Automation, Job destruction, and Monetary policy

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Abstract

This paper shows that automation-specific productivity shocks affect job creation and destruction differently depending on the structure of the labor market. When job separation is exogenous, the shock mainly increases job creation, leading to a decline in unemployment. However, when separation is endogenous—determined by workers' heterogeneous disutility of work—the shock causes a larger increase in job destruction than in job creation. As a result, unemployment increases—consistent with empirical findings—since it reflects the excess of job destruction over job creation. The paper also finds that the threat of automation—when the decision to automate is endogenous—worsens the inflation-output gap stabilization trade-off and raises welfare losses, particularly due to the presence of nominal and rigidity frictions. This mechanism necessitates a stronger policy response to output fluctuations within the optimal monetary policy framework. These results highlight the need for monetary policy to account for automation-driven macroeconomic volatility.

Keywords: Automation threat, job destruction, job creation, unemployment, optimal monetary policy

JEL Codes: E24, E25, E32, E52, O33

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1 Introduction

Extensive research on automation's long-term effects highlights its impact on high productivity, job displacement, wage stagnation, and inequality.[1] From a policy perspective, studies focus on fiscal and public policies to leverage productivity gains from automation while mitigating its adverse effects on inequality.[2]

However, while long-term effects are well studied, short-term impacts remain underexplored, particularly regarding job destruction in labor markets and the optimal monetary policy response.[3] For instance, Leduc and Liu (2024) analyze the business cycle implications of automation using a U.S. data-fitted model, yet neglect endogenous job destruction. As a result, their model predicts a decline in unemployment following an automation-specific shock—contradicting empirical findings.[4] Additionally, the interaction between automation and optimal monetary policy remains largely unexplored.

In our context, automation broadly refers to the adoption of labor-saving technologies—such as robots—that substitute human labor in the production process. While the adoption of automation is endogenous, it is also affected by an automation-specific productivity shock that enhances robot productivity.

The contribution of this paper is to fill these gaps by providing new insights into the short-term implications of firms' automation decisions. Specifically, it seeks to answer two key questions: Does an automation-specific productivity shock destroy more jobs than it creates in the short run in a closed economy like the U.S.? What is the optimal monetary policy response to the threat of

[1] See, *inter alia*, Autor and Dorn (2013); Goos, Manning, and Salomons (2014); Graetz and Michaels (2018); Zeira (1998); Acemoglu and Restrepo(2018b, 2019, 2020); Acemoglu, Lelarge, and Restrepo (2020); OECD (2020); de Vries, Gentille, Miroudot, and Wacker (2020);Alonso, Berg, Kothari, Papageorgiou, and Rehman (2020); Dauth, Findeisen, Suedekum, and Woessner (2021); Acemoglu, Autor, Hazell, and Restrepo (2022); Acemoglu and Autor (2011); Berg, Buffie, and Zanna (2018); Sedik and Yoo (2021); Hubmer and Restrepo (2022); Guimarães & Gil, 2022a, 2022a, 2022b, and Charalampidis (2023)

[2] See, Mulas-Granados, Varghese, Boranova, deChalendar, and Wallenstein (2019),Brussevich, Dabla-Norris, and Khalid (2019), Acemoglu, Manera, and Restrepo (2020), Berg et al. (2021), Korinek, Martin, and Stiglitz (2021), Acemoglu, Autor, and Johnson (2023), Cazzaniga et al. (2024),Ghazanchyan, Goumilevski, and Mourmouras (2024), Brollo et al. (2024), Berg, F. Buffie, Comunale, Papageorgiou, and Luis-Felipe (2024).

[3] For exceptions in short-term research, see Charalampidis (2020a), Charalampidis (2020b), Charalampidis (2023), Leduc and Liu (2024), Charalampidis and Razafitsiory (2024).

[4] Acemoglu and Restrepo (2018b), Acemoglu, Anderson, et al. (2022), and Charalampidis (2020b) show that automation propagation increases unemployment.

automation?

The analysis builds on the endogenous automation decision framework of Leduc and Liu (2024), where firms with vacancies decide whether to pay a cost to purchase a robot and automate or to keep the position and try to hire a worker in a labor market with search and matching frictions (SAM, henceforth).[5] In this framework, the productivity of robots is subject to an automation-specific shock that, on average, exceeds the productivity of workers; and robot-based output is an imperfect substitute for labor-based output. While the original model assumes households have homogeneous disutility of work, we extend it by incorporating heterogeneous disutility of work into two nested models to study the role of endogenous job destruction and its implications for job dynamics and monetary policy.

