NBER WORKING PAPER SERIES

FROM IMITATION TO INNOVATION:
WHERE IS ALL THAT CHINESE R&D GOING?

Michael König
Zheng Michael Song
Kjetil Storesletten
Fabrizio Zilibotti

Working Paper 27404
http://www.nber.org/papers/w27404

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2020, Revised December 2021

We thank three referees, Daron Acemoglu, Philippe Aghion, Joe Altonji, Ufuk Akcigit, Manuel Amador, Marco Bassetto, Christopher Flynn, Chang-Tai Hsieh, Chad Jones, Patrick Kehoe, Juan Pablo Nicolini, Jesse Perla, Torsten Persson, Chris Tonetti, Daniel Xu, Gianluca Violante, conference participants at the ABFER Annual Conference 2017, the ASSA Annual Meeting 2019, the Bank of Canada-IMF-University of Toronto Meeting on the Chinese Economy, the 2021 China Econometric Society Meeting, CIFAR, The Economics of Creative Destruction (Paris, June 9–12 2021), and seminar participants at the Arizona State University, Cambridge University, Columbia University, Collegio Carlo Alberto, the Federal Reserve of Minneapolis, Fudan University, Hong Kong University of Science and Technology, the National University of Singapore, New York University, Ohio State University, Peking University, Princeton University, Stanford University, Tsinghua University, the University of California at Berkeley, the University of Chicago, University College London, University of Hong Kong, University of Houston, the University of Notre Dame, University of St. Andrews, and Yale University. Zheng Song acknowledges financial support from the Research Grant Council of Hong Kong. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 27404
June 2020, Revised December 2021
JEL No. L16,O31,O47,O53

ABSTRACT

We construct an endogenous growth model with random interactions where firms are subject to distortions. The TFP distribution evolves endogenously as firms seek to upgrade their technology over time either by innovating or by imitating other firms. We use the model to quantify the effects of misallocation on TFP growth in emerging economies. We structurally estimate the stationary state of the dynamic model targeting moments of the empirical distribution of R&D and TFP growth in China during the period 2007–12. The estimated model fits the Chinese data well. We compare the estimates with those obtained using data for Taiwan and perform counterfactuals to study the effect of alternative policies. R&D misallocation has a large effect on TFP growth.

Michael König
Vrije Universiteit Amsterdam
School of Business and Economics
Amsterdam
Netherlands
m.d.konig@vu.nl

Zheng Michael Song
Department of Economics
Chinese University of Hong Kong
Shatin, N.T., Hong Kong
zheng.michael.song@gmail.com

Kjetil Storesletten
Department of Economics
University of Minnesota
4-141 Hanson Hall
1925 Fourth Street S
Minneapolis, MN 55455
kjetil.storesletten@econ.uio.no

Fabrizio Zilibotti
Department of Economics
Yale University
28 Hillhouse Avenue
New Haven, CT 06520
and NBER
fabrizio.zilibotti@yale.edu

1 Introduction

In this paper, we construct and estimate a model of endogenous technical change with random interactions where firms are subject to distortions. The goal of the paper is to quantify the dynamic effects of misallocation on the investments firms make to improve their productivity growth.

In the theory, the evolution of the total factor productivity (TFP) distribution hinges on profit-maximizing firms seeking to upgrade their technology. To this end, firms face a binary choice: they can either adopt better technologies used by other firms (*imitation*) or break new ground and search for new technologies (*innovation*). Focusing on innovation requires an investment and entails some opportunity cost of foregoing learning through random interactions. The firms' relative TFP determines the comparative advantage of the two alternative strategies. Firms that are farther from the technology frontier can gain more from random interactions. Conversely, for firms closer to the technology frontier, the scope for imitating other firms is limited, and they must innovate in order to improve their technology. The investment decision is affected by firm-specific labor and capital market distortions (wedges). These wedges affect the investments in innovation because a positive wedge reduces the gains associated with a future TFP increase.

We structurally estimate the theory exploiting the stationary equilibrium of the dynamic model. We use the Simulated Method of Moments (SMM), targeting moments of the empirical distribution of R&D and TFP growth that are salient in the theory. We use data from manufacturing firms in mainland China (henceforth, China) in the period 2007–12. We are motivated by the observation that in recent years, the rapid economic growth in China has been accompanied by a boom in R&D expenditure and growing emphasis by the government on innovation (see, e.g., Ding and Li (2015), Zilibotti (2017)).[1] However, where is all this R&D going? A common concern is that these investment decisions are distorted by policies and frictions (e.g., credit constraints) that are pervasive in China. Our methodology allows us to assess the contribution of these investments to aggregate growth.

We proxy the choice between imitation and innovation by the firms' R&D investment behavior on the extensive margin. We classify firms making R&D investments as innovators and firms not making R&D investments as imitators. We study the robustness of the results to the choice of the proxy. We measure distortions using the methodology proposed by Hsieh and Klenow (2009). In our theory, the presence of heterogeneous output wedges lowers the correlation between TFP and propensity to pursue innovation—when the decision to invest in R&D is distorted, the firm's size matters more than its TFP. We document that in our data the propensity of firms to invest in R&D is positively correlated with TFP and size—the latter correlation being stronger. Moreover, conditional on TFP, TFP growth is higher for R&D firms than for nonR&D firms. All these observations are in line with the predictions of the theory. We estimate the model. The estimated model matches well the target moments from a quantitative perspective. The benchmark model predicts an annual aggregate TFP growth rate of 3.6%, which is close to the empirical counterpart for China for 2007–12. This moment is not targeted in the estimation.

Next, we extend the model to allow for heterogeneous R&D costs across firms. To this aim, we introduce "innovation wedges" that are distinct distortions from the standard output wedges and allow them to be correlated with firm-level TFP. The estimated pattern is suggestive of an active industrial

[1]The transition toward innovation-based growth is a central theme in the government's strategy. The 13th Five-Year Plan (2016–20) emphasizes the promotion of research in strategic and frontier fields. The National Innovation-Driven Development Strategy Outline issued in June 2016 states that China should become an innovation-oriented economy by 2020 and a technological innovation powerhouse by 2050. While China invested barely 1% of its GDP in the 1990s, R&D investments increased to 2.4% of GDP by 2020.

policy, which is arguably a salient feature of China. Finally, motivated by the findings of Chen et al. (2021), we explore an extension in which some Chinese firms may respond to fiscal incentives by fudging R&D expenditure, that is, relabeling part of their operational expenditure as R&D, in order to cash in on public subsidies.

For contrast, we estimate the model using plant-level data from Taiwan, for which census data on R&D investments are also available. Taiwan is a natural comparison for China, not only for its geographic and cultural proximity, but also for the structural similarities between the two economies in which the manufacturing sector plays a central role. The results for Taiwan are qualitatively similar to those obtained for China, albeit with one notable difference: the productivity of R&D is higher. In particular, both the TFP growth of R&D firms and the rate of technology diffusion are larger for Taiwanese firms. We find that if China had the same R&D technology as Taiwan, TFP growth would be significantly higher even with the Chinese level of misallocation.

We use the estimated model to perform a set of counterfactual policy experiments. In one of them, we reduce the variance of wedges by 50%. The reduction in misallocation triggers a dynamic adjustment towards a new stationary equilibrium with higher growth. Because the reduction in misallocation strengthens the comparative advantage of high-TFP firms, the transition is associated with an increase in TFP dispersion across firms and an acceleration of growth. Another set of counterfactuals studies the effect of nontargeted R&D subsidies. We find a nonmonotonic effect on growth: a subsidy inducing a moderate increase in R&D investments speeds up TFP growth. However, very large subsidies slow down TFP growth. The reason is that in our model productivity growth hinges on both innovation and imitation. Inducing too many firms to innovate has an opportunity cost in terms of foregone technology diffusion that outweighs the benefits of innovation. Therefore, our theory provides a novel insight to the debate on innovation policy: it is important to induce the "right firms" to pursue an innovation strategy.

Finally, we embed our theory in a model of technology catch-up through international spillovers where reducing misallocation has effects on the transition but not on the steady-state growth of non-frontier economies. Even in this model, an exogenous change in misallocation has a large effect on both transitional growth and the long-run GDP level relative to the frontier.

Related literature: Our study is related to various streams of the growth and development literature. First, it contributes to the debate on the determinants of success and failure in technological convergence (e.g., Hall and Jones (1999), Klenow and Rodriguez-Clare (1997), Acemoglu and Zilibotti (2001), Hsieh and Klenow (2010)). The importance of technology diffusion stretches back to the seminal work of Griliches (1957). R&D investments and spillovers are core elements of the neo-Schumpeterian theory à la Aghion and Howitt (1992); see also Griliches (1998). While this literature highlights a process of creative destruction where new firms are carriers of innovation, recent research by Garcia-Macia et al. (2019) finds that the lion's share of aggregate growth stems from TFP growth by incumbent firms. This evidence is consistent with the tenets of our theory.

The dichotomy between innovation and imitation in the process of development is emphasized by Acemoglu et al. (2006). The important role of misallocation as a determinant of aggregate TFP differences is related to the influential work of Hsieh and Klenow (2009). Our study builds on their methodology, although it attempts to endogenize the distribution of TFP across firms, which is instead exogenous in their work. The importance of misallocation in China is also emphasized, among others, by Song et al. (2011), Hsieh and Song (2015), Cheremukhin et al. (2017), Brandt et al. (2016), and Tombe and Zhu (2019).

Our paper also contributes to the recent literature describing the endogenous evolution of the distribution of firm size and TFP. This includes, among others, Jovanovic and Rob (1989), Luttmer (2007, 2012), Ghiglino (2012), Perla and Tonetti (2014), Acemoglu and Cao (2015), Lucas and Moll (2014), König et al. (2016), Benhabib et al. (2014, 2021), Akcigit et al. (2018). While a number of these studies emphasize random interactions, the theoretical paper by König et al. (2016) is the only one highlighting a trade-off between innovation and imitation. Our theoretical model builds on that paper.

Finally, our paper is related to the burgeoning theoretical and empirical literature on firm dynamics with R&D investments and creative destruction. These studies include, among others, Bloom et al. (2002), Klette and Kortum (2004), Lentz and Mortensen (2008), Acemoglu and Cao (2015), Akcigit and Kerr (2018), Acemoglu et al. (2018), and Akcigit et al. (2021). Our paper contributes to this literature by providing a new method for structurally estimating the effects of R&D on growth. A common problem in the empirical literature is the selection of firms into R&D. Our theory provides an endogenous selection mechanism that we incorporate when we estimate the model.

Related literature on R&D in China: Our paper is also related to the empirical literature studying R&D policy in China. Ding and Li (2015) provide a comprehensive overview of the instruments adopted by the Chinese government intervention to foster R&D. The systematic policy intervention to stimulate innovation had its first impetus in 1999 and accelerated in 2006 with the adoption of the Medium– and Long–term National Plan for Science and Technology Development. The policy instruments are manifold. The first is direct government funding of research through the establishment of tech parks, research centers, and a series of mission-oriented programs. The most important among such programs is Torch, a program intended to kick-start innovation and start-ups through the creation of innovation clusters, technology business incubators, and the promotion of venture capital. Another important part of the government strategy is tax incentives for innovation. This takes the form of tax bonuses applicable to wages, bonus and allowances of R&D personnel, corporate tax rate cuts, and R&D subsidies. For instance, firms are granted a 150% tax allowance against taxable profits on the level of R&D expenditure and 100% tax allowance against taxable profits on donations to R&D foundations. In addition, firms that qualify as innovative can obtain exemptions from import duties and VAT on imported items for R&D purposes. Firms that are invited to join science and technology parks are often exempted from property taxes and urban land use taxes. Finally, "innovative firms" receive subsidies on investments.

The policy interventions leave ample margins for discretion. For instance, central and local governments can decide which firms to invite to be part of science and technology parks, which firms receive priority in High-Tech Special Economic Zones, etc. In short, incentives can be heterogenous across provinces, local communities, sectors, and even at the firm level, often as a function of political connections (Bai et al., 2016).

Some empirical studies evaluate the effects of R&D investment and R&D policy in China. Hu and Jefferson (2009) use data for Chinese large and medium–size enterprises for the period 1995–2001. The authors estimate the patents–R&D elasticity is 0.3 when evaluated at the sample mean of the real R&D expenditure (and even lower at the median). This is smaller than similar estimates for the U.S. and European firms which find elasticities in the range of 0.6–1. While their study is based on data from the 1990s, Dang and Motohashi (2015) find similar results using data for the period 1998–2012.

Jia and Ma (2017) use a panel dataset of Chinese listed companies covering 2007–13 to assess the effects of tax incentives on firm R&D expenditures and analyze how institutional conditions shape these effects. They show that tax incentives have significant effects on the R&D expenditure reported by firms. A 10% reduction in R&D user costs leads firms to increase R&D expenditures by 4% in the short run. They also document considerable effect heterogeneity: tax incentives significantly stimulate R&D in private firms but have less influence on state-owned enterprises' R&D expenditures.

Chen et al. (2021) analyze InnoCom, a large–scale program providing incentive for R&D investment through corporate income tax cuts. They exploit variation over time in discontinuous tax incentives to R&D and find that there is significant bunching at the various R&D policy notches. Moreover, many firms appear to respond to the tax incentive by relabeling nonR&D expenditures as R&D expenses.

Finally, Holmes et al. (2015) study the role of multinational firms as a vehicle of technology transfer to China. We consider international knowledge spillover in an extension.

Road Map: The paper is structured as follows; Section 2 presents the theory. Section 3 discusses the data and some descriptive evidence. Section 4 presents the econometric methodology. Sections 5–8 discuss the estimation results, robustness analysis, and counterfactual experiments. Section 9 concludes. The supplementary appendix contains technical results and additional tables and figures. Further technical details are deferred to a web appendix.

2 Theory

Consider a dynamic economy populated by a unit measure of monopolistically competitive firms. Firms produce differentiated goods that are combined into a homogeneous final good by a Dixit-Stiglitz aggregator with a constant elasticity of substitution $\eta > 1$ between goods, implying $Y = \left(\int_0^1 Y_i^{(\eta-1)/\eta} di\right)^{\eta/(\eta-1)}$.

Firms are owned by overlapping generations of two-period–lived manager-entrepreneurs as in Song et al. (2011). In each period, the firm is owned by an old entrepreneur who is residual claimant on the firms' profits, but run by a young manager. In the first period of her life, the manager decides the strategy to improve the firm's TFP in the next period having access to frictionless credit markets. In the following period, she turns into an old entrepreneur, hires a young manager to run the firm, and appropriates and consumes the firm's profits.

In this environment, we can break down the firm's problem into two steps. First, there is a static maximization problem: the firm's manager hires a composite production input to maximize profits given the firm's current TFP. Second, there is an intertemporal investment problem: the firm makes an investment decision that affects the next period's TFP and profits. The OLG structure simplifies the dynamic problem by turning it into a sequence of two-period decisions. This allows us to retain analytical tractability and avoid complications that would make the structural estimation problem infeasible.

Static production efficiency: The firm's technology is represented by a constant returns to scale Cobb Douglas production function:

$$Y_i(t) = A_i(t) K_i(t)^{\alpha} L_i(t)^{1-\alpha},$$

where $\alpha \in (0,1)$, $K_i(t)$ is capital, $L_i(t)$ is labor, and $A_i(t)$ is TFP. As in Hsieh and Klenow (2009), firms have heterogeneous $A_i(t)$ and rent capital and labor from competitive markets subject to distortions. We summarize all distortions into a single output wedge that we view as a catch-all for a variety of firm-specific distortions on labor and credit markets—the latter being especially important in China as documented by Song et al. (2011) and Hsieh and Song (2015). More formally, firms maximize profits taking factor prices as given, but their decisions are distorted by a set of output wedges τ_i. Note that

$\tau_i < 0$ indicates a negative wedge, or an implicit output subsidy.[2] We assume a small open economy where firms rent capital at an exogenous rental rate r.

Because the characterization of the static equilibrium is as in Hsieh and Klenow (2009), we omit details. Here, we summarize the two equilibrium conditions that are sufficient to derive the dynamic equilibrium and that we use in the empirical analysis. Firm i's current (period t) profits are given by

$$\pi_i(t) \propto (A_i(t)(1-\tau_i(t)))^{\eta-1}. \tag{1}$$

Profits increase in TFP and decrease in the wedge. Moreover, the firm's value added satisfies

$$P_i(t)\, Y_i(t) \propto (A_i(t)(1-\tau_i(t)))^{\eta-1}. \tag{2}$$

Intuitively, the firm's value added—or its size—is increasing in TFP and decreasing in the wedge. Equations (1)–(2) then imply that TFP satisfies

$$A_i(t) \propto \frac{[Y_i(t)P_i(t)]^{\frac{\eta}{\eta-1}}}{[K_i(t)]^{\alpha}\,[N_i(t)]^{1-\alpha}}. \tag{3}$$

In the theoretical section, we assume that τ takes on only two values, $\tau \in \{\tau_h, \tau_l\}$ where $\tau_l < \tau_h$. The stochastic realizations of τ follow a persistent Markov process. Namely, the probability that τ remains constant exceeds 50% in each state. In the empirical analysis, τ has a continuous support.

Dynamics of TFP: The endogenous evolution of the productivity distribution is determined by the strategy firms adopt to increase their productivity. We assume that advancements occur over a productivity ladder where each successful attempt to move up the ladder results in a constant accrual of log TFP: $\log(A_{i,t+1}) = \log(A_{i,t}) + \tilde{a}$, where $\tilde{a} > 0$ is a constant (thus, $\log(A) \in \{\tilde{a}, 2\tilde{a}, ...\}$). We define $a \equiv \log(A)/\tilde{a}$ and denote the ranking in the productivity ladder by $a \in \mathbb{N}^+$. Moreover, $\mathcal{A}$ denotes the TFP distribution, $\mathcal{A}_1, \mathcal{A}_2, ...$ denotes the proportion of firms at each rung of the ladder, and $F_a = \sum_{j=1}^{a} \mathcal{A}_j$ denotes the associated cumulative distribution. We model innovation as a step-by-step process: in each period, TFP can either increase by one step or stay constant.[3] We abstract from entry and exit—a limitation to which we return below.

Firms can increase their TFP through either *innovation* or *imitation.* We model imitation as an attempt to acquire knowledge through random interactions with other firms (e.g., by adopting better managerial practices). This strategy hinges on the existing TFP distribution because firms only learn when they meet more productive firms. Innovation is modeled as an exploration of new avenues and is independent of other firms' TFP. Although both strategies could in principle require investments, the crux of the choice is the cost difference. Therefore, we normalize the cost of imitation to zero, and let the innovation cost be nonnegative.

Imitation: A firm pursuing the imitation strategy is randomly matched with another firm in the empirical distribution. If the firm meets a more productive firm, its TFP increases by one notch with probability $q > 0$. Otherwise, it retains its initial TFP.

Innovation: An innovating firm can improve its TFP via two channels. First, it can make a discovery unrelated to the knowledge set of other firms. The probability of success through this channel is p,

[2] The wedge τ_i can alternatively be interpreted as a geometric average of capital and labor wedges. More formally, let τ_{Ki} and τ_{Li} denote firm-specific "taxes" on capital and labor, respectively. The output wedge τ_i is then defined by the following equation: $1 - \tau_i \equiv (1+\tau_{Ki})^{-\alpha}(1+\tau_{Li})^{-(1-\alpha)}$.

[3] König et al. (2016) allow for more general stochastic processes, where a successful firm can make improvements of different magnitudes. For simplicity, we abstract from this possibility.

where p is drawn from an i.i.d. distribution with cumulative distribution function $G : [0, \overline{p}] \to [0, 1]$ where $\overline{p} \leq 1$. Firms observe the realization of p before deciding whether to innovate or imitate. The heterogeneity in p avoids the stark implication that the position of the firm in the TFP distribution fully determines the innovation-imitation choice that would be rejected by the data.

If innovation fails, the firm gets a second chance to improve its technology via (passive) imitation. However, in this case the probability of success is different from that of a firm actively pursuing imitation, being equal to $\delta q (1 - F_a) \geq 0$. Thus, the total probability of success of a firm pursuing innovation is $p_i + (1 - p_i) \delta q (1 - F_a)$. We impose no restriction on the second-chance parameter δ. If $\delta > 1$, the innovation investment facilitates the absorption of new ideas through random interactions, whereas if $\delta < 1$, focusing on innovation reduces the imitation potential.

2.1 Equilibrium dynamics with costless innovation

Consider first the case studied by König et al. (2016) in which innovation entails no investment cost and $\delta < 1$. Then, the manager chooses the strategy that maximizes TFP growth, as this also maximizes expected profit. In particular, firm i chooses the innovation strategy if and only if

$$p_i \geq Q(a, \tau; \mathcal{A}) \equiv \frac{q(1-\delta)(1-F_a)}{1 - \delta q (1 - F_a)}, \tag{4}$$

where, recall, $\mathcal{A}$ denotes the TFP distribution. Since $\partial Q / \partial a < 0$, the proportion of innovating firms will be nondecreasing in the initial TFP. Intuitively, imitation is less effective for high-TFP firms because they are less likely to meet a more productive firm. Although thus far τ has no bearing on the innovation-imitation decision, we specify it as an argument of the function to prepare the analysis of the more general case where τ matters. Note that the ex-post TFP growth gap between innovating and imitating firms is increasing in the TFP level.[4]

The law of motion of TFP: We can now write the law of motion of the distribution of log TFP, $\mathcal{A}_a(t)$. Define the indicator function

$$\chi^{\text{im}}(a, p, \tau; \mathcal{A}) = 1 - \chi^{\text{in}}(a, p, \tau; \mathcal{A}) = \begin{cases} 1 & \text{if} \quad p \leq Q(a, \tau; \mathcal{A}), \\ \\ 0 & \text{if} \quad p > Q(a, \tau; \mathcal{A}). \end{cases} \tag{5}$$

In plain words, χ^{im} is unity when the firm finds it optimal to imitate, while $\chi^{\text{in}}(a, p, \tau; \mathcal{A})$ is unity when it finds it optimal to innovate. The law of motion for the TFP distribution is characterized by the following system of integro-difference equations:

[4] A larger a has two opposite effects on next period's (expected) TFP gap between innovating and imitating firms. On the one hand, it reduces the potential growth through imitation, thereby increasing the gap. On the other hand, it lowers $Q(a, \tau; \mathcal{A})$, inducing firms with lower p to innovate. This negative selection is a second-order effect which is always dominated by the former effect.

$$
\begin{aligned}
&\mathcal{A}_a(t+1)-\mathcal{A}_a(t) \\
&= \int_0^{\overline{p}} \left[\begin{array}{c} \chi^{\text{in}}\left(a-1,p,\tau;\mathcal{A}\right)\times\left(p+(1-p)\,\delta q\left(1-F_{a-1}(t)\right)\right)\mathcal{A}_{a-1}(t)+ \\ +\chi^{\text{im}}\left(a-1,p,\tau;\mathcal{A}\right)\times q\left(1-F_{a-1}(t)\right)\mathcal{A}_{a-1}(t) \\ -\chi^{\text{in}}\left(a,p,\tau;\mathcal{A}\right)\times\left(p+(1-p)\,\delta q\left(1-F_a(t)\right)\right)\mathcal{A}_a\left(t\right) \\ -\chi^{\text{im}}\left(a,p,\tau;\mathcal{A}\right)\times q(1-F_a(t))\mathcal{A}_a\left(t\right) \end{array} \right] dG\left(p\right) \qquad (6) \\
&= \int_{Q(a-1,\tau;\mathcal{A})}^{\overline{p}} \left(p+(1-p)\,\delta q\left(1-F_{a-1}(t)\right)\right)\mathcal{A}_{a-1}(t)\ dG\left(p\right) \\
&+ G\left(\min\{Q\left(a-1,\tau;\mathcal{A}\right),\overline{p}\}\right)\times q\left(1-F_{a-1}(t)\right)\mathcal{A}_{a-1}(t) \\
&- \int_{Q(a,\tau;\mathcal{A})}^{\overline{p}} \times\left(p+(1-p)\,\delta q\left(1-F_a(t)\right)\right)\mathcal{A}_a\left(t\right)dG\left(p\right) \\
&- G\left(\min\{Q\left(a,\tau;\mathcal{A}\right),\overline{p}\}\right)\times q(1-F_a(t))\mathcal{A}_a\left(t\right).
\end{aligned}
$$

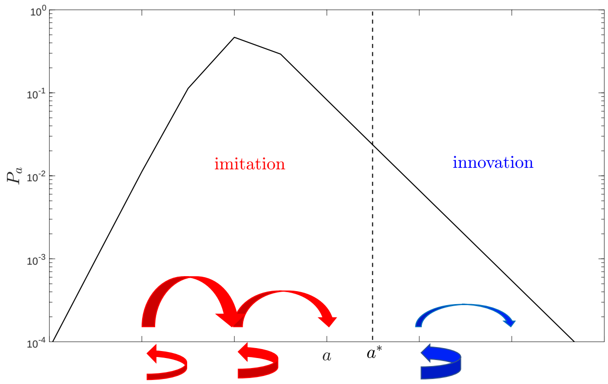
The first and second lines inside the first integral sign capture the inflow into TFP a of, respectively, successful innovating and imitating firms whose TFP was $a-1$ in period t. The third and fourth lines inside the integral capture the outflow of TFP a of, respectively, successful innovating and imitating firms whose TFP was a in period t. Note that for sufficiently low a, all firms imitate. In that case, $G=1$ and the integrals in the expression vanish. Conversely, the share of imitating firms vanishes as $a\to\infty$.

