RESHORING, AUTOMATION, AND LABOR MARKETS UNDER TRADE UNCERTAINTY

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Abstract. We study the implications of uncertainty in global value chains (GVC) for reshoring (the opposite of offshoring), automation, and U.S. labor markets. Rising GVC uncertainty creates incentive for firms to reduce exposures to foreign suppliers by moving production and distribution processes to domestic suppliers. However, we argue that reshoring does not necessarily bring jobs back to the home country or boost domestic wages, especially when firms have access to labor-substituting technologies such as automation. Automation poses a threat against low-skill workers in wage bargaining, depressing their wages and increasing the skill premium and wage inequality.

I. Introduction

The COVID-19 pandemic has exposed important vulnerabilities in global value chains (GVC). In a recent McKinsey survey, corporate CEOs identified supply chain turmoils as one of the greatest threats to growth for their companies and their countries, along with inflation, pandemics, labor shortages, and geopolitical instability. With the ongoing health risks, climate risks, and geopolitical conflicts, GVC uncertainty is unlikely to abate any time soon. In this new economic environment, moving some production and distribution processes from abroad back to domestic suppliers (i.e., reshoring) may be an attractive option to mitigate the risks of supply chain disruptions.[1]

One possibility is that reshoring might bring jobs to the home country and boost wages for domestic workers, much like the opposite effects of the China shock initially studied by **?**. However, we argue that reshoring may not necessarily increase domestic employment and

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[1]According to a Thomas Industrial Survey, about two-thirds of North American manufactuQs reported they are likely to bring manufacturing production and sourcing back to North America because of concerns about the global supply chain disruptions following the COVID-19 pandemic. In addition, about a quarter of those manufactuQs are considering expanding industrial automation.

wages, especially in the presence of labor-substituting technologies such as automation in frictional labor markets.

In the past three decades, advanced economies that have offshored production processes have also experienced a steady increase in the adoptions of automation technologies such as artificial intelligence, machine learning, and robotics. Automation raises labor productivity (**?**) and also reduces unit labor costs and worker wages (**?**). The increased availability of automation technology has reduced the needs of offshoring. Indeed, import growth has slowed significantly relative to GDP since the trade collapse during the Great Recession. Recent surges in GVC uncertainty may have accelerated the trends in reshoring. Reshoring raises domestic labor demand and, all else being equal, pushes up real wages. However, the option to automate helps mitigate the increase in labor costs because the option to automate production poses a threat against workers—especially to low-skill workers who can be easily substituted by robots—in wage bargaining. This automation threat channel—originally studied by **?**—helps contain the rise in labor costs, reinforcing the incentive for reshoring stemming from GVC uncertainty. Since robots substitute for low-skill workers and complements high-skill workers, increased automation spurred by reshoring also raises the skill wage premium and income inequality.

In this paper, we formalize this logic by developing a macro framework featuring automation, heterogeneous worker skills, and international trade frictions. We use this framework to examine the impacts of a persistent rise in GVC uncertainty on reshoring, automation, and domestic labor markets. We build on the model of **?**, and generalize it to a small open economy with iceberg cost in shipping goods across borders. The model features an automation threat channel through which increased robot adoptions reduce the wages of low-skill workers by diminishing the bargaining power of those workers. As a result, the mere threat of automation, captured by the probability of automation, pushes down wages, making reshoring relatively more attractive. This effect is compounded when firms do actually automate, since the associated productivity boost lowers domestic marginal costs of production further.

Using this framework, we show that, in the presence of automation technologies, a persistent rise in GVC uncertainty results in more reshoring than in an environment where automation is more costly. Reshoring stimulates automation investment and thus raising employment of high-skill labor, which is a complementary input to automation equipment. The effects of increased reshoring on low-skill employment can be ambiguous. Despite being automatable, demand for low-skill workers can rise because the option to automate raises the value of an unfilled position, leading firms to post more vacancies, which translates into higher employment. This job-creating effect offsets the job-displacing impact of automation.

In our small open economy model, a homogeneous final good is produced by using domestic and foreign intermediate goods with a constant elasticity of substitution (CES) technology. In the domestic intermediate goods sector, firms can use two types of technologies, a labor-only technology that uses low-skill workers as the only input, and an automated process that uses both robots and high-skill workers as inputs. Trade is subject to time-varying iceberg costs with stochastic volatility meant to capture GVC uncertainty from geopolitical, climate, and health risks.

Following an increase in GVC uncertainty, firms would have incentive to reshore some previously offshored production to mitigate the risks of supply chain disruptions. If a firm chooses to reshore, it must then make a choice of technology by deciding whether to produce with low-skill labor or to automate this process using a robot and high-skill labor. To use the automation technology, a firm needs to pay a random fixed cost in the beginning of the period. We implement this automation decision by letting the firm automate an unfilled job vacancy carried over from the previous period. We also explore the robustness of our results when firms can automate existing jobs. A vacancy in our model can be interpreted as a continuum bundle of tasks, which are ex ante identical, but a fraction of which can be automated depending on costs of automation. At this stage of the decisions, the tasks can be indexed by the realized automation costs. A task will be automated if and only if the cost of automation lies below a threshold determined by the net benefit of automation, in which case the firm adopts a robot for production and takes the job vacancy offline. The probability of automation is thus the cumulative density of the realized automation costs evaluated at the automation threshold.

We assume that low-skill workers search for jobs in a frictional labor market, subject to the search frictions in the standard Diamond-Mortensen-Pisarides (DMP) framework. Low-skill wages are determined by Nash bargaining between a firm and a worker. Because firms have the option to automate an unfilled position in the future, the threat of automation acts as an outside option for the firm and weighs on bargained wages. Unlike the standard DMP framework, we assume that vacancy creation incurs a random fixed cost (**??**), such that an unfilled vacancy retains value in equilibrium and captures the firms' outside option and ability to automate in the future.

In our model, heightened GVC uncertainty operates through a rich set of channels. First, trade uncertainty has an expenditure switching effect that redirects the demand for intermediate goods toward domestic producers. This effect stimulates the demand for low-skill labor, but it also increases automation and the demand for high-skill workers. A greater use of automated processes has a job-displacing effects on low-skill jobs, but also a job-creation effect by raising the automation probability (i.e., the threat of automation) and

thus boosting the value of unfilled vacancies and vacancy posting. Second, as an offset of the first channel, GVC uncertainty induces greater precautionary savings, reducing demand for domestic goods and blunting the incentive to automate production. The contraction in the domestic economy also reduces demand for foreign intermediate goods and trade. We show that for a large set of parameter values, the expenditure switching effect dominates the precautionary saving effect, such that GVC uncertainty leads to greater automation and international trade in the steady state, while also boosting skilled and unskilled employment.

Our model produces a rich set of empirically testable predictions. First, the model predicts that an increase in GVC uncertainty triggered by, for example, the recent trade war between the United States and China should stimulate automation investment, because the threat of automation helps mitigate the increase in domestic labor costs and thus facilitate reshoring. Second, increased reshoring and automation triggered by GVC uncertainty should depress the low-skill wages relative to high-skill wages, raising the skill wage premium and income inequality. Third, GVC uncertainty can have an ambiguous effect on the volume of international trade: GVC uncertainty can reduce trade by shifting production to domestic suppliers; but it also boosts the incentive to automate production, raising productivity and demand for both domestic and foreign goods. Thus, the net effect of GVC uncertainty on trade can be ambiguous.

We document empirical evidence that supports the model predictions. We measure GVC uncertainty using aggregate trade policy uncertainty (TPU) constructed by **?**, interacted with a measure of initial exposures to offshoring of two-digit NAICS industries. We also use industry-level data on robots, international trade, employment, value added, and wages to construct measures of automation, offshoring, labor productivity, and the skill premium. We show that, controlling for industry and time fixed effects, an increase in GVC uncertainty stimulates automation and reduces offshoring. These effects are statistically significant and economically important. However, other types of uncertainty (such as economic policy uncertainty, or EPU) do not have the same effects on automation and offshoring, suggesting that the effects from GVC uncertainty (proxied by TPU) are unique, consistent with our model predictions.

We further document evidence that GVC uncertainty raises labor productivity and the skill premium, and these effects work through the automation channel. We establish these channeling effects using a two-stage least squares regression. In the first stage, we regress a measure of automation (robot density) on GVC uncertainty, controlling for industry and time fixed effects. In the second stage, we regress labor productivity (or skill premium) on the robot density predicted from the first stage regression. This is formally equivalent to an instrumental-variable (IV) regression, where we use GVC uncertainty as an instrument for

robot density. We find that an increase in robot density driven by GVC uncertainty leads to an increase in both labor productivity and the skill premium, and these effects are significant both statistically and economically. The increase in labor productivity primarily reflects a decline in employment (rather than an increase in value added), suggesting that automation raises labor productivity through the substitution of workers with robots.

Our paper contributes to a relatively new but growing literature on the effects of reshoring. Empirically, drawing clear conclusions about the effects of reshoring has been challenging given the novelty of the practice and thus the lack of data. Nonetheless, a few papers have assessed the empirical links between reshoring and automation. For instance, **?** find a positive relationship between reshoring and investment in Industry 4.0 technologies for 1,700 firms in Austria, Germany, and Switzerland. Kinkel (2020) finds a similar result when concentrating on reshoring activities by German firms. Our results are broadly in line with these empirical findings.

