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RESHORING, AUTOMATION, AND LABOR MARKETS UNDER TRADE UNCERTAINTY

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Abstract. We study the implications of trade uncertainty for reshoring, automation, and U.S. labor markets. Rising trade uncertainty creates incentive for firms to reduce exposures to foreign suppliers by moving production and distribution processes to domestic producers. 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 improves labor productivity and facilitates reshoring, but it can also displace jobs. Furthermore, automation poses a threat that weakens the bargaining power of low-skilled workers in wage negotiations, depressing their wages and raising the skill premium and wage inequality. The model predictions are in line with industry-level empirical evidence.

I. Introduction

The COVID-19 pandemic has exposed important vulnerabilities in global supply chains. Ongoing trade tensions as well as increasing risks from climate change and geopolitical conflicts are making global production strategies riskier than in the past. In this new economic environment, moving some production and distribution processes from abroad back to domestic suppliers (i.e., reshoring) is becoming an increasingly attractive option to mitigate the risks of supply chain disruptions.[1]

How this process will unfold and what the impacts on labor markets will be remain highly uncertain. One possibility is that reshoring could increase jobs in the home country and boost wages for domestic workers, reversing the effects of the China shock originally studied

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[1] According to a Thomas Industrial Survey, about two-thirds of North American manufacturers 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 manufacturers are considering expanding industrial automation.

by Autor et al. (2013). In this paper, we argue that reshoring may not necessarily increase domestic employment and wages when labor-substituting technologies, such as automation, are available for firms to lower labor costs.

Over the past three decades, advanced economies that offshored production processes have also experienced a steady increase in the adoption of automation technologies, such as artificial intelligence, machine learning, and robotics. Empirical evidence suggests that automation raises labor productivity (Graetz and Michaels, 2018) and reduces unit labor costs and worker wages (Acemoglu and Restrepo, 2020). The increased ability to automate labor-intensive production processes could reduce firms' need to offshore to contain labor costs. In line with these changing incentives, import growth has slowed significantly relative to GDP since the trade collapse during the Great Recession.

Coupled with a greater ability to automate, recent increases in trade uncertainty may have accelerated the trend in reshoring. While reshoring tends to raise domestic labor demand and real wages, firms' option to automate helps mitigate the increase in labor costs, since it acts as a threat against workers—especially low-skilled workers who can be easily substituted by robots—in wage bargaining. This automation threat channel—originally studied by Leduc and Liu (2023)—helps contain the rise in labor costs, reinforcing the incentive for reshoring. Since robots substitute for low-skilled workers and complement high-skilled workers, increased automation spurred by reshoring may also raise the skilled wage premium and income inequality.

In this paper, we formalize this perspective by developing a macro framework featuring automation, heterogeneous worker skills, and international trade frictions. We use this framework to examine the impacts of a rise in trade uncertainty on reshoring, automation, and domestic labor markets. We build on the model of Leduc and Liu (2023) featuring an automation threat channel, and generalize it to a small open economy with trade in intermediate inputs. Trade is subject to time-varying iceberg costs with stochastic volatility meant to capture trade uncertainty arising from geopolitical, climate, and trade policy risks. To produce a final good, firms use a mixture of domestic and foreign intermediate goods. We capture the interaction between reshoring and automation by assuming that domestic intermediate goods producers can use two types of technologies: a labor-only technology that uses low-skilled workers, and an automated process that uses both robots and high-skilled workers as inputs.[2]

[2]We focus on automation decisions at the business cycle frequency. However, automation can also be the results of long-run technological improvements that can allow the automation of tasks previously done by labor. We view this form of automation as occurring relatively infrequently and instead focus on an environment with fixed production technologies.

We assume that low-skilled workers search for jobs in a frictional labor market, subject to search frictions as in the standard Diamond-Mortensen-Pisarides (DMP) framework. Low-skilled wages are determined by Nash bargaining between a firm and a worker. Because firms have the option to automate unfilled vacancies, the threat of automation acts as an outside option for the firm and weighs on bargained wages.[3] This effect is compounded when firms do actually automate, since the associated productivity boost lowers domestic marginal costs of production further.

In our framework, heightened trade uncertainty operates through three key channels. First, trade uncertainty has an expenditure-switching effect that redirects the demand for intermediate goods toward domestic producers (i.e., reshoring).[4] This expenditure-switching effect stimulates automation investment, raising the demand for high-skilled workers. While a greater use of automated processes has a job-creating effect through raising the value of unfilled vacancies, this channel is more than offset by the job-displacing effect of automation on low-skilled workers. Second, trade uncertainty also generates greater precautionary savings, which reduces the real interest interest and further stimulates automation. Third, as an offset, heightened trade uncertainty raises the option value of waiting, discouraging automation investment.

We show that, with our calibration, the positive effects from expenditure switching and precautionary savings dominate the negative option-value effect, such that trade uncertainty boosts automation, raises unemployment for low-skilled workers, and also raises the skilled wage premium. These effects of trade uncertainty are amplified for an economy that is more open to trade, with more automated production, or facing more persistent trade uncertainty.

Our model produces a rich set of empirically testable predictions. First, the model predicts that an increase in trade uncertainty would increase reshoring and stimulate automation investment. Second, increased automation triggered by trade uncertainty would raise labor productivity. Third, the increased threat of automation would depress wages and employment of low-skilled workers, while raising wages of high-skilled workers, resulting in an increase in the skill wage premium. These effects should be stronger in an economy more open to international trade.

[3]Unlike the standard DMP framework, we assume that vacancy creation incurs a random fixed cost (Fujita and Ramey, 2007; Leduc and Liu, 2020), such that an unfilled vacancy retains value in equilibrium and captures the firms' outside option and ability to automate in the future.

[4]To keep the analysis tractable, we model reshoring or offshoring in a reduced-form way. We do not model firms' choices of production locations. We interpret importing of intermediate goods as production that could have been done domestically but is instead *offshored*. Similarly, we interpret a decline in imports of intermediate goods as *reshoring*.

The model predictions are consistent with industry-level empirical evidence. We use data on industrial robots, intermediate goods imports, employment, value added, and wages in two-digit NAICS industries to construct measures of automation, offshoring, labor productivity, and the skill premium. We measure trade uncertainty using aggregate trade policy uncertainty (TPU) constructed by Caldara et al. (2020), interacted with a measure of initial exposures to offshored production. We show that, controlling for industry and time fixed effects, an increase in trade uncertainty is associated with larger increases in automation and larger declines in offshoring in industries that are more exposed to offshoring.

We also find that an increase in trade uncertainty is associated with larger increases in labor productivity and the skill premium in industries that are more exposed to offshoring and that these effects work partly through an automation channel. We examine the channeling effects using a two-stage least squares approach (Bertrand and Mullainathan, 2001). In the first stage, we regress a measure of automation (robot density) on trade uncertainty, controlling for industry and time fixed effects. In the second stage, we regress each variable of interest (including labor productivity, employment, value added, and the skill premium) on robot density predicted from the first stage regression. The estimated coefficient in the second-stage regression indicates the sensitivity of each of the macroeconomic variables to changes in robot density that comes from trade policy uncertainty. We find that an increase in robot density driven by trade uncertainty is associated with an increase in both labor productivity and the skill premium. 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 substituting for workers.[5]

Our work 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, Dachs et al. (2019) find a positive relationship between reshoring and investment in Industry 4.0 technologies for 1,700 firms in Austria, Germany, and Switzerland. More broadly, our paper is also related to the literature on the effects of trade policy on the structure of trade and global supply chains (Fajgelbaum et al., 2021; Alfaro and Chor, 2023; Utar et al., 2023; Grossman et al., 2024).[6]

[5]While these results are broadly in line with our theoretical predictions, we note that we are using a relatively small sample of industries over a relatively short time period and therefore one should interpret our empirical results with caution.

