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Haste makes waste? Quantity-based subsidies under heterogeneous innovations☆

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ABSTRACT

With quantity-based innovation targets and subsidy programs launched since the mid-2000s, China has seen a patent surge, accounting for 46% of the world's total patent applications in 2020; however, the overall patent quality has been declining after 2008. This paper develops a Schumpeterian growth model featuring innovating firms' quantity–quality trade-off between radical and incremental innovations, and decomposes subsidies' aggregate impact into quantity and quality channels. We calibrate the model to Chinese firm-level data in the early 2010s. Our quantitative analysis shows that the quality channel effects are negative and dominant, and quantity-based subsidies in that period reduce the TFP growth rate and welfare by 0.19 percentage points and 3.31%, respectively. We evaluate welfare gains under a constrained planner's problem, and propose skill subsidies which are quality-biased and effectively recover the optimal allocation.

1. Introduction

Subsidies are widely used to stimulate innovation. This paper studies the impact of innovation subsidies in China since the middle 2000s, when, partly due to the fear of falling into the "middle-income trap", the Chinese government launched a series of initiatives to ensure the country's success in transiting to an innovation-oriented economy (Ding and Li, 2015). We first document that innovation targets set by the central and local governments are largely quantity-based. The quantity of patents, in particular, has been extensively adopted as a concrete indicator of innovation achievement. Under a large scale of innovation subsidies to help achieve these targets, China's invention patent applications have increased from slightly above 10 thousand in 1990, or 1.08% of the world's total, to around 1.5 million in 2020, accounting for 45.69% of the global total, raising concerns about the underlying patent quality.

To study the macro impact of such subsidies from micro-level incentives, we collect a panel of innovating firms from 1998 to 2013 and use the information on forward citations to classify patents into high-quality radical ones and low-quality incremental ones. Consistent with anecdotal evidence, we find a robust decline in the share of radical patents after the mid-2000s, in terms of the

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absolute level, and especially compared to a clear rising trend before the mid-2000s. In addition, the relative quality of incremental patents to radical ones, measured as the ratio of the average number of forward citations received by the former to the latter, displays a clear decline after the mid-2000s, suggesting a crowding effect that as more incremental innovations are pursued, their average impact decreases.

Then we develop a structural growth model featuring innovating firms' endogenous choices between radical and incremental innovations to quantitatively study the impact of quantity-based subsidies. Our model builds on Schumpeterian models with heterogeneous innovations (Akcigit and Kerr, 2018). Radical innovations significantly impact productivity, while incremental innovations build on existing radical ones and make marginal improvements, with their impact gradually diminishing as more incremental innovations are pursued. Different from existing works in which radical and incremental innovations are random outcomes, we introduce a scarce R&D resource and allow the pursuit of different kinds of innovations to be endogenous, which generates a micro-level quantity–quality trade-off between radical and incremental innovations. Motivated by empirical patterns, we further assume that radical innovations are more skill-intensive in that a larger proportion of skilled labor is needed to realize one such invention.

Policymakers cannot precisely identify the quality of innovations and base their policies on the number of innovation outcomes, e.g., the number of patents. As firms face a trade-off between radical and incremental inventions, quantity-based subsidies encourage overall innovations but also bring an undesired shift of R&D efforts toward cheaper but incremental trials. Under a general equilibrium context, when all innovating firms expand their R&D expenditures, the skill premium also increases, further tilting firms' R&D efforts away from the more skill-intensive radical innovations. To dissect their growth and welfare implications, we decompose the impact of quantity-based subsidies into three channels, each corresponds to an empirical finding just mentioned: a positive *quantity* channel that the subsidies promote innovations and creative destruction; a negative *quality-composition* channel that quantity-based subsidies lower the aggregate weight on radical innovations; and a negative *quality-crowding* channel that more incremental trials reduce their average production value.

We then calibrate the theoretical model to moments of Chinese innovating industrial firms from 2011 to 2013. In particular, we use moments regarding radical and incremental patents in the data to discipline parameters related to radical and incremental innovations in the model, showing that the introduction of quantity-based innovation subsidies accounts for 29% of the quantity surge, 56% of the decline in the radical patent share, and 75% of the decline in the relative quality of incremental patents observed between the pre- and post-2008 periods. Although the quantity channel tends to enhance overall growth, the quality channels are much more dominant, especially the *quality-crowding* channel. Overall, quantity-based subsidies reduce the equilibrium growth rate by 0.19 percentage points, or 10% of the actual TFP growth decline from 2001–2007 to 2008–2014, and reduce the aggregate welfare by 3.31%.

China is still relatively scarce in innovative, skilled labor despite its fast economic catch-up. In 2018, 27% of the Chinese population between age 25 and 34 have completed tertiary education, which is much lower than in other major patent-holding economies. Within the model's framework, we further evaluate the impact of two alternative subsidies: education subsidy and skilled labor subsidy, which effectively recover the social planner's allocation. In the model, skill is acquired through formal education before a worker enters the labor market, and these subsidies raise the skill supply. Since radical innovations are more skill-intensive, increasing the supply of skilled labor substantially reduces the R&D cost of pursuing such inventions. Thus, in contrast to quantity-based innovation subsidies, the alternatives we propose are quality-biased — they significantly promote aggregate growth and welfare by improving both innovation quantity and quality.

Our paper highlights the importance of considering firms' endogenous responses in designing effective innovation policies. In that regard, the paper is related to three strands of literature. The first is the creative destruction literature with heterogeneous firms (Klette and Kortum, 2004; Akcigit and Kerr, 2018; Acemoglu et al., 2022). In a model of creative destruction, Ates and Saffie (2021) characterize a quantity–quality trade-off induced by financial frictions among entrants, while such trade-off in our model is on the intensive innovation margin. Our model builds on Akcigit and Kerr (2018), which develops a model in which firms pursue radical and incremental innovations randomly. As mentioned, the key deviation in our model is to endogenize this decision to capture the quantity–quality trade-off faced by innovating firms. We also incorporate heterogeneity of R&D input structure and human capital, a crucial dimension for innovation in developing countries.

Our work also relates to studies investigating China's R&D policies and patent surges (Hu and Jefferson, 2009; Fang et al., 2017; Ang et al., 2014). Li (2012) finds that local innovation subsidy programs help stimulate patent applications. Chen et al. (2019) find that subsidies positively impact incremental innovations but not radical ones. A few recent papers (Chen et al., 2021; Branstetter et al., 2023; Wei et al., 2023) take a more structural approach to examine China's innovation policies. Wei et al. (2023) studies the InnoCom program in a three-stage static framework and finds that it hurts welfare due to bureaucratic bean counting, and patent trade exacerbates that loss. Our model of creative destruction emphasizes firms' quantity–quality trade-off and the role of quality crowding. Branstetter et al. (2023) investigate China's patenting system, and they argue that narrow patent protection in China skews R&D efforts toward incremental innovations. Our paper addresses a similar issue but caused by innovation subsidies. König et al. (2022) study the impact of R&D misallocation in China. They find that a large subsidy might even reduce the growth rate as it distorts firms' imitation–innovation decisions. Subsidies may hurt growth in our framework but through a different channel.