By emphasizing the effects of uncertainty on reshoring and automation, our paper also complements recent work that examines the effects of changes in automation on trade. In particular, a growing body of literature has documented the interaction between automation and offshoring and showed that automation tends to reduce offshoring (**???????**). We look at the link between trade and automation from a different angle by showing how trade uncertainty induces reshoring and automation, especially in offshorable industries. By showing that TPU-induced automation increases skill premium, we also contribute to the literature documenting the effects of automation on skill premium (e.g., **?**).[2]

More broadly, our paper adds to an extensive literature on the general effects of uncertainty (e.g., **????**). Our study is also related to **?**, who construct an alternative measure of TPU based on firm-level and aggregate data. They show that an increase in TPU reduces business investment, both in the data and in an open-economy DSGE model. **?** study the impacts of uncertainty shocks in a two-country DSGE model and argue that uncertainty contributes to the large volatility of trade relative to GDP (see also **?**). Complementary to these studies, our paper examines how trade policy uncertainty can drive business decisions of reshoring and automation.

II. The model

This section presents a small open economy model featuring labor search frictions, endogenous decisions of automation and offshoring.

[2] **?** document that automation and offshoring increase the wage of high-skill relative to middle-skill workers.

II.1. **Key features in the model.** Final goods are produced using intermediate goods that are imported or domestically produced. Domestic intermediate goods can be produced using two types of technologies, a labor-only technology that uses unskilled workers as the only input and an automation technology that uses both robots and skilled workers as inputs.

We follow the approach of **?** to modeling automation. We assume that an automating firm adopts a robot at a random fixed cost and hire a skilled worker from a competitive spot skilled labor market. If the firm chooses to operate the labor-only technology, then it does not need pay the fixed cost of automation and it can hire an unskilled worker subject to labor market search frictions.

In the beginning of a period t, firms carry over the stock of unfilled vacancies from the previous period, a fraction of which is automated by adopting robots. The stock of vacancies v_t available for hiring workers consists of the remaining vacancies after automation, the jobs separated in the beginning of the period, and newly created vacancies. The job seekers (the mass of which is u_t) randomly match with the vacancies (v_t) in the labor market, with the number of new matches (m_t) determined by a matching technology. Production then takes place, using either a labor-only or an automation technology. The unfilled vacancies and the pool of employed workers at the end of the period are carried over to the next period, and the same sequence of economic activities repeats in period $t + 1$.

Compared to the standard DMP model, our model introduces several new features. First, we replace the free-entry assumption in the DMP model with costly vacancy creation, as in **?** and **?**. Since creating a new vacancy incurs a fixed cost, a vacancy has a positive value even if it is not filled by an unskilled worker. The number of vacancies becomes a slow-moving state variable (instead of a jump variable as in the standard DMP framework), enabling our model to match the persistent vacancy dynamics in the data.

Second, we introduce endogenous automation decisions. In the beginning of period t, each firm draws a fixed cost of automation, which determines whether the firm will automate production or post the vacancy for hiring a worker. If the automation cost lies below a threshold value, then the firm automates production by adopting a robot and hiring skilled workers to operate the robot. In that case, the firm obtains the automation value and the vacancy would be taken offline. If the automation cost exceeds the threshold, then the firm posts the vacancy for hiring an unskilled worker. Exogenous changes in the relative price of robots affect the probability of automation, which in turn affects the composition of domestic intermediate goods that are produced using unskilled workers vs. the automation technology.

Third, we allow for worker skill heterogeneity, with skilled and unskilled workers, who are all members of the representative household. In our model, robots and skilled workers

are complementary inputs, whereas they are substitutes for unskilled workers. This feature allows us to examine the joint effects of automation and offshoring on employment of workers with different skills and also on income inequality stemming from the skill premium.

Fourth, we introduce offshoring by allowing final goods producers to import intermediate goods. Changes in trade costs caused by, for example, global supply chain disruptions or trade wars, can affect the effective costs of offshoring, which in turn affects the relative demand for intermediate goods that are imported vs. domestically produced. Such changes in relative demand in turn drive changes in automation decisions, employment, and income distribution.

Finally, we extend the closed-economy framework of **?** by incorporating not only offshoring but also nominal rigidities.

II.2. **The frictional labor market for unskilled workers.** In the beginning of period t, there are N_{t-1} existing job matches for unskilled workers. The measure of unemployed job seekers is given by

$$u_t = 1 - (1 - \delta)N_{t-1}, \tag{1}$$

where $\delta \in (0, 1)$ denotes the job separation rate and we have assumed full labor force participation and normalized the size of unskilled labor to one.

The stock of vacancies v_t at the beginning of period t consists of unfilled vacancies carried over from period $t-1$ that are not automated, plus the separated employment matches and newly created vacancies. The law of motion for vacancies is given by

$$v_t = (1 - q^v_{t-1})(1 - q^a_t)v_{t-1} + \delta N_{t-1} + \eta_t, \tag{2}$$

where q^v_{t-1} denotes the job filling rate in period $t-1$, q^a_t denotes the automation probability in period t, and η_t denotes newly created vacancies (i.e., entry).

In the labor market, new job matches (denoted by m_t) are formed between job seekers and open vacancies based on the matching function

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{3}$$

where μ is a scale parameter that measures matching efficiency and $\alpha \in (0, 1)$ is the elasticity of job matches with respect to the number of job seekers.

The flow of new job matches adds to the employment pool, whereas job separations subtract from it. Aggregate employment evolves according to the law of motion

$$N_t = (1 - \delta)N_{t-1} + m_t. \tag{4}$$

At the end of period t, the searching workers who failed to find a job match remain unemployed. Thus, unemployment is given by

$$U_t = u_t - m_t = 1 - N_t. \tag{5}$$

For convenience, we define the job finding probability q_t^u as

$$q_t^u = \frac{m_t}{u_t}. \tag{6}$$

Similarly, we define the job filling probability q_t^v as

$$q_t^v = \frac{m_t}{v_t}. \tag{7}$$

II.3. **The representative household.** The representative household has the utility function

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t\left(\ln C_t - \chi N_t\right), \tag{8}$$

where $\mathbb{E}[\cdot]$ is an expectation operator, $\beta \in (0,1)$ is a subjective discount factor, C_t denotes consumption, and N_t denotes the fraction of unskilled household members who are employed.

The representative household faces the sequence of budget constraints

$$C_t + \frac{B_t}{P_t R_t} + \frac{\mathcal{E}_t B_t^*}{P_t R_t^*} = \frac{B_{t-1}}{P_t} + \frac{\mathcal{E}_t B_{t-1}^*}{P_t} + w_{nt}N_t + w_{st}\bar{s} + \phi(1-N_t) + d_t - T_t, \quad \forall t \geq 0, \tag{9}$$

where B_t denotes the household's holdings of domestic nominal bond at the risk-free nominal interest rate R_t, B_t^* denotes the holdings of foreign bond at the world interest rate R_t^*, $\mathcal{E}_t$ denotes the nominal exchange rate (i.e., units of domestic currency per unit of foreign currency), w_{nt} and w_{st} denote the real wage rates of unskilled and skilled workers (also in units of final consumption goods), respectively, d_t denotes the household's share of firm profits, and T_t denotes lump-sum taxes. The parameter ϕ measures the flow benefits of unemployment. For simplicity, we assume that the aggregate supply of skilled labor is fixed at $\bar{s}$.

Denote by $V_t(B_{t-1}, N_{t-1})$ the value function for the representative household. The household's optimizing problem can be written in the recursive form

$$V_t(B_{t-1}, N_{t-1}) \equiv \max_{C_t, N_t, B_t} \ln C_t - \chi N_t + \mathbb{E}_t D_{t,t+1} V_{t+1}(B_t, N_t), \tag{10}$$

subject to the budget constraint (9) and the employment law of motion (4) for unskilled workers, which can be written as

$$N_t = (1-\delta)N_{t-1} + q_t^u u_t, \tag{11}$$

where we have used the definition of the job finding probability $q_t^u = \frac{m_t}{u_t}$, with the measure of job seekers u_t given by Eq. (1). In the optimizing decisions, the household takes the economy-wide job finding rate q_t^u as given.

The stochastic discount factor (SDF) is given by

$$D_{t,t+1} \equiv \beta \frac{\Lambda_{t+1}}{\Lambda_t}. \tag{12}$$

where $\Lambda_t = \frac{1}{C_t}$ is the marginal utility of consumption.

Define the employment surplus (i.e., the value of employment relative to unemployment) as $S_t^H \equiv \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t}$. The optimizing decision for employment implies that the employment surplus satisfies the Bellman equation

$$S_t^H = w_{nt} - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t D_{t,t+1}(1 - q_{t+1}^u)(1 - \delta) S_{t+1}^H. \tag{13}$$

The employment surplus has a straightforward economic interpretation. If the household adds a new unskilled worker in period t, then the current-period gain would be wage income net of the opportunity costs of working, including unemployment benefits and the disutility of working. The household also enjoys the continuation value of employment if the employment relation continues. Having an extra unskilled worker today adds to the employment pool tomorrow (provided that the employment relation survives job separation); however, adding a worker today would also reduce the pool of searching workers tomorrow, a fraction q_{t+1}^u of whom would be able to find jobs. Thus, the marginal effect of adding a new worker in period t on employment in period $t+1$ is given by $(1 - q_{t+1}^u)(1 - \delta)$, resulting in the effective continuation value of employment shown in the last term of Eq. (13).