The first is our benchmark model which extends Leduc and Liu (2024)'s automation framework in three key ways. First, following Trigari (2009), we introduce heterogeneous disutility of work, where each household member experiences a labor disutility shock and decides to work based on an endogenous disutility threshold. This threshold determines endogenous separation between firms and workers, allowing the model to capture how an automation-specific shock influences both endogenous job creation and destruction. Second, building on Trigari (2009), we incorporate nominal frictions and monetary policy, enabling an analysis of how the automation threat shapes optimal monetary policy. Third, we broaden the shock structure by introducing risk premium, cost-push, and monetary policy shocks, while removing the discount factor shock. Consequently, unlike Leduc and Liu (2024), which estimates the model using four U.S. time series, we extend it to six, incorporating inflation and nominal interest rate data in the Bayesian estimation.

The second model (named endogenous job destruction model) builds on the model in Leduc and Liu (2024) and considers an environment without nominal frictions and monetary policy in order to isolate the impact of endogenous separations between firms and workers on the transmission of an automation-specific shock. This ensures that the analysis remains unaffected by nominal rigidities. To maintain consistency with Leduc and Liu (2024), this model is estimated using the

[5] This represents alternative modeling approach to the task-based paradigm (e.g., Zeira (1998); Autor, Levy, and Murnane (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018b); Acemoglu, Anderson, et al. (2022)); but as argued by Acemoglu and Restrepo (2018a), the literature on the modeling of automation is young and there is no consensus on the most appropriate approach.

same four U.S. time series. We compare its impulse responses to those of Leduc and Liu (2024), where separation and job destruction are exogenous. Additionally, we use our benchmark model as a robustness check for this comparison.

Following Leduc and Liu (2024), we define the threat of automation as the scenario where firms endogenously decide whether to automate or hire workers, meaning the probability of automation varies over the business cycle. In contrast, an economy without the threat of automation assumes a fixed automation probability, set at its steady-state level, with no cyclical fluctuations. All our analyses on the transmission of an automation-specific shock, as discussed earlier, are conducted under the threat of automation. To examine the optimal monetary policy response to this threat, we compare the optimal policy in our benchmark model to that in its counterfactual without automation threat.

Our estimation results support the credibility of the proposed model for several reasons. In the frictionless economy, the Endogenous Job Destruction model provides a better fit to the data than its counterfactual version without the automation threat, confirming the importance of modeling automation as an endogenous decision. Moreover, the variance decomposition results closely align with those in Leduc and Liu (2024), showing that macroeconomic fluctuations are primarily driven by neutral technology shocks. In the economy with nominal frictions, our benchmark model similarly outperforms its fixed-automation counterpart, further validating the relevance of incorporating endogenous automation. Again, the variance decomposition reveals that neutral technology shocks account for most of the fluctuations, consistent with findings in Leduc and Liu (2024).

In the absence of nominal frictions, automation-specific productivity shocks affect job creation and destruction differently depending on the labor market structure. When job separation is exogenous, as in Leduc and Liu (2024), the shock boosts both automation and vacancy values, raising the probability of automation and vacancy creation. Although more vacancies are automated, the overall stock of vacancies and hiring increase, leading to lower unemployment. In contrast, when separation is endogenous—as in our model with heterogeneous disutility of work—the shock raises the relative profitability of robots, prompting firms to reduce wages. This discourages labor market participation among high-disutility workers, resulting in greater job destruction than creation. Consequently, unemployment rises, in line with empirical evidence. With the presence of nominal frictions, both our benchmark model and its counterfactual version without the threat of automation feature endogenous separation in the labor market. They confirm the findings from the frictionless case, predicting that an automation-specific productivity shock leads to more job destruction than creation.

In the presence of the nominal frictions, The threat of automation has important implications for monetary policy. It exacerbates the trade-off between inflation and output gap stabilization, leading to greater welfare losses due to the presence of nominal and rigidity frictions. This mechanism necessitates a stronger policy response to output fluctuations within the optimal monetary policy framework. The worsening of this trade-off stems from the fact that the threat of automation amplifies output gap volatility, particularly in response to cost-push shocks. These findings suggest that policymakers should account for the macroeconomic fluctuations induced by automation when designing monetary policy.

Related Literature. Our research contributes to three key areas of the existing literature.

First, we build on the limited but growing literature analyzing the short-term effects of automation. Existing studies, such as Charalampidis (2020a), Charalampidis (2020b), Charalampidis (2023), Leduc and Liu (2024), and Charalampidis and Razafitsiory (2024), primarily rely on models featuring exogenous job destruction. By introducing endogenous job destruction into the analysis, our research provides novel insights into how automation influences the labor market fluctuations.

Second, we extend the analysis of monetary policy by examining its transmission in the presence of the threat of automation. While existing studies on monetary policy, such as Svensson and O. (1997, 1999), Faia (2008), Galí and Monacelli (2005), Monacelli (2005), Galí (2011), and Justiniano and Preston (2010), provide valuable insights into policy effectiveness, they do not consider the role of automation. By addressing how the threat of automation influences monetary policy transmission, our work fills this critical gap in the literature.

