.

Table B.3: Inflow and Outflow in Industry ($i = l, j = l$)

State	Inflow	Outflow
n=0:	$\mu_{hl}(0)\sigma + \mu_{ll}(1)[\bar{x}_{ll}(1) + \tau(1-\theta)x_{ll}^e(1)] + \mu_{lh}(1)\tau(1-\theta)x_{lh}^e(1)$ $\sum_{n \geq 2} \mu_{ll}(n)[\bar{x}_{ll}(n) + \tau(1-\theta)x_{ll}^e(n)]\phi + \sum_{n \geq 2} \mu_{lh}(n)\tau(1-\theta)x_{lh}^e(n)\phi$	$= \mu_{ll}(0)[2x_{ll}^l(0) + \tau x_{ll}^e(0)]$
n=1:	$\mu_{ll}(0)[2x_{ll}^l(0) + \tau(1-\theta)x_{ll}^e(0)] + \mu_{hl}(0)\tau(1-\theta)x_{hl}^e(0)/2 + [\mu_{hl}(1) + \mu_{lh}(1)]\sigma +$ $\mu_{ll}(2)[\bar{x}_{ll}(2) + \tau(1-\theta)x_{ll}^e(2)](1-\phi) + \mu_{lh}(2)\tau(1-\theta)x_{lh}^e(2)(1-\phi)$	$= \mu_{ll}(1)[x_{ll}(1) + \bar{x}_{ll}(1) + \tau x_{ll}^e(1)]$
n ≥ 2:	$\mu_{ll}(n-1)x_{ll}(n-1) + [\mu_{hl}(n) + \mu_{lh}(n)]\sigma + \mu_{ll}(n+1)\tau(1-\theta)x_{ll}^e(n+1)(1-\phi) +$ $\mu_{ll}(n+1)[\bar{x}_{ll}(n+1) + \tau(1-\theta)x_{ll}^e(n+1)](1-\phi)$	$= \mu_{ll}(n)[x_{ll}(n) + \bar{x}_{ll}(n) + \tau x_{ll}^e(n)]$

Note: This table lists the inflow to and outflow from all possible states (i.e. gap sizes) given a (l, l) leader-follower configuration.

For any industry, from the industrial production function we have

$$\begin{aligned}
 y &= [y_1^\delta + y_2^\delta]^{\frac{1}{\delta}} = [p_1^{\delta/(\delta-1)} + p_2^{\delta/(\delta-1)}]^{\frac{1-\delta}{\delta}} \\
 &= \left[\left(\frac{1-\delta\omega_1}{\delta(1-\omega_1)} c_1 \right)^{\delta/(\delta-1)} + \left(\frac{1-\delta\omega_2}{\delta(1-\omega_2)} c_2 \right)^{\delta/(\delta-1)} \right]^{\frac{1-\delta}{\delta}} \\
 &= c_2^{-1} \left[\left(\frac{1-\delta\omega_1}{\delta(1-\omega_1)} \frac{c_1}{c_2} \right)^{\delta/(\delta-1)} + \left(\frac{1-\delta\omega_2}{\delta(1-\omega_2)} \right)^{\delta/(\delta-1)} \right]^{\frac{1-\delta}{\delta}} \\
 &= \lambda^{n_2} [f_1(n)^{\delta/(\delta-1)} + f_2(n)^{\delta/(\delta-1)}]^{\frac{1-\delta}{\delta}}
 \end{aligned}$$

where the last equality holds as both ω_1 and ω_2 are determined by the gap n .