The household's optimizing consumption-savings decision implies the intertemporal Euler equation for domestic bonds

$$1 = \mathbb{E}_t D_{t,t+1} \frac{R_t}{\pi_{t+1}}, \tag{14}$$

where $\pi_t = \frac{P_t}{P_{t-1}}$ denotes the inflation rate. We also obtain a similar Euler equation for foreign bond holdins, which is given by

$$1 = \mathbb{E}_t D_{t,t+1} \frac{\mathcal{E}_{t+1}}{\mathcal{E}_t} \frac{R_t^*}{\pi_{t+1}}. \tag{15}$$

Combining these two Euler equation, we obtain the uncovered interest parity (UIP) condition

$$0 = \mathbb{E}_t D_{t,t+1} \frac{1}{\pi_{t+1}} \left(R_t - \frac{\mathcal{E}_{t+1}}{\mathcal{E}_t} R_t^* \right). \tag{16}$$

II.4. **The aggregation sector.** Denote by Y_t the final consumption goods, which is a basket of differentiated retail products $Y_t(j)$ indexed by $j \in [0, 1]$. The aggregation technology is given by

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon - 1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon - 1}}, \tag{17}$$

where $\epsilon > 1$ is the elasticity of substitution between retail products.

The aggregation sector faces perfect competition and free entry. Expenditure-minimizing implies the downward-sloping demand schedule for each retail product j, given by

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t, \tag{18}$$

where $P_t(j)$ denote the price of the type-j retail product. Zero-profit implies that the price level P_t is related to the individual prices by

$$P_t = \left(\int_0^1 P_t(j)^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}. \tag{19}$$

II.5. **Retail goods producers.** A continuum of retailers each produces a differentiated product using homogeneous wholesale goods. One unit of wholesale goods can be transformed into one unit of retail goods. Thus, the production function is given by

$$Y_t(j) = \Gamma_t(j), \tag{20}$$

where $\Gamma_t(j)$ denotes the input of wholesale goods used by retailer j.

Retailers are price-takers in the input markets and monopolistic competitors in the product markets. They each sets a price for their own product, taking as given the downward-sloping demand schedule (18) and the price index in Eq. (19). Price adjustments are costly. In particular, we follow **?** and postulate a quadratic cost function of price adjustments given by

$$\frac{\Omega_p}{2}\left(\frac{P_t(j)}{\pi P_{t-1}(j)} - 1\right)^2 Y_t, \tag{21}$$

where the parameter Ω_p measures the size of the adjustment costs and π denotes the steady-state inflation.

Retailer j chooses its price $P_t(j)$ to maximize the expected present value of profit flows

$$\mathbb{E}\sum_{i=0}^{\infty} D_{t,t+i}\left[\left(\frac{P_{t+i}(j)}{P_{t+i}} - p_{w,t+i}\right)Y^d_{t+i}(j) - \frac{\Omega_p}{2}\left(\frac{P_{t+i}(j)}{\pi P_{t+i-1}(j)} - 1\right)^2 Y_{t+i}\right], \tag{22}$$

where p_{wt} denotes the real marginal cost, which is the relative price of wholesale goods.

In a symmetric equilibrium, all retailers choose the same optimal price such that $P_t(j) = P_t$ for all j. The profit-maximizing decision leads to the Phillips curve relation

$$p_{wt} = \frac{\epsilon - 1}{\epsilon} + \frac{\Omega_p}{\epsilon}\left[\frac{\pi_t}{\pi}\left(\frac{\pi_t}{\pi} - 1\right) - \mathbb{E}_t D_{t,t+1}\frac{Y_{t+1}}{Y_t}\frac{\pi_{t+1}}{\pi}\left(\frac{\pi_{t+1}}{\pi} - 1\right)\right]. \tag{23}$$

In the special case with flexible prices (i.e., with $\Omega_p = 0$), the optimal pricing equation implies that the real marginal cost equals the inverse of a constant markup.

II.6. **Wholesale goods producers.** A homogeneous wholesale good is produced using two types of intermediate inputs, one produced by domestic firms (denoted by Y_{dt}) and the other imported from the foreign country (Y_{ft}). The production of final goods uses the constant elasticity of substitution (CES) production function

$$\Gamma_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{ft}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{24}$$

where the parameter θ measures the elasticity of substitution between home-produced and imported intermediate goods, and the parameter α_d measures the importance of domestic intermediate goods for final goods production. We assume that intermediate goods are tradable while final goods are non-tradable.

The domestic intermediate good is itself a CES aggregate of two types of intermediate goods produced using the labor-only technology and the automation technology, respectively. In particular, the quantity of domestically produced intermediate goods Q_{dt} is given by

$$Q_{dt} = \left[\alpha_n^{\frac{1}{\sigma}} Y_{nt}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n)^{\frac{1}{\sigma}} Y_{at}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{25}$$

where Y_{nt} denotes the intermediate goods produced using the labor-only technology, Y_{at} denotes the intermediate goods produced using the automation technology, the parameter σ is the elasticity of substitution between the two types of intermediate goods, and the parameter α_n governs the relative importance of Y_{nt} in the aggregation technology.

Some domestically produced intermediate goods are exported to the foreign country. Denote the quantity of exports by X_t. We assume that international trade is subject to the iceberg trade cost τ_t: for every unit of goods delivered to the destination, $\tau_t > 1$ units of goods need to be shipped. Therefore

$$Q_{dt} = Y_{dt} + \tau_t X_t. \tag{26}$$

The time-varying trading cost τ_t captures factors such as global supply chain disruptions or changes in transportation costs caused by trade wars or global uncertainty. We assume that the level of τ_t follows the stationary stochastic process

$$\tau_t = (1-\rho_\tau)\tau + \rho_\tau \tau_{t-1} + \exp(\sigma_{\tau t})\varepsilon_{\tau t}, \tag{27}$$

where τ is the mean of τ_t, $\rho_\tau \in (-1, 1)$ is a persistence parameter, and $\varepsilon_{\tau t}$ is a white noise innovation. The term $\sigma_{\tau t}$ is a stochastic volatility of the trade cost shock or trade uncertainty shock, and it follows the process

$$\sigma_{\tau t} = (1-\rho_{\sigma\tau})\sigma_\tau + \rho_\sigma \sigma_{\tau,t-1} + \eta_\tau u_{\tau t}. \tag{28}$$

Here, $\rho_{\sigma\tau} \in (-1, 1)$ is the persistence and η_τ is the standard deviation of the trade uncertainty shock, $u_{\tau t}$ is a white noise innovation, and σ_τ is the average standard deviation of the trade cost shock.

Denote by P_{dt} the price of domestically produced intermediate goods and by P_{ft} the price of imported intermediate goods faced by home producers. Wholesalers take as given the relative prices of intermediate goods $p_{dt} \equiv \frac{P_{dt}}{P_t}$ and $p_{ft} = \frac{P_{ft}}{P_t}$ and choose the intermediate inputs to minimize costs. The optimizing decisions of wholesalers imply that

$$\frac{p_{dt}}{p_{wt}} = \left(\frac{\alpha_d Y_t}{Y_{dt}}\right)^{\frac{1}{\theta}}, \quad \frac{p_{ft}}{p_{wt}} = \left(\frac{(1-\alpha_d) Y_t}{Y_{ft}}\right)^{\frac{1}{\theta}}. \tag{29}$$

Zero-profit implies that the relative price of wholesale goods p_{wt} is related to the intermediate goods prices by

$$p_{wt} = \left[\alpha_d \; p_{dt}^{1-\theta} + (1-\alpha_d) \; p_{ft}^{1-\theta}\right]^{\frac{1}{1-\theta}}. \tag{30}$$

Similarly, the optimal choices of domestic intermediate goods producers imply that

$$\frac{p_{nt}}{p_{dt}} = \left(\frac{\alpha_n Y_{dt}}{Y_{nt}}\right)^{\frac{1}{\sigma}}, \quad \frac{p_{at}}{p_{dt}} = \left(\frac{(1-\alpha_n) Y_{dt}}{Y_{at}}\right)^{\frac{1}{\sigma}}, \tag{31}$$

where the terms p_{nt} and p_{at} denote the relative price of domestic intermediate goods produced using labor-only and automation technology, respectively, both in terms of final consumption goods unit. Zero-profit implies that

$$p_{dt} = \left[\alpha_n \; p_{nt}^{1-\sigma} + (1-\alpha_n) \; p_{at}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{32}$$

II.7. **Domestic production of intermediate goods.** A firm makes automation decisions in the beginning of the period t. Adopting a robot requires a sunk cost x in units of consumption goods. The fixed cost is drawn from the i.i.d. distribution $G(\nu)$. A firm chooses to adopt a robot if and only if the cost of automation is less than the benefit. For any given benefit of automation, there exists a threshold value ν_t^* in the support of the distribution $G(\nu)$, such that automation occurs if and only if $x \leq \nu_t^*$. If the firm adopts a robot to replace the job position, then the vacancy will be taken offline and not available for hiring a worker. Thus, the automation threshold ν_t^* depends on the value of automation (denoted by J_t^a) relative to the value of a vacancy (denoted by J_t^v). In particular, the threshold for automation decision is given by

$$\nu_t^* = J_t^a - J_t^v. \tag{33}$$

The probability of automation is then given by the cumulative density of the automation costs evaluated at ν_t^*. That is,

$$q_t^a = G(\nu_t^*). \tag{34}$$

The flow of automated job positions adds to the stock of automated positions (denoted by A_t), which becomes obsolete at the rate $\rho^o \in [0,1]$ in each period.[3] Thus, A_t evolves according to the law of motion

$$A_t = (1-\rho^o)A_{t-1} + q_t^a(1-q_{t-1}^v)v_{t-1}, \tag{35}$$

where $q_t^a(1-q_{t-1}^v)v_{t-1}$ is the number of newly automated job positions.

