How Minimum Wages Affect Automation and Innovation in a Schumpeterian Economy

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Abstract

This study explores the effects of minimum wage on automation and innovation in a Schumpeterian growth model. We find that raising the minimum wage decreases low-skilled workers' employment and has an ambiguous impact on innovation and automation. Specifically, suppose the substitution elasticity between low-skilled workers and high-skilled workers in production is less (greater) than unity. In that case, raising the minimum wage leads to an increase (a decrease) in automation and innovation. We also provide a quantitative analysis by simulating the effects of minimum wage on the macroeconomy. Finally, we test our theoretical results by estimating the elasticity of substitution between low-skilled and high-skilled workers and the minimum wage impact on automation and innovation in China.

JEL classification: E24, O30, O40
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> Higher minimum wages could stimulate the economy and boost wages, for example. Or if employers focus on high-skilled workers in the short term, that could boost productivity and the economy in the long term, eventually providing jobs for the low skilled. The Economist (2016)

1 Introduction

Would a higher minimum wage boost automation and innovation? Or would the consequent decrease in low-skilled production lead to a reallocation of high-skilled labor from innovation and automation to the production of goods and services? An answer to these questions is essential for the assessment of minimum wage policies on macroeconomic growth. An example is President Biden's proposal to double the US minimum wage from $7.5 to $15, recently purged by Congress from the America Rescue Plan of 2021. Is more expensive unskilled labour a sufficient incentive for automation? Was that decision beneficial or harmful for the innovative future of the US economy? We find that both scenarios are possible. Which scenario occurs crucially depends on a structural parameter that determines the elasticity of substitution between low-skilled workers and high-skilled workers in production.

Specifically, we consider a Schumpeterian growth model in which the production of goods requires both low-skilled workers and high-skilled workers. In contrast, the automation process and the innovation process require only high-skilled workers. Within this growth-theoretic framework, we find that raising the minimum wage decreases the employment of low-skilled workers and has ambiguous effects on automation and innovation. Specifically, the minimum wage impact on automation and innovation depends on the elasticity of substitution between low-skilled workers and high-skilled workers in production. If this elasticity of substitution is less (greater) than unity, raising the minimum wage leads to an increase (a decrease) in automation and innovation.

The intuition of the above results is the following. Because the minimum wage is binding in the low-skilled labor market but not in the high-skilled labor market, raising the minimum wage reduces low-skilled employment but does not affect high-skilled employment. The decrease in low-skilled production workers leads to a reduction (an increase) in high-skilled production workers if the two types of workers are gross complements (substitutes), in which case the amount of high-skilled workers for automation and innovation increases (decreases). We also provide a quantitative analysis by simulating the quantitative effects of minimum wage on unemployment, capital intensity, automation, innovation, economic growth and social welfare.

Finally, we test our theoretical results by estimating the elasticity of substitution between low-skilled and high-skilled workers and the effects of minimum wage on automation and innovation in China. We find that the substitution elasticity between low-skilled workers and high-skilled workers in China exceeds unity. In this case, our theory predicts that increasing the minimum wage harms automation and innovation. Using patent data in China, we indeed find that minimum wage negatively affects both invention patents and automation patents.

This study relates to the literature on innovation and economic growth. The seminal article by Romer (1990) develops the first R&D-based growth model in which the creation of new products drives economic growth. Then, subsequent studies by Aghion and Howitt (1992), Grossman and Helpman (1991) and Segerstrom et al. (1990) develop the Schumpeterian growth model in which the quality improvement of products drives economic growth. In this literature, some studies, such as Askenazy (2003), Meckl (2004), Agenor and Lim (2018), Chu, Kou and Wang (2020) and Chu, Fan, Furukawa, Kou and Liu (2021), introduce minimum wage into variants of the R&D-based growth model to explore the relationship between unemployment and innovation.[1] This study differs from these previous studies by introducing automation into the analysis and analyzing the relationship between minimum wage and automation. Suppose we set aside automation in the model. In that case, our result relates to previous studies on minimum wage and innovation by showing that the elasticity of substitution between low-skilled workers and high-skilled workers in production determines the effect of minimum wage on innovation.

This study also relates to the literature on automation and economic growth.[2] The seminal study in this literature is Zeira (1998), who develops a growth model with capital-labor substitution. Subsequent investigations by Zeira (2006), Peretto and Seater (2013), Aghion et al. (2017), Acemoglu and Restrepo (2018) and Hemous and Olson (2021) introduce this capital-labor substitution into variants of the R&D-based growth model to explore the relationship between automation and innovation.[3] This study complements these interesting studies by introducing minimum wage into a Schumpeterian growth model with automation to explore the relationship between unemployment and automation. Alesina et al. (2018) examine the effects of labor market regulation (modelled as the firing cost of workers) on the skill premium and technologies in the high-skilled sector relative to the low-skilled sector. Prettner and Strulik (2020) develop a variety-expanding R&D-based growth model with unemployment driven by fair wage as in Akerlof and Yellen (1990) to analyze the effect of automation on unemployment. Instead, we focus on the impact of minimum wage on the relationship between unemployment and automation, which turns out to be ambiguous and depends on the elasticity of substitution between low-skilled workers and high-skilled workers in production.

Therefore, our study also relates to the growing empirical literature on how minimum wage affects the automation of low-skilled jobs.[4] In summary, recent studies in this literature find different effects. For example, Logan and Neumark (2018) find that raising minimum wage increases the automation of low-skilled jobs, whereas Downey (2021) find that raising minimum wage decreases the profitability of automation and reduces the automation of low-skilled jobs. Our growth-theoretic model shows that the elasticity of substitution between low-skilled workers and high-skilled workers in production determines which effect prevails in the economy.

The rest of this study is organized as follows. Section 2 describes the theoretical model. Section 3 presents the results. Section 4 provides empirical evidence. Section 5 concludes.

[1] There are other approaches of incorporating unemployment into the R&D-based growth model; see Mortensen and Pissarides (1998) for search frictions, Parello (2010) for efficiency wage, Peretto (2011) for wage bargaining, and Ji *et al.* (2016) and Chu *et al.* (2016, 2018) for trade unions.

[2] See Aghion *et al.* (2017) for a comprehensive discussion of this literature.

[3] See Chu *et al.* (2019) for a discussion of these studies.

[4] There is also a branch of studies that examine the effects of minimum wage on the level of employment; see Cengiz *et al.* (2019) for a recent study and a discussion of earlier studies.

2 A Schumpeterian growth model with automation and minimum wage

The Schumpeterian growth model originates from Aghion and Howitt (1992). Chu, Cozzi, Furukawa and Liao (2019) incorporate capital-labor substitution as in Zeira (1998) into the Schumpeterian growth model with an automation-innovation cycle. We generalize their production function to allow for a non-unitary elasticity of substitution between low-skilled workers and high-skilled workers in production and introduce minimum wage into the model to explore its effects on unemployment, automation and innovation.

2.1 Household

The utility function of the representative household is given by

$$U = \int_0^\infty e^{-\rho t} \ln c_t dt, \tag{1}$$

where c_t is the household's consumption of final good (numeraire) and the parameter $\rho > 0$ determines the rate of subjective discounting. The household maximizes (1) subject to the following asset-accumulation equation:

$$\dot{a}_t + \dot{k}_t = r_t a_t + (R_t - \delta)k_t + w_{h,t}H + \overline{w}_{l,t} l_t + b_t (L - l_t) - \tau_t - c_t. \tag{2}$$

a_t is the value of assets owned by the household. r_t is the real interest rate. k_t is the amount of physical capital owned by the household. $R_t - \delta$ is the rental price of capital net of depreciation. The household has $H + L$ members. Each of H members supplies one unit of high-skilled labor and earns the high-skilled wage rate $w_{h,t}$, which is above the minimum wage and determined as an equilibrium outcome in the high-skilled labor market. Each of L members supplies one unit of low-skilled labor. Employed low-skilled workers l_t earn the low-skilled wage rate $\overline{w}_{l,t}$, which is determined by the minimum wage set by the government. Unemployed low-skilled workers $L - l_t$ receive an unemployment benefit $b_t < \overline{w}_{l,t}$. The household pays a lump-sum tax τ_t to the government. Dynamic optimization yields the Euler equation as

$$\frac{\dot{c}_t}{c_t} = r_t - \rho. \tag{3}$$

Also, the no-arbitrage condition $r_t = R_t - \delta$ holds.

2.2 Final good

Competitive firms produce final good y_t using the following Cobb-Douglas aggregator over a unit continuum of differentiated intermediate goods:

$$y_t = \exp\left(\int_0^1 \ln x_t(i) di \right). \tag{4}$$

$x_t(i)$ denotes intermediate good $i \in [0,1]$. Profit maximization yields the conditional demand function for $x_t(i)$ as

$$x_t(i) = \frac{y_t}{p_t(i)}, \tag{5}$$

where $p_t(i)$ is the price of $x_t(i)$.

2.3 Unautomated intermediate goods

There is a unit continuum of industries $i \in [0,1]$ that produce differentiated intermediate goods. If an industry is not automated, then the production process uses low-skilled labor $l_t(i)$ and high-skilled labor $h_{x,t}(i)$. An industry leader, who owns the latest technology in an unautomated industry, dominates the market until the arrival of an automation or the next innovation. The industry leader's production function is given by

$$x_t(i) = z^{n_t(i)} \left\{ (1-\beta) \left[l_t(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} + \beta \left[h_{x,t}(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} \right\}^{\frac{\varepsilon}{\varepsilon-1}}, \tag{6}$$

where the parameter $z > 1$ is the step size of a quality improvement and the integer $n_t(i)$ is the number of quality improvements that have occurred in industry i as of time t. The parameter $\beta \in (0,1)$ determines the intensity of high-skilled labor relative to low-skilled labor in production, whereas the parameter $\varepsilon \in (0,\infty)$ is the elasticity of substitution between $l_t(i)$ and $h_{x,t}(i)$. From cost minimization, the conditional demand functions for $l_t(i)$ and $h_{x,t}(i)$ are given by

$$\overline{w}_{l,t} = \frac{(1-\beta)\xi_t(i) z^{n_t(i)}}{\left[l_t(i) \right]^{\frac{1}{\varepsilon}}} \left\{ (1-\beta) \left[l_t(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} + \beta \left[h_{x,t}(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} \right\}^{\frac{1}{\varepsilon-1}}, \tag{7}$$

$$w_{h,t} = \frac{\beta \xi_t(i) z^{n_t(i)}}{\left[h_{x,t}(i) \right]^{\frac{1}{\varepsilon}}} \left\{ (1-\beta) \left[l_t(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} + \beta \left[h_{x,t}(i) \right]^{\frac{\varepsilon-1}{\varepsilon}} \right\}^{\frac{1}{\varepsilon-1}}, \tag{8}$$

where ξ_t is the Lagrange multiplier from the cost minimization problem. Using (7) and (8), we obtain $l_t(i)/h_{x,t}(i) = \{[\beta/(1-\beta)](\overline{w}_{l,t}/w_{h,t})\}^{-\varepsilon}$. We substitute this relative labor demand function into (6) to derive

$$l_t(i) = \frac{x_t(i)}{z^{n_t(i)}} \left(\frac{\overline{w}_{l,t}}{1-\beta} \frac{1}{\psi_t} \right)^{-\varepsilon}, \tag{9}$$

$$h_{x,t}(i) = \frac{x_t(i)}{z^{n_t(i)}} \left(\frac{w_{h,t}}{\beta} \frac{1}{\psi_t} \right)^{-\varepsilon}, \tag{10}$$

where we have defined the following transformed variable:

$$\psi_t \equiv \left[(1-\beta) \left(\frac{\overline{w}_{l,t}}{1-\beta} \right)^{1-\varepsilon} + \beta \left(\frac{w_{h,t}}{\beta} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}.$$

