ROBOTS OR WORKERS?

A MACRO ANALYSIS OF AUTOMATION AND LABOR MARKETS

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Abstract. We study the implications of automation for labor market fluctuations in a DMP framework, generalized to incorporate automation decisions. If a job opening is not filled with a worker, a firm can choose to automate that position and use a robot instead of a worker to produce output. The threat of automation strengthens the firm's bargaining power against job seekers in wage negotiations, depressing equilibrium real wages in a business cycle boom. The option of automation increases the value of a vacancy, raising the incentive for job creation, and thereby amplifying fluctuations in vacancies and unemployment relative to the standard DMP framework. Since adopting robots improves measured productivity, aggregate output rises more than wages and employment in good times, leading to a counter-cyclical labor income share. Over the medium term, our model predicts steady declines in the labor income share caused by steady declines in the cost of automation, inline with what has actually transpired in the recent three decades in the United States.

I. Introduction

Recent development in robotics and artificial intelligence has raised concerns that robots could render human workers redundant (Autor, 2015). Based on occupation-level data, Frey and Osborne (2015) estimate that about 47 percent of U.S. employment is at risk of being displaced by computerization. Acemoglu and Restrepo (2017) document evidence that increases in the usage of industrial robots had significant impact on U.S. local labor markets. The pessimistic view that machines will replace workers can be traced back to at least Keynes (1930), who predicted (incorrectly) that the introduction of new technologies in the 1920s would take away jobs and lead to widespread unemployment.

However, the notion of "machines replacing workers" is a over-simplification of the macroeconomic impact of automation. While robots have been increasingly adopted to perform

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standardized tasks previously performed by human workers, new tasks for which workers have a comparative advantage are being created. And the development of those new tasks is often spurred by automation of the standardized tasks (Acemoglu and Restrepo, 2018). Thinking through the impact of automation on the macroeconomy requires a coherent theoretical framework. In this paper, we present a general equilibrium framework with a frictional labor market and the option of automation to study the interactions between automation and labor market variables, including wages, productivity, job creation, and labor income share.

Our model builds on the standard Diamond-Mortensen-Pissarides (DMP) labor-search model and generalizes it to incorporate automation decisions. The model has two key features. First, firms create vacancies at a fixed cost. A vacancy is created if the realized i.i.d. draw of the vacancy creation cost is below the value of the vacancy. Thus, unlike the standard DMP model, there is no free entry in our model and a vacancy carries a positive value (Leduc and Liu, 2019). Second, we incorporate endogenous automation decisions. After posting a vacancy, a firm can fill the position with a worker and obtain the employment value. If the position is not filled, the firm draws an automation cost. If the realized automation cost is below the expected benefit of automation, then the position is automated, in which case the firm uses a robot in place of a worker to produce output. If the unfilled position is not automated because of high cost draws, then the position remains open and the firm receives the continuation value of the vacancy.

In the aggregate economy, newly hired workers add to the employment pool, and a fraction of the employment stock is separated in each period. Similarly, newly adopted robots add to the automation stock, which becomes obsolete over time at a constant rate. Aggregate output is the sum of output produced by workers and by robots.

We study the model's propagation mechanism of business cycle shocks by estimating the model to fit quarterly U.S. time series data. These time series include unemployment, vacancies, real wage growth, and non-farm business sector labor productivity growth, with a sample ranging from 1964:Q2 to 2018:Q4. Our estimated model implies a steady-state probability of automation of about 10 percent per quarter, in line with the microeconomic evidence (Frey and Osborne, 2015; Nedelkoska and Quintini, 2018).

Our estimation suggests that automation-specific technology shocks explain about 20 percent of the observed fluctuations in unemployment and vacancies, and over 70 percent of the fluctuations in labor productivity growth. A neutral technology shock accounts for about 15 percent of the fluctuations in unemployment and vacancies, and most of the fluctuations in real wage growth. Consistent with the findings of Hall (2017), a discount factor shock in our model plays a quantitatively important role for explaining the dynamics of unemployment and vacancies, accounting for about 50-60 percent of their fluctuations. A job separation shock explains a modest fraction (15 percent) of the fluctuations in vacancies, but it is not important for other labor market variables, in line with Shimer (2005).

Our model also suggests that the threat of automation dampens wage fluctuations relative to unemployment and vacancies. The volatility of the vacancy-unemployment ratio (i.e., the v-u ratio), which is a measure of labor market tightness, is about 10 times that of the real wage rate, much higher than that obtained from the standard DMP model, which has difficulties in generating the observed relative volatility of the v-u ratio because of flexible wage adjustments (Shimer, 2005). In our model, the option of automating an unfilled position raises the reservation value for firms and thus strengthens the firm's bargaining power. Following a positive technology shock, a worker's productivity rises, putting upward pressure on the real wage rate. However, the value of automation and thus the incidence of automation also increase, raising the the firm's reservation value (which is the value of a vacancy) and weakening the work's bargaining power. This would put downward pressure on the real wage rate. Our model thus creates an endogenous real wage rigidity, contributing to generating large fluctuations in the labor market tightness.