If the firm adopts a robot, then it optimally chooses the input of skilled workers s_t, with the production function

$$y_{at} = Z_t \zeta_t^{\gamma_a} s_t^{1-\gamma_a}, \tag{36}$$

where $\gamma_a \in (0,1)$ denotes the elasticity of output with respect to the robot input, Z_t is an aggregate productivity (i.e., total factor productivity or TFP) that applies to both labor-only and automating firms, and ζ_t is the automation-specific productivity.

The level of TFP follows the stationary AR(1) stochastic process

$$Z_t = (1-\rho_z)Z + \rho_z Z_{t-1} + \exp(\sigma_{zt})\varepsilon_{zt}, \tag{37}$$

where Z is the mean of Z_t, $\rho_z \in (-1,1)$ is a persistence parameter, and ε_{zt} is a white noise innovation. The term σ_{zt} is a stochastic volatility of the TFP shock, or TFP uncertainty, which follows the stochastic process

$$\sigma_{zt} = (1-\rho_{\sigma z})\sigma_z + \rho_{\sigma z}\sigma_{z,t-1} + \eta_z u_{zt}. \tag{38}$$

Here, $\rho_{\sigma z} \in (-1,1)$ is the persistence and η_z is the standard deviation of the TFP uncertainty shock, u_{zt} is a white noise innovation, and σ_z is the average standard deviation of the TFP shock.

The firm takes the skilled real wage rate w_{st} as given and chooses s_t to maximize the profit before paying the robot operation cost κ_a. The value of automation is then given by

$$J_t^a = \pi_t^a(1-\kappa_a) + (1-\rho^o)\mathbb{E}_t D_{t,t+1} J_{t+1}^a, \tag{39}$$

where $\pi_t^a \equiv \max_{s_t} p_{at} Z_t \zeta_t^{\gamma_a} s_t^{1-\gamma_a} - w_{st}s_t = \gamma_a p_{at} Z_t \zeta_t^{\gamma_a} s_t^{1-\gamma_a}$.

If the automation cost exceeds the threshold ν_t^*, then the firm chooses not to adopt a robot and instead, it chooses to post the vacancy in the labor market for hiring an unskilled worker. In addition, newly separated jobs and newly created vacancies add to the stock of vacancies for hiring unskilled workers. Following **?**, we assume that creating a new vacancy incurs an entry cost e in units of consumption goods. The entry cost is drawn from an i.i.d. distribution $F(e)$. A new vacancy is created if and only if the net value of entry is non-negative. The benefit of creating a new vacancy is the vacancy value J_t^v. Thus, the

[3] If a vacancy is "filled" by a robot, it will be taken offline once and for all. Even if the robot later becomes obsolete, the vacated position does not return to the stock of vacancies.

number of new vacancies η_t is given by the cumulative density of the entry costs evaluated at J_t^v. That is,

$$\eta_t = F(J_t^v). \tag{40}$$

Posting a vacancy incurs a per-period fixed cost κ (in units of final consumption goods). If the vacancy is filled (with the probability q_t^v), the firm obtains the employment value J_t^e. Otherwise, the firm carries over the unfilled vacancy to the next period, which will be automated with the probability q_{t+1}^a. If the vacancy is automated, then the firm obtains the automation value J_{t+1}^a net of the expected robot adoption costs; otherwise, the vacancy will remain open, and the firm receives the vacancy value J_{t+1}^v. Thus, the vacancy value satisfies the Bellman equation

$$J_t^v = -\kappa + q_t^v J_t^e + (1-q_t^v)\mathbb{E}_t D_{t,t+1}\left\{q_{t+1}^a J_{t+1}^a - \int_0^{\nu_t^*} \nu dG(\nu) + (1-q_{t+1}^a)J_{t+1}^v\right\}. \tag{41}$$

If a firm successfully hires an unskilled worker, then it can produce Z_t units of intermediate goods. The value of employment satisfies the Bellman equation

$$J_t^e = p_{nt}Z_t - w_{nt} + \mathbb{E}_t D_{t,t+1}\left\{(1-\delta)J_{t+1}^e + \delta J_{t+1}^v\right\}. \tag{42}$$

Hiring a worker generates a flow profit $p_{nt}Z_t - w_{nt}$ in the current period (in final consumption unit). If the job is separated in the next period (with probability δ), then the firm receives the vacancy value J_{t+1}^v. Otherwise, the firm receives the continuation value of employment.

II.8. **The Nash bargaining wage.** When a job match is formed, the wage rate is determined through Nash bargaining. The bargaining wage optimally splits the joint surplus of a job match between the unskilled worker and the firm. The worker's employment surplus is given by S_t^H in Eq. (13). The firm's surplus is given by $J_t^e - J_t^v$. The possibility of automation affects the value of a vacancy and thus indirectly affects the firm's reservation value and its bargaining decisions.

The Nash bargaining problem is given by

$$\max_{w_{nt}} \quad \left(S_t^H\right)^b \left(J_t^e - J_t^v\right)^{1-b}, \tag{43}$$

where $b \in (0,1)$ represents the bargaining weight for workers.

Define the total surplus as

$$S_t \equiv J_t^e - J_t^v + S_t^H. \tag{44}$$

Then the bargaining solution is given by

$$J_t^e - J_t^v = (1-b)S_t, \quad S_t^H = bS_t. \tag{45}$$

The bargaining outcome implies that the firm's surplus is a constant fraction $1-b$ of the total surplus S_t and the household's surplus is a fraction b of the total surplus.

The bargaining solution (45) and the expression for household surplus in equation (13) together imply that the Nash bargaining wage w_{nt}^N satisfies the Bellman equation

$$\begin{aligned}\frac{b}{1-b}(J_t^e - J_t^v) &= w_{nt}^N - \phi - \frac{\chi}{\Lambda_t} \\ &\quad + \mathbb{E}_t D_{t,t+1}(1-q_{t+1}^u)(1-\delta)\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v). \end{aligned} \tag{46}$$

We do not impose any real wage rigidity. Thus, the equilibrium real wage rate for unskilled workers is just the Nash bargaining wage rate. That is, $w_{nt} = w_{nt}^N$.

II.9. **Government policy.** The government finances unemployment benefit payments ϕ for unemployed workers through lump-sum taxes. We assume that the government balances the budget in each period such that

$$\phi(1 - N_t) = T_t. \tag{47}$$

The monetary authority follows the Taylor rule

$$R_t = R\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi}\left(\frac{Y_t}{Y}\right)^{\phi_y}, \tag{48}$$

where R denotes the steady-state nominal interest rate, ϕ_π and ϕ_y determines the responsiveness of monetary policy against deviations of inflation from the target and of output from its steady state.

II.10. **External sector.** Define the real exchange rate as

$$\mathcal{Q}_t = \frac{\mathcal{E}_t P_t^*}{P_t}, \tag{49}$$

where we normalize the exogenous foreign price level to $P_t^* = 1$ for all t.

No arbitrage implies that the price of imported intermediate goods P_{ft} should equal to the exchange-rate-adjusted price P_t^* charged by foreign producers, with the iceberg trading cost $\tau_t > 1$ accounted for. Thus, we have $P_{ft} = \tau_t \mathcal{E}_t P_t^*$. It follows that the relative price of imported goods $p_{ft} \equiv P_{ft}/P_t$ is given by

$$p_{ft} = \tau_t \frac{\mathcal{E}_t P_t^*}{P_t} = \tau_t \mathcal{Q}_t, \tag{50}$$

To close the model, we follow **?** and specify the export demand schedule

$$X_t = \left(\tau_t \frac{P_{dt}}{\mathcal{E}_t P_t^*}\right)^{-\theta} X_t^* = \left(\frac{\tau_t p_{dt}}{\mathcal{Q}_t}\right)^{-\theta} X_t^*, \tag{51}$$

where X_t^* denotes an exogenous foreign demand shifter. Demand for exported intermediate goods is inversely related to the effective price of exports, consisting of both the relative price p_{dt}, converted to foreign goods unit by the real exchange rate, and the iceberg trading cost τ_t. We assume that the demand elasticity for home exports is identical to the demand elasticity for imported intermediate goods (both elasticities are given by θ). This downward-sloping

export demand schedule reflects our assumption that the home country is not "small" in the usual sense. Instead, external demand for its exports depends on the relative price of domestically produced intermediate goods (in addition to the shipping cost). Under this specification, export demand declines if the relative price of domestic goods inclusive of transportation costs rise or if the real exchange rate appreciates (i.e., $\mathcal{Q}_t$ falls).