Third, we complement the literature on policies related to automation, particularly in the areas of fiscal policy, public policy, and governance improvements. Notable contributions include Mulas-Granados et al. (2019), Brussevich et al. (2019), Acemoglu, Manera, and Restrepo (2020), Berg et al. (2021), Korinek et al. (2021), Acemoglu et al. (2023), Cazzaniga et al. (2024), Ghazanchyan et al. (2024), Brollo et al. (2024), and Berg et al. (2024). Our analysis expands this literature by exploring an alternative policy dimension—namely, the role of monetary policy.

The rest of the paper is structured as follows: Section 2 presents the benchmark model, Section 3 outlines the empirical approach, Section 4 analyzes the impact of an automation-specific shock on labor market fluctuations, and Section 5 explores how the threat of automation influences the optimal monetary policy response. Finally, Section 6 concludes.

2 Model

The model integrates key features from two existing frameworks. The first is the New Keynesian DSGE model of Trigari (2009), which incorporates nominal and rigidity frictions, habit formation in consumption, monetary policy, and search and matching frictions in the labor market. It also distinguishes between the intensive and extensive margins of labor and models endogenous separations, driven by heterogeneity in households' disutility of work. The second is the model developed by Leduc and Liu (2024), which introduces endogenous automation adoption. In this framework, firms with costly vacancies draw random automation costs to decide whether to pay a cost to purchase a robot and automate or to keep the position and try to hire a worker in a labor market with search and matching frictions (SAM, henceforth).

Our model builds on Leduc and Liu (2024) by incorporating additional features from Trigari (2009), including nominal frictions, habit formation in consumption, monetary policy, intensive labor margins, and endogenous job separations—elements absent from the original automation framework. In contrast to the model in Leduc and Liu (2024) which use a discount factor shock as a demand shock, we introduce a risk premium shock to capture a demand shock. Final consumption goods are produced using a combination of human labor and robots and are exchanged in monopolistically competitive markets. Households choose consumption and savings optimally.

While the timing structures of the two original models differ, we follow the timing in Leduc and Liu (2024) as closely as possible and adjust the elements from Trigari (2009) accordingly. In each period t, the economy begins with predetermined stocks of vacancies, employed workers, and unemployed individuals. Aggregate shocks are realized. Workers and job seekers draw idiosyncratic disutility of work χ_t, which determines the endogenous separation rate. A fraction of existing vacancies is automated. Remaining vacancies and job seekers match in the labor market. Matches form, and employment and unemployment levels are updated. Production then takes place using both workers and robots, and final goods are supplied to consumers. This process repeats in the next period.

2.1 The Labor Market At the beginning of period t, there are N_{t-1} existing job matches. An exogenous job separation shock displaces a fraction δ_t^x of those matches, where δ_t^x follows the stationary stochastic process, $ln\delta_t^x = (1-\rho_\delta)ln\delta^x + \rho_\delta ln\delta_{t-1}^x + \epsilon_{\delta t}$, with $\epsilon_{\delta t} \sim N(0, \sigma_\delta^2)$. Then, labor disutility shocks, χ_t, are drawn from the distribution $H(.)$ for all agents of the economy. A fraction, δ_t^n, of the existing matches that survived exogenous separations is now mutually resolved because their desutilities of work surpasse the threshold desutility for accepting work, $\bar{\chi}_t$, where

$$\delta_t^n \equiv Pr(\chi_t \geqslant \underline{\chi}_t) = 1 - H(\underline{\chi}_t) \tag{1}$$

Consequently, the total separations rate is given by $\delta_t \equiv \delta_t^x + \delta_t^n(1-\delta_t^x)$. With the size of the labor force normalized to one, the measure of unemployed job seekers is given by,

$$u_t = 1 - (1-\delta_t)N_{t-1} \tag{2}$$

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, $\delta_t N_{t-1}$, and newly created vacancies, η_t. The law of motion for vacancies is given by

$$v_t = (1-q_t^a)(1-q_{t-1}^v\gamma_{t-1})v_{t-1} + \delta_t N_{t-1} + \eta_t \tag{3}$$

where q^v_{t-1} denotes the job filling rate in period $t-1$ and q^a_t denotes the automation probability in period t [6] . The fraction of the potential matches (m_t) that will produce is given by:

$$\gamma_t \equiv 1 - \frac{\delta^n_t}{u_t} < 1 \tag{4}$$

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

$$m_t = \mu u^\alpha_t v^{1-\alpha}_t \tag{5}$$

where μ measures efficiency and $\alpha \in (0,1)$ is the elasticity of job matches with respect to the number of job seekers. For convenience, we define the job finding probability q^u_t and the job filling probability q^v_t, respectively, as