Lastly, this paper is related to research on the role of human capital in innovation and economic growth, dating back to Nelson and Phelps (1966). In Vandenbussche et al. (2006), as innovation is more intensive in skilled labor than imitation, skilled labor significantly impacts growth when a country approaches the technology frontier. Akcigit et al. (2020) incorporate higher education policy into an endogenous growth model. They find that the impact of R&D subsidies can be strengthened if combined with higher education policies that alleviate financial constraints for the young. Our paper follows this line of research in emphasizing the input dimension of R&D and the importance of human capital and education in promoting innovation.

The rest of the paper is organized as follows. Section 2 provides institutional background and describes motivational facts, and Section 3 introduces the model. The quantitative analysis is the focus of Section 4. Concluding remarks are presented in Section 5.

2. Institutional background and motivational facts

This section first provides an overview of quantity-based innovation targets set by China's central and local governments since the mid-2000s and the associated patent surge. We then construct firm-level panel data to study the decline in patent quality in recent years.

2.1. Institutional background and patent quantity

China started to emphasize the importance of building an "innovation-oriented" economy in the mid-2000s. In 2006, the Chinese central government released the *Outlines of Medium and Long-term National Plan for Science and Technology Development (2006–2020)*, which pronounced the building of an innovative economy as a new national strategy (Ding and Li, 2015; König et al., 2022). One critical and specific metric in the documentation is that by 2020, the total number of granted invention patents by Chinese nationals rank top 5 globally.[1] In 2010, China National Intellectual Property Administration issued the *National Patent Development Strategy 2011–2020*, which explicitly set the following *quantity* targets:

1. The total number of invention patents will rank top 2 in the world, and total patents reach 2 million in 2015;
2. Invention patents per million population will increase by 100% in 2015 and by 300% in 2020;
3. At least 8% of above-scale industrial enterprises will apply for patents in 2015 and 10% in 2020.

With these documents released by the central government, many local governments have also made explicit targets on the number of patents. In Table A.1 in the Appendix, we list several patent quantity targets set in the 2000s and 2010s in developed areas like Beijing and Shanghai, as well as in relatively less developed northeastern Heilongjiang province and southwestern Guizhou province.

To help achieve these targets, the central and local governments issued supportive policies to promote firms' innovation activities. To encourage patent filing, the State Intellectual Property Office issued the *Measures of Patent Fee Deferral* in 2006. Many local governments have since issued additional incentives for patenting (Ding and Li, 2015). For example, the Beijing city government subsidizes up to 2150 Chinese Yuan (CNY) for an invention patent application. The Zhejiang provincial government grants each invention patent a one-time 3000 CNY subsidy. By 2008, 29 of 32 provincial governments have introduced patent subsidy programs in mainland China (Li, 2012).[2]

With the explicit quantity targets and associated subsidy policies, China has seen a dramatic surge in the total number of invention patents.[3] Fig. 2.1 presents the evolution of the total number of newly applied patents (panel (a)) and patents per researcher (panel (b)). China's total number of patent applications in the 1980s and 90s was substantially smaller than the US. It accounted for 1.02% of the world's patent applications in 1990. In 2011, China replaced the US as the world's No. 1 patent application country. By 2020, this share increased to 45.69% of the world's total. The number of patents per researcher in China started at a much lower level in the early 1990s. Both countries progressed at a comparable rate in the 1990s. The US-China gap shrank in the 2000s, suggesting China's technological catch-up in that decade. Over the recent 10–15 years, when the Chinese government set quantity targets and adopted various innovation subsidies, patents per researcher in China have increased much faster than in the US. By 2018, an average Chinese researcher produced almost twice as many patents as their US counterparts.[4]

The patent surge raises concerns on whether Chinese innovators are becoming more productive or are incentivized to focus primarily on quantity while ignoring the underlying quality of patents, which we, by assembling a panel data of Chinese innovating firms, turn next to.

2.2. Firm-level data and patent quality

Data source. We construct an input–output panel data of firm-level R&D activities from three sources: (i) Annual Survey of Industrial Enterprises (ASIE), covering above-scale Chinese industrial firms from 1998–2013; (ii) a supplementary Firm Innovation Activity Database containing industrial firms' R&D personnel and expenditures from 2008–2014; (iii) Innography and Orbis Patent Database, providing patent information from 1985 onwards. We focus on applied and eventually granted patents and restrict to domestic firms with records of at least one invention patent during the sample period.[5]

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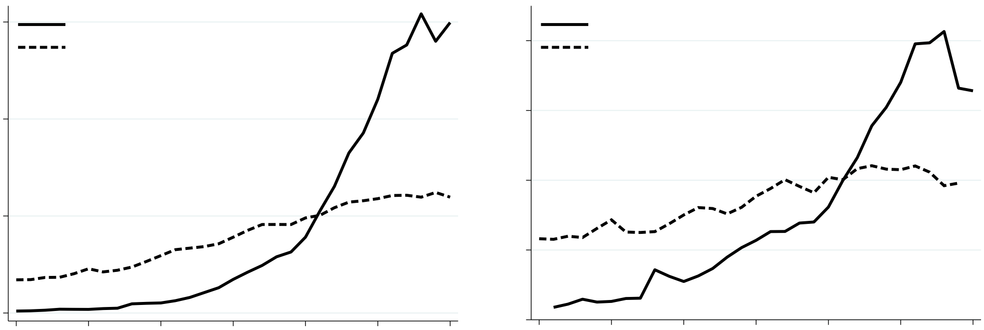
1 Other specific targets listed in the documentation include the following. By 2020, the share of total R&D expenditures in GDP will achieve 2.5% or more; the contribution of technological progress to economic growth will account for more than 60%; the dependence on foreign technology will reduce to less than 30%; the total number of forward citations of international scientific papers by Chinese nationals will rank top 5 globally.

2 Another widely adopted policy is the intellectual property rights pledge financing (Ding and Li, 2015).

3 There are three types of patents in China: invention, utility model, and industrial design. Invention patents account for 29% of total Chinese applications in 2020. As applications of the last two do not require substantial review, we focus on invention patents, referred to as "patent" throughout the paper.

4 Appendix A.1 confirms that the evolution of patent grants exhibits very similar patterns.

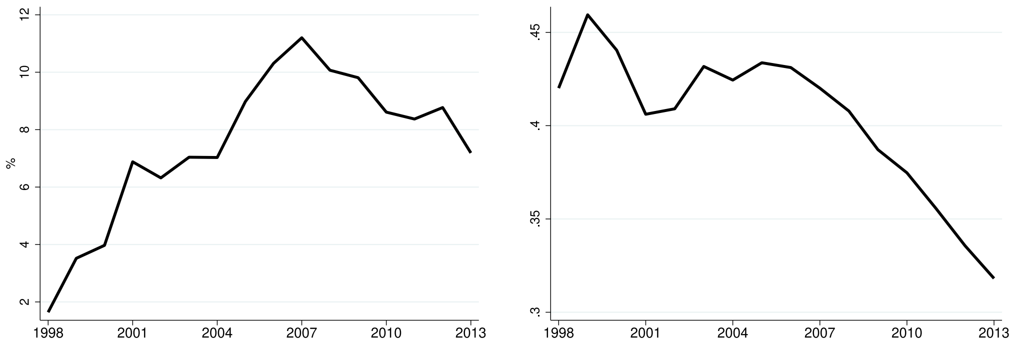
5 Appendix A.2.1 describes data sources. Construction process of the firm-level sample is given in Appendix A.2.2. Appendix A.2.3 details variable construction.