II.11. **Search equilibrium.** In a search equilibrium, the markets for the nominal bonds, final good, intermediate goods, and skilled labor all clear. We also assume that trade is balanced such as the export revenue equals the import costs.

Market clearing for domestic intermediate goods along with that for skilled labor implies that

$$Y_{nt} = Z_t N_t, \quad Y_{at} = Z_t(\zeta_t A_t)^{\gamma_a} \bar{s}^{1-\gamma_a}. \tag{52}$$

Final goods market clearing requires that consumption spending, vacancy posting costs, robot operation costs, robot adoption costs, and vacancy creation costs add up to aggregate final goods output. This requirement yields the aggregate resource constraint

$$C_t + \kappa v_t + \kappa_a A_t + (1 - q_{t-1}^v) v_{t-1} \int_0^{\nu_t^*} \nu dG(\nu) + \int_0^{J_t^v} e dF(e) + \frac{\Omega_p}{2} \left(\frac{\pi_t}{\pi} - 1 \right)^2 Y_t = Y_t. \tag{53}$$

In a symmetric equilibrium with all firms set identical prices, aggregate output of final goods equals the aggregate quantity of wholesale goods, such that

$$Y_t = \Gamma_t.$$

We focus on a balanced-trade equilibrium. In such an equilibrium, the revenue from exporting intermediate goods equals the costs of importing foreign intermediate goods, such that

$$\tau_t p_{dt} X_t = p_{ft} Y_{ft}. \tag{54}$$

Assuming that the initial foreign asset holdings are $B_{-1} = B_{-1}^* = 0$. Then, with balanced trade, the current account balance is also zero for all periods and we have $B_t = B_t^* = 0$ for all t.

III. Parameter calibration

We use our model to study the macroeconomic impact of trade uncertainty shocks. We solve the model based on third-order approximations to the equilibrium conditions. To solve the model requires assigning values to the parameters. We now describe our approach to calibrating the model parameters. Table 1 shows the calibrated parameter values.

We have a quarterly model. We set the subjective discount factor to $\beta = 0.99$, such that the steady-state real interest rate is 4 percent per year. We set the matching function elasticity to $\alpha = 0.5$, in line with the literature (**??**). Following **?**, we set the worker

TABLE 1. Calibrated parameters

	Parameter Description	value
β	Subjective discount factor	0.99
α	Elasticity of matching function	0.50
ϕ	Unemployment benefit	0.25
b	Nash bargaining weight	0.50
δ	Job separation rate	0.10
ρ^o	Automation obsolescence rate	0.03
κ_a	Flow cost of automated production	0.98
μ	Matching efficiency	0.6606
κ	Vacancy posting cost	0.0949
α_n	Share of worker-produced intermediate goods	0.39
σ	Elasticity of substitution between domestic intermediate goods	2.03
$\bar{e}$	Scale of vacancy creation cost distribution	3.07
$\bar{\nu}$	Scale of automation cost distribution	4.95
α_d	weight on domestic intermediate input (home bias)	0.85
$\theta - 1$	trade elasticity	0.5
$\bar{\tau}$	Average iceberg trading cost	1.74
$\bar{Z}$	Average level of TFP	1
$\bar{s}$	Supply of skilled workers	0.3
γ_a	Share of automation equipment in production	0.32
ζ	Automation-specific productivity	5.4259
χ	Disutility of working	0.2072
ρ_z	Persistence of first-moment TFP shock	0.95
σ_z	Volatility of first-moment TFP shock	-4.605
ρ_τ	Persistence of first-moment trade cost shock	0.99
σ_τ	Volatility of first-moment trade shock	-6.14
$\rho_{\sigma z}$	Persistence of TFP uncertainty shock	0.75
η_z	Volatility of TFP uncertainty shock	0.01
$\rho_{\sigma\tau}$	Persistence of trade uncertainty shock	0.96
η_τ	Volatility of trade uncertainty shock	0.37

bargaining weight to $b = 0.5$ and the unemployment benefit parameter to $\phi = 0.25$. Based on the data from the Job Openings and Labor Turnover Survey (JOLTS), we calibrate the steady-state job separation rate to $\delta = 0.10$ at the quarterly frequency. We set $\rho^o = 0.03$, so that automation equipment depreciates at an average annual rate of 12 percent, in line with the depreciation rate of industrial robots used by the International Federation of Robotics (IFR) for estimating the average life span of robots and for constructing their measure of the operation stocks of robots. Followinig **?**, we set the flow fixed cost of automation to $\kappa_a = 0.98$. We calibrate the vacancy posting cost $\kappa = 0.0949$ such that the flow cost of vacancy posting is about 1 percent of aggregate output. We set the matching efficiency parameter to $\mu = 0.6606$ such that the quarterly job filling rate is $q^v = 0.71$ in the steady state, as calibrated by **?**.

We follow **?** and assume that the distribution functions $F(e)$ for vacancy creation costs and $G(\nu))$ for automation costs both follow a uniform distribution, such that

$$F(e) = \frac{e}{\bar{e}}, \quad G(\nu)) = \frac{\nu}{\bar{\nu}}. \tag{55}$$

We calibrate the scale parameters of the vacancy creation cost function ($\bar{e}$) and the automation adoption cost function ($\bar{\nu}$) based on the estimation of **?**. Specifically, we set $\bar{e} = 3.07$ and

$\bar{\nu} = 4.95$. Under these calibrated parameters, our quarterly model predicts a steady-state automation probability of $q^a = 0.096$, or about 38 percent at the annual frequency, which lies within the range of firm-level estimates. For example, in a recent study based on the 2019 Annual Business Survey (ABS) of the U.S. Census Bureau, **?** find that about 47.6 percent of U.S. firms had adopted at least one type of advanced technologies by 2018.[4] However, not all firms adopted advanced technologies for the purpose of automating tasks performed by labor. A significant fraction of firms adopted advanced technologies for other purposes, such as upgrading production processes or improving the quality or reliability of those processes. **?** report that, in total, 30.4 percent of U.S. workers are employed at firms using advanced technologies for automating tasks. Exposure to automation is higher in manufacturing, with 52 percent of manufacturing workers employed at firms using at least one of the advanced technologies for automation. Outside of manufacturing, the exposure to automation is lower, at 28.3 percent. The model-implied automation probability in the steady state (38 percent), which corresponds to the measured automation exposures, lies within this empirical range.

Based on **?**, we calibrate the weight of worker-produced intermediate goods in final goods production to $\alpha_n = 0.39$ and the elasticity of substitution between intermediate goods produced by automation equipment and by workers to $\sigma = 2.03$.[5]

Following **?**, we set the output elasticity with respect to automation equipment to $\gamma_a = 0.32$. We normalize the average level of TFP to $\bar{Z} = 1$. We also normalize the supply of skilled workers to $\bar{s} = 0.3$, matching the median ratio of employment of college-educated workers to aggregate employment in the period from 2000 to 2019. We calibrate the average level of the automation-specific productivity to $\zeta = 5.4259$ such that the model implies a steady-state skill premium of 55 percent, in line with the ratio of median weekly earnings of workers with a bachelor's degree or higher to those of workers with some college or associate degrees.

We set the average iceberg trading cost to $\bar{\tau} = 1.74$, which lies within the range of empirical estimates as surveyed by **?**. Following **?**, we calibrate the weight on domestically produced intermediate goods in the aggregation technology for final goods to $\alpha_d = 0.85$, reflecting home bias in goods consumption. Trade elasticity in our setup is governed by the elasticity of substitution between domestic and imported goods and equals $\theta - 1$. Trade elasticity estimates vary across countries and the levels of aggregation. It can also vary with the time

[4]Those advanced technologies include artificial intelligence, robotics, dedicated equipment, specialized software, and cloud computing. The concept of automation equipment in our model is consistent with the broad set of advanced technologies in the ABS.

[5]**?** calibrate these two parameters to target the 2016 level of robot density in the U.S. manufacturing sector of 0.02 and the cumulative increase of robot density of about 300% from 2002 to 2016 while the relative price of robots declined by 40% during the same period.

horizon. For example, **?** find that the trade elasticity is lower at the macro level than at the micro level for some sectors, although they are not significantly different in other sectors. **?** use tariff changes associated with changes in the most-favored nation (MFN) status of trading partners to estimate the trade elasticity in the short run versus the long run. They find that the short-run trade elasticity is much smaller than the long-run elasticity (0.76 vs. 2). Our study focuses on short-run fluctuations. As a baseline, we follow **?** and set $\theta = 1.5$ to have a trade elasticity of 0.5. We also consider a trade elasticity of 0.76 following **?** as a robustness check. We normalize the export demand shifter to $X_t^* = 1$ and the foreign prices to $p_{ft}^* = P_t^* = 1$.