Using (9) and (10), we find that the marginal cost of production for the leader in an unautomated industry i is given by $\psi_t / z^{n_t(i)}$. Aghion and Howitt (1992) and Grossman and

Helpman (1991) assume that the markup ratio is given by the quality step size z, due to limit pricing between current and previous quality leaders. Here we follow Howitt (1999) and Dinopoulos and Segerstrom (2010) to assume that previous quality leaders exit the market and need to pay a re-entry cost. In this case, the unconstrained profit-maximizing monopolistic price would be infinite, so we consider price regulation as in Evans *et al.* (2003) to impose a policy constraint on the markup ratio μ such that

$$p_t(i) \leq \mu \frac{\psi_t}{z^{n_t(i)}}. \tag{11}$$

To maximize profit, the industry leader chooses $p_t(i) = \mu\psi_t / z^{n_t(i)}$. In this case, the wage payment in an unautomated industry is

$$\overline{w}_{l,t} l_t(i) + w_{h,t} h_{x,t}(i) = \frac{1}{\mu} p_t(i) x_t(i) = \frac{1}{\mu} y_t, \tag{12}$$

and the amount of monopolistic profit in an unautomated industry is

$$\pi_t^l(i) = p_t(i) x_t(i) - [\overline{w}_{l,t} l_t(i) + w_{h,t} h_{x,t}(i)] = \frac{\mu - 1}{\mu} y_t. \tag{13}$$

2.4 Automated intermediate goods

If an industry is automated, then production uses capital as in Zeira (1998). The production function is

$$x_t(i) = \frac{A}{Z_t} z^{n_t(i)} k_t(i), \tag{14}$$

where $A > 0$ is a relative productivity parameter and $k_t(i)$ denotes capital input used in an automated industry i. $Z_t \equiv \exp\left(\int_0^1 n_t(i) di \ln z\right)$ denotes aggregate technology across industries and captures an erosion effect of new technologies that reduce the adaptability of existing physical capital. Given the productivity level $z^{n_t(i)}$, the marginal cost function of the leader in an automated industry i is $Z_t R_t / [A z^{n_t(i)}]$.[5] Due to price regulation, the monopolistic price $p_t(i)$ is once again a markup μ over the marginal cost $Z_t R_t / [A z^{n_t(i)}]$ such that

$$p_t(i) = \mu \frac{Z_t R_t}{A z^{n_t(i)}}. \tag{15}$$

The capital rental payment in an automated industry is

$$R_t k_t(i) = \frac{1}{\mu} p_t(i) x_t(i) = \frac{1}{\mu} y_t, \tag{16}$$

and the amount of monopolistic profit in an automated industry is

$$\pi_t^k(i) = p_t(i) x_t(i) - R_t k_t(i) = \frac{\mu - 1}{\mu} y_t. \tag{17}$$

[5] Alternatively, one can consider a simpler production function $x_t(i) = A k_t(i)$, in which case the marginal cost function is simply R_t / A. However, the aggregation for Z_t would become much more complicated.

2.5 Automation-innovation cycle

This section derives the equilibrium condition that supports a stylized and tractable automation-innovation cycle, which can be explained as follows. When the next automation arrives and an industry becomes automated, it uses capital as the factor input. In order for the automation to reduce the marginal cost of production (so that the automation is adopted), we need the following condition to hold: $Z_t R_t / A < \psi_t$. Then, when next innovation arrives and an automated industry becomes unautomated, it uses the two types of workers as factor inputs. In order for the innovation to reduce the marginal cost of production (so that the innovation is adopted), we need the following condition to hold: $\psi_t / z < Z_t R_t / A$. Combining these two conditions yields $\psi_t / z < Z_t R_t / A < \psi_t$. In Lemma 1, we derive the steady-state equilibrium expression for this condition, in which $g_y \equiv \dot{y}_t / y_t$ denotes the steady-state growth rate of output and θ denotes the steady-state share of automated industries.

Lemma 1 *The steady-state equilibrium condition for the automation-innovation cycle is*

$$\frac{1}{z} < \left[\frac{\mu}{A}\left(g_y + \rho + \delta\right)\right]^{\frac{1}{1-\theta}} < 1.$$

Proof. See Appendix A. ■

2.6 Innovation and automation

Equations (13) and (17) imply $\pi_t^l(i) = \pi_t^l$ and $\pi_t^k(i) = \pi_t^k$. Therefore, we follow the standard treatment to focus on the symmetric equilibrium in which $v_t^l(i) = v_t^l$ and $v_t^k(i) = v_t^k$,[6] where v_t^l denotes the value of an unautomated invention and v_t^k denotes the value of an automation. The no-arbitrage condition that determines the value v_t^l of an unautomated invention is

$$r_t = \frac{\pi_t^l + \dot{v}_t^l - (\alpha_t + \lambda_t) v_t^l}{v_t^l}, \tag{18}$$

which equates the interest rate to the rate of return on v_t^l given by the sum of profit π_t^l and capital gain $\dot{v}_t^l$ minus expected capital loss $(\alpha_t + \lambda_t) v_t^l$, where α_t is the arrival rate of automation and λ_t is the arrival rate of innovation. Similarly, the no-arbitrage condition that determines the value v_t^k of an automation is

$$r_t = \frac{\pi_t^k + \dot{v}_t^k - \lambda_t v_t^k}{v_t^k}, \tag{19}$$

which equates the interest rate to the rate of return on v_t^k given by the sum of profit π_t^k and capital gain $\dot{v}_t^k$ minus expected capital loss $\lambda_t v_t^k$, where λ_t is the arrival rate of innovation. The condition in Lemma 1 ensures that the previous automation becomes obsolete when the next innovation arrives.

[6] See Cozzi *et al.* (2007) for a microfoundation of the symmetric equilibrium in the Schumpeterian model.

Competitive entrepreneurs perform innovation in industry i by employing high-skilled labor $h_{r,t}(i)$. The arrival rate of innovation in industry i is given by

$$\lambda_t(i) = \varphi_t h_{r,t}(i), \tag{20}$$

where $\varphi_t \equiv \varphi h_{r,t}^{\eta-1}$ in which $\varphi > 0$ is an innovation productivity parameter. The aggregate arrival rate of innovation is $\lambda_t = \varphi h_{r,t}^{\eta}$, where $h_{r,t}$ denotes aggregate R&D labor, and the parameter $\eta \in (0,1)$ captures the intratemporal duplication externality in Jones and Williams (2000).[7] To ensure equilibrium uniqueness, we will restrict the parameter space to $\eta \in (0, 0.5]$, which is sufficient for the equilibrium to be unique as we will show below. In a symmetric equilibrium, the free-entry condition of R&D becomes

$$\lambda_t v_t^l = w_{h,t} h_{r,t} \Leftrightarrow \varphi v_t^l = w_{h,t} h_{r,t}^{1-\eta}. \tag{21}$$

Competitive entrepreneurs also perform automation in industry i by employing high-skilled labor $h_{a,t}(i)$. The arrival rate of automation in industry i is given by

$$\alpha_t(i) = \phi_t h_{a,t}(i), \tag{22}$$

where $\phi_t \equiv \phi(1-\theta_t) h_{a,t}^{\eta-1}$ in which $\phi > 0$ is an automation productivity parameter and θ_t is the endogenous share of automated industries at time t. As in Chu, Cozzi, Furukawa and Liao (2019), the term $1-\theta_t$ in ϕ_t captures an increasing difficulty effect of automation under which more industries that are already automated make the next automation more difficult.[8] The aggregate arrival rate of automation is $\alpha_t = \phi h_{a,t}^{\eta}$, where $h_{a,t}$ denotes aggregate automation labor and we have used the condition that $h_{a,t}(i) = h_{a,t}/(1-\theta_t)$. In a symmetric equilibrium, the free-entry condition of automation becomes

$$\alpha_t v_t^k = w_{h,t} h_{a,t}/(1-\theta_t) \Leftrightarrow \phi(1-\theta_t) v_t^k = w_{h,t} h_{a,t}^{1-\eta}. \tag{23}$$

2.7 Government

To be consistent with balanced growth, we assume that the government sets the minimum wage as a certain percentage γ of average wage income, where $\gamma > 0$ is the minimum-wage policy instrument. We will show that the minimum wage $\overline{w}_{l,t}$ is binding in the low-skilled labor market if γ is sufficiently large. The government collects a lump-sum tax τ_t to finance the unemployment benefit subject to the balanced-budget condition given by

$$\tau_t = b_t \left(L - l_t\right). \tag{24}$$

[7] Davidson and Segerstrom (1998) show that constant returns to scale in multiple R&D actitivities can lead to equilibrium instability and perverse comparative statics. Our model features innovation and automation, so the decreasing returns to scale in innovation and automation helps to ensure equilibrium stability.

[8] Otherwise, $h_{a,t}(i) = h_{a,t}/(1-\theta_t)$ would become unbounded as $\theta_t \to 1$.