Changes in y from a successful investment by the leader and follower in an industry with

gap n , denoted as a_n^L and a_n^F respectively, are

$$\begin{aligned} a_n^L &\equiv \ln \tilde{y} - \ln y \\ &= [f_1(n+1)^{\delta/(\delta-1)} + f_2(n+1)^{\delta/(\delta-1)}]^{1-\delta} - [f_1(n)^{\delta/(\delta-1)} + f_2(n)^{\delta/(\delta-1)}]^{1-\delta}, \end{aligned}$$

if a follower improves n steps

$$\begin{aligned} a_n^F(n) &\equiv \ln \tilde{y} - \ln y \\ &= n \ln \lambda + [f_1(0)^{\delta/(\delta-1)} + f_2(0)^{\delta/(\delta-1)}]^{1-\delta} - [f_1(n)^{\delta/(\delta-1)} + f_2(n)^{\delta/(\delta-1)}]^{1-\delta} \end{aligned}$$

if a follower improves 1 step

$$\begin{aligned} a_n^F(1) &\equiv \ln \tilde{y} - \ln y \\ &= \ln \lambda + [f_1(n-1)^{\delta/(\delta-1)} + f_2(n-1)^{\delta/(\delta-1)}]^{1-\delta} - [f_1(n)^{\delta/(\delta-1)} + f_2(n)^{\delta/(\delta-1)}]^{1-\delta} \end{aligned}$$

It follows that $\sum_{m=1}^n a_{m-1}^L + a_n^F(n) = n \ln \lambda$, and $a_n^L + a_{n+1}^F(1) = \ln \lambda$.

The aggregate growth rate of output is,

$$\begin{aligned} g &= \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) \{x_{ij}(n) a_n^L + (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) [\phi a_n^F(n) + (1-\phi) a_n^F(1)]\} \\ &\quad + \mu_{hh}(0) (2x_{hh}^h(0) + \tau x_{hh}^e(0)) a_0^L + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0)) a_0^L + \mu_{ll}(0) (2x_{ll}^l(0) + \tau x_{ll}^e(0)) a_0^L \\ &= \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) \{x_{ij}(n) a_n^L + (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) [\phi (n \ln \lambda - \sum_{m=1}^n a_{m-1}^L) + (1-\phi) (\ln \lambda - a_{n-1}^L)]\} \\ &\quad + \mu_{hh}(0) (2x_{hh}^h(0) + \tau x_{hh}^e(0)) a_0^L + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0)) a_0^L + \mu_{ll}(0) (2x_{ll}^l(0) + \tau x_{ll}^e(0)) a_0^L \\ &= \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) [\phi n \ln \lambda + (1-\phi) \ln \lambda] \\ &\quad + \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) [x_{ij}(n) a_n^L - (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) (\phi \sum_{m=1}^n a_{m-1}^L + (1-\phi) a_{n-1}^L)] \\ &\quad + \mu_{hh}(0) (2x_{hh}^h(0) + \tau x_{hh}^e(0)) a_0^L + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0)) a_0^L + \mu_{ll}(0) (2x_{ll}^l(0) + \tau x_{ll}^e(0)) a_0^L \\ &= \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) [\phi n \ln \lambda + (1-\phi) \ln \lambda] \end{aligned}$$

The second equation follows from $\sum_{m=1}^n a_{m-1}^L + a_n^F(n) = n \ln \lambda$, and $a_n^L + a_{n+1}^F(1) = \ln \lambda$. The last equality holds as the rest of terms is equal to zero. To see this point, note that the

coefficient in front of a_0^L is

$$\begin{aligned}
& - \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) \phi - \sum_{i=h,l} \sum_{j=h,l} \mu_{ij}(1) (\bar{x}_{ij}(1) + \tau x_{ij}^e(1)) (1 - \phi) \\
& + \mu_{hh}(0) (2x_{hh}^h(0) + \tau x_{hh}^e(0)) + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0)) + \mu_{ll}(0) (2x_{ll}^l(0) + \tau x_{ll}^e(0))
\end{aligned}$$

which equals zero under the stationary distribution.

The coefficient in front of $a_n^L, n \geq 1$, is

$$\begin{aligned}
& \sum_{i=h,l} \sum_{j=h,l} \mu_{ij}(n) x_{ij}(n) - \sum_{i=h,l} \sum_{j=h,l} \sum_{m \geq n+1} \mu_{ij}(m) \phi (\bar{x}_{ij}(m) + \tau x_{ij}^e(m)) \\
& - \sum_{i=h,l} \sum_{j=h,l} \mu_{ij}(n+1) (1 - \phi) (\bar{x}_{ij}(n+1) + \tau x_{ij}^e(n+1))
\end{aligned}$$

which also equals zero under stationary distribution.