We calibrate the disutility of working to $\chi = 0.2072$ such that the model implies a steady-state unemployment rate of 5.9 percent, matching the average unemployment rate from 2000 to 2019.

For the parameters in the first-moment TFP shock processes, we set $\rho_z = 0.95$ and $\sigma_z = -4.605$. The implied average volatility of the TFP shock is $100 \times \exp(-4.605) = 1$ percent, in line with the real business cycle literature. For the first-moment shock to trading costs, we set $\rho_\tau = 0.99$ and $\sigma_\tau = -6.14$, which are estimated by **?**. With this calibration, the volatility of the trading cost shock is $100 \times \exp(-6.14) = 0.215$ percent. For the second-moment shocks, we set $\rho_{\sigma z} = 0.75$, in line with **?** and **?**. We set the standard deviation of the TFP uncertainty shock to $\eta_z = 0.01$, following **?** and **?**. We calibrate the trade uncertainty shock parameters based on the study by **?**. Specifically, we set $\rho_{\sigma\tau} = 0.96$ and $\eta_\tau = 0.37$.

IV. Empirical Evidence

Our theoretical model predicts that GVC uncertainty can stimulate automation investment and reduce imported intermediate goods. The increased automation driven by GVC uncertainty in turn raises labor productivity and the skill wage premium and reduces domestic employment. We now present some empirical evidence supporting the model predictions.

We measure GVC uncertainty by the U.S. trade policy uncertainty (TPU) index, which is one of the category-specific Economic Policy Uncertainty (EPU) index developed by **?**. The TPU index reflects the frequency of articles in several major U.S. newspapers that discuss economic policy uncertainty and contain one or more phrases related to trade policy (such as "import tariffs," "import barriers," "WTO," "trade policy," and "trade agreement").[6] The monthly TPU index is available starting from 1960.

We measure automation using robot density in U.S. manufacturing industries. Specifically, we define robot density in industry j and year t ($Robot_{jt}$) as the operational stock of industrial robots per thousand employees. We obtain the data of industrial robots for each two-digit

[6] **?** develop a different measure of trade policy uncertainty based on firm-level and aggregate data.

TABLE 2. Summary Statistics

	Mean	count	SD	Min	Max	IQR
log Robot density	.615	161	2.731	-6.570	6.040	3.520
$\log TPU\times$						
Initial share of intermediate imports	.345	264	.246	.059	1.553	.152
log Share of intermediate imports	-2.234	264	.684	-4.188	-.961	.708
$\log EPU\times$						
Initial share of intermediate imports	.456	264	.318	.080	1.558	.199
log Labor Productivity	5.176	264	.488	4.136	6.522	.628
log Employment	6.476	264	.611	5.174	7.630	1.070
log Real Value Added	11.652	264	.769	10.055	13.563	.920
log Skill premium	.482	180	.103	.247	.733	.145
Observations	264					

Note: The table shows the summary statistics of the variables used in the regressions. Robot density is defined as the operation stock of industrial robots per thousand employees in each industry. The share of intermediate imports is the ratio of imported intermediate goods to gross output in each industry. TPU is the trade policy uncertainty index, which is an aggregate time series constructed by **?**. Labor productivity is the ratio of value added to employment in each industry. Skill premium is the ratio of hourly earnings of workers with a college degree or above to those with high school education. See the text for data sources.

manufacturing industry based on the International Standard Industrial Classification (ISIC, Rev. 4) from the International Federation of Robotics (IFR). We obtain employment data for each two-digit manufacturing industry based on the North American Industry Classification System (NAICS 2017) from the NEBR-CES database. We match the industries by converting two-digit ISIC codes to NAICS codes. The matched sample contains 12 industries (at the NAICS two-digit level) for the years from 2004 to 2018.

To help identify the differential effects of GVC uncertainty on automation across industries with different exposures to offshoring, we construct a measure of offshoring exposure using the initial share of imported intermediate goods in gross output (i.e., in the beginning year of our sample) for each two-digit NAICS manufacturing industries. We obtain data on the gross imports of intermediate products from OECD Trade in Value Added. The annual sample covers 15 two-digit NAICS industries for the years from 1997 to 2018.

Since we have annual data on industrial robots and imports of intermediate goods, we aggregate the TPU index from the monthly frequency to the annual frequency by taking the within-year average.

Table 2 reports the summary statistics of our data. Robot density (in log units) in the data displays substantial variations across industries and time, with a standard deviation of 2.73, which is over 4 times of its sample mean. The interaction between TPU (in log units) and the initial share of intermediate imports—a proxy for GVC uncertainty—also displays significant variations, with a standard deviation (0.246) of about 70 percent of its mean. The share of imported intermediate goods (in log units)—our measure of offshoring activity—has more modest variations across industries and time, with a standard deviation of about 30

TABLE 3. Association between trade policy uncertainty, automation, and offshoring

	(1) log (Robot density)	(2) log (Import share)	(3) log (Robot density)	(4) log (Import share)
Initial import share $\times \log(TPU)$	5.298***	-0.878*		
	(1.353)	(0.452)		
Initial import share $\times \log(EPU)$			-11.79	-0.764
			(6.819)	(0.520)
Industry FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	161	330	161	330
F Statistic	15.32	3.778	2.990	2.158
R^2	0.917	0.989	0.915	0.988
Years	2004:2018	1997:2018	2004:2018	1997:2018
No. of industries	12	15	12	15

Note: Column (1) reports the estimates of the regression of robot density on GVC uncertainty proxied by the interaction between TPU and initial exposures to offshoring. Column (2) reports the estimates of the regression of the share of imported intermediate goods in gross output on GVC uncertainty. Columns (3) and (4) report the results when TPU is replaced by economic policy uncertainty (EPU). All regressions control for industry and time fixed effects. Standard errors clustered at the industry level are shown in parentheses. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

percent of the mean (in absolute value). The interaction between EPU (in log units) with the initial share of intermediate imports—a placebo measure of GVC uncertainty—also has a standard deviation of about 70 percent of its mean. The real outcome variables, including labor productivity, employment, value added, and the skill premium are relatively stable, with standard deviations between 6 and 20 percent of their respective means.

To examine the effects of GVC uncertainty on automation, we consider the empirical specification

$$\ln Robot_{jt} = \alpha_0 + \alpha_1 ImpShare_j \times \ln TPU_t + \eta_j + \theta_t + \varepsilon_{jt}, \tag{56}$$

where $ImpShare_j$ is the share of imported intermediate goods in gross output in industry j at the beginning of our sample (2004), as a proxy for the initial exposure of the industry to offshoring. The parameter α_0 is a constant intercept, the terms η_j and θ_t denote industry and time fixed effects, respectively, and ε_{jt} is regression residuals.

The key parameter of interest is α_1, which measures the sensitivity of an industry's robot density to changes in trade policy uncertainty, depending on the industry's initial exposure to offshoring. Our theory suggests that an increase in trade policy uncertainty should be associated with an increase in robot density; for an industry that is more exposed to offshoring, trade policy uncertainty should lead to a larger increase in robot density. Thus, the theory predicts that $\alpha_1 > 0$.

This prediction is supported by data, as shown in Table 3 (Column (1)). The table shows that, after controlling for the industry and time fixed effects, an increase in trade policy

uncertainty is associated with a larger increase in robot density in industries that are more exposed to offshoring, i.e., industries with a larger initial share of intermediate imports. This effect is statistically significant at the 99 percent confidence level. The effect is also economically important. A one-standard-deviation increase in the logarithm of the TPU index (interacted with the initial exposure to offshoring) is associated with an increase in robot density of about 1.3 log points ($5.298 \times 0.246 \approx 1.30$), which is about a half of the standard deviation of the logarithm of the robot density (2.73).

Our model does not have clear predictions about the effects of GVC uncertainty on offshoring. Heightened GVC uncertainty can reduce imports of intermediate goods. However, it also stimulates automation investment that boosts aggregate labor productivity. With higher productivity, demand for intermediate goods from both domestic and foreign sources would increase. Thus, the net effects of GVC uncertainty on offshoring can be ambiguous.

Empirically, an increase in GVC uncertainty reduces offshoring, as shown in Table 3 (Column (2)). The column shows the regression of the share of imported intermediate goods in gross output on the interaction between TPU and the initial exposures to offshoring, controlling for industry and time fixed effects. The estimation suggests that an increase in TPU is associated with a significant decline in offshoring (measured by the share of imported intermediate goods in gross output) for industries that are initially more exposed to offshoring. The estimated correlation is also economically important. A one-standard-deviation increase in GVC uncertainty—proxied by the interaction between the log of TPU and the initial exposure to offshoring—is associated with a reduction in the share of imported intermediate goods of about 0.216 log points ($-0.878 \times 0.246 \approx -0.216$), which is about one third of the standard deviation of the logarithm of the share of imported intermediate goods ($0.216/0.683 \approx 0.32$).