The increase in automation value in good times also induces a stronger incentive for firms to create job positions. With a greater fraction of job positions automated, aggregate output rises at a faster pace than employment, leading to an increase in aggregate productivity. Meanwhile, since wages are endogenous rigid, the labor income share declines. The countercyclical labor income share is consistent with U.S. evidence.

Our model is a stylized way of thinking about automation and labor markets. To keep the model tractable, we assume that automation applies to a job position. We interpret a job position broadly as consisting of a bundle of tasks, which are ex ante identical, but a fraction of which will be automated depending on the realization of the idiosyncratic costs for automation. This approach simplifies our analysis significantly. Acemoglu and Restrepo (2018) use an alternative approach to studying automation. Building on the earlier work of Zeira (1998), they consider a job consisting of a continuum of tasks, a fraction of which are automatable, the others need to be performed by human workers (see also Autor and Salomons (2018)). These studies abstract from labor market frictions. Our paper adds to the literature by incorporating automation in a DMP framework. Furthermore, by estimating the general equilibrium model to fit U.S. time-series data, our work also provides a quantitative assessment of the importance of automation for propagating labor market dynamics over the business cycles.

II. The model with labor market frictions and automation

This section presents a DSGE model that generalizes the standard DMP model to incorporate endogenous decisions of 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 realizes. Workers who lose their jobs adds to the stock of unemployment from the previous period, forming the pool of job seekers u_t. Firms post vacancies v_t at a fixed cost κ. The stock of vacancies v_t includes the unfilled vacancies that were not automated at the end of period $t-1$, the jobs separated in the beginning of period t, and new vacancies created in the beginning of period t. Creating a new vacancy incurs a fixed cost, which is drawn from an i.i.d. distribution $G(\cdot)$ as in Leduc and Liu (2019). In the labor market, a matching technology transforms job seekers and vacancies into an employment relation, with a wage rate determined through Nash bargaining between the employer and the job seeker. Once an employment relation is formed, production takes place, and the firm receives the employment value. An unfilled vacancy can be either carried forward to the next period or automated at a fixed cost. Similar to the vacancy creation cost, the automation cost x is drawn from an i.i.d. distribution $F(x)$. If a firm draws an automation cost that is below a threshold value x_t^*, then the firm adopts a robot and closes the job opening. In that case, the firm obtains the automation value. Otherwise, the vacancy remains open and the firm receives the continuation value of the vacancy. Newly adopted robots add to the stock of automation, which becomes obsolete over time at a constant rate ρ^o. Final goods output is the sum of the goods produced by workers and by robots. The final good is used for household consumption and also for paying the costs of vacancy posting, new vacancy creation, and robot adoption.

II.1. **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, so that the measure of unemployed job seekers is given by

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

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

The job separation rate shock δ_t follows the stationary stochastic process

$$\ln \delta_t = (1-\rho_\delta)\ln \bar{\delta} + \rho_\delta \ln \delta_{t-1} + \varepsilon_{\delta t}, \tag{2}$$

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 in the beginning of period t consists of the vacancies in period $t-1$ that were not filled with workers and not automated, plus the displaced job positions and newly created vacancies. The law of motion for vacancies is given by

$$v_t = (1 - q^v_{t-1})(1 - q^a_{t-1}))v_{t-1} + \delta_t N_{t-1} + \eta_t, \tag{3}$$

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

In the labor markert, new job matches are formed between job seekers and open vacancies based on the matching function

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{4}$$

where m_t denotes the number of job matches (or hiring) and $\alpha \in (0,1)$ is the elasticity of job matches with respect to the number of job seekers.

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

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

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

$$U_t = u_t - m_t = 1 - N_t. \tag{6}$$

For convenience, we define the job finding probability q^u_t as

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

Similar, we define the job filling probability q^v_t as

$$q^v_t = \frac{m_t}{v_t}. \tag{8}$$

II.2. **The firms.** If a firm successfully hires a worker, then it can produce Z_t units of intermediate goods. The technology shock Z_t follows the stochastic process

$$\ln Z_t = (1 - \rho_z) \ln \bar{Z} + \rho_z \ln Z_{t-1} + \varepsilon_{zt}. \tag{9}$$

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.[1]

The value of employment satisfies the Bellman equation

$$J^e_t = Z_t - w_t + \mathbb{E}_t D_{t,t+1} \left\{ (1 - \delta_{t+1}) J^e_{t+1} + \delta_{t+1} J^v_{t+1} \right\}, \tag{10}$$

[1]The model can easily be extended to allow for trend growth. We do not present that version of the model to simplify presentation.

where $D_{t,t+1}$ is a stochastic discount factor of the households. Hiring a worker generates a flow profit $Z_t - w_t$ in the current period. If the job is separated in the next period (with probability δ_{t+1}), then the firm receives the vacancy value J^v_{t+1}. Otherwise, the firm receives the continuation value of employment.