Stationary distribution: Next, we characterize the stationary distribution associated with the system of difference equations. For ease of exposition, we first consider the special case of zero innovation cost for which a sharper analytical characterization is available.

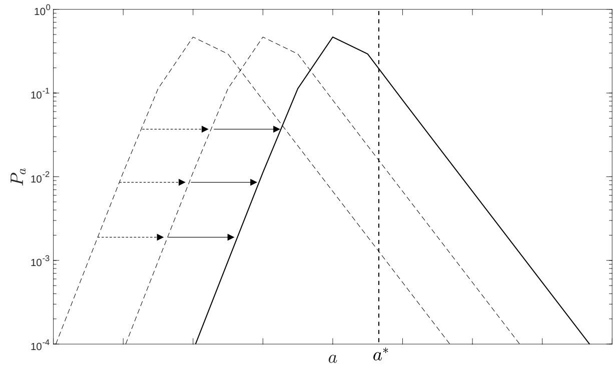
Proposition 1 *Consider the model of innovation-imitation described in the text whose equilibrium law of motion satisfies equation (6), where each firm draws p from a distribution $G:[0,\overline{p}]\to[0,1]$. Assume that $q>\hat{p}$, where $\hat{p}\equiv\int_0^{\overline{p}}p\ dG(p)$. Assume the cost of both imitation and innovation is equal to zero. Then, there exists a traveling wave solution of the form $\mathcal{A}_a(t)=f(a-\nu t)$ with velocity $\nu=\nu\left(q,\delta,g\left(p\right)\right)>0$, with left and right Pareto tails. For a given t, $\mathcal{A}_a$ is characterized as follows: (i) for a sufficiently large, $\mathcal{A}_a(t)=O\left(e^{-\rho(a-\nu t)}\right)$, where the exponent ρ is the solution to the transcendental equation $\rho\nu=\hat{p}\left(e^{\rho}-1\right)$; (ii) for a sufficiently small, $\mathcal{A}_a(t)=O\left(e^{\lambda(a-\nu t)}\right)$, where the exponent λ is the solution to the transcendental equation $\lambda\nu=q(1-e^{-\lambda})$.*

Intuitively, a traveling wave is a TFP distribution that is stationary after removing the (endogenous) constant growth trend. In particular, if we denote by $a^*(p,t)$ the threshold TFP such that, at time t and conditional on drawing p, all firms with TFP $a\le a^*(p,t)$ imitate and all firms with TFP $a>a^*(p,t)$ innovate, then, $a^*\left(p,t+\Delta t\right)=a^*\left(p,t\right)+\nu\Delta t$. Thus, the function a^* is the inverse of the threshold function Q along the balanced growth path, $a^*(p,t)\equiv Q^{-1}\left(p,\tau,\mathcal{A}(t)\right)$ where $\mathcal{A}(t)$ is the stationary distribution at time t. The proof in the appendix generalizes the result that random growth with a lower reflecting barrier generates a Pareto tail–a result formalized by Kesten (1973) and applied in economics by Gabaix (1999 and 2009). Strictly speaking, our model does not feature a reflecting barrier. However, low-TFP firms have a comparative advantage in imitation because they have a higher probability of meeting a more productive firm and are therefore more likely to successfully imitate. In fact, firms with very low TFP imitate irrespective of their realization of p. Thus, the subdistribution

Figure 1: Equilibrium Dynamics with a Stationary Distribution



Panel A



Panel B

Note: Panel A displays the threshold a^* and the stationary TFP distribution. Panel B plots a traveling wave.

of imitating firms catches up, which prevents the upper end of the distribution from diverging provided that q is sufficiently large.

A distinctive feature that distinguishes our model from earlier contributions is that the stationary distribution features a Pareto tail of low-TFP firms. The left tail originates from the fact that, although the probability of matching with a better firm tends to unity at very low TFP levels, the probability of successful adoption is $q < 1$. This prevents the convergence of the subdistribution of imitating firms to a mass point. Figure 1 illustrates the equilibrium dynamics of the stationary distribution in a simplified version of the model in which all firms draw the same p. Panel A displays the threshold and the force implying convergence.[5] Panel B illustrates the traveling wave.

Proposition 1 yields no algebraic representation of the velocity of the traveling wave. In fact, ν can only be defined implicitly and solved for numerically. Numerical analysis shows that the growth rate is increasing in the parameters q, δ, and $\bar{p}$, implying that both the TFP of innovation and the rate at which ideas diffuse affect aggregate TFP growth.[6]

2.2 Equilibrium dynamics with costly innovation

Next, we generalize the analysis to an environment in which innovation requires a costly investment, which we label the R&D cost. The complete expression for the discounted value of profits—cf. equation (1)—is given by

$$\pi_i(t) = \frac{1}{1+r} \times ((1-\tau_i(t))A_i(t))^{\eta-1} \times \tilde{\Pi}(t). \tag{7}$$

Profits are increasing in the firm-specific TFP and decreasing in the wedge. Moreover, profits have a secular trend $\tilde{\Pi}(t) \equiv (\alpha^\alpha(1-\alpha)^{1-\alpha}(\eta-1))^{\eta-1}\eta^{-\eta} \times Y(t)/\left(r^\alpha w(t)^{1-\alpha}\right)^{(\eta-1)}$, where w is the equilibrium

[5] The solutions for ρ and λ are in an implicit form and involve transcendental equations. Standard methods allow one to show that the equations $\rho\nu = q\left(e^\rho - 1\right)$ and $\lambda\nu = \bar{p}\left(1 - e^{-\lambda}\right)$ admit closed-form solutions for ρ and λ if, respectively, $q/\nu \cdot e^{-q/\nu}/\nu \leq e^{-1}$ and $\bar{p}/\nu \cdot e^{-q/\nu} \leq e^{-1}$. In particular, $\lambda = W(-q/\nu \cdot e^{-q/\nu}) + q/\nu$ and $\rho = W(-\bar{p}/(2\nu) \cdot e^{-\bar{p}/(2\nu)}) + \bar{p}/(2\nu)$, where W denotes the Lambert-W function.

[6] Analytical comparative statics can be obtained under a triangular approximation of the stationary distribution in a simpler version of the model with no heterogeneity in p. The analytical results under this approximation, which are consistent with the numerical results of the full model, are in the web appendix.

wage rate. The expression for w is provided in appendix equation (A11). Holding constant firm-specific productivity and wedge, each firm's profit changes over time via two channels. On the one hand, the demand for all varieties increases over time as income grows. This market size effect increases profits. On the other hand, the progress of competitors erodes the market share of firms with a stagnating productivity as long as $\eta > 1$. In a stationary equilibrium, wages and aggregate output grow at the same rate. Moreover, the average growth of $A(i)$ equals the growth rate of $w^{1-\alpha}$. Thus, in steady state the average growth of profits is the same as the growth rate of aggregate output and wages.

Consider, next, the R&D cost for innovating firms. We assume that

$$c_i(t) = \left(A_i(t)^{\theta}\,\bar{A}(t)^{1-\theta}\right)^{\eta-1} \times \bar{c} \times \tilde{\Pi}(t), \tag{8}$$

where $\bar{c} > 0$ and $\theta \in [0,1]$ are parameters. The choice of the functional form for the R&D cost is guided by our desire to ensure that the model features a stationary equilibrium. This requires that costs be higher when profits are larger. In particular, since profits are proportional to $A_i^{\eta-1}$, by analogy, the first term in equation (8) is raised to the power of $\eta - 1$. The specification ensures that the relative level of the firm TFP—but not its absolute value—matters for the R&D decision. More specifically, the first term in the cost function (8) is a geometric combination of A_i and $\bar{A}$, where $\bar{A}(t) \equiv \int_0^1 A_i\,di$ denotes the cross-sectional average TFP at time t. The assumption that the R&D cost is increasing in A_i captures the idea that pursuing an innovation strategy requires managerial time whose opportunity cost is increasing in the firm's TFP.[7] In addition, the R&D cost follows the trend $\tilde{\Pi}(t)$. In a balanced growth environment, the average R&D cost grows at the same rate as profits, wages, and output. The trend in R&D costs reflects the growing cost of inputs such as lab equipment and researchers.

Firms pursue an innovation strategy if and only if the R&D cost c_i is smaller than the expected increase in the present value of profits associated with pursuing innovation rather than imitation. As in the model without R&D costs, the solution has threshold properties. In particular, firm i uses the innovation strategy if and only if $p_i \geq Q(a_1, \tau_j; \mathcal{A})$. In a stationary equilibrium with positive R&D costs, the function Q is given by:

$$Q(a, \tau_j; \mathcal{A}) = \frac{q(1-\delta)(1-F_a)}{1-\delta q(1-F_a)} + \frac{e^{(1-\theta)(\eta-1)(\overline{a}-a)}}{(e^{\eta-1}-1)\,\mathbb{E}\left[(1-\tau')^{\eta-1}\,|\tau_j\right]}\,\frac{\bar{c}(1+r)(1+g)^{\eta-2}}{1-\delta q(1-F_a)}, \tag{9}$$

where g is the (endogenous) steady-state growth rate, $\overline{a} \equiv \log \bar{A}$ and $\mathbb{E}[\tau'|\tau]$ denotes the conditional expectation of next-period wedge. The expression in equation (9) is the same as that in equation (4) except for the new second term. Note that although $\bar{a}$ trends over time, the second term in the right-hand side expression depends on $(\overline{a} - a)$, which is consistent with a stationary equilibrium.

There are two key differences relative to equation (4). First, the R&D cost makes imitation more attractive *ceteris paribus*. Therefore, conditional on the realization of p, the threshold Q will be larger than in equation (4). Second, the wedge affects the choice: a larger wedge τ_i deters innovation by reducing the future profit proportionally to TFP without affecting the R&D cost. More formally, $\partial Q/\partial\tau_i > 0$: firms with larger wedges are less likely to engage in R&D.

[7]If $\theta = 0$, the R&D investment is independent of firm-specific TFP (e.g., it only consists of general inputs like lab equipment or hired researchers). Yet, the model delivers balanced growth because in a stationary equilibrium the entire distribution of TFP grows at a common rate. In the polar opposite case of $\theta = 1$, the R&D cost only depends on the firm's TFP, related to managerial time. The flexible specification with $\theta \in (0,1)$ is useful for our quantitative analysis because it improves the model's ability to account for how R&D expenditure relative to value added varies with TFP in the data, as discussed below.

The law of motion of the TFP distribution (cf. equation (6)) must then take into account the heterogeneity in wedges:

$$\mathcal{A}_a(t+1) - \mathcal{A}_a(t)$$
$$= \sum_{j\in\{l,h\}} \omega_{\tau_j}(t) \times \int_0^{\overline{p}} \left[\begin{array}{c} \chi^{\text{in}}(a-1,p,\tau_j;\mathcal{A}) \times (p + (1-p)\,\delta q\,(1-F_{a-1}(t)))\,\mathcal{A}_{a-1}(t) + \\ +\chi^{\text{im}}(a-1,p,\tau_j;\mathcal{A}) \times q\,(1-F_{a-1}(t))\,\mathcal{A}_{a-1}(t) \\ -\chi^{\text{in}}(a,p,\tau_j;\mathcal{A}) \times (p + (1-p)\,\delta q\,(1-F_a(t)))\,\mathcal{A}_a(t) \\ -\chi^{\text{im}}(a,p,\tau_j;\mathcal{A}) \times q(1-F_a(t))\mathcal{A}_a(t) \end{array} \right] dG(p)\,, \quad (10)$$

where $\omega_{\tau_l}, \omega_{\tau_h}$ denote the proportion of low- and high-wedge firms, respectively. The model is closed by the law of motion for ω_{τ_l}. Let ρ_h and ρ_l denote the arrival rate of movements to τ_h and τ_l, respectively. The law of motion is then given by $\omega_{\tau_l}(t+1) - \omega_{\tau_l}(t) = (1-\rho_h)(1-\omega_{\tau_l}(t)) - (1-\rho_l)\,\omega_{\tau_l}(t)$, where ω_{τ_l} converges in the long run to $\bar{\omega}_{\tau_l} \equiv (1-\rho_h)\,/\,[(1-\rho_h)+(1-\rho_l)]$.

The next proposition characterizes the stationary equilibrium. The proof is an extension of the proof of Proposition 1 and is available in the web appendix.

Proposition 2 *The characterization of Proposition 1 carries over to a model with costly R&D investments where $\bar{c} > 0$. More formally, there exists a traveling wave solution of the form $\mathcal{A}_a(t) = f(a-\nu t)$ with velocity $\nu = \nu(q,\delta,G(p),\bar{c},\tau_h,\tau_l,\bar{\omega}_{\tau_l}) > 0$, with left and right Pareto tails. Conditional on ν, the characterization of the tails is the same as in Proposition 1.*

Predictions of the theory: In summary, the model has four testable implications:

1. *ceteris paribus*, the proportion of firms engaged in R&D is increasing in TFP;

2. *ceteris paribus*, firms with higher wedges are less likely to engage in R&D. Then, equation (2) implies that, conditional on TFP, larger firms are more likely to engage in R&D;

3. expected TFP growth is falling in current TFP, especially for nonR&D firms;

4. the gap in average TFP growth between R&D firms and nonR&D firms is increasing in TFP.

3 Data and descriptive evidence

We consider firm-level data for China and, in an extension, Taiwan. The Chinese data are from the Annual Survey of Industries conducted by China's National Bureau of Statistics for 1998–2007 and 2011–13. This survey is a census of all state-owned firms and the private firms with more than five million RMB (20 million RMB since 2010) in revenue in the industrial sector. To estimate firm-level TFP growth, we focus on a balanced panel for all manufacturing firms in 2007–12 including all firms that are in our sample in both 2007 and 2012. The data for R&D expenditure at the firm level are for the year 2007.[8] Although this is a firm-level survey, most of the Chinese firms were single-plant firms during this period. The Taiwanese data is at the plant level, collected by Taiwan's Ministry of Economic Affairs, for the years 1999–2004.[9] To make the Taiwanese sample more comparable to its Chinese counterpart, we drop firms with annual sales below 18 million Taiwan dollars.

[8] We do not use the 2013 firm data because China's National Bureau of Statistics adjusted the definition of firm employment in 2013, making the 2013 employment data inconsistent with those in the earlier years.

[9] More than 90% of Taiwanese and Chinese manufacturing plants are owned by single-plant firms in the time periods we study. Following Aw et al. (2011), we ignore the distinction between plants and firms.

Table 1: Summary Statistics

Year	Number of Firms	Number of R&D Firms	Median Value Added (million USD)	Mean Value Added (million USD)	Median R&D Intensity (%)	Aggregate R&D Intensity (%)
			Balanced Panel of Chinese Firms			
2007	123368	18140	1.48	5.81	1.73	1.86
2012	123368	N.A.	3.33	11.45	N.A.	N.A.
			Private Chinese Firms in the Balanced Panel			
2007	117983	15828	1.43	4.67	1.65	1.54
2012	117771	N.A.	3.26	9.57	N.A.	N.A.
			Balanced Panel of Taiwanese Firms			
1999	11229	1487	0.16	2.91	8.50	3.14
2004	11229	1144	0.17	4.78	6.42	2.93

Note: R&D intensity is the ratio of R&D expenditure to value added. Median R&D intensity is the median R&D intensity among firms performing some R&D. Aggregate R&D intensity is the ratio of aggregate R&D expenditure to aggregate value added for all firms. Missing information is due to the lack of R&D data in 2012.

Table 1 reports summary statistics for the Chinese and Taiwanese balanced panels. Chinese firms are on average larger than Taiwanese firms. Part of the difference is accounted for by the Chinese state-owned enterprises (SOE). The fraction of firms reporting positive R&D expenditure in 2007 is 15% (data are not available after 2007). The corresponding fraction of R&D firms in the Taiwanese sample is 13% in 1999 and 10% in 2004. We restrict attention to balanced samples of firms for consistency with the theory, whose focal point is the difference in TFP growth between firms pursuing an innovation strategy and firms pursuing an imitation strategy. This comparison is only feasible for firms that are in the sample in both years. For completeness, Appendix Table A2 provides descriptive statistics for the full sample of Chinese firms in 2007, which also includes firms exiting the sample between 2008 and 2012. Exiters are on average smaller, less productive, and have a lower propensity to invest in R&D, as one might expect. In addition, throughout our analysis, we ignore firms in the bottom 10% the TFP distribution for which measurement error is likely to be very pronounced. These firms are on average very small accounting altogether for a mere 1.14% of the total value added of Chinese manufacturing firms in 2007.

We take investment in R&D as a proxy for the pursuit of an innovation strategy. We classify firms reporting positive R&D expenditure as innovators and all other firms as imitators. We test the robustness of the results to alternative classifications. We focus on the extensive margin of R&D for three reasons. First, it is consistent with the discrete-choice model we estimate. Second, there are important fixed costs of setting up an R&D lab, and only a small fraction of firms perform any R&D. Third, the intensive margin is subject to a more severe measurement error.[10]

[10]This issue has been noted in the literature that studies firm-level R&D expenditure in Western countries (see, e.g.,

Figure 2 shows the distribution of R&D and TFP growth conditional on TFP in the initial year and conditional on firm size (measured by value added). We estimate TFP following the methodology proposed by Hsieh and Klenow (2009). This requires a calibration of the production parameter α and the demand elasticity η. We allow α to vary across industries and set α_j in (two-digit) industry j equal to the measured industry-specific labor income share. Following Hsieh and Song (2015), we set $\eta = 5$. To control for observable sources of heterogeneity, we regress TFP on province, industry, and age dummies and take the residual as the measure of firm TFP. As a robustness analysis, we have also estimated TFP using the methodology of Ackerberg et al. (2015), who follow the implementation proposed by Brandt et al. (2017) for estimating production functions for Chinese manufacturing industries. The empirical moments we target are very similar when we use this alternative procedure—see Appendix Figure A1.

The industry classification refers to 30 two-digit manufacturing industries. We normalize firm-level value added by the median value in the industry to which each firm belongs. We do not explicitly separate R&D expenditure when estimating TFP. This could potentially bias the TFP estimates for R&D firms. The problem has no perfect solution because we do not have R&D data after 2007. To assess the importance of this potential problem, we use data for the period 2001–07, when R&D data is available, to adjust TFP by subtracting R&D expenditure from labor costs. Then, we plotted a version of Figure 2 based on the adjusted data. The empirical moments are almost indistinguishable from the original figure. We conclude that the problem is likely quantitatively small.

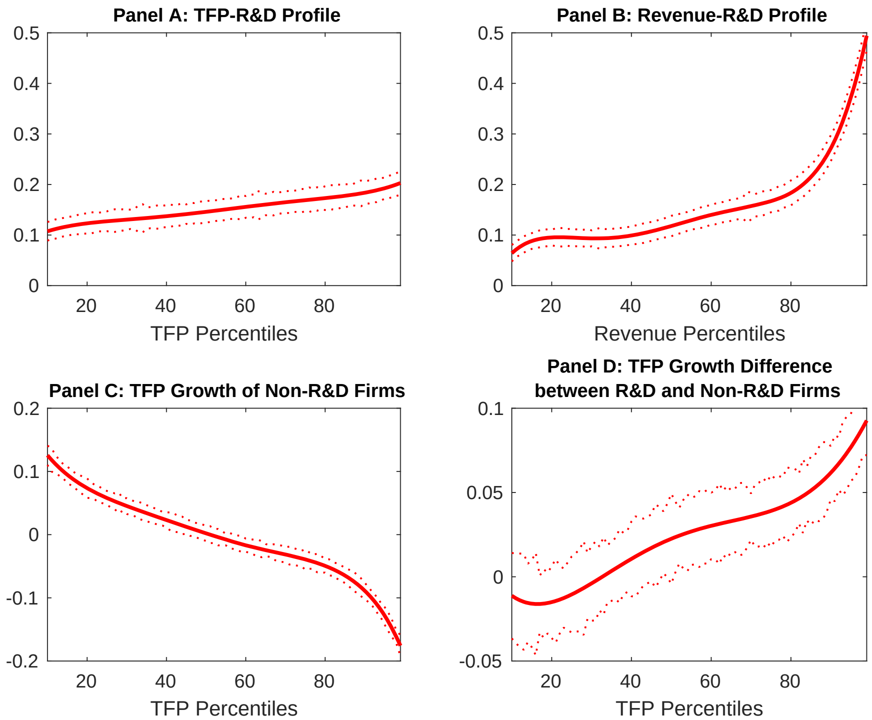
Panel A shows the share of R&D firms by TFP percentile. The positive correlation is in line with the prediction of our theory that more productive firms do more R&D. The share of R&D firms increases from 11.6% in the lowest decile to 20% in the top percentile of the TFP distribution. Panel B shows that firm size is also positively correlated with the share of R&D firms. The relationship is significantly steeper than in Panel A: almost 50% of the firms in the top percentile of the size distribution invest in R&D. Since larger firms are on average more productive, TFP is a driver of both panels. However, the steeper profile in Panel B indicates that factors other than TFP must matter. In our model, a firms' size is determined by the product of its TFP and one minus its wedge. Thus, firms subject to positive (negative) wedges are smaller (larger) than what their TFP alone would predict. The wedge also affects the profit and, hence, the incentive to pursue an innovation strategy. Note that, in the absence of wedges, Panels A and B would be identical. In the presence of wedges, we expect Panel B to be steeper than Panel A which is consistent with the empirical observation.

Panels C and D show relationships between TFP growth and the distribution of initial TFP. Panel C shows that the TFP growth rate is decreasing in TFP among nonR&D firms. In other words, there is strong convergence in TFP across nonR&D firms. This is consistent with the main tenet of our theory that learning through random interactions and imitation is easier for less productive firms. A concern is that the negative relationship might partly be due to measurement error in TFP. If measurement error is classic, firms with a negative (positive) measurement error at t are overrepresented among low- (high-)TFP firms at t. Reversion to the mean would then exaggerate the convergence pattern. In the estimation section below, we model measurement error explicitly and allow it to influence the graph in Panel C. In addition, to mitigate concerns with survivor's bias, we trim the lower tail of the distribution, which comprises mostly very small firms, as discussed above.