(a) No. of Patent Applications (mn)

(b) Patents per Researcher

Fig. 2.1. Patent Quantity in China and the United States.
Note: X-axis: year. This figure shows the number of patents (millions) and No. of patents per researcher in China and the US..



(a) Share of Radical Patents (%)

(b) Relative Quality of Incremental to Radical Patents

Fig. 2.2. Evolution of Patent Quality in China.
Note: X-axis: year. A patent is classified as radical if it is cited by at least 1 US patent and the gap in application years between the cited and citing patents must be within 5 years. The relative quality of incremental to radical patents is the ratio of the average number of forward citations of the former to the latter. The high volatility at the beginning few years is largely due to the limited sample size, as shown in Table A.3 in the Appendix.

We label a Chinese patent as radical if it is cited by at least one US patent and the gap in application years between the cited and citing patents must be within 5 years, and as incremental otherwise.[6] Fig. 2.2 presents the evolution of patent quality in our firm-level sample. The left panel shows the share of radical patents, which displays a clear rising trend from 1998 to 2007 — which partly reflects increasing international exposure and the associated learning process of Chinese innovating firms starting from a low level (Baslandze et al., 2021) — and declines from 2008 onward. The post-2008 decline is more significant if compared to the pre-2008 trend. In the right panel, we show the relative quality of incremental to radical patents, defined as the ratio of the average number of forward citations of the former to the latter. That ratio is relatively stable from 1998 to 2007, but steadily declines after 2008. As more incremental patents are created, their average quality declines, suggesting a crowding effect of incremental innovations.[7]

Lastly, we present the firm-level skill composition of researchers, which is later used to infer the heterogeneous innovation skill intensities in model calibration. We identify a firm as high-type if it creates at least one radical patent from 2008 to 2013, and as low-type otherwise. Among an innovating firm's R&D personnel, we label those with a medium or senior professional title as skilled personnel. Skill intensity, defined as the ratio between skilled personnel and total R&D personnel, is 34.12% for high-type firms and 25.42% for low-type firms in the 2011–2013 period. More details are provided in Appendix A.2.6.

[6] We downloaded and updated patent data in October 2022, which is 9 years after the last year (2013) in our sample. The five-year restriction is to minimize the impact of truncation.

[7] These findings are robust to alternative definitions of radical patent and are evident across firm demographic characteristics, including ownership, exporting status, industries, patent categories, entrants vs. incumbents, internal vs. external patents as detailed in Appendix A.2.5.

Facing quantity-based subsidies, firms may find it profitable to maximize the number of innovations and shift from radical innovations to cheaper incremental ones with lower quality. A micro-level quantity–quality trade-off that innovating firms experience and quantity targets may help explain the observed patent surge along with their quality decline. In that spirit, we build a Schumpeterian growth model featuring heterogeneous innovations to evaluate the aggregate impact of quantity-based innovation policies.

3. The model

This section develops a growth model with heterogeneous innovations to study the economic consequences of quantity-based subsidies. The model is in continuous time, denoted by t. The economy admits a representative household that maximizes the discounted sum of utility

$$U = \int_0^\infty \exp(-\rho t) \, \frac{C(t)^{1-\nu} - 1}{1-\nu} \, dt, \tag{1}$$

where $\rho > 0$ is the discount factor, ν the elasticity of intertemporal substitution, and $C(t)$ is the flow of final good consumed.

There is a final good produced competitively by packaging a continuum of intermediate varieties

$$Y(t) = \frac{1}{1-\epsilon} N(t)^\epsilon \int_0^1 q_\omega(t)^\epsilon y_\omega(t)^{1-\epsilon} d\omega, \tag{2}$$

where $y_\omega(t)$ is the quantity of intermediate good ω, and $q_\omega(t)$ denotes its quality. $\epsilon \in (0,1)$ governs the value-added share of intermediate varieties. $N(t)$ is the number of packagers whose total supply is fixed at 1. The final good producers' demand for intermediate variety ω is given by $p_\omega = q_\omega^\epsilon y_\omega^{-\epsilon}$.

Production. Each intermediate good $\omega \in [0,1]$ is produced by a firm that currently owns the leading technology in that product line, that is, offering the highest quality q_ω.[8] Denote Ω_f the set of product lines owned by an individual firm f, and $Q_f \equiv \{q_\omega, \omega \in \Omega_f\}$ its product portfolio. Denote n_f as the cardinality of the set Q_f, which represents the number of product lines that the firm owns and we refer to as "firm size". For simplicity, we drop the subscript f when it causes no confusion. A firm that loses all product lines exits the economy permanently, so we have $n \geq 1$ for incumbent firms.

Production of intermediate goods uses unskilled labor $y_\omega(t) = \bar{q}(t)\ell_\omega(t)$, where $\bar{q}(t) \equiv \int_0^1 q_\omega(t)d\omega$ is the economy-wide average productivity at time t, capturing a cross-firm spillover of innovations. We follow the standard approach in the Schumpeterian growth literature and assume a two-stage price-bidding game (Acemoglu et al., 2012).[9] In equilibrium, the firm owning the leading technology can charge a monopolistic price until being replaced by a successful innovator. Given this setting, the firm that owns the leading technology in product line ω will charge a constant markup, and the profit is $\pi_\omega = \pi q_\omega$, where $\pi \equiv \epsilon \left[(1-\epsilon)\bar{q}/w^\ell\right]^{\frac{1-\epsilon}{\epsilon}}$ is the economy-wide average profit level and a constant on the balanced growth path as shown below.

R&D Heterogeneity. Intermediate goods firms also spend on R&D to pursue innovations. R&D efforts are assumed to be undirected. Upon a successful innovation, a firm improves the quality of a random product line by a step-size from its current frontier.[10] Innovations are heterogeneous; specifically, two kinds of innovations exist: radical (d) vs. incremental (m). We use subscript i to index innovations, i.e., $i = d, m$. Incremental innovations build on one existing radical innovation. The quality improvement associated with radical innovations is fixed and large, while that of incremental innovations is small and gradually diminishes toward zero.