Following Leduc and Liu (2019), we assume that creating a new vacancy incurs an entry cost e in units of consumption goods. The entry cost is drawn from an i.i.d. distribution $F(e)$. A new vacancy is created if and only if the net value of entry is non-negative. The benefit of creating a new vacancy is the vacancy value J^v_t. Thus, the number of new vacancies η_t is given by the cumulative density of the entry costs evaluated at J^v_t. That is,

$$\eta_t = F(J^v_t). \tag{11}$$

Posting a vacancy incurs a per-period fixed cost κ (in units of final consumption goods). If the vacancy is filled (with probability q^v_t), the firm obtains the employment value J^e_t. If the vacancy is not filled, then the firm can choose to automate the position and close the vacancy (with probability q^a_t), in which case the firm obtains the automation value J^a_t. If the firm does not automate the unfilled position, then it receives the continuation value of the vacancy. Thus, the vacancy value satisfies the Bellman equation

$$J^v_t = -\kappa + q^v_t J^e_t + (1 - q^v_t) q^a_t J^a_t + (1 - q^v_t)(1 - q^a_t)\mathbb{E}_t D_{t,t+1} J^v_{t+1}. \tag{12}$$

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

$$A_t = (1 - \rho^o)A_{t-1} + q^a_t v_t, \tag{13}$$

where $q^a_t v_t$ is the number of jobs that are newly automated in period t.

Once adopted, a robot produced $Z_t\zeta_t$ units of output, where ζ_t denotes an equipment-specific technology shock, which follows a stochastic process that is independent of the neutral technology shock Z_t. In particular, ζ_t follows the stationary process

$$\ln \zeta_t = (1 - \rho_\zeta) \ln \bar{\zeta} + \rho_\zeta \ln \zeta_{t-1} + \varepsilon_{\zeta t}. \tag{14}$$

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^2_ζ. The term $\bar{\zeta}$ is the steady-state level of the automation-specific technology shock.

Operating the robot incurs a flow fixed cost of κ_a. The value of automation satisfies the Bellman equation

$$J^a_t = Z_t\zeta_t - \kappa_a + (1 - \rho^o)\mathbb{E}_t D_{t,t+1} J^a_{t+1}, \tag{15}$$

where the term κ_a captures the costs of energy, facilities, and space for automated production.

Automating a vacancy 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 adopt a robot if and only if the cost of automation is less than the benefit. For any given benefit of automation, there exists a threshold value x_t^* in the support of the distribution $G(x)$, such that automation occurs if and only if $x \leq x_t^*$. The threshold value x_t^* depends on the value of automation J_t^a relative to the continuation value of a vacancy. In particular, the threshold for automation decision is given by

$$x_t^* = J_t^a - \mathbb{E}_t D_{t,t+1} J_{t+1}^v. \tag{16}$$

Thus, the probability of automation is the cumulative density of the automation costs evaluated at x_t^*. More formally, the automation probability is determined by

$$q_t^a = G(x_t^*). \tag{17}$$

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

$$\mathbb{E} \sum_{t=0}^{\infty} \beta^t \Theta_t \left(\ln C_t - \chi N_t \right), \tag{18}$$

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

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

$$\ln \theta_t = \rho_\theta \ln \theta_{t-1} + \varepsilon_{\theta t}. \tag{19}$$

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 in (18) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{r_t} = B_{t-1} + w_t N_t + \phi(1 - N_t) + d_t - T_t, \quad \forall t \geq 0, \tag{20}$$

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

$$V_t(B_{t-1}, N_{t-1}) \equiv \max \ \ln C_t - \chi N_t + \beta \mathbb{E}_t \theta_{t+1} V_{t+1}(B_t, N_t), \tag{21}$$

subject to the budget constraint (20) and the employment law of motion (5), the latter of which can be written as

$$N_t = (1-\delta_t)N_{t-1} + q^u u_t, \tag{22}$$

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

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 (20). We show in the Appendix that the employment surplus satisfies the Bellmand equation

$$S_t^H = w_t - \phi - \frac{\chi}{\Lambda_t} + \mathbb{E}_t D_{t,t+1}(1-q_{t+1}^u)(1-\delta_{t+1})S_{t+1}^H, \tag{23}$$

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 the firms' decisions.

The employment surplus has a straightforward economic interpretation. If the household adds a new worker in period t, then the current-period gain would be wage income net of the opportunity costs of working, including unemployment benefit 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 (if 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. (23).

We also show in the appendix that the household's optimizing consumption-savings decision implies the intertemporal Euler equation

$$1 = \mathbb{E}_t D_{t,t+1} r_t. \tag{24}$$

II.4. **The Nash bargaining wage.** When a job match is formed, the wage rate is determined through Nash bargaining. The bargaining wage optimally splits of 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. (23). 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 their bargaining decisions.