The correlations of trade policy uncertainty with automation and offshoring do not hold for other types of uncertainty such as the economic policy uncertainty (EPU), as shown in Columns (3) and (4) of Table 3. Specifically, when we replace TPU by EPU in the same regressions, we obtain insignificant coefficients on the interaction between exposures to offshoring and EPU. The estimated coefficient in the regression for robot density has the wrong sign. These findings suggest that, consistent with the model mechanism, trade policy uncertainty boosts automation whereas other types of uncertainty do not.

Our model further predicts that, by stimulating automation, heightened GVC uncertainty can boost labor productivity and increase the skilled wage premium. Thus, the effects of GVC uncertainty on labor productivity and skill premium work through the automation channel. To examine the empirical importance of this automation channel, we estimate a

TABLE 4. Two-stage least square regressions

	(1) log Labor Prod.	(2) log Employment	(3) log Value Added	(4) log Skill premium
log Robot density	0.0521***	-0.0461**	0.00602	0.0396**
	(0.0183)	(0.0211)	(0.0223)	(0.0160)
Industry FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	161	161	161	161
First Stage F Statistic	15.32	15.32	15.32	15.32
Years	2004:2018	2004:2018	2004:2018	2004:2018
No. of industries	12	12	12	12

Note: This table shows the second-stage regressions using the robot density predicted from the first-stage regression shown in Column (1) of Table 3 as the regressor. All regressions control for industry and time fixed effects. Standard errors clustered at the industry level are shown in parentheses. The levels of statistical significance are denoted by asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

two-stage least squares (2SLS) specification. The first stage is the same regression specification (56). In particular, we regress robot density on the interactions between exposures to offshoring and TPU. In the second stage, we regress the variables of interest (labor productivity and skill premium) on the predicted robot density from the first stage regression. This is formally equivalent to an instrumental-variable (IV) regression, where we use GVC uncertainty (i.e., the interaction between offshoring exposure and TPU) as an instrument for robot density. The estimated coefficient on the predicted robot density in the second-stage regression captures the effects of GVC uncertainty on labor productivity (or skill premium) through the automation channel.

We measure labor productivity for a two-digit NACIS industry by the ratio of real value added to total employment in that industry, using data from the NBER-CES. We construct a measure of the skill premium using data from the Current Population Survey (CPS). In particular, the skill premium is measured by the earnings per hour of skilled workers (i.e., with a college degree or above) divided by those of unskilled workers (with a high school degree).

Table 4 displays the second-stage regression results.[7] The table shows that an increase in robot density driven by an increase in TPU leads to a statistically significant increase in both labor productivity and the skill premium. An increase in robot density driven by TPU also reduces employment significantly, although it does not have significant effects on value added. Thus, the increase in labor productivity primarily reflects the substitution of workers with robots in production.

[7]The first-stage regression has an F statistic of 15, suggesting that the instrument (i.e., TPU interacted with offshoring exposures) is relevant.

The effects of GVC uncertainty—working through the automation channel—on labor productivity, employment, and the skill premium are economically important. A one-standard-deviation increase in GVC uncertainty raises the log-level of robot density by 1.3 (as shown in the first-stage regression). Thus, through increasing robot density, the increase in GVC uncertainty raises labor productivity by about 6.8 percent relative to its sample average value ($1.3 \times 0.0521 \approx 0.068$). The same shock raises the skill premium by about 5 percent relative to its average value ($1.3 \times 0.0396 \approx 0.05$). The shock also reduces employment by about 6 percent ($1.3 \times (-0.0461) \approx -0.06$).

These findings lend empirical support to our model's mechanism.

Appendix A. Summary of equilibrium conditions

A search equilibrium is a system of 33 equations for 33 variables summarized in the vector

$$[C_t, R_t, Y_t, Y_{ft}, Y_{dt}, Q_{dt}, Y_{at}, Y_{nt}, X_t, A_t, p_{dt}, p_{ft}, \mathcal{E}_t, \mathcal{Q}_t, p_{at}, p_{nt}, p_{wt}, \pi_t,$$
$$m_t, u_t, v_t, q_t^u, q_t^v, q_t^a, N_t, U_t, \eta_t, J_t^e, J_t^v, J_t^a, \nu_t^*, w_{nt}, w_{st}].$$

We write the equations in the same order as in the dynare code.

(1) Euler equation for domestic bonds

$$1 = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \frac{R_t}{\pi_{t+1}}. \tag{A1}$$

(2) Euler equation for foreign bonds

$$1 = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \frac{\mathcal{E}_{t+1}}{\mathcal{E}_t} \frac{R_t^*}{\pi_{t+1}}. \tag{A2}$$

(3) Matching function

$$m_t = \mu u_t^\alpha v_t^{1-\alpha}, \tag{A3}$$

(4) Job finding rate

$$q_t^u = \frac{m_t}{u_t}, \tag{A4}$$

(5) Vacancy filling rate

$$q_t^v = \frac{m_t}{v_t}, \tag{A5}$$

(6) Employment dynamics

$$N_t = (1-\delta)N_{t-1} + m_t, \tag{A6}$$

(7) Number of searching workers

$$u_t = 1 - (1-\delta)N_{t-1}, \tag{A7}$$

(8) Unemployment

$$U_t = 1 - N_t, \tag{A8}$$

(9) Vacancy dynamics

$$v_t = (1 - q_{t-1}^v)(1 - q_t^a)v_{t-1} + \delta N_{t-1} + \eta_t, \tag{A9}$$

(10) Automation dynamics

$$A_t = (1-\rho^o)A_{t-1} + q_t^a(1 - q_{t-1}^v)v_{t-1}, \tag{A10}$$

(11) Employment value

$$J_t^e = p_{nt} Z_t - w_{nt} + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left[\delta J_{t+1}^v + (1-\delta) J_{t+1}^e\right], \tag{A11}$$

(12) Vacancy value

$$J_t^v = -\kappa + q_t^v J_t^e + (1 - q_t^v)\mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left\{ (1 - q_{t+1}^a) J_{t+1}^v + q_{t+1}^a J_{t+1}^a - \int_0^{\nu_{t+1}^*} \nu dG(\nu) \right\}. \quad \text{(A12)}$$

(13) Automation value

$$J_t^a = p_{at}\gamma_a Z_t \zeta_t^{\gamma_a} \left(\frac{\bar{s}}{A_t} \right)^{1-\gamma_a} (1 - \kappa_a) + (1 - \rho^o)\mathbb{E}_t \beta \frac{C_t}{C_{t+1}} J_{t+1}^a, \quad \text{(A13)}$$

(14) Automation threshold

$$\nu_t^* = J_t^a - J_t^v, \quad \text{(A14)}$$

(15) Robot adoption

$$q_t^a = \left(\frac{\nu_t^*}{\bar{\nu}} \right)^{\eta_a}, \quad \text{(A15)}$$

(16) Vacancy creation

$$\eta_t = \left(\frac{J_t^v}{\bar{e}} \right)^{\eta_e}, \quad \text{(A16)}$$

(17) Final good output (imposing $Y_t = \Gamma_t$)

$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1 - \alpha_d)^{\frac{1}{\theta}} Y_{ft}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \quad \text{(A17)}$$

(18) Domestic intermediate goods production

$$Q_{dt} = \left[\alpha_n^{\frac{1}{\sigma}} Y_{nt}^{\frac{\sigma-1}{\sigma}} + (1 - \alpha_n)^{\frac{1}{\sigma}} Y_{at}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \text{(A18)}$$

(19) Domestic intermediate goods feasibility constraint.

$$Q_{dt} = Y_{dt} + \tau_t X_t, \quad \text{(A19)}$$

(20) Intermediate goods produced by workers

$$Y_{nt} = Z_t N_t, \quad \text{(A20)}$$

(21) Intermediate goods produced by robots

$$Y_{at} = Z_t (\zeta_t A_t)^{\gamma_a} \bar{s}^{1-\gamma_a}, \quad \text{(A21)}$$

(22) Demand for domestically produced intermediate goods

$$\frac{p_{dt}}{p_{wt}} = \left(\frac{\alpha_d Y_t}{Y_{dt}} \right)^{\frac{1}{\theta}}, \quad \text{(A22)}$$

(23) Demand for imported intermediate goods

$$\frac{p_{ft}}{p_{wt}} = \left(\frac{(1 - \alpha_d) Y_t}{Y_{ft}} \right)^{\frac{1}{\theta}}, \quad \text{(A23)}$$

(24) Relative price of worker-produced domestic intermediate goods

$$\frac{p_{nt}}{p_{dt}} = \left(\frac{\alpha_n Y_{dt}}{Y_{nt}}\right)^{\frac{1}{\sigma}}, \tag{A24}$$

(25) Relative price of robot-produced domestic intermediate goods

$$\frac{p_{at}}{p_{dt}} = \left(\frac{(1-\alpha_n) Y_{dt}}{Y_{at}}\right)^{\frac{1}{\sigma}}, \tag{A25}$$

(26) Foreign demand for exported intermediate goods

$$X_t = \left(\frac{\tau_t p_{dt}}{\mathcal{Q}_t}\right)^{-\theta} X_t^*, \tag{A26}$$