2.8 Aggregation

Once again, aggregate technology Z_t is defined as

$$Z_t \equiv \exp\left(\int_0^1 n_t(i)di \ln z\right) = \exp\left(\int_0^t \lambda_\omega d\omega \ln z\right), \tag{25}$$

where the second equality uses the law of large numbers, which equates the average number of quality improvements $\int_0^1 n_t(i)di$ that have occurred as of time t to the total number of innovation arrivals $\int_0^t \lambda_\omega d\omega$ up to time t. Then, differentiating the log of Z_t in (25) with respect to time yields the growth rate of technology given by

$$g_{z,t} \equiv \frac{\dot{Z}_t}{Z_t} = \lambda_t \ln z. \tag{26}$$

Substituting (6) and (14) into (4) yields the following aggregate production function:[9]

$$\ln y_t = \int_0^{\theta_t} \ln\left[\frac{A}{Z_t} z^{n_t(i)} k_t\left(i\right)\right] di + \int_{\theta_t}^1 \ln\left\{z^{n_t(i)}\left[\left(1-\beta\right)\left[l_t(i)\right]^{\frac{\varepsilon-1}{\varepsilon}} + \beta\left[h_{x,t}(i)\right]^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right\} di$$

$$\Longrightarrow y_t = \left(\frac{Ak_t}{\theta_t}\right)^{\theta_t}\left\{\frac{Z_t\left[\left(1-\beta\right) l_t^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_{x,t}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}}{1-\theta_t}\right\}^{1-\theta_t}, \tag{27}$$

where we have used $k_t(i) = k_t/\theta_t$, $l_t(i) = l_t/\left(1-\theta_t\right)$ and $h_{x,t}(i) = h_{x,t}/\left(1-\theta_t\right)$. The share θ_t of automated industries determines the degree of capital intensity in the aggregate production function. The evolution of θ_t is determined by

$$\dot{\theta}_t = \alpha_t(1-\theta_t) - \lambda_t\theta_t, \tag{28}$$

where $\alpha_t = \phi h_{a,t}^\eta$ and $\lambda_t = \varphi h_{r,t}^\eta$ are respectively the arrival rates of automation and innovation. Using (2), one can derive the familiar law of motion for capital as follows:[10]

$$\dot{k}_t = y_t - c_t - \delta k_t. \tag{29}$$

From (9), (10) and (16), the capital and labor shares of income are respectively

$$R_t k_t = \frac{\theta_t}{\mu} y_t, \tag{30}$$

$$\overline{w}_{l,t} l = \frac{\left(1-\theta_t\right) y_t}{\mu}\left(1-\beta\right)^\varepsilon \left(\frac{\overline{w}_{l,t}}{\psi_t}\right)^{1-\varepsilon}, \tag{31}$$

$$w_{h,t} h_{x,t} = \frac{\left(1-\theta_t\right) y_t}{\mu}\beta^\varepsilon \left(\frac{w_{h,t}}{\psi_t}\right)^{1-\varepsilon}. \tag{32}$$

[9] One can easily allow for an exogenous technological process Z_t^* (capturing e.g., foreign technical progress) in (27) by introducing Z_t^* to (6) and (14).

[10] In Appendix B, we provide the detailed derivations.

2.9 Decentralized equilibrium

The equilibrium is a time path of allocations $\{a_t, k_t, c_t, y_t, x_t(i), l_t(i), k_t(i), h_{x,t}(i), h_{r,t}(i), h_{a,t}(i)\}$ and a time path of prices $\{r_t, R_t, \overline{w}_{l,t}, w_{h,t}, p_t(i), v_t^l(i), v_t^k(i)\}$ such that the following conditions hold in each instance:

- the household maximizes utility taking $\{r_t, R_t, \overline{w}_{l,t}, w_{h,t}\}$ as given;
- competitive final-good firms produce y_t to maximize profit taking $p_t(i)$ as given;
- each monopolistic intermediate-good firm i produces $x_t(i)$ and chooses $\{l_t(i), h_{x,t}(i), k_t(i), p_t(i)\}$ to maximize profit taking $\{\overline{w}_{l,t}, w_{h,t}, R_t\}$ as given;
- competitive entrepreneurs choose $\{h_{r,t}(i), h_{a,t}(i)\}$ to maximize expected profit taking $\{w_{h,t}, v_t^l(i), v_t^k(i)\}$ as given;
- the market-clearing condition for final good holds such that $y_t = c_t + \dot{k}_t + \delta k_t$;
- the market-clearing condition for capital holds such that $\int_0^{\theta_t} k_t(i)di = k_t$;
- the market-clearing condition for high-skilled labor holds such that $\int_0^1 h_{r,t}(i)di + \int_{\theta_t}^1 h_{a,t}(i)di + \int_{\theta_t}^1 h_{x,t}(i)di = h_{r,t} + h_{a,t} + h_{x,t} = H$;
- the minimum wage in the low-skilled labor market implies $\int_{\theta_t}^1 l_t(i)di = l_t < L$;
- the value of inventions is equal to the value of the household's assets such that $\int_0^{\theta_t} v_t^k(i)di + \int_{\theta_t}^1 v_t^l(i)di = a_t$; and
- the government balances the fiscal budget.

2.10 Steady-state equilibrium allocation

From (13) and (17), the amount of monopolistic profit in both automated and unautomated industries is

$$\pi_t^l = \pi_t^k = \frac{\mu - 1}{\mu} y_t. \tag{33}$$

The balanced-growth values of an innovation and an automation are respectively

$$v_t^l = \frac{\pi_t^l}{\rho + \alpha + \lambda} = \frac{\pi_t^l}{\rho + \phi h_a^\eta + \varphi h_r^\eta}, \tag{34}$$

$$v_t^k = \frac{\pi_t^k}{\rho + \lambda} = \frac{\pi_t^k}{\rho + \varphi h_r^\eta}. \tag{35}$$

Substituting (34) and (35) into the free-entry conditions in (21) and (23) yields

$$\frac{\varphi h_a^{1-\eta}}{\phi(1-\theta) h_r^{1-\eta}} = \frac{\rho + \phi h_a^\eta + \varphi h_r^\eta}{\rho + \varphi h_r^\eta},$$

which can be reexpressed as

$$\frac{\varphi}{\phi}+\left(\frac{h_a}{h_r}\right)^{\eta}=\left(\frac{h_r}{h_a}\right)^{1-\eta}+\left(\frac{h_r}{h_a}\right)^{1-2\eta}\frac{\phi}{\varphi+\rho/h_r^{\eta}}. \tag{36}$$

This R&D condition shows that there is a positive relationship between h_a and h_r if $\eta \leq 1/2$;[11] see Figure 1 for an illustration.

We make use of (32) to obtain

$$w_{h,t}h_{x,t}=\frac{(1-\theta_t)\,y_t}{\mu}\frac{\beta^{\varepsilon}\left(w_{h,t}/\overline{w}_{l,t}\right)^{1-\varepsilon}}{(1-\beta)^{\varepsilon}+\beta^{\varepsilon}\left(w_{h,t}/\overline{w}_{l,t}\right)^{1-\varepsilon}}. \tag{37}$$

Based on (31) and (32), we can derive $w_{h,t}/\overline{w}_{l,t}=[\beta/(1-\beta)]\left(l_t/h_{x,t}\right)^{1/\varepsilon}$. Substituting this condition into (37) and using (23), (33) and (35), we obtain

$$\phi\,(\mu-1)=\frac{\beta\left(\rho+\varphi h_r^{\eta}\right)h_a^{1-\eta}}{(1-\beta)\,l^{\frac{\varepsilon-1}{\varepsilon}}\left(H-h_a-h_r\right)^{\frac{1}{\varepsilon}}+\beta\left(H-h_a-h_r\right)}, \tag{38}$$

where we have used the market-clearing condition for high-skilled labor $h_x+h_a+h_r=H$. The labor-market condition in (38) shows that for any given amount of low-skilled labor l, there is a negative relationship between h_a and h_r.

Low-skilled labor l in (38) is still an endogenous variable. To solve for l, we use the following rule that sets the minimum wage as a percentage γ of the labor share of output per capita:

$$\overline{w}_{l,t}=\gamma\frac{1-\theta_t}{\mu}\frac{y_t}{H+L}, \tag{39}$$

where $(1-\theta_t)/\mu$ is the labor income share. Substituting (5), (6) and $\xi_t(i)=p_t(i)/\mu$ into (7) and then the resulting expression into (39) yields

$$l=\min\left\{\frac{H+L}{\gamma}\frac{(1-\beta)\,l^{\frac{\varepsilon-1}{\varepsilon}}}{(1-\beta)\,l^{\frac{\varepsilon-1}{\varepsilon}}+\beta\left(h_x\right)^{\frac{\varepsilon-1}{\varepsilon}}},L\right\}. \tag{40}$$

In summary, (36), (38), (40) and $h_x+h_a+h_r=H$ together solve for the steady-state equilibrium allocation $\{h_r,h_a,h_x,l\}$. We can substitute $h_x=H-h_a-h_r$ into (40) to obtain the following implicit function:

$$l(h_x)=l(H-h_a-h_r). \tag{41}$$

[11] Equation (36) can be rewritten as

$$\frac{\rho}{h_r^{\eta}}=\frac{\phi}{\frac{\varphi}{\phi}\left(\frac{h_a}{h_r}\right)^{1-2\eta}+\left(\frac{h_a}{h_r}\right)^{1-\eta}-\left(\frac{h_a}{h_r}\right)^{-\eta}}-\varphi,$$

where the left-hand side is decreasing in h_r and the right-hand side is decreasing in h_a/h_r given $\eta\leq 1/2$. Thus, we can define a monotonically increasing function $f(.)$ such that $h_a/h_r=f(h_r)$. It implies $h_a=h_rf(h_r)$, which is increasing in h_r because $f'>0$.

Then, we substitute (41) into (38) to obtain

$$\phi(\mu-1) = \frac{\beta(\rho+\varphi h_r^\eta) h_a^{1-\eta}}{(1-\beta)[l(H-h_a-h_r)]^{\frac{\varepsilon-1}{\varepsilon}}(H-h_a-h_r)^{\frac{1}{\varepsilon}} + \beta(H-h_a-h_r)}. \tag{42}$$

This labor-market condition continues to feature a negative relationship between h_a and h_r as shown in the proof of Lemma 2. Therefore, the equilibrium allocation $\{h_r, h_a\}$ is unique; see Figure 1 for an illustration. Finally, we obtain $\{h_x, l\}$ using $h_x = H - h_a - h_r$ and (40).