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

Aggregate employment evolves according to the law of motion

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

At the end of period t, the period-t unemployment rate is:

$$ur_t = u_t - \gamma_t m_t = 1 - N_t \tag{8}$$

2.2 Final good producer A perfectly competitive firm aggregates intermediate goods sold by retailers to final good Y_t, priced at P_t, according the aggregation technology $Y_t = (\int Y_t(j)^{(\Upsilon-1)/\Upsilon} dj)^{\Upsilon/(\Upsilon-1)}$, where Υ is the substitution elasticity and $j \in [0,1]$ index retailers. The final good's price is then

[6] Not all m_t matches produce because not all workers in those matches have low labor disutility $\chi < \underline{\chi}_t$. Only a fraction of these matches will produce. The rest of the workers of those matches will return directly to the pool of unemployed and the posts will return directly to the pool of unmatched vacancies. The fraction of the matches that will produce is given by:

$$\gamma_t \equiv \frac{(1-\delta^n_t)(1-N_{t-1}+\delta^x_t N_{t-1})}{\delta^n_t(1-\delta^x_t)N_{t-1} + (1-N_{t-1}+\delta^x_t N_{t-1})} = \frac{(1-\delta^n_t)(1-N_{t-1}+\delta^x_t N_{t-1})}{u_t} = \frac{u_t - \delta^n_t}{u_t} = 1 - \frac{\delta^n_t}{u_t} < 1$$

given by $P_t = \left(\int_0^1 P_t(j)^{(1-\Upsilon)} dj\right)^{1/(1-\Upsilon)}$ and the demand for each j retail variety, priced at $P_t(j)$, is given by $Y_t(j) = (P_t(j)/P_t)^{-\Upsilon} Y_t$. Profits are zero: $F_t = P_t Y_t - \int_0^1 P_t(j) Y_t(j) dj = 0$.

2.3 Retailers The continuum of $j \in [0,1]$ retailers operate in monopolistic competition, and buy units of the wholesale good at price $\bar{P}_t$ and differentiate them to $Y_t(j)$ according to a linear production function. Subsequently, the retailer sets price $P_t(j)$ to maximize the present discounted value of current and future expected profits subject to a downward-sloping demand and price adjustment costs. Period-t profits are given by

$$F_t(j) = [(1+\iota)P_t(j) - \bar{P}_t]Y_t(j) - \frac{\xi}{2}\left(\frac{\upsilon_{\pi,t} P_t(j)}{\Pi_{t-1}^{\gamma} P_{t-1}(j)} - 1\right)^2 Y_t P_t \tag{9}$$

The subsidy ι leads to a unitary marginal cost in steady state. The variable $\upsilon_{\pi,t}$ is an autoregressive shock reflecting fluctuations in the price markup, $ln\upsilon_{\pi,t} = \rho_\pi ln\upsilon_{\pi,t-1} + \epsilon_{\pi,t}, \epsilon_{\pi,t} \sim N(0, \sigma_\pi^2)$. Future profits are discounted based on the discount factor of households. The first-order condition associated with the maximization of $E_t \sum_{s=0}^{\infty} \dfrac{1}{P_{t+s}} D_{t,t+s} F_{t+s}(j)$ (anticipating symmetry $P_T(j) = P_T$ $\forall j \in [0,1]$ and using $\iota = 1/(\Upsilon - 1)$) is given by:

$$0 = (\frac{\Upsilon}{\xi})(\frac{\bar{P}_t}{P_t} - 1) - \frac{\upsilon_{\pi,t}\Pi_t}{\Pi_{t-1}^{\gamma}}\left(\frac{\upsilon_{\pi,t}\Pi_t}{\Pi_{t-1}^{\gamma}} - 1\right) + E_t D_{t,t+1} \frac{Y_{t+1}}{Y_t} \frac{\upsilon_{\pi,t+1}\Pi_{t+1}}{\Pi_t^{\gamma}}\left(\frac{\upsilon_{\pi,t+1}\Pi_{t+1}}{\Pi_t^{\gamma}} - 1\right) \tag{10}$$

2.4 Wholesale good producer Wholesale production, in turn, has a CES structure. It is a composite of goods produced by workers ($Y_{n,t}$) and goods produced by robots ($Y_{a,t}$):

$$Y_t = \left[\alpha_n Y_{n,t}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n) Y_{a,t}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{11}$$

where σ is the substitution elasticity between the two goods, and α_n determines the steady state factor income shares. Such an aggregation captures imperfections in the substitutability of workers and robots in the production process. The wholesale good is traded in a perfectly competitive market at price $\bar{P}_t$, where $P_{A,t}$ is the unit price of robot-based goods, and $P_{N,t}$ is the unit price of worker-based goods.