[6]The literature has also studied the importance of global supply chains in optimal trade policy; see, for example, Blanchard et al. (2017); Grossman et al. (2023); Antràs et al. (2024).

By emphasizing the effects of uncertainty on reshoring and automation, our paper 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 (De Backer et al., 2018; Artuc et al., 2019; Stemmler, 2019; Faber, 2020; Carbonero et al., 2020; Krenz et al., 2021; Bonfiglioli et al., 2022). Mandelman and Zlate (2022) argue that offshoring and automation reduce employment and wages of middle-skill occupations but enhance those for the high-skilled. We examine the nexus between offshoring and automation from a different angle by showing how trade uncertainty induces reshoring and boosts automation investment and how the interactions between reshoring and automation affect the responses of domestic labor market variables to trade uncertainty.

Our paper also adds to an extensive literature on the effects of trade policy uncertainty (e.g., Handley and Limão, 2015, 2017; Feng et al., 2017; Crowley et al., 2018; Alessandria et al., 2019; Handley and Limão, 2022; Rodrigue et al., 2024), and more broadly, on the macroeconomic effects of uncertainty (e.g., Bloom, 2009; Fernández-Villaverde et al., 2011; Alessandria et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017; Novy and Taylor, 2020). We employ the TPU index from Caldara et al. (2020), who show that an increase in TPU reduces business investment, both in the data and in an open-economy DSGE model. Complementary to these studies, our paper examines how trade 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.

II.1. **Key features in the model.** Final consumption 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.

Following Leduc and Liu (2023), we assume that a firm that chooses to use the automation technology can adopt a robot at a random sunk 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 can hire an unskilled worker subject to labor market search frictions in the spirit of the standard DMP framework.

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 four new features. First, we replace the free-entry assumption in the DMP model with costly vacancy creation, as in Fujita and Ramey (2007) and Leduc and Liu (2020). 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 sunk 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.

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 versus domestically produced. Such changes in relative demand in turn drive changes in automation decisions, employment, and income distribution.

II.2. **The frictional labor market for unskilled workers.** At 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 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^u_t as

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

Similarly, we define the vacancy filling probability q^v_t as

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

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

$$C_t + B_t = r_{t-1}B_{t-1} + w_{nt}N_t + w_{st}\bar{s} + \phi(1-N_t) + d_t - T_t, \quad \forall t \geq 0, \tag{9}$$

where B_t denotes the household's holdings of a risk-free bond (in units of final goods) at the real interest rate r_t, 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 with the measure of job seekers u_t. 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 Λ_t denotes the Lagrange multiplier for the budget constraint (9).

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).

Finally, the household's optimizing consumption-savings decision implies the intertemporal Euler equation

$$1 = \mathbb{E}_t D_{t,t+1} r_t. \tag{14}$$

II.4. **Final goods production.** A homogeneous final 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}). Importing goods is subject to a delivery lag such that imported intermediate goods today can be used for final goods production tomorrow. The production function of final goods is given by

$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{15}$$

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. To keep the analysis tractable, we interpret importing of intermediate goods as part of the production that could have been undertaken domestically but is instead offshored.[7]

Denote by p_{dt} and p_{ft} the relative prices of intermediate goods (i.e., in units of final consumption goods) produced domestically and imported, respectively. The relative price of imported goods faced by domestic final goods producers is given by

$$p_{ft} = \frac{\tau_t P_t^*}{P_t} = \tau_t \mathcal{Q}_t, \tag{16}$$

where τ_t denotes an iceberg trade cost, P_t is the price of final consumption goods, P_t^* is the foreign price level, and $\mathcal{Q}_t \equiv \frac{P_t^*}{P_t}$ is the real exchange rate. The small open economy takes the foreign price level P_t^* as exogenously given. Without loss of generality, we normalize $P_t^* = 1$ such that the real exchange rate is isomorphic to the domestic price level.

We assume that, for every unit of goods delivered to the destination, $\tau_t > 1$ units of goods need to be shipped. The trade cost τ_t is an exogenous process with a time-varying volatility, which captures trade uncertainty related to factors such as trade wars, geopolitical tensions, or climate change risks that might cause global supply chain disruptions. Sepecifically, we assume that the trade cost follows the stationary stochastic process

$$\ln(\tau_t) = (1-\rho_\tau)\ln(\bar{\tau}) + \rho_\tau \ln(\tau_{t-1}) + \sigma_{\tau t}\varepsilon_{\tau t}, \tag{17}$$

[7]In addition, we treat the rest of the world as a uniform area subject to the same degree of trade uncertainty. Thus, we abstract from the possibility that higher trade uncertainty in a specific region could lead firms to diversify the sourcing of their products to other regions. While an interesting and relevant issue, it is beyond the scope of this paper.

where $\bar{\tau}$ 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, which we interpret as trade uncertainty, and it follows the process

$$\sigma_{\tau t} = (1 - \rho_{\sigma\tau})\sigma_\tau + \rho_{\sigma\tau}\sigma_{\tau,t-1} + \eta_\tau u_{\tau t}. \tag{18}$$

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.

Final goods producers 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

$$V_t(Y_{f,t-1}) = \max_{Y_{dt}, Y_{ft}} \quad Y_t - p_{dt}Y_{dt} - p_{ft}Y_{ft} + \mathbb{E}_t D_{t,t+1} V_{t+1}(Y_{ft}), \tag{19}$$

subject to the technology constraint (15), where $V_t(Y_{f,t-1})$ denotes the value function, which depends on the state variable $Y_{f,t-1}$. The first-order conditions for this optimizing problem are given by

$$p_{dt} = \frac{\partial Y_t}{\partial Y_{dt}}, \quad p_{ft} = \mathbb{E}_t D_{t,t+1} V'_{t+1}(Y_{ft}). \tag{20}$$

The envelope condition implies that

$$V'_t(Y_{f,t-1}) = \frac{\partial Y_t}{\partial Y_{f,t-1}}. \tag{21}$$

Combining (20) and (21), we obtain

$$p_{dt} = \left(\frac{\alpha_d Y_t}{Y_{dt}}\right)^{\frac{1}{\theta}}, \quad p_{ft} = \mathbb{E}_t D_{t,t+1} \left(\frac{(1-\alpha_d)Y_{t+1}}{Y_{ft}}\right)^{\frac{1}{\theta}}. \tag{22}$$

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

$$Q_{dt} = \left[\alpha_n^{\frac{1}{\sigma}} Y_{nt}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n)^{\frac{1}{\sigma}} Y_{at}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{23}$$

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. Thus, we have Denote the quantity of exports by X_t.

$$Q_{dt} = Y_{dt} + \tau_t X_t. \tag{24}$$

where X_t denotes exports.