(27) Balanced trade condition:

$$\tau_t p_{dt} X_t = p_{ft} Y_{ft}, \tag{A27}$$

(28) Import price:

$$p_{ft} = \tau_t \mathcal{Q}_t, \tag{A28}$$

(29) Resource constraint

$$C_t + \kappa v_t + \kappa_a A_t + (1 - q_{t-1}^v) v_{t-1} \int_0^{\nu_t^*} \nu dG(\nu) + \int_0^{J_t^v} e dF(e) + \frac{\Omega_p}{2}\left(\frac{\pi_t}{\pi} - 1\right)^2 Y_t = Y_t, \tag{A29}$$

(30) Nash bargaining wage

$$\frac{b}{1-b}(J_t^e - J_t^v) = w_{nt} - \phi - \chi C_t + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}}(1 - q_{t+1}^u)(1-\delta)\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v), \tag{A30}$$

(31) Skilled wage

$$w_{st} = (1-\gamma_a) p_{at} Z_t \left(\frac{\zeta_t A_t}{\bar{s}}\right)^{\gamma_a}. \tag{A31}$$

(32) The Phillips curve

$$p_{wt} = \frac{\epsilon - 1}{\epsilon} + \frac{\Omega_p}{\epsilon}\left[\frac{\pi_t}{\pi}\left(\frac{\pi_t}{\pi} - 1\right) - \mathbb{E}_t D_{t,t+1} \frac{Y_{t+1}}{Y_t} \frac{\pi_{t+1}}{\pi}\left(\frac{\pi_{t+1}}{\pi} - 1\right)\right]. \tag{A32}$$

(33) The Taylor rule

$$R_t = R\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi}\left(\frac{Y_t}{Y}\right)^{\phi_y}, \tag{A33}$$

Appendix B. Delivery lags

Suppose that importing goods requires a delivery lag: imported intermediate goods today can be used for final goods production tomorrow. The production function of wholesale goods is given by

$$\Gamma_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}. \tag{B.1}$$

Wholesalers take all prices as given and choose Y_{dt} and Y_{ft} to maximize the expected present value of profit flows. The optimizing problem is described by the Bellman equation

$$V_t(Y_{f,t-1}) = \max_{Y_{dt}, Y_{ft}} \quad p_{wt}\Gamma_t - p_{dt}Y_{dt} - p_{ft}Y_{ft} + \mathbb{E}_t D_{t,t+1} V_{t+1}(Y_{ft}), \tag{B.2}$$

subject to the technology constraint (B.1), where $V_t(Y_{f,t-1})$ denotes the value function, which depends on the endogenous state variable $Y_{f,t-1}$.

The first-order conditions for this optimizing problem are given by

$$p_{dt} = p_{wt}\frac{\partial Y_t}{\partial Y_{dt}}, \quad p_{ft} = \mathbb{E}_t D_{t,t+1} V'_{t+1}(Y_{ft}). \tag{B.3}$$

The envelope condition implies that

$$V'_t(Y_{f,t-1}) = p_{wt}\frac{\partial Y_t}{\partial Y_{f,t-1}}. \tag{B.4}$$

Combining (B.3) and (B.4), we obtain

$$p_{dt} = p_{wt}\left(\frac{\alpha_d Y_t}{Y_{dt}}\right)^{\frac{1}{\theta}}, \quad p_{ft} = \mathbb{E}_t D_{t,t+1} p_{w,t+1}\left(\frac{(1-\alpha_d)Y_{t+1}}{Y_{ft}}\right)^{\frac{1}{\theta}}. \tag{B.5}$$

Appendix C. Summary of equilibrium conditions: Delivery lags

A search equilibrium is a system of 33 equations for 33 variables summarized in the vector

$$[C_t, R_t, Y_t, Y_{ft}, Y_{dt}, Q_{dt}, Y_{at}, Y_{nt}, X_t, A_t, p_{dt}, p_{ft}, \mathcal{E}_t, \mathcal{Q}_t, p_{at}, p_{nt}, p_{wt}, \pi_t,$$
$$m_t, u_t, v_t, q_t^u, q_t^v, q_t^a, N_t, U_t, \eta_t, J_t^e, J_t^v, J_t^a, \nu_t^*, w_{nt}, w_{st}].$$

We write the equations in the same order as in the dynare code.

(1) Euler equation for domestic bonds

$$1 = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \frac{R_t}{\pi_{t+1}}. \tag{C.1}$$

(2) Euler equation for foreign bonds

$$1 = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \frac{\mathcal{E}_{t+1}}{\mathcal{E}_t} \frac{R_t^*}{\pi_{t+1}}. \tag{C.2}$$

(3) Matching function

$$m_t = \mu u_t^\alpha v_t^{1-\alpha}, \tag{C.3}$$

(4) Job finding rate

$$q_t^u = \frac{m_t}{u_t}, \tag{C.4}$$

(5) Vacancy filling rate

$$q_t^v = \frac{m_t}{v_t}, \tag{C.5}$$

(6) Employment dynamics

$$N_t = (1-\delta)N_{t-1} + m_t, \tag{C.6}$$

(7) Number of searching workers

$$u_t = 1 - (1-\delta)N_{t-1}, \tag{C.7}$$

(8) Unemployment

$$U_t = 1 - N_t, \tag{C.8}$$

(9) Vacancy dynamics

$$v_t = (1 - q_{t-1}^v)(1 - q_t^a)v_{t-1} + \delta N_{t-1} + \eta_t, \tag{C.9}$$

(10) Automation dynamics

$$A_t = (1-\rho^o)A_{t-1} + q_t^a(1 - q_{t-1}^v)v_{t-1}, \tag{C.10}$$

(11) Employment value

$$J_t^e = p_{nt}Z_t - w_{nt} + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left[\delta J_{t+1}^v + (1-\delta)J_{t+1}^e\right], \tag{C.11}$$

(12) Vacancy value

$$J_t^v = -\kappa + q_t^v J_t^e + (1 - q_t^v)\mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left\{ (1 - q_{t+1}^a) J_{t+1}^v + q_{t+1}^a J_{t+1}^a - \int_0^{\nu_{t+1}^*} \nu dG(\nu) \right\}. \quad \text{(C.12)}$$

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$$J_t^a = p_{at}\gamma_a Z_t \zeta_t^{\gamma_a} \left(\frac{\bar{s}}{A_t} \right)^{1-\gamma_a} (1 - \kappa_a) + (1 - \rho^o)\mathbb{E}_t \beta \frac{C_t}{C_{t+1}} J_{t+1}^a, \quad \text{(C.13)}$$

(14) Automation threshold

$$\nu_t^* = J_t^a - J_t^v, \quad \text{(C.14)}$$

(15) Robot adoption

$$q_t^a = \left(\frac{\nu_t^*}{\bar{\nu}} \right)^{\eta_a}, \quad \text{(C.15)}$$

(16) Vacancy creation

$$\eta_t = \left(\frac{J_t^v}{\bar{e}} \right)^{\eta_e}, \quad \text{(C.16)}$$

(17) Final good output (imposing $Y_t = \Gamma_t$)

$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1 - \alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \quad \text{(C.17)}$$

(18) Domestic intermediate goods production

$$Q_{dt} = \left[\alpha_n^{\frac{1}{\sigma}} Y_{nt}^{\frac{\sigma-1}{\sigma}} + (1 - \alpha_n)^{\frac{1}{\sigma}} Y_{at}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \text{(C.18)}$$

(19) Domestic intermediate goods feasibility constraint.

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$$\frac{p_{dt}}{p_{wt}} = \left(\frac{\alpha_d Y_t}{Y_{dt}} \right)^{\frac{1}{\theta}}, \quad \text{(C.22)}$$

(23) Demand for imported intermediate goods

$$p_{ft} = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} p_{w,t+1} \left(\frac{(1 - \alpha_d) Y_{t+1}}{Y_{ft}} \right)^{\frac{1}{\theta}}, \quad \text{(C.23)}$$

(24) Relative price of worker-produced domestic intermediate goods

$$\frac{p_{nt}}{p_{dt}} = \left(\frac{\alpha_n Y_{dt}}{Y_{nt}}\right)^{\frac{1}{\sigma}}, \tag{C.24}$$

(25) Relative price of robot-produced domestic intermediate goods

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(30) Nash bargaining wage

$$\frac{b}{1-b}(J_t^e - J_t^v) = w_{nt} - \phi - \chi C_t + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}}(1 - q_{t+1}^u)(1-\delta)\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v), \tag{C.30}$$

(31) Skilled wage

$$w_{st} = (1-\gamma_a) p_{at} Z_t \left(\frac{\zeta_t A_t}{\bar{s}}\right)^{\gamma_a}. \tag{C.31}$$

(32) The Phillips curve

$$p_{wt} = \frac{\epsilon - 1}{\epsilon} + \frac{\Omega_p}{\epsilon}\left[\frac{\pi_t}{\pi}\left(\frac{\pi_t}{\pi} - 1\right) - \mathbb{E}_t D_{t,t+1} \frac{Y_{t+1}}{Y_t} \frac{\pi_{t+1}}{\pi}\left(\frac{\pi_{t+1}}{\pi} - 1\right)\right]. \tag{C.32}$$

(33) The Taylor rule

$$R_t = R\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi}\left(\frac{Y_t}{Y}\right)^{\phi_y}, \tag{C.33}$$