Lemma 2 *The steady-state equilibrium allocation $\{h_r, h_a, h_x, l\}$ is unique.*

Proof. See Appendix A. ■

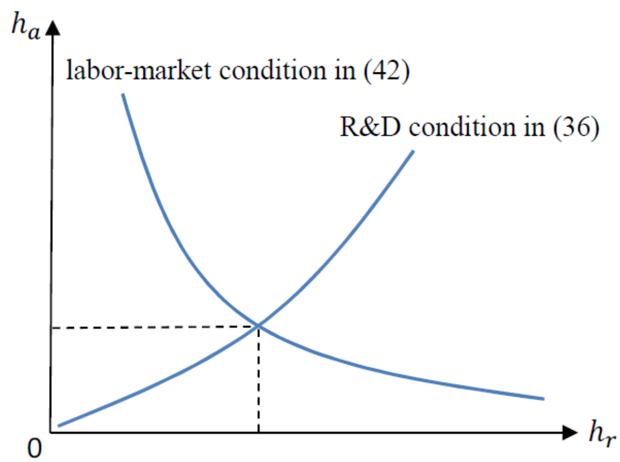

Figure 1: Steady-state equilibrium

3 How minimum wage affects R&D and automation

In the proof of Proposition 1, we show that if γ is sufficiently large, then the minimum wage is binding in the low-skilled labor market and causes unemployment such that $l < L$. Intuitively, a binding minimum wage gives rise to an excess supply of low-skilled workers and causes their employment level to be below full employment. Then, any further increase in the minimum-wage policy instrument γ reduces the level of low-skilled employment such that

$$\frac{dl}{d\gamma} < 0. \tag{43}$$

Intuitively, raising the minimum wage reduces the demand for low-skilled workers l and their employment level. Given that the employment of low-skilled labor is already below full employment (i.e., $l < L$), any increase in the minimum wage γ would increase the unemployment rate u that is given by

$$\underset{+}{u(\gamma)} = \frac{1}{H+L}[L - \underset{-}{l(\gamma)}]. \tag{44}$$

As for the effects of the minimum wage on the allocation of high-skilled workers, we need to consider two cases for the elasticity of substitution between low-skilled workers and high-skilled workers in production. If $\varepsilon > 1$, then the right-hand side (RHS) of (38) is decreasing in l. In this case, an increase in l must be accompanied by an increase in h_a and h_r and a decrease in h_x; see Figure 2 for an illustration. Conversely, if $\varepsilon < 1$, then the RHS of (38) is increasing in l. In this case, an increase in l must be accompanied by a decrease in h_a and h_r and an increase in h_x; see Figure 2 for an illustration. We summarize the above results as follows:

$$h_a = h_a(l)\,;\; h_{a,l} \equiv \frac{dh_a}{dl} \gtrless 0 \;\text{ if } \varepsilon \gtrless 1,$$

$$h_r = h_r(l)\,;\; h_{r,l} \equiv \frac{dh_r}{dl} \gtrless 0 \;\text{ if } \varepsilon \gtrless 1,$$

$$h_x = h_x(l)\,;\; h_{x,l} \equiv \frac{dh_x}{dl} \lessgtr 0 \;\text{ if } \varepsilon \gtrless 1.$$

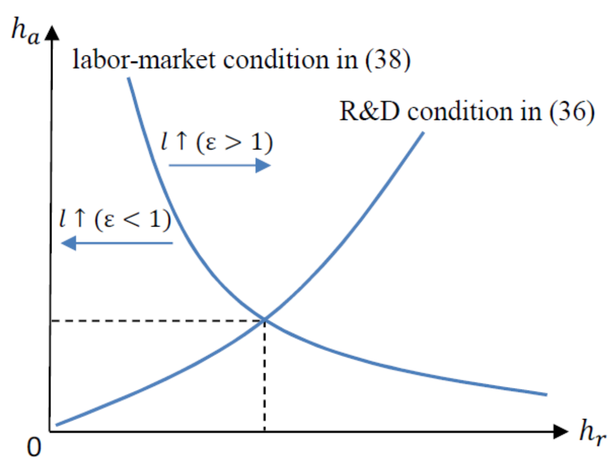

Figure 2: Comparative statics

Therefore, if the elasticity of substitution between low-skilled workers and high-skilled workers in production is less than unity (i.e., $\varepsilon < 1$), then we obtain

$$\underbrace{\frac{dh_x}{dl}}_{+}\underbrace{\frac{dl}{d\gamma}}_{-} < 0, \quad \underbrace{\frac{dh_a}{dl}}_{-}\underbrace{\frac{dl}{d\gamma}}_{-} > 0, \quad \underbrace{\frac{dh_r}{dl}}_{-}\underbrace{\frac{dl}{d\gamma}}_{-} > 0. \tag{45}$$

In other words, the decrease in low-skilled production workers l (due to the higher minimum wage) leads to a decrease in high-skilled production workers h_x given the gross complementarity between the two types of workers. As a result, the amount of high-skilled workers for automation h_a and R&D h_r increases.

If the elasticity of substitution between low-skilled workers and high-skilled workers in production is greater than unity (i.e., $\varepsilon > 1$), then we obtain

$$\underbrace{\frac{dh_x}{dl}}_{-}\underbrace{\frac{dl}{d\gamma}}_{-} > 0, \quad \underbrace{\frac{dh_a}{dl}}_{+}\underbrace{\frac{dl}{d\gamma}}_{-} < 0, \quad \underbrace{\frac{dh_r}{dl}}_{+}\underbrace{\frac{dl}{d\gamma}}_{-} < 0. \tag{46}$$

In this case, the opposite effects prevail that the decrease in low-skilled production workers l (due to the higher minimum wage) leads to an increase in high-skilled production workers h_x given the gross substitutability between the two types of workers. As a result, the amount of high-skilled workers for automation h_a and R&D h_r decreases.

Finally, we explore the effects of minimum wage on economic growth. The steady-state equilibrium growth rate of aggregate technology Z_t is

$$g_z(\gamma) = \lambda(\gamma) \ln z = [h_r(\gamma)]^\eta \varphi \ln z. \tag{47}$$

Given that y_t and k_t grow at the same rate on the balanced growth path, the aggregate production function in (27) implies that the steady-state equilibrium growth rate of output y_t is also

$$g_y(\gamma) = g_z(\gamma) = [h_r(\gamma)]^\eta \varphi \ln z. \tag{48}$$

Therefore, whether the equilibrium growth rate is increasing or decreasing in the minimum wage also depends on the elasticity of substitution between low-skilled workers and high-skilled workers in production. We summarize all the above results in Proposition 1.

Proposition 1 *An increase in the minimum wage has the following effects: (a) a negative effect on the employment of low-skilled workers; (b) a positive effect on the unemployment rate; (c) a negative effect on high-skilled production workers and a positive effect on automation, R&D and economic growth if the elasticity of substitution between low-skilled workers and high-skilled workers in production is less than unity; and (d) a positive effect on high-skilled production workers and a negative effect on automation, R&D and economic growth if the elasticity of substitution between low-skilled workers and high-skilled workers in production is greater than unity.*

Proof. See Appendix A. ■

3.1 Quantitative analysis

In this section, we provide a quantitative illustration by simulating the effects of the minimum wage on the macroeconomy. The model could feature scale effects as in Aghion and Howitt (1992). We sidestep this issue by normalizing high-skilled labor H to unity. Then, the model features the following structural parameters $\{\varepsilon, \rho, \mu, \eta, \delta, \beta, z, \varphi, \phi, A, L\}$ and a policy variable γ. We assign their parameter values as follows.

We consider two values for the substitution elasticity $\varepsilon \in \{0.5, 1.5\}$ that is within the range of empirical estimates reported in Katz and Autor (1999).[12] Given that the estimates in Katz and Autor (1999) are based on US data, we also consider US data when constructing other moments for the calibration. We set the discount rate ρ to 0.05 and the markup ratio μ to 1.05. We follow Jones and Williams (2000) to set the intratemporal duplication externality parameter η to 0.5. As for the capital depreciation rate δ, we calibrate its value using an investment-capital ratio of 0.0768 in the US. We set the distribution parameter β between high-skilled and low-skilled workers to 0.634, which corresponds to a value of 0.366 for the intensity of low-skilled labor in Ben-Gad (2008). We calibrate the quality step size z using a long-run technology growth rate of 0.0125 in the US. We calibrate the R&D productivity parameter φ using an innovation arrival rate of one-third as in Acemoglu and Akcigit (2012). We calibrate the automation productivity parameter ϕ using a labor-income share of 0.56 in the US; see Karabarbounis and Neiman (2014). For the parameter A, we choose a value that satisfies the condition for the automation-innovation cycle in Lemma 1. We calibrate the low-skilled members L using the unemployment rate of 0.06 in the US. Finally, we calibrate the value of γ using the skill premium $w_{h,t}/\overline{w}_{l,t} = 1.974$ in 2008 in the US; see Acemoglu and Autor (2011). Based on the calibrated values of γ, we then compute the implied values for minimum wage as a ratio of GDP per capita, which range from 0.428 to 0.437.[13] These values are in line with minimum wage as a ratio of GDP per capita in the US, which has an average value of 0.419 from 1960 to 2019. We summarize all the parameter values in Table 1.

Table 1: Calibration

ε	ρ	μ	η	δ	β	z	φ	ϕ	A	L	γ
0.500	0.050	1.050	0.500	0.064	0.634	1.039	1.312	1.129	0.136	1.080	0.764
1.500	0.050	1.050	0.500	0.064	0.634	1.039	1.284	1.105	0.136	1.216	0.780

In the rest of this section, we simulate the effects of the minimum wage γ on the output growth rate g_y, the unemployment rate u, labor allocations $\{h_r, h_a, h_x, l\}$, the share θ of automated industries and the steady-state level of social welfare U.[14] Figure 3 simulates the effects of the minimum wage γ when the elasticity of substitution between low-skilled workers and high-skilled workers in production is 0.5 (i.e., $\varepsilon < 1$). In this case, Figure 3a and 3b show that raising the minimum wage γ has a positive effect on the growth rate of output and the unemployment rate. Quantitatively, we find that a 10% increase in the minimum wage increases the growth rate of output by 0.01 percentage points and the unemployment rate by 2.63 percentage points. The increase in the unemployment rate is due to the decrease in low-skilled production labor as shown in Figure 3f. A 10% increase in the minimum wage decreases the employment of low-skilled labor by 5.72 percents, which is within the range of estimates reported in Neumark (2018). As for the positive effect on economic growth, it

[12] The substitution elasticity ε is more likely to be greater than unity according to recent estimates, see for example Ben-Gad (2008) and Acemoglu and Autor (2011); however, $\varepsilon < 1$ is still possible empirically.

[13] Data sources: OECD Statistics and Federal Reserve Economic Data.

[14] See Appendix C for the derivation of the steady-state level of social welfare.

is due to the positive effect of γ on innovation labor in Figure 3c, which in turn is due to the negative effect of γ on high-skilled production labor in Figure 3e. The quantitatively small effect of minimum wage on economic growth is consistent with the empirical evidence discussed in Sabia (2015).

Figure 3d shows that raising γ also has a positive effect on automation labor, which in turn leads to the positive effect on the share of automated industries in Figure 3g. Finally, Figure 3h shows that raising the minimum wage γ has a negative effect on social welfare,[15] which is mainly driven by the decrease in the level of output as a result of the reduction in low-skilled production labor despite the increase in the growth rate.