Finally, Panel D compares the TFP growth for R&D firms and nonR&D firms at different percentiles of the TFP distribution. In line with the prediction of our theory, TFP growth is higher for R&D firms

Lichtenberg 1992, Acemoglu et al., 2010). The problem is especially severe in China because R&D expenditure is vaguely defined in China's industrial survey. For instance, the survey does not distinguish between R&D performed and R&D paid for by the firm.

Figure 2: Chinese Firms in the Balanced Panel 2007–12



Note: The X-axis in Panels A, C, and D is the 2007 TFP percentile. The X-axis in Panel B is the 2007 value added percentile. The solid lines in Panel A and B plot the 2007 fraction of R&D firms in each TFP and value added percentile, respectively. The solid line in Panel C plots the median annualized 2007–12 TFP growth among nonR&D firms in each TFP percentile. The solid line in Panel D plots the difference between the median 2007–12 TFP growth R&D and nonR&D firms within each percentile. A firm's TFP growth is the residual of the regression of TFP growth on industry, age, and province fixed effects. All the solid lines are smoothed by a fifth-order polynomial. The dotted lines plot the 95% confidence intervals by bootstrap.

than for nonR&D firms at most percentiles.

The same patterns emerge from a set of multiple regressions whose results are reported in Table 2. Panels A and B of Table 2 are related to Panels A–B and Panels C–D of Figure 2, respectively. Panel A shows the results for a linear probability model whose dependent variable is a dummy for R&D firms. All regressions use annual data and include industry fixed effects and year dummies, with standard errors clustered at the industry level. We also include provincial dummies. The table shows that the fraction of R&D firms is robustly correlated with the log of TFP. The estimated coefficient increases significantly when we include an estimated output wedge among the regressors.[11] Both the positive correlation with TFP and the negative correlation with the output wedge line up with the predictions of the theory. A large output wedge discourages firms from investing in R&D by reducing profits. Columns (3)–(4) show that the results are not driven by exporting firms nor SOEs.

We cannot include firm fixed effects in this regression analysis because we do not have data on R&D investments after 2007. However, we have performed the same analysis on an earlier sample (2001–07)

[11]The measurement of output wedges—which follows Hsieh and Klenow (2009)—is discussed in Section 4. Here, we note that measurement error might exaggerate the negative correlation between the estimated TFP and the output wedge, driving part of the strong opposite-sign pattern for the estimated coefficients in Table 2. We address this issue in our structural estimation below.

Table 2: Balanced Panel of Chinese firms, 2007–2012.

PANEL A

Dependent variable: R&D decision in 2007.

	(1) $R\&D_d$	(2) $R\&D_d$	(3) $R\&D_d$	(4) $R\&D_d$
log(TFP)	0.062***	0.368***	0.343***	0.305***
	(0.0074)	(0.0284)	(0.0259)	(0.0232)
wedge		-0.410***	-0.378***	-0.332***
		(0.0357)	(0.0323)	(0.0296)
export_d			0.053***	0.054***
			(0.0134)	(0.0132)
SOE_d				0.205***
				(0.0232)
R-squared	0.143	0.208	0.211	0.224

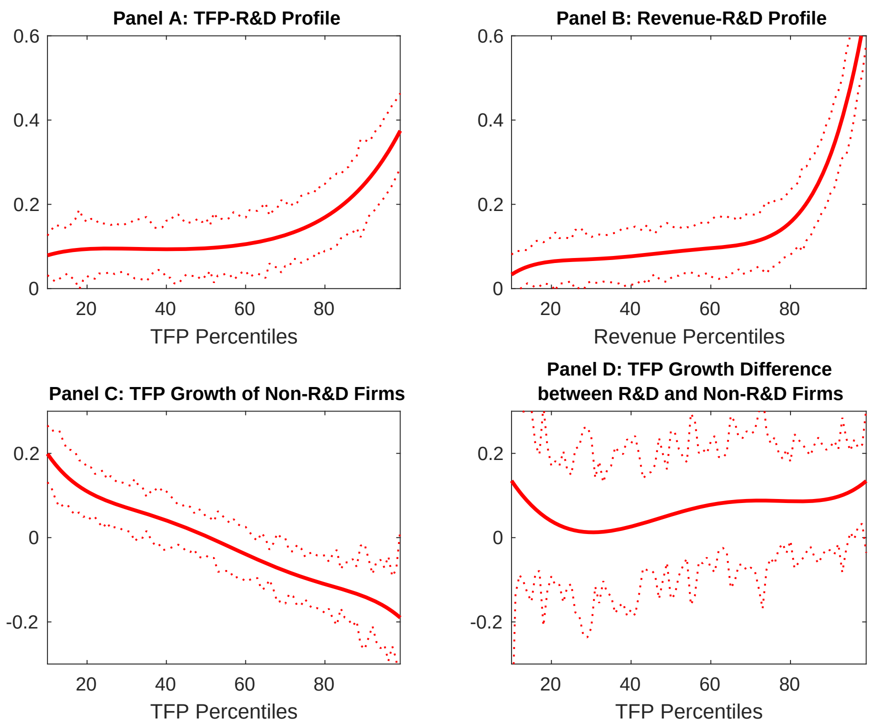
PANEL B

Dependent variable: TFP growth.

	(1) TFP growth	(2) TFP growth	(3) TFP growth	(4) TFP growth	(5) TFP growth
log(TFP)	-0.062***	-0.062***	-0.062***	-0.062***	-0.062***
	(0.0035)	(0.0036)	(0.0035)	(0.0036)	(0.0036)
$R\&D_d$	0.036***	0.037***	0.034***		
	(0.0042)	(0.0040)	(0.0035)		
export_d		-0.006	-0.006*	-0.006	-0.007*
		(0.0038)	(0.0035)	(0.0037)	(0.0035)
SOE_d			0.029**		0.029**
			(0.0115)		(0.0113)
R&D intensity_h				0.044***	0.041***
				(0.0060)	(0.0058)
R&D intensity_m				0.042***	0.038***
				(0.0069)	(0.0056)
R&D intensity_l				0.025***	0.023***
				(0.0035)	(0.0033)
R-squared	0.122	0.122	0.123	0.122	0.123

Note: Panel A: the dependent variable $R\&D_d$ is a dummy variable switching on for firms that report positive R&D expenditure. Panel B: the dependent variable is annualized TFP growth 2007–12. Explanatory variables: log(TFP) is the logarithm of TFP; Wedge indicates the firm's output wedge $-\log(1-\tau_i)$ and is calculated as described in Section 2; export_d is a dummy variable for exporters; SOE_d is a dummy variable for state-owned firms; R&D intensity_h is a dummy variable for high R&D intensity switching on if the firm R&D expenditure over sales is in the 67th percentile and above (among all R&D firms); R&D intensity_m is the analogue dummy for medium R&D intensity (between 33rd and 66th percentiles); R&D intensity_l is the analogue dummy for low R&D intensity (below the 33rd percentile.) All the explanatory variables are from 2007. Standard errors are reported in parentheses. The number of observations is 109,799. Observations are weighted by employment and standard errors are clustered by industry. All regressions include industry, age, and province fixed effects. We drop firms with TFP in the bottom 10 percentiles.

Figure 3: Taiwanese Firms in the Balanced Panel 1999–2004



Note: This figure is the analogue of Figure 2 for the sample of Taiwanese firms.

for which R&D information is available in both the initial and final year. Including firm fixed effect implies that the effect of R&D are identified by firms adopting (or dropping) R&D over time. The results for the 2001–07 panel—see Appendix Table A1—are qualitatively similar to those in Table 2: as firms become more productive over time they become more likely to perform R&D.

Panel B reports the results of regressions with average TFP growth during 2007–12 as the dependent variable. TFP growth is regressed on the initial log-TFP level and on an R&D dummy in 2007. The tables show a robust negative correlation between TFP growth and initial TFP (consistent with Panel C of Figure 2) and a robust positive correlation between TFP growth and an R&D dummy (consistent with Panel D of Figure 2). The results are robust to controlling for SOE and export firm dummies. Columns (4) and (5) focus on the intensive margin of R&D by breaking the R&D dummy into three separate dummies, one per each tercile of R&D expenditure. All three dummies are both statistically and economically significant. A higher (lower) investment in R&D is associated with a higher (lower) future TFP growth. The growth difference between the upper and lower terciles is statistically significant.[12]

Appendix Figure A2 shows that the patterns in Figure 2 are robust to a more stringent classification counting only those firms with R&D-to-value added ratio exceeding 1.73% (median among R&D firms) as innovative. While this criterion by construction reduces the share of innovative firms, the four panels are qualitatively similar. The same is true for a version of the multiple regressions in Table 2 where we apply the more stringent classification of R&D firms. The sign of the coefficients of interest is the

[12] We have also run separate regressions similar to those of Panel A to detect whether the selection into high versus low R&D intensity is driven by the TFP level. However, the data show no clear pattern.

same as in Table 2 and all coefficients are highly significant. Details are available upon request.

Another potential concern is that the results might be driven by a subset of industries (e.g., semiconductors) for which R&D is especially salient. However, we find that the patterns do not change significantly if we exclude the top five R&D-intensive industries. We also find that the results are similar when partitioning the sample into subgroups: exporting versus nonexporting firms, SOEs versus non-SOEs, and sorting firms by regions.

Finally, we study how Panels A and B in Figure 2 change if we use the full sample of firms in 2007, including firms exiting the sample before 2012, instead of restring attention to the balanced panel. In both panels, we observe an approximately parallel downward shift of the schedule, namely, exiters have a lower propensity to engage in R&D than surviving firms—see Appendix Figure A3. However, the selection into R&D by TFP and size—which is the focal point of our analysis—is almost unchanged. This finding is confirmed by running the multiple regressions in Panel A of Table 2 on the full sample. The estimated coefficients of interest are all very similar—see Appendix Table A3. Note that we cannot produce Panels C and D in Figure 2 for the full sample because we can only calculate TFP growth for firms that are present in the data both in 2007 and in 2012.

The empirical patterns are similar in Taiwan for both the intensive and the extensive margin—see Figure 3 and Appendix Table A4—with two noteworthy quantitative differences. First, the R&D-TFP profile in Panel A is steeper in Taiwan than in China. Moving from the 60th to the 99th TFP percentile the share of Taiwanese R&D firms increases from 10% to over 35%. Second, Panel D has very large standard errors. However, the regression analysis in Table A4 confirms a robust and highly significant positive correlation between R&D and future TFP growth, similar to the empirical patterns for China.

4 Estimation

The estimation targets two sets of moments: moments that are informative about the economic mechanism of the model and moments that are informative about measurement error. For the former, we focus on a set of selected quantiles in Figure 2. We consider four intervals of the distribution of TFP and size in each of the four panels: the 10th to 49th percentile, the 50th to 79th percentile, the 80th to 94th percentile, and the top five percentiles.[13] This choice yields sixteen empirical target moments. Appendix Figure A4 plots the confidence intervals around these moments.

We calibrate the parameters α, η, θ, and $\tilde{a}$, and structurally estimate the remaining parameters using simulated method of moments. The calibration of α and η, discussed above, is external to the model. Throughout the analysis, we classify firms performing R&D as pursuing an innovation strategy.

4.1 Measurement error and wedges

Measurement error: Measurement error (m.e.) is a common concern in models of misallocation *à la* Hsieh and Klenow (2009) because it potentially affects both the measured moments of TFP and the imputed wedges. In our model, m.e. affects the target moments in Appendix Figure A4. On the one hand, it generates an attenuation bias in the relationships between the propensity to engage in R&D and both TFP (Panel A) and size (Panel B), flattening both profiles. On the other hand, it exaggerates TFP convergence in Panel C, steepening the profile. We now propose an explicit model of m.e. and discuss its estimation.

[13] We zoom on the upper tail of the distribution because large and high-TFP firms are more likely to engage in R&D. As discussed above, we ignore the lowest decile of the TFP distribution to mitigate concerns about survivors' bias.

We assume that value added and inputs (capital and labor) are measured with classical m.e.:

$$\begin{aligned}
\ln\left(\widehat{P_i Y_i}\right) &= \ln\left(P_i Y_i\right) + \mu_y, \\
\ln\left(\widehat{K_i^{\alpha} N_i^{1-\alpha}}\right) &= \ln\left(K_i^{\alpha} N_i^{1-\alpha}\right) + \mu_I,
\end{aligned}$$

where μ_y and μ_I are i.i.d. measurement errors with variances $\hat{v}_y$ and $\hat{v}_I$. The notation with hats denotes observed variables, while no hat denotes true variables.

We make the key identifying assumption that the firm-specific wedges τ_i are constant over the unit of time we consider, that is, the 2007–12 period.[14] Under this assumption, the time series variation (2007–12) in value added and input measures at the firm level can be used to infer the extent of m.e. Equations (2) and (3) imply that inputs are proportional to value added times the output wedge, i.e., $(1-\tau_i)(P_{it}Y_{it}) \propto (r_t)^{\alpha}(w_t)^{1-\alpha}(K_{it})^{\alpha}(L_{it})^{1-\alpha}$. Then, a constant τ_i implies that

$$\Delta \ln\left[(K_{it})^{\alpha}(L_{it})^{1-\alpha}\right] = \Delta \ln\left(P_{it}Y_{it}\right) - \Delta \ln\left[(r_t)^{\alpha}(w_t)^{1-\alpha}\right],$$

where $\Delta \ln X_t \equiv \ln X_t - \ln X_{t-1}$. The variance of (true) value added growth can then be identified as follows:

$$\begin{aligned}
& cov\left(\Delta \ln\left(\widehat{P_{it}Y_{it}}\right), \Delta \ln\left(\widehat{(K_{it})^{\alpha}(L_{it})^{1-\alpha}}\right)\right) \\
= \; & cov\left(\Delta \ln\left(P_{it}Y_{it}\right) + \Delta\mu_{yt}, \Delta \ln\left(P_{it}Y_{it}\right) - \Delta \ln\left[(r_t)^{\alpha}(w_t)^{1-\alpha}\right] + \Delta\mu_{It}\right) \\
= \; & var\left(\Delta \ln\left(P_{it}Y_{it}\right)\right). \qquad (11)
\end{aligned}$$

The second equality follows from the assumptions that m.e. is classical—implying that $\Delta\mu_{yt}$ and $\Delta\mu_{It}$ are white noise—and that the input price $(r)^{\alpha}(w_t)^{1-\alpha}$ is identical across firms. Therefore, the cross-sectional covariance is not affected by the aggregate input price growth. The variance of m.e. in value added and inputs can then be identified as

$$\begin{aligned}
var\left(\Delta \ln\left(\widehat{P_{it}Y_{it}}\right)\right) - cov\left(\Delta \ln\left(\widehat{P_{it}Y_{it}}\right), \Delta \ln\left(\widehat{(K_{it})^{\alpha}(L_{it})^{1-\alpha}}\right)\right) &= 2\hat{v}_{\mu y} \qquad (12) \\
var\left(\Delta \ln\left(\widehat{(K_{it})^{\alpha}(L_{it})^{1-\alpha}}\right)\right) - cov\left(\Delta \ln\left(\widehat{P_{it}Y_{it}}\right), \Delta \ln\left(\widehat{(K_{it})^{\alpha}(L_{it})^{1-\alpha}}\right)\right) &= 2\hat{v}_{\mu I}. \qquad (13)
\end{aligned}$$

We measure the empirical covariances in equations (12) and (13) using data on growth rates in revenue and inputs between 2007 and 2012—see Appendix Table A5. M.e. in revenue and inputs translates into m.e. in TFP. Equation (3) implies that m.e. in TFP is $\hat{a} - a = [\eta/(\eta-1)]\,\mu_y - \mu_I$, where $a \equiv \log A$. The variance of m.e. in TFP is, then, $\hat{v}_{\mu a} = [\eta/(\eta-1)]^2\,\hat{v}_{\mu y} + \hat{v}_{\mu I}$. We set $\eta = 5$ and use the empirical $\hat{v}_{\mu a}$ as a target moment in the joint estimation of the parameters of the model. In the appendix we characterize analytically the effect of m.e. on the moments of the model.[15] This analytical mapping

[14] In the balanced sample, the variance of $\ln(1-\tau_i)$ is approximately constant, increasing slightly from 0.724 in 2007 to 0.769 in 2012. In the full sample, the dispersion declines slightly, from 0.806 to 0.794.

[15] In principle, we could estimate two of three empirical variances $\hat{v}_{\mu a}$, $\hat{v}_{\mu y}$, and $\hat{v}_{\mu I}$, (the third being a combination of the other two) in the estimation. However, the variances must be constrained to be non-negative. In the estimation of the benchmark model the constraint $\hat{v}_{\mu I} \geq 0$ turns out to be binding. This holds true for all data samples we consider. To keep the number of estimated parameters low, we impose $\hat{v}_{\mu I} = 0$ and set $\hat{v}_{\mu y} = [(\eta-1)/\eta]^2\,\hat{v}_{\mu a}$ when adding m.e. to the empirical moments. We retain $\hat{v}_{\mu I} = 0$ for all models we estimate.

speeds up computations significantly so that estimation becomes feasible. Adding m.e. by way of simulations would be time-consuming and turn into a computational curse for the estimation.

Distribution of output wedges: The estimated output wedges and TFP are correlated. To keep the simulated model consistent with the data, we assume a distribution of output wedges that has the same correlation between output wedges and TFP as in the empirical distribution. This correlation affects the size of aggregate distortions as discussed by Restuccia and Rogerson (2008). More formally, we assume the following relationship:

$$-\ln(1-\tau_i) = b \cdot (a_{it} - a_t) + \varepsilon_{it}^{\tau}, \tag{14}$$

where a_t is the mean of a_{it}, and we assume that $\varepsilon_{it}^{\tau} \sim \mathcal{N}(0, var(\varepsilon_{it}^{\tau}))$. We are interested in the coefficient b in equation (14) and $var(\varepsilon_{it}^{\tau})$. Estimating b by OLS yields a biased estimate because of m.e. However, the m.e. model above implies the following unbiased estimate of b,

$$b = \frac{cov(a_{it}, -\ln(1-\tau_i))}{var(a_{it})} = \frac{cov(\hat{a}_{it}, -\ln(1-\hat{\tau}_i)) - \left(\frac{\eta}{\eta-1}\right) \cdot \hat{v}_{\mu y} - \hat{v}_{\mu I}}{var(\hat{a}_{it}) - \left(\frac{\eta}{\eta-1}\right)^2 \hat{v}_{\mu y} - \hat{v}_{\mu I}}. \tag{15}$$

Then, equation (14) implies $var(\varepsilon_{it}^{\tau}) = var(\ln(1-\tau_i)) - b^2 var(a_{it})$, where $var(\ln(1-\tau_i)) = var(\log(1-\hat{\tau}_i)) - \hat{v}_{\mu y} - \hat{v}_{\mu I}$ and, by construction, $var(\hat{a}_{it}) = var(a_{it}) + \hat{v}_{\mu a}$. The resulting unbiased estimates are $b = 0.779$ and $var(\varepsilon_{it}^{\tau}) = 0.042$ (compared to biased OLS estimates of 0.802 and 0.047, respectively).[16] Moreover, one third of the variance of measured wedges is due to m.e.

4.2 The technology of R&D

Cost function. The parameter θ in equation (8) captures the elasticity of a firm's innovation cost to its TFP. We calibrate this parameter by targeting the *relative* cross-sectional distribution of the R&D cost-to-value added ratio. Formally, we target the ratio $\mathbb{E}[\psi_j|a_j] / \mathbb{E}[\psi_i|a_i]$, where ψ denotes the ratio of innovation costs to value added and a_i and a_j denote TFP in the i'th and j'th percentile. This ratio can be expressed analytically as

$$\frac{\mathbb{E}[\psi_j|a_j]}{\mathbb{E}[\psi_i|a_i]} = \exp\left(\frac{1-\eta}{\eta}(1-\theta+b)(a_i - a_j)\right). \tag{16}$$

We use data on R&D costs, and more specifically the R&D-to-value added ratio for firms in the top five percent of the TFP distribution relative to firms in the 10th-49th percentile. Empirically, this ratio declines with TFP, being 37% higher for low-TFP R&D firms (10-49th percentile) than for larger high-TFP firms (top five percentiles). The parameter b is adjusted for m.e. in line with equation (15). Equation (16) then implies an elasticity of $\theta \approx 0.25$. Appendix Figure A5 shows that this model accurately fits the slope of the relationship between R&D intensity and TFP percentiles in the data.

Step size. In the model, firms that are successful in either innovating or imitating increase their log TFP by a step size $\tilde{a}$. The choice of $\tilde{a}$ has no appreciable effect on the model's ability to fit the cross-sectional data of Figure 2. However, it affects the estimate of the parameters $\bar{c}$ and $\bar{p}$. The reason

[16] Note that the distribution of τ_i is by construction consistent with equation (14). Hence the variance of τ_i depends on both b, ε_i^{τ}, and the variance of A—something we return to in Section 8. When we simulate the model, the firm-specific wedge τ is drawn each period in line with (14) and with an i.i.d. draw of ε_{it}^{τ}. Since firm-specific TFP is highly autocorrelated and $b \neq 0$, the output wedges are positively autocorrelated.

is that, in the theory, profits are an increasing convex function of $\tilde{a}$—see equation (1). Because the fraction of R&D firms is a target of the estimation, a larger $\tilde{a}$ induces a larger estimated value of $\bar{c}$ and a lower estimate of $\bar{p}$.

Ideally, one could estimate $\tilde{a}$ jointly with the other parameters of the model. However, this is computationally infeasible. Instead, we set $\tilde{a}$ so as to target a realistic average cost of innovation as a share of value added. In particular, we set $\tilde{a} = 0.78$ which implies—conditional on the estimated parameters—an average cost of innovation of 3.7% of the industrial value added in the benchmark economy.[17] This ratio is about twice the aggregate R&D-to-value added ratio in the Chinese data. We view this as a realistic target in light of the innovation management literature documenting that formal R&D is only a part of the costs incurred by firms pursuing innovation. The purchase of new equipment often reflects the introduction of new technologies although it is recorded as capital investment. Hiring STEM workers is another facet of an innovation-oriented strategy. Finally, in an innovative firm, managers divert more of their attention to the introduction of new products or more efficient processes.[18]

Productivity of innovation. We assume that firms draw p from an i.i.d. uniform probability distribution with support $[0, \bar{p}]$, where $\bar{p}$ is structurally estimated.

4.3 Simulated method of moments (SMM)

We estimate the remaining parameters using SMM (McFadden 1989). The estimated parameters minimize the distance between the target moments and the stationary distribution of the model. Analytical tractability is key for our procedure. We simulate the model under a parameter configuration, add m.e. to the moments, and calculate the distance from the targeted empirical moments. Then, we iterate on the parameter vector. The system of ordinary difference equations allows us to calculate the stationary distribution efficiently. We could in principle have simulated the distribution of a large number of firms for every trial of a parameter configuration. However, such an alternative approach would be computationally too demanding.

In all our trials, the numerical simulations converge to a unique stationary distribution irrespective of initial conditions, provided that the learning parameter q is not too small. When this parameter is sufficiently close to zero, there exists no ergodic distribution. The web appendix provides details of the numerical implementation.

The sample is randomly generated by bootstrapping for $K = 500$ times. Denote by $g_{m,k}$ the mth moment in the kth sample and by $g_m(\phi)$ the vector of the corresponding moments in the model, where ϕ is the vector of parameters that we estimate. We minimize the weighted sum of the distance between the empirical and simulated moments:

$$\hat{\phi} = \arg\min_{\phi} h(\phi)' \; W \; h(\phi),$$

where W is the moment weighting matrix and $h_m(\phi) = \left[g_m(\phi) - \frac{1}{K}\sum_k^K g_{m,k} \right] / g_m(\phi)$ is the percentage deviation between the theoretical and empirical moments, averaged across K samples. We use the

[17]This calculation assumes a risk-adjusted discount rate of 10% which we view as reasonable given pervasive financial and contractual imperfections in China and the high systematic risk of innovative activities.

