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AUTOMATION, BARGAINING POWER, AND LABOR MARKET FLUCTUATIONS

SYLVAIN LEDUC AND ZHENG LIU

ABSTRACT. We argue that the threat of automation weakens workers’ bargaining power in wage negotiations, dampening wage adjustments and amplifying unemployment fluctuations. We make this argument based on a business cycle model with labor market search frictions, generalized to incorporate automation decisions. In the model, procyclical automation threats create endogenous real wage rigidity that amplifies labor market fluctuations. The automation mechanism is consistent with empirical evidence. It is also quantitatively important for explaining the large volatilities of unemployment and vacancies relative to that of real wages, a puzzling observation through the lens of standard business cycle models.

I. INTRODUCTION

Advances in robotics and artificial intelligence have raised concerns that automation might replace jobs and reduce wages. Yet, recent empirical studies suggest that the relation between automation and aggregate employment can be ambiguous (Autor, 2015; Acemoglu and Restrepo, 2018, 2020; Acemoglu et al., 2022). Still, to the extent that automation is a labor-saving technology, the *threat* of automation might nonetheless restrain wage growth, even if the technology is not actually adopted. The option to automate may become particularly attractive in a tight labor market, in which competition for hiring adds pressure for firms to raise wages.

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In this paper, we argue that the increased threat of automation in business cycle expansions weakens workers' bargaining power in wage negotiations. It creates an endogenous real wage rigidity that helps explain the observed large fluctuations in unemployment and vacancies relative to real wages, a puzzling observation through the lens of the standard business cycle models.

We formalize this argument based on a general equilibrium framework with labor market search frictions generalized to incorporate automation decisions, which allows us to examine the role of bargaining power for the joint dynamics of unemployment, vacancies, and real wages. In line with [Acemoglu and Restrepo \(2018\)](#) and [Zeira \(1998\)](#), firms in our model first make a choice of technologies (adopting an automated production process or not) and then post non-automated job positions (i.e., vacancies) for hiring workers. The decision to automate depends on the net benefits of automation, which varies along the business cycle and leads to endogenous fluctuations in the probability of automation (i.e., the automation threat).¹ In a business cycle expansion, increased automation tends to boost labor productivity and raise real wages. However, the increased automation probability also dampens wage increases because it weakens workers' bargaining power. By lowering the correlation between real wages and labor productivity, the automation channel creates endogenous real wage rigidity that helps amplify labor market fluctuations.

In our model, the effects of an increase in automation on employment can be ambiguous. Automation equipment can substitute for workers in production, thus displacing jobs. On the other hand, the option to automate an unfilled job position raises the expected value of a job vacancy, boosting firms' incentive to create new vacancies and thereby raising the job finding rate and employment.²

To quantify the net macroeconomic effects of the automation channel, we estimate the model to fit U.S. time series of unemployment, vacancies, real wage growth, and labor productivity growth using the Bayesian methods. Our estimation suggests that the automation channel is quantitatively important. Absent the automation threat, the volatility of the labor market tightness (measured by the ratio of vacancies to unemployment, i.e., the v/u ratio) relative to that of the real wage would be 36 percent smaller than the benchmark model would predict. Furthermore, the automation probability in our estimated model is procyclical. Thus, the threat of automation rises in an expansion, increasing real wage

¹In general, automation can also take the form of technological advancements that enable firms to automate some tasks previously performed by human workers. We view automation through this channel as occurring relatively infrequently, and we abstract from it to focus on the role of automation at the business cycle frequency.

²The *a priori* ambiguous employment effects of automation in our model are consistent with the firm-level evidence ([Acemoglu et al., 2022](#)).

rigidity.³ Since automation raises labor productivity while depressing real wages, it leads to countercyclical fluctuations in the labor share of income, as observed in the data (Ríos-Rull and Santaella-Llopis, 2010).⁴

The automation mechanism is robust to introducing heterogeneous worker skills. In a generalized version of the model, we assume that automation equipment is a substitute for low-skill workers but a complement to high-skill workers. In this model, an increase in high-skill wages in a business cycle expansion would raise the cost of operating automation equipment, mitigating the incentive for firms to automate and resulting in greater fluctuations in low-skill wages. Thus, the amplification effects through the automation channel are somewhat attenuated by the cyclical fluctuations in skilled wages. However, the model continues to predict that the threat of automation depresses low-skill wages and boosts labor productivity, leading to countercyclical labor share fluctuations. Importantly, introducing skill heterogeneity allows us to study the effects of automation on the relative demand for skills and the skill wage premium. In line with the skill-upgrading effects of automation reported in the firm-level study by Acemoglu et al. (2022), our model predicts that an increase in automation is associated with an increase in demand for high-skill workers, raising the skill wage premium.

The automation mechanism and the main predictions of the model are broadly in line with empirical evidence. Using an unbalanced panel of industries at the two-digit level based on the North American Industry Classification System (NAICS) during the past two decades, we present evidence that a decline in the relative price of computing equipment—a proxy for automation costs—is associated with significantly larger increases in vacancies and the v/u ratio and greater declines in unemployment and real wages in industries that are more exposed to automation risks. These results are robust to controlling for industry-level unionization rates or ability to offshore—factors that could confound the effects from the threat of automation.

Given the rising importance of automation since the early 2000s, our model implies that the volatility of the v/u ratio should rise and the correlation between real wages and labor productivity should fall. These implications are consistent with aggregate U.S. time series data. Empirically, the standard deviation of the v/u ratio initially declined from the 1980s to the 1990s, and then increased steadily in the 2000s and 2010s. The correlation between

³The procyclicality of automation investment implied by the model is consistent with macroeconomic evidence. For example, from 1985:Q1 to 2019:Q4, real investment in information processing equipment—a broad proxy for automation—has a positive correlation with real GDP of 0.58.

⁴Karabarbounis and Neiman (2013) focus on the trend declines in the labor share since the mid-1970s for 59 countries. Their analysis attributes about half of the declines in the labor share to declines in the relative price of investment goods. We focus on the cyclical dynamics of the labor share.

real wages and labor productivity initially increased from the 1980s to the 1990s and then declined substantially since the early 2000s. These time-series patterns in the data provide additional support for the model’s mechanism.

Our business-cycle study complements the empirical literature that typically focuses on longer-run implications of automation (Acemoglu and Restrepo, 2020, 2021; Graetz and Michaels, 2018; Arnoud, 2018; Dinlersoz and Wolf, 2018). Automation in our model represents a labor-substituting technology, in line with Acemoglu and Restrepo (2018). Empirical evidence suggests that steady progress in labor substituting technologies (such as computerization) during the recent few decades has reduced demand for workers with routine skills, contributing to increases in job polarization in the U.S. labor market (Autor et al., 2003; Autor, 2015).

The automation threat in our paper is also related to the literature on changes in worker bargaining power. For instance, skill-biased technological change may have contributed to the decline in unionization rates since the late 1950s, thus weakening workers’ bargaining power (Acemoglu et al., 2001; Açıkgöz and Kaymak, 2014; Dinlersoz and Greenwood, 2016). In a recent study, Taschereau-Dumouchel (2020) argues that unionization threats distort hiring decisions. Firms facing greater threats of unionization hire fewer workers, produce less, and pay a more concentrated distribution of wages. Krueger (2018) argues that declines in worker bargaining power can help explain why wage growth remained weak during periods when unemployment reached historically low levels in the United States. Stansbury and Summers (2020) also emphasize that forces that reduced worker power have contributed to sluggish wage growth and a declining labor share. They further show that, while globalization and technological changes have played some part in reducing worker power, they are less important factors than declines in unionization and increases in shareholder power within firms. Our model highlights the importance of automation threats for wage bargaining and employment fluctuations over business cycles.

To our knowledge, our study provides the first quantitative general equilibrium evaluation of the interactions between automation and labor market fluctuations over the business cycle.

II. THE MODEL WITH LABOR MARKET FRICTIONS AND AUTOMATION

This section presents a dynamic stochastic general equilibrium (DSGE) model that generalizes the standard Diamond-Mortensen-Pissarides (DMP) model to incorporate endogenous decisions of automation. Compared to the standard DMP model, our model introduces two 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 a

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. If the automation cost lies below a threshold value, then the firm adopts automation equipment and 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 a worker. Unlike the standard DMP model with free entry where an unfilled vacancy has no value, our model with vacancy creation costs implies that an unfilled vacancy has a positive value that varies endogenously and, in particular, increases with automation.

To keep automation decisions tractable, we impose some assumptions on the timing of events. In the beginning of period t , a job separation shock δ_t is realized. Workers who lose their jobs add to the stock of unemployment from the previous period, forming the pool of job seekers u_t . Firms carry over the stock of unfilled vacancies from the previous period, a fraction of which is automated. 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. Job seekers (u_t) randomly match with vacancies (v_t) in the labor market, with the number of new matches (m_t) determined by a matching technology. Final consumption goods are a composite of two types of intermediate goods—one produced with workers and the other with automation equipment—with a constant elasticity of substitution (CES) between the two types. 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 $t + 1$.

II.1. Final goods producers. Production of final consumption goods requires two types of intermediate inputs, one produced by workers (Y_{nt}) and the other by automation equipment (Y_{at}). The production function is given by

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

where Y_t denotes aggregate output of the final goods. The parameter σ measures the elasticity of substitution between the two types of intermediate inputs, and the parameter α_n is a weight on worker-produced intermediate inputs in the final goods production.

Final goods are traded in a perfectly competitive market. We use the final good as a numeraire, the price of which is normalized to one. Final goods producers take the relative prices of the intermediate goods as given and optimally choose Y_{nt} and Y_{at} to maximize profits. With constant returns and free entry, equilibrium profits are zero. The optimal

choices of intermediate inputs imply that

$$p_{nt} = \alpha_n \left(\frac{Y_t}{Y_{nt}} \right)^{\frac{1}{\sigma}}, \quad p_{at} = (1 - \alpha_n) \left(\frac{Y_t}{Y_{at}} \right)^{\frac{1}{\sigma}}, \quad (2)$$

where p_{nt} and p_{at} denote the relative price of intermediate goods produced by workers and by automation, respectively.

II.2. The Labor Market. In the beginning of period t , there are N_{t-1} existing job matches. A job separation shock displaces a fraction δ_t of those matches, such that the measure of unemployed job seekers is given by

$$u_t = 1 - (1 - \delta_t)N_{t-1}, \quad (3)$$

where we have assumed full labor force participation and normalized the size of the labor force to one.

The job separation shock δ_t follows the stationary stochastic process

$$\ln \delta_t = (1 - \rho_\delta) \ln \bar{\delta} + \rho_\delta \ln \delta_{t-1} + \varepsilon_{\delta t}, \quad (4)$$

where ρ_δ is the persistence parameter and the term $\varepsilon_{\delta t}$ is an i.i.d. normal process with a mean of zero and a standard deviation of σ_δ . The term $\bar{\delta}$ denotes the steady-state rate of job separation.

The stock of vacancies v_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

$$v_t = (1 - q_{t-1}^v)(1 - q_t^a)v_{t-1} + \delta_t N_{t-1} + \eta_t, \quad (5)$$

where q_{t-1}^v denotes the job filling rate in period $t - 1$, q_t^a 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 Cobb-Douglas matching function

$$m_t = \mu u_t^\alpha v_t^{1-\alpha}, \quad (6)$$

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 stock of employment, whereas job separations subtract from it. Aggregate employment evolves according to the law of motion

$$N_t = (1 - \delta_t)N_{t-1} + m_t. \quad (7)$$

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

$$U_t = u_t - m_t = 1 - N_t. \quad (8)$$

For convenience, we define the job finding probability q_t^u and the job filling probability q_t^v , respectively, as

$$q_t^u = \frac{m_t}{u_t}, \quad q_t^v = \frac{m_t}{v_t}.$$

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

$$\mathbb{E} \sum_{t=0}^{\infty} \beta^t \Theta_t (\ln C_t - \chi N_t), \quad (9)$$

where $\mathbb{E}[\cdot]$ is an expectation operator and C_t denotes consumption. The parameter $\beta \in (0, 1)$ denotes the subjective discount factor, the parameter $\chi > 0$ denotes a weight on the disutility of working, and the term Θ_t denotes an exogenous shock to the subjective discount factor.