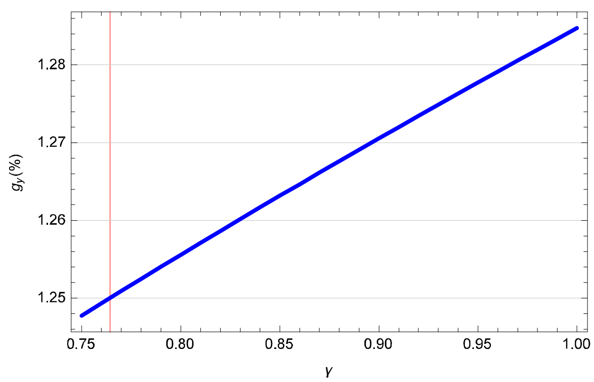

Figure 3a: Effect of γ on g_y ($\varepsilon = 0.5$)

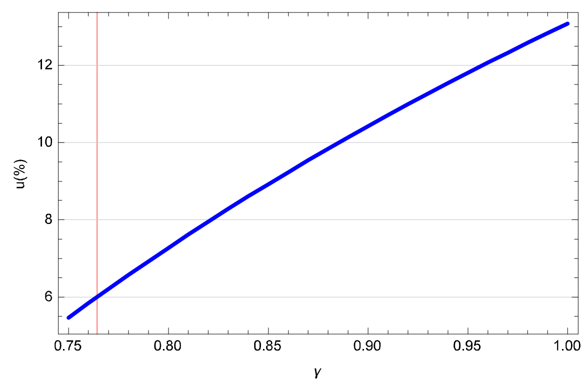

Figure 3b: Effect of γ on u ($\varepsilon = 0.5$)

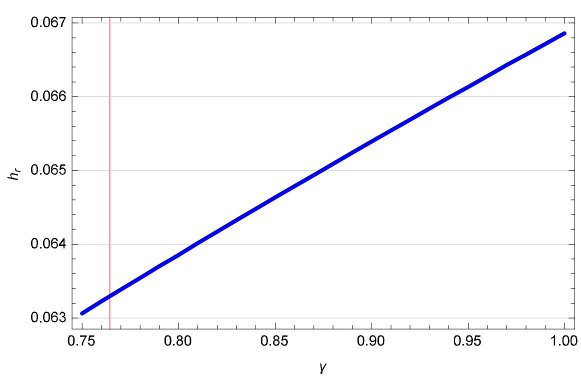

Figure 3c: Effect of γ on h_r ($\varepsilon = 0.5$)

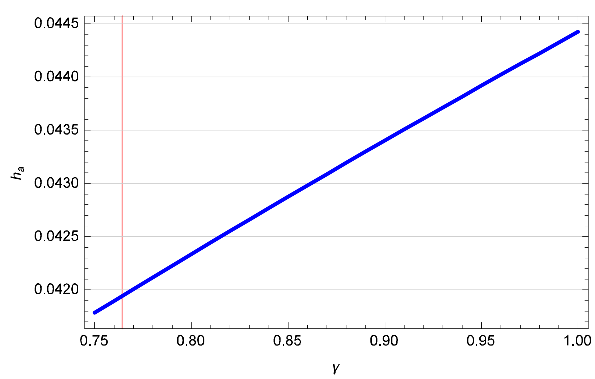

Figure 3d: Effect of γ on h_a ($\varepsilon = 0.5$)

[15] The welfare changes are expressed in the usual equivalent variation in consumption.

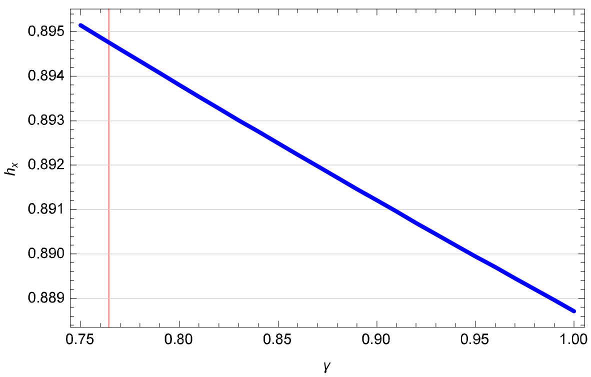

Figure 3e: Effect of γ on h_x ($\varepsilon = 0.5$)

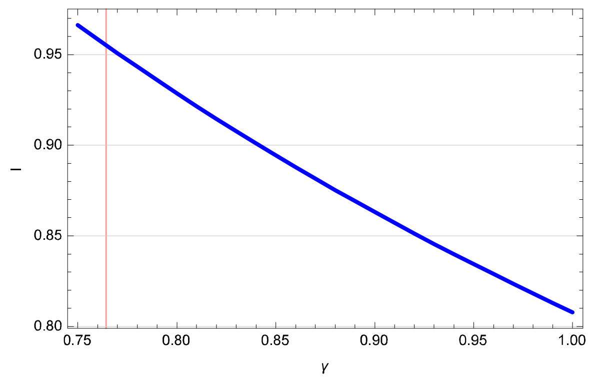

Figure 3f: Effect of γ on l ($\varepsilon = 0.5$)

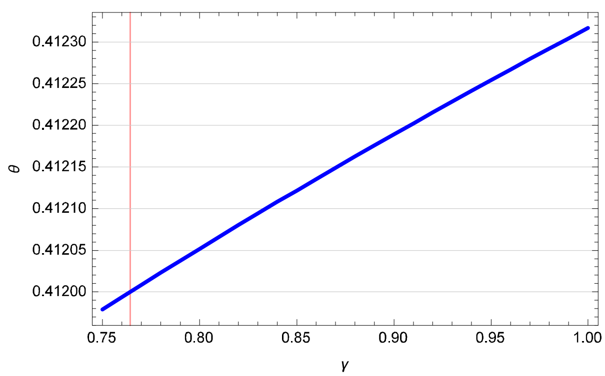

Figure 3g: Effect of γ on θ ($\varepsilon = 0.5$)

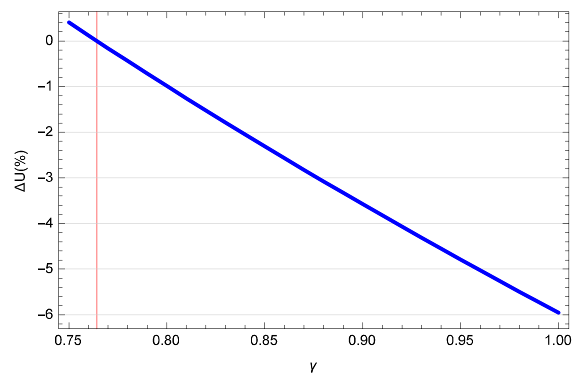

Figure 3h: Effect of γ on U ($\varepsilon = 0.5$)

Figure 4 simulates the effects of the minimum wage γ when the elasticity of substitution between low-skilled workers and high-skilled workers in production is 1.5 (i.e., $\varepsilon > 1$). In this case, Figure 4a and 4b show that raising the minimum wage γ continues to have a positive effect on the unemployment rate but now a negative effect on the growth rate of output. Quantitatively, we find that a 10% increase in the minimum wage decreases the growth rate of output by 0.01 percentage points and increases the unemployment rate by 5.56 percentage points, which shows that the effect of minimum wage on unemployment is increasing in the elasticity ε of substitution between low-skilled and high-skilled workers. As before, the increase in the unemployment rate is due to the decrease in low-skilled production labor as shown in Figure 4f. As for the negative effect on economic growth, it is due to the negative effect of γ on innovation labor in Figure 4c, which in turn is due to the now positive effect of γ on high-skilled production labor in Figure 4e. Figure 4d shows that raising γ has a negative effect on automation labor, which in turn leads to the negative effect on the share of automated industries in Figure 4g. Finally, Figure 4h shows that raising the minimum wage γ continues to have a negative effect on social welfare, which is now driven by the decrease in the growth rate of output in addition to the decrease in the level of output (as a result of the reduction in low-skilled production labor).

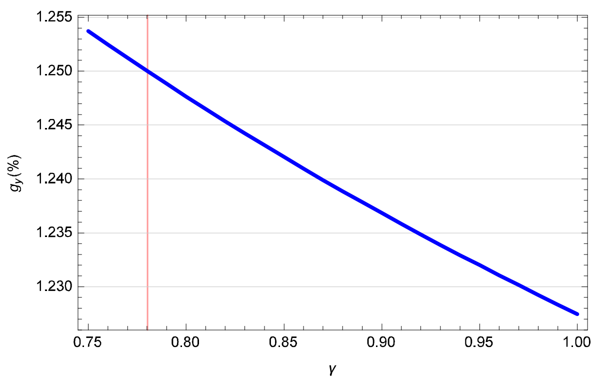

Figure 4a: Effect of γ on g_y ($\varepsilon = 1.5$)

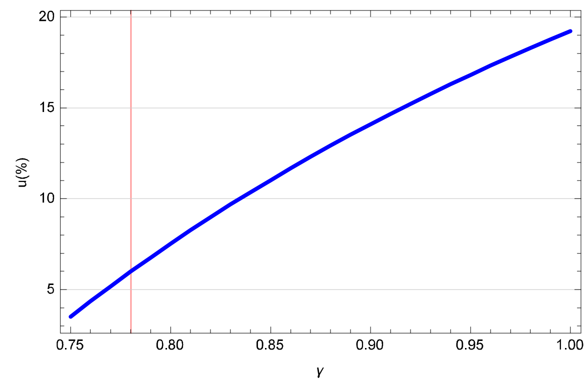

Figure 4b: Effect of γ on u ($\varepsilon = 1.5$)

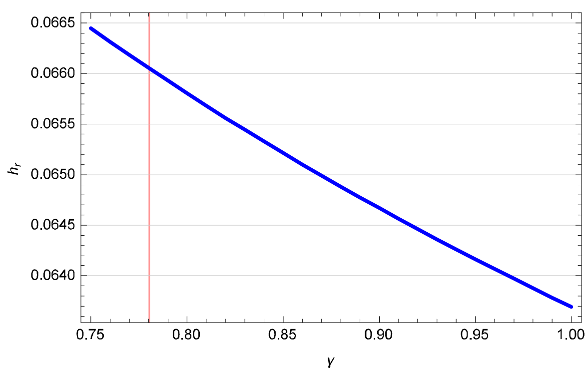

Figure 4c: Effect of γ on h_r ($\varepsilon = 1.5$)