The optimal choices of domestic intermediate goods producers imply that

$$\frac{p_{nt}}{p_{dt}} = \left(\frac{\alpha_n Y_{dt}}{Y_{nt}}\right)^{\frac{1}{\sigma}}, \quad \frac{p_{at}}{p_{dt}} = \left(\frac{(1-\alpha_n) Y_{dt}}{Y_{at}}\right)^{\frac{1}{\sigma}}. \tag{25}$$

The zero-profit condition for domestic intermediate goods producers implies that

$$p_{dt} = \left[\alpha_n \, p_{nt}^{1-\sigma} + (1-\alpha_n) \, p_{at}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{26}$$

II.5. **Domestic production of intermediate goods.** A firm makes automation decisions at the beginning of the period t. Adopting a robot requires a sunk cost ν in units of consumption goods. The sunk 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 $\nu \leq \nu_t^*$. 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

$$\nu_t^* = J_t^a - J_t^v. \tag{27}$$

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

$$q_t^a = G(\nu_t^*). \tag{28}$$

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.[8] Thus, A_t evolves according to the law of motion

$$A_t = (1-\rho^o)A_{t-1} + q_t^a(1-q_{t-1}^v)v_{t-1}, \tag{29}$$

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

$$y_{at} = Z_t \zeta^{\gamma_a} s_t^{1-\gamma_a}, \tag{30}$$

where $\gamma_a \in (0,1)$ denotes the elasticity of output with respect to the robot input, Z_t denotes a total factor productivity (TFP) shock, and ζ denotes an automation-specific productivity.

TFP follows a stationary $AR(1)$ stochastic process

$$\ln(Z_t) = (1-\rho_z)\ln(\bar{Z}) + \rho_z \ln(Z_{t-1}) + \sigma_z \varepsilon_{zt}, \tag{31}$$

[8] 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.

where $\bar{Z}$ is the mean of Z_t, $\rho_z \in (-1,1)$ is a persistence parameter, ε_{zt} is a white noise innovation, and σ_z is the standard deviation of the TFP shock.[9]

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

$$J_t^a = \pi_t^a(1-\kappa_a) + (1-\rho^o)\mathbb{E}_t D_{t,t+1} J_{t+1}^a, \tag{32}$$

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

If the automation sunk 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 Leduc and Liu (2020), we assume that creating a new vacancy incurs an entry cost e in units of consumption goods, which 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 number of new vacancies η_t is given by the cumulative density of the entry costs evaluated at J_t^v. That is,

$$\eta_t = F(J_t^v). \tag{33}$$

Posting a vacancy incurs a per-period fixed cost κ (in units of final consumption goods). If the vacancy is filled (with 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

$$J_t^v = -\kappa + q_t^v J_t^e + (1-q_t^v)\mathbb{E}_t D_{t,t+1}\left\{ q_{t+1}^a J_{t+1}^a - \int_0^{\nu_{t+1}^*} \nu dG(\nu) + (1-q_{t+1}^a)J_{t+1}^v \right\}. \tag{34}$$

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

$$J_t^e = p_{nt}Z_t - w_{nt} + \mathbb{E}_t D_{t,t+1}\left\{(1-\delta)J_{t+1}^e + \delta J_{t+1}^v\right\}. \tag{35}$$

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.

[9]We focus on trade uncertainty in the main analysis, although we also examine the effects of TFP uncertainty, which is measured by time-varying volatility of the TFP shock (see Appendix B).

II.6. **The Nash bargaining wage.** When a job match is formed, the wage rate is determined through Nash bargaining. The bargaining wage 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

$$\max_{w_{nt}} \quad \left(S_t^H\right)^b \left(J_t^e - J_t^v\right)^{1-b}, \tag{36}$$

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

Define the total surplus as

$$S_t \equiv J_t^e - J_t^v + S_t^H. \tag{37}$$

Then the bargaining solution is given by

$$J_t^e - J_t^v = (1-b)S_t, \quad S_t^H = bS_t. \tag{38}$$

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

$$\begin{aligned} \frac{b}{1-b}(J_t^e - J_t^v) &= w_{nt}^N - \phi - \frac{\chi}{\Lambda_t} \\ &\quad + \mathbb{E}_t D_{t,t+1}(1-q_{t+1}^u)(1-\delta)\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v). \end{aligned} \tag{39}$$

In the baseline model, we assume that real wages are flexible and are given by the Nash bargaining wage (i.e., $w_{nt} = w_{nt}^N$).

II.7. **Export demand.** To close the model, we follow Chang et al. (2015) and specify the export demand schedule

$$X_t = \left(\tau_t \frac{P_{dt}}{P_t^*}\right)^{-\theta} X_t^* = \left(\frac{\tau_t p_{dt}}{\mathcal{Q}_t}\right)^{-\theta} X_t^*, \tag{40}$$

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).

II.8. **Government policy and search equilibrium.** 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

$$\phi(1 - N_t) = T_t. \tag{41}$$

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

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

$$Y_{nt} = Z_t N_t, \quad Y_{at} = Z_t(\zeta A_t)^{\gamma_a} \bar{s}^{1-\gamma_a}. \tag{42}$$

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. The aggregate robot operation cost is given by $\gamma_a p_{at} Y_{at}$. Thus, the aggregate resource constraint

$$C_t + \kappa v_t + \kappa_a \gamma_a p_{at} Y_{at} + (1 - q_{t-1}^v) v_{t-1} \int_0^{\nu_t^*} \nu dG(\nu) + \int_0^{J_t^v} edF(e) = Y_t. \tag{43}$$

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

$$\tau_t p_{dt} X_t = p_{ft} Y_{ft}. \tag{44}$$

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

Appendix A summarizes the equilibrium conditions.

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. 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 (Blanchard and Galí, 2010; Gertler and Trigari, 2009a). Following Hall and Milgrom (2008), we set the worker 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

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	0.1128
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	8.57
α_d	weight on domestic intermediate input (home bias)	0.85
θ	Substitution elasticity between domestic and imported goods	0.8
$\bar{\tau}$	Average iceberg trade 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	3.4422
χ	Disutility of working	0.3741
ρ_z	Persistence of TFP shock	0.95
σ_z	Volatility of TFP shock	0.01
ρ_τ	Persistence of first-moment trade cost shock	0.99
σ_τ	Volatility of first-moment trade shock	0.00215
$\rho_{\sigma\tau}$	Persistence of trade uncertainty shock	0.96
η_τ	Volatility of trade uncertainty shock	0.37

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 Leduc and Liu (2023), we set the flow fixed cost of automation to $\kappa_a = 0.98$. We calibrate the vacancy posting cost $\kappa = 0.1128$ 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 den Haan et al. (2000).

We follow Leduc and Liu (2023) 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

$$F(e) = \frac{e}{\bar{e}}, \quad G(\nu) = \frac{\nu}{\bar{\nu}}. \tag{45}$$

We calibrate the scale parameter of the vacancy creation cost function to $\bar{e} = 3.07$ to match the estimation of Leduc and Liu (2023). We calibrate the scale of the automation cost function to $\bar{\nu} = 8.57$ such that the model implies 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, Acemoglu et al. (2022) 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 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 Firooz et al. (2023), 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 $\sigma = 2.03$.[10]