The Nash bargaining problem is given by

$$\max_{w_t} \quad \left(S_t^H\right)^b \left(J_t^e - J_t^v\right)^{1-b}, \tag{25}$$

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

Define the total surplus as

$$S_t \equiv J_t^e - J_t^v + S_t^H. \tag{26}$$

Then the bargaining solution is given by

$$J_t^e - J_t^v = (1-b)S_t, \quad S_t^H = bS_t. \tag{27}$$

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

The bargaining solution (27) and the expression for household surplus in equation (23) together imply that the Nash bargaining wage w_t^N satisfies the Bellman equation

$$\begin{aligned} \frac{b}{1-b}(J_t^e - J_t^v) &= w_t^N - \phi - \frac{\chi}{\Lambda_t} \\ &+ \mathbb{E}_t D_{t,t+1}(1-q_{t+1}^u)(1-\delta_{t+1})\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v). \end{aligned} \tag{28}$$

II.5. **Government policy.** The government finances unemployment benefit payments ϕ for unemployed workers through lump-sum taxes. We assume that the government balances the budget in each period so that

$$\phi(1-N_t) = T_t. \tag{29}$$

II.6. **Search equilibrium.** In a search equilibrium, the markets for bonds and goods all clear. Since the aggregate bond supply is zero, the bond market-clearing condition implies that

$$B_t = 0. \tag{30}$$

Goods market clearing requires that consumption spending, search and recruiting costs, and vacancy creation costs add up to aggregate production. This requirement yields the aggregate resource constraint

$$C_t + \kappa v_t + v_t \int_0^{x_t^*} x dG(x) + \int_0^{J_t^v} e dF(e) = Y_t, \tag{31}$$

where Y_t denotes aggregate output. In this equation, the first integration term on the left-hand side corresponds to the aggregate cost of automation, with $x_t^* = J_t^a - \mathbb{E}_t D_{t,t+1} J_{t+1}^v$. The second integral corresponds to the aggregate cost of vacancy creation.

Aggregate output is sum of goods produced by workers and by robots. Specifically, it is given by

$$Y_t = Z_t N_t + Z_t \zeta_t A_t. \tag{32}$$

III. Empirical Strategies

We solve the model by log-linearizing the equilibrium conditions around the deterministic steady state.[2] 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

$$F(e) = \left(\frac{e}{\bar{e}}\right)^{\eta_v}, \quad G(x) = \left(\frac{x}{\bar{x}}\right)^{\eta_a}, \tag{33}$$

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.[3] We estimate the scale parameters $\bar{e}$ and $\bar{x}$ by fitting the model to U.S. time series data.

III.1. **Parameter calibration.**

Table 1 shows the calibrated parameter values.

We consider a quarterly model. We set $\beta = 0.99$, so that the model implies a 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 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 equipment depreciates at an average rate of 12 percent per year. We normalize the level of labor productivity to $\bar{Z} = 1$ and equipment-specific productivity to $\bar{\zeta} = 1$.

We target a steady-state unemployment rate of $U = 0.055$. We can then solve for the steady-state employment $N = 1 - U$, hiring $m = \bar{\delta}N$, and the number of job seekers $u = 1 - (1 - \bar{\delta})N$. The job finding rate is given by $q^u = \frac{m}{u}$. We target a steady-state job filling rate q^v of 0.6415 per month based on the empirical estimation in Davis et al. (2013) using establishment-level JOLTS data.[4] The implied stock of vacancies is $v = \frac{m}{q^v}$. The scale of the matching efficiency is then given by $\mu = \frac{m}{u^\alpha v^{1-\alpha}} = 0.7765$. We set the flow cost of operating robots to $\kappa_a = 0.98$. Given the average productivities $\bar{Z} = \bar{\zeta} = 1$, this implies a quarterly profit of 2 percent of the revenue by using a robot for production. The steady-state automation value J^a can then be solved from the Bellman equation (15).

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[2] Details of the equilibrium conditions, the steady state, and the log-linearized system are presented in the appendix.

[3] We also experiment with different values of η to match some key moments in the distribution of the automation probabilities across occupations documented by Frey and Osborne (2017).

[4] Davis et al. (2013) estimate that the daily job filling rate averages about 0.05. Assuming that one month consists of 20 business days, we can infer the monthly job filling rate q^v from the daily rate $f = 0.05$ by using the relation $f^m = f + f(1-f) + f(1-f)^2 + \cdots + f(1-f)^{19} = 1-(1-f)^{20} = 0.6415$. The quarterly job filling rate is given by $q^v = 1 - (1 - f^m)^3 = 0.9539$.