The discount factor shock $\theta_t \equiv \frac{\Theta_t}{\Theta_{t-1}}$ follows the stationary stochastic process

$$\ln \theta_t = \rho_\theta \ln \theta_{t-1} + \varepsilon_{\theta t}. \quad (10)$$

In this shock process, ρ_θ is the persistence parameter and the term $\varepsilon_{\theta t}$ is an i.i.d. normal process with a mean of zero and a standard deviation of σ_θ . Here, we have implicitly assumed that the mean value of θ is one.

The representative household chooses consumption C_t and savings B_t to maximize the utility function (9) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi(1 - N_t) + d_t - T_t, \quad \forall t \geq 0, \quad (11)$$

where r_t denotes the gross real interest rate, w_t denotes the real wage rate, 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.

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

$$V_t(B_{t-1}, N_{t-1}) \equiv \max_{C_t, N_t, B_t} \ln C_t - \chi N_t + \beta \mathbb{E}_t \theta_{t+1} V_{t+1}(B_t, N_t), \quad (12)$$

subject to the budget constraint (11) and the employment law of motion (7).

Define the employment surplus (i.e., the value of employment relative to unemployment) as $S_t^H \equiv \frac{1}{\Lambda_t} \frac{\partial V_t(B_{t-1}, N_{t-1})}{\partial N_t}$, where Λ_t denotes the Lagrangian multiplier for the budget constraint (11). The optimizing decision for employment implies that the employment surplus

satisfies the Bellman equation

$$S_t^H = w_t - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t D_{t,t+1} (1 - q_{t+1}^u) (1 - \delta_{t+1}) S_{t+1}^H, \quad (13)$$

where $D_{t,t+1} \equiv \frac{\beta \theta_{t+1} \Lambda_{t+1}}{\Lambda_t}$ is the stochastic discount factor, which applies to both the household's intertemporal optimization and firms' decisions.⁵

The employment surplus has a straightforward economic interpretation. If the household adds a new worker in period t , then the current-period gains 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 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 $(1 - q_{t+1}^u)(1 - \delta_{t+1})$, resulting in the effective continuation value of employment shown in the last term of Eq. (13).

The household's optimizing consumption-savings decision leads to the intertemporal Euler equation

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

II.4. The firms. A firm makes automation decisions in the beginning of the period t . Adopting automation equipment requires a fixed cost x in units of consumption goods. The fixed cost is drawn from the i.i.d. distribution $G(x)$. A firm chooses to automate if and only if the cost of automation is less than the benefit. For any given benefit of automation, there exists a threshold value x_t^* in the support of the distribution $G(x)$, such that automation occurs if and only if $x \leq x_t^*$.⁶ If the firm automates production, then the vacancy will be taken offline (i.e., it will not be available for hiring a worker). Thus, the automation threshold x_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 the automation decision is given by

$$x_t^* = J_t^a - J_t^v. \quad (15)$$

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

$$q_t^a = G(x_t^*). \quad (16)$$

⁵For details, see the [online appendix](#).

⁶Our approach to modeling automation decisions here is similar in spirit to a [McCall \(1970\)](#) style search friction applied to automation equipment.

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.⁷ Thus, A_t evolves according to the law of motion

$$A_t = (1 - \rho^o)A_{t-1} + q_t^a(1 - q_{t-1}^v)v_{t-1}, \quad (17)$$

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

A firm operating the automation technology produces $Z_t\zeta_t$ units of output, where Z_t denotes a neutral technology shock and ζ_t denotes an automation-specific shock. The neutral technology shock Z_t follows the stochastic process

$$\ln Z_t = (1 - \rho_z) \ln \bar{Z} + \rho_z \ln Z_{t-1} + \varepsilon_{zt}. \quad (18)$$

The parameter $\rho_z \in (-1, 1)$ measures the persistence of the technology shock. The term ε_{zt} is an i.i.d. normal process with a zero mean and a finite variance of σ_z^2 . The term \bar{Z} is the steady-state level of the technology shock.⁸ The automation-specific technology shock ζ_t follows a stochastic process that is independent of the neutral technology shock Z_t . In particular, ζ_t follows the stationary process

$$\ln \zeta_t = (1 - \rho_\zeta) \ln \bar{\zeta} + \rho_\zeta \ln \zeta_{t-1} + \varepsilon_{\zeta t}. \quad (19)$$

The parameter $\rho_\zeta \in (-1, 1)$ measures the persistence of the automation-specific technology shock. The term $\varepsilon_{\zeta t}$ is an i.i.d. normal process with a zero mean and a finite variance of σ_ζ^2 . The term $\bar{\zeta}$ is the steady-state level of the automation-specific technology shock.

To simplify the analysis and concentrate on the main mechanism, we assume that operating the automation technology incurs a flow fixed cost κ_a that captures the costs of facilities and the space for automated production.⁹ The value of automation satisfies the Bellman

⁷If a vacancy for a job is automated, it will be taken offline once and for all. Even if the automation equipment becomes obsolete later, the vacated position does not return to the stock of vacancies. In the steady state, the number of obsolete automation equipment equals the number of newly created vacancies (i.e., $\rho^o A = \eta$).

⁸The model can easily be extended to allow for trend growth.

⁹The flow cost of operating the automation technology is not directly observable. A proxy for the operating costs can be the wages of skilled labor hired to maintain the automation equipment, as we illustrate in a generalized version of our benchmark model with heterogeneous worker skills in Section VI.3. In the U.S. data, real wages for skilled workers (measured by the wages of new hires with a bachelor's degree, deflated by the chained personal consumption expenditures price index) are roughly acyclical. For example, for the period from 2001 to 2019, the real skilled wage growth has a small positive correlation with the v/u ratio of about 0.16. An alternative proxy for the operation costs of automation is the quantity of energy usage. In the U.S. manufacturing sector for which we have data on energy usage, the growth rate of energy input has

equation

$$J_t^a = p_{at}Z_t\zeta_t - \kappa_a + (1 - \rho^o)\mathbb{E}_t D_{t,t+1}J_{t+1}^a. \quad (20)$$

If the automation cost exceeds the threshold x_t^* , then the firm would not automate. Instead, the firm would post the vacancy in the labor market for hiring a worker. In addition, newly separated jobs and newly created vacancies add to the stock of vacancies for hiring workers. Following [Leduc and Liu \(2020\)](#), we assume that creating a new vacancy incurs an entry cost e (in units of final 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 number of new vacancies (denoted by η_t) is given by the cumulative density of the entry costs evaluated at J_t^v . That is,

$$\eta_t = F(J_t^v). \quad (21)$$

Posting a vacancy incurs a per-period fixed cost κ (also in units of final consumption goods). If the vacancy is filled (with the probability q_t^v), then 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

$$J_t^v = -\kappa + q_t^v J_t^e + (1 - q_t^v)\mathbb{E}_t D_{t,t+1} \left\{ q_{t+1}^a J_{t+1}^a - \int_0^{x_t^*} x dG(x) + (1 - q_{t+1}^a) J_{t+1}^v \right\}. \quad (22)$$

This Bellman equation reveals that the vacancy value varies endogenously (unlike the standard DMP model with free entry, where an unfilled vacancy has no value). In particular, automation can affect the vacancy value through both the automation probability q^a and the automation value J^a .

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

$$J_t^e = p_{nt}Z_t - w_t + \mathbb{E}_t D_{t,t+1} \left\{ (1 - \delta_{t+1})J_{t+1}^e + \delta_{t+1}J_{t+1}^v \right\}. \quad (23)$$

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

a correlation with the growth rate of manufacturing output of about 0.3 for the years from 1987 to 2019. Thus, our assumption of an acyclical automation operating cost is not at odds with the data.

II.5. 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 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 effective bargaining power.

Specifically, the Nash bargaining wage solves the problem

$$\max_{w_t} (S_t^H)^b (J_t^e - J_t^v)^{1-b}, \quad (24)$$

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

Define the total surplus as

$$S_t \equiv J_t^e - J_t^v + S_t^H. \quad (25)$$

Then the bargaining solution implies that

$$J_t^e - J_t^v = (1 - b)S_t, \quad S_t^H = bS_t, \quad (26)$$

such 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 (26) and the expression for household surplus in equation (13) together imply that the Nash bargaining wage w_t^N satisfies the Bellman equation

$$\begin{aligned} \frac{b}{1-b}(J_t^e - J_t^v) &= w_t^N - \phi - \frac{\chi}{\Lambda_t} \\ &+ \mathbb{E}_t D_{t,t+1} (1 - q_{t+1}^u) (1 - \delta_{t+1}) \frac{b}{1-b} (J_{t+1}^e - J_{t+1}^v). \end{aligned} \quad (27)$$

We do not impose any real wage rigidity. Thus, the equilibrium real wage rate is just the Nash bargaining wage rate. That is, $w_t = w_t^N$.

II.6. Government policy. The government finances unemployment benefit payments ϕ for unemployed workers through lump-sum taxes on the representative household. We assume that the government balances the budget in each period such that

$$\phi(1 - N_t) = T_t. \quad (28)$$

II.7. Search equilibrium. In a search equilibrium, the markets for bonds, final goods, and intermediate goods all clear. Since the aggregate bond supply is zero, the bond market-clearing condition implies that

$$B_t = 0. \quad (29)$$

Market clearing for intermediate goods implies that

$$Y_{nt} = Z_t N_t, \quad Y_{at} = Z_t \zeta_t A_t. \quad (30)$$

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 production. This requirement yields the aggregate resource constraint

$$C_t + \kappa v_t + \kappa_a A_t + (1 - q_{t-1}^v) v_{t-1} \int_0^{x_t^*} x dG(x) + \int_0^{J_t^v} e dF(e) = Y_t. \quad (31)$$

III. EMPIRICAL STRATEGIES

We solve the model by log-linearizing the equilibrium conditions around the deterministic steady state.¹⁰ We calibrate a subset of the parameters to match steady-state observations and the empirical literature. We estimate the remaining structural parameters and the shock processes to fit U.S. time-series data.

We focus on the parameterized distribution functions

$$F(e) = \left(\frac{e}{\bar{e}}\right)^{\eta_v}, \quad G(x) = \left(\frac{x}{\bar{x}}\right)^{\eta_a}, \quad (32)$$

where $\bar{e} > 0$ and $\bar{x} > 0$ are the scale parameters and $\eta_v > 0$ and $\eta_a > 0$ are the shape parameters of the distribution functions. We set $\eta_v = 1$ and $\eta_a = 1$, so that both the vacancy creation cost and the automation cost follow a uniform distribution.¹¹ We estimate the scale parameters \bar{e} and \bar{x} , along with the flow cost of automation κ_a and the shock processes by fitting the model to U.S. time series data.

III.1. Steady-state equilibrium and parameter calibration. Table 1 shows the calibrated parameter values. We consider a quarterly model. We set $\beta = 0.99$, so that the model implies an annualized real interest rate of about 4 percent in the steady state. We set $\alpha = 0.5$ following the literature (Blanchard and Galí, 2010; Gertler and Trigari, 2009). In line with Hall and Milgrom (2008), we set $b = 0.5$ and $\phi = 0.25$. Based on the data from the Job Openings and Labor Turnover Survey (JOLTS), we calibrate the steady-state job separation rate to $\bar{\delta} = 0.10$ 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 average depreciation rate of private information equipment during the period from 1990 to 2019.¹² We normalize

¹⁰Details of the equilibrium conditions, the steady state, and the log-linearized system are presented in the [online appendix](#).

¹¹Our assumption of the uniform distribution for the vacancy creation cost is in line with Fujita and Ramey (2007). We have estimated a version of the model in which we include the parameter η_a in the set of parameters to be estimated. We obtain a posterior estimate of η_a close to one and very similar estimates for the other parameters. For simplicity and for obtaining a closed-form solution for the steady-state equilibrium, we assume that $\eta_a = 1$ in our benchmark model.