It follows that

$$g = \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) [\phi n \ln \lambda + (1 - \phi) \ln \lambda].$$

Note that

$$\begin{aligned}
& \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) (n\phi + 1 - \phi) \\
& = \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) (1 - \phi) + \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) \phi \\
& \quad + \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 2} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) \phi + \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 3} \mu_{ij}(n) (\bar{x}_{ij}(n) + \tau x_{ij}^e(n)) \phi + \dots \\
& = \mu_{hh}(0) (2x_{hh}^h(0) + \tau x_{hh}^e(0)) + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0)) + \mu_{ll}(0) (2x_{ll}^l(0) + \tau x_{ll}^e(0)) \\
& \quad + \sum_{i=h,l} \sum_{j=h,l} \sum_{n \geq 1} \mu_{ij}(n) x_{ij}(n)
\end{aligned}$$

that is,

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

with $\mu(0) x(0) \equiv \sum_{i=h,l} \mu_{ii}(0) (2x_{ii}^i(0) + \tau x_{ii}^e(0)) + \mu_{hl}(0) (x_{hl}^h(0) + x_{hl}^l(0) + \tau x_{hl}^e(0))$.

Appendix C Calibration

C.1 Two Ways of Decomposing Compositional Changes

Note that, from the growth rate formula, changes in the growth rate can come from both the x terms, which are summarized as the direct effect and the Schumpeterian effect, and the μ terms, which can be further decomposed into a replacement effect and a pro-competitive effect. For this later part, there are two symmetric methods.

Method A:

$$\begin{aligned}
& \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\mu_2(\psi, n) - \mu_1(\psi, n)] \\
& \approx \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(n) f_2(\psi|n) - \tilde{\mu}_1(n) f_1(\tau|n)] \\
& \approx \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(n) f_2(\psi|n) - \tilde{\mu}_1(n) f_2(\psi|n) + \tilde{\mu}_1(n) f_2(\psi|n) - \tilde{\mu}_1(n) f_1(\psi|n)] \\
& = \underbrace{\sum_{\psi} \sum_{n=0} x_1(\psi, n) [f_2(\psi|n) - f_1(\psi|n)] \tilde{\mu}_1(n)}_{\text{replacement effect}} + \underbrace{\sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(n) - \tilde{\mu}_1(n)] f_2(\psi|n)}_{\text{pro-competitive effect}}.
\end{aligned}$$

where $f_s(\psi|n), s = 1, 2$ denotes the distribution of ψ conditional on a given value of n , and $\tilde{\mu}_s(n) \equiv \sum_{\psi} \mu_s(\psi, n)$ is the marginal distribution of n in economy $s, s = 1, 2$.

Method B:

$$\begin{aligned}
& \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\mu_2(\psi, n) - \mu_1(\psi, n)] \\
& \approx \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(\psi) h_2(n|\psi) - \tilde{\mu}_1(\psi) h_1(n|\psi)] \\
& \approx \sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(\psi) h_2(n|\psi) - \tilde{\mu}_2(\psi) h_1(n|\psi) + \tilde{\mu}_2(\psi) h_1(n|\psi) - \tilde{\mu}_1(\psi) h_1(n|\psi)] \\
& = \underbrace{\sum_{\psi} \sum_{n=0} x_1(\psi, n) [\tilde{\mu}_2(\psi) - \tilde{\mu}_1(\psi)] h_1(n|\psi)}_{\text{replacement effect}} + \underbrace{\sum_{\psi} \sum_{n=0} x_1(\psi, n) [h_2(n|\psi) - h_1(n|\psi)] \tilde{\mu}_2(\psi)}_{\text{pro-competitive effect}}.
\end{aligned}$$

where $h_s(n|\psi), s = 1, 2$ denotes the distribution of n conditional on a given value of ψ , and

$\tilde{\mu}_s(\psi) \equiv \sum_n \mu_s(\psi, n)$ is the marginal distribution of ψ in economy $s, s = 1, 2$.