The producers take prices as given and optimally choose $Y_{n,t}$ and $Y_{a,t}$ to maximize profits:

$$\bar{F}_t = \bar{P}_t Y_t - P_{N,t} Y_{n,t} - P_{A,t} Y_{a,t} \tag{12}$$

The optimal choices of intermediate inputs imply the following demands:

$$Y_{n,t} = (\alpha_n)^{\sigma} \left(\frac{P_{N,t}}{P_t} \frac{1}{\bar{P}_t / P_t} \right)^{-\sigma} Y_t \qquad Y_{a,t} = (1-\alpha_n)^{\sigma} \left(\frac{P_{A,t}}{P_t} \frac{1}{\bar{P}_t / P_t} \right)^{-\sigma} Y_t \tag{13}$$

As a result of the above, the price of the wholesale output is:

$$\frac{\bar{P}_t}{P_t} = \left[(\alpha_n)^{\sigma} \left(\frac{P_{N,t}}{P_t} \right)^{1-\sigma} + (1-\alpha_n)^{\sigma} \left(\frac{P_{A,t}}{P_t} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{14}$$

2.5 Wholesale Production Inputs

2.5.1 Firms producing with robots

When a wholesale-sector firm with a vacancy considers automation, it faces a decision: to adopt a robot or not. The adoption of a robot incurs a cost x_t in units of consumption goods, drawn randomly from a cumulative density function $G(x)$. The firm chooses to adopt a robot if and only if the cost is less than the benefit, leading to a threshold value x_t^* such that automation occurs if and only if $x_t \leqslant x_t^*$. This threshold depends on the value of automation (J_t^a) relative to the value of a vacancy (J_t^v):

$$x_t^* = J_t^a - J_t^v \tag{15}$$

Consequently, the probability of automating a vacancy, q_t^a, is given by

$$q_t^a = G(x_t^*), \tag{16}$$

and the flow of automated job positions adds to the stock of automated positions (A_t), which depreciate at a rate $\rho^o \in [0, 1]$ per period. Thus, A_t evolves according to the law of motion

$$A_t = (1 - \rho^o)A_{t-1} + q^a_t(1 - q^v_{t-1}\gamma_{t-1})v_{t-1} \tag{17}$$

where $q^a_t(1 - q^v_{t-1}\gamma_{t-1})v_{t-1}$ captures the number of newly automated job positions. Each robot produces $Z_t\zeta_t$ units of wholesale ouput, where Z_t is a neutral technology shock that follows the stochastic process: $lnZ_t = (1-\rho_z)lnZ+\rho_z lnZ_{t-1}+\epsilon_{zt}$, with $\epsilon_{z,t} \sim N(0, \sigma^2_Z)$, and ζ_t is a technological shock specific to robots (i.e., a robot productivity shock) that follows the process: $ln\zeta_t = (1 - \rho_\zeta)ln\zeta + \rho_\zeta ln\zeta_{t-1} + \epsilon_{\zeta t}$, $\epsilon_{\zeta t} \sim N(0, \sigma^2_\zeta)$. Thus, overall robot-based production is:

$$Y_{A,t} = A_t Z_t \zeta_t \tag{18}$$

Moreover, firms operating robots incur a fixed operating cost flow κ_a in units of output. Consequently, its value function J^a_t satisfies the Bellman equation

$$J^a_t = \frac{P_{At}}{P_t} Z_t\zeta_t - \kappa_a + (1 - \rho^o)\mathbb{E}_t D_{t,t+1} J^a_{t+1} \tag{19}$$

2.5.2 Firms entering the market

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 $F(e)$. 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,

$$\eta_t = F(J^v_t) = \mathbb{P}(e \leqslant J^v_t) \tag{20}$$

2.5.3 Firms posting a job offer

Keeping a vacancy online requires a cost equal to κ units of consumption goods associated with posting a job offer. Let J^e_t represent the expected average employment value across the spectrum of labor disutility χ_t, with the probability q_t^v of the vacancy being filled. This value is defined as:

$$J_t^e = \int_0^{\underline{\chi}_t} J_t^e(\chi_t) \frac{dH(\chi_t)}{H(\underline{\chi}_t)} \tag{21}$$

If the vacancy, however, is not filled, the firm carries it over to the next period, in which it may be automated with 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 following Bellman equation

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

2.6 Workers-based firms If a match between a firm and a worker is formed, the firm produces $Z_t h_t$ units of consumption goods, and subsequently, the overall workers-based production is:

$$Y_{N,t} = N_t Z_t h_t \tag{23}$$

Then, the value of employment $(J_t^e(\chi_t))$ satisfies the Bellman equation:

$$J_t^e(\chi_t) = (P_{N,t}/P_t) Z_t h_t - w_t(\chi_t) h_t + \mathbb{E}_t D_{t,t+1} \Big((1 - \delta_{t+1}) J_{t+1}^e + \delta_{t+1} J_{t+1}^v \Big) \tag{24}$$