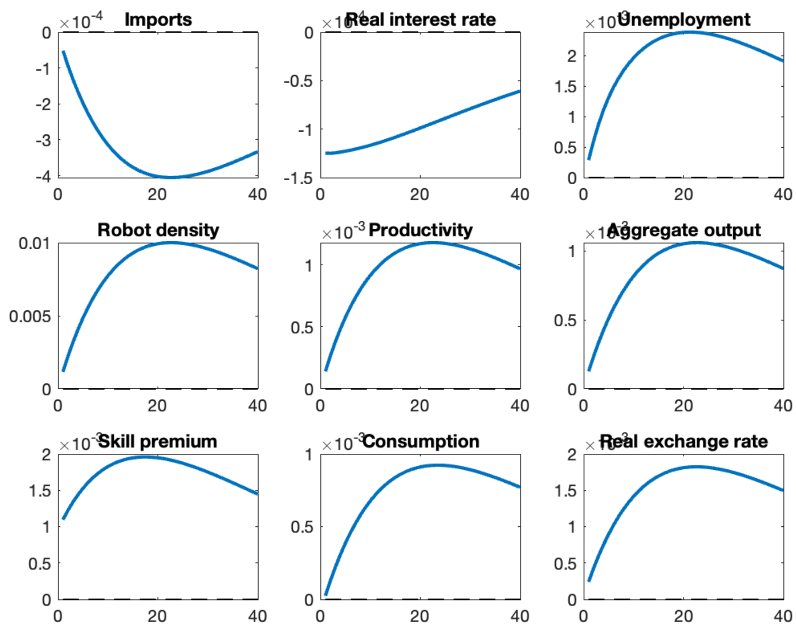
Following Leduc and Liu (2023), we set the output elasticity with respect to automation equipment to $\gamma_a = 0.32$. We normalize the average level of TFP to $\bar{Z} = 1$. We also normalize the supply of skilled workers to $\bar{s} = 0.3$, matching the median ratio of employment of college-educated workers to aggregate employment in the period from 2000 to 2019. We calibrate the average level of the automation-specific productivity to $\zeta = 3.4422$ 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 from Bureau of Labor Statistics.

We set the average iceberg trade cost to $\bar{\tau} = 1.74$, which lies within the range of empirical estimates as surveyed by Anderson and van Wincoop (2004). 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. We calibrate the elasticity of substitution between domestic goods and imported goods to $\theta = 0.8$, which is in line with empirical literature. For example, Boehm et al. (2023) find that the elasticity of trade flows to exogenous changes in tariffs is about -0.76 in the short run and about -2 in the long run (see also Di Giovanni et al., 2023). Since our model focuses on the short-run fluctuations induced by trade uncertainty, our calibration of $\theta = 0.8$ is consistent with the short-run elasticity estimated by Boehm et al. (2023). We normalize the export demand shifter to $X_t^* = 1$ which implies a steady-state export share of about 10.8% of GDP.

We calibrate the disutility of working to $\chi = 0.3741$ such that the model implies a steady-state unemployment rate of 5.9 percent, matching the average unemployment rate from 2000 to 2019.

[10] Firooz et al. (2023) 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.

Figure 1. Impulse responses to a trade uncertainty shock in the baseline model



For the parameters in the TFP shock processes, we set $\rho_z = 0.95$ and $\sigma_z = 0.01$, in line with the real business cycle literature. For the first-moment shock to trading costs, we set $\rho_\tau = 0.99$ and $\sigma_\tau = 0.00215$ based on the estimates of Caldara et al. (2020). The trade uncertainty shock parameters are also calibrated based on the study of Caldara et al. (2020). Specifically, we set $\rho_{\sigma\tau} = 0.96$ and $\eta_\tau = 0.37$.

IV. Macroeconomic effects of trade uncertainty

To study the macroeconomic effects of trade uncertainty, we use our calibrated parameters and solve the model based on third-order perturbations around the steady-state equilibrium. We then compute impulse responses to a trade uncertainty shock following the approach of Fernández-Villaverde et al. (2011) and Leduc and Liu (2016).[11] To illustrate the model's mechanism, we perform several counterfactual exercises.

IV.1. **Trade uncertainty in the baseline model.** Figure 1 presents the impulse responses of several key macroeconomic variables following a one-standard-deviation shock to trade uncertainty. An increase in trade uncertainty reduces imports, redirecting production of

[11] The impulse responses of a given variable to a trade uncertainty shock are measured by the differences between the values of that variable in the presence of the shock and its value in the stochastic steady state (i.e., its ergodic mean).

intermediate goods from foreign sources toward domestic producers (i.e., reshoring). This expenditure-switching effect stimulates automation investment. Trade uncertainty further boosts automation through a precautionary-savings channel, which lowers the real interest rate and therefore raises the present value of automation. However, trade uncertainty could discourage automation through an option-value channel. Under our calibration, the positive effects from expenditure switching and precautionary savings dominate the option-value effect, such that trade uncertainty leads to an increase in automation measured by the robot density.

Increased automation raises labor productivity, stimulating the incentive for creating new vacancies. However, with our calibration, this job-creating effect is more than offset by the job-displacing effect of automation, leading to an increase in unemployment of low-skilled workers. Nonetheless, aggregate output and consumption both rise persistently because the productivity gains stemming from automation outweigh the drags from lowered imports and domestic production by low-skilled workers. The automation-driven productivity gains also lowers the domestic price level, leading to a real exchange rate depreciation (i.e., an increase in $\mathcal{Q}_t$).

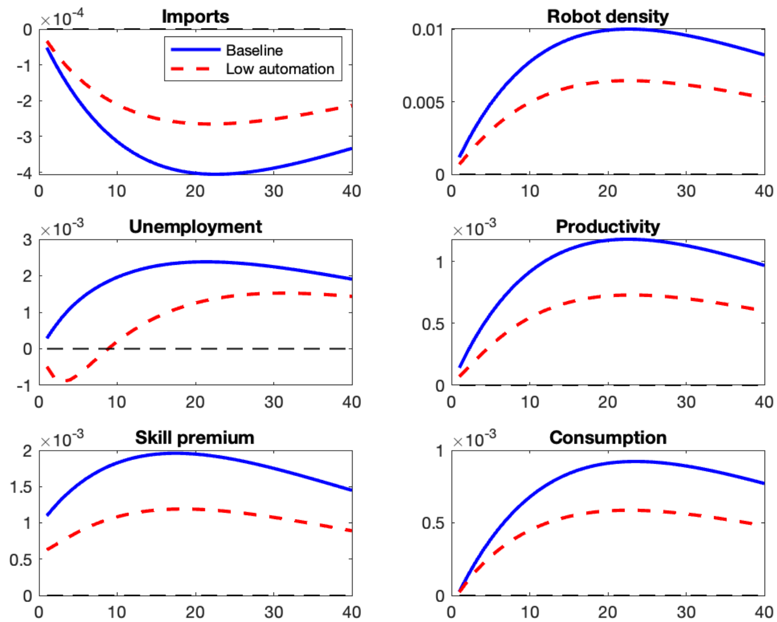
The increased threat of automation also weakens the bargaining power of low-skilled workers in wage negotiations, lowering their wages. In contrast, high-skilled workers are a complementary input with automation equipment. Thus, automation raises demand for high-skilled workers, pushing up the high-skilled wage while depressing the low-skilled wage, resulting in a higher skilled wage premium.

IV.2. **Transmission channels.** The model embeds two important transmission channels for trade uncertainty shocks: an automation channel and a trade channel.

To examine the importance of the automation channel, we consider a counterfactual version of the model with a lower share of the automation sector. In particular, we raise the value of α_n to 0.8 from the baseline calibration of 0.39.

Figure 2 shows the impulse responses to a trade uncertainty shock in the counterfactual model with a lower share of automation (red dashed line), compared to those in the baseline model (blue solid line). The impulse responses are qualitatively similar to those from the baseline model, although the magnitudes of the responses are different. With a lower share of automation, the declines in imports and the increases in robot density, labor productivity, the skill premium, and consumption are relatively muted compared to those in the baseline model. Unemployment actually falls initially since the job-displacing effect from automation is weaker when the share of automated prodution is lower. Thus, the automation channel amplifies the effects of trade uncertainty.

FIGURE 2. Impulse responses to a trade uncertainty shock: lower automation share vs. the baseline model.