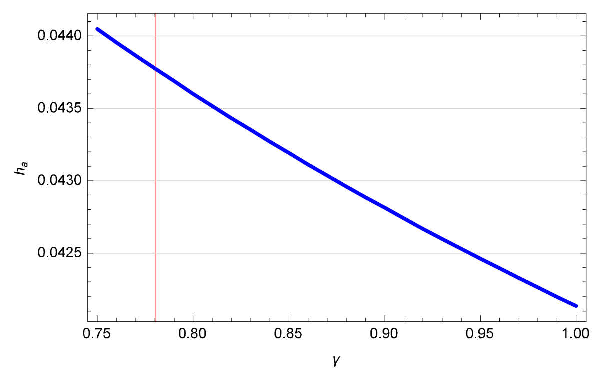

Figure 4d: Effect of γ on h_a ($\varepsilon = 1.5$)

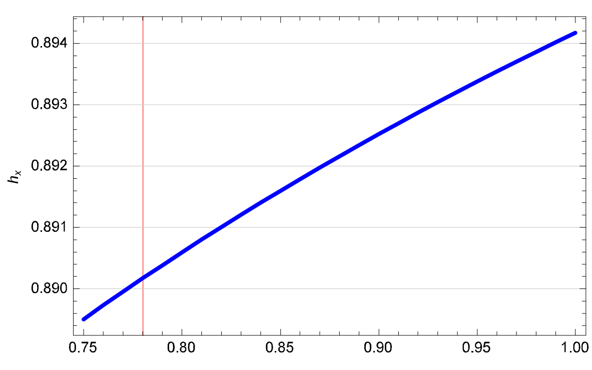

Figure 4e: Effect of γ on h_x ($\varepsilon = 1.5$)

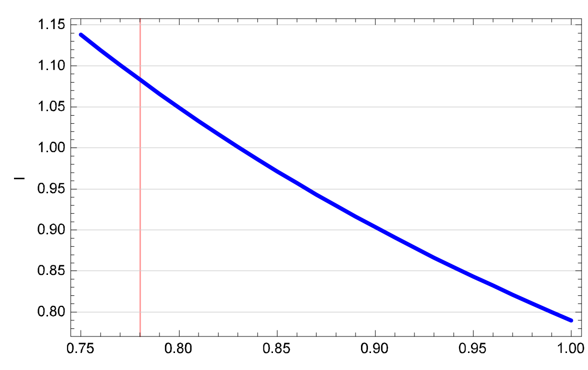

Figure 4f: Effect of γ on l ($\varepsilon = 1.5$)

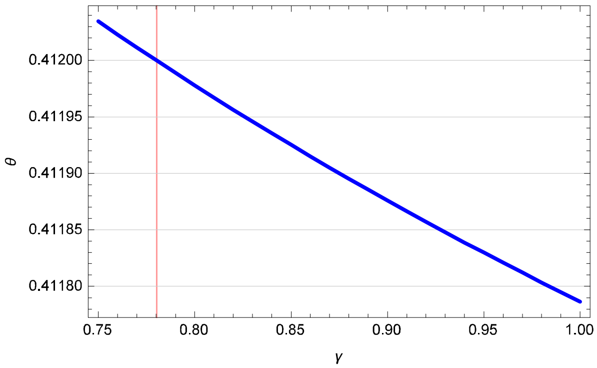

Figure 4g: Effect of γ on θ ($\varepsilon = 1.5$)

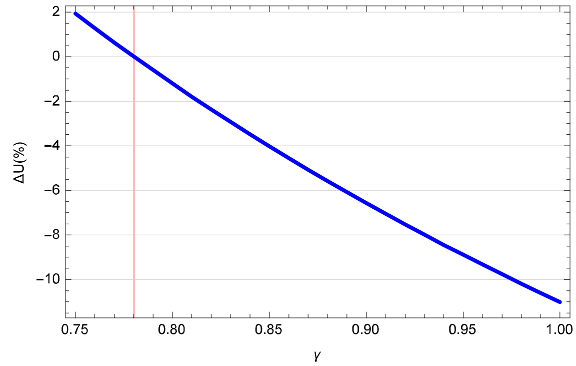

Figure 4h: Effect of γ on U ($\varepsilon = 1.5$)

4 Empirical evidence

In this section, we provide an empirical test of the theoretical results by exploring the effects of minimum wage on innovation and automation using Chinese firm-level patent application data.[16] We first estimate the elasticity of substitution between high-skilled and low-skilled workers in China using the China Economic Census Data in 2004. Specifically, we define workers with up to lower secondary education as low-skilled workers and workers with upper secondary education or above as high-skilled workers.[17] Fang and Lin (2014) show that the average wage of workers with education up to lower secondary education is close to the minimum wage in China.[18] Therefore, we take the local minimum wage as a proxy for the wage rate of low-skilled workers. Then, we use the average wage rate of other workers as a proxy for the wage rate of high-skilled workers.

Combining (7) and (8), we derive the relative wage as a function of the relative employment of production workers. Then, we take log and adopt the following estimation equation to estimate the elasticity of substitution as $\varepsilon = -1/\zeta_1$:

$$\ln(w_h/w_l)_i = \zeta_0 + \zeta_1 \ln(h/l)_i + \epsilon_i,$$

where $(w_h/w_l)_i$ and $(h/l)_i$ represent the relative wage and the relative employment between high-skilled and low-skilled workers employed by firm i, respectively. Table D1 in Appendix D provides the estimation results. In column 1, we directly regress relative wage on relative labor. Then, we further control for industry fixed effects, ownership-type fixed effects and city fixed effects from columns 2 to 4. The estimated elasticity of substitution given by

[16]See Appendix D for the description of all the data used in the empirical analysis.

[17]Chen and Hamori (2009) and Ge and Yang (2014) document positive effects of education on individuals' income in China.

[18]Fang and Lin (2014) compute wages by education using the Urban Household Survey, whereas we use the firm-level China Economic Census, which does not contain data on wages by the levels of education.

$-1/\zeta_1$ is 3.18, which implies that low-skilled and high-skilled workers are gross substitutes.[19] We further estimate the elasticity of substitution in each sector, and the estimated values of the elasticity are within the range of $[2.49, 5.63]$. This is consistent with estimates in the literature; see for example Ben-Gad (2008) and Acemoglu and Autor (2011).[20]

Given that the elasticity of substitution between high-skilled and low-skilled workers is larger than unity in China, our theory predicts that an increase in the minimum wage leads to negative effects on innovation and automation. In order to test the impacts of minimum wage on innovation and automation, we make use of three other databases in China: (1) annual firm-level manufacturing survey data from the National Bureau of Statistics of China (NBSC), (2) firm-level patent application from China National Intellectual Property Administration (CNIPA), and (3) city-level minimum wage and economic data. City-level minimum wages are collected from local government websites, and city-level economic data come from China City Statistical Yearbook (CCSY).[21] We use the total number of patent applications or the number of invention patent applications as a proxy for firm-level innovation and the number of automation-related patent applications as a proxy for firm-level automation invention.

We examine our story using the following empirical specification:

$$patent_{it} = \vartheta \min\_wage_{c,t-1} + \varsigma_1 X_{i,t-1} + \varsigma_2 \chi_{c,t-1} + \kappa_i + \kappa_t + \bar{\epsilon}_{it}.$$

$patent_{it}$ is the log value of the number of patent applications by firm i in year t.[22] $\min\_wage_{c,t-1}$ is the log value of monthly minimum wage in city c in year $t-1$.[23] $X_{i,t-1}$ is a vector of firm-level control variables in year $t-1$, whereas $\chi_{c,t-1}$ is a vector of city-level control variables in year $t-1$. Firm-level control variables $X_{i,t-1}$ include the log of firm-level total asset and the firm-level factor intensity measured by the capital-labor ratio. City-level control variables $\chi_{c,t-1}$ include the log of GDP per capita and the log of population. κ_i denotes firm fixed effects, whereas κ_t denotes year fixed effects. The standard errors $\bar{\epsilon}_{it}$ are clustered at city level. With firm fixed effects, the coefficient ϑ on $\min\_wage_{c,t-1}$ captures the difference in patent applications within firms.[24] Our sample period is from 2000 to 2013, and we have

[19] Alternatively, we have used macro-level data from the CEIC Database to estimate the elasticity of substitution in China. Following Acemoglu (2002), we add a time trend for the annual time-series data. Wage and labor in high-tech sectors (other sectors) are used to proxy the wage rate and the number of high-skill (low-skill) workers given that workers in high-tech sectors are largely more educated; see Ciccone and Giovanni (2005). The estimated value of $-1/\zeta_1$ is also significantly larger than one.

[20] Few studies focus on the Chinese labor market, but several studies have shed light on other developing countries, with the estimated values larger than one. For example, Psacharopoulos and Hinchliffe (1972) provide an estimated range from 2.1 to 2.5 for 9 developing coutries, Angrist (1995) finds a value of $\varepsilon = 2$ for the Palestinian labor market, and Behar (2009) finds an elasticity of about 2 for 43 developing countries.

[21] Fan *et al.* (2018) provide an empirical study on the effects of minimum wage on firm-level FDI in China; see their paper for a discussion on the institutional background of minimum wages in China.

[22] The average time for patents to be granted from the patent office is about 2-3 years in China. Hence, we use patent applications instead of granted patents to reflect the output of innovation. Moreover, because patent applications reflecting the output of innovation are still subject to delay, we use one-year lagged minimum wage as the explanatory variable. Given that some firms have zero patent applications in certain years, we add one to the number of patent applications.

[23] If we use the minimum wage in year t, the results still hold.

[24] If we use the city fixed effects instead of the firm fixed effects, our results still hold with a similar mangitude of estimated coefficients on minimum wage.

2,243,093 observations of Chinese manufacturing firms after data cleaning. Table D2 and D3 in Appendix D provide their summary statistics and description. ϑ captures the effects of minimum wage on firms' patent applications. According to our theoretical results, we should expect $\vartheta < 0$ given that the elasticity of substitution is larger than unity in China.

Table 2: Minimum wage on innovation

	All Patents		Invention Patents	
	(1)	(2)	(3)	(4)
min_wage	-0.08715***	-0.10516***	-0.03260***	-0.04423***
	(0.01971)	(0.01964)	(0.01125)	(0.01113)
Firm-level Controls	No	Yes	No	Yes
City-level Controls	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2357656	2357656	2357656	2357656
Adj R-Squared	0.444	0.446	0.425	0.427

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic after adding 1. Firm-level controls include the log of asset and firm-level factor intensity (capital-labor ratio). City-level controls include the log of per capita city GDP and the log of city population.