Under the calibrated parameters, Table C.1 presents the decomposition results using these two methods. Method A tends to obtain a larger “replacement effect,” while Method B obtains a larger “pro-competitive effect.” As there is no clear criteria as to which method is superior to the other, we use the average from those two methods as the benchmark values for these two effects reported in Table 4.3 in the paper.

Table C.1: Decomposition with Method A & B

	Replacement effect	Pro-competitive effect
Method A	0.0100	0.0052
Method B	0.0013	0.0139
Average	0.0056	0.0096
Average (%)	37.60%	63.87%

Note: This table list the relative contribution of the replacement effect and the pro-competitive effect following two approaches of decomposition.

C.2 Constructing the Counterfactual Entry Rate

Baseline Counterfactual One of the ingredients we need to construct the counterfactual target of entry rate in 1990 for the baseline model is the elasticity of entry rates with respect to the “Time (days) to start a business” measure, estimated from a cross-section of Chinese provinces in 2008. More specifically, we define a market as 4-digit industry cross province and regress the market-level entry rate on time to start a business, controlling for industry fixed effects, province controls (GDP per capita, industrial GDP share and population) and market controls (number of firms, total employment, revenue, employment weighted SOE share). Standard errors are clustered as 4-digit industry level. Table C.2 reports the result of the estimation. The elasticity of entry rate to the entry barrier measure is -0.00158. That is, one additional day until starting a business lowers the entry rate by 0.158 percentage points.

Then we linearly extrapolate the time to start a business for Shanghai from 2004 to 2020 backward to 1990 and obtain 74.74 days in 1990.²³ Compared with 46 days in 2004, this

²³The time series of the “time to start a business” measure for Shanghai appears linear (Figure A.1).

is a difference of 28.72 days. Combined with an elasticity of -0.00158 , the counterfactual reduction of entry rate is 4.54 percentage points.

Table C.2: Time (Days) to Start a Business and Entry Rate, the Chinese Provincial Sample

	Entry Rate
Time (Days)	-0.00158^{***} (-5.05)
R^2	0.4025
4-digit Industry F.E.	Yes
Province controls	Yes
Market controls	Yes
Observations	11606

t statistics in parentheses

Province controls include GDP per capita, 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.

Standard errors are clustered at 4-digit industry level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative Counterfactual Reductions of Entry Rates We construct counterfactual entry rates in 1990 using two alternative methods here.

Method 1. Using Start a Business Score. We use the longest time series of Start a Business Score from World Bank’s flagship *Doing Business* survey available for China and its cities, that of Shanghai, and extrapolate from the observed 2004-2020 data linearly back to 1990.²⁴ This yields a score of 9.63 in 1990 and implies a reduction of 37.03 in the score between 1990 and 2004. To put the extrapolated 9.63 into context, Cambodia’s score in 2004 or Myanmar’s in as late as 2014 fall in the same ballpark as the extrapolated value (World Bank, 2020). We consider it reasonable, as the industry was almost entirely in the state control with an entry rate of 3% from mostly state-owned entities and the legal framework to recognise and protect private companies was not in place until 1994.

To obtain the elasticity of entry rate with respect to the score, however we can no longer use the Chinese cross-section data from the 2018 special report, as Starting a Business score is not included as a measure there. Instead, we merge the country-level *Doing Business* survey with a European panel from *CompNet*. The advantage of *CompNet* is that it

²⁴The time series of the Starting a Business score for Shanghai appears linear (Figure A.1).

publishes the distributional statistics of firm dynamics, market concentration measures and productivity growth, at a 2-digit industry level by country for a large number of European countries. This allows us to define outcomes, such as the industry-level entry rate used here, in this European cross-country panel, in a way similar to how we construct them from the Chinese micro data.²⁵ In the European panel, we regress the country-industry-year level entry rates on country-year level Starting a Business score, controlling for country-industry and year fixed effects, industry controls (total employment and capital), and country-year controls (output share of manufacturing and share of export in manufacturing). The resulting elasticity is 0.00114 (Table C.3). One unit increase in the Starting a Business score correlates with 0.114 percentage point increase in the entry rate.