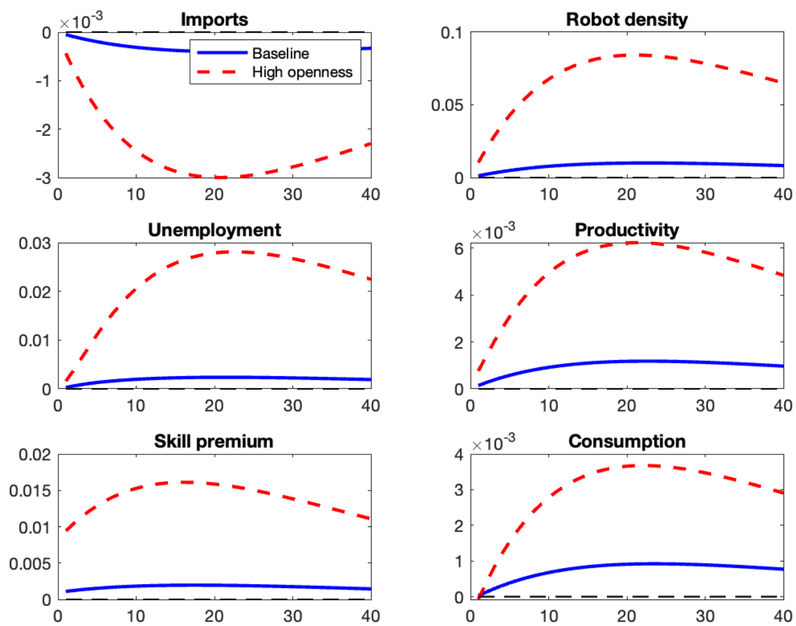
Exposure to trade (or equivalently, offshoring) is also important for the transmission of trade uncertainty shocks. To illustrate this, we consider a counterfactual with high openness to international trade. Specifically, we lower the home-bias parameter α_d to 0.6 from the baseline value of 0.85.

Figure 3 shows the impulse responses in this counterfactual (red dashed line) versus those in the baseline model (blue solid line). When the economy is more open to international trade, the effects of trade uncertainty are amplified. Trade uncertainty leads to larger declines in imports, larger increases in robot density, unemployment, productivity, consumption, and the skill premium.

IV.3. **Persistence of trade uncertainty.** Trade uncertainty may be more persistent than past data suggest for the calibration of the baseline model. Trade tensions, geopolitical and climate change risks may be part of a new normal with persistently elevated trade uncertainty. We consider a counterfactual case with a higher persistence of the trade uncertainty shock by raising the persistence parameter $\rho_{\sigma\tau}$ from 0.96 in the baseline calibration to 0.99, proxying for a quasi-permanent regime with higher trade uncertainty.

Figure 4 shows the impulse responses in this counterfactual case (red dashed line) versus those in the baseline model (blue solid line). Near-permanent trade uncertainty generates a stronger expenditure-switching effect, resulting in greater reshoring (i.e., larger declines in

FIGURE 3. Impulse responses to a trade uncertainty shock: higher openness vs. the baseline model.



imports) and larger increase in automation investment. The stronger expenditure-switching effect in this case is such that it raises domestic employment of low-skilled workers in the short run, although the job displacing effects of automation dominates over time, leading to a rise in unemployment. The larger boom in automation investment also results in greater gains in productivity and larger increases in skill premium and consumption than in the baseline model.

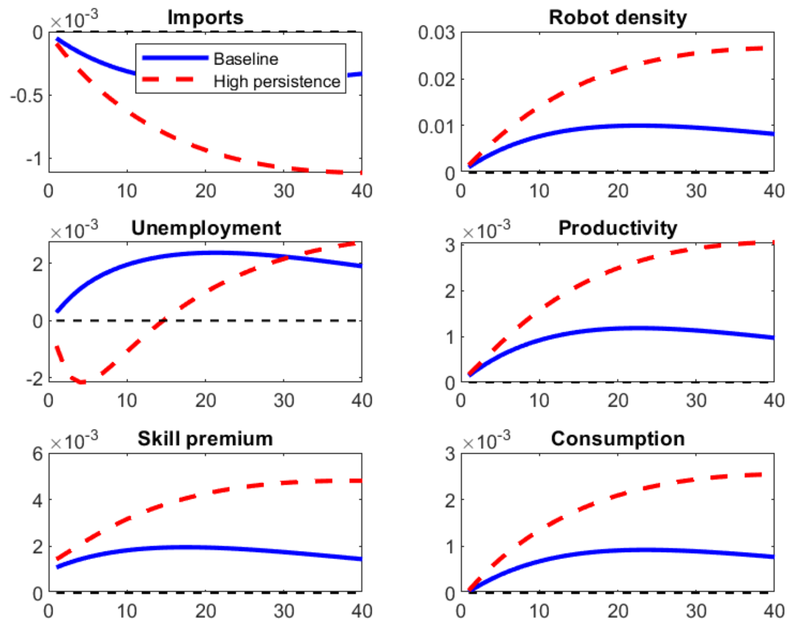
IV.4. **The role of wage rigidity.** In the baseline model, we assume that real wages are flexible. We now examine the robustness of the results to wage stickiness. Following the literature (Hall, 2005a; Shimer, 2005), we assume that the real wage of low-skilled workers is a geometrically weighted average of the Nash bargaining wage and the wage rate in the previous period, such that

$$w_{nt} = w_{n,t-1}^{\gamma_w}(w_{nt}^N)^{1-\gamma_w}, \tag{46}$$

where $\gamma_w \in (0,1)$ represents the degree of real wage rigidity. We follow Leduc and Liu (2016) and set the real wage rigidity parameter to $\gamma_w = 0.8$, which is in line with Gertler and Trigari (2009b), who calibrate the probability of non-renegotiation of wage contracts at 0.89.

Figure 5 compares the impulse responses from the case with wage rigidities (red dashed line) to those in the baseline case with flexible wages (blue solid line). As in the standard

Figure 4. Impulse responses to a trade uncertainty shock: more persistent trade uncertainty shock vs. the baseline model.



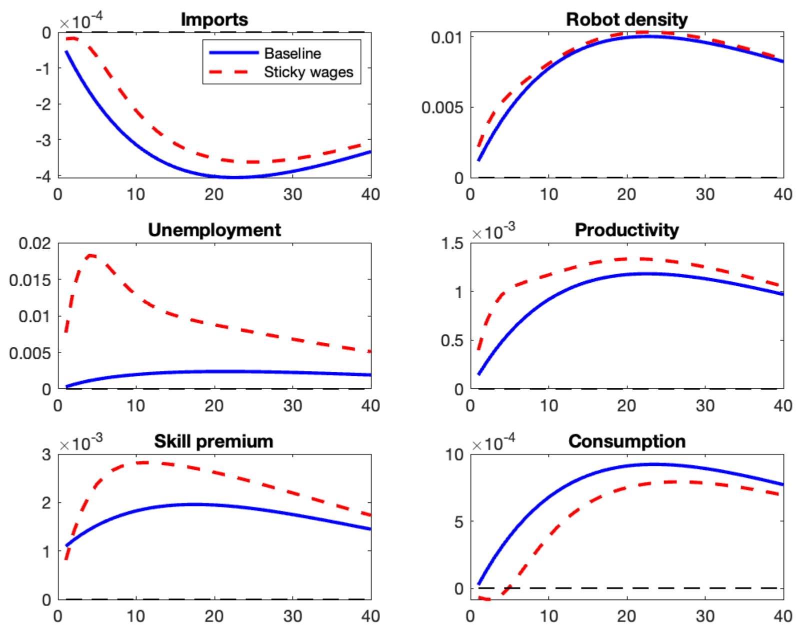
DMP framework, wage rigidities amplify the increase in unemployment following the trade uncertainty shock, reflecting the Shimer volatility puzzle (Shimer, 2005; Hall, 2005b). The impulse responses of the other macroeconomic variables are similar to those in the baseline model.