¹²To calibrate the depreciation rate of automation equipment, we use the ratio of the depreciation of private information equipment (KPPM0ET@CAPSTOCK in Haver) to the net stock of private information equipment (EPPM0ET@CAPSTOCK in Haver), both evaluated at historical cost. The sample average of

the level of labor productivity to $\bar{Z} = 1$ and the average automation-specific productivity to $\bar{\zeta} = 1.5$, reflecting the relative average efficiency of the automation technology.

Based on the empirical estimates of [Eden and Gaggli \(2018\)](#), we calibrate the weight of worker-produced intermediate goods in final goods production to $\alpha_n = 0.535$. We calibrate the elasticity of substitution between intermediate goods produced by automation capital and by workers to $\sigma = 3$ based on the studies of [Eden and Gaggli \(2018\)](#) and [Berg et al. \(2018\)](#).¹³

We target a steady-state unemployment rate of $U = 0.0595$, corresponding to the average unemployment rate in our sample from 1985 to 2018. The steady-state employment rate is given by $N = 1 - U$, hiring rate by $m = \bar{\delta}N$, the number of job seekers by $u = 1 - (1 - \bar{\delta})N$, and the job finding rate by $q^u = \frac{m}{u}$. We target a steady-state job filling rate q^v of 0.71 per quarter, in line with the calibration of [den Haan et al. \(2000\)](#). The implied stock of vacancies is $v = \frac{m}{q^v}$. The scale of the matching efficiency is then given by $\mu = \frac{m}{u^\alpha v^{1-\alpha}}$.

Conditional on the estimated value of κ_a and the normalization of the average productivity levels (\bar{Z} and $\bar{\zeta}$), we solve for the steady-state automation value J^a from the Bellman equation (20). Then, given the estimated values of \bar{e} and \bar{x} (see below for estimation details), we use the vacancy creation condition (21), the automation adoption condition (15), and the law of motion for vacancies (5) to obtain the steady-state probability of automation, which is given by

$$q^a = \frac{J^a}{\bar{x} + \bar{e}(1 - q^v)v}.$$

Given q^a and v , the law of motion for vacancies implies that the flow of new vacancies is given by $\eta = q^a(1 - q^v)v$. The vacancy value is then given by $J^v = \bar{e}\eta$. The stock

the depreciation rate is about 13 percent for the period from 1990 to 2019. The calibrated depreciation rate of automation equipment is also 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.

¹³In the literature, there is substantial uncertainty about the value of the elasticity of substitution (EOS) between automation capital and labor. [Graetz and Michaels \(2018\)](#) and [Acemoglu et al. \(2020\)](#) assume that robots and labor are perfect substitutes in tasks that can be performed by robots, implying an infinite elasticity. Using the relative factor income shares and relative input quantities in aggregate data, [Eden and Gaggli \(2018\)](#) obtain an estimated EOS of about 8 between routine labor and a composite between nonroutine labor and ICT capital, although they argue that an EOS between aggregate routine labor and ICT capital in the range between 2.14 and 3.27 is also plausible. [Cheng et al. \(2021\)](#) estimate the EOS between labor and automation capital among automating firms using Chinese data and exploiting geographic and industry variations of government subsidies for automation under the ‘‘Made In China 2025’’ program. They obtain an estimated elasticity of about 3.8. Based on this literature, we choose a relatively conservative EOS value of 3. In a version of the model with perfect substitution between automation capital and workers, we obtained qualitatively similar results.

TABLE 1. Calibrated parameters

Parameter	Description	value
β	Subjective discount factor	0.99
ϕ	Unemployment benefit	0.25
α	Elasticity of matching function	0.50
μ	Matching efficiency	0.6594
$\bar{\delta}$	Job separation rate	0.10
ρ^o	Automation obsolescence rate	0.03
κ	Vacancy posting cost	0.0409
b	Nash bargaining weight	0.50
η_v	Elasticity of vacancy creation cost	1
η_a	Elasticity of automation cost	1
χ	Disutility of working	0.3812
\bar{Z}	Mean value of neutral technology shock	1
$\bar{\zeta}$	Mean value of equipment-specific technology shock	1.5
σ	Elasticity of substitution between intermediate goods	3
α_n	Share of worker-produced intermediate goods	0.535

of automation equipment A can be solved from the law of motion (17), which reduces to $\rho^o A = \eta$ in the steady state. Thus, in the steady state, the newly created vacancies equal the flow of automated jobs that become obsolete. The law of motion for employment implies that, in the steady state, the flow of hiring equals the flow of separated jobs.

With A and N solved, we have $Y_n = \bar{Z}N$ and $Y_a = \bar{Z}\bar{\zeta}A$, and aggregate output is solved from Eq. (1). We calibrate the vacancy posting cost to κ , such that the steady-state vacancy posting cost is 1 percent of aggregate output (i.e., $\kappa v = 0.01Y$), in line with Blanchard and Galí (2010).

Given J^v and J^a , we obtain the cutoff point for robot adoption $x^* = J^a - J^v$. The match value J^e can be solved from the Bellman equation for vacancies (22), and the equilibrium real wage rate can be obtained from the Bellman equation for employment (23). Steady-state consumption is solved from the resource constraint (31). We then infer the value of χ from the expression for bargaining surplus in Eq. (27).

III.2. Estimation. We estimate the structural parameters \bar{e} , \bar{x} , and κ_a and the shock processes by fitting the DSGE model to quarterly U.S. time series.

III.2.1. Data and measurement. We fit the model to four quarterly time series: the unemployment rate, the job vacancy rate, the growth rate of the real wage rate, and the growth

rate of average labor productivity in the nonfarm business sector. The sample covers the period from 1985:Q1 to 2018:Q4.¹⁴ We provide details of the macro time-series data in Appendix A.

The unemployment rate in the data corresponds to the end-of-period unemployment rate in the model U_t . The measurement equation for unemployment is given by

$$U_t^{data} - \bar{U}^{data} = \hat{U}_t, \quad (33)$$

where U_t^{data} and \bar{U}^{data} denote the logged unemployment rate in the data and its sample mean, respectively, and \hat{U}_t denotes the log deviations of the unemployment rate in the model from its steady-state value.

Similarly, the measurement equation for vacancies is given by

$$v_t^{data} - \bar{v}^{data} = \hat{v}_t, \quad (34)$$

where v_t^{data} and \bar{v}^{data} denote the logged vacancy rate and its sample mean in the data and \hat{v}_t denotes the log deviations of the vacancy rate in the model from its steady-state value. Our vacancy series for the periods prior to 2001 is the vacancy rate constructed by [Barnichon \(2010\)](#) based on the Help Wanted Index. For the periods after 2001, we use the vacancy rate from JOLTS.

In the data, we measure labor productivity by real output per person in the nonfarm business sector. We use the demeaned quarterly log growth rate of labor productivity and relate it to our model variable according to

$$\gamma_{p,t}^{data} - \bar{\gamma}_p^{data} = \hat{Y}_t - \hat{N}_t - (\hat{Y}_{t-1} - \hat{N}_{t-1}), \quad (35)$$

where $\gamma_{p,t}^{data}$ denotes the log growth rate of labor productivity in the data, $\bar{\gamma}_p^{data}$ denotes the sample average of labor productivity growth, and \hat{Y}_t and \hat{N}_t denote the log deviations of aggregate output and employment from their steady-state levels in our model.

We measure the real wage rate in the data by real compensation per worker in the nonfarm business sector. We relate the observed real wage growth to the model variables by the measurement equation

$$\gamma_{w,t}^{data} - \bar{\gamma}_w^{data} = \hat{w}_t - \hat{w}_{t-1}, \quad (36)$$

where $\gamma_{w,t}^{data}$ denotes the log growth rate of the real wage rate in the data, $\bar{\gamma}_w^{data}$ denotes the sample average of real wage growth, and \hat{w}_t denotes the log deviations of real wages from the steady-state level in the model.

¹⁴Matching the observed fluctuations in labor productivity helps discipline the automation mechanism of our model, especially because of the productivity slowdown since the mid-2000s ([Fernald, 2015](#)).

TABLE 2. Estimated parameters

Parameter description	Priors		Posterior		
	Type	[mean, std]	Mean	5%	95%
\bar{e} scale for fixed cost of vacancy creation	G	[5, 1]	3.0703	2.2635	3.9291
\bar{x} scale for fixed cost of automation	G	[5, 1]	4.9483	3.4679	6.4300
κ_a flow cost of automation	B	[0.9, 1]	0.9788	0.9568	0.9999
ρ_z AR(1) of neutral technology shock	B	[0.8, 0.1]	0.9830	0.9696	0.9967
ρ_θ AR(1) of discount factor shock	B	[0.8, 0.1]	0.9760	0.9593	0.9930
ρ_δ AR(1) of separation shock	B	[0.8, 0.1]	0.9272	0.8838	0.9651
ρ_ζ AR(1) of automation-specific shock	B	[0.8, 0.1]	0.8924	0.8553	0.9300
σ_z std of tech shock	IG	[0.01, 0.1]	0.0168	0.0152	0.0188
σ_θ std of discount factor shock	IG	[0.01, 0.1]	0.0469	0.0366	0.0578
σ_δ std of separation shock	IG	[0.01, 0.1]	0.0502	0.0446	0.0548
σ_ζ std of automation-specific shock	IG	[0.01, 0.1]	0.0650	0.0566	0.0739
Log data density			1209.16		

Note: This table shows our benchmark estimation results. For the prior distribution types, we use G to denote the gamma distribution, B the beta distribution, and IG the inverse gamma distribution.

III.2.2. *Prior distributions and posterior estimates.* The prior and posterior distributions of the estimated parameters from our benchmark model are displayed in Table 2.

The priors for the structural parameters \bar{e} and \bar{x} are drawn from the gamma distribution. We assume that the prior mean of each of these three parameters is 5, with a standard deviation of 1. The priors of the flow cost of automation κ_a are drawn from the beta distribution, with a mean of 0.9 and a standard deviation of 1. The priors of the persistence parameter of each shock are drawn from the beta distribution with a mean of 0.8 and a standard deviation of 0.1. The priors of the volatility parameter of each shock are drawn from an inverse gamma distribution with a mean of 0.01 and a standard deviation of 0.1.

The posterior estimates and the 90 percent probability intervals for the posterior distributions are displayed in the last three columns of Table 2. The posterior mean estimate of the vacancy creation cost parameter is $\bar{e} = 3.07$. The posterior mean estimate of the automation cost parameter is $\bar{x} = 4.95$. The posterior mean estimate of the flow cost of operating automation equipment is $\kappa_a = 0.98$. The 90 percent probability intervals indicate that the posterior estimates are significantly different from the priors, suggesting that the data are informative about these structural parameters.

The estimated and calibrated parameters imply a steady-state automation probability of $q^a = 0.096$ in our quarterly model, 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. \(2022\)](#) find that about 47.6 percent of U.S. firms had adopted at least one type of advanced technologies by

2018.¹⁵ 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. 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 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.

The posterior estimation suggests that the shocks to both neutral technology and the discount factor are highly persistent, whereas the automation-specific shock is less persistent but more volatile. The 90 percent probability intervals suggest that the data are also informative for these shock processes.

The estimated model can generate second moments of automation investment that are in line with broader measures of automation investment in the data. Specifically, in our model, automation investment corresponds to the flow of newly adopted automation equipment, which is given by

$$I_{at} \equiv q_t^a (1 - q_{t-1}^v) v_{t-1}. \quad (37)$$

Under the estimated parameters and shocks, the model implies that the unconditional volatility of automation investment relative to that of aggregate output is about 4.71 and the correlation of automation investment with aggregate output is about 0.62. In comparison, in the quarterly U.S. data from 1985 to 2018, the year-over-year growth of real investment in information processing equipment—a proxy for automation investment—has a volatility of about 5.04 times that of real GDP growth and a correlation with real GDP growth of about 0.72.

IV. ECONOMIC IMPLICATIONS

Based on the calibrated and estimated parameters, we examine the model’s transmission mechanism and its quantitative performance for explaining labor market dynamics.

IV.1. Impulse responses. To illustrate the mechanism through which the threat of automation drives labor market dynamics, we calculate the impulse responses of the key variables following each shock.

¹⁵Those 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.