2.7 Household. Perfect consumption insurance exists among household members. The household does not determine the labor hours h_t; they are established through Nash bargaining as in Trigari (2009). The utility of a household member with random labor disutility $\chi_t \sim H(\chi_t)$ is expressed as: $ln(C_t - \gamma_C C_{t-1}) - \ell(h_t, \chi_t)$, where C_t denotes final consumption goods, γ_C captures external habit formation and $\ell(h_t, \chi_t)$ captures labor disutility from work, defined as: $\ell(h_t, \chi_t) \equiv \left(\Omega \frac{h_t^{1+\omega}}{1+\omega} + \chi_t \right) \mathbf{1}\chi$. Here, $\mathbf{1}_\chi$ is an indicator function that equals one when the household member is employed and zero otherwise. The parameters Ω and ω represent the scale of hours disutility and the inverse of intertemporal elasticity of substitution for leisure, respectively.

The representative household's utility function is $\mathbb{E}\sum_{t=0}^{\infty}\beta^t\left(ln(C_t-\gamma_C C_{t-1})-L(h_t,\chi_t)\right)$, where $L(h_t,\chi_t)=\int_0^{\chi_t}\ell(h_t,\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)}N_t$ represents the aggregation of labor disutility $\ell(h_t,\chi_t)$ across all household members, $\beta\in(0,1)$ is the subjective discount factor.

The representative household chooses consumption C_t and nominal savings B_t to maximize its utility function subject to the sequence of budget constraints:

$$P_tC_t+\frac{B_t}{r_t^n}=\theta_{t-1}B_{t-1}+P_tN_th_t\int_0^{\chi_t}w_t(\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)}+P_t\phi(1-N_t)+d_t-T_t,\forall t\geqslant 0 \tag{25}$$

where w_t denotes the hourly real wage, d_t denotes nominal firm profits, T_t denotes nominal lump-sum taxes, T_t denotes nominal lump-sum taxes. The parameter ϕ measures the flow benefits of unemployment, and r_t^n denotes the gross nominal interest rate. θ_t represents an autoregressive risk premium shock which follows the stationary stochastic process: $ln\theta_t=\rho_\theta ln\theta_{t-1}+\epsilon_{\theta t}$, with $\epsilon_{\theta t}\sim N(0,\sigma_\theta^2)$.

The household stochastic discount factor is given by $D_{t,t+1}\equiv\beta\frac{\Lambda_{t+1}}{\Lambda_t}$, where Λ_t is the Lagrange multiplier associated with the budget constraint (25). The household's bond Euler equation is given by, $1=\mathbb{E}_t\beta\theta_t\dfrac{\Lambda_{t+1}}{\Lambda_t}\frac{r_t^n}{\Pi_{t+1}}$.

The employment surplus (i.e., the value of employment relative to unemployment) is defined as

$$\begin{aligned}S_t^H=&\left(h_t\int_0^{\chi_t}w_t(\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)}-\phi-\frac{1}{\Lambda_t}\int_0^{\chi_t}\ell(h_t,\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)}\right)\\&+\beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}(1-\delta_{t+1}^n)(1-\delta_{t+1}^x)(1-\gamma_{t+1}q_{t+1}^u)S_{t+1}^H\end{aligned} \tag{26}$$

If the household adds a new worker, it gains the average wage income that takes into account labor hours, 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 endogenous and exogenous job separations); however, adding a worker today would also reduce the pool of searching workers tomorrow, a fraction $\gamma_t q_{t+1}^u$ 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 $(1-\gamma_{t+1}q_{t+1}^u)(1-\delta_{t+1})$, resulting in the continuation value of employment shown in the last term of equation (26).

The value function of a matched worker in period t is given by

$$\begin{aligned}
W_t(\chi_t) =& w_t(\chi_t)h_t - \frac{1}{\Lambda_t}\ell(h_t,\chi_t) \\
&+\beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}\Bigg[(1-\delta^x_{t+1})(1-\delta^n_{t+1})\int_0^{\underline{\chi}_{t+1}} W(\chi_{t+1})\frac{dH(\chi_{t+1})}{H(\underline{\chi}_{t+1})} \\
&+\delta_{t+1}q^u_{t+1}\gamma_{t+1}\int_0^{\underline{\chi}_{t+1}} W(\chi_{t+1})\frac{dH(\chi_{t+1})}{H(\underline{\chi}_{t+1})} + \delta_{t+1}(1-q^u_{t+1}\gamma_{t+1})U_{t+1}\Bigg]
\end{aligned} \tag{27}$$