R&D uses skilled labor, unskilled labor, and research time as inputs. Each firm is endowed with 1 unit of non-tradable research time. We introduce research time to capture R&D inputs that are scarce and non-tradable, such as a manager's time to supervise projects, etc.[11] When a firm owning n product lines hires h_i units of skilled labor, ℓ_i units of unskilled labor, and uses e_i fraction of its research time to pursue innovations of kind i, it adds one more product line to its portfolio at the following Poisson flow rate

$$X_i = z_i \, n^{1-\phi}\left(e_i \, h_i^{\gamma_i} \ell_i^{1-\gamma_i}\right)^\phi, \tag{3}$$

where $z_i \geq 0$ is the firm's R&D productivity in pursuing kind i innovations. Parameter $\phi \in (0,1)$ is the elasticity of successful innovations to R&D expenditures. Parameter $\gamma_i \in (0,1)$ governs the skill intensity of kind i innovations. Following empirical results in Section 2.2, we assume $\gamma_m < \gamma_d$; that is, incremental innovations are less skill-intensive than radical ones.

If firm f successfully adds a product line ω to its portfolio following a radical innovation, it raises the quality of product ω by

$$q_\omega(t_+) = q_\omega(t) + \lambda\bar{q}(t), \tag{4}$$

where $\lambda > 0$ is an exogenous parameter governing the step-size of radical innovations.

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8 We use "intermediate good", "intermediate variety" and "product line" interchangeably in the paper.

9 In stage 1, firms decide whether to pay an arbitrarily small but positive market-entry cost. In stage 2, all firms that have paid the cost in stage 1 compete in a Bertrand competition. The firm that owns the leading technology and produces the highest quality goods would announce a limit price, which makes all others earn a non-positive profit in stage 2. Therefore, they optimally decide not to enter and compete in stage 1.

10 We focus on external innovations, which are the vast majority among innovations in China, as shown in Table A.9. We also craft an extension allowing for internal innovations in Appendix D.4.

11 The scarce R&D inputs induce a firm-level trade-off between radical and incremental innovations, which becomes more clear once we present the innovation cost function.

The quality improvement following a successful incremental innovation, however, depends on its distance from the most recent radical innovation, i.e., times of incremental improvements already created in that product line. Denote τ_ω this distance for product line ω, that is, if product line ω is experiencing the τ_ω-th incremental innovation from its most recent radical one, the quality improvement is

$$q_\omega(t_+) = q_\omega(t) + \eta\alpha^{\tau_\omega - 1}\bar{q}(t), \tag{5}$$

where $\eta \in (0, \lambda)$ governs the initial step-size, and $\alpha \in (0, 1)$ governs how fast the effect diminishes. The effect of incremental innovations weakens until a radical one arrives and resets the clock. This setting captures a positive externality of radical innovations, and a negative externality of incremental ones, with the latter helping reconcile the crowding effect documented in Section 2.2.

Now we are ready to derive the associated R&D cost functions. Following (Klette and Kortum, 2004), it is useful to transform variables into their *per line* correspondences. Denote $x_d \equiv X_d/n$ as the radical *innovation intensity* per line, $x_m \equiv X_m/n$ the incremental *innovation intensity* per line, and w^h and w^ℓ competitive wage rates for skilled and unskilled labor, respectively. For an individual firm whose innovation intensities are x_d and x_m, the associated function of R&D cost *per line* is given by[12]

$$R(x_d, x_m; z_d, z_m) = \left[\Theta_d(x_d)^{\frac{1}{2}} + \Theta_m(x_m)^{\frac{1}{2}}\right]^2, \tag{6}$$

where $\Theta_i(x_i) \equiv \Delta_i \left(w^h\right)^{\gamma_i} \left(w^\ell\right)^{1-\gamma_i} \left(x_i/z_i\right)^{\frac{1}{\phi}}$ and $\Delta_i \equiv \gamma_i^{-\gamma_i}(1-\gamma_i)^{\gamma_i - 1}$, for $i = d, m$. We further assume $\phi < 0.5$ to maintain a decreasing return to scale in R&D inputs and avoid corner solutions in x_d or x_m. The cost function indicates a clear trade-off between radical and incremental innovations at the firm level, and is a direct consequence of the scarce research time, e, required in producing both kinds of innovations.[13]

Quantity-based subsidy. Though innovations are heterogeneous in their magnitude of quality improvement, a successful innovation, radical or incremental, always brings the firm a new product line. At any point in time t, we assume a successful innovation embodies a certain number of patents — radical innovations correspond to radical patents and incremental innovations to incremental patents. The total number of active patents a firm holds is therefore proportional to the number of product lines the firm controls.

We define quantity-based subsidy to innovating firms as any subsidies that reward the number of active patents a firm holds, i.e., n, disregarding the underlying quality. In particular, we use the form $n \times b_n\bar{q}$ in the model, where b_n denotes the detrended amount of subsidy per patent. Conceptually, the b_n term summarizes all explicit subsidies — cash or cash-like subsidies that show up in the firm's balance sheet, and implicit ones — cheaper land cost, accessibility to loans, etc., that an innovating firm receives as long as the subsidies are quantity-based.[14]

Incumbent firms. The economy admits two types of firms regarding R&D productivity. The high-type (H) firms are capable of pursuing both radical and incremental innovations ($z_{\mathrm{H}d}, z_{\mathrm{H}m} > 0$). The low-type (L) are capable of pursuing only incremental innovations ($z_{\mathrm{L}d} = 0, z_{\mathrm{L}m} > 0$).[15] The state variables of an incumbent firm include its type $j = \mathrm{H}, \mathrm{L}$; its product portfolio Q; and the economy's average productivity $\bar{q}$. Denote r the interest rate and δ the creative destruction rate. The value function for a type j firm is written as

$$\begin{aligned} rV_j(Q,\bar{q}) - \dot{V}_j(Q,\bar{q}) = \max_{x_{jd},x_{jm}} \sum_{q_\omega \in Q} \Big\{ &\underbrace{\pi q_\omega}_{\text{profit}} + \underbrace{\delta\left[V_j\left(Q\backslash\{q_\omega\},\bar{q}\right) - V_j(Q,\bar{q})\right]}_{\text{loss from creative destruction}} \Big\} \\ &+ \underbrace{n \times x_{jd}\left[\mathbb{E}_{\omega'} V_j\left(Q \cup \{q_{\omega'} + \lambda\bar{q}\},\bar{q}\right) - V_j(Q,\bar{q})\right]}_{\text{return from radical innovations}} \\ &+ \underbrace{n \times x_{jm}\left[\mathbb{E}_{\omega'} V_j\left(Q \cup \{q_{\omega'} + \eta\alpha^{\tau_{\omega'}-1}\bar{q}\},\bar{q}\right) - V_j(Q,\bar{q})\right]}_{\text{return from incremental innovations}} \\ &- \underbrace{n \times R(x_{jd}, x_{jm}; z_{jd}, z_{jm})}_{\text{R\&D cost}} + \underbrace{n \times b_n\bar{q}}_{\text{quantity-based subsidy}} . \end{aligned} \tag{7}$$

The first line is each product line's profit flow, plus the value loss from creative destruction. $Q\backslash\{q_\omega\}$ denotes the remaining portfolio after losing line ω to a successful innovator. The second line is the value change from a successful radical innovation of the firm, which adds product line ω' into the portfolio. The expectation is over ω' as which line the innovation lands on is random. The third line is the value change following a successful incremental innovation. The last line includes the R&D cost and quantity-based subsidies.