Conditional on J^a and the estimated values of $\bar{e}$ and $\bar{x}$ (see below for estimation details), we use the vacancy creation condition (11), the automation adoption condition (16), and law of motion for vacancies (3) to obtain the steady-state probability of automation, which is given by

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

Given q^a and v, the stock of automation A can be solved from the law of motion (13), which reduces to $\rho^o A = q^a v$ in the steady state. Aggregate output is given by $Y = \bar{Z}(N + \bar{\zeta} A)$. Given the solution for Y, we calibrate the vacancy posting cost to $\kappa = 0.1225$, implying that the steady-state vacancy posting cost is about one percent of aggregate output (i.e., $\kappa v = 0.01Y$).

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 $J^v = \bar{e}\eta$.

Given J^v and J^a, we obtain the cutoff point for robot adoption $x^* = J^a - \beta J^v$. The match value J^e can be solved from the Bellman equation for vacancies (12), and the equilibrium real wage rate can be obtained from the Bellman equation for employment (10). Steady-state consumption is solved from the resource constraint (31). We then infer the value of $\chi = 0.6956$ from the expression for bargaining surplus in Eq. (28).

III.2. **Estimation.** We now describe our estimation approach.

III.2.1. *Data and measurement.* We fit the DSGE model to four quarterly U.S. time series: the unemployment rate, the job vacancy rate, the growth rate of average labor productivity in the non-farm business sector, and the growth rate of the real wage rate. The sample covers the range from 1964:Q2 to 2018:Q4.

The unemployment rate in the data (denoted by U_t^{data}) corresponds to the end-of-period unemployment rate in the model U_t. We demean the unemployment rate data (in log units) and relate it to our model variable according to

$$\ln(U_t^{data}) - \ln(U^{data}) = \hat{U}_t, \tag{34}$$

where U^{data} denotes the sample average of the unemployment rate in the data and $\hat{U}_t$ denotes the log-deviations of the unemployment rate from its steady-state value in the model.

Similarly, we use demeaned vacancy rate data (also in log units) and relate it to the model variable according to

$$\ln(v_t^{data}) - \ln(v^{data}) = \hat{v}_t, \tag{35}$$

where v^{data} denotes the sample average of the vacancy rate data and $\hat{v}_t$ denotes the log-deviations of the vacancy rate from its steady-state value in the model. 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 JOLTS vacancy rate.

In the data, we measure labor productivity by the average labor productivity in the non-farm business sector. We use the demeaned quarterly log-growth rate of productivity (denoted by $\Delta \ln p_t^{data}$) and relate it to our model variable according to

$$\Delta \ln(p_t^{data}) - \Delta \ln(p^{data}) = \hat{Y}_t - \hat{N}_t - (\widehat{Y_{t-1}} - \widehat{N_{t-1}}), \tag{36}$$

where $\Delta \ln(p^{data})$ denotes the sample average of 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 the average hourly earnings of production and nonsupervisory workers in private industries, deflated by the chain personal consumption expenditure (PCE) price index. We related the observed real wage growth to the model variables by the measurement equation

$$\Delta \ln(w_t^{data}) - \Delta \ln(w^{data}) = \hat{w}_t - \hat{w}_{t-1}, \tag{37}$$

where w_t^{data} denotes the real wage rate in the data, $\Delta \ln(w_t^{data})$ denotes the log growth rate of real wages, and $\hat{w}_t$ denotes the log-deviations of real wages from its steady-state level in our model.

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 persistence parameter of each shock follow 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 follow an inverse gamma distribution with a prior 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 $\bar{e} = 7.07$. The posterior mean estimates of the automation cost parameter is $\bar{x} = 6.17$. These parameters imply a steady-state automation probability of about 10 percent per quarter, which lies in the range estimated in the empirical literature (Frey and Osborne, 2015; Nedelkoska and Quintini, 2018). The 90-percent confidence intervals indicate that the data are informative about these structural parameters.

The posterior estimation suggests that the neutral technology shock, the discount factor shock, and the automation-specific technology shock are all highly persistent, with the posterior means of the AR(1) parameters at $\rho_z = 0.9765$, $\rho_\theta = 0.9788$, and $\rho_\zeta = 0.978$. The job separation shock is slightly less persistent, with $\rho_\delta = 0.9466$. The standard deviations of the neutral technology shock ($\sigma_z = 0.0234$) is smaller than the other shocks. The estimated volatility of the automation-specific shock is the greater than the other shocks, with $\sigma_\zeta = 0.0773$). The discount factor shock is also highly volatile, with $\sigma_\theta = 0.0568$. The job separation shock has a modest volatility of $\sigma_\delta = 0.0428$.

IV. Economic implications

We now examine the model's transmission mechanism and its quantitative performance for explaining the labor market dynamics.

IV.1. **The model's transmission mechanism.** The equilibrium dynamics in our model are driven by both the exogenous shocks and the model's internal propagation mechanism. To help understand the contributions of the shocks and the model's mechanism, we examine forecast error variance decompositions and impulse response functions.