[18]Colarelli O'Connor (2019) summarizes the findings of a study of 40 companies over 25 years by Colarelli O'Connor et al. (2018) as follows: "Innovation is much bigger than R&D. It involves three distinct capabilities: Discovery, Incubation, and Acceleration (DIA). R&D is just one part of the Discovery capability—invention." The other activities "often require[s] as much time and resources and deserves as much emphasis, as inventing the technologies themselves."

identity matrix as the benchmark weighting matrix to avoid the potential small-sample bias—see Altonji and Segal (1996).

5 Results

We first estimate a benchmark parsimonious model that reproduces the theoretical model without any added new features. Then, we consider some extensions. We keep the parameters θ and $\tilde{a}$ constant across specifications at the level calibrated to the benchmark economy.

5.1 Parsimonious model

In the benchmark model—which we label the *Parsimonious* model, henceforth, PAM—we estimate five parameters: q, $\bar{c}$, $\bar{p}$, δ, and $v_{\mu a}$.[19] Before turning to the results, we summarize the sources of identification of the structural parameters.

Identification. The parameter q is the probability of successful imitation conditional on meeting a more productive firm. It is mostly pinned down by the TFP convergence rate across imitating firms (Panel C of Figure 2) conditional on m.e. The parameter δ (passive imitation) is identified by the TFP convergence rate across both imitating and innovating firms (Panels C and D of Figure 2). Lack of convergence within the set of innovating firms would imply δ close to zero, while strong convergence would imply a large δ. The parameter $\bar{p}$ is pinned down by the extent to which, conditional on TFP, innovating firms grow faster than imitating firms (Panel D of Figure 2). Given the other parameters, the innovation cost parameter $\bar{c}$ is disciplined by the total share of innovating firms. Finally, the standard deviation of m.e. affects Panels A, B, and C in Figure 2. Measurement error flattens the schedules in Panels A and B while steepening the schedule in Panel C. In other words, m.e. creates the impression of a stronger convergence in the data than there is in reality. Thus, a larger estimate of $v_{\mu a}$ implies a lower estimate of q.

Results. The estimation results are displayed in column (1) of Table 3. The estimated coefficient $q = 0.175$ implies that there is significant convergence in TFP even after removing m.e. The estimated δ is close to zero indicating that R&D has a high opportunity cost in terms of foregoing learning through random interactions. The estimated average probability of p is about 4.8% (i.e., $\bar{p}/2 = 0.096/2$.) Given the costs and benefits of the two strategies, the model predicts that about 12% of the firms invest in R&D compared to 15% in the data. The estimated variance of m.e. in TFP is $\sigma^2_{\mu a} = 0.3$. This implies that m.e. accounts for 30% of the variance of log TFP and 92% of the variance of TFP growth.

Figure 4 shows that the PAM fits the data fairly accurately, matching well the convergence pattern in Panel C and the differential growth between R&D and nonR&D firms in Panel D.[20] However, the model overpredicts the steepness of the profiles in Panels A and B.

[19] Recall that the innovation cost is $c_i(t) \propto \bar{c}(1+r) \cdot \left(A_i(t)^{\theta}\,\bar{A}(t)^{1-\theta}\right)^{\eta-1}$. With slight abuse of notation, we always report the estimate of $\bar{c}$ inclusive of the gross interest rate.

[20] M.e. has a significant effect on the estimates. Ignoring it would increase the estimates for q and δ to $q = 0.702$ and $\delta = 0.500$, implying a faster convergence. The reason is that in the absence of m.e., Panel C—TFP growth conditional on TFP for nonR&D firms—dictates a fast catching up rate for low-TFP firms, as discussed above.

Table 3: Estimation, Chinese Firm Balanced Panel 2007–2012.

	(1)	(2)	(3)	(4)	(5)	(6)
					Higher R&D cutoff	
	PAM	FLM	IPM	FRM	PAM	IPM
Imitation prob. q	0.175	0.271	0.361	0.275	0.294	0.546
	(0.031)	(0.019)	(0.019)	(0.051)	(0.058)	(0.052)
Second chance δ	0.008	0.020	0.001	0.019	0.141	0.001
	(0.011)	(0.021)	(0.027)	(0.024)	(0.106)	(0.080)
Innov. prod. $\bar{p}$	0.096	0.114	0.113	0.237	0.107	0.111
	(0.008)	(0.006)	(0.006)	(0.016)	(0.013)	(0.010)
Innov. cost $\bar{c}$	1.627	3.374	2.318	10.486	3.601	9.393
	(0.136)	(0.174)	(0.177)	(1.363)	(0.448)	(2.403)
Std.dev. m.e. $\sigma_{\mu a}$	0.549	0.472	0.431	0.459	0.476	0.391
	(0.014)	(0.008)	(0.005)	(0.025)	(0.022)	(0.011)
Std.dev.innov. subs. σ_c		1.243	1.092	0.011		1.969
		(0.038)	(0.037)	(0.036)		(0.213)
Policy inter. c_a			1.888	-10.46		2.499
			(0.159)	(1.042)		(0.356)
Fake share Υ				0.099		
				(0.005)		
J-Statistic	1.518	0.507	0.368	0.362	2.690	0.516

Note: The table shows the estimated parameters for the different models discussed in the text. Columns (1)–(4) are for the Parsimonious (PAM), Flexible (FLM), Industrial Policy (IPM), and Fake R&D (FRM) model, respectively. Columns (5)–(6) presents the results for the models estimated on moments applying a more stringent definition of R&D. Bootstrapped standard errors in parentheses.

5.2 Heterogeneous innovation costs

In this section, we allow for heterogeneity in the innovation cost parameter $\bar{c}$. Heterogeneity could arise from technological factors or from additional wedges that directly distort the imitation-innovation decision. These include R&D subsidies, government investments in local infrastructure, science parks, and credit constraints, which have particularly severe effects on R&D investments.

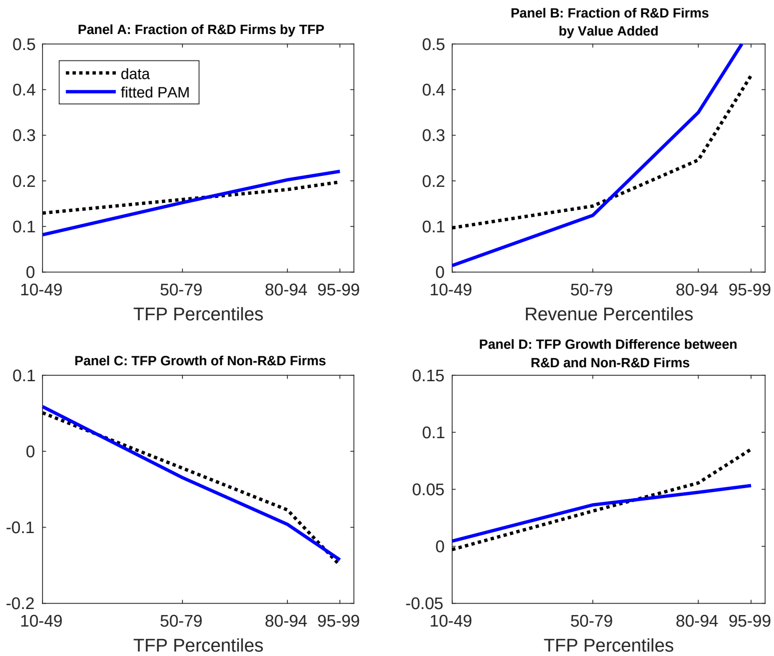
Figure 4 shows that the models with heterogeneous innovation fit more accurately the target moments, especially Panel B. Intuitively, the imitation-innovation decision now depends also on the realization of c_i, thereby reducing the importance of TFP and size. This flattens the schedules in Panels A and B that were too steep in the PAM.

We consider three specifications. In the first—which we label the *Flexible* model, henceforth, FLM—innovation wedges are i.i.d. across firms. In the second, we allow the wedges to be correlated with observable firm characteristics, capturing the idea that local and central governments may target their support to firms with certain characteristics. We label this specification the *Industrial Policy* model, henceforth, IPM. Finally, we consider a specification where some firms can strategically misreport innovation expenditures in order to attract subsidies without actually distorting their optimal imitation-innovation decisions. We label this model the *Fake R&D* model, henceforth, FRM.

Flexible model: In the FLM, the effective innovation cost is given by

$$c_i(t) \propto \left[\bar{c} - \exp\left(\xi_i(t) - \frac{\sigma_c}{2}\right) + 1\right] \cdot \left(A_i(t)^{\theta}\, \bar{A}(t)^{1-\theta}\right)^{\eta-1},$$

Figure 4: Parsimonious Model (PAM)



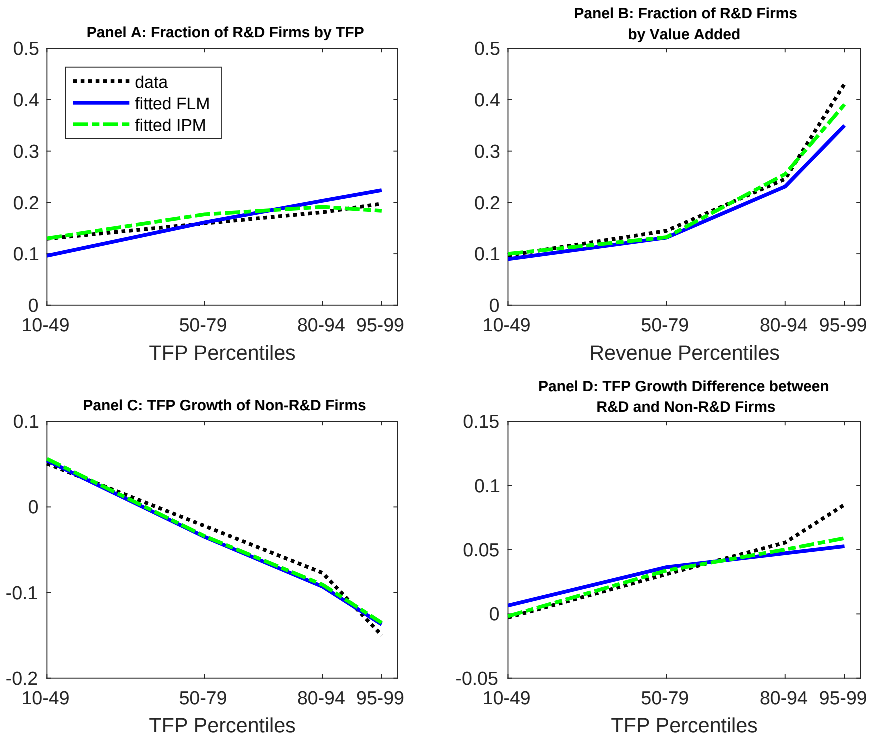
Note: The figure shows the fit of the PAM. It plots the moments predicted by the model against their empirical counterparts for China 2007–12. The X-axis in Panel A, C and D is the first-period TFP percentiles defined on four intervals: the 10th to 49th, the 50st to 79th, the 80th to 94th and the 95th to 99th. The X-axis in Panel B is the first-period value added percentiles defined on the same four intervals. The solid lines in Panel A and B plot the first-period fraction of R&D firms in each TFP and value added interval, respectively. Panel C plots the median annualized TFP growth among nonR&D firms in each TFP interval in the data against the corresponding expected growth rate for firms in the model. Panel D plots the difference between the median TFP growth between R&D and nonR&D firms in the data against the corresponding difference in expected growth in the model. A firm's TFP growth is the residual of the regression of TFP growth on industry, age and province fixed effects.

where $\xi_i \sim \mathcal{N}\left(0, \sigma_c^2\right)$. Note that $\mathbb{E}\left[\bar{c} - \exp\left(\xi_i(t) - \sigma_c/2\right) + 1\right] = \bar{c}$, so σ_c is a mean-preserving spread.

Figure 5 shows that the fit of the FLM improves upon that of the PAM. This is reflected in a lower residual sum of squares, mostly attained in Panel B. The estimated parameters are in the ballpark of the PAM estimates with two noteworthy differences. First, the estimate of $\bar{c}$ is larger than in the PAM. The reason is selection: *ceteris paribus*, subsidized firms (some of them facing a negative effective innovation cost) have a stronger incentive to pursue an innovation strategy. With an unchanged $\bar{c}$ too many firms want to do R&D. To match the empirical share of R&D firms, the model requires a larger average innovation cost. Second, the estimate of m.e. is now lower because the R&D cost dispersion flattens the TFP-size profile in Panel D, mitigating the need for large m.e. The implied lower observed TFP convergence is offset by a larger estimate of the q parameter. The ratio between innovation expenditure and value added is 1.1% in the FLM. This calculation excludes both positive and negative wedges from the cost paid by the firm.

Industrial Policy: Next, we allow the innovation wedges to be correlated with TFP. This captures the possibility that the government engages in some form of industrial policy targeting firms with particular characteristics (e.g., location) that are correlated with TFP. In the estimation, we do not impose any sign on this correlation. We assume the effective innovation cost c_i to be of the form

Figure 5: Flexible (FLM) and Industrial Policy (IPM) models



Note: The figure shows the fit of the FLM and IPM. See Figure 4 for additional information.

$$c_i\,(t) \propto \left[\bar{c} - \exp\left(\xi_i(t) - \frac{\sigma_c}{2}\right) + 1 + c_a\,(G(a_i) - 1/2)\right] \cdot \left(A_i\,(t)^{\theta}\,\bar{A}(t)^{1-\theta}\right)^{\eta-1},$$

where G is the cumulative density of a_i. $c_a > 0$ means the industrial policy favors low-TFP firms, while $c_a < 0$ means the opposite. This specification ensures that the dispersion in innovation costs is again a mean-preserving spread over $\bar{c}$ so the parameter $\bar{c}$ is comparable across specifications.[21]

Column (3) in Table 3 reports the estimation result for the IPM. The fit of the model further improves relative to the FLM—the J-Statistic declines by 30%. Figure 5 shows the fit of the targeted moments for the IPM along with the FLM. The estimated value of the new parameter c_a is positive, indicating a negative correlation between TFP and innovation wedges. In other words, more productive firms are "taxed." To understand the source of identification of this parameter, compare the results for the two models in Panel A in Figure 5. In the estimated FLM, the schedule of Panel A is too steep. A positive correlation between TFP and innovation wedges reduces the propensity of high-TFP firms to innovate thereby flattening the schedule in Panel A. While increasing σ_c would attain the same result, it would also flatten the schedule in Panel B (which is already flatter in the FLM than in the data) compromising the fit of the relationship between size and TFP.

Fake R&D: Chen et al. (2021) suggests that many Chinese firms respond to subsidies by reclassifying operational expenditure as R&D. To explore this hypothesis, we augment our theory with a simple model of moral hazard. We assume that a positive proportion of firms can falsely report to be investing

[21]To see this, note that $\int_{-\infty}^{a} G(a)g(a)da = [G(a)]^2/2$, implying that $\mathbb{E}\left[G(a_i) - 1/2\right] = 0$.

in R&D in order to collect subsidies without suffering any punishment. Misreporting firms are then incorrectly classified as R&D firms. More precisely, we assume that a share Υ of firms can collect subsidies by just *claiming* to invest in R&D. After collecting the subsidy, each firm in this group decides whether it is optimal for them to actually engage in R&D. Since the econometrician cannot see which firms fudge R&D expenditure, misreporting biases the estimated productivity of innovation investments toward zero. The share Υ of privileged firms is the only additional parameter in the structural model.

Column (4) in Table 3 reports the results. According to our estimate, about 10% of firms can fudge R&D. While the fit of the two models is very similar, the two specifications paint a somewhat different picture.[22] In the FRM, two thirds of the R&D firms in the data are fakers. This flattens the schedules in Panels A and B. Moreover, in the FRM, high-TFP firms are subsidized rather than taxed as shown by the change in the sign of the parameter c_a. This indicates that the truthful R&D firms are highly positively selected. Related to that, the productivity of R&D investments is substantially higher: $\bar{p} = 0.24$ instead of $\bar{p} = 0.11$. After taking selection into account, TFP growth in truthful R&D exceeds that of nonR&D firms by almost 12 percentage points in the highest TFP percentile we target. This insight is consistent with the casual observation that China has a number of innovative and internationally successful firms such as Lenovo or Tencent. Appendix Figure A6 illustrates the quantitative results in detail. The figure highlights that high-TFP firms have a stronger comparative advantage in pursuing innovation. Conversely, many low-TFP firms reporting spending on R&D are fudgers.

Intensive margin: In Section 3, we noted a positive correlation between R&D expenditure and future TFP growth among the R&D firms. Motivated by this empirical observation, we now perform robustness analysis on the R&D intensity. We pursue two alternative exercises.

First, we classify as innovative only those firms with R&D intensity above the empirical median for R&D firms. We recalculate the target moments based on this alternative classification. The results for the PAM and IPM are reported in columns (5)-(6) of Table 3. Treating firms that make small investments in R&D as imitators does not alter the broad picture. The estimated cost of R&D is larger in order to match the smaller proportion of R&D firms. The estimated diffusion parameters q and δ are also larger. The findings are similar in the IPM. Appendix Figure A7 shows the fit of the targeted moments for both the PAM and IPM.

Second, we introduce a distinction between high- and low-R&D firms. In the data, we assign a firm to the high-R&D group if its R&D expenditure-to-value added ratio is higher than the median 1.73% ratio. Appendix Figure A8 displays the data moments. In line with the regressions in Panel B of Table 2, future TFP growth is higher for high-R&D firms. In the appendix, we lay out and estimate a generalized version of our theory in which firms are assigned to two distinct technologies entailing different costs and success probabilities. To estimate this version of the model, we add two additional target moments, namely the ratios of R&D expenditure to value added for high- relative to low-R&D firms We must also estimate the proportion of high-R&D firms as one additional parameter. The results are summarized in Appendix Table A6. The estimated model can accurately reproduce

[22] Note that the FRM nests the IPM as a particular case when the proportion of fudging firms is $\Upsilon = 0$. Because the estimate of σ_c collapses to zero, both the IPM and FRM fit the data very accurately with the same number of parameters. However, the data cannot discriminate between the two models. Technically, the estimation finds two local minima. One corresponds to column (4) in Table 3. The other is a corner solution where no firms can fake R&D and the estimated parameters are as in column (3) of Table 3. In the calculation of bootstrapped standard errors, some simulations yield a lower J-Statistic in the former model, while others yields the opposite result. When calculating the bootstrapped standard errors of the estimates in column (4), we only consider draws where the minimum is interior.

the empirical relationship between R&D intensity and TFP growth in the data. The main limitation of the extension is that it does not allow firms to choose the project size. This would require a more significant departure from our discrete-choice model and is left to future research.

6 Nontargeted moments

In this section, we discuss predictions of the model for empirical moments we do not target in the estimation.

6.1 Indirect inference

The estimation targets pairwise empirical correlations but not the joint correlation structure between the variables. We now use indirect inference methods to investigate whether the model is consistent with the empirical conditional correlations. To this aim, we consider a set of multiple linear regressions. In the first ones, the dependent variable is the discrete choice of pursuing an innovation strategy, while the right hand-side variables are TFP levels (in logarithms) and the wedges. Panel A of Table 4 shows the results. Column (1) restates the empirical relationship in Panel A of Table 2: the probability for a firm to invest in R&D is increasing in both TFP and output subsidies (i.e., a negative coefficient on the output wedge τ). Running the same regression on the simulated model (including m.e.) yields the same qualitative results for all models. In the PAM, the R&D decision is more elastic to TFP and wedges than in the data, while the heterogeneous cost models provide a better quantitative match to the data.[23]

Next, in Panel B of Table 4 we run linear regressions where the firms' TFP growth is the dependent variable while the initial TFP level and R&D decision (in the initial year) are the explanatory variables. Column (1) restates the empirical relationship from Table 2 that TFP growth is falling in initial TFP and that TFP growth is larger for R&D firms. Running the same regression on the simulated models replicates the empirical correlations. Moreover, all models yield elasticities that are in the ballpark of the empirical estimates. In conclusion, the indirect inference analysis shows that the model fits well the (nontargeted) joint correlation structure between TFP growth, the R&D decision, initial TFP level, and size (wedges).

6.2 TFP distribution

In our model, the stationary TFP distribution is a *traveling wave* that evolves at a constant endogenous speed. The distribution is tent-shaped with two Pareto tails—cf. Proposition 2. In this section, we compare the stationary TFP distribution and the growth rate predicted by the theory with their empirical counterparts.

TFP dispersion: Figure 6 compares the predicted and empirical TFP distributions for the PAM, FLM, IPM, and FRM. The estimated model has a lower dispersion than TFP in the data: the PAM accounts for 72% of the empirical variance, while the three heterogeneous cost models account for between 44% and 62% of the empirical variance. The inability of the model to account for the full empirical dispersion can be attributed to factors that are omitted in our stylized theory. For instance, firms could be subject to exogenous i.i.d. shocks to TFP that do not affect the cost of innovation. These

[23] The standard errors of the structurally estimated parameters are based on simulating a sample of the same size as the empirical one and estimating the regression in the same way as on the empirical sample.

Table 4: Indirect Inference, Balanced Panel of Chinese Firms, 2007–2012.

PANEL A

Dependent Variable: R&D decision in 2007

	(1) Data	(2) PAM	(3) FLM	(4) IPM	(5) FRM
log(TFP)	0.368***	0.712***	0.287***	0.298***	0.322***
	(0.0284)	(0.0145)	(0.0167)	(0.0181)	(0.0167)
wedge	-0.410***	-0.824***	-0.274***	-0.327***	-0.357***
	(0.0357)	(0.0177)	(0.0202)	(0.0214)	(0.0203)

PANEL B

Dependent Variable: TFP Growth

	(1) Data	(2) PAM	(3) FLM	(4) IPM	(5) FRM
log(TFP)	-0.062***	-0.094***	-0.104***	-0.112***	-0.081***
	(0.0035)	(0.0002)	(0.0003)	(0.0003)	(0.0004)
$R\&D_d$	0.036***	0.034***	0.033***	0.028***	0.053***
	(0.0042)	(0.0005)	(0.0005)	(0.0005)	(0.0008)

Note: The first column reports the regression results from the data. All regressions include industry, age, and province fixed effects. Columns (2)-(5) report the results from the simulated data. See Table 2 for variable definitions.

shocks would increase the TFP dispersion without significantly altering firms' imitation-innovation choice. We also note that the dispersion of TFP is sensitive to the step-size parameter $\tilde{a}$. A larger $\tilde{a}$ yields a higher dispersion. In Panel A, we show that estimating the model under the assumption of $\tilde{a} = 1.12$ allows us to match the empirical distribution well. However, such a model overpredicts the empirical average R&D-to-value added ratio.[24]

The model matches the upper tail better than the lower tail of the empirical distribution, whose measurement is notoriously noisy. Nevertheless, our model makes some progress on understanding the lower tail because most existing theories of random interactions between firms do not feature any lower Pareto tail.