V. Empirical Evidence

Our theoretical model predicts that trade uncertainty can stimulate automation investment and reduce imported intermediate goods. The increased automation driven by trade uncertainty in turn raises labor productivity, value added, and the skilled wage premium, and reduces domestic employment. To lend credence to these predictions, we now present some empirical evidence supporting the model predictions. We note that the empirical evidence throughout this section serves as suggestive evidence and we do not claim to identify causal effects.

V.1. **Data.** We measure trade uncertainty using the U.S. trade policy uncertainty (TPU) index constructed by Caldara et al. (2020), which is based on 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,"

FIGURE 5. Impulse responses to a trade uncertainty shock: Sticky wages vs. the baseline model.



"trade policy," and "trade agreement"). The monthly TPU index is available starting from 1960.[12]

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 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 cross-walking 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. We restrict our sample to the years before the pandemic era.

To help explore the differential effects of trade uncertainty across industries with different exposures to offshoring, we construct a measure of industry-level 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

[12] Caldara et al. (2020) also develop a firm-level measure of TPU and another aggregate measure TPU based on a stochastic volatility model for U.S. import tariffs.

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 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 Caldara et al. (2020). 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.

imports of intermediate products from OECD Trade in Value Added, and on gross output from the Bureau of Economic Analysis. The annual sample covers 15 two-digit NAICS industries for the years from 1997 to 2018.

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).

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 four times its sample mean. The interaction between TPU (in log units) and the initial share of intermediate imports 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 percent of the mean (in absolute value). 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.

Table 3. Trade policy uncertainty, automation, and offshoring

	(1) log (Robot density)	(2) log (Import share)
Initial import share $\times \log(TPU)$	5.298***	-0.878*
	(1.353)	(0.452)
Industry FE	✓	✓
Time FE	✓	✓
Observations	161	330
R^2	0.917	0.989
Years	2004:2018	1997:2018
No. of industries	12	15

Note: Column (1) reports the estimates of the regression of robot density on trade 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 trade uncertainty. 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.

V.2. **TPU, automation, and offshoring.** To examine the empirical correlations of automation and offshoring with trade uncertainty, we consider the empirical specification

$$\ln Robot_{jt} = \alpha_0 + \alpha_1 ImpShare_j \times \ln TPU_t + \eta_j + \theta_t + \varepsilon_{jt}, \tag{47}$$

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 terms η_j and θ_t denote industry and time fixed effects, respectively, and ε_{jt} denotes the 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 and this response is stronger for industries that are more exposed to offshoring. Specifically, the impulse responses in Figure 3 shows that, in an economy with higher openness, trade uncertainty should lead to a larger increase in robot density. Thus, the theory predicts that $\alpha_1 > 0$.

This prediction is supported by the 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 correlation is statistically significant at the 99 percent confidence level and 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

TABLE 4. Trade policy uncertainty, offshoring, and macroeconomic variables

	(1) log(Labor productivity)	(2) log(Employment)	(3) log(Value added)	(4) log(Skill premium)
Initial import share × log(TPU)	0.324**	-0.151	0.173	0.175*
	(0.128)	(0.219)	(0.208)	(0.0804)
Industry FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	264	264	264	180
R^2	0.970	0.942	0.960	0.810
Years	1997:2018	1997:2018	1997:2018	2004:2018
No. of industries	12	12	12	12

Note: Columns (1), (2), (3), and (4) report the results of regressing labor productivity, employment, value added, and skill premium on the interaction between TPU and initial exposures to offshoring, respectively. 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.

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 also predicts that heightened trade uncertainty reduces offshoring, especially in industries that are initially more exposed to offshoring (see the impulse response of imports to TPU in Figure 3). This model prediction aligns well with empirical evidence, as shown in Table 3 (Column (2)). This column shows the regression of offshoring (measured by 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 significantly larger decline in offshoring for industries that are initially more exposed to offshoring. The estimated correlation is also economically important. A one-standard-deviation increase in trade 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 ($0.216/0.683 \approx 0.32$).

While our model does not feature multiple countries, trade policy uncertainty might have heterogeneous effects on imports from different origin countries. Table C.1 explores how U.S. imports from different origins are affected by TPU. We see that the most significant effect of TPU is on imports from China, which is broadly consistent with the observation that the escalation of trade tensions between U.S. and China has significantly reduced U.S. firms' offshoring to China.

V.3. **TPU and other macroeconomic variables.** Our model further predicts that heightened trade policy uncertainty should increase labor productivity, the skilled wage premium, and value added, while reducing employment (see Figure 1). These model predictions are broadly consistent with the data, as shown in Table 4.

The table shows the same regressions as in (47), where we replace the dependent variable with each of the macroeconomic variables of interest. As shown in the table, an increase in TPU leads to a greater increase in labor productivity and the skill premium in industries more exposed to offshoring in the initial period. These effects are statistically significant and economically important. In particular, a one-standard-deviation increase in the logarithm of TPU (interacted with the initial exposure to offshoring) is associated with an increase in labor productivity of about 0.08 log points ($0.324 \times 0.246 \approx 0.08$), which is about 16% of the standard deviation of the logarithm of labor productivity (0.49). Moreover, the same increase in TPU is associated with an increase in skill premium of about 0.04 log points ($0.175 \times 0.246 \approx 0.04$), which is about 42% of the standard deviation of the logarithm of skill premium (0.1).

The correlations between TPU with employment and value added are imprecisely estimated, reflecting the noise in the relatively small sample. However, the sign of the estimated coefficients are in line with our theoretical predictions.

V.4. **The automation channel.** In our model, the effects of trade uncertainty on employment, labor productivity and skill premium work through the automation channel. Specifically, as shown in Figure 2, in an economy with a larger share of automated production, trade uncertainty leads to larger increases in labor productivity and the skill premium. With more automation, trade uncertainty also reduces employment of low-skilled workers, although the effects are small under our calibration.

We now present some empirical evidence that is consistent with our model's automation channel. Trade uncertainty can influence macroeconomic variables through multiple channels. To highlight the automation channel, we follow the two-stage estimation procedure of Bertrand and Mullainathan (2001). In the first stage, we regress robot density on the interactions of TPU with initial exposures to offshoring, which is the same regression specification in Eq. (47). In the second stage, we regress the variables of interest (labor productivity, skill premium, etc.) on the predicted robot density from the first stage regression. We interpret the estimated coefficient on the predicted robot density in the second-stage regression (shown in Table 5) as reflecting the sensitivity of those macroeconomic variables to trade policy uncertainty through the automation channel.

Table 5 shows that an increase in robot density driven by an increase in TPU is associated with 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

TABLE 5. Two-stage least squares: Empirical importance of automation

	(1) log(Labor productivity)	(2) log(Employment)	(3) log(Value added)	(4) log(Skill premium)
Predicted 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
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 $p < 0.1$.

does not have significant effects on value added. Thus, the increase in labor productivity primarily reflects the job-displacing effects of automation.