IV.1.1. *Forecast error variance decompositions.* Table 3 displays the unconditional forecast error variance decompositions for the four observable labor market variables used for our estimation.[5]

The variance decompositions suggest that the discount factor shock is important for the observed business cycle dynamics of unemployment and vacancies, accounting for about 50-60 percent of their fluctuations. Automation-specific shock explains about 20 percent and the neutral technology shock accounts for about 15 percent of the variances of unemployment and vacancies. Fluctuations in the real wage growth are mostly driven by the neutral technology shock, which accounts for over 90 percent of the wage fluctuations. The observed labor productivity fluctuations are mainly driven by the automation-specific shock, which explains about 70 percent of the variance. It is also partly explained by neutral technology shocks, which account for about 20 percent of the variance.

The importance of the discount factor shock for unemployment and vacancies has been emphasized by Hall (2017) and confirmed in an estimated DSGE model by Leduc and Liu (2019). Since a discount factor shock directly affects the present values of a job match, an open vacancy, and the employment surplus for a job seeker, it contributes to explaining the observed fluctuations in unemployment and vacancies.

[5]We have also computed the conditional forecast error variance decompositions with forecasting horizons between 4 quarters and 16 quarters and found that they deliver the same message as the unconditional variance decomposition.

In our model with automation, there is a new mechanism that propagates neutral and automation-specific technology shocks to drive fluctuations in unemployment and vacancies. Since firms have the option of automation if a vacancy is not filled, it raises the vacancy value, which creates two effects. First, the increased vacancy value induces more vacancy creation, boosting the job finding rate and employment. Second, the increased vacancy value also raises the firm's outside option in wage bargaining, leading to smaller real wage adjustments over the business cycles. Both effects serve to amplify the fluctuations in unemployment and vacancies, while dampening wage fluctuations. This mechanism through automation enables both neutral technology shock and automation-specific shock to drive fluctuations in the labor market variables.

Job separation shocks do not play a big role in labor market fluctuations, except for vacancies, for which they account for about 17 percent of the variance. As noted by Shimer (2005), job separation shocks generate a counterfactually positive correlation between unemployment and vacancies. Accordingly, in our estimated model, this shock plays a relatively minor role.

IV.1.2. *Impulse responses.* Figure 1 shows the impulse responses of several key labor market variables to a one-standard-deviation neutral technology shock, in two different models: our benchmark model (the black solid lines) and a standard DMP model (the blue dashed line). The standard model here corresponds to a version our benchmark, where we keep the automation probability and the automation stock at their steady-state levels.

Figure 2 shows the impulse responses of the labor market variables to a one-standard-deviation discount factor shock in the benchmark model and the counterfactual DMP model.

[discussions to be included]

V. Conclusion

[To be added]

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	0.7765
$\bar{\delta}$	Job separation rate	0.10
ρ^o	Automation obsolescence rate	0.03
κ	Vacancy posting cost	0.1225
b	Nash bargaining weight	0.50
η_v	Elasticity of vacancy creation cost	1
η_a	Elasticity of automation cost	1
r_a	Flow cost of automated production	0.98
χ	Mean value of preference shock	0.6956
$\bar{Z}$	Mean value of neutral technology shock	1
$\bar{\zeta}$	Mean value of equipment-specific technology shock	1

Table 2. Estimated parameters

		Priors		Posterior		
	Parameter description	Type	[mean, std]	Mean	5%	95%
$\bar{e}$	scale for vacancy creation cost	G	[5, 1]	7.0736	5.6958	8.4619
$\bar{x}$	scale for robot adoption cost	G	[5, 1]	6.1681	4.3781	7.7361
ρ_z	AR(1) of neutral technology shock	B	[0.8, 0.1]	0.9765	0.9699	0.9844
ρ_θ	AR(1) of discount factor shock	B	[0.8, 0.1]	0.9788	0.9668	0.9926
ρ_δ	AR(1) of separation shock	B	[0.8, 0.1]	0.9466	0.9187	0.9722
ρ_ζ	AR(1) of automation-specific shock	B	[0.8, 0.1]	0.9780	0.9703	0.9855
σ_z	std of tech shock	IG	[0.01, 0.1]	0.0234	0.0213	0.0252
σ_θ	std of discount factor shock	IG	[0.01, 0.1]	0.0568	0.0465	0.0690
σ_δ	std of separation shock	IG	[0.01, 0.1]	0.0469	0.0428	0.0507
σ_ζ	std of automation-specific shock	IG	[0.01, 0.1]	0.0773	0.0595	0.0915

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.

Table 3. Forecasting Error Variance Decomposition

Variables	Neutral technology shock	Discount factor shock	Job separation shock	Automation-specific shock
Unemployment	16.31	60.35	1.29	22.05
Vacancy	13.94	51.08	16.94	18.04
Productivity growth	19.97	7.70	0.02	72.31
Real wage growth	95.72	3.85	0.02	0.41

Note: The numbers reported are the posterior mean contributions (in percentage terms) of each of the four shocks in the benchmark estimation to the forecast error variances of the variables listed in the rows.