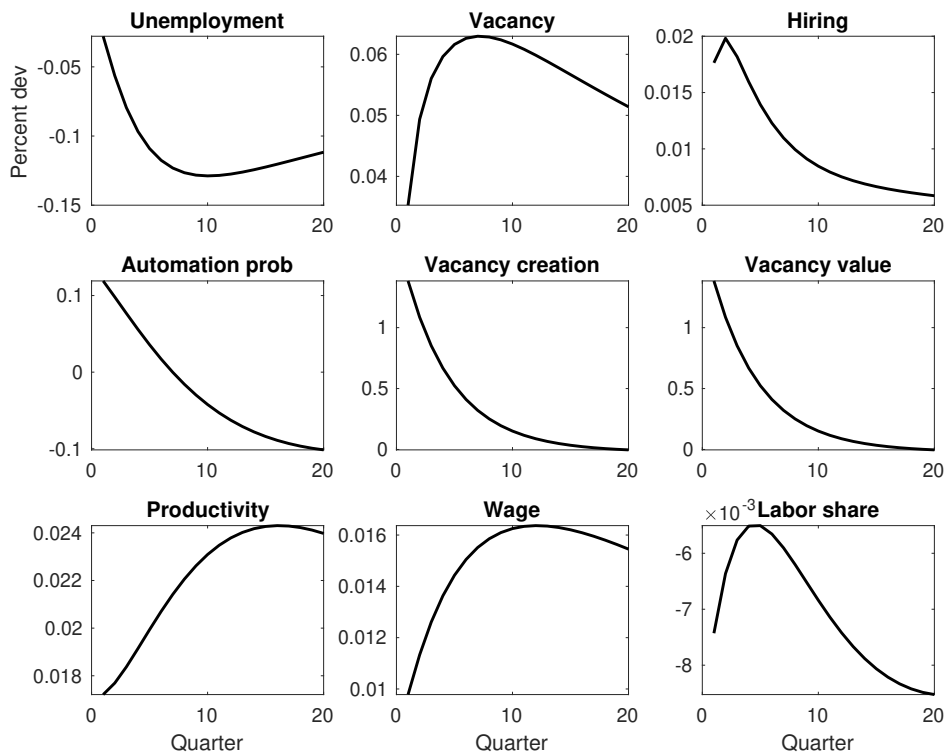


FIGURE 1. Impulse responses to a one-standard-deviation positive neutral technology shock in the benchmark model.

Figure 1 shows the impulse responses of several key macro variables to a positive neutral technology shock (i.e., a one-standard-deviation increase in the neutral productivity) in the benchmark model. The shock leads to persistent declines in unemployment and persistent increases in vacancies and hiring. The shock also raises the value of automation. Under our parameters, the value of automation rises more than does the value of a vacancy, raising the net value of robot adoption and therefore leading to an increase in the automation probability in the short run. Over time, the increase in the value of vacancies dominates that in the value of automation, leading to a decline in the automation probability about six quarters after the shock.

Increased automation following the neutral technology shock also raises labor productivity, reinforcing the initial expansionary impact of the shock. However, the increase in vacancy value also strengthens the firm's bargaining power in wage negotiations, dampening the responses of real wages. With muted wage responses and persistent increases in labor productivity, the shock leads to a persistent decline in the labor income share.

Figure 2 shows the impulse responses to a positive discount factor shock. The shock raises the present values of a job match and an open vacancy. Thus, it generates a persistent boom in employment, vacancies, and hiring. Similar to the neutral technology shock, the discount

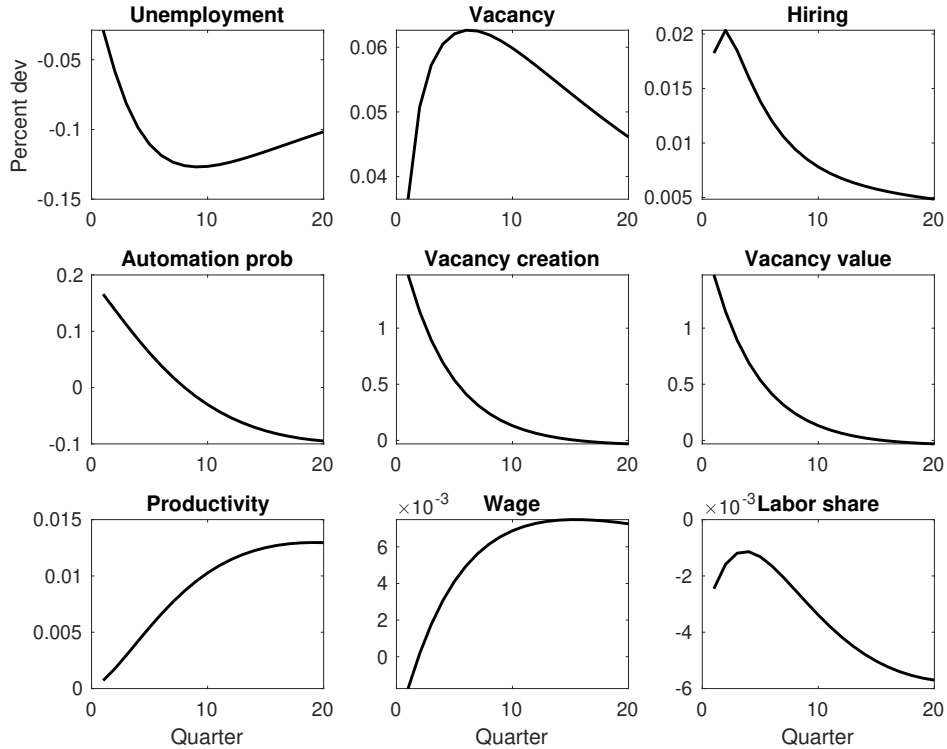


FIGURE 2. Impulse responses to a one-standard-deviation positive discount factor shock in the benchmark model.

factor shock also raises the net value of automation (i.e., the difference between the value of a robot and the value of a vacancy), increasing the automation probability and raising labor productivity. The increased automation threat reduces workers' bargaining power, leading to a modest short-run decline in the real wage, while the labor income share falls persistently.

Figure 3 shows the impulse responses to a positive automation-specific shock. The shock directly raises the value of automation. Since the option of automation boosts the value of vacancies, the increase in automation leads to more vacancy creation. The increase in vacancies raises the job finding rate and hiring, reducing unemployment. As in the case with a neutral technology shock (or a discount factor shock), the automation-specific shock also weakens workers' bargaining power, such that the rise in labor productivity does not translate fully into a rise in wages, leading to a persistent decline in the labor share.¹⁶

IV.2. Automation vs. other amplification mechanisms. Our model suggests that the automation threat effectively weakens workers' bargaining power and mutes wage changes,

¹⁶We report the impulse responses to a job separation shock in the [online appendix](#). As we discuss there, a job separation shock raises both unemployment and vacancies. Consistent with [Shimer \(2005\)](#), this counterfactual positive correlation between unemployment and vacancies renders the job separation shock unimportant for driving labor market dynamics.

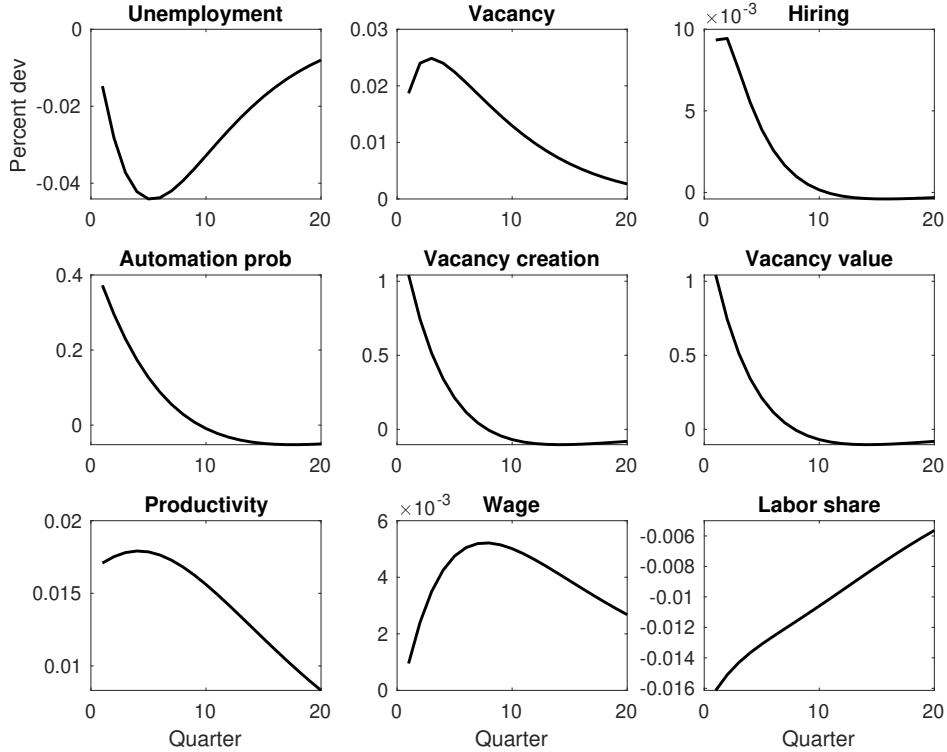


FIGURE 3. Impulse responses to a one-standard-deviation positive automation-specific shock in the benchmark model.

therefore amplifying labor market fluctuations. The literature has studied other amplification mechanisms in the standard DMP framework without automation threats. For example, [Hagedorn and Manovskii \(2008\)](#) argue that, in the standard DMP framework, reducing workers’ bargaining weight or raising the workers’ value of nonmarket activity, such as unemployment insurance (UI) benefits, can amplify fluctuations in unemployment and vacancies.

To evaluate the quantitative importance of the automation channel relative to these alternative amplification mechanisms, we study a counterfactual specification without the automation threat (labeled “no automation threat”), which is a version of our benchmark model with the automation probability q_t^a held constant at its steady-state level. We consider two variations of the “no automation threat” specification, one with a higher UI benefit (raising ϕ from 0.25 to 0.4) and the other with a lower worker bargaining weight (reducing b from 0.5 to 0.3).

Figure 4 displays the impulse responses to a positive discount factor shock in the benchmark model (black solid lines), the counterfactual with no automation threats (blue dashed lines), and the counterfactual with no automation threats and with a higher UI benefit

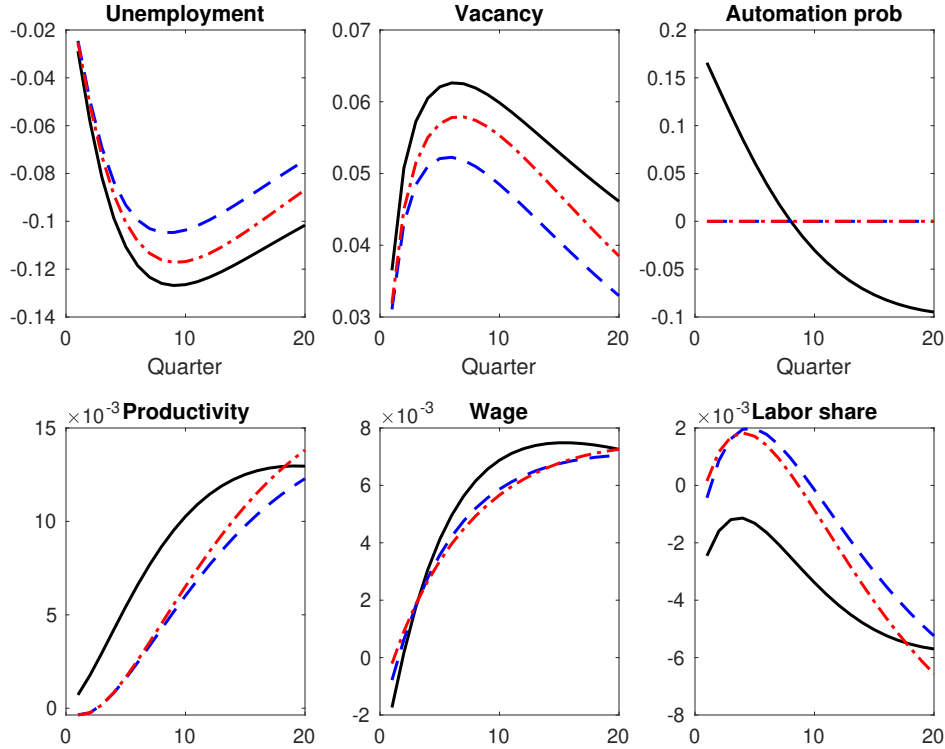


FIGURE 4. Impulse responses to a positive discount factor shock in the benchmark model (black solid lines), the counterfactual with no automation threats (blue dashed lines), and the counterfactual with no automation threats and high unemployment insurance (UI) benefits (red dot-dash lines).