Combining the two pieces of information, the counterfactual reduction of entry is 37.03×0.00114 or 4.22 percentage points under Method 1.

Table C.3: The Starting a Business Score and Entry Rate, the European Sample

	Entry Rate
World Bank Starting a Business Score	0.00114*** (3.38)
R^2	0.908
Country-Sector F.E.	Yes
Year F.E.	Yes
Sector controls	Yes
Economy controls	Yes
Observations	1400

t statistics in parentheses

Sector controls include sector (2-digit industry) level employment and capital.

Economy controls include output share of manufacturing out of the non-financial business sector and share of export in manufacturing.

Standard errors are clustered at country-sector level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Method 2. Using the China series. World Bank's *Doing Business* Survey publishes data for China (the whole country), Shanghai and Beijing separately. In Method 1, we use the score for Shanghai, as this is the longest time series of the three options, but obviously Shanghai is not representative of China. So in Method 2, we follow Method 1 except that we use China's Starting a Business score from 2014-2020 to extrapolate linearly the

²⁵See Appendix A.4 for details of the *CompNet* sample.

change in the score between 1990 and 2004, which yields a change of 47.74.²⁶ Combining it with the elasticity of 0.00114 from the cross-country panel, we arrive at a counterfactual reduction of entry rate of 47.74×0.00114 or 5.44 percentage points under Method 2.

Both methods produce a counterfactual reduction of entry rate that is within a $\pm 20\%$ interval around the baseline counterfactual reduction of 4.54 percentage points.

C.3 Robustness of the Growth Rate Differential Decomposition

In this section, we vary the counterfactual policy-induced reduction in entry rate from 20% below the baseline level to 20% above the baseline level. In each scenario, we recalibrate the model with the new target of the counterfactual entry rate, compute the growth rate differential, and conduct the decomposition as in the main text. The results are in Table C.4.

When we suppose the counterfactual change of the entry rate is 20% more than assumed in the main text corresponding to “20% more entry barrier reduction,” the resulting aggregate growth rate of the recalibrated economy is 1.74 percentage points lower than the baseline model growth rate. Of the growth rate differential, 3.41% is due to the direct effect, -2.07% the Schumpeterian effect, 37.54% the replacement effect, and 61.12% the pro-competitive effect.

When we suppose the counterfactual change of the entry rate is 20% less than assumed in the main text corresponding to “20% less entry barrier reduction,” the resulting aggregate growth rate of the recalibrated economy is only 1.13 percentage points lower than the baseline model growth rate. Of the growth rate differential, 2.94% is due to the direct effect, -7.69% the Schumpeterian effect, 38.38% the replacement effect, and 66.37% the pro-competitive effect.

It is remarkable that across these different scenarios, the importance of the replacement effect and that of the pro-competitive effect are quite stable at close to 40% and a little over 60% respectively, suggesting that the changing market structure is an important channel for the growth impact of entry barrier reduction in the Chinese context.

²⁶The time series of the Starting a Business score for China appears linear (Figure A.1).

Table C.4: Decomposition of Growth Rate Differences between the Baseline and Counterfactual Economy, Robustness Check

growth rate diff.	direct	Schumpeterian	replacement	pro-competitive
<i>20% more entry barrier reduction</i>				
0.0174	0.0006	0.0004	0.0068	0.0110
	3.41%	-2.07%	37.54%	61.12%
<i>20% less entry barrier reduction</i>				
0.0113	0.0003	-0.0009	0.0044	0.0076
	2.94%	-7.69%	38.38%	66.37%

Note: This table shows the growth difference between the baseline and an counterfactual economy in which entry barrier reduction is 20% more (or less) than the magnitude we showed in the main text, and the decomposition of the growth difference into the direct, Schumpeterian, replacement, and pro-competitive effects. The decomposition is not exact. We adjust the raw values such that sub-entries sum to 100%.