The sensitivities of labor productivity, employment, and the skill premium to trade policy uncertainty through the automation channel are economically important. A one-standard-deviation increase in trade uncertainty (i.e., log TPU interacted with the initial exposure to offshoring) is associated with an increase in robot density of 1.3 log points (as shown in the first-stage regression). Through this increase in robot density driven by TPU, labor productivity rises by about 6.8%, which is about 14% of the standard deviation of log labor productivity ($1.3 \times 0.0521/0.488 \approx 13.9$). The same shock to trade uncertainty is associated with an increase in the skill premium of about 5%, or half of the standard deviation of the log skill premium ($1.3 \times 0.0396/0.103 \approx 0.5$). Following the same shock to TPU, employment rises by about 6%, which is 10% of the standard deviation of log employment ($1.3 \times (-0.0461)/0.611 \approx -0.1$). These results suggest that the automation channel is empirically important for the transmission of trade policy uncertainty.

VI. CONCLUSION

Trade uncertainty has risen in recent years, stemming from risks associated with tariffs, geopolitical tensions, and climate change. This uncertainty has led to a reconsideration of the costs and benefits of offshoring to lower production costs.

In this paper, we examined the role of automation in facilitating the reshoring of previously offshored production processes back to the domestic market. In our model, domestic firms can produce intermediate goods using either a labor-only technology or an automation technology. Through an expenditure-switching effect, heightened trade uncertainty raises domestic production but not necessarily domestic employment because automation is a labor-substituting technology. Although automation raises productivity and thus labor demand, the job-displacing effect dominates under our calibration. As such, trade uncertainty boosts automation investment while raising unemployment of low-skilled workers. Increased automation also leads to a higher skilled wage premium.

Our model's predictions are in line with industry-level empirical evidence. Our evidence suggests that, in industries more exposed to offshoring, heightened trade uncertainty reduces offshoring while stimulating automation relative to other industries. Consistent with our model's predictions, this translates into higher productivity and pushes up the skill premium, while lowering employment.

We focus on the positive aspects of the interactions between reshoring, automation, employment, and wages, taking government policy as given. Our model implies that, in line with Leduc and Liu (2023), the threat of automation (e.g., stemming from trade uncertainty) could weaken the bargaining power of low-skilled workers. Such endogenous variations in workers' bargaining power can create a potential source of inefficiency that may call for policy interventions. Studying policy implications in a theoretical framework like ours is a promising avenue for future research, and it would complement the recent work of Grossman et al. (2023), who examine optimal policy in a model with critical production input in the face of global supply chain disruptions.

Appendix A. Summary of equilibrium conditions

A search equilibrium is a system of 30 equations for 30 variables summarized in the vector

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

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

(1) Household's bond Euler equation:

$$1 = \mathrm{E}_t \beta \frac{C_t}{C_{t+1}} r_t, \tag{A.1}$$

(2) Matching function

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{A.2}$$

(3) Job finding rate

$$q_t^u = \frac{m_t}{u_t}, \tag{A.3}$$

(4) Vacancy filling rate

$$q_t^v = \frac{m_t}{v_t}, \tag{A.4}$$

(5) Employment dynamics

$$N_t = (1-\delta) N_{t-1} + m_t, \tag{A.5}$$

(6) Number of searching workers

$$u_t = 1 - (1-\delta) N_{t-1}, \tag{A.6}$$

(7) Unemployment

$$U_t = 1 - N_t, \tag{A.7}$$

(8) Vacancy dynamics

$$v_t = (1 - q_{t-1}^v)(1 - q_t^a) v_{t-1} + \delta N_{t-1} + \eta_t, \tag{A.8}$$

(9) Automation dynamics

$$A_t = (1 - \rho^o) A_{t-1} + q_t^a (1 - q_{t-1}^v) v_{t-1}, \tag{A.9}$$

(10) Employment value

$$J_t^e = p_{nt} Z_t - w_{nt} + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left[\delta J_{t+1}^v + (1-\delta) J_{t+1}^e \right], \tag{A.10}$$

(11) Vacancy value

$$J_t^v = -\kappa + q_t^v J_t^e + (1 - q_t^v) \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left\{ (1 - q_{t+1}^a) J_{t+1}^v + q_{t+1}^a J_{t+1}^a - \int_0^{\nu_{t+1}^*} \nu dG(\nu) \right\}. \tag{A.11}$$

(12) Automation value

$$J_t^a = p_{at}\gamma_a Z_t \zeta^{\gamma_a} \left(\frac{\bar{s}}{A_t}\right)^{1-\gamma_a} (1-\kappa_a) + (1-\rho^o)\mathbb{E}_t \beta \frac{C_t}{C_{t+1}} J_{t+1}^a, \tag{A.12}$$

(13) Automation threshold

$$\nu_t^* = J_t^a - J_t^v, \tag{A.13}$$

(14) Robot adoption

$$q_t^a = \left(\frac{\nu_t^*}{\bar{\nu}}\right)^{\eta_a}, \tag{A.14}$$

(15) Vacancy creation

$$\eta_t = \left(\frac{J_t^v}{\bar{e}}\right)^{\eta_e}, \tag{A.15}$$

(16) Final good output

$$Y_t = \left[\alpha_d^{\frac{1}{\theta}} Y_{dt}^{\frac{\theta-1}{\theta}} + (1-\alpha_d)^{\frac{1}{\theta}} Y_{f,t-1}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{A.16}$$

(17) Domestic intermediate goods production

$$Q_{dt} = \left[\alpha_n^{\frac{1}{\sigma}} Y_{nt}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n)^{\frac{1}{\sigma}} Y_{at}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{A.17}$$

(18) Domestic intermediate goods feasibility constraint.

$$Q_{dt} = Y_{dt} + \tau_t X_t, \tag{A.18}$$

(19) Intermediate goods produced by workers

$$Y_{nt} = Z_t N_t, \tag{A.19}$$

(20) Intermediate goods produced by robots

$$Y_{at} = Z_t (\zeta A_t)^{\gamma_a} \bar{s}^{1-\gamma_a}, \tag{A.20}$$

(21) Demand for domestically produced intermediate goods

$$p_{dt} = \left(\frac{\alpha_d Y_t}{Y_{dt}}\right)^{\frac{1}{\theta}}, \tag{A.21}$$

(22) Demand for imported intermediate goods

$$p_{ft} = \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} \left(\frac{(1-\alpha_d) Y_{t+1}}{Y_{ft}}\right)^{\frac{1}{\theta}} \tag{A.22}$$

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

$$\frac{p_{nt}}{p_{dt}} = \left(\frac{\alpha_n Y_{dt}}{Y_{nt}}\right)^{\frac{1}{\sigma}}, \tag{A.23}$$

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

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

(25) Foreign demand for exported intermediate goods

$$X_t = \left(\frac{\tau_t p_{dt}}{\mathcal{Q}_t}\right)^{-\theta} X_t^*, \tag{A.25}$$

(26) Balanced trade condition:

$$\tau_t p_{dt} X_t = p_{ft} Y_{ft}, \tag{A.26}$$

(27) Import price:

$$p_{ft} = \tau_t \mathcal{Q}_t, \tag{A.27}$$

(28) Resource constraint

$$C_t + \kappa v_t + \kappa_a \gamma_a p_{at} Y_{at} + (1 - q_{t-1}^v) v_{t-1} \int_0^{\nu_t^*} \nu dG(\nu) + \int_0^{J_t^v} e dF(e) = Y_t. \tag{A.28}$$

(29) Nash bargaining wage

$$\frac{b}{1-b}(J_t^e - J_t^v) = w_{nt} - \phi - \chi C_t + \mathbb{E}_t \beta \frac{C_t}{C_{t+1}} (1 - q_{t+1}^u)(1-\delta) \frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v), \tag{A.29}$$

(30) Skilled wage

$$w_{st} = (1-\gamma_a) p_{at} Z_t \left(\frac{\zeta}{\bar{s}}\right)^{\gamma_a}. \tag{A.30}$$

Appendix B. Additional model results: Other shocks

The effects of trade uncertainty are different from those of a first-moment shock to trade costs. Figure B.1 shows the impulse responses to a first-moment trade cost shock. When trade cost rises, imports fall persistently. Since it's a first-moment shock, the magnitude of declines in imports is much larger than that following a trade uncertainty shock. In the short run, imported goods and domestic goods are complementary for producing final goods. Thus, the declines in imports lead to a recession, with higher unemployment and lower automation, labor productivity, and consumption. The decline in automation investment also reduces the demand for high-skilled workers, resulting in a fall in the skill premium.