(red dotted-dashed lines).¹⁷ Absent automation threats, the responses of unemployment and vacancies would be more muted than in the benchmark. Raising UI benefits in this case would increase workers' outside option and amplify the responses of the labor market variables (Hagedorn and Manovskii, 2008). A key difference from the benchmark model lies in the responses of wages and the labor share. In our baseline model, the automation threat generates a short-run decline in wages and persistent declines in the labor share. Without the automation threat, however, the counterfactual with higher UI benefits generates less downward pressures on the real wage, leading to a short-run increase in the labor share.

In the counterfactual case without automation threats, mechanically lowering workers' bargaining weight can also dampen wage adjustments and therefore amplify the responses of unemployment and vacancies, consistent with Hagedorn and Manovskii (2008). Figure 5 shows the impulse responses to a positive discount factor shock in the benchmark model (black solid lines), the counterfactual with no automation threats (blue dashed lines), and

¹⁷The impulse responses to a neutral technology shock in these counterfactual models display similar patterns, as we show in the [online appendix](#).

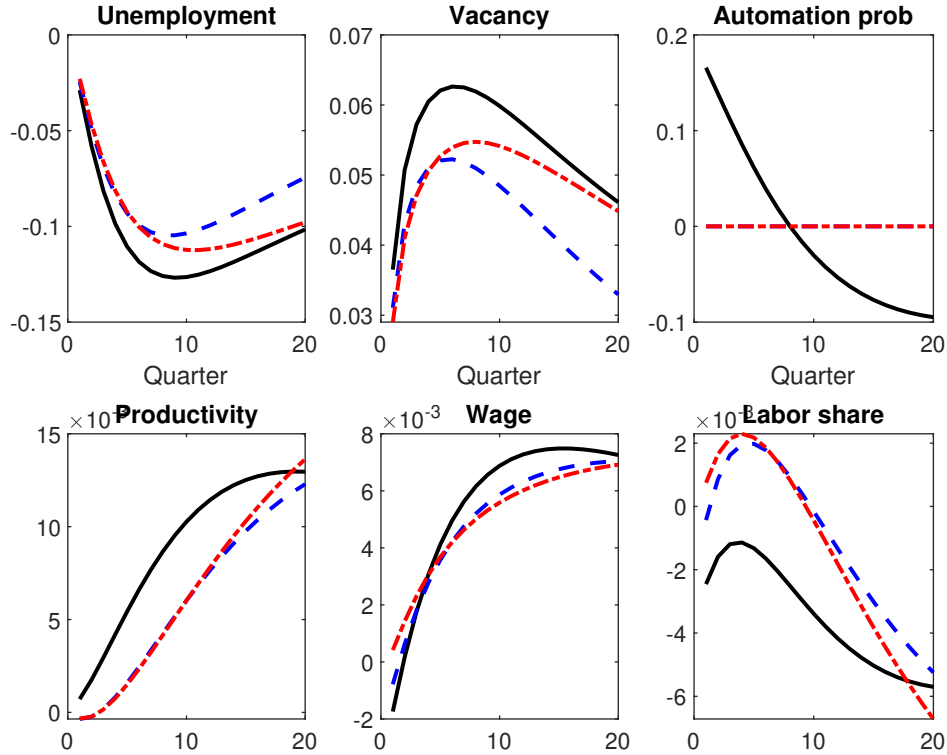


FIGURE 5. Impulse responses to a positive discount factor shock in the benchmark model (black solid lines), the counterfactual with no automation threats (blue dashed lines), and the counterfactual with no automation threats and a low worker bargaining weight (red dot-dash lines).

the no-automation counterfactual with a lower worker bargaining weight (red dotted-dashed lines). Similar to the case with higher UI benefits, the real wage rate does not fall as much as in the benchmark model, such that the labor share rises in the short run, in contrast to the persistent declines under the threat of automation. These impulse responses suggest that the automation channel is an important mechanism for amplifying labor market fluctuations and generating a countercyclical labor income share.

To further illustrate the quantitative importance of the automation mechanism for labor market fluctuations, we compare the predictions from a few counterfactual models without automation threats for the volatility of labor market tightness (i.e., the v/u ratio), the correlation between real wage growth and labor productivity growth, and the volatility of the v/u ratio relative to that of real wages (i.e., the volatility ratio) with the corresponding moments in the benchmark model. For ease of comparison, we normalize each of these labor market moments in the benchmark model to one and we calculate the corresponding moments in the counterfactual models relative to those in the benchmark. Table 3 displays these moments, all expressed relative to the corresponding statistics in the benchmark model.

TABLE 3. Quantitative importance of automation threat

		(a)	(b)	(c)
	Counterfactual model	$std(\ln(v/U))$	$corr(\Delta \ln(w), \Delta \ln(p))$	$\frac{std(\ln(v/U))}{std(\ln(w))}$
(1)	No automation threat	0.69	1.10	0.64
(2)	No automation threat and high UI benefits	0.96	0.81	0.82
(3)	No automation threat and low worker bargaining weight	0.96	1.24	0.81

Note: The rows in the table correspond to the alternative models: (1) the counterfactual with the automation probability held constant at the steady-state level (“No automation threat”); (2) the model with no automation threat and a higher unemployment insurance (UI) benefit (with ϕ raised from 0.25 to 0.4); and (3) the model with no automation threat and a lower worker bargaining weight (with b reduced from 0.5 to 0.3). The columns report (a) the standard deviations of the v/u ratio, (b) the correlation between real wage growth and labor productivity growth, and (c) the ratio of the standard deviation of the v/u ratio to that of real wages, all expressed relative to the corresponding statistics in the benchmark model.

The counterfactual model with no automation threats (row 1 of Table 3) predicts a lower volatility of the v/u ratio (31 percent lower), a higher correlation between real wage growth and labor productivity growth (10 percent higher), and a lower volatility of the v/u ratio relative to that of real wages (36 percent lower) than those in the benchmark model. These results reflect the [Shimer \(2005\)](#) volatility puzzle facing the standard DMP model.

The table also shows that, absent automation threats, raising UI benefits (row 2) or reducing workers’ bargaining weight (row 3) can amplify the fluctuations in the v/u ratio, bringing its volatility closer to that in the benchmark model (from 69 percent to 96 percent). The volatility ratio, however, is about 20 percent lower than that in the benchmark, because real wages fluctuate more than those in the benchmark. Overall, these counterfactual exercises illustrate that the threat of automation creates meaningful wage rigidity that amplifies labor market fluctuations.¹⁸

V. EVIDENCE FOR THE MODEL’S MECHANISM

Our model’s mechanism suggests that the procyclical automation probability dampens real wage fluctuations. By weakening workers’ bargaining power, automation reduces the

¹⁸In another counterfactual, we raised the worker bargaining weight (b) from 0.5 to 0.75 and the scale parameter of automation costs \bar{x} from 4.9 to 9.8. This counterfactual captures the earlier decades when unionization rates were higher and automation was less prevalent. We find that, in this counterfactual model, the correlation between wage growth and labor productivity growth is roughly 25 percent lower than that in the benchmark model, while the v/u volatility and the volatility ratio are both roughly comparable to those in the benchmark model. This finding suggests that higher unionization rates (and lower automation adoption) in the earlier decades could help explain the disconnect between wages and labor productivity, contributing to labor market fluctuations. In the more recent decades, the steady declines in unionization rates allowed other mechanisms such as automation to play a more prominent role in explaining the disconnect between wages and labor productivity.

correlation between real wages and labor productivity. This creates endogenous real wage rigidity and amplifies fluctuations in unemployment and vacancies. We now present some cross-sectional and time-series evidence that is consistent with the model’s mechanism.

V.1. Cross-sectional evidence. We first present cross-sectional evidence that supports the model’s mechanism. We estimate the following dynamic panel regression

$$\ln(Y_{it}) = a_0 + a_1 \ln(Y_{i,t-1}) + a_2 \ln(P_t) \times AP_i + \gamma_i + \eta_t + \varepsilon_{it}, \quad (38)$$

where the dependent variable Y_{it} includes the v/u ratio, vacancies, unemployment, and the real wage rate in industry i and quarter t . The main independent variable of interest is the interaction term $\ln(P_t) \times AP_i$, which is a proxy for time-varying automation threats. Here, P_t denotes the aggregate time series of the relative price of computer equipment and AP_i denotes the automation potential of industry i , which is a fixed characteristic of tasks in an industry, as we discuss in more detail below. By combining an aggregate relative price with physical characteristics of tasks in an industry, our proxy for the threat of automation is likely exogenous to movements in labor market variables in any given sector. We include the lagged dependent variable as a regressor to control for serial correlations in the dependent variable in our quarterly panel. The terms γ_i and η_t measure the industry fixed effects and the time fixed effects, respectively. The term ε_{it} is a regression residual.

The coefficient a_2 measures the relative sensitivity of the industry variable Y_{it} to changes in the aggregate computer prices, depending on the industry-specific automation risks. Our model suggests that, for an industry with a higher risk of automation (i.e., with a higher level of AP_i), a decline in computer prices should lead to a larger increase in the job vacancy rate and the v/u ratio. Since automation threats reduce workers’ bargaining power and therefore dampen wage changes, the effect of a decline in computer prices on real wages is *a priori* ambiguous.

To obtain an empirical estimate of the parameter of interest (a_2), we estimate the regression specified in Eq. (38) using industry-level data in the United States. We obtain industry-level job vacancy rates from JOLTS and unemployment rates and real wages from the Bureau of Labor Statistics (BLS). We focus on the pre-pandemic periods up to 2019. Our unbalanced panel of vacancies, unemployment, and the v/u ratio covers 15 NAICS two-digit industries for the period 2001:Q1 to 2019:Q4. The quarterly panel of real wages covers 12 two-digit industries for the periods from 1985:Q1 to 2019:Q4.

To measure industry-specific automation exposures (AP_i), we use the technological automation potential for two-digit industries constructed by the McKinsey Global Institute (see Manyika et al. (2017)). This measure captures the weighted average of the automation potential of tasks in an industry based on their physical characteristics. The relative price of

TABLE 4. Summary statistics

	(1)				
	Mean	count	SD	Min	Max
$\ln(v)$	1.04	1140	0.40	-0.51	1.93
$\ln(u)$	1.67	1140	0.45	0.17	3.08
$\ln(v/u)$	-0.63	1140	0.72	-3.25	1.31
$\ln(w)$	3.00	1680	0.22	2.49	3.54
$\ln(\text{ComputerPrice}) \times AP$	2.72	1972	0.90	1.19	5.33
$\ln(\text{ComputerPrice})$	5.91	1972	1.45	4.41	8.88
AP	0.46	1972	0.10	0.27	0.73

computer equipment is the ratio of the quality-adjusted chain price index for private investment in computers and peripherals to the chained personal consumption expenditures price index (PCEPI), with both price series taken from the Bureau of Economic Analysis (BEA). We use the time series of the relative price of computing equipment to capture changes in aggregate economic conditions such as technological changes that drive automation decisions. We provide detailed descriptions of these data in Appendix B.