First, we examine the impact of minimum wage on innovation, using the total number of patent applications at the firm level. As expected, columns (1) and (2) in Table 2 show that minimum wage is negatively and significantly associated with firms' patent applications. This implies that an increase in minimum wage decreases patent applications at the firm level. Given that patents are classified into three categories,[25] among which invention patents are most relevant for innovation, we further test our theory upon replacing the dependent variable in columns (1) and (2) by the number of invention patents. In columns (3) and (4), we focus on the number of invention patent applications. The significantly negative coefficients of $\min\_wage_{c,t-1}$ in columns (3) and (4) support our theoretical result that an increase in minimum wage has a negative effect on innovation when the elasticity of substitution between low-skilled workers and high-skilled workers is greater than unity. According to the estimated coefficients in columns 2 and 4 of Table 2, a 10% increase in minimum wage would reduce patent applications by approximately 8.3% and 8.9% for an average firm, respectively.[26]

We now examine the effect of minimum wage on automation. Based on the application description, a patent would be taken as automation-related if its application description includes the word "automation". We could then measure the number of automation-related patent applications at the firm level. The corresponding results are shown in columns (1) and (2) of Table 3. In this case, the coefficients of $\min\_wage_{c,t-1}$ remain negative and significant. To further test our story, we assume that a patent relates to automation if the application

[25] These three categories are invention, utility model, and design.

[26] We multiply the estimated coefficients by 10 percentage and then divide the average value of patent applications. The average values of patent applications are 0.126 and 0.049 for columns 2 and 4, respectively.

Table 3: Minimum wage on automation

	Automation		Automation and Robot	
	(1)	(2)	(3)	(4)
min_wage	-0.00037**	-0.00043**	-0.00053*	-0.00059**
	(0.00017)	(0.00017)	(0.00031)	(0.00028)
Firm-level Controls	No	Yes	No	Yes
City-level Controls	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2357656	2357656	2357656	2357656
Adj R-Squared	0.163	0.163	0.178	0.178

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses. All dependent variables are logarithmic after adding 1. Firm-level controls include the log of asset and the firm-level factor intensity (capital-labor ratio). City-level controls include the log of per capita city GDP and the log of city population.

description includes the words "automation" or "robot". The corresponding results are reported in columns (3) and (4), in which the negative and significant coefficients continue to support our following theoretical result: when the elasticity of substitution between low-skilled workers and high-skilled workers is greater than unity, an increase in the minimum wage has a negative effect on automation.[27] According to the coefficient estimates in columns 2 and 4 of Table 3, a 10% increase in minimum wage would reduce automation-related patent applications by approximately 13.9% and 28.8% for an average firm, respectively.[28] Hence, the impact of minimum wage on automation is economically significant although their estimated coefficients are relatively small.

5 Conclusion

This study explored the effects of the minimum wage in a Schumpeterian growth model with automation. We find that raising the minimum wage has an ambiguous impact on innovation and automation, which crucially depends on substitution elasticity between low-skilled workers and high-skilled workers in the production process. In an economy in which the two types of workers are gross substitutes (complements), raising the minimum wage would have a negative (positive) effect on innovation and automation. Therefore, the substitution

[27] This decrease in automation invention does not mean that firms use less capital. Instead, we find that minimum wage has a positive and significant effect on the capital-output ratio of firms. Simulating our model, we also find that when the elasticity of substitution between low-skill and high-skill workers is greater than unity, a higher minimum wage increases the capital-output ratio $k/y = \theta/[\mu(g_y + \rho + \delta)]$, in which the negative effect on g_y dominates the negative effect on θ. Results are available upon request.

[28] The average values of automation-related patent applications are 0.0003 and 0.0002 for columns 2 and 4, respectively.

elasticity between low-skilled and high-skilled workers is an essential factor that empirical studies should consider when evaluating the minimum-wage impact on innovation and automation. We test our theoretical results by estimating the elasticity of substitution between low-skilled workers and high-skilled workers and the effects of minimum wage on automation and innovation in China. We find that the substitution elasticity between low-skilled workers and high-skilled workers in China is larger than unity, with consequent adverse effects of minimum wage hikes on both invention and automation. Therefore the 14th five-year plan of 2021-2025 may face challenges when incentivizing innovation while rebalancing the inequalities.

In the US economy, a higher than unitary elasticity also seems likely, as suggested by recent empirical analyses. Hence, as in our calibration section's second scenario, the Biden administration's proposed increase in the minimum wage would likely replace unskilled with skilled workers in production. The resulting research laboratories personnel cuts would then generate less innovation and less automation.

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Appendix A: Proofs

Proof of Lemma 1. Using the no-arbitrage condition $r = R - \delta$ and the Euler equation $r = g_y + \rho$, we can reexpress the equilibrium condition that supports a cycle of automation and innovation as

$$\frac{1}{z} < \frac{Z}{A}\left(\frac{g_y + \rho + \delta}{\psi}\right) < 1. \tag{A1}$$

We substitute (5), (6), (11) and (27) into (A1) to derive

$$\frac{1}{z} < \left(\frac{1}{A}\right)^{\frac{1}{1-\theta}}\left(\frac{\theta y}{k}\right)^{\frac{\theta}{1-\theta}}\left[\mu\left(g_y + \rho + \delta\right)\right] < 1. \tag{A2}$$

From capital income $Rk = \theta y/\mu$, the steady-state capital-output ratio is given by

$$\frac{k}{y} = \frac{\theta}{\mu R} = \frac{\theta}{\mu\left(r + \delta\right)} = \frac{\theta}{\mu\left(g_y + \rho + \delta\right)}. \tag{A3}$$

Substituting (A3) into (A2) yields the steady-state equilibrium condition for the automation-innovation cycle. ■

Proof of Lemma 2. From (36), it is easy to verify that there is a positive relationship between h_a and h_r if $\eta \leq 1/2$. Moreover, we reexpress (41) as

$$l\left(h_x\right) = l\left(H - h_a - h_r\right), \tag{A4}$$

where

$$l_{h_x} \equiv \frac{dl}{dh_x} = -\frac{\left[\beta\left(\varepsilon - 1\right)/\varepsilon\right]\left[\left(H - h_a - h_r\right)l\right]^{\frac{-1}{\varepsilon}}}{\left(1-\beta\right)l^{\frac{-2}{\varepsilon}} + \left(\beta/\varepsilon\right)\left(H - h_a - h_r\right)^{\frac{\varepsilon-1}{\varepsilon}}l^{\frac{-(1+\varepsilon)}{\varepsilon}}}. \tag{A5}$$

Equation (A5) shows that l is monotonically decreasing (increasing) in h_x if $\varepsilon > 1 (< 1)$. We make use of (42) and (A5) to derive

$$\frac{dh_a}{dh_r} = -\frac{\left[\left(1-\beta\right)\left(H - h_a - h_r\right)^{\frac{1}{\varepsilon}}l^{\frac{\varepsilon-1}{\varepsilon}} + \beta\left(H - h_a - h_r\right)\right]\eta\varphi h_r^{\eta-1} + \Phi\left(\rho + \varphi h_r^{\eta}\right)}{\left(\rho + \varphi h_r^{\eta}\right)\left\{\left[\left(1-\beta\right)\left(H - h_a - h_r\right)^{\frac{1}{\varepsilon}}l^{\frac{\varepsilon-1}{\varepsilon}} + \beta\left(H - h_a - h_r\right)\right]\left(1-\eta\right)/h_a + \Phi\right\}}, \tag{A6}$$

where

$$\Phi \equiv \frac{\left[\left(1-\beta\right)/\varepsilon\right]\left(H - h_a - h_r\right)^{\frac{1-\varepsilon}{\varepsilon}}l^{\frac{\varepsilon-1}{\varepsilon}}\Delta}{\left(1-\beta\right)l^{\frac{-2}{\varepsilon}} + \left(\beta/\varepsilon\right)\left(H - h_a - h_r\right)^{\frac{\varepsilon-1}{\varepsilon}}l^{\frac{-(1+\varepsilon)}{\varepsilon}}} + \beta, \tag{A7}$$

$$\Delta \equiv \left(1-\beta\right)l^{\frac{-2}{\varepsilon}} + \frac{\beta}{\varepsilon}\left(H - h_a - h_r\right)^{\frac{\varepsilon-1}{\varepsilon}}l^{\frac{-(1+\varepsilon)}{\varepsilon}}\left[1 - \left(\varepsilon - 1\right)^2\right]. \tag{A8}$$

Equations (A7) and (A8) show $\Phi > 0$ and $\Delta \geq 0$ if $\varepsilon \leq 2$. Therefore, (42) features a negative relationship between h_a and h_r if $\varepsilon \leq 2$. Based on (36) and (42), we obtain that the equilibrium allocation $\{h_r, h_a\}$ is unique. From (A5), we know that l is monotonically decreasing in h_x or increasing in h_x. Using this condition and $h_x = H - h_a - h_r$, we obtain that the equilibrium allocation $\{h_x, l\}$ is also unique. ■

Proof of Proposition 1. We make use of (36), (38) and $h_x = H - h_a - h_r$ to derive

$$h_{a,l} \equiv \frac{dh_a}{dl} = \left(\frac{\Omega}{\Theta}\right) \frac{(\varepsilon - 1)(1-\beta)}{\varepsilon (l/h_x)^{1/\varepsilon}}, \tag{A9}$$

$$h_{r,l} \equiv \frac{dh_r}{dl} = \left(\frac{\Pi}{\Theta}\right) \frac{(\varepsilon - 1)(1-\beta)}{\varepsilon (l/h_x)^{1/\varepsilon}}, \tag{A10}$$

$$h_{x,l} \equiv \frac{dh_x}{dl} = -\left(\frac{dh_a}{dl} + \frac{dh_r}{dl}\right), \tag{A11}$$

where

$$\Omega \equiv \left[\frac{\eta}{h_r} + \frac{1-\eta}{h_a} + \frac{1-2\eta}{h_a}\left(\frac{h_a}{h_r}\right)^{\eta} \frac{\phi h_r^{\eta}}{\varphi h_r^{\eta} + \rho} + \left(\frac{h_r}{h_a}\right)^{1-\eta} \frac{\rho\eta\phi h_r^{\eta-1}}{(\varphi h_r^{\eta} + \rho)^2}\right] > 0,$$

$$\Pi \equiv \left(\frac{h_r}{h_a}\right)\left[\frac{\eta}{h_r} + \frac{1-\eta}{h_a} + \frac{1-2\eta}{h_a}\left(\frac{h_a}{h_r}\right)^{\eta} \frac{\phi h_r^{\eta}}{\varphi h_r^{\eta} + \rho}\right] > 0,$$

$$\Theta \equiv \left[(1-\beta) h_x^{\frac{1}{\varepsilon}} l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x\right]\left[\frac{\eta\varphi h_r^{\eta-1}\Pi}{\rho + \varphi h_r^{\eta}} + \frac{(1-\eta)\Omega}{h_a}\right] + (\Pi + \Omega)\left[\frac{1-\beta}{\varepsilon}\left(\frac{h_x}{l}\right)^{\frac{1-\varepsilon}{\varepsilon}} + \beta\right] > 0.$$