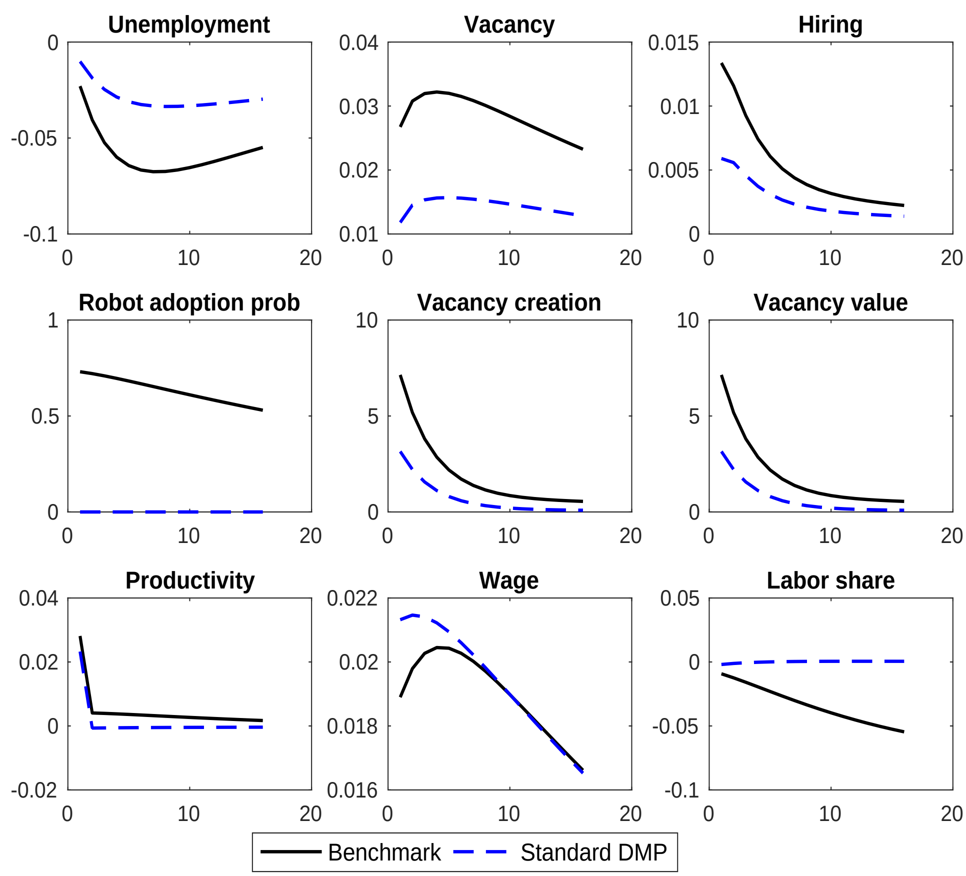

FIGURE 1. Impulse responses to a positive neutral technology shock: benchmark model vs. standard DMP model.