Since computer prices are common for all industries, the main source of cross-industry variations of our key independent variable stems from AP_i . As shown in the summary statistics presented in Table 4, there are meaningful variations in AP_i across industries, ranging from low scores of about 0.3 (educational services, professionals, and management) to high scores above 0.6 (accommodation and food services, manufacturing, and transportation and warehousing). The standard deviation of AP_i is about 22 percent of its average level (0.1/0.46). This cross-industry variation, along with the time-series variation in computer prices, leads to substantial variations in the interaction term between computer prices and AP_i .¹⁹

We estimate the empirical specification (38) using the Arellano-Bond estimator for dynamic panel data.²⁰ Table 5 reports the estimation results. The columns show the regression

¹⁹An alternative measure of industry-level automation exposures is robot density (e.g., the operation stock of industrial robots per thousand employees). However, the IFR—the main source of robot data—covers mainly manufacturing industries. This would create a challenge for our empirical work since our industry-level data on vacancies, unemployment, and wages include many non-manufacturing industries (e.g., retail, wholesale, real estate, education, and professional services) that are not covered by the IFR data. For this reason, we focus on the automation potentials (AP_i) constructed by McKinsey as our baseline measure for automation exposures.

²⁰The Arellano-Bond estimator first takes the differences of all variables in Eq. (38) to remove the constant and the industry fixed effects. It then applies the generalized method of moments (GMM) approach

TABLE 5. Automation threat and labor market outcomes: Cross-sectional evidence

Dep. Var.	$\ln(v/u)$	$\ln(v)$	$\ln(u)$	$\ln(w)$
$\ln(\text{ComputerPrice}) \times AP$	-0.411** (0.174)	-0.354** (0.141)	0.216* (0.115)	0.002* (0.001)
Lagged $\ln(v/u)$	0.470*** (0.028)			
Lagged $\ln(v)$		0.393*** (0.028)		
Lagged $\ln(u)$			0.407*** (0.029)	
Lagged $\ln(w)$				0.979*** (0.004)
Constant	0.868** (0.365)	1.096*** (0.315)	0.856*** (0.259)	0.061*** (0.010)
Observations	1125	1125	1125	1668
Time Periods	2001Q1:2019Q4	2001Q1:2019Q4	2001Q1:2019Q4	1985Q1:2019Q4
No. of industries	15	15	15	12

Note: This table shows the panel estimation results using NAICS two-digit industry-level data under the empirical specification in Eq. (38). Each column indicates the dependent variable of each regression, including the v/u ratio (v/u), the vacancy rate (v), the unemployment rate (u), and the real wage rate (w), all in log units and at the quarterly frequency. In each regression, the independent variables include one lag of the dependent variable, the interaction between the relative price of computers and peripherals and the industry-specific automation potential (AP), and industry and time fixed effects. Standard errors are reported in parentheses. The stars denote the p-values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

results for alternative industry-level dependent variables, including the v/u ratio (v/u), the vacancy rate (v), the unemployment rate (u), and the real wage rate (w), all in log units. The first row shows the estimated coefficient a_2 on the interaction term between computer prices (also in log units) and the industry-specific automation risks.

The table shows that, in an industry more exposed to automation risks (i.e., with a higher AP_i), a decline in computer prices is associated with a greater increase in both the v/u ratio and the vacancy rate and a greater decline in the unemployment rate.²¹ The estimated impact of the automation threat (measured by the interaction term) on these labor market variables are statistically significant and economically important. For instance, a 1 percent increase in our measure of the automation threat (i.e., a 1 percent decline in the interaction between computer prices and AP_i) raises vacancies by 0.35 percent relative to its mean. This magnitude is in line with our model’s predicted impulse responses of vacancies to an

to estimating the parameters of interest, using lagged dependent variables as a part of the instrumental variables. We implement this estimator with the command “xtabond2” in Stata. Since the estimator uses first differences of the variables, the coefficient a_2 measures the sensitivity of changes in the dependent variable for each industry to changes in the relative price of computer equipment, depending on the industry’s exposure to automation risks measured by AP_i .

²¹Our discussion here focuses on the effects of a decline in computer prices. If the estimated coefficient a_2 is negative, as in the case for the v/u ratio (for instance), it means that a decline in computer prices raises the v/u ratio.

automation-specific shock shown in Figure 3.²² A decline in computer prices is also associated with a significant reduction in real wages in industries more exposed to automation risks, consistent with the independent evidence documented by Acemoglu and Restrepo (2021).²³

Our industry-level evidence suggests that the diffusion of automation in the past two decades had significantly different impacts on labor market variables in industries that face different exposures to automation risks. This evidence lends empirical support to our model’s implication that the threat of automation weakens workers’ bargaining power, restraining wage increases, and thus amplifying labor market fluctuations.

A potential confounding factor, however, could be variations in unionization rates over time, because changes in unionization rates could also induce changes in bargaining power and impact labor market fluctuations. To address this concern, we now add a control for industry-specific variations in unionization rates in the regressions.²⁴ Table 6 displays the regression results. It shows that, after controlling for variations in unionization rates (both across time and across industries), we obtain similar point estimates of the coefficient a_2 to those obtained in the benchmark specification reported in Table 5. The main difference is in the wage regression, where the point estimate of a_2 becomes larger (0.006 vs. 0.002), although it is less precisely estimated than in the benchmark specification.

Similar to changes in unionization, changes in offshoring could also affect U.S. labor market outcomes and potentially confound the effects of automation. However, industry-level data on offshoring (i.e., importing of intermediate goods) are available only for tradable sectors such as agriculture, manufacturing, and mining. Thus, we cannot add an explicit control

²²In the model, a one-standard-deviation positive shock to the automation-specific technology—or equivalently, a 6.5 percent increase in the shock—raises vacancies about 2 percent on impact (see Figure 3). The empirical estimate reported in Table 5 suggests that a 6.5 percent increase in the automation threat would raise vacancies by about $6.5 \times 0.35 \approx 2.3$ percent. A similar calculation suggests that the magnitude of the impulse responses of unemployment to an automation-specific shock in our model is comparable to the empirical estimate reported in Table 5.

²³We have also estimated a similar empirical specification for industry-level labor shares using the BLS annual data from 1987 to 2019 (not reported in the paper). The estimation suggests that an increase in automation threat leads to a larger reduction in the labor share in an industry that is more exposed to automation, in line with our model’s implications. However, these effects (i.e., the coefficient a_2) are imprecisely estimated, partly because the sample is relatively small (at the annual frequency, instead of quarterly).

²⁴We measure the two-digit industry-level unionization rates by the shares of private employed wage and salary workers that are members of a labor union. The data are available at the annual frequency from the BLS (through Haver Analytics), from 2000 to 2021. We extrapolate the annual unionization data to a quarterly frequency by assuming that, for each industry, the unionization rate stays the same within a year.

TABLE 6. Automation threat and labor market outcomes: Controlling for unionization

Dep. Var.	$\ln(v/u)$	$\ln(v)$	$\ln(u)$	$\ln(w)$
$\ln(\text{ComputerPrice}) \times AP$	-0.435** (0.178)	-0.301** (0.143)	0.284** (0.118)	0.006 (0.005)
Lagged $\ln(v/u)$	0.471*** (0.028)			
Lagged $\ln(v)$		0.383*** (0.029)		
Lagged $\ln(u)$			0.405*** (0.029)	
Lagged $\ln(w)$				0.973*** (0.008)
$\ln(\text{Union})$	0.0447 (0.070)	-0.101** (0.0498)	-0.111** (0.044)	-0.002 (0.002)
Constant	0.843** (0.367)	1.669*** (0.306)	0.349 (0.243)	0.078*** (0.019)
Observations	1125	1125	1125	960
Time Periods	2001q2:2019q4	2001q2:2019q4	2001q2:2019q4	2000q1:2019q4
No. of industries	15	15	15	12

Note: This table shows the panel estimation results using NAICS two-digit industry-level data under the empirical specification in Eq. (38), adding controls for industry-specific unionization rates (*Union*, in log units). The unionization rate data are available at the annual frequency, which are extrapolated to quarterly frequency (by assuming that the within-year values are identical to the annual value). The other variables are the same as those reported in Table 5. Standard errors are reported in parentheses. The stars denote the p-values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

for offshoring in the industry-level regressions, because the sample covers a number of non-manufacturing industries with little exposure to offshoring. As an alternative, we isolate the effects of automation from those of offshoring by re-estimating the industry-level regressions without the tradable sectors. We find that the main results obtained in our benchmark specification are robust.²⁵

V.2. Time-series evidence. Our model’s mechanism is also broadly consistent with time-series data. Since the early 2000s, the importance of automation in the United States has risen steadily. As shown in Figure 6, the ratio of real investment in information processing equipment to real GDP and robot density (i.e., the operation stock of robots per thousand manufacturing employees)—two different measures of automation—have both increased substantially during the past two decades (left panel). Our model mechanism suggests that, given the increases in automation, the volatility of labor market tightness (i.e., the v/u ratio) should increase and the correlation between real wages and labor productivity should decrease during this period. These model implications are broadly consistent with the U.S. time-series data.

Figure 7 shows that the standard deviation of labor market tightness initially declined from the 1980s to the 1990s, consistent with the “Great Moderation” hypothesis. Since the

²⁵The detailed results are shown in Appendix C.

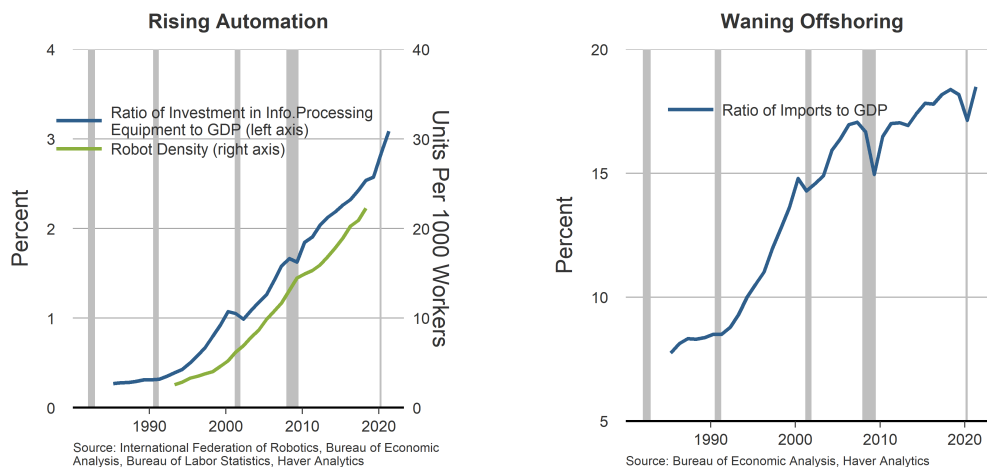


FIGURE 6. Trends in automation and offshoring in the United States. The left panel shows two measures of automation: the ratio of real investment in information processing equipment to real GDP (blue line) and the robot density measured by the operation stock of industrial robots per thousand manufacturing employees (green line). The right panel shows the ratio of real imports to real GDP. The shaded bars indicate NBER recession dates.

Source: U.S. Bureau of Economic Analysis, Bureau of Labor Statistics, Haver Analytics, International Federation of Robotics, and authors' calculations.

early 2000s, however, the volatility of the v/u ratio has increased steadily. The volatility of the v/u ratio in the 2010s (prior to the global pandemic) was about double that in the 1990s. The correlation between real wages and labor productivity initially increased from the 1980s to the 1990s, and then declined substantially since the early 2000s. The correlation in the 2010s was less than half of that in the 1990s.