Appendix D Additional Empirical Results

D.1 Alternative Measures of Entry Barriers

In this section, we present the cross-sectional empirical results relating market-level and firm-level outcomes to administrative and regulatory entry barriers analogous to Table 5.1 for an alternative measure of entry barriers. In the main text, we use the entry barrier index constructed from four sub-indicators under the Starting a Business section from the *Doing Business* Database, using principle component analysis. In this section, we relate the outcomes directly to the Starting a Business rank reported in the Database. Table D.1 shows that the empirical pattern that we focus on still holds.

D.2 Employment-Based Measures of Concentration

In this section, we report results using employment-based measures of concentration instead of revenue-based measures of concentration. Because the measure of entry barriers is at the province level, we define markets as 4-digit industry cross province. One may wonder if this notion of market is more accurate for product market or for labor market. We confirm here that from the view of the labor market, market concentration in terms of the HHI in employment and top 10 firm's employment share is also negatively correlated with entry barriers. The results are reported in Table D.2. Using employment based market concentration measures still yield the positive correlations between market entry barrier and market concentration measures.

Table D.1: Robustness Check: Entry Barrier, Market Structure, and Growth

	Market Structure		Job Reallocation		Firm Labor Productivity Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
	log normalized HHI	top 10 Share	2008-2009	2011-2013	2008-2009	2011-2013
Starting a Business rank	0.0118*** (5.76)	0.00252*** (9.36)	-0.00317*** (-6.16)	-0.00374*** (-10.10)	-0.00338** (-2.19)	-0.00200*** (-2.81)
R^2	0.403	0.633	0.099	0.193	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 capita, 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 World Bank Starting a Business Rank respectively, controlling for 4-digit CIC industry fixed effects, with standard errors clustered at 4-digit CIC industry level. Province controls include GDP per capita, the industrial GDP share, and total population in 2008. Market controls include total employment, total revenue, and employment weighted SOE share in 2008. Firm controls include firm age, employment, sales, ownership types, and export to output ratio in 2008.

D.3 Firms by Ownership Types and Exporting Status

Our sample period also covers China's entry into WTO in 2001, which in principle facilitated both foreign firms entering the Chinese market and Chinese firms exporting to other countries. In this section, we examine the role of foreign firms as well as the role of domestic exporting firms. We first repeat our regressions of the firm-level labor productivity here for state-owned firms (SOEs), privately owned firms (POEs), and foreign-owned firms (FOEs) separately. Next, we examine non-exporters and exporters separately.

SOEs, POEs and FOEs As shown by Table D.3, firms in the ASIE sample are predominantly privately owned (roughly 80%); the share of POEs has been increasing while the shares of SOEs and FOEs show a slightly decreasing trend. An interesting question is whether FOEs behaved differently than POEs or whether pro-competitive and growth-enhancing effects could be driven by FOEs instead of domestic POEs. If so, the framework to examine the pro-competitive and pro-growth effect would necessarily entail an

Table D.2: Entry Barrier, Growth, and Market Structure

	log normalized HHI		top 10 share	
	(1) revenue based	(2) employment based	(3) revenue based	(4) employment based
Entry Barrier Index (PF)	0.155*** (9.42)	0.126*** (7.48)	0.0252*** (13.10)	0.0280*** (13.34)
R^2	0.405	0.532	0.642	0.686
4-digit Industry F.E.	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes
Market controls	Yes	Yes	Yes	Yes
Observations	10861	10859	11479	11567

t statistics in parentheses

Province controls include GDP per capita, 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.