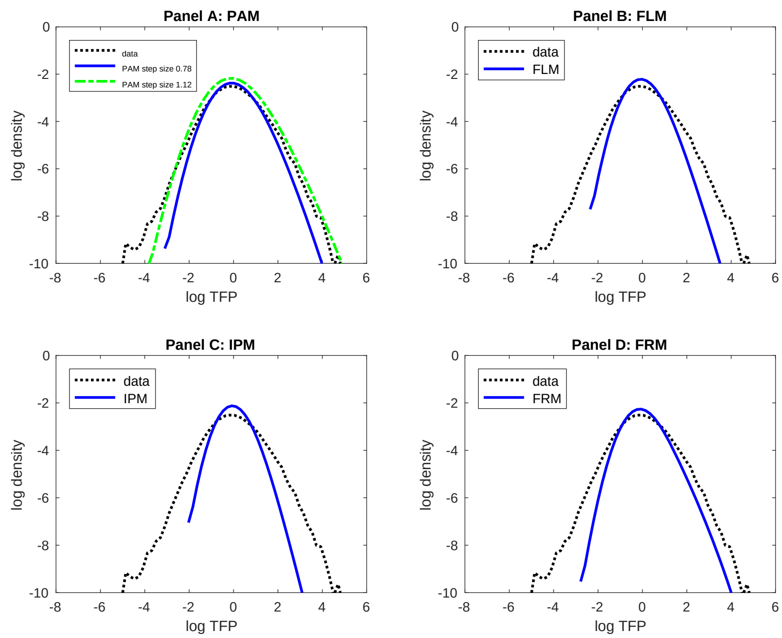
TFP growth: The model yields predictions about the speed of growth of the traveling wave. The aggregate TFP growth in the data is 3%.[25] The PAM implies a steady-state annualized aggregate TFP growth rate of 3.6%. The corresponding figure in the IPM is 5.1%.

In our model, the aggregate growth rate is determined by both innovation and knowledge diffusion. To quantify the role of each channel we evaluate what aggregate growth would be if only one channel were operating for one period while holding fixed the firms' R&D decisions. In the PAM, innovation

[24] The step size $\tilde{a}$ does not affect the fit of the targeted moments. In particular, Figure 4 would look essentially identical for $\tilde{a} = 1.12$.

[25] We calculate the aggregate growth rate in the data using the methodology of Hsieh and Klenow (2009). We first calculate TFP growth at the two-digit industry level and then aggregate up using industry deflators and value added shares.

Figure 6: TFP Distribution



Note: The dotted lines represent the log density of log TFP in the data. The solid and dashed lines are the steady-state log density of log TFP for various models. Panel A shows two versions of the PAM–the benchmark model and the one with smaller step size. Panel B: FLM, Panel C: IPM, and Panel D: FRM.

and imitation account for 20% and 80% of TFP growth, respectively. The share accounted for by passive imitation from innovating firms is negligible. Note that the decomposition would yield very different results if innovation were shut down permanently. Absent innovation, the long-run growth would be zero as long as the initial TFP distribution is bounded.

6.3 Patents

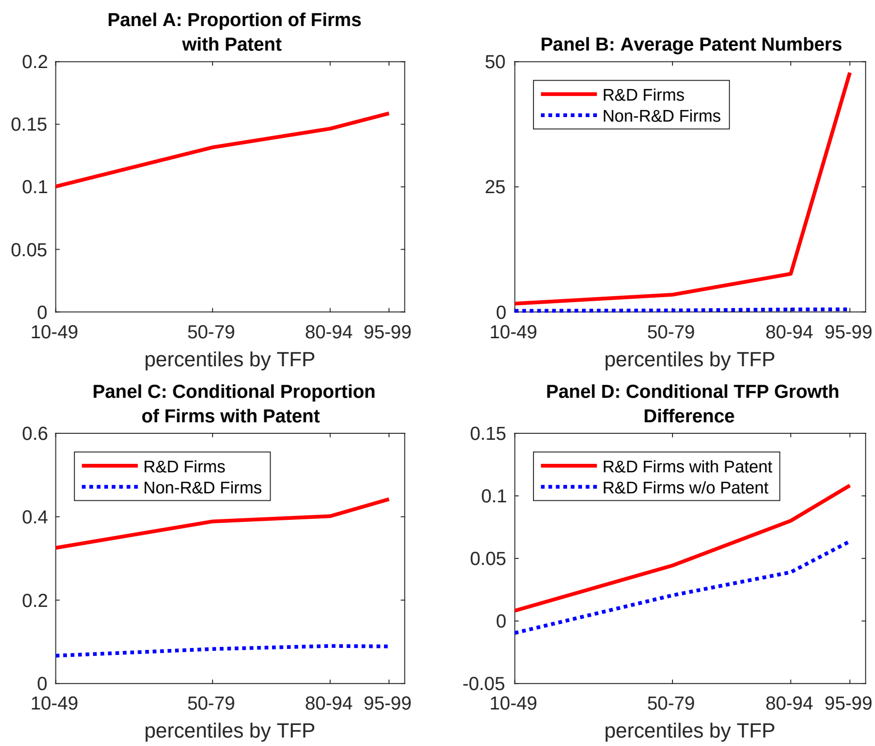
Our theory predicts that firms that are larger and more productive invest more in attempting to innovate and should therefore innovate more. Moreover, among those trying, firms that are successful at innovating should grow faster than those that are failing. In Section 3 we measured innovation investments by R&D expenditures. Alternatively, we could try to measure the outcome of this investment activity. A common empirical measure of successful innovation is patents. In this section, we show that the predictions of our theory are broadly consistent with data on patents.

To this end, we collect data for all the patents approved by China's State Intellectual Property Office (SIPO). We match the SIPO data with the 2012 NBS data. In the 2007–12 balanced panel of matched firms, there are 14,492 firms (out of ca. 123,000) that were granted one or more patents for which they applied for during 2007–12. The total number of patents these firms applied for during that period is 146,896. This implies that on average each NBS firm with a positive number of patents applied for 10.1 patents.[26] Note that, since the average time for granting a patent is about three years,

[26] In the unbalanced panel, 28,081 NBS firms (out of a total of ca. 275,000) have one or more patent for which they applied for during 2007–12. The total number of patents these NBS firms applied for during that period is 228,634. This implies that on average each NBS firm with a positive number of patents applied for 8.1 patents.

a lot of patents sought during 2007–12 were granted after 2016. The magnitudes above are therefore a lower bound to the actual number of patents.

Figure 7: Patents of Chinese Firms, Balanced Panel 2007–12



Note: All patents in the figure refer to invention patents applied for during 2007–12. We group all firms in the 2007–12 balanced panel into percentiles by their initial TFP. Panel A plots the proportion of firms with patents in each percentile. Panel B plots the average number of patents among R&D firms (solid line) and among nonR&D firms (dotted line) in each percentile. Panel C plots the proportion of R&D firms with one or more patents (solid line) and the proportion for nonR&D firms (solid line). The solid line in Panel D plots the TFP growth difference between R&D firms with patents and nonR&D firms. The dotted line plots the TFP growth difference between R&D firms without patents and nonR&D firms.

Panel A of Figure 7 shows that the propensity for patenting innovations is increasing in the TFP level, consistent with Panel A of Figure 2. Panel B plots the average number of patents as a function of TFP broken down by R&D and nonR&D firms. Essentially all patents are sourced from firms reporting some R&D activity. The same pattern emerges from Panel C, which plots the proportion of R&D firms and the proportion for nonR&D firms with one or more patent. Clearly, R&D is strongly correlated with patenting. This evidence shows that the data on R&D expenditures well captures innovation investments. Panel D displays the most interesting finding. Firms with a positive number of patents experience larger TFP growth than R&D firms without a patent. The gap increases with TFP, being largest for the top two deciles of the TFP distribution. This is consistent with our model, where R&D firms that are successful at innovation grow faster than those that are not able to innovate, and this difference is increasing in TFP.

This evidence is also suggestive of the hypothesis that some firms that report R&D but do not patent innovations may be fudgers–consistent with the FRM we estimated. This evidence is only suggestive. Non-patenting R&D firms could simply be firms that invested in R&D but had bad luck. However, it is interesting to observe that the number of patents per firm increases sharply from the second-highest TFP quantile to the highest quantile (top five percent) in Panel B, precisely consistent with the prediction of the FRM that it is mostly low-TFP firms that have an incentive to opportunistically report R&D expenditure without actually engaging in it.

7 Estimating the model on alternative samples: the case of Taiwan

In this section we reestimate the model using data for Taiwanese firms for the years 1999-2004. The goal of this analysis is twofold. First, we would like to compare the productivity of Chinese R&D investments to those of other economies. We focus on Taiwan both because similar data are available and because it is an export-oriented economy with an important manufacturing sector that has commonalities with China.[27] Second, we would like to assess the robustness of our results across different samples.

The results are summarized in Table 5. Appendix Figure A9 displays the fit of the targeted moments for the PAM and IPM. The model fits well for the empirical moments—the J-Statistic of the PAM is lower for Taiwan than for China while that of the IPM is about the same.

Table 5: Estimation for Taiwan, 1999–2004.

	PAM	FLM	IPM
Imitation prob. q	0.286	0.501	0.371
	(0.086)	(0.129)	(0.120)
Second chance δ	0.027	0.002	0.001
	(0.023)	(0.058)	(0.047)
Innov. prod. $\bar{p}$	0.184	0.207	0.206
	(0.026)	(0.031)	(0.032)
Innov. cost $\bar{c}$	3.301	4.669	5.247
	(0.475)	(0.717)	(0.809)
Std.dev. m.e. $\sigma_{\mu a}$	0.722	0.538	0.622
	(0.074)	(0.073)	(0.112)
Std.dev. innov. subs. σ_c		1.371	1.378
		(0.146)	(0.108)
Policy inter. c_a			-2.385
			(0.792)
J-Statistic	0.861	0.570	0.503

Note: Estimated parameters of various models using the Taiwanese 1999-2004 balanced panel sample. Bootstrapped standard errors in parentheses.

The estimated parameters are qualitatively in line with those for China. However, there are some noteworthy quantitative differences. First, the productivity of innovation is larger in Taiwan: the estimated average probability of success in innovation is around 9% (i.e., $\bar{p}/2 = 0.184/2$), while it was just 5% in the China sample. However, the cost parameter $\bar{c}$ is also larger in the Taiwanese sample. Second, the estimate for q is higher, implying faster technological diffusion and convergence among Taiwanese firms than among Chinese firms. The estimated parameters are stable across different specifications. Interestingly, the parameter estimates for the R&D technology in Taiwan are in the ballpark of the estimates of $\bar{p}$ and q in the FRM for China.

[27] To ensure that the estimates are comparable across data samples, we estimate all models with the same step size on the TFP ladder as in the benchmark model, 0.78.

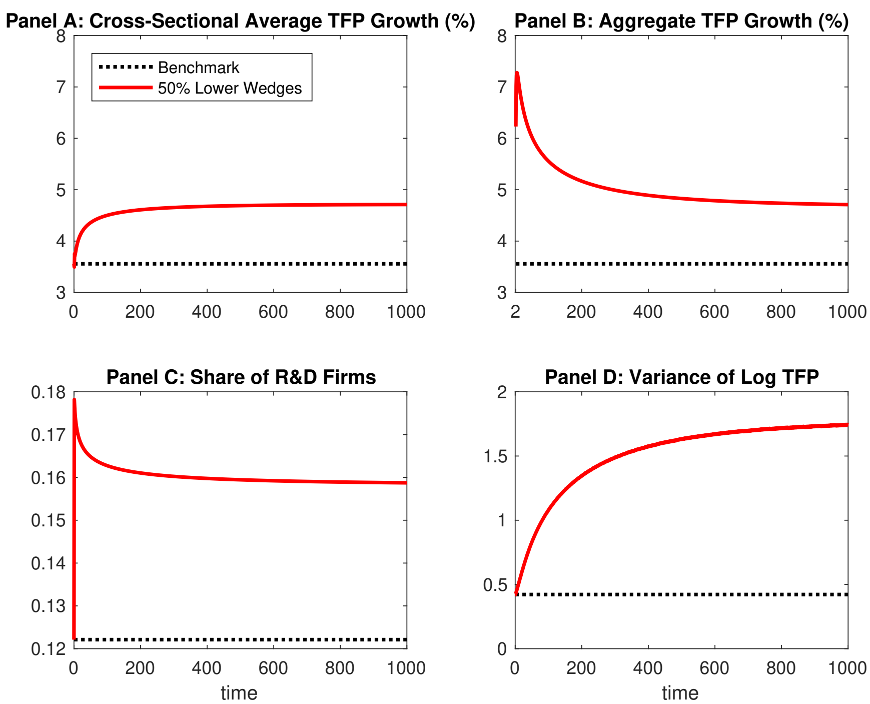
In conclusion, our theory can account for the R&D behavior and TFP growth for both Taiwanese and Chinese firms. However, both innovation and technology diffusion are faster in Taiwan.

Earlier China Sample: As a further robustness check, we have also estimated the model using data for Chinese firms from the earlier period 2001–07, see Appendix Table A7 and Appendix Figure A10. The results are qualitatively similar and in all cases statistically significant, although R&D investments are a less important driver of TFP growth than in the period 2007–12. This finding accords with the argument of Acemoglu et al. (2006) that innovation becomes more important as an economy approaches the world technology frontier.

8 Counterfactuals

In this section, we report the results of some counterfactual policy experiments we performed based on the estimated model. We focus our discussion on the PAM and IPM.

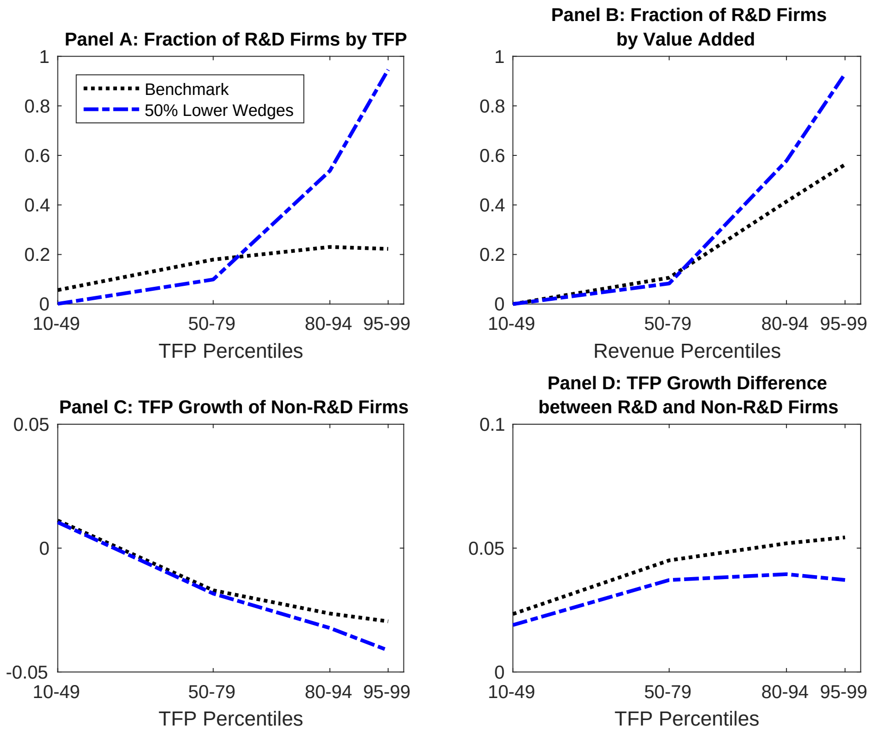
Figure 8: Transition after Lowering Wedges



Note: The graph displays the transition following a 50% reduction in the variance of wedges. Panel A plots the growth rate of cross-sectional average TFP. Panel B plots the growth rate of aggregate TFP. Panel C plots the share of R&D firms, and Panel D plots the cross-sectional variance of log TFP.

Reducing misallocation: Our main counterfactual experiment is an exogenous reduction in misallocation. Hsieh and Klenow (2009) document large static efficiency gains from reducing misallocation in China. In our model there are additional dynamic effects through the R&D investments. Output wedges make R&D decisions depend more on firm size and less on TFP, flattening the schedule of Panel A in Figure 4 relative to Panel B in the same figure. If misallocation were removed altogether, the correlation between size and R&D would be driven by TFP differences only, in which case the schedules

Figure 9: Steady-State Moments in the Counterfactual Model



Note: The dashed lines display the moments in steady state for the counterfactual experiment where we reduce the variance of wedges by 50%. The dotted line displays the moments predicted by the benchmark estimated PAM.

in Panels A and B would be identical.

We study the dynamic effects of an unanticipated instant reduction in the variance of the logarithm of output wedges $\log(1-\tau_i)$. We engineer this reduction by halving both b^2 and $var(\varepsilon_i^\tau)$.[28] Figures 8 and A11 display the transition of the economy from the initial to the counterfactual steady state for the PAM and IPM, respectively.[29] The two upper panels show the evolution of the growth rates in the cross-sectional average TFP and in aggregate TFP, respectively.[30] To ease the visualization, Panel B does not display the initial jump in aggregate TFP arising from the static effect of improved resource allocation following the reduction in the dispersion of wedges.

When we lower the dispersion in wedges (and the correlation of wedges with TFP), more high-TFP firms and fewer low-TFP firms invest in R&D. This has two effects on the TFP distribution. First, the

[28] To see why this achieves a 50% lower dispersion in wedges on impact, recall that $var(\log(1-\tau)) = b^2 \cdot var(\log(A)) + var(\varepsilon_i^\tau)$. The correlation parameter b, which we inferred from the data, is quantitatively important, especially for the dynamic effects: in our counterfactual, the decrease in the parameter b is actually the main source of dynamic gains. The reason is that the wedge on high-TFP firms—that efficiency considerations would require investing in R&D—is the main distortion on R&D decisions. Note that our experiment is not directly comparable with that performed by Hsieh and Klenow (2009) because they assume wedges and TFP follow a bivariate lognormal distribution, implying that the variance of log TFPR is a sufficient statistic for the static effect of distortions on aggregate TFP.

[29] It would be a formidable task to calculate numeric transitions in which the cost of R&D changes with the growth rate every period in line with equation 8. For this reason, we approximate the path of the innovation cost using the constant growth rate in the future steady state.

[30] Recall that the cross-sectional average TFP is the (unweighted) average TFP across firms, $\bar{A} \equiv \int_0^1 A_i \, di$. Aggregate TFP in our economy is calculated as $Z \equiv Y/\left(K^\alpha L^{1-\alpha}\right)$, where K and L denote aggregate capital and labor, respectively.

wave travels at a faster speed because more of the firms with a comparative advantage in innovation (i.e., high-TFP firms) pursue the innovation strategy. The growth rate of cross-sectional average TFP (Panel A) reflects the speed of the traveling wave of the TFP distribution. Note that this is a state variable that does not jump upon the reduction of misallocation. Instead, the speed of the traveling wave (hence, the growth rate of cross-sectional average TFP) increases gradually.

The second salient effect is an increase over time in TFP dispersion. Intuitively, as we lower misallocation, more high-TFP firms invest in R&D and grow faster, pulling away from the median. Panel D in Figure 8 shows that the cross-sectional variance of TFP increases over time to more than three times its initial magnitude. The increase in the TFP dispersion increases aggregate value added because more inputs are allocated to the firms with the highest TFP, thereby increasing the covariance between inputs and TFP. This effect gives aggregate TFP growth an additional kick that lasts for as long as the TFP dispersion grows. It is largest in the early stage of the transition and is dampened over time as the growth in the TFP dispersion declines.

The evolution of aggregate TFP growth in Panel B of Figure 8 stems from a combination of the two effects. In the long run, we observe an increase in aggregate TFP growth from the initial 3.6% to 4.7% (see column (1) in Table 6). The transition is long and hump shaped: after an initial spike, aggregate TFP growth slowly declines to the new steady state. The hump reflects the dynamics of the two components. In the initial phase of the transition, the main driver for aggregate TFP growth is the increasing TFP dispersion. In the long run, the dispersion of the distribution settles down to a constant level and the aggregate TFP growth coincides with the growth rate of the cross-sectional average TFP.

Panel C in Figure 8 shows that R&D investments shoot up by almost 50% upon impact and then decline smoothly. The sharp initial increase is partly driven by a change in income distribution between labor and profits. As the dispersion of wedges is curtailed, both aggregate TFP and the share of value added accruing to profits grow. This strengthens the incentives for firms to invest in R&D. The initial increase in R&D investments is dampened over time because the increase in TFP dispersion increases misallocation after the shock.[31] In the new steady state, the share of R&D firms (16%) is significantly higher than in the initial steady state (12%).

Figures 9 and A12 show how the counterfactual reduction in misallocation affects the predictions for the targeted moments in the PAM and the IPM, respectively.[32] There are large changes in Panels A and B. The schedule in Panel A becomes significantly steeper, reflecting the larger correlation between R&D and TFP. In the counterfactual PAM economy, 95% of the firms in the top five TFP percentiles and 54% of the firms in the 80th–94th TFP percentiles invest in R&D—the corresponding numbers for the IPM are 66% and 30%. In contrast, hardly any firms with TFP below the median invests in R&D. Moreover, the size-R&D profile in Panel B is now much more similar to the TFP-R&D profile—reflecting the higher correlation between size and TFP. Panel D shows that the TFP growth difference between R&D and nonR&D firms is slightly smaller in the counterfactual. This is due to a selection effect: wedges deter firms from investing in R&D, except for those drawing a very high p. This implies positive selection on p. Lowering distortions reduces the positive selection.

The main lesson of this counterfactual experiment is that misallocation has significant quantitative effects on TFP growth both in the short and in the long run. Moreover, reducing misallocation widens

[31] To see this, recall that given the relationship we assumed between wedges and TFP in equation (14), the variance of $\log(1-\tau_i)$ is $b^2 var(a_i) + var(\varepsilon_i^\tau)$. Therefore, a larger $var(a_i)$ will imply a larger dispersion in τ_i. This effect partially offsets the initial decline in wedges.

[32] Since these figures show simulated results, we do not add m.e. This is different from Figure 4 where we add m.e. to the simulations in order to make the results comparable with the data.

the dispersion in the stationary TFP distribution. In our model, firms' heterogeneity has no effect on wage inequality because the labor market is competitive. However, in models with realistic labor market frictions (e.g., search and ex-post rent sharing) and assortative matching between workers and firms (Lindenlaub (2017)), reducing wedges and misallocation would also increase wage inequality.

International spillovers: Our model predicts that a reduction in misallocation yields a permanent growth effect of a reduction of misallocation. Arguably, this is too optimistic. Many economists believe that the fast growth of China stems, at least in part, from technological convergence due to international spillovers. As China approaches the world economic frontier, this source of growth is destined to dry up.

In this section, we embed our theory in a model of technological convergence where growth arises from both random interactions and international spillovers, which we assume to increase with the distance to the world frontier as in Acemoglu et al. (2006). More formally, we assume that aggregate TFP growth in the nonfrontier economy j equals $g_{jt} = \Gamma(MIS_j, \mathcal{A}_{jt}) + \Delta(TFP_{ft}/TFP_{jt})$, where Γ is the outcome of our benchmark model, $\mathcal{A}$ stands for the TFP distribution, and Δ captures learning from the frontier economy. Γ is a decreasing function of the level of misallocation MIS_j which is parameterized by b^2 and $var\left(\varepsilon_i^\tau\right)$, following our theory.[33]

We assume $\Delta(x) = \zeta \times log(x) - d$, where ζ is a convergence parameter and d captures knowledge depreciation. In the long run, all countries grow at the same constant rate g which is set by the frontier economy, while the TFP gap between the frontier and nonfrontier economies is determined by the relative misallocation.[34]

We calibrate $\zeta = 2\%$ consistent with standard estimates of the cross-country convergence rate. We set $d = 0.0312$ so that the model matches the aggregate growth rate of TFP in Chinese manufacturing in our sample (3%). Finally, we set the TFP growth rate for the frontier economy (i.e., $\tilde{\Gamma}(MIS_f) - x$) to 2%.[35] Under this calibration, the current level of misallocation of China implies that its GDP per capita converges in the long run to 46% of the frontier economy's level.