Our model suggests that these time-series changes in labor market dynamics might be partly driven by the rising threat of automation. To get a quantitative sense of the extent to which automation has contributed to the changes in labor market dynamics over time, we consider a counterfactual version of the model, in which we reduce the steady-state share of intermediate goods produced by automation equipment relative to those produced by workers. Specifically, we raise the weight on intermediate goods produced by workers in the final goods production function from the calibrated value of $\alpha_n = 0.535$ to 0.682, such that the steady-state ratio of automation investment to aggregate output is about one-third of that in the benchmark model. This counterfactual captures the economy in earlier decades (such as the late 1980s and the early 1990s) when automation was less prevalent. For example, in the late 1980s and early 1990s, the ratio of information processing equipment investment to real GDP was about one-third of the sample median from 1985 to 2019. With

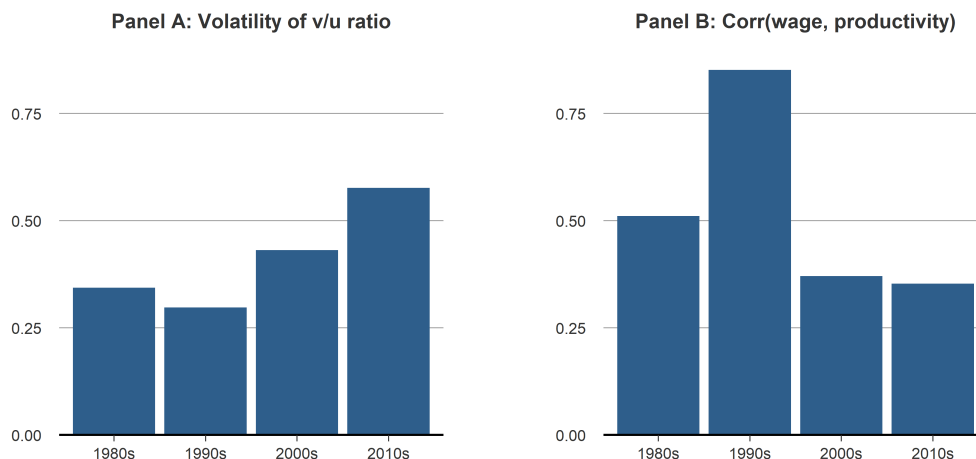


FIGURE 7. Changes in labor market volatilities and correlations over time. The left panel shows the standard deviations of labor market tightness measured by the v/u ratio for each of the four decades from 1980 to 2019. The right panel shows the correlations between year-over-year growth in real wages and in labor productivity in each of those four decades.

Source: Bureau of Labor Statistics, JOLTS, Haver Analytics, and authors' calculations.

a lower automation share, which translates into a lower automation probability, the volatility of labor market tightness is about half of that in the benchmark model, while the correlation between wage growth and labor productivity growth is about 30 percent higher. These patterns are consistent with the observed increases in the volatility of the v/u ratio and the substantial decline in the correlation between wage growth and productivity growth since the early 2000s shown in Figure 7.

Our model mechanism does not inherently rely on firms' ability to substitute automation equipment for workers but on the possibility of adopting labor-saving technologies, such as offshoring of intermediate goods production. For example, [Arseneau and Leduc \(2014\)](#) show that the threat of offshoring can affect domestic wages through its impact on firms' outside options. [Elsby et al. \(2013\)](#) show that rising offshoring has played an important role in explaining the declines in the labor share from the mid-1980s up to the Great Recession in the late 2000s. Since the 2010s, however, the importance of offshoring has diminished, as the increase in the ratio of real imports to real GDP in the United States has slowed significantly following the trade collapse in 2008-2009 (right panel of Figure 6). Recent supply-chain disruptions stemming from the U.S.-China trade wars and the COVID-19 pandemic further highlight the fragility of global supply chains ([Antràs, 2020](#)). The use of automation

technologies, in contrast, has been steadily rising, suggesting that the importance of the automation channel has increased relative to the offshoring channel, at least since the 2010s.

VI. ROBUSTNESS OF THE MODEL MECHANISM

Our benchmark model shows that the threat of automation can effectively weaken workers' bargaining power, resulting in sluggish adjustments in real wages and therefore amplifying fluctuations in unemployment and vacancies. We now consider three variations of the benchmark model and examine the robustness of the model's main transmission mechanism.²⁶

VI.1. Production lags. In the benchmark model, automation equipment becomes productive without delays. In reality, however, it may take some time for newly adopted equipment to become productive, reflecting adjustment costs in using the new equipment. We now consider a variation of the benchmark model with production lags associated with the automation technology. For simplicity, we consider a one-period lag, such that a firm that operates the automation technology can produce intermediate goods using automation equipment built in the previous period.

With production lags, the profit flow generated from an automation equipment built in period t can be materialized in period $t + 1$. Thus, the present value of automation would become

$$J_t^a = (1 - \rho^o) \mathbb{E}_t D_{t,t+1} [p_{a,t+1} Z_{t+1} \zeta_{t+1} - \kappa_a + J_{t+1}^a]. \quad (39)$$

The market-clearing condition for intermediate goods produced by the automation technology is now given by

$$Y_{at} = Z_t \zeta_t A_{t-1}, \quad (40)$$

where the input is the previous-period stock of automation equipment A_{t-1} instead of the current-period equipment.

The market-clearing condition (31) for final goods also needs to be modified such that the per-period fixed cost of operating the automation technology is given by $\kappa_a A_{t-1}$.

For ease of comparison, we solve this version of the model with production lags using the same parameters as in the benchmark model. The implications of the model are very similar to those of the benchmark. For example, the unconditional volatility of the labor market tightness and the volatility ratio in this model are, respectively, about 97 percent and 98 percent of those corresponding moments in the benchmark model. The impulse responses to each shock are also very similar to those in the benchmark model, as we show in the [online appendix](#). Thus, our model mechanism is not sensitive to introducing production lags.

²⁶To conserve space, we sketch the key ingredients of each model in the text and describe the full equilibrium system in the [online appendix](#).

VI.2. Automating jobs. In our benchmark model, we assume that firms can automate a vacancy if that vacancy is not filled with a worker. A plausible alternative way of thinking about automation is to allow firms to automate an existing job instead of an open vacancy. We now consider such an alternative setup.

In the beginning of period t , after observing all aggregate shocks, a firm can decide whether or not to replace a worker in an existing job match with automation equipment. The firm draws a cost x of automation from an i.i.d. distribution $F(x)$ and chooses to automate if the cost lies below the expected benefits of automation. There exists a threshold level of the automation cost—denoted by x_t^* —such that the firm automates the job position if and only if $x \leq x_t^*$. Thus, the automation probability is given by $q_t^a = F(x_t^*)$. If the firm automates the job, it obtains the automation value J_t^a (see Eq. (20)), but gives up the employment value J_t^e . Thus, the automation threshold is given by $x_t^* = J_t^a - J_t^e$.

The employment value takes into account the possibility of automation and is given by

$$J_t^e = p_{nt}Z_t - w_t + \mathbb{E}_t \beta \theta_{t+1} \frac{C_t}{C_{t+1}} \left\{ \delta_{t+1} J_{t+1}^v + (1 - \delta_{t+1}) \left[q_{t+1}^a J_{t+1}^a - \int_0^{x_t^*} x dG(x) + (1 - q_{t+1}^a) J_{t+1}^e \right] \right\}. \quad (41)$$

A job match yields the flow profit $p_{nt}Z_t - w_t$ in period t . In period $t + 1$, the job can be exogenously separated (with the probability δ_{t+1}), in which case the firm obtains the vacancy value J_{t+1}^v . If the job is not separated, it can be automated with the probability q_{t+1}^a , in which case the firm obtains the automation value J_{t+1}^a net of the equipment adoption costs. If the job is neither separated nor automated, then the firm obtains the continuation value of employment J_{t+1}^e .

Since a fraction of nonseparated jobs are automated, employment follows the law of motion

$$N_t = (1 - \delta_t)(1 - q_t^a)N_{t-1} + m_t. \quad (42)$$

We simulate the model based on the calibrated and estimated parameters as in the benchmark model. We recalibrate the relative productivity of automation such that the model with automated jobs implies the same steady-state probability of automation as that in the benchmark model.

Figure 8 shows the impulse responses of a few key macro and labor market variables following a positive discount factor shock. The shock raises the net present value of automation and thus increases the probability of automation. The increase in automation probability has two opposing effects on employment. Automation directly replaces workers in this model, pushing up the unemployment rate. At the same time, automation improves labor productivity, raising the employment value and boosting employment. With the calibrated parameters, the employment-boosting effect dominates the job-displacing effect, such that a positive discount factor shock leads to persistent declines in the unemployment rate. The

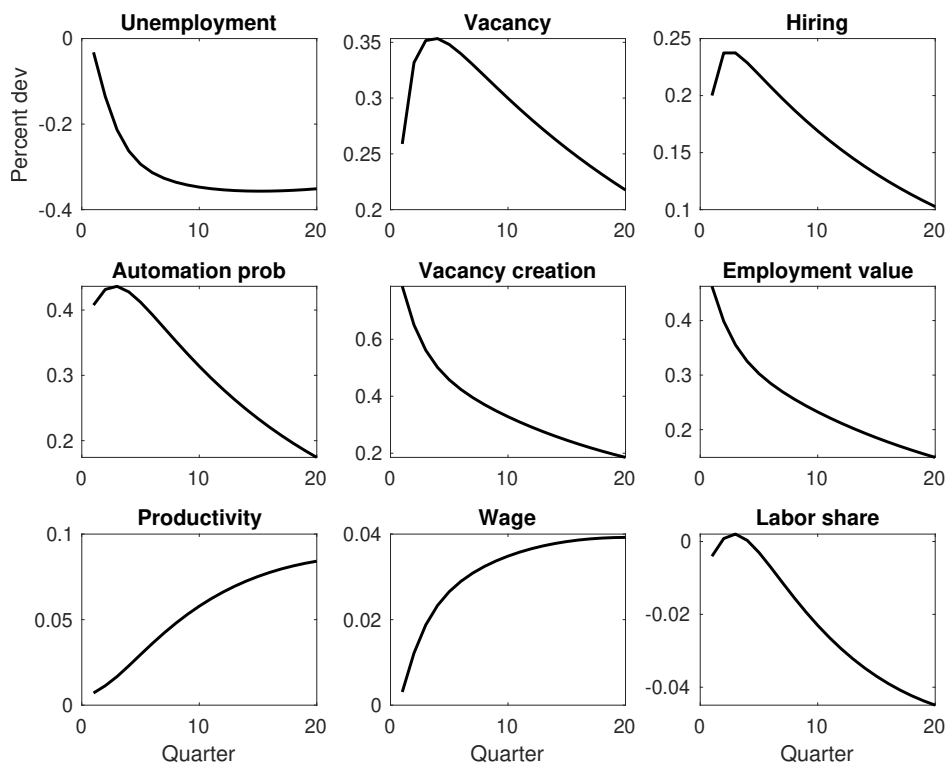


FIGURE 8. Impulse responses to a positive discount factor shock in the alternative model with automated jobs instead of vacancies.

discount factor shock increases the value of vacancies, encouraging firms to create new vacancies and leading to large and persistent increases in the stock of vacancies. As a result, the labor market tightness (i.e., the v/u ratio) increases persistently (not shown in the figure).

Increased automation probability leads to a muted response of the real wage rate, reflecting that the threat of automation weakens workers' bargaining power. Since labor productivity rises and wage responses are relatively muted, the labor share declines following a positive discount factor shock, as in our benchmark model. Thus, the automation channel that we have identified in the benchmark model is robust when we consider automating jobs instead of vacancies.

VI.3. Heterogeneous worker skills. In our benchmark model, workers are homogeneous. We now generalize the benchmark model to incorporate heterogeneity in worker skills. We show that the model mechanism survives this generalization. Furthermore, the model implies that automation has a skill-upgrading effect that raises the relative demand for skilled workers and the skill wage premium, in line with firm-level evidence (Acemoglu et al., 2022).

The economy has two types of workers, skilled and unskilled, and all workers are members of the representative household family. A firm can produce a homogeneous consumption good by either hiring an unskilled worker from the frictional labor market or adopting an

automation equipment and hiring skilled workers in a competitive spot labor market to operate the equipment. Thus, automation equipment is a complementary input for skilled workers but a substitute for unskilled workers.²⁷

To keep the model tractable, we assume that the aggregate supply of skilled workers is inelastic and fixed at \bar{s} .²⁸ Skilled workers face a spot labor market with the competitive wage rate w_{st} . Unskilled workers face search frictions in the labor market, and they each receive either the unskilled wage rate w_{nt} if employed or the UI benefit ϕ if unemployed.

The household utility function remains the same (see Eq. (9)). The budget constraint now includes the additional wage income from skilled workers and is given by

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_{nt}N_t + w_{st}\bar{s} + \phi(1 - N_t) + d_t - T_t. \quad (43)$$

Since the supply of skilled workers is inelastic, introducing skilled workers does not affect the household's optimizing decisions relative to the benchmark model. The only required modification in the household's problem is that, in the employment surplus expression (13), the wage rate w_t should be replaced by the unskilled wage rate w_{nt} .