Symmetrically, the value function of an unemployed worker in period t is given by:

$$U_t = \phi + \beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}\left[q^u_{t+1}\gamma_{t+1}\int_0^{\underline{\chi}_{t+1}} W(\chi_{t+1})\frac{dH(\chi_{t+1})}{H(\underline{\chi}_{t+1})} + (1-q^u_{t+1}\gamma_{t+1})U_{t+1}\right] \tag{28}$$

The surplus of a matched worker is given by the difference between (27) and (28):

$$\begin{aligned}
S^H_t(\chi_t) &= W(\chi_t) - U_t \\
&= w_t(\chi_t)h_t - \phi - \frac{1}{\Lambda_t}\ell(h_t,\chi_t) \\
&+ \beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}\left[(1-\delta_{t+1})(1-\gamma_{t+1}q^u_{t+1})\left(\int_0^{\underline{\chi}_{t+1}} W(\chi_{t+1})\frac{dH(\chi_{t+1})}{H(\underline{\chi}_{t+1})} - U_{t+1}\right)\right]
\end{aligned} \tag{29}$$

Averaging over χ_t the above equation yields the average surplus of a match for the household, obtained already in equation (26). To do so, we need the following definitions of the average surplus and of the average value of a worker:

$$S^H_t = \int_0^{\underline{\chi}_t} S^H_t(\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)} \tag{30}$$

$$W_t = \int_0^{\underline{\chi}_t} W_t(\chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)} \tag{31}$$

$$S^H_t = W_t - U_t \tag{32}$$

2.8 The Nash bargaining wage and hours Given the worker's employment surplus, $S^H_t(\chi_t)$, and the firm's surplus, $J^e_t(\chi_t) - J^v_t$, the Nash-bargaining hourly real wage (w^N_t) maximizes the following problem

$$\max_{S_t^H(\chi_t), J_t^e(\chi_t) - J_t^v} \quad (S_t^H(\chi_t))^b (J_t^e(\chi_t) - J_t^v)^{1-b} \tag{33}$$

$$s.t. \;\; J_t^e(\chi_t) - J_t^v + S_t^H(\chi_t) = S_t(\chi_t), \tag{34}$$

where $b \in (0,1)$ represents the bargaining weight for workers and $S_t(\chi_t)$ is the total surplus. The solution to this maximization problem results in the relation: $S_t^H(\chi_t) = [b/(1-b)](J_t^e(\chi_t) - J_t^v)$, and upon averaging over χ_t, we obtain: $S_t^H = \frac{b}{1-b}(J_t^e - J_t^v)$.

Substituting the value functions and rearranging terms while averaging over χ_t, we arrive at the equation for the Nash bargaining average wage:

$$\begin{aligned} \frac{b}{1-b}(J_t^e - J_t^v) &= w_t^N h_t - \phi - \frac{1}{\Lambda_t}\int_0^{\underline{\chi}_t} \ell(h_t, \chi_t)\frac{dH(\chi_t)}{H(\underline{\chi}_t)} \\ &+ \beta \mathbb{E}_t \frac{\Lambda_{t+1}}{\Lambda_t}\left[(1-\delta_{t+1}^n)(1-\delta_{t+1}^x)(1-\gamma_{t+1} q_{t+1}^u)\frac{b}{1-b}(J_{t+1}^e - J_{t+1}^v)\right] \end{aligned} \tag{35}$$

The model do not imposes any real wage rigidity. Thus, the equilibrium real wage rate is just the Nash bargaining wage rate : $w_t = w_t^N$. Based on the equation (35), the threshold disutility for accepting work, $\bar{\chi}_t$, affects positively wages in the negociation.

The optimality condition for hours worked, h_t, selected by the match, is given by

$$p_{n,t} Z_t \Lambda_t = \frac{\partial \ell(h_t, \chi_t)}{\partial h_t} \tag{36}$$

where the left-hand side represents the utility derived from the value of the marginal product of an additional hour of work, while the right-hand side represents the marginal utility of an additional hour of leisure. Given the separability between h_t and χ_t in $\ell(h_t, \chi_t)$, the above condition implies that h_t does not depend on χ_t, and it is thus common across all workers.