Figure B.2 shows that, unlike trade uncertainty, TFP uncertainty encourages offshoring, resulting in an increase in imports. TFP uncertainty has a recessionary effect, raising unemployment and reducing consumption. Unlike trade uncertainty that boosts automation, TFP uncertainty lowers to persistent declines in robot density after the initial increases. Accordingly, labor productivity declines persistently following initial increases.

FIGURE B.1. Impulse responses to a first-moment trade cost shock.

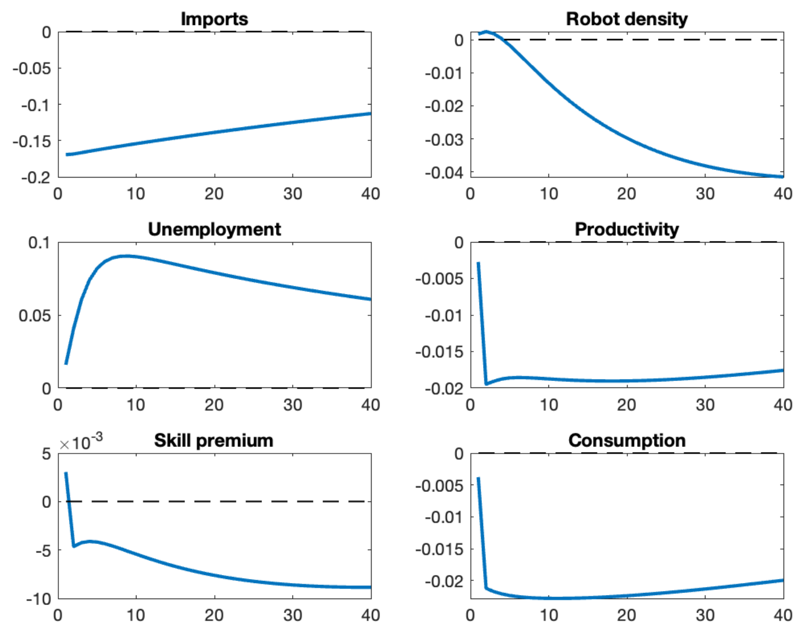


FIGURE B.2. Impulse responses to a TFP uncertainty shock.

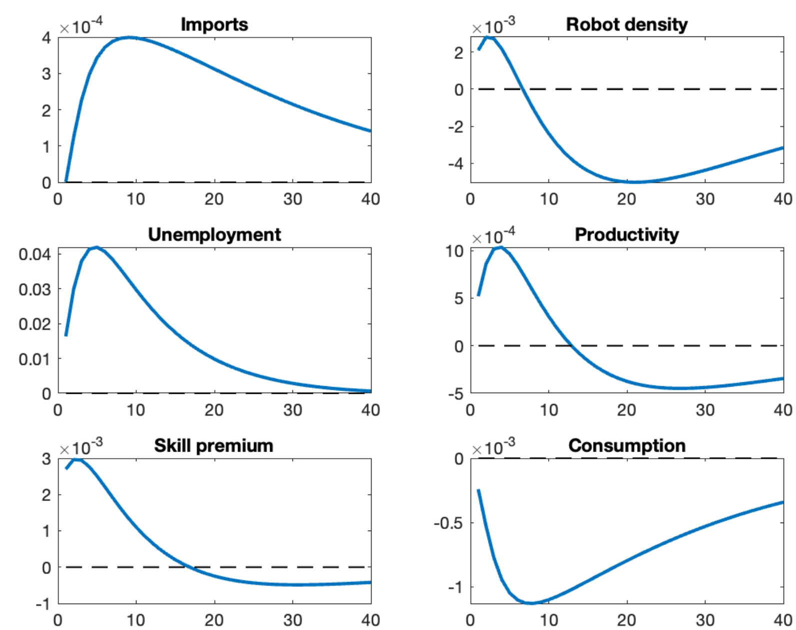


FIGURE B.3. Impulse responses to a first-moment TFP shock.

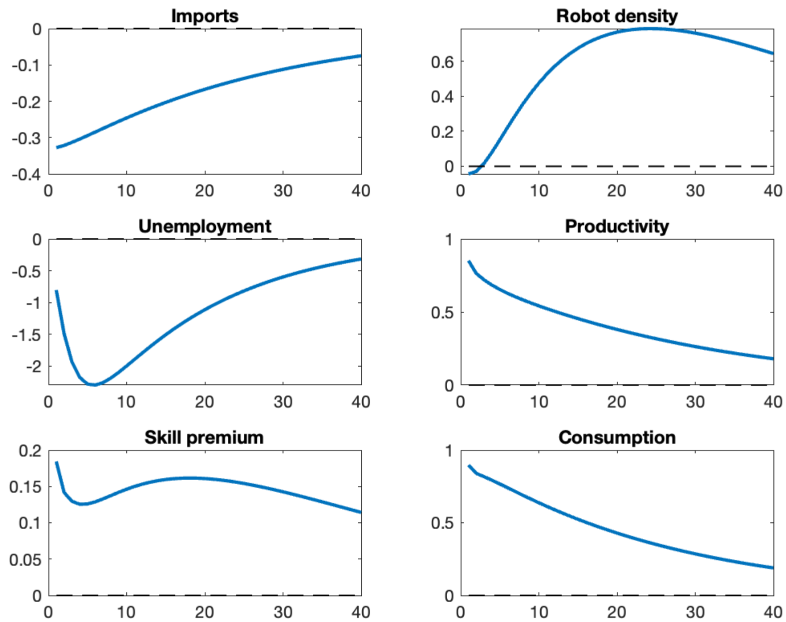


Figure B.3 shows the impulse responses to a first-moment shock to TFP. An increase in TFP lowers unemployment and stimulates automation investment, leading to persistent increases in productivity and aggregate consumption. The rise in automation also leads to a higher skill wage premium. The increase in productivity leads to real exchange rate depreciation (not shown in the figure), resulting in lower imports.

APPENDIX C. ADDITIONAL EMPIRICAL RESULTS

Table C.1 shows that TPU has a greater negative effects on the import shares of industries that are more exposed to offshoring in the three largest trading partners of the United States: Mexico, Canada, and China. The effects for China are statistically significant at the 99 percent level, possibly reflecting the sharp increases in bilateral trade tensions between the U.S. and China since 2016.

Table C.1. Trade policy uncertainty and import shares from different origins

	(1) log(Mexico import share)	(2) log(Canada import share)	(3) log(China import share)
Initial import share × log(TPU)	-1.443	-0.244	-1.594***
	(1.072)	(0.211)	(0.318)
Industry FE	✓	✓	✓
Time FE	✓	✓	✓
Observations	323	330	308
R^2	0.986	0.984	0.887
Years	1997:2018	1997:2018	1997:2018
No. of industries	15	15	14

Note: Each column reports the results of regressing import share from a particular origin on the interaction between TPU and initial exposures to offshoring. China import share, for example, measures U.S. intermediate imports from China in a particular industry divided by gross output in that industry. 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 $p < 0.1$.

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