An intermediate goods producer (i.e., a firm) can choose a technology at the beginning of each period: one requires an unskilled worker as the only input, and the other requires automation equipment along with s_t skilled workers as inputs. If the firm hires an unskilled worker for production, then it can produce $y_{nt} = Z_t$ units of output. If the firm chooses the automation technology, then it optimally chooses the input of skilled workers s_t , with the production function

$$y_{at} = Z_t \zeta_t^{\gamma_a} s_t^{1-\gamma_a}, \quad (44)$$

where $\gamma_a \in (0, 1)$ denotes the output elasticity of the equipment input.

If a firm chooses the automation technology, then it takes the skilled wage rate w_{st} as given and chooses s_t to maximize the profit before paying the fixed costs of operating the automation equipment. The value of automation is given by

$$J_t^a = \pi_t^a + (1 - \rho^o) \mathbb{E}_t \beta \theta_{t+1} \frac{C_t}{C_{t+1}} J_{t+1}^a, \quad (45)$$

²⁷Our approach here is similar to that in [Krusell et al. \(2000\)](#), who study a neoclassical model in which capital equipment complements skilled labor but substitutes for unskilled labor.

²⁸Given our focus on business cycles, assuming a constant supply of skilled workers seems innocuous since human capital accumulation is likely a slow-moving process. In the data, the share of skilled workers (e.g., those with a bachelor's degree or higher) has been rising steadily over time, and it shows little cyclical fluctuation. See [He and Liu \(2008\)](#) for a general equilibrium extension of the [Krusell et al. \(2000\)](#) model that incorporates endogenous skill accumulation.

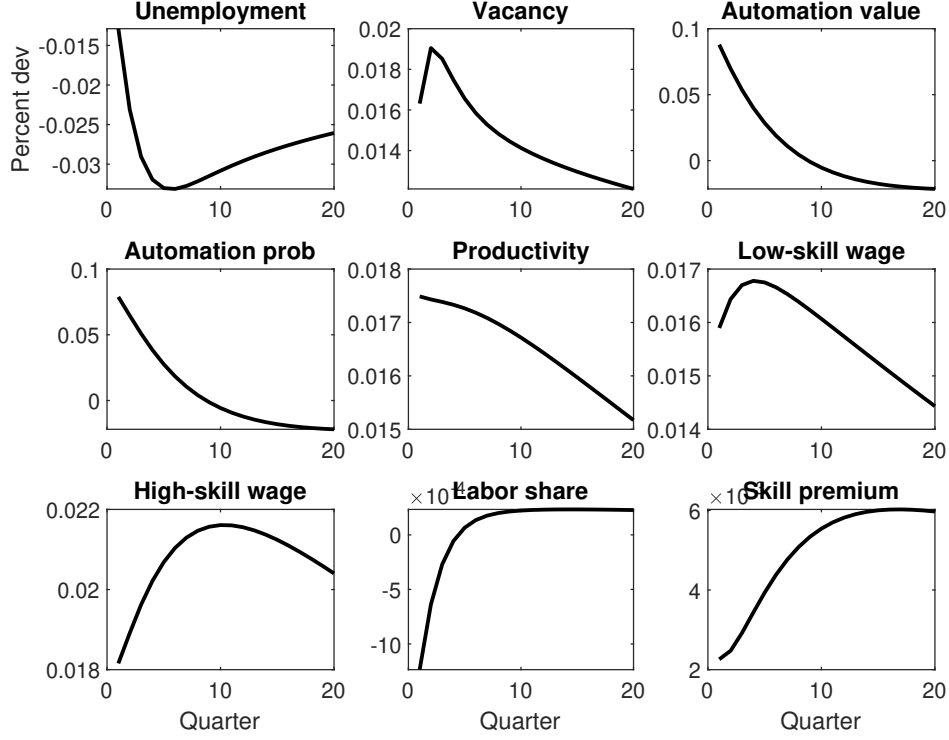


FIGURE 9. Impulse responses to a positive neutral technology shock in the model with heterogeneous worker skills.

where $\pi_t^a \equiv \max_{s_t} p_{at} Z_t \zeta_t^{\gamma_a} s_t^{1-\gamma_a} - w_{st} s_t - \kappa_a$. Therefore, different from our benchmark model, automation now entails both a flow fixed cost and a variable cost through the use of skilled workers as a complementary input.

We use the calibrated and estimated parameters in the benchmark model (where appropriate), and calibrate three additional parameters in this generalized model. We set $\gamma_a = 0.32$, such that the skilled labor share is 68 percent of the revenue generated by the automation technology. We normalize the supply of skilled workers and calibrate the average level of the automation-specific productivity (relative to the neutral technology) 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.

Figure 9 shows the impulse responses following a positive neutral technology shock. The shock lowers unemployment and raises vacancies in the short run, although the responses are somewhat smaller in magnitude than those in the benchmark model. The shock boosts the present value of automation, raising the automation probability and labor productivity, which is measured by the ratio of aggregate output to aggregate employment, including both skilled and unskilled workers.

The increased threat of automation raises the firm’s reservation value in wage bargaining, restraining wage increases for unskilled workers. Since automation equipment and skilled workers are complementary inputs in production, increases in automation raises the skilled wage rate, resulting in a persistent increase in the skill premium.

Under our calibration, despite the wage increases for both types of workers, the model predicts that the labor share (defined as the ratio of aggregate labor income—including skilled and unskilled labor—to aggregate output) falls in response to a positive neutral technology shock.²⁹

Since skilled workers are required to operate the automation equipment, the flow cost of using the automation technology increases with skilled wages. All else being equal, a business cycle boom that raises skilled wages would reduce the net value of automation, mitigating the increase in the automation probability. This feature is parallel to that for operating the manual technology, under which an increase in the wage rate of unskilled workers would reduce the present value of employment and thus discourage hiring. Nonetheless, the central mechanism of our benchmark model remains robust: increased automation weakens (unskilled) workers’ bargaining power, dampens wage increases, and thus amplifies labor market fluctuations.

VII. CONCLUSION

We studied the role of automation in explaining the observed labor market dynamics in a tractable quantitative general equilibrium framework. The threat of automation raises the firm’s reservation value in wage bargaining, reducing the worker’s effective bargaining power and dampening increases in real wages in a business cycle boom. By lowering the correlation between wages and labor productivity, automation creates a source of real wage rigidity that amplifies labor market fluctuations. The automation mechanism is supported by empirical evidence and quantitatively important.

A natural extension of our model framework is to incorporate firm heterogeneity in automation adoption. Recent surveys by the U.S. Census Bureau find that the use of automation technology is not widespread across firms; instead, it is highly skewed towards large and high-productivity firms (Zolas et al., 2020; Acemoglu et al., 2022). In a more general framework with firm heterogeneity and labor market search frictions, one could study how worker bargaining power and wages may depend on firm size through heterogeneous automation decisions. Research along these lines is an important and promising avenue for future work.

²⁹The impulse responses to a discount factor shock and an automation-specific shock are reported in the [online appendix](#).

APPENDIX A. MACRO TIME-SERIES DATA

We fit the DSGE model to four time series of quarterly U.S. data, including the unemployment rate, the job vacancy rate, real wage growth, and labor productivity growth. The sample covers the period from 1985:Q1 to 2018:Q4.

- (1) **Unemployment:** civilian unemployment rate (age 16 years and over) from the Bureau of Labor Statistics, seasonally adjusted monthly series (LRUSECON in Haver).
- (2) **Job vacancies:** for pre-2001 periods, we use the vacancy rate constructed by [Bar-nichon \(2010\)](#) based on the Help Wanted Index. For the periods starting in 2001, we use the job openings rate from the Job Openings and Labor Turnover Survey (JOLTS), seasonally adjusted monthly series (LIJTTLA@USECON in Haver).
- (3) **Real wages:** real compensation per worker in the nonfarm business sector. We first compute the nominal wage rate as the ratio of nonfarm business compensation for all persons (LXNFF@USECON in Haver) to nonfarm business employment (LXNFM@USECON) and then deflate it using the nonfarm business sector implicit price deflator (LXNFI@USECON).
- (4) **Labor productivity:** nonfarm business sector real output per person (LXNFS@USECON in Haver).

APPENDIX B. INDUSTRY-LEVEL DATA

The empirical regressions presented in Section [V.1](#) use industry-level data of the job vacancy rate, the unemployment rate, real wages, and the labor income share, along with the cross-sectional data of automation potentials and the time-series data of the relative price of computer equipment. Below, we describe the source and sample range of each variable used in the regressions.

- (1) **Job vacancy rate:** covers 15 two-digit NAICS industries in private nonfarm sectors from 2001 to 2019. Monthly values are converted to quarterly by taking the quarter-end values. The 15 industries include accommodation and food services; manufacturing; transportation, warehousing, and utilities; retail trade; mining and logging; other services; construction; wholesale trade; finance and insurance; arts, entertainment, and recreation; real estate and rental and leasing; health care and social assistance; information; professional and business services; and educational services. Source: JOLTS.
- (2) **Unemployment rate:** covers 15 two-digit NAICS industries in private nonfarm sectors from 2001 to 2019. Monthly values are converted to quarterly by taking the quarter-end values. The 15 industries are the same as those for the job vacancy rate. Source: BLS.

- (3) **Real wages:** average hourly earnings of production and nonsupervisory workers in 12 two-digit NAICS industries from 1985 to 2019, deflated by the chained personal consumption expenditures price index (PCEPI). Monthly values are converted to quarterly by taking the quarter-end values. The 12 industries are the same as those for vacancies and unemployment, plus utilities and minus accommodation and food services, arts/ entertainment/recreation, real estate and leasing, and health care/social assistance. Source: BLS.
- (4) **Automation potentials:** technical potential for automation by industry estimated by the McKinsey Global Institute. The index of automation potential is constructed based on the within-industry mix of activity types including “manage,” “expertise,” “interface,” “collect data,” “process data,” “unpredictable physical,” and “predictable physical.” The index is constructed for 19 industries, including accommodation and food services; manufacturing; transportation and warehousing; agriculture; retail trade; mining; other services; construction; wholesale trade; finance and insurance; arts, entertainment, and recreation; real estate; administrative; health care and social assistance; information; professionals; management; and education services. Source: [Manyika et al. \(2017\)](#) (Exhibit E4).
- (5) **Computer prices:** quarterly chain price index of private investment in computers and peripherals, with quality adjusted based on hedonic studies. This computer price series is deflated by the PCEPI to obtain the relative price of computers. Source: BEA.
- (6) **Unionization rate:** share of private employed wage and salary workers that are members of a labor union, available at the annual frequency for the periods of 2000-2021. Source: BLS/Haver Analytics.

APPENDIX C. ROBUSTNESS: CONTROLLING FOR OFFSHORING

Table [A1](#) shows the regression results when we remove the tradable sectors (manufacturing and mining) from the baseline sample. The results are robust to this alternative sample, indicating that the empirical relations between automation and the labor market variables that we obtained using the industry-level data are not driven by offshoring.

TABLE A1. Automation threat and labor market outcomes: Excluding tradable sectors from sample

Dep. Var.	$\ln(v/u)$	$\ln(v)$	$\ln(u)$	$\ln(w)$
$\ln(\text{ComputerPrice}) \times AP$	-0.282* (0.169)	-0.200 (0.141)	0.222** (0.107)	0.003* (0.001)
Lagged $\ln(v/u)$	0.385*** (0.031)			
Lagged $\ln(v)$		0.379*** (0.030)		
Lagged $\ln(u)$			0.259*** (0.032)	
Lagged $\ln(w)$				0.980*** (0.004)
Constant	0.625* (0.343)	0.847*** (0.302)	1.191*** (0.237)	0.049*** (0.008)
Observations	975	975	975	1390
Time Periods	2001q2:2019q4	2001q2:2019q4	2001q2:2019q4	1985q2:2019q4
No. of industries	13	13	13	10

Note: This table shows the panel estimation results using NAICS two-digit industry-level data under the empirical specification in Eq. (38), with tradable sectors (manufacturing and mining) excluded from the sample to control for potential effects of offshoring. The variables in the regressions are identical to those in the baseline regressions reported in Table 5. Standard errors are reported in parentheses. The stars denote the p-values: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

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