2.9 Endogenous separations Similar to (Trigari, 2009), firms and workers might find it optimal to disolve their match when its total surplus $S_t(\chi_t)$ attains zero. This happens when labor disutility

χ_t reaches a high upper bound $\underline{\chi}_t$. According to equation (34), a zero surplus implies:

$$S_t(\underline{\chi}_t) = J_t^e(\underline{\chi}_t) - J_t^v + S_t^H(\underline{\chi}_t) = 0 \tag{37}$$

Substituting the value functions and rearranging terms leads to an equation for the upper bound of the disutility of labor $\underline{\chi}_t$:

$$\begin{aligned} S(\underline{\chi}_t) = 0 = &\frac{P_{N,t}}{P_t} Z_t h_t - \phi - \frac{1}{\Lambda_t}\ell(h_t, \underline{\chi}_t) + \kappa - q_t^v \gamma_t J_t^e \\ &+ \beta \mathbb{E}_t \frac{\Lambda_{t+1}}{\Lambda_t}\Bigg[(1-\delta_{t+1})(1 - b q_{t+1}^u \gamma_{t+1})\frac{1}{1-b}(J_{t+1}^e - J_{t+1}^v) + J_{t+1}^v \\ &- (1 - q_t^v \gamma_t)\left(q_{t+1}^a J_{t+1}^a - \int_0^{x_{t+1}^*} x dG(x) + (1 - q_{t+1}^a) J_{t+1}^v\right)\Bigg] \end{aligned} \tag{38}$$

The novelty associated with this paper lies in how the inclusion of automation influences the desutility threshold $\underline{\chi}_t$ according to equation (38). As automation value rises, it boosts the future vacancy value, decreasing the firm's surplus matched with a worker at the margin [7] and then endogenously separate the firm with a such desutility to match with another worker having a lesser desutiluty to sustain a positive total surplus. Therefore, the threat of automation implies a downward pressure on the disutility threshold, leading to an increase in endogenous separations.

As in Trigari (2009), the monetary policy also plays an important role on the changes in the desutility threshold. When a contractionary aggregate shock, such as a persistent increase in the monetary policy shock, occurs, it reduces the firm's surplus matched with a worker at the margin and then separate endogenously the firm with a such desutility to match with another worker having a lesser desutiluty to sustain a positive total surplus. Consequently, a contractionary monetary policy exerts downward pressure on the disutility threshold, leading to an increase in endogenous separations.

2.10 Government policy The government finances unemployment benefit payments ϕ for unemployed workers and fiscal subsidies through lump-sum taxes: $T_t = P_t\phi(1-N_t) + \iota P_t Y_t$. Furthermore,

[7] A worker at the margin is a worker where the realization of his preference shock correspond to the threshold value $\underline{\chi}_t$

monetary policy sets the nominal interest rate according to the following rule:

$$\frac{r_t^n}{r^n} = \left(\frac{r_{t-1}^n}{r^n}\right)^{\psi_r} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\psi_\pi} \left(\frac{Y_t}{Y}\right)^{\psi_y}\right] \hat{\epsilon}_t^{mp},\ \hat{\epsilon}_t^{mp} \sim N(0, \sigma_{mp}^2) \tag{39}$$

where the nominal interest rate reacts to inflation, the output and its own lag.

2.11 Job creation, job destruction, and employment We define labor market flows following the methodology of Trigari (2009). The author initially notes from observation that flows of workers out of employment relationships exceed flows of jobs out of firms. Consequently, a fraction of firms experiencing separations from workers must attempt to refill the vacancies left open and succeed in doing so within the same period. To address this observation, it is assumed that firms undergoing exogenous separations immediately repost the resulting vacancies, while those facing endogenous separations do not. This implies that $\rho_t^x N_{t-1}$ separations are reposted, and $\gamma_t q_t^v \rho_t^x N_{t-1}$ separations are refilled within the same period. Additionally, it is assumed that a job is neither created nor destroyed by a firm that both loses and gains a worker in the same period.

Job creation is thus defined as the net number of newly created matches, accounting for matches serving to refill reposted vacancies. The job creation rate is expressed as:

$$jc_t = \frac{\gamma_t m_t}{N_{t-1}} - \gamma_t q_t^v \delta_t^x \tag{40}$$

Similarly, job destruction is defined as the total number of separations net of those that are reposted and successfully refilled. The job destruction rate is given by:

$$jd_t = \delta_t - \gamma_t q_t^v \delta_t^x \tag{41}$$

Finally, employment growth can be expressed as, $(N_t - N_{t-1})/N_{t-1} = jc_t - jd_t$.

2.12 Market Clearing In equilibrium, the markets for bonds, final goods, and intermediate goods all clear. Since the aggregate bond supply equals zero, the bond market-clearing condition implies that

$$B_t = 0 \tag{42}$$

Market clearing for intermediate goods implies that

$$Y_{n,t} = Z_t h_t N_t \quad Y_{at} = Z_t \zeta_t A_t \tag{43}$$

Final goods market clearing requires that consumption spending, vacancy posting costs, robot operation costs, robot adoption costs, vacancy creation costs, and adjustements in prices add up to aggregate production. This equality can be found (see appendix for more details) by starting from the household budget constraint and substituting in the government budget constraint and the profits