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 log normalized HHI (column [1]-[2]) and top 10 share (column [3]-[4]) on the Entry Barrier Index respectively, controlling for 4-digit CIC industry fixed effects, with standard errors clustered at 4-digit CIC industry level. Province controls include GDP per capita, the industrial GDP share, and total population in 2008. Market controls include total employment, total revenue, and employment weighted SOE share in 2008.

international trade element. We provide evidence against this hypothesis.

To do that, we rerun the firm-level empirical specifications similar to that in Table 5.1 but distinguishing the SOEs, FOEs, and POEs separately. Specifically, we regress the 2008-09 and 2011-13 labor productivity growth of three types of enterprises (SOE, FOE, POE) on the index of entry barrier in 2008, controlling for four-digit industry fixed effects, province characteristics as well as firm characteristics. The results are in Table D.4. Clearly, the empirical pattern that we focus on, namely entry barrier being negatively correlated with growth is driven by domestic POEs.

Table D.3: Share of Firms by Ownership Types and Exporting Status (%)

Year	SOE	FOE	POE	Non-Exporters	Exporters
2008	1.37	18.89	79.73	78.41	21.59
2009	1.30	18.65	80.05	79.44	20.56
2011	1.20	18.90	79.90	78.26	21.74
2012	1.14	17.74	81.12	79.35	20.65
2013	0.91	16.12	82.97	80.84	19.16

Note: This table the share (percent) of firms by ownership types and exporting status in the ASIE sample.

Table D.4: Entry Barrier and Firm-Level Labor Productivity Growth

	SOE		FOE		POE	
	(1)	(2)	(3)	(4)	(5)	(6)
	2008-09	2011-13	2008-09	2011-13	2008-09	2011-13
Entry Barrier Index (PF)	0.0351 (1.08)	-0.0133 (-0.41)	0.0659*** (2.74)	-0.0139 (-0.74)	-0.0643*** (-4.16)	-0.0384*** (-5.07)
R^2	0.223	0.171	0.057	0.036	0.039	0.023
4-digit Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1056	1056	20831	20831	66883	66883

t statistics in parentheses

Province controls include GDP per capita, industrial GDP share, and total population 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 firm-level labor productivity growth in 2008-09 and 2011-13 (column [7]-[8]) on the Entry Barrier Index, controlling for 4-digit CIC industry fixed effects, with standard errors clustered at 4-digit CIC industry level. Province controls include GDP per capita, the industrial GDP share, and total population in 2008. Firm controls include firm age, employment, sales, ownership types, and export to output ratio in 2008.

Exporting firms On the other hand, the entry to WTO allows more domestic firms to become exporting firms (about 20% of our sample) and we ask if the productivity growth

acceleration may be driven by exporting, which may also correlate negatively with measures of entry barriers.

As shown by Table D.5, we regress firm-level labor productivity growth on entry barrier index as in our baseline specification for non-exporters and exporters separately. The empirical pattern that labor productivity growth is negatively associated with market entry barriers mainly holds for domestic non-exporters.

Table D.5: Entry Barrier and Labor Productivity Growth of Exporting Firms

	non-exporters		exporters	
	(1)	(2)	(3)	(4)
	2008-09	2011-13	2008-09	2011-13
Entry Barrier Index (PF)	-0.0594*** (-4.02)	-0.0413*** (-5.44)	0.0411* (1.76)	0.0169 (1.20)
R^2	0.038	0.022	0.047	0.037
4-digit Industry F.E.	Yes	Yes	Yes	Yes
Province controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	62977	62977	25891	25891

t statistics in parentheses

Province controls include GDP per capita, industrial GDP share, and total population in 2008.

Firm controls include age, employment, sales, and ownership types.

Standard errors are clustered at 4-digit industry level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports the results from regressing labor productivity growth on the index of Entry Barriers in 2008 for non-exporters and exporters respectively, controlling for 4-digit industry fixed effects, province characteristic and firm characteristic.

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This working paper has been produced by
the School of Economics and Finance at
Queen Mary University of London

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