[12] Under our specification of the innovation production function, a firm's innovation cost scales up linearly with the number of product lines. We craft an extension allowing for decreasing return to scale in innovation in Appendix D.3.

[13] In Appendix D.2, we relax this assumption and examine the consequences of a weakened firm-level quantity–quality trade-off.

[14] In the model, subsidizing the patent stock: $n \times b_n\bar{q}$, or subsidizing new patents: $nx \times b_x\bar{q}$, generate identical outcomes. See more details in Appendix B.4.

[15] Note $z_{\mathrm{L}m}$ might differ from $z_{\mathrm{H}m}$. We introduce this firm heterogeneity for quantitative purposes. The setting helps us infer R&D input structure from observable firm-level data in the quantified model.

The value functions are linear in the economy's average productivity $\bar{q}$, making detrending all values by $\bar{q}$ straightforward. Another useful property is that firms of the same type always choose the same innovation intensity per line, regardless of their differences in product portfolio or size.[16] By construction, low-type firms optimally choose $x_{\mathrm{L}d} = 0$. We end up tracking three innovation intensities: $x_{\mathrm{H}d}$, $x_{\mathrm{H}m}$ for high-type firms, and $x_{\mathrm{L}m}$ for low-type firms. For the remaining theoretical analysis, we focus on high-type firms, as they are the ones facing a quantity–quality trade-off between radical and incremental innovations.

Entrant firms. At any point, there is a total mass of 1 of potential entrants pursuing incremental innovations at a fixed Poisson rate x_{E}. Upon a successful innovation, the potential entrant enters the economy with one product line in its portfolio. Entrants are of low-type by default; however, after making a one-time overhead investment of $K(p) = [-\ln(1-p) - p]\,\chi\bar{q}$, they receive probability p of becoming high-type. The value function for a potential entrant is

$$rV_{\mathrm{E}} = x_{\mathrm{E}}\left[\max_{p}\ \left\{pV_{\mathrm{H}} + (1-p)V_{\mathrm{L}} - K(p)\right\} - V_{\mathrm{E}}\right], \tag{8}$$

where $V_j \equiv \mathbb{E}_{\omega'} V_j\left(\left\{q_{\omega'} + \eta\alpha^{\tau_{\omega'}-1}\bar{q}\right\}, \bar{q}\right)$, $j = \mathrm{H}, \mathrm{L}$ are the expected values of a type j firm with one product line. Since entrant firms are ex-ante identical, they end up choosing the same amount of overhead investment. We denote p^* as the associated probability.

Education. The representative household also supplies a mass L of workers, each facing a constant death rate of $d > 0$. At each point, a flow dL of young workers join the economy, who work as unskilled without any investment in education; however, they can spend time in school to become skilled. Upon entry, each individual randomly draws a talent type θ from a *Pareto* distribution.[17] It requires $1/\theta$ units of education service for an individual of type θ to become skilled. Education service is produced by existing skilled labor employed in education at the competitive wage rate and with technology $S = \xi\ h^{\text{teacher}}$, where $\xi > 0$ captures the overall efficiency of the economy's education infrastructures. Getting education is a preferable choice if and only if the expected lifetime return from doing so — earning a skilled wage minus paying the education cost — exceeds the lifetime value of earning an unskilled wage.[18]

3.1. Equilibrium

We focus on a balanced growth path equilibrium, in which the average productivity of the economy, $\bar{q}(t)$, grows at a constant rate g, while other aggregate variables grow proportionally and all relevant distributions are stationary. We track two distributions, one over τ, i.e., the step-size of incremental innovations, and the other over n, i.e., firm sizes.[19] Denote δ_d and δ_m the creative destruction rate due to radical and incremental innovations, respectively. The expected step-size of an incremental innovation is given by

$$\bar{\eta} = \eta\bigg/\left(\alpha + \frac{1-\alpha}{\delta_d/\delta}\right). \tag{9}$$

The expected quality improvement from incremental innovations decreases with a faster decay rate, i.e., a smaller α. Additionally, as the fraction of radical innovations in the economy, δ_d/δ, decreases, the expected step-size also becomes smaller. This property allows us to simultaneously explain the decline in the share of radical patents, as well as the widening gap between incremental and radical patents documented in Fig. 2.2.

Denote $\mu_{j,n}$ the mass of type j firms who own n product lines. We can write the creative destruction rates $\delta_d = \sum_n \mu_{\mathrm{H},n} \times nx_{\mathrm{H}d}$; $\delta_m = \sum_j \sum_n \mu_{j,n} \times nx_{jm} + x_{\mathrm{E}}$. The aggregate rate of creative destruction is $\delta = \delta_d + \delta_m$. Moreover, the total number of active product lines sums to 1. Formally, the following proposition holds.[20]

Proposition 1. *Definition of the creative destruction rate δ guarantees that $\sum_j \sum_n \mu_{j,n} \times n = 1$.*

3.2. Properties of the economy

The quantity–quality trade-off. High-type firms in the economy face a quantity–quality trade-off between creating more innovations and creating better innovations. Innovation subsidies may impact such trade-offs in an undesired way, as seen from an individual firm's optimal decisions. For expositional convenience, we drop the firm type subscript j whenever it causes no confusion.

Innovating firms' value function takes the form $V(Q, \bar{q}) = \sum_\omega Aq_\omega + nB\bar{q}$. The first term denotes profit from owning product lines, while the second contains net values from R&D. Regarding firms' choices over innovations, we have the following proposition.[21]

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[16] This property is obtained as the elasticity of innovation on firm size n is set as $1-\phi$ in the innovation production function, so the innovation cost scales up linearly with the number of product lines. We craft an extension allowing for decreasing return to scale in innovation in Appendix D.3.

[17] More specifically, we use Pareto distribution $\mathbb{P}\left\{\theta \le \tilde{\theta}\right\} = 1 - \tilde{\theta}^{-2}$, for $\tilde{\theta} \in [1, \infty)$.

[18] Appendix B.1 shows that young people obtain education when surpassing a certain talent threshold θ^*, the value of which depends on the skill premium as well as productivity in the education sector.

[19] Detailed derivations regarding these two stationary distributions are given in Appendix B.2.

[20] Proof of Proposition 1 can be found in Appendix B.3.

[21] Appendix B.4 derives the value function and proves Proposition 2.

Proposition 2. *The ratio between radical and incremental innovation intensities satisfies*

$$\frac{x_d}{x_m} \propto \underbrace{\frac{A(1+\lambda)+B}{A(1+\bar{\eta})+B}}_{\text{innovation return}} \times \underbrace{\left(\frac{w^h}{w^\ell}\right)^{-(\gamma_d-\gamma_m)}}_{\text{input structure}}. \tag{10}$$

The term "innovation return" on the right-hand side captures the ratio of returns between radical and incremental innovations. The direct return of radical innovations is from its productivity improvement effect, as captured by $A(1+\lambda)$. Similarly, that of incremental innovations is captured by $A(1+\bar{\eta})$. The fact $\lambda > \bar{\eta}$ indicates that the direct return of radical innovations is greater.