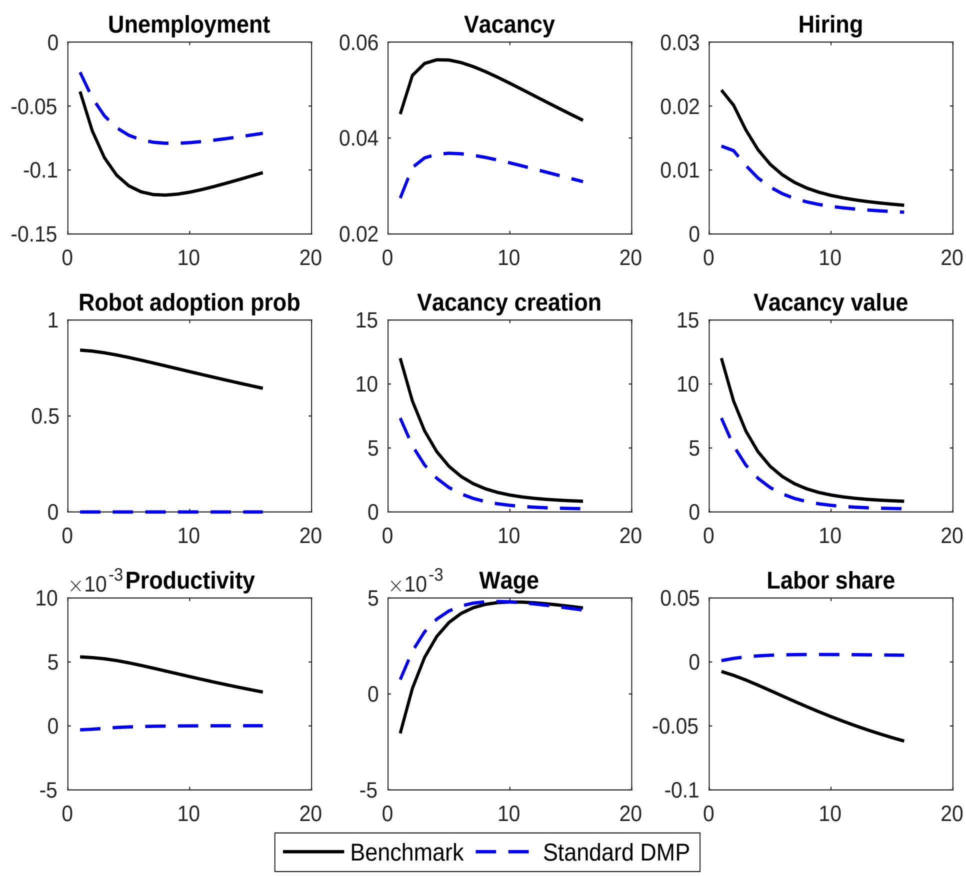

FIGURE 2. Impulse responses to a positive discount factor shock: benchmark model vs. standard DMP model.

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Appendix A. Summary of equilibrium conditions

A search equilibrium is a system of 19 equations for 19 variables summarized in the vector

$$\left[C_t, r_t, Y_t, m_t, u_t, v_t, q_t^u, q_t^v, q_t^a, N_t, U_t, \eta_t, J_t^e, J_t^v, J_t^a, A_t, x_t^*, w_t^N, w_t\right].$$

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

(1) Household's bond Euler equation:

$$1 = \mathrm{E}_t \beta \theta_{t+1} \frac{C_t}{C_{t+1}} r_t, \tag{A1}$$

(2) Matching function

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{A2}$$

(3) Job finding rate

$$q_t^u = \frac{m_t}{u_t}, \tag{A3}$$

(4) Vacancy filling rate

$$q_t^v = \frac{m_t}{v_t}, \tag{A4}$$

(5) Employment dynamics:

$$N_t = (1-\delta_t) N_{t-1} + m_t, \tag{A5}$$

(6) Number of searching workers:

$$u_t = 1 - (1-\delta_t) N_{t-1}, \tag{A6}$$

(7) Unemployment:

$$U_t = 1 - N_t, \tag{A7}$$

(8) Vacancy dynamics

$$v_t = (1-q_{t-1}^v)(1-q_{t-1}^a) v_{t-1} + \delta_t N_{t-1} + \eta_t, \tag{A8}$$

(9) Automation dynamics

$$A_t = (1-\rho^o) A_{t-1} + q_t^a v_t, \tag{A9}$$

(10) Employment value

$$J_t^e = Z_t - w_t + \mathbb{E}_t \beta \theta_{t+1} \frac{C_t}{C_{t+1}} \left\{ (1-\delta_{t+1}) J_{t+1}^e + \delta_{t+1} J_{t+1}^v \right\}, \tag{A10}$$

(11) Vacancy value

$$J_t^v = -\kappa + q_t^v J_t^e + (1-q_t^v) q_t^a J_t^a + (1-q_t^v)(1-q_t^a) \mathbb{E}_t \beta \theta_{t+1} \frac{C_t}{C_{t+1}} J_{t+1}^v. \tag{A11}$$

(12) Automation value

$$J_t^a = Z_t\zeta_t - \kappa_a + (1-\rho^o)\mathbb{E}_t\beta\theta_{t+1}\frac{C_t}{C_{t+1}}J_{t+1}^a, \tag{A12}$$

(13) Automation threshold

$$x_t^* = J_t^a - \mathbb{E}_t\beta\theta_{t+1}\frac{C_t}{C_{t+1}}J_{t+1}^v. \tag{A13}$$

(14) Robot adoption

$$q_t^a = \left(\frac{x_t^*}{\bar{x}}\right)^{\eta_a} \tag{A14}$$

(15) Vacancy creation

$$\eta = \frac{J_t^v}{\bar{e}} \tag{A15}$$

(16) Aggregate output

$$Y_t = Z_tN_t + Z_t\zeta_tA_t. \tag{A16}$$

(17) Resource constraint

$$C_t + \kappa v_t + \frac{\eta_a}{1+\eta_a}q_t^a x_t^* v_t + \frac{1}{2}\eta_t J_t^v = Y_t, \tag{A17}$$

(18) Nash bargaining wage:

$$\frac{b}{1-b}(J_t^e - J_t^v) = w_t^N - \phi - \chi C_t + \mathbb{E}_t\frac{\beta\theta_{t+1}C_t}{C_{t+1}}(1-q_{t+1}^u)(1-\delta_{t+1})\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v). \tag{A18}$$

(19) Actual real wage (with real wage rigidity)

$$w_t = w_{t-1}^{\gamma}(w_t^N)^{1-\gamma}, \tag{A19}$$