It is helpful to note that we set $\eta \leq 1/2$ and $\varepsilon \leq 2$ so that the steady-state equilibrium allocation $\{h_r, h_a, h_x, l\}$ is unique. Equations (A9) and (A10) show that both h_a and h_r are increasing (decreasing) in l if $\varepsilon > 1 (< 1)$. Given this result, it is easy to verify that there is a negative (positive) relationship between h_x and l if $\varepsilon > 1 (< 1)$. Based on (40), we take the differentials of l with respect to γ to obtain

$$\frac{dl}{d\gamma} = -\frac{\left[(1-\beta) l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x^{\frac{\varepsilon-1}{\varepsilon}}\right]^2}{(1-\beta)(H+L)\left\{(1-\beta) l^{\frac{-2}{\varepsilon}} + (\beta/\varepsilon) h_x^{\frac{\varepsilon-1}{\varepsilon}} l^{\frac{-(1+\varepsilon)}{\varepsilon}} \underbrace{[1 + (\varepsilon - 1)(l/h_x) h_{x,l}]}_{\equiv \Lambda}\right\}}. \tag{A12}$$

We substitute (A11) into Λ and then use the sufficient conditions of the unique equilibrium (i.e., $\eta \leq 1/2$ and $\varepsilon \leq 2$) to obtain

$$\Theta\Lambda = \left[(1-\beta) h_x^{\frac{1}{\varepsilon}} l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x\right]\left[\frac{\eta\varphi h_r^{\eta-1}\Pi}{\rho + \varphi h_r^{\eta}} + \frac{(1-\eta)\Omega}{h_a}\right] + (\Pi + \Omega)\left\{\beta + \frac{1-\beta}{\varepsilon}\left(\frac{h_x}{l}\right)^{\frac{1-\varepsilon}{\varepsilon}}\left[1 - (\varepsilon - 1)^2\right]\right\} > 0.$$

As a result, (A12) shows that there is a negative relationship between l and γ. Given this result, we make use of (44) to derive that there is a positive relationship between u and γ. Combining (A12) and (A9)-(A11), we obtain that both h_a and h_r are decreasing (increasing) in γ if $\varepsilon > 1 (\varepsilon < 1)$ and h_x is increasing (decreasing) in γ if $\varepsilon > 1 (\varepsilon < 1)$. Finally, we use (48) to obtain that g is decreasing (increasing) in γ if $\varepsilon > 1 (\varepsilon < 1)$. ∎

Appendix B: The capital-accumulation equation

Using (2) and $\tau_t = b_t (L - l_t)$, we obtain

$$\dot{a}_t + \dot{k}_t = r_t a_t + (R_t - \delta) k_t + \overline{w}_{l,t} l_t + w_{h,t} H - c_t. \tag{B1}$$

Given $a_t = \theta_t v_t^k + (1 - \theta_t) v_t^l$, we derive $\dot{a}_t = \theta_t \dot{v}_t^k + v_t^k \dot{\theta}_t + (1 - \theta_t) \dot{v}_t^l - v_t^l \dot{\theta}_t$. Substituting (28) into this condition, we obtain

$$\dot{a}_t = \theta_t \dot{v}_t^k + v_t^k [\alpha_t (1 - \theta_t) - \lambda_t \theta_t] + (1 - \theta_t) \dot{v}_t^l - v_t^l [\alpha_t (1 - \theta_t) - \lambda_t \theta_t]. \tag{B2}$$

Substituting (B2) and $a_t = \theta_t v_t^k + (1 - \theta_t) v_t^l$ into (B1), we obtain

$$\begin{aligned} & \theta_t \dot{v}_t^k + v_t^k [\alpha_t (1 - \theta_t) - \lambda_t \theta_t] + (1 - \theta_t) \dot{v}_t^l - v_t^l [\alpha_t (1 - \theta_t) - \lambda_t \theta_t] + \dot{k}_t \\ = \ & r_t \left[\theta_t v_t^k + (1 - \theta_t) v_t^l \right] + (R_t - \delta) k_t + \overline{w}_{l,t} l_t + w_{h,t} H - c_t. \end{aligned} \tag{B3}$$

Using (18) and (19) yields

$$\begin{aligned} \dot{k}_t = & -\alpha_t (1 - \theta_t) v_t^k + \theta_t \pi_t^k + (1 - \theta_t) \pi_t^l \\ & -\lambda_t v_t^l + R_t k_t - \delta k_t + \overline{w}_{l,t} l_t + w_{h,t} H - c_t. \end{aligned} \tag{B4}$$

Moreover, we make use of (13), (17), (30), (31) and (32) to derive

$$\dot{k}_t = y_t - c_t - \delta k_t - \alpha_t (1 - \theta_t) v_t^k - \lambda_t v_t^l + w_{h,t} h_{a,t} + w_{h,t} h_{r,t}. \tag{B5}$$

Substituting (21) and (23) into (B5), we obtain

$$\dot{k}_t = y_t - c_t - \delta k_t. \tag{B6}$$

Appendix C: The welfare function

The steady-state level of social welfare U can be expressed as

$$\rho U = (\ln c_0) + \frac{g_y}{\rho}. \tag{C1}$$

The law of motion capital is $\dot{k}_t = y_t - c_t - \delta k_t$. Using this condition, one can derive the following steady-state consumption-output ratio:

$$\frac{c}{y} = 1 - (g_y + \delta)\frac{k}{y}. \tag{C2}$$

Substituting (C2) into (C1) and using (27), the steady-state level of social welfare U can be re-expressed as

$$\rho U = \ln\left[1 - (g_y + \delta)\frac{k}{y}\right] + \theta \ln A + \theta \ln\left(\frac{k}{\theta}\right) + (1-\theta)\ln\left\{\frac{\left[(1-\beta)\, l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}}{1-\theta}\right\} + \frac{g_y}{\rho}, \tag{C3}$$

where Z_0 is normalized to unity. The steady-state capital-output ratio and the capital-technology ratio are respectively

$$\frac{k}{y} = \frac{\theta}{R\mu} = \frac{\theta}{\mu(r+\delta)} = \frac{\theta}{\mu(g_y + \rho + \delta)}, \tag{C4}$$

$$\frac{k}{Z} = \frac{\theta\left[(1-\beta)\, l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}}{A(1-\theta)}\left(\frac{A}{\theta}\frac{k}{y}\right)^{\frac{1}{1-\theta}}. \tag{C5}$$

Substituting (C4) and (C5) into (C3), we obtain

$$\rho U = \ln\left[1 - (g_y + \delta)\frac{k}{y}\right] + \left(\frac{\theta}{1-\theta}\right)\ln\left(\frac{A}{\theta}\frac{k}{y}\right) + \ln\left\{\frac{\left[(1-\beta)\, l^{\frac{\varepsilon-1}{\varepsilon}} + \beta h_x^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}}{1-\theta}\right\} + \frac{g_y}{\rho}, \tag{C6}$$

where we have used $Z_0 = 1$.

Appendix D: Data

Data Description

This paper employs four sets of data: (1) an annual firm-level manufacturing survey from the National Bureau of Statistics of China (NBSC), (2) firm-level patent applications from China National Intellectual Property Administration (CNIPA), (3) city-level minimum wage and economic data, and (4) firm-level data from China Economic Census in 2004.

The firm-level manufacturing survey provides us with both the basic firm information (e.g., firm name, address, employment, gross output and value added, etc.) and the complete information on the three major accounting statements (i.e., balance sheets, profit and loss accounts, and cash flow statements). Due to the misreporting problem, we follow Cai and Liu (2009) and the General Accepted Accounting Principles to delete the problematic observations.[29]

The second dataset is the patent data from CNIPA, which includes information on each patent application in China since 1985. From this dataset, we can obtain detailed information of the applicant's name, address, patent name, and the patent category. We merge the above two firm-level datasets by firms' name. In the empirical analysis, we use the total number of patent applications or the number of invention patent applications as a proxy for firm-level innovation and use the number of automation-related patent applications as a proxy for firm-level automation invention.

The third dataset is the minimum wage and economic data at the city level. We manually collect the Chinese city-level minimum-wage data from the official websites of the local governments, given there is no uniform data source for the minimum wage data. Other city-level economic data, such as GDP per capita and population size, are obtained from the China City Statistical Yearbook. Based on firms' address information, we then further match the above firm-level data with a city's minimum wage and economic data.

Finally, the last dataset is from China Economic Census in 2004, which provides us with comprehensive information for both the number and the composition of employees in each unit of economic sectors in China. In the subsequent empirical analysis, we mainly use this data to estimate the elasticity of substitution between high- and low-skilled workers.

Other Tables

Table D1 provides the estimated elasticity of substitution. Table D2 and Table D3 provide the summary statistics and the data sources of the key variables in the main regressions in Section 4.

[29]See Brandt, Van Viesebroeck, and Zhang (2012) for more details of processing the mis-reportings.

Table D1: The estimated elasticity of substitution

	(1)	(2)	(3)	(4)
$ln(h/l)$	-0.3175***	-0.3156***	-0.3168***	-0.3140***
	(0.0109)	(0.0098)	(0.0097)	(0.0088)
Industry Fixed Effects	No	Yes	Yes	Yes
Ownership-type Fixed Effects	No	No	Yes	Yes
City Fixed Effects	No	No	No	Yes
Observations	623282	623282	623282	623282
Adj R-Squared	0.192	0.197	0.200	0.349

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are reported in parentheses.

Table D2: Summary statistics of the key variables

Variables	(1) Observations	(2) Mean	(3) Median	(4) Std. Dev.
Dependent Variables				
All Patents	2357656	0.12608	0	0.51164
Invention	2357656	0.04949	0	0.28877
Automation and Robot	2357656	0.00031	0	0.01850
Automation	2357656	0.00020	0	0.01418
Control Variables				
Minimum Wage	2357656	6.43521	6.42972	0.41999
GDP per capita	2357656	10.3791	10.3763	0.91255
Population	2357656	6.25010	6.33378	0.60396
Asset	2357656	10.0591	9.90093	1.44034
Capital/Labor	2357656	3.83813	3.88398	1.37500

Notes: All dependent variables are logarithmic after adding 1. All independent variables and control variables are in year $t-1$.

Table D3: Data sources of the key variables

Variables	(1) Definition	(2) Data source
All Patents	The log of patent applications	CNIPA
Invention	The log of invention patent applications	CNIPA
Automation and Robot	The log of utility-model patent applications	CNIPA
Automation	The log of design patent applications	CNIPA
Min_Wage	The log of monthly minimum wage at city level	Local government websites
Capital/Labor	The log of factor intensity (Capital/Labor)	NBSC
GDP per capita	The log of GDP per capita at city level	CCSY
Population	The log of population at city level	CCSY