The indirect return, B, is identical for both kinds of innovations and is largely affected by subsidies. A sizable subsidy shrinks the gap in total returns between radical and incremental innovations and raises firms' incentive to pursue proportionately more of the latter. The term "input structure" indicates that, if all firms are doing more R&D, the equilibrium skill premium will rise, making skill-intensive radical innovations more expensive. Consequently, firms are further incentivized to pursue incremental innovations.

Growth and welfare. Along a balanced growth path, the aggregate welfare is

$$U = \frac{1}{1-\nu}\left[\frac{{C_0}^{1-\nu}}{\rho-(1-\nu)g} - \frac{1}{\rho}\right]. \tag{11}$$

A critical determinant of welfare is the aggregate growth rate, $g = \delta_d\lambda+\delta_m\bar{\eta}$, where $\bar{\eta}$ denotes the expected step-size of incremental innovations. As δ_d and δ_m represent aggregate quantity of radical and incremental innovations, the growth rate can be viewed as a weighted sum of their step-sizes.[22] Accordingly, the growth rate differential, e.g., between economies with and without a particular policy, can be decomposed into

$$\Delta g = \underbrace{\Delta\delta \times \left[\frac{\delta_d}{\delta}\lambda + \left(1-\frac{\delta_d}{\delta}\right)\bar{\eta}\right]}_{\text{(i) quantity-creative destruction}} + \underbrace{\delta \times \left[\Delta\frac{\delta_d}{\delta}\times(\lambda-\bar{\eta})\right]}_{\text{(ii) quality-composition}} + \underbrace{\delta \times \left[\left(1-\frac{\delta_d}{\delta}\right)\times\Delta\bar{\eta}\right]}_{\text{(iii) quality-crowding}}. \tag{12}$$

The first term refers to the quantity channel, while the second and third are the quality channels. The *quantity-creative destruction* term captures that the aggregate growth rate changes if a policy induces changes in the aggregate creative destruction rate, δ, or equivalently the total number of innovations. As aforementioned, we focus on external innovations which are the vast majority in China. A policy that changes the aggregate share of radical innovations, δ_d/δ, further affects aggregate growth through (a) it changes the composition of radical and incremental innovations, whose impacts on productivity are different, captured by the second *quality-composition* channel; and (b) changing the average number of incremental innovations following a radical one in any product line changes the average productivity impact of incremental innovations, which we label the third *quality-crowding* channel. The three channels connect to the patent surge in Fig. 2.1, and the two facts regarding patent quality decline in Fig. 2.2 in the Chinese context.

A quantity-based subsidy might promote overall growth and welfare through the quantity channel; however, the positive effect could be compromised or even overwhelmed if the subsidy negatively impacts innovation quality. Which effect dominates is a quantitative issue addressed in the following section.

4. Quantitative analysis

This section first calibrates the model using Chinese data, and evaluates the impact of *quantity-based* subsidies on patent quantity surge, quality decline, and the overall TFP growth. We then analyze a planner's problem, which yields a constrained first-best, and propose an alternative, quality-biased, innovation policy — subsidizing the skill, which we show effectively recovers the planner's allocation.

4.1. Calibration and model fit

To calibrate the model's benchmark economy to 2011–2013 aggregate- and firm-level data, we further include two extra policy parameters: the corporate tax rate u — hence firms' profit flow changing from πq to $(1-u)\pi q$ — and the R&D tax credit multiplier b_r, i.e., the total R&D expenditures changing from $R(x_d, x_m)$ to $(1-b_r u)R(x_d, x_m)$.

Calibration strategy. The extended model has 20 parameters. We start with those that can be externally calibrated, directly inferred, or taken from the literature. We set the discount rate $\rho = 0.02$. For the inverse intertemporal substitution elasticity, we set $\nu = 3$ in the baseline and check the robustness with alternative values. The elasticity of substitution in final goods production ϵ is set to match a profit rate of 22% among ASIE firms. The total population L is normalized to 1.

In the R&D sector, we follow (Acemoglu et al., 2018) relying on microeconometric innovation literature, and estimate an innovation elasticity parameter $\phi = 0.49$.[23] Without loss of generality, we assume that the initial step-size of incremental innovations

[22] Difference between the contribution of one extra radical innovation versus that of an incremental one is $(\lambda-\bar{\eta})+\delta_m(\partial\bar{\eta}/\partial\delta_d - \partial\bar{\eta}/\partial\delta_m)$. The latter term corresponds to the externality induced by our particular way of modeling the quality decay of incremental innovations.

[23] We regress the number of patents on (log) R&D expenditure, controlling for (log) R&D staff, as well as year, location (province), industry, ownership types, and establishment year fixed effects, using the Poisson quasi-maximum likelihood estimator with robust standard errors clustered at the firm level. The estimate is quite close to values used in the literature.

Table 4.1
Internally calibrated parameters.

Para	Equation	Meaning	Target
$z_{\mathrm{H}d}$	(7)	H-type's radical productivity	share of radical innov.
$z_{\mathrm{H}m}$	(7)	H-type's incremental productivity	H-type's R&D intensity
$z_{\mathrm{L}m}$	(7)	L-type's incremental productivity	L-type's R&D intensity
γ_d	(3)	skill intensity in radical innov.	H-type's skill intensity
γ_m	(3)	skill intensity in incremental innov.	L-type's skill intensity
b_n	(7)	quantity-based subsidy	subsidy-to-R&D ratio
λ	(4)	step-size of radical innov.	TFP growth rate
α	(5)	speed of quality decay	average citation ratio
ξ		education productivity	skill premium
x_{E}	(8)	entrants' innov. rate	entrants' patent share
χ		cost of becoming H-type	fraction of H-type incumbents

Note: This table summarizes the internally calibrated parameters and their corresponding target moments.

Table 4.2
Benchmark calibration.

Para	$z_{\mathrm{H}d}$	$z_{\mathrm{H}m}$	$z_{\mathrm{L}m}$	γ_d	γ_m	b_n	λ	α	ξ	x_{E}	χ
Value	1.029	1.038	1.016	0.796	0.453	0.029	0.158	0.862	0.035	0.068	0.138
Data (%)	8.01	17.78	15.02	34.12	25.42	20.42	1.97	33.28	243	21.00	26.98
Model (%)	8.01	17.49	15.02	34.08	25.41	20.44	1.97	33.27	243	20.98	26.99

Note: This table presents the calibration results and model fit on targeted moments.

$\eta = \alpha\lambda$, with the latter two parameters calibrated internally. In the education sector, we set the death rate d so that an individual works for around 35 years. We set u and b_r to match a 25% corporate tax rate and a 150% tax credit multiplier in China.[24]

The remaining 11 parameters are internally calibrated to moments, which, unless stated otherwise, are calculated from our firm-level sample for 2011–2013. For each of the parameters, we pick a most informative moment implied by the model. The first set of remaining parameters regards R&D productivity. The model contains three such parameters: radical and incremental innovation productivity for high-type firms, $z_{\mathrm{H}d}$ and $z_{\mathrm{H}m}$; and incremental innovation productivity for low-type firms, $z_{\mathrm{L}m}$. To discipline $z_{\mathrm{H}m}$ and $z_{\mathrm{L}m}$, we use the average R&D intensity, defined as the ratio of total R&D expenditures to value-added,[25] of high- and low-type firms. The ratio $z_{\mathrm{H}d}/z_{\mathrm{H}m}$ affects the share of radical innovations high-type firms choose to pursue. Therefore, we use the share of radical patents, to discipline the value of $z_{\mathrm{H}d}$.