Next, we counterfactually reduce misallocation by 50%. We assume an initial TFP gap between China and the frontier economy of 3.6 in line with the China-US gap estimated by Shen et al. (2015). Figure 10 shows the results for the PAM (the IPM yields similar results). The TFP gap relative to the frontier economy falls on impact and keeps shrinking thereafter, both because of the declining international spillovers and the transitional dynamics of the random interaction model. In the long run, TFP converges to 81% of the frontier level (as opposed to 46% in the status quo). While part of this gain accrues from the static effect of reducing misallocation, Figure 10 shows that the additional dynamic gains arising from the mechanism of our model are quantitatively large: the static effect instantaneously cuts the gap from 3.68 to 2.13 while the ensuing dynamic effect further decreases it to 1.23. Throughout transition, growth is hump-shaped, being faster than in the benchmark economy for decades.[36]

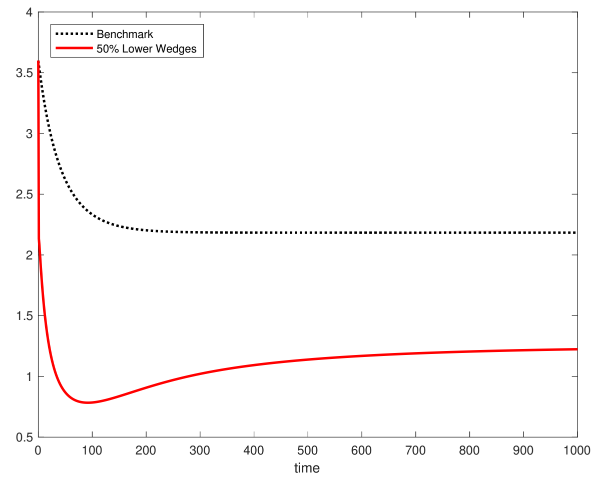
[33] Recall also that while during transition growth depends on the evolving TFP distribution $\mathcal{A}_{jt}$, the long-run distribution is pinned down by the level of misallocation, i.e., $\mathcal{A}_j = \mathcal{A}(MIS_j)$.

[34] More formally, if we denote the steady state expression of Γ_j by $\tilde{\Gamma}(MIS_j) \equiv \Gamma\left(MIS_j, \mathcal{A}(MIS_j)\right)$, the steady-state TFP difference between a generic economy k and the frontier economy f is given by: $log(TFP_f/TFP_k) = \left(\tilde{\Gamma}(MIS_f) - \tilde{\Gamma}(MIS_k)\right)/\zeta$.

[35] We acknowledge that this TFP growth rate is higher than one observes in frontier economies like the US in recent history. If we assumed lower growth rates, the calibrated model would predict that China becomes the world leader in the long run. While we are agnostic in this regard, such a scenario would defeat the purpose of an extension aiming to quantify the effects of misallocation in a model where changes in misallocation only affects the speed of transition.

[36] China temporarily becomes the world leader during the transition. The simulation takes into full account the conse-

Figure 10: TFP Gap During Transition with International Spillovers



Note: Evolution over time of the ratio between the TFP of the frontier economy and that of the benchmark economy (China) in the model with international spillovers. The dotted and solid lines display simulated transitions in the estimated model and in the counterfactual where output wedges are reduced by 50%, respectively.

The take-home message of this section is that in a model with international spillovers, a reduction in misallocation has a significant effect on the speed of transition and on the long-run GDP level even in a scenario in which the catching-up economy does not become the world technology leader in the long run.

The innovation technology: In this section, we study the effect of counterfactual changes in the parameters of the technology of innovation. Table 6 and Appendix Table A8 summarize the results for the PAM and IPM, respectively, focusing on the fraction of R&D firms and the growth rate in steady state. Column (1) reports the result of the estimated model for comparison. Column (2) summarizes the long-run effect of the reduction in misallocation discussed above. In columns (3), (4), and (5), we change the structural parameters q , $\bar{p}$, and $\bar{c}$ to the estimated level in Taiwan while keeping the other parameters and the wedges at the estimated level for China. In all three scenarios, we observe a significant increase in steady-state TFP growth, driven by the faster rate of both innovation and imitation. When we set only the parameter q to the Taiwanese level, the proportion of R&D firms falls by one and half percentage point. When we change both $\bar{p}$ and $\bar{c}$, the proportion of R&D firms increases. Finally, when we set $q, \bar{c}$, and $\bar{p}$ to their respective Taiwanese estimated levels, the share of R&D firms is about the same as in the estimated model. However, the steady-state TFP growth rate is significantly higher (+1.5%).

The results are similar for the IPM—see columns (2)–(4) of Appendix Table A8. For instance, simultaneously setting $q, \bar{c}$, and $\bar{p}$ to the respective Taiwanese levels increases TFP growth from 5.1% to 5.8%, albeit reducing the share of R&D firms.

In columns (6) and (7) of Table 6, we consider uniform taxes or subsidies on R&D that change the baseline cost of innovation $\bar{c}$ so that, respectively, 5% and 20% of the Chinese firms invest in R&D. Taxing R&D reduces TFP growth while subsidizing R&D increases it relative to the baseline economy. However, the effect of subsidies is not monotonic. This is shown in column (8), where we consider a drastic policy inducing (e.g., through arbitrarily large R&D subsidies) all firms to pursue

quences of this shift back and forth.

the innovation strategy.[37] The growth rate is lower than in the intermediate case of column (7). The result is even starker in the IPM, where the growth rate of the economy where a large subsidy induces all firms pursue innovation is lower than in the baseline estimated economy—see columns (1) and (8) in Appendix Table A8.

Taking stock, the counterfactual analysis in this section provides two key insights. First, the technology of innovation is more productive in Taiwan than in China. Given misallocation, China would grow faster if it had access to the same innovation technology as Taiwan. Second, a moderate increase in R&D subsidies across the board relative to its current level increases TFP growth. This is in line with the predictions of models of endogenous technical change (e.g., Aghion and Howitt (1992)). However, the effect is nonmonotonic and turns around for sufficiently large subsidies. This "too much of a good thing" result stems from the opportunity cost of forgoing the benefit of random interactions.

Our counterfactual analysis ignores the cost of R&D subsidies. In an economy plagued by large misallocation, a significant portion of the R&D subsidies would induce the *wrong* firms to pursue innovation. Therefore, reducing misallocation entails a double dividend: it improves overall efficiency and increases the effectiveness of R&D subsidies.

Table 6: Counterfactuals, Parsimonious model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PAM estim. model	50% lower output wedges	Taiwan's q	Taiwan's $\bar{p}$ and $\bar{c}$	Taiwan's $\bar{p}$, $\bar{c}$, and q	Increase $\bar{c}$ so share R&D firms = 5%	Decrease $\bar{c}$ so share R&D firms = 20%	All firms do R&D
Fraction of R&D Firms (%)	12.2	15.8	10.7	14.1	12.2	5	20	100
Steady State TFP Growth (%)	3.56	4.70	4.49	4.92	6.03	2.41	4.42	3.80

Note: The table reports statistics for the counterfactual experiments for the PAM discussed in the text. Column (1) reports the predicted moments of the estimated PAM for comparison.

9 Conclusion

In this paper, we construct and structurally estimate a theory of TFP growth driven by innovation and technology diffusion through random interactions. In the theory, both the TFP level and firm-specific distortions are sources of comparative advantages: firms with high TFP and firms with negative output wedges have a stronger incentive to invest in R&D. The theory bears testable predictions about the evolution of the TFP distribution. We estimate the model to earn new insights about the nature and effects of the R&D expenditure boom in China in recent years. In spite of the numerous distortions emphasized by earlier studies, R&D investments appear to have contributed significantly to the productivity growth of China. However, the return to productivity of R&D investments is lower in China than in Taiwan. Moreover, pervasive output wedges often induce the wrong firms (and,

[37] Although this case features no stationary distribution (namely, the variance of TFP increases perpetually) it is possible to calculate analytically the (approximate) growth rate when setting $\delta \approx 0$ (recall that the estimates of δ are always very small).

conversely, deter the right ones) from investing in R&D, thereby reducing the productivity of R&D investments.

Relative to earlier Schumpeterian growth theory, our study incorporates both innovation and technology diffusion into a common framework. Moreover, it shifts the focus from the overall investment in innovation to the efficient assignment of firms to innovation and imitation activities. While innovation is the ultimate engine of growth, an excessive (or ill-targeted) policy emphasis on innovation can actually backfire. The reason is that less productive firms have a high growth potential through imitation which they forgo when they focus on innovation. Similar to innovation, successful imitation carries positive externalities to less productive firms. Another important message of the paper is that misallocation has significant dynamic effects. To the extent that larger firms have stronger incentives (and fewer constraints) to pursue R&D investments, misallocation distorts the natural comparative advantage of firms in leading the innovation process, and ultimately slows down economic growth.

Our study has some limitations that should be addressed in future research. First, we infer wedges by exploiting the variation in size and TFP across firms, following Hsieh and Klenow (2009). The assumptions underlying this methodology have been subject to debate and dispute in the literature. Future work could aim to infer wedges more directly from observable policy distortions. Second, we focus on the balanced panel of firms that are in the sample both in 2007 and 2012, abstracting from entry and exit. While churning and the formation of new firms are important features of the Chinese data, we believe that a study focusing on the R&D investments of incumbent firms is no less important. In 2007, our balanced sample captures 71% of the R&D investments (which is the focal point of our study) and 63% of the value added of firms in the total sample. Finally, future work should explore in more depth firm dynamics and the role of an intensive margin of R&D.

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Supplementary Appendix

A Theory

In this section, we provide the proof of Proposition 1 and an expression for the equilibrium profits (Equation (7)) and wage rate.

Proof of Proposition 1. From the monotonicity of $Q(a,\tau;\mathcal{A})$ in a it follows that there exists a threshold function $a^*(\tau;\mathcal{A})$ such that[38]

$$\begin{aligned} &Q(a,\tau;\mathcal{A}) \geq \overline{p} \text{ if } a \leq a^*(\tau;\mathcal{A}), \\ &Q(a,\tau;\mathcal{A}) < \overline{p} \text{ if } a > a^*(\tau;\mathcal{A}). \end{aligned} \tag{A1}$$

All firms with $a \leq a^*(\tau;\mathcal{A})$ imitate, while some firms with $a > a^*(\tau;\mathcal{A})$ (i.e., those with a sufficiently large p) innovate. To simplify notation, we write $a^*(t) = a^*(\tau;\mathcal{A})$ and $Q(a) = Q(a,\tau;\mathcal{A})$ when this is no source of confusion.

The difference equation governing the evolution of the log-TFP distribution can then be broken down as follows:

$$\begin{aligned} &\mathcal{A}_a(t+1) - \mathcal{A}_a(t) \\ &= \begin{cases} q\left[(1-F_{a-1}(t))\,\mathcal{A}_{a-1}(t) - (1-F_a(t))\mathcal{A}_a(t)\right] & \text{if} \quad a < a^*(t), \\ \left(\begin{array}{c} q\,(1-F_{a-1}(t))\,\mathcal{A}_{a-1}(t) \\ -G(Q(a))\left[q(1-F_a(t))\mathcal{A}_a(t)\right] \\ -\int_{Q(a)}^{\overline{p}}\left[(p+(1-p)\,\delta q\,(1-F_a(t)))\,\mathcal{A}_a(t)\right]dG(p) \end{array}\right) & \text{if} \quad a = a^*(t)+1, \\ \left(\begin{array}{c} G(Q(a-1)) \times q\,(1-F_{a-1}(t))\,\mathcal{A}_{a-1}(t) \\ +\int_{Q(a-1)}^{\overline{p}}\left[(p+(1-p)\,\delta q\,(1-F_{a-1}(t)))\,\mathcal{A}_{a-1}(t)\right]dG(p) \\ -G(Q(a)) \times q\,(1-F_a(t))\,\mathcal{A}_a(t) \\ -\int_{Q(a)}^{\overline{p}}\left[(p+(1-p)\,\delta q\,(1-F_a(t)))\,\mathcal{A}_a(t)\right]dG(p) \end{array}\right) & \text{if} \quad a > a^*(t)+1. \end{cases} \end{aligned} \tag{A2}$$

To understand this law of motion, note that (i) if $a < a^*(t)$, all firms with TFP a and $a-1$ imitate; (ii) if $a > a^*(t)+1$, all firms with TFP a facing a realization $p > Q(a)$ and all firms with TFP $a-1$ facing a realization $p > Q(a-1)$ innovate, while all other firms with TFP a and $a-1$ imitate; (iii) if $a = a^*(t)+1$, all firms with TFP a facing a realization $p > Q(a)$ innovate, and all other firms with TFP a and $a-1$ imitate. Going from the p.m.f to the corresponding c.d.f. yields:

$$\begin{aligned} F_a(t+1) - F_a(t) &= \sum_{b=1}^{a} \mathcal{A}_b(t+1) - \mathcal{A}_b(t) \\ &= \begin{cases} -q\,(1-F_a(t))\,(F_a(t)-F_{a-1}(t)) & \text{if} \quad a \leq a^*(t) \\ \left(\begin{array}{c} -G(Q(a))\,q\,(1-F_a(t))\,(F_a(t)-F_{a-1}(t)) \\ -\int_{Q(a)}^{\overline{p}}\left[\begin{array}{c} (p+(1-p)\,\delta q\,(1-F_a(t))) \times \\ (F_a(t)-F_{a-1}(t)) \end{array}\right]dG(p) \end{array}\right) & \text{if} \quad a > a^*(t) \end{cases} \end{aligned} \tag{A3}$$

[38] Note that this notation involves a slight abuse of notation relative to the function a^* in the text.

Define the complementary cumulative distribution function $H_a(t) = 1 - F_a(t)$. Equation (A3) can be rewritten as:

$$
\begin{aligned}
H_a(t+1) - H_a(t) &= -\sum_{b=1}^{a} \left(\mathcal{A}_b(t+1) - \mathcal{A}_b(t)\right) \\
&= \begin{cases} qH_a(t)\left(H_{a-1}(t) - H_a(t)\right) & \text{if} \quad a \le a^*(t) \\ \left(\begin{array}{c} G\left(Q\left(a\right)\right) qH_a\left(t\right)\left(H_{a-1}\left(t\right) - H_a\left(t\right)\right) \\ + \int_{Q(a)}^{\overline{p}} \left[\begin{array}{c} \left(p + (1-p)\,\delta q H_a\left(t\right)\right) \times \\ \left(H_{a-1}\left(t\right) - H_a\left(t\right)\right) \end{array} \right] dG\left(p\right) \end{array} \right) & \text{if} \quad a > a^*(t) \end{cases}
\end{aligned} \tag{A4}
$$

Note that $F_a(t+1) \le F_a(t)$ (and conversely, $H_a(t+1) \ge H_a(t)$.) Since the probability mass is conserved to one (and $\lim_{a\to+\infty} F_a = 1$), the fact that F_a is decreasing over time t for every a implies that the distribution must shift to the right (i.e. towards higher values of a). A distribution that is shifted in this way is called a traveling wave (Bramson, 1983). We now prove that there exists a traveling wave solution of the form $F_a(t) = \tilde{f}(a - \nu t)$ (or, equivalently $H_a(t) = \tilde{h}(a - \nu t)$) with velocity $\nu > 0$. The formal argument follows Bramson (1983) and König et al. (2016) . The traveling wave solution above implies that $F_a(t+1) - F_a(t) = \tilde{f}(x - \nu) - \tilde{f}(x)$, where $x \equiv a - \nu t$. For $\nu \approx 0$, we can take the first order approximation $\tilde{f}(x-\nu) - \tilde{f}(x) \approx -\nu \tilde{f}'(x)$, and thus $F_a(t+1) - F_a(t) \approx -\nu \tilde{f}'(x)$. Therefore, we can rewrite (A3) as:

$$
-\nu \tilde{f}'(x) = \begin{cases} -q\left(1 - \tilde{f}(x)\right)\left(\tilde{f}(x) - \tilde{f}(x-1)\right) & \text{if} \quad x \le x^* \\ \left(\begin{array}{c} -G\left(Q\left(x\right)\right)\left[q(1-\tilde{f}(x))\left(\tilde{f}(x) - \tilde{f}(x-1)\right)\right] \\ -\int_{Q(x)}^{\overline{p}} \left[\begin{array}{c} \left(p + (1-p)\,\delta q\left(1 - \tilde{f}(x)\right)\right) \times \\ \left(\tilde{f}(x) - \tilde{f}(x-1)\right) \end{array} \right] dG\left(p\right) \end{array} \right) & \text{if} \quad x > x^* \end{cases} \tag{A5}
$$

or, identically,

$$
-\nu \tilde{h}'(x) = \begin{cases} q\tilde{h}\left(x\right)\left(\tilde{h}\left(x-1\right) - \tilde{h}(x)\right) & \text{if} \quad x \le x^* \\ \left(\begin{array}{c} G\left(Q\left(x\right)\right)\left[q\tilde{h}\left(x\right)\left(\tilde{h}\left(x-1\right) - \tilde{h}(x)\right)\right] \\ +\int_{Q(x)}^{\overline{p}} \left[\begin{array}{c} \left(p + (1-p)\,\delta q\tilde{h}\left(x\right)\right) \times \\ \left(\tilde{h}\left(x-1\right) - \tilde{h}\left(x\right)\right) \end{array} \right] dG\left(p\right) \end{array} \right) & \text{if} \quad x > x^* \end{cases} \tag{A6}
$$

Consider, first, the range $x \le x^*$. Using the upper part of (A5) yields the following Delay Differential Equation (DDE):[39]

$$
-\nu \tilde{f}'(x) = -q\left(1 - \tilde{f}(x)\right)\left(\tilde{f}(x) - \tilde{f}(x-1)\right). \tag{A7}
$$

This equation allows us to characterize the (asymptotic) left tail of the distribution. Taking the limit for $x \to -\infty$, we can take the following first-order (i.e., linear) approximation:

$$
\nu \tilde{f}'(x) \simeq q\left(\tilde{f}(x) - \tilde{f}(x-1)\right).
$$

[39]See also Asl and Ulsoy (2003), Bellman and Cooke (1963), and Smith (2011).

Next, we guess that this linear DDE has a solution of the form $\tilde{f}(x) = c_1 e^{\lambda x}$ for $x \to -\infty$. Replacing $\tilde{f}(x)$ by its guess and $\tilde{f}'(x)$ by its derivative, and simplifying terms, allows us to verify the guess as long as the following transcendental equation in λ is satisfied:

$$\lambda\nu \simeq q(1 - e^{-\lambda}). \tag{A8}$$

The solution to this transcendental equation is given by

$$\lambda = \frac{\nu W\left(-\frac{qe^{-\frac{q}{\nu}}}{\nu}\right) + q}{\nu},$$

where W denotes the Lambert W-function, and we require that $\frac{qe^{-\frac{q}{\nu}}}{\nu} \leq \frac{1}{e}$.

Consider, next, the range of large x where the solution for $x > x^*$ applies in (A6). Then, we can write the following DDE

$$-\nu\tilde{h}'(x) = \left(\begin{array}{c} G(Q(x))\left[q\tilde{h}(x)\left(\tilde{h}(x-1) - \tilde{h}(x)\right)\right] \\ + \int_{Q(x)}^{\overline{p}} \left[\begin{array}{c} \left(p + (1-p)\,\delta q\tilde{h}(x)\right) \times \\ \left(\tilde{h}(x-1) - \tilde{h}(x)\right) \end{array} \right] dG(p) \end{array} \right). \tag{A9}$$

We use this DDE to characterize the right tail of the distribution as $x \to +\infty$. Again, we take a linear approximation:

$$\nu\tilde{h}'(x) \simeq \hat{p}\left(\tilde{h}(x) - \tilde{h}(x-1)\right),$$

where $\hat{p} = \int_0^{\overline{p}} p\, dG(p)$. For the latter, note that $\lim_{x\to\infty} Q(x) = 0$ since as we take x to be arbitrarily large, imitation becomes totally ineffective and firms choose to innovate almost surely. We guess a solution of the DDE of the form $\tilde{h}(x) = c_2 e^{-\rho x}$ for $x \to +\infty$. The guess is verified as long as the following transcendental equation holds:

$$\rho\nu \simeq \hat{p}(e^{\rho} - 1).$$

The solution to the transcendental equation satisfies

$$\rho = \frac{-\nu W\left(-\frac{\hat{p}e^{-\frac{\hat{p}}{\nu}}}{\nu}\right) - \hat{p}}{\nu}, \tag{A10}$$

where W denotes the Lambert W-function, and we require that $\frac{\hat{p}e^{-\frac{\rho}{\nu}}}{\nu} \leq \frac{1}{e}$. This concludes the proof. ■

Equilibrium expression for profits and wage rate: We provide the equilibrium expression for profits and for the wage rate, given an aggregate labor supply of $L = 1$, exogenous distributions of wedges and TFP, and the assumption of a small open economy.

The CES production function implies that each firm faces an isoelastic demand $Y_i = P_i^{-\eta} Y$, whence,

$$P_i Y_i = Y^{\frac{1}{\eta}} \left(A_i K_i^{\alpha} L_i^{1-\alpha}\right)^{1-\frac{1}{\eta}}.$$

Each firms chooses capital and labor to maximize profits subject to wedges and demand equation:

$$\max_{\{K_i,L_i\}} \pi_i = (1-\tau_i)\, P_i Y_i - wL_i - rK_i.$$

Solving the maximization problem by standard methods, substituting in the optimal values of L_i and K_i, using the expression for P_iY_i above, and rearranging terms yields:

$$\pi_i = \frac{1}{\eta} P_i Y_i = \Pi \left(A_i \left(1-\tau_i\right)\right)^{(\eta-1)},$$

where $\Pi \equiv \Big((1-\alpha)^{(1-\alpha)}\, \alpha^{\alpha}(\eta-1)\Big)^{\eta-1} \eta^{-\eta} \frac{Y}{(w^{1-\alpha}r^{\alpha})^{\eta-1}}$. This is Equation (7) in the text.

The equilibrium expression for the wage rate is:

$$w^{1-\alpha} = \left(1-\frac{1}{\eta}\right) \frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{r^{\alpha}} \left(\int_0^1 (1-\tau_i)^{\eta-1} A_i^{\eta-1}\right)^{\frac{1}{\eta-1}}. \tag{A11}$$

B Data and descriptive statics

In this section we provide some details of the analysis in Section 3.

Alternative methodology for estimating TFP, based on Brandt et al. (2017)

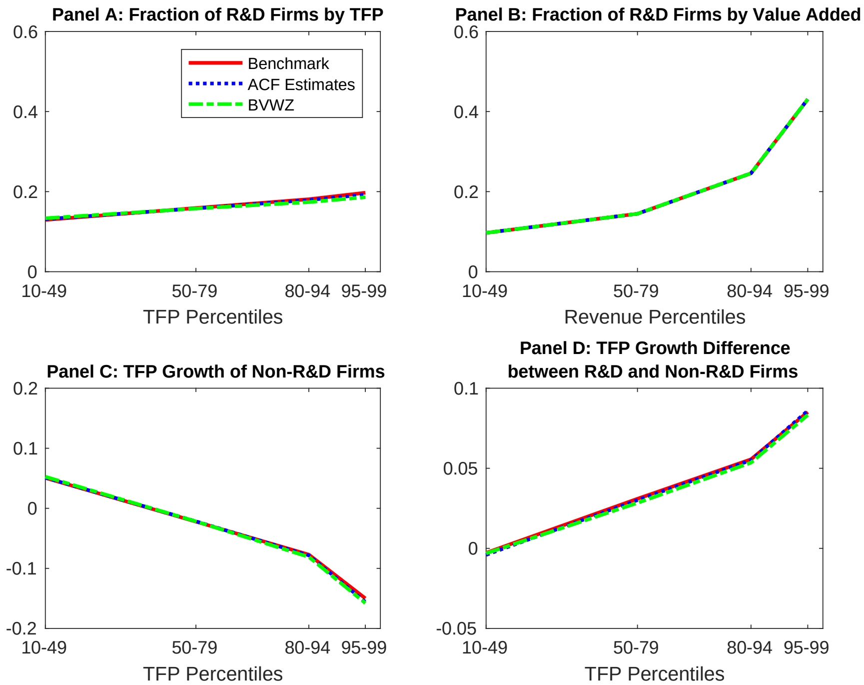
We estimate firm-level TFP using the methodology of Hsieh and Klenow (2009). This is consistent with our theoretical model and allows us to directly compare our results with those in the literature on misallocation. However, this approach has been criticized in the empirical industrial organization literature. If firms optimally choose the inputs in the production process to solve a dynamic maximization problem, then the estimation may suffer from an endogeneity problem. The error term of the model can contain determinants of production decisions that are observed by the firm but not by the econometrician, leading to inconsistent estimates of TFP.

In this section, we show that the target moments of our estimation are essentially unchanged if we estimate TFP using the methodology of Ackerberg et al. (2015) that addresses an endogeneity problem in the estimation of production functions. We follow the implementation of Ackerberg et al. (2015) proposed by Brandt et al. (2017), which is also related to De Loecker and Warzynski (2012). Because Brandt et al. (2017) postulate a gross production function while we estimate TFP using a value added approach, we perform an adjustment for the two methods to be consistent. The details of the estimation are deferred to the web appendix. The results are shown in Figure A1. The data moments are indistinguishable from those used targets in our estimation. We conclude that our results are robust to using this alternative estimation method for TFP.

Regression with firm fixed effects 2001–07

In this section, we present the result of regressions similar to those in Table 2, although for an earlier sample in China, 2001-2007. Since this sample has R&D data for more than one year, this sample allows us to also run regressions with firm fixed effects. Note that the regressions in Table A1 are all on annual data, the reason being that we only have R&D data for 2001-2003 and 2005-2007. The regressions in columns (1)-(3) are pooled regressions, while columns (4)-(5) are firm fixed effects (FE)

Figure A1: China 2007–12 Sample with Alternative TFP Measurement



Note: The figure shows the equivalent moments to Appendix Figure A4 when TFP is estimated using the methodology of Brandt et al. (2017) based on Ackerberg et al. (2015).

regressions. All pooled regressions include dummies for year, province, industry, and age effects while the FE regressions have year and firm effects. In the FE regressions, the dummies for province, industry, and age, as well as the dummies for export firms and state ownership, are all subsumed in the firm fixed effects.

The results in Table A1 show that, first, all the results from our main sample (2007-2012) in Table 2 hold up for the earlier sample (see the pooled regressions in Table A1). Second, the qualitative results hold up (significantly so) even when controlling for firm fixed effects. When comparing columns (2) and (5), we observe that the coefficients in the FE regressions are about half the size in magnitude but still highly significant. Moreover, the coefficients have always the same sign as in the pooled regressions. We conclude that our main empirical findings on the drivers of firms doing R&D—namely that R&D is positively associated with TFP and negatively associated with output wedges—hold true both in the cross section and within firms over time.

Alternative classification of innovative firms

In our main analysis, we classify all firms that report doing some R&D as innovative. However, many firms invest a very small amount of resources in R&D, raising questions of whether innovation is truly a salient strategy for these firms. In this appendix, we propose an alternative classification where firms are deemed innovative only if they invest more than 1.73% of their value added. This threshold is the median R&D intensity among R&D firms in our balanced sample. Conversely, firms investing less than 1.73% are regarded as imitators. Figure A2 shows the data moments corresponding to Figure 2 when applying this more stringent definition of innovators. As one would expect, the percentage of R&D

Table A1: Regressions with Firm Fixed Effects, 2001–07.

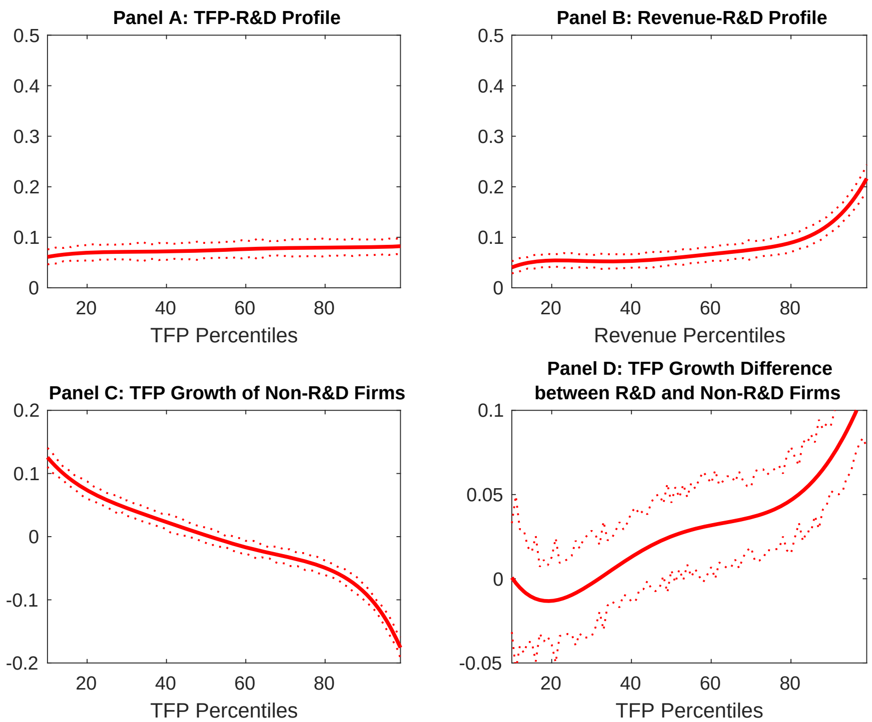
Dependent variable: R&D dummy

	(1)	(2)	(3)	(4)	(5)
	Pooled regressions			FE regressions	
	R&D$_d$	R&D$_d$	R&D$_d$	R&D$_d$	R&D$_d$
log(TFP)$_t$	0.059***	0.377***	0.323***	0.003***	0.186***
	(0.0049)	(0.0235)	(0.0191)	(0.0007)	(0.0054)
wedge		-0.432***	-0.361***		-0.225***
		(0.0297)	(0.0240)		(0.0066)
export$_d$			0.045***		
			(0.0118)		
SOE$_d$			0.124***		
			(0.0148)		
Firm effects	-	-	-	+	+
Year effects	+	+	+	+	+
Industry effects	+	+	+	-	-
Age effects	+	+	+	-	-
Province effects	+	+	+	-	-
R-squared	0.396	0.449	0.456	0.581	0.582

Note: The table shows regressions of an indicator of R&D on annual data for China 2001-2007. The independent variable is R&D$_d$, a dummy variable for R&D that equals one if firm R&D expenditure is positive and zero otherwise. log(TFP) is the logarithm of TFP. Wedge refers to the calibrated firm output wedge (see Section 2 for details). export$_d$ is a dummy variable for exports. SOE$_d$ is a dummy variable for state-owned firms. Standard errors are reported in parenthesis. The number of observations are 441,039 in columns (1)-(3) and 70,273 in columns (4)-(5). Observations are weighted by employment and standard errors are clustered by industry. Regressions in columns (4)-(5) include firm and year fixed effects. Regressions in columns (1)-(3) include year, industry, age, and province fixed effects. We drop firms with TFP in the bottom 10 percentiles.

firms is now lower. Moreover, the elasticity of R&D to TFP and size is lower than for the main sample. However, the qualitative patterns are the same in Figures 2 and A2.

Figure A2: More stringent classification of innovative firms.



Note: The figure shows the equivalent moments to Figure 2 if only firms with R&D expenditure above 1.73% are classified as R&D firms.

Full sample of Chinese firms in 2007

A2 provides a comparison between the descriptive statistics in 2007 for the balanced sample of Chinese firms we use in our analysis (*survivors*) and those that exited the sample before 2012. We ignore which of these firms literally ceased to exist, which ones shrank and fell below the survey threshold in later years, and which ones disappeared because of mergers and acquisitions.[40] Surviving firms account for ca. 63% of the total manufacturing value added. The median surviving firms is more than twice as large as the median exiting firm. Exiting firms are less likely to perform R&D and, conditional on performing it, they invest less.

Figure A3 displays the analogue of Panels A and B in Figure 2 for the full sample of firms in 2007, including exiters. Both panels show that exiters have a lower propensity to engage in R&D than surviving firms. Note that in both panels A and B the schedules for the full sample are almost parallel to the sample of survivors which we use. Namely, there is no major difference between survivors and exiters in the selection into R&D by TFP and size.

[40]Note that the threshold for being in the NBS data in 2007 is that sales exceeds 5 million Yuan, or about 1 million USD. This threshold increased to 20 million Yuan in 2011 and afterwards and some of the exiters are therefore firms with sales below 20 million Yuan in 2012.

This finding is confirmed by the multiple regressions in Table A3 that are very similar to those in Panel A of Table 2.

Table A2: Summary statistics for China 2007, survivors vs. exiters.

	(1) Survivors	(2) Exiters	(3) Full sample
Number of firms	123368	172704	296072
Median value added (million USD)	1.48	0.62	0.91
Share of R&D firms (in %)	14.7	8.5	11.1
Aggregate value added of R&D firms as share of total v.a. (in %)	42.7	34.4	39.6
Aggregate R&D expenditure as share of total v.a. (in %)	42.7	34.4	39.6
Median R&D Intensity for R&D firms (in %)	1.86	1.26	1.63

Note: Summary statistics for China 2007 for the full sample (including exiters) versus the balanced panel (survivors only). Survivors refers to firms present both in 2007 and 2012. Exiters refers to firms present in 2007 that exit the data before 2012.

Table A3: Regression Analysis for All Chinese Firms in 2007.

Dependent variable: R&D decision in 2007.

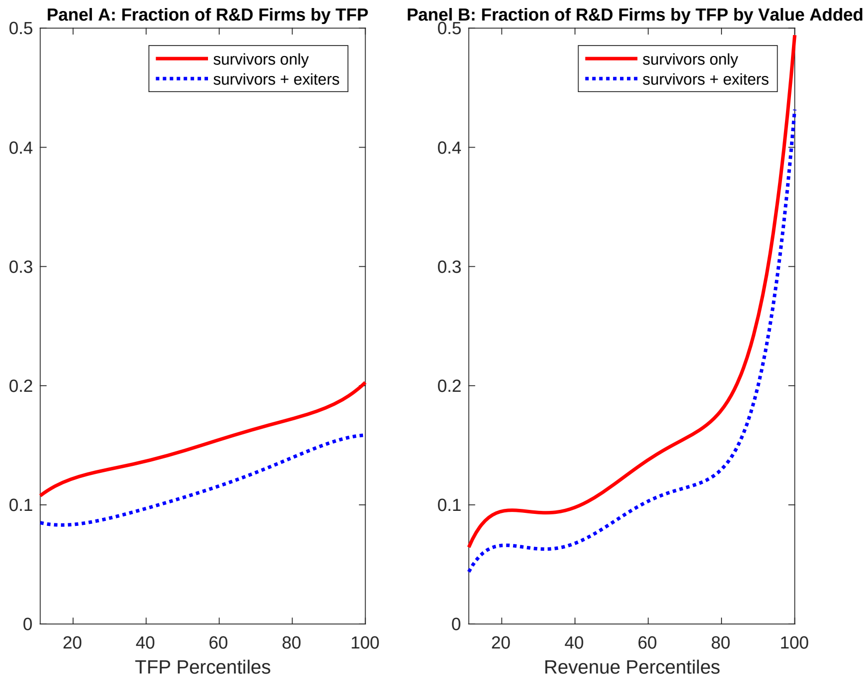
	(1) R&D$_d$	(2) R&D$_d$	(3) R&D$_d$	(4) R&D$_d$
log(TFP)	0.592***	0.353***	0.329***	0.299***
	(0.0063)	(0.0257)	(0.0230)	(0.0204)
wedge		-0.393***	-0.364***	-0.327***
		(0.0319)	(0.0283)	(0.0254)
export$_d$			0.051***	0.053***
			(0.0134)	(0.0132)
SOE$_d$				0.182***
				(0.0202)
R-squared	0.134	0.206	0.209	0.221

Note: Panel A: the table reports regressions equivalent to those in Table A3 for the full sample of firms in 2007, i.e., including firms that exit the sample before 2012. All the explanatory variables are from 2007. Standard errors are reported in parenthesis. The number of observations is 263,504. Observations are weighted by employment and standard errors are clustered by industry. All regressions include industry, age, and province fixed effects. We drop firms with TFP in the bottom 10 percentiles.

Regression results for Taiwan

In Table A4 we report the regression results discussed in the text for Taiwan. By comparing Table A4 with Table 2, it is clear that all qualitative results are the same for Taiwan as for our 2007-12 China data. However, R&D in Taiwan is more highly correlated with TFP and more negatively correlated with wedges, and TFP growth is more strongly related to R&D. In particular, the coefficients on TFP and wedges in Panel A (explaining the R&D decision) of Table A4 are about twice as large in magnitude

Figure A3: China 2007–12 Non-balanced Sample including Exiters



Note: The dotted lines show the moments equivalent to those of panels A and B in Figure 2 for the full sample of firms in 2007, i.e., including firms that exit the sample before 2012. The solid lines reproduce the moments in Figure 2, calculated for the balanced sample of surviving firms,

as in Table 2. Morever, the coefficient on R&D in Panel B (explaining TFP growth) of Table A4 are about three times as large in magnitude as in Table 2.

Target moments of the empirical distribution

Figure A4 displays the empirical moments that we target in the estimation. Each observation represents a quantile of the distribution based on Figure 2.

C Estimation

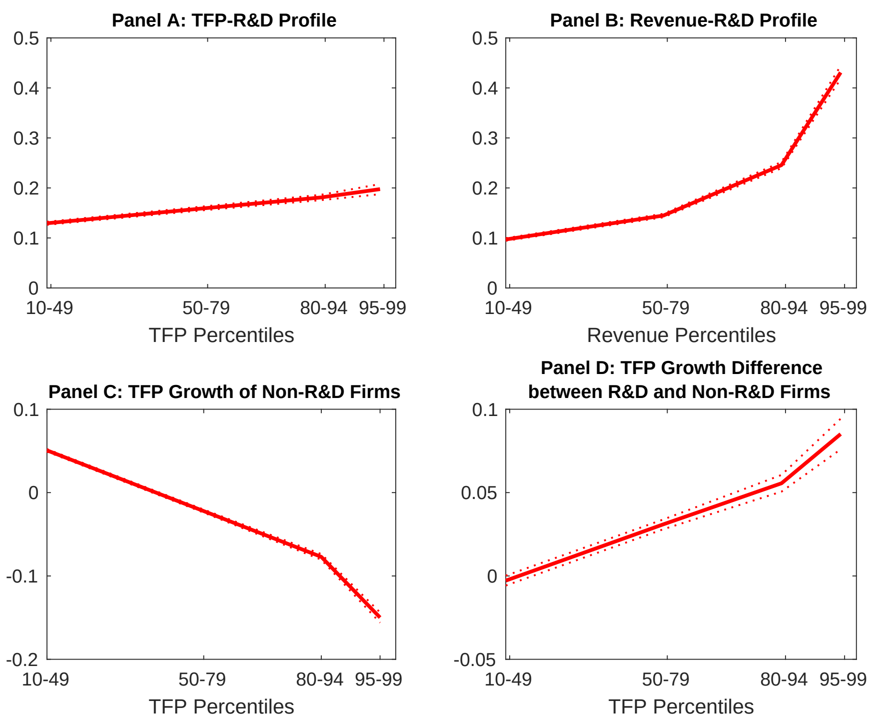
Measurement error: Mapping

This appendix describes how we incorporate measurement error when calculating the theoretical moments. We provide an analytical mapping from the theoretical distribution of a variable x to the observed distribution of true x plus m.e. This analytical mapping is critical to speed up the structural estimation, avoiding a computational curse that would arise if we had to rely on simulations.

The presentation focuses on TFP. The approach for adding m.e. to the theoretical (true) distribution of value added is equivalent, replacing a and μ with y and μ_y below.

Denote by $\hat{a}$ and a the observed and true log TFP: $\hat{a} = a + \mu$, where μ is m.e. Consider the following discrete state space: $a \in \{\delta, \cdots, N\delta\}$, $\hat{a} \in \{\delta, \cdots, N\delta\}$, and $\mu \in \{-N^{\mu}\delta, \cdots, -\delta, 0, \delta, \cdots, N^{\mu}\delta\}$. We set $N^{\mu} = 4$.

Figure A4: Chinese Firms in the Balanced Panel 2007–12



Note: The figure shows the empirical moments of the balanced panel for China 2007–12. See also Figure 4. The dotted lines represents standard errors.

Table A4: Balanced Panel of Taiwanese Firms, 1999–2004.

PANEL A: Correlations between firm characteristics and R&D decision.

	(1) $R\&D_d$	(2) $R\&D_d$	(3) $R\&D_d$
log(TFP)	0.087***	0.614***	0.573***
	(0.0078)	(0.0184)	(0.0189)
wedge		-0.720***	-0.673***
		(0.0234)	(0.0236)
$export_d$			0.088***
			(0.0227)
Industry effects	+	+	+
Age effects	+	+	+
Year effects	+	+	+
Observations	44,326	44,326	44,326
R-squared	0.219	0.396	0.404

PANEL B: Correlations between firm initial characteristics and TFP growth.

	(1) TFP growth	(2) TFP growth	(3) TFP growth
log(TFP)	-0.064***	-0.066***	-0.066***
	(0.0046)	(0.0047)	(0.0055)
$R\&D_d$	0.103***	0.093***	
	(0.0162)	(0.0168)	
$export_d$		0.039***	0.039***
		(0.0063)	(0.0063)
R&D $intensity_h$			0.072**
			(0.0262)
R&D $intensity_m$			0.106***
			(0.0278)
R&D $intensity_l$			0.097***
			(0.0150)
Industry effects	+	+	+
Age effects	+	+	+
Observations	9,996	9,996	9,996
R-squared	0.081	0.083	0.084

Note: The table reports the analogues of the regression results in Table 2 for the Taiwanese firms. There are two differences relative to Table 2: (1) Panel A reports pooled regressions with year fixed effects (for Taiwan, data for R&D expenditure is available for multiple years); and (2) there is no province dummy for Taiwan.

Let the theoretical distribution of a be denoted by $\mathcal{A}(a)$. The first task is to convert $\mathcal{A}(a)$ to $\mathcal{A}(\hat{a})$ – i.e., the distribution of observed TFP with m.e., which can be compared with the data. To this end, we first derive the transition matrix $\mathcal{A}(\hat{a}|a)$. For $j \in \{2, \cdots, N-1\}$, we have

$$\mathcal{A}(\hat{a} = a_j | a = a_i) = \mathcal{A}(\mu = (j-i)\delta). \tag{A12}$$

For $j = 1$ or N, we have $\mathcal{A}(\hat{a} = a_1 | a = a_i) = \sum_{k \geq i-1} \mathcal{A}(\mu = -k\delta)$ and $\mathcal{A}(\hat{a} = a_N | a = a_i) = \sum_{k \geq N-i} \mathcal{A}(\mu = k\delta)$. So, the unconditional probability of $\hat{a}$ is

$$\mathcal{A}(\hat{a} = a_j) = \sum_i \mathcal{A}(\hat{a} = a_j | a = a_i) \mathcal{A}(a = a_i). \tag{A13}$$

Note that when $\mathcal{A}(\hat{a})$ is observable while $\mathcal{A}(a)$ is unknown, one can use $\mathcal{A}(\hat{a} = a_j | a = a_i)$ in (A12) to back out $\mathcal{A}(a)$ by solving the system of equations in (A13).

We now derive the conditional TFP growth. Let us start with observed TFP growth of imitating firms.

$$\begin{aligned} \mathbb{E}^{IM}[\Delta\hat{a}|\hat{a}] &= \mathbb{E}^{IM}[\Delta a + \Delta\mu|\hat{a}] \\ &= \mathbb{E}[q(1-F(a))|\hat{a}] - \mathbb{E}[\mu|\hat{a}] \\ &= \sum_i q(1-F(a)) \mathcal{A}(a = a_i|\hat{a} = a_j) - \sum_k k\delta \mathcal{A}(\mu = k\delta|\hat{a} = a_j). \end{aligned} \tag{A14}$$

To go from the theoretical (conditional) distribution of true TFP growth conditional on true a to TFP growth with m.e. conditional on $\hat{a}$, we need conditional probabilities of $\mathcal{A}(a = a_i|\hat{a} = a_j)$ and $\mathcal{A}(\mu = k\delta|\hat{a} = a_j)$.

The posterior distribution of a follows

$$\mathcal{A}(a = a_i|\hat{a} = a_j) = \frac{\mathcal{A}(\hat{a} = a_j|a = a_i) \mathcal{A}(a = a_i)}{\mathcal{A}(\hat{a} = a_j)}, \tag{A15}$$

To obtain the posterior distribution of μ, first notice that

$$\begin{aligned} \mathcal{A}(\hat{a} = a_j \cap \mu = k\delta) &= \mathcal{A}(\hat{a} = a_j|\mu = k\delta) \mathcal{A}(\mu = k\delta) \\ &= \mathcal{A}(a = a_{j-k}) \mathcal{A}(\mu = k\delta). \end{aligned}$$

for $j \in \{2, \cdots, N-1\}$. Note that for $j = 1$ or N, we have the following boundary cases:

$$\begin{aligned} \mathcal{A}(\hat{a} = a_1|\mu = -i\delta) \mathcal{A}(\mu = -i\delta) &= \sum_{k \leq i+1} \mathcal{A}(a = a_k) \mathcal{A}(\mu = -i\delta), \\ \mathcal{A}(\hat{a} = a_N|\mu = i\delta) \mathcal{A}(\mu = i\delta) &= \sum_{k \geq N-i} \mathcal{A}(a = a_k) \mathcal{A}(\mu = i\delta). \end{aligned}$$

Then, the posterior distribution of μ follows

$$\begin{aligned} \mathcal{A}(\mu = k\delta|\hat{a} = a_j) &= \frac{\mathcal{A}(\hat{a} = a_j|\mu = k\delta) \mathcal{A}(\mu = k\delta)}{\mathcal{A}(\hat{a} = a_j)} \\ &= \frac{\mathcal{A}(\hat{a} = a_j \cap \mu = k\delta)}{\mathcal{A}(\hat{a} = a_j)}. \end{aligned} \tag{A16}$$

We can thus use (A14), together with (A15) and (A16), to generate TFP growth of imitating firms with measurement errors.

Table A5: Measurement Error Moments

	Empirical variances				Implied m.e. variance		
	$var(\Delta Y)$	$var(\Delta I)$	$cov(\Delta Y, \Delta I)$	$var(TFP)$	$\hat{v}_{\mu y}$	$\hat{v}_{\mu I}$	$\hat{v}_{\mu a}$
2007-2012 China	0.456	0.328	0.156	1.059	0.150	0.086	0.320
2001-2007 China	0.470	0.098	0.043	1.269	0.214	0.027	0.361
1999-2004 Taiwan	1.128	0.124	-0.005	2.363	0.567	0.065	0.950

Note: The first four columns refer to variances of growth in revenue, inputs, and TFP, respectively. Y, I and TFP represent $\log(P_{it}Y_{it})$, $\log(K_{it}^{\alpha}L_{it}^{(1-\alpha)})$, and $\log(A_{it})$, respectively. The fourth column is cross-sectional dispersion in TFP. We use the full sample (i.e., keeping the firms with initial TFP in the bottom ten percentiles). The results in the trimmed sample are similar. The implied variance of measurement error is derived from equations (12)-(13) and the expression for m.e. in TFP.

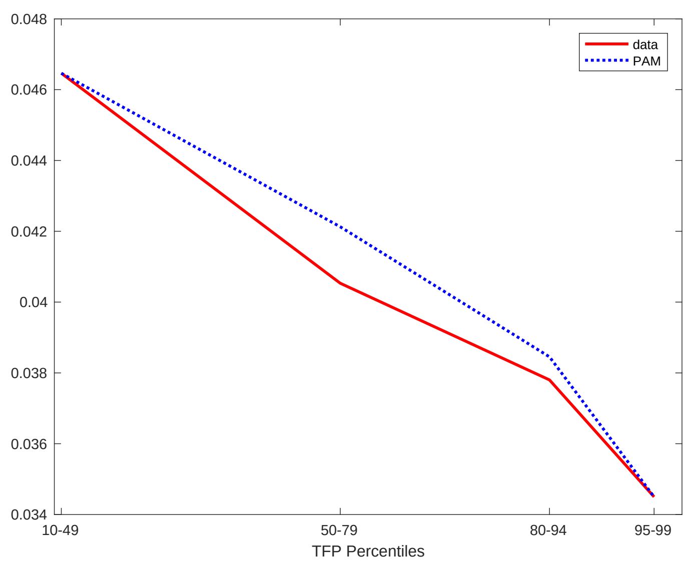
Measurement error: Moments

Table A5 reports the empirical moments we use to derive the moments involving measurement error.

Calibration of θ

Figure A5 displays how the ratio of R&D intensity for R&D firms changes with TFP in the data (solid line) and in the benchmark PAM model. The figure shows R&D intensity for each quantile relative to the intensity for firms in the lowest quantile, normalized to unity. The technological parameter θ is calibrated to match the slope between the first and last quantile in Figure A5.

Figure A5: Ratio of R&D to Value Added, PAM vs. Data



Note: The figure shows the average ratio of R&D to value added for R&D firms in the data (solid line) and the Parsimonious model (dotted line) for four quantiles of the TFP distribution.

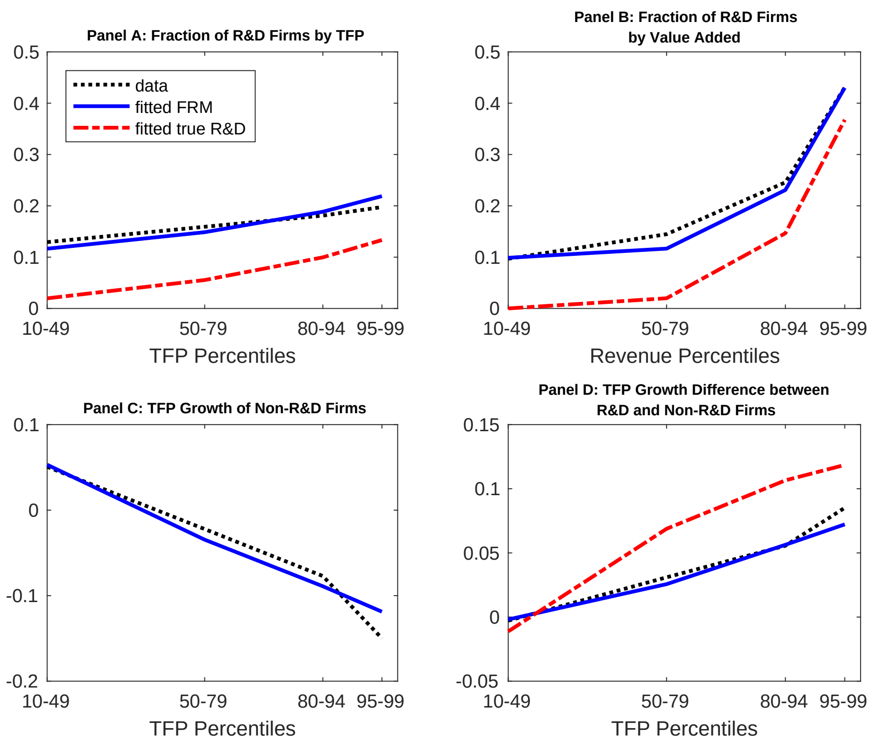
D Results

In this section we report robustness estimation results referred to in the text.

D.1 Estimation of the Fake R&D model

Figure A6 shows the fit of the Fake R&D model (FRM). The blue line in each panel represents moments from simulated data based on firms claiming to do (or not to do) R&D. The corresponding moments for a true classification of R&D investments are represented by red lines in the figure.

Figure A6: China: Fake R&D Model



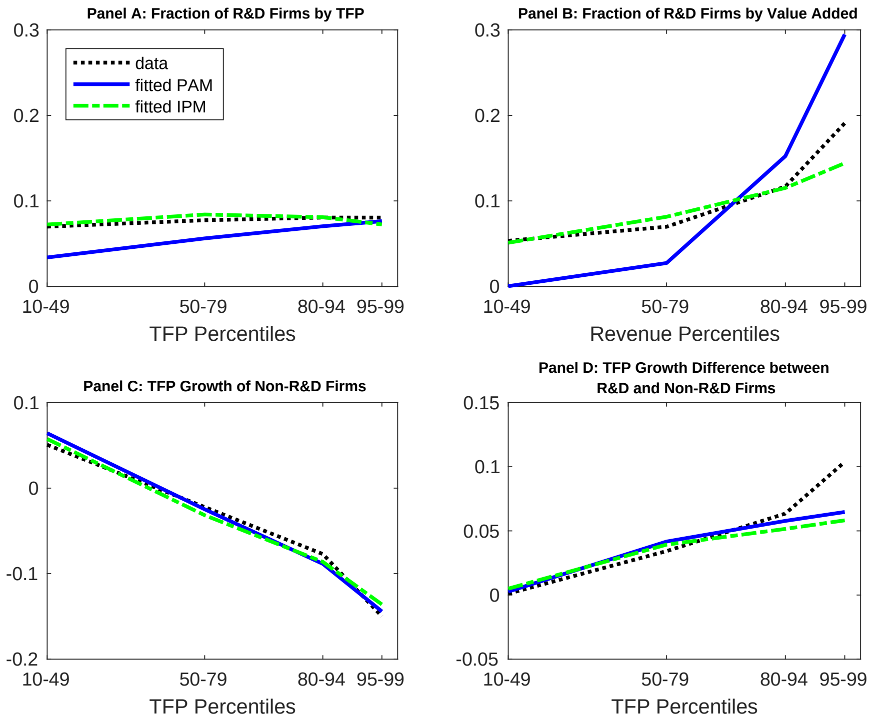
Note: Each panel of Figure A6 displays three schedules: (i) the dotted line shows the moments in the data, (ii) the dashed line shows the fit of the model (which refers to measured R&D), and (iii) the solid line shows results restricted to the firms which, according to the model predictions, truly perform R&D. See also Figure 4.

D.2 Intensive Margin

In this section, we lay out and document the fit of the two exercises discussed in Section 5.2 that deal with an intensive margin and heterogeneity in R&D intensities.

High R&D threshold: Figure A7 is the analogue to Figure A4 and shows how the 16 target moments are affected by applying the more stringent classification of innovation, based on Figure A2. Figure A7 also shows the fit of the PAM and IPM when reestimated based on these adjusted moments. The estimated coefficients for this estimation of the PAM and IPM are reported in columns (5)-(6) of Table 3.

Figure A7: Models with Higher R&D Cutoff



Note: The models are estimated to match empirical moments where only firms with R&D intensity exceeding (1.73% of value added are classified as innovative firms. See Figure 4 for additional information.

High- and low-R&D firms: In this section, we introduce a distinction between high- and low-R&D firms. In the data, we assign a firm to the high-R&D group if its R&D expenditure-to-value added ratio is higher than the median 1.73% ratio. Figure A8 displays the data moments. Panels A1 and A2 are the analogues of Panel A in Figure 4 broken down by high- and low-R&D firms. Two features of the data are noteworthy: First, future TFP growth is higher for high-R&D firms. Second, the propensity to engage in R&D conditional on TFP and size are similar for the two groups of firms.

Then, we augment the theory with the assumption that there exist two distinct technologies entailing different costs and success probabilities. More formally, firms are randomly assigned to either of the technologies with parameters $\{\bar{c}_l, \bar{p}_l\}$ and $\{\bar{c}, \bar{p}\}$, respectively. Each firm draws a probability of success p from the distribution to which it is assigned. The distribution of wedges is assumed to be independent of the assignment.

The targets of our estimation are now the empirical moments in Figure A8. In addition, we target the ratio of R&D expenditure to value added for high- relative to low-R&D firms, which is a factor of 8.6 in the data. The proportion of high-R&D firms is an additional parameter that we estimate.

The estimates for the PAM and IPM are reported in Columns (3)-(4) of Table A6. In the PAM, firms assigned to the $\{\bar{c}_l, \bar{p}_l\}$ group face both a lower cost and a lower average probability of success if they choose the innovation strategy.[41] In the IPM, the estimated productivities $\bar{p}_l$ and $\bar{p}$ are very

[41]The proportion of firms drawing from the $\{\bar{c}_l, \bar{p}_l\}$ process is estimated to be 13%. Since the high-R&D firms are by construction 50% of the total R&D firms, this implies that many firms assigned to the $\{\bar{c}, \bar{p}\}$ process choose to imitate because innovation is too costly. In contrast, a large proportion of firms assigned to the $\{\bar{c}_l, \bar{p}_l\}$ process choose the innovation strategy.

similar (in fact, $\bar{p}_l > \bar{p}$.) Still, selection guarantees that among the firms choosing the innovation strategy TFP growth is significantly higher for high-R&D than for low-R&D firms, consistent with the data. Intuitively, because of the high investment cost, only the very best firms (i.e., those drawing very high p's) assigned to the $\{\bar{c}, \bar{p}\}$ process choose to innovate. Appendix Figure A8 shows that both the PAM and IPM fit well the target moments.

Table A6: Estimation of Model with Two R&D Technologies.

	(1)	(2)	(3)	(4)
			High & Low R&D	
	PAM	IPM	PAM	IPM
Imitation prob. q	0.175	0.271	0.223	0.359
	(0.031)	(0.019)	(0.026)	(0.052)
Second chance δ	0.008	0.020	0.058	0.019
	(0.011)	(0.021)	(0.027)	(0.026)
Innov. prod. $\bar{p}$	0.096	0.114	0.103	0.107
	(0.008)	(0.006)	(0.007)	(0.012)
$\bar{p}_l$			0.076	0.115
			(0.009)	(0.010)
Innov. cost $\bar{c}$	1.627	3.374	3.015	3.085
	(0.136)	(0.174)	(0.208)	(0.791)
$\bar{c}_l$			0.094	1.612
			(0.135)	(0.979)
Std.dev. m.e. $\sigma_{\mu a}$	0.549	0.472	0.531	0.433
	(0.014)	(0.008)	(0.015)	(0.024)
Std.dev.innov. subs. σ_c		1.243		1.206
		(0.038)		(0.113)
Policy inter. c_a				2.015
				(0.316)
High $\bar{p}$ share			0.872	0.682
			(0.029)	(0.047)
J-Statistic	1.518	0.507	3.310	0.882

Note: Columns (3)–(4) of the table shows the estimated parameters for the models with two R&D technologies For convenience, columns (1)–(2) restate the estimates from Table 3 for PAM and IPM in the benchmark model. Sample: Chinese Firm Balanced Panel 2007–2012.

Figure A8 shows the fit of the PAM with two R&D technologies (small and large R&D projects). The estimated coefficients for the PAM model with two R&D technologies are reported in columns (3)–(4) of Table A6. The empirical moments for the high- and low-intensive R&D firms are illustrated by black dotted lines in Figure A8.

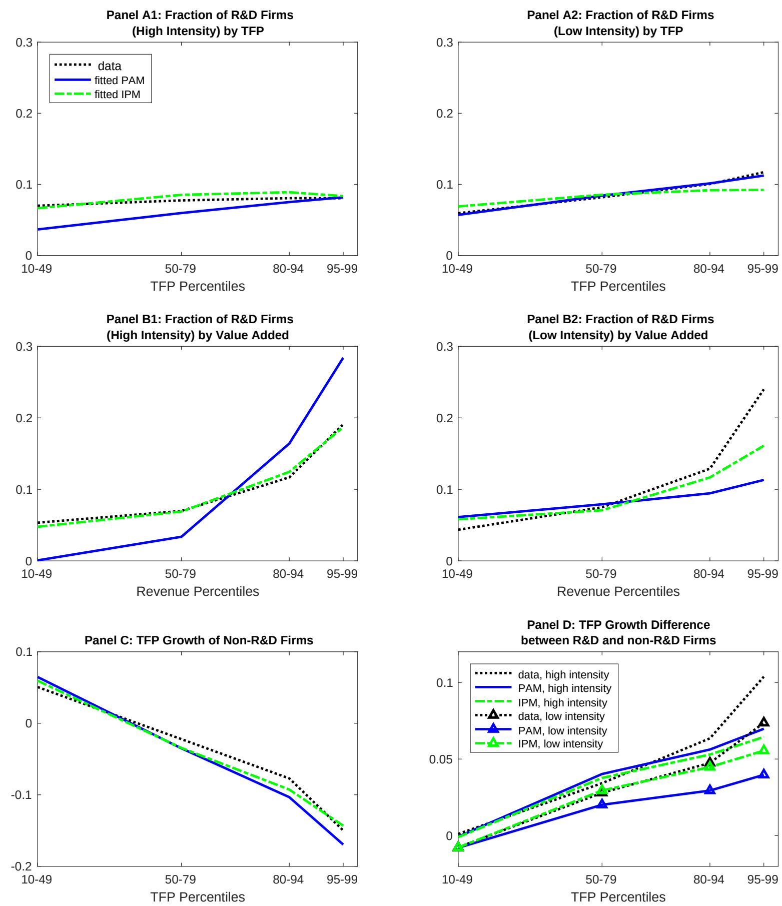
E Estimating the Model on Different Samples

Figures A9 and A10 show the fit of the PAM and IPM for Taiwan and for China in the earlier sample (2001–07), respectively.

F Counterfactuals

This section provides robustness analysis for the counterfactuals.

Figure A8: High- and low-R&D firms

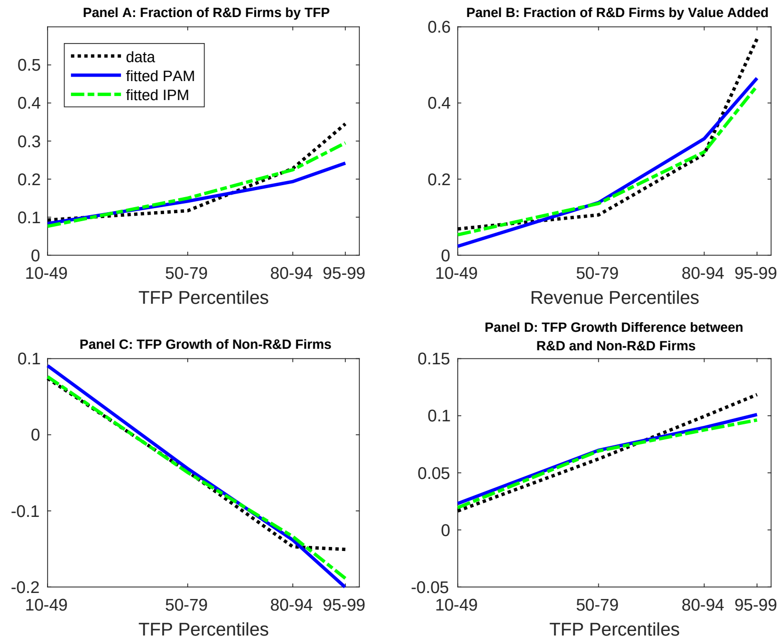


Note: The figure shows empirical and theoretical moments for the extension to two R&D technologies. Panels A1-A2 and B1-B2 correspond to Panels A and B in Figure 4, reported separately for firms with high- versus low-cost R&D technology. Panels C and D correspond to their counterparts in Figure 4,

Models with heterogeneity in innovation costs

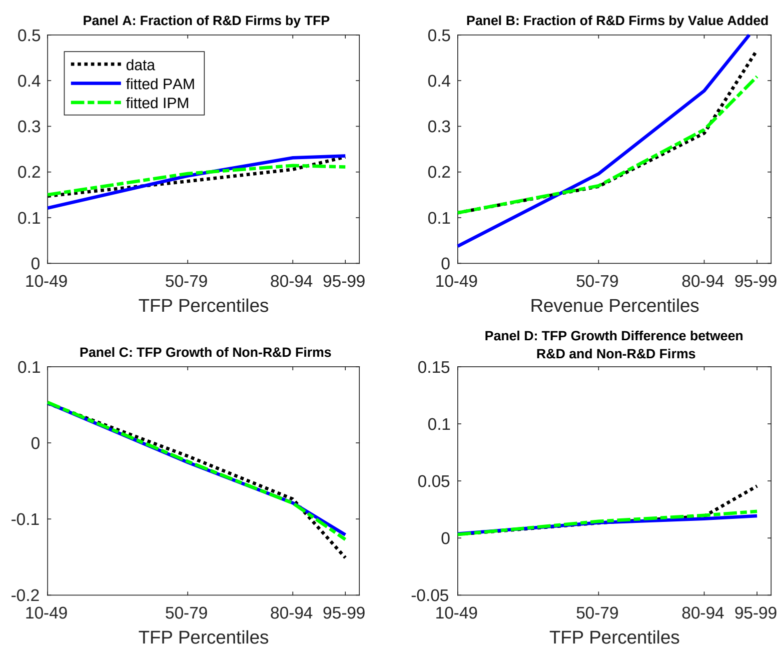
Figures A11–A12 are the analogues of Figures 8–9 in the manuscript for the IPM that we estimated on the benchmark balanced sample for China, 2007–12. Table A8 is the analogue of Table 6 in the manuscript for the IPM.

Figure A9: Taiwan 1999–2004: PAM and IPM



Note: See Figure 4.

Figure A10: China 2001–07: PAM and IPM



Note: See Figure 4.

Table A7: Estimation for China 2001–2007, balanced panel.

	(1) PAM	(2) FLM	(3) IPM
Imitation prob. q	0.036	0.090	0.093
	(0.032)	(0.046)	(0.039)
Second chance δ	0.033	0.164	0.069
	(0.071)	(0.084)	(0.117)
Innov. prod. $\bar{p}$	0.034	0.046	0.045
	(0.011)	(0.013)	(0.012)
Innov. cost $\bar{c}$	0.530	1.174	0.906
	(0.159)	(0.325)	(0.198)
Std.dev. m.e. $\sigma_{\mu a}$	0.682	0.575	0.580
	(0.038)	(0.025)	(0.026)
Std.dev. innov. subs. σ_c		0.644	0.559
		(0.145)	(0.119)
Policy inter. c_a			0.513
			(0.163)
J-Statistic	1.085	0.703	0.371

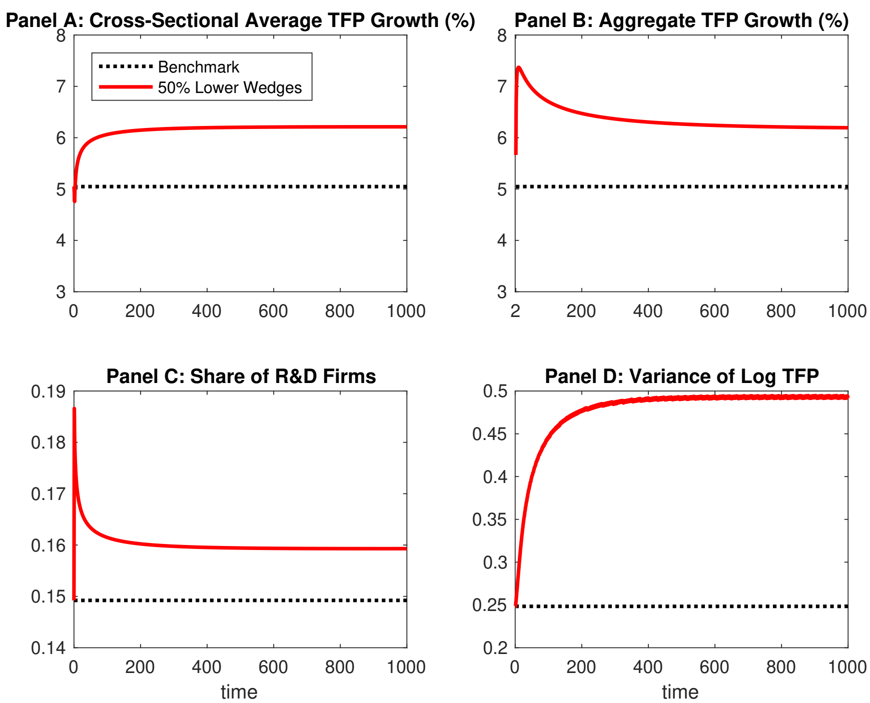
Note: Estimated parameters of various models using the Chinese 2001–2007 sample. Bootstrapped standard errors in parentheses.

Table A8: Counterfactuals, Industrial Policy Model

	(1) IPM estim. model	(2) 50% lower output wedges	(3) Taiwan's q	(4) Taiwan's $\bar{p}$ and $\bar{c}$	(5) Taiwan's $\bar{p}$, $\bar{c}$, and q	(6) Increase $\bar{c}$ so share R&D firms = 5%	(7) Decrease $\bar{c}$ so share R&D firms = 20%	(8) All firms do R&D
Fraction of R&D Firms (%)	14.9	16.0	14.8	8.24	8.17	5	20	100
Steady State TFP Growth (%)	5.05	6.20	5.11	5.71	5.78	3.64	5.39	4.41

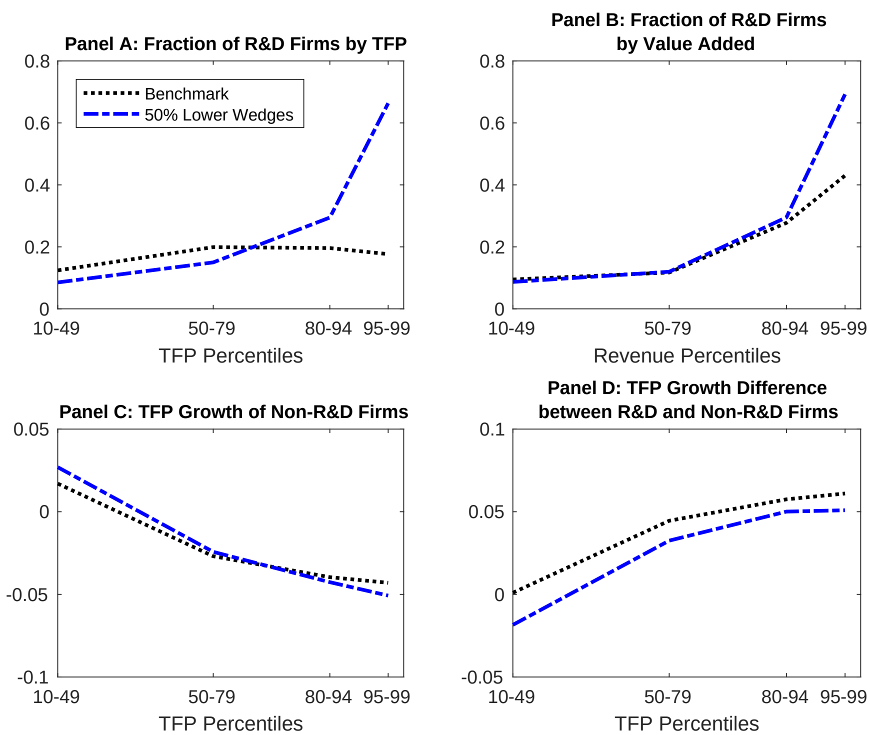
Note: The table reports statistics for the counterfactual experiments for the IPM discussed in the text. Column (1) reports the predicted moments of the estimated IPM for comparison.

Figure A11: Transition: Lower Wedges in IPM



Note: This figure is the IPM analogue of Figure 8.

Figure A12: Steady-State: Lower Wedges in IPM



Note: This figure is the IPM analogue of Figure 9.