The second set of parameters regards skill intensities in R&D: γ_d and γ_m. Recall that low-type firms are creating only incremental patents, so we can use the observed skill intensity of them to discipline γ_m. With the value of γ_m determined, we can further discipline γ_d by targeting the observed skill intensity of high-type firms.

We pin down the amount of subsidy, b_n, by the aggregate subsidy-to-R&D expenditure ratio.[26] Following the formula of aggregate growth rate, we set the step-size of radical innovations, λ, to match an annual TFP growth rate of 1.97% in 2008–2014 estimated by Bai and Zhang (2017). As we map step-size of incremental innovations to the number of forward citations received by incremental patents, the decay rate α, which determines the average step-size of incremental innovations, can be disciplined by the ratio between average forward citations received by incremental and radical patents.[27]

We use the skill premium to discipline productivity in the education sector ξ, which determines the total supply of skilled labor and the equilibrium wage rates.[28] Consistent with the model's setting, entrant firms' innovation rate x_{E} is disciplined by the share of patents created by new entrants in the economy. The cost coefficient for entrants to become high-type, χ, is set to match the percentage of high-type firms among incumbents. In the end, we jointly calibrate all 11 parameters to minimize the total sum of distance between model-generated and data moments. Table 4.1 summarizes the internally calibrated parameters and their corresponding target moments.

Model fit. Table 4.2 presents the calibration results and model fit, the benchmark model well replicates the targeted moments. We show how the total distance and each moment change with respect to the corresponding parameter's value in Appendix C.3.

Estimates of γ_d and γ_m confirm that R&D activities pursuing radical innovations rely more heavily on skilled labor than incremental ones. The relatively large difference between the two values, 0.796 vs. 0.453, is necessary to account for the observed

24 The values of all externally calibrated parameters and their sources are summarized in Table C.1 in the Appendix.

25 In the model, firms with the same R&D productivity choose the same level of R&D expenditures per line, but their value-added may differ due to idiosyncratic draws of product quality. "Average" means a within-type semi-aggregation that gives a "representative" value-added for each type of firm.

26 In the data, we define subsidy as the sum of government research funds, subsidy to innovative firms in the ASIE database, and HTE tax exemptions, where HTE refers to High-Tech Enterprises. HTE recognition, also known as the InnoCom Program, is a critical pro-innovation subsidy program China has initiated. For more discussion on HTEs, please see Appendix C.4.

27 Appendix C.2 provides more details.

28 To obtain the skill premium, we run a Mincer regression using data from the Urban Household Survey 2009, the coefficient in front of the dummy for "graduate degree" is 2.43. Specifically, we regress wage on the education group dummy controlling for household age, age squared, gender, race, and marital status.

Table 4.3
Innovation Quantity & Quality in the Baseline (B.M.) and Counterfactual Economy (C.F.) w./o. Quantity-Based Subsidies.

Variable	Meaning	B.M.	C.F.	Δ_{Model}	Δ_{Data}	$\frac{\Delta_{\text{Model}}}{\Delta_{\text{Data}}}$
$\delta - x_E$	Incumbent innovation	25.53%	23.18%	10.14%	34.57%	29.33%
δ_d/δ	Radical share	8.01%	10.39%	−22.91%	−40.89%	56.03%
$\bar{\eta}/\lambda$	Step-size ratio	33.27%	39.27%	−15.28%	−20.27%	75.38%

Note: Δ_{Model} represents changes from the counterfactual to the model benchmark, Δ_{Data} is changes between the pre- and post-2008 period, both columns are presented in relative terms. Step-size ratio denotes the relative step-size of incremental to radical innovations.

9% gap between skill intensities of high- and low-type firms, as more than 70% of innovations created by high-type firms, are incremental.

To give a sense of the magnitude of quantity-based subsidy b_n, we contrast it to the average value-added of innovating firms, and the ratio is slightly above 3%. Our estimate of λ implies that a radical innovation improves the quality of a product by 15.8%. This number is close to that obtained in the literature. For example, Akcigit and Kerr (2018) estimated a step-size of 11.2%, while (Acemoglu et al., 2018) reported a step-size of 13.2%. Our estimate of $\alpha = 0.862$ is lower than what is reported in Akcigit and Kerr (2018) about US patents, implying a faster quality decay among incremental patents in China.

The calibrated model generates a creative destruction rate $\delta = 32.31\%$. As our paper corresponds innovation to patents, we define a patent-level creative destruction rate in a year as the ratio of newly created patents to that of the patent stock. For the 2011–2013 sample period, we estimate a patent-level creative destruction rate that ranges from 30% to 34%, which is consistent with the model counterpart and close to other estimates in the literature, e.g., Branstetter et al. (2023).

The model also predicts that firms with a higher innovation intensity have a larger expected size. We examine the model-generated relative size between high- and low-type firms and contrast it to the data counterpart (Appendix Table C.2). Lastly, we compare the patent number distribution in the model and the data (Appendix Figure C.3), and provide supportive evidence that the magnitude of quantity–quality trade-off implied by the calibrated model is in line with what is revealed in the data. Details of the aforementioned model fit examinations can be found in Appendix C.4.

4.2. Effects of quantity-based subsidies

We are now ready to evaluate the impact of quantity-based subsidies. To that end, we compare the baseline outcome with a counterfactual economy in which all such subsidies are shut down, i.e., $b_n = 0$. Table 4.3 presents the results.

Quantity-based subsidies implemented in China generate a relative increase of 10.14% in innovation quantity, measured by incumbents' creative destruction. However, such subsidies reduce overall innovation quality in two dimensions. Firstly, the share of radical innovations declines from 10.39% to 8.01%, a relative decrease of 22.91%. Secondly, the relative quality of incremental to radical innovations decreases, indicated by a decline in the average step-size ratio from 39.27% to 33.27%, or a relative decrease of 15.28%.

In the data, compared to the pre-2008 period, we see a relative increase of 34.57% in patent quantity, a relative decrease of 40.89% in the share of radical patents, and a relative decrease of 20.27% in the average citation ratio between incremental and radical patents.[29] Our quantified model implies that quantity-based subsidies account for about 29% of the patent surge, 56% of the radical share decline, and 75% of the widening gap between incremental and radical innovations, observed in the post-2008 period.

By changing firms' innovation incentives, quantity-based subsidies further affect aggregate growth and welfare. In our exercise, the aggregate growth rate decreases from 2.16% in the counterfactual economy without subsidies to 1.97% in the baseline. Bai and Zhang (2017) report that the Chinese TFP growth rate decreases by 1.91 percentage points, from 3.88% in 2001–2007 to 1.97% in 2008–2014. A drop of 0.19 percentage points in the model's TFP growth rate accounts for about 10% of the change between the pre- and post-2008 periods in the data.

We then follow Eq. (12) and decompose such effects into three channels, as shown in Table 4.4. Subsidies raise innovation quantity, leading to a 0.17 percentage points increase in aggregate growth rate; however, this positive quantity effect is overwhelmed by the negative quality effects. A pool of proportionately less radical innovations reduces growth. This channel, which corresponds to δ_d/δ, brings a 0.07 percentage points drop in aggregate growth. In addition, the average productivity enhancement from incremental innovations falls as quantity-based subsidies induce more incremental R&D trials. This last channel, which corresponds to $\bar{\eta}/\lambda$, brings a 0.26 percentage points drop in aggregate growth rate. Overall, the quality-crowding effect dominates, generating a negative net effect on growth. As a result, the introduction of quantity-based subsidies causes a welfare loss of 3.31% to the economy.

To summarize, although quantity-based subsidies promote overall innovations, they also skew R&D efforts toward incremental innovations, hence imposing negative effects on growth and welfare. Among the undesirable consequences, quality-crowding, i.e., the average quality of incremental innovations declines as more such innovations are pursued, accounts for most of the losses. Note the growth and welfare implications are based on the comparison between two balanced growth paths, while what happens on the

[29] See Appendix D.1 for details of the estimation. Essentially we fit a linear pre-2008 trend and extrapolate that trend to obtain the "natural" level for years after 2008. By calculating the deviation of actual values from these predicted values in relative terms, we obtain and report the relative changes here.

Table 4.4
Growth decomposition.

Δ_{Growth}	(i) quantity	(ii) quality-composition	(iii) quality-crowding	
−0.19	0.17	−0.07	−0.26	(p.p.)
	−89.47%	36.84%	136.84%	

Note: For each of the channels, we add the corresponding change in (i) δ; (ii) δ_d/δ; (iii) $\bar{\eta}$ to the pre-2008 economy, and see how it affects the aggregate growth rate. The second row shows the contribution of each channel, calculated by dividing the corresponding number by −0.19 p.p.

transitional path is not addressed in the analysis. Moreover, the assumption of scarce research time, together with parameter values regarding the degree of quality decay and heterogeneity in skill intensities, determines the strength of the three channels and the sign of the net impact. We present a formal discussion of them in Appendix D.2.

The baseline model, designed to deliver a clean characterization of the firm-level quantity–quality trade-off and facilitate aggregation, is subject to two oversimplification concerns. One is that the innovation cost scales up linearly with firm size, the other resides in the assumption that all innovations trigger creative destruction, i.e., being external. To alleviate these concerns, we first extend the model to allow for decreasing return to scale in pursuing innovations. In another extension, we introduce internal innovations as a third choice for incumbent firms. Appendix D.3 and D.4 provide details on the model setting, calibration, and the growth and welfare implications of these two extensions, respectively. The extended models deliver similar results to those in the baseline case, reaffirming the robustness of the conclusions.

4.3. Quality-biased policy

This section analyzes the implementation of a constrained planner's allocation, and accordingly, proposes innovation policies that are quality-biased. In particular, we allow the planner to decide the skill supply but let individual firms produce and price as in the market economy, as we are not interested in alleviating the monopoly distortion. Since the economy contains an education sector with endogenous creation of skilled labor, the planner needs to choose a talent threshold above which the young shall obtain education, θ^*_{SP}, to maximize social welfare.

Social welfare, as defined in Eq. (11), is a hump-shaped function of the education threshold. An increase in skill supply initially raises welfare as it promotes innovation and growth but reduces welfare after passing a threshold, as the negative effect from a shrinking unskilled workforce and lower initial consumption level eventually dominates.[30] The socially optimal allocation of skilled labor supply is 14.36% of the population, more than tripled comparing to the market equilibrium level of 4.04%. As more skilled labor promotes innovation, the aggregate growth rate increases from 1.97% to 5.51%, and the aggregate welfare improves dramatically by 16.85%.

A natural follow-up question is whether policymakers can find implementable subsidies to recover the planner's allocation and improve welfare. Here we propose a quality-biased policy: subsidizing the skill. In particular, we consider two forms of skill subsidies. One is an *education subsidy*, with which the government covers $b_e \in [0, 100\%]$ portion of the education cost. The other is a *skilled labor subsidy*, with which the government covers $b_h \in [0, 100\%]$ portion of the skilled wage cost to innovating firms. Recall that young workers choose whether to obtain skill based on the education cost and the skill premium. Therefore, policymakers are able to implement any desired labor supply allocation with proper combinations of b_e and b_h. If the desired skill supply is high, simultaneous usage of both subsidies is required. We formalize the argument into the following proposition.[31]

Proposition 3. *For any given $\theta^*_{SP} \in [1, \theta^*_{CE})$, there exists a set $\mathcal{G}$ of different combinations of $(b_e, b_h) \in [0, 1]^2$ to implement the allocation in a market equilibrium. Moreover,*

(i) to implement the given θ^*_{SP}, policymakers face a linear trade-off between b_e and b_h;
(ii) when the talent threshold θ^*_{SP} is low enough, the set $\mathcal{G}$ does not contain $(0, b_h)$ or $(b_e, 0)$.

Lastly, we contrast the effects of "quality-biased" skill subsidies to quantity-based subsidies in Appendix D.7.[32] Different from quantity-based subsidies, the skill subsidies help improve both innovation quantity and quality, and promote growth and welfare, as they raise the skill supply and reduce equilibrium skill premium, therefore are biased toward more skill-intensive radical innovations.

5. Conclusion

Motivated by the Chinese patent quantity surge and quality decline, we construct a Schumpeterian growth model featuring heterogeneous innovations to study the impact on growth and welfare of quantity-based subsidies widely adopted in China since the middle 2000s. We decompose the impact into positive quantity and negative quality channels. The model-based quantitative analysis shows that such subsidies reduce the aggregate welfare by 3.31%, as the negative *quality-crowding* channel dominates. We

[30] Aggregate welfare is affected by intertemporal elasticity of substitution, ν. Appendix D.5 details how we solve the planner's problem, and displays the hump-shaped welfare curves under different values of ν.

[31] See proof of Proposition 3 in Appendix D.6.

[32] We also evaluate the effects of R&D tax credit, which turn out to be similar to quantity-based subsidies in our framework.

further evaluate welfare gains under a constrained planner's problem, and propose quality-biased skill subsidies which effectively recover the optimal allocation.

We necessarily abstract from other essential features, e.g., transition from imitation to innovation, to focus on the quantity–quality trade-off. In addition, the way skill accumulation is modeled is simplified to keep the framework tractable. In reality, patent subsidies work immediately, while building up a skill pool takes generations of time. Skill subsidies can also take many forms in the real world, for example, attracting overseas-trained talents to work at home seems an important channel for China's technology catch-up. We leave detailed investigations along these dimensions for future research.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmoneco.2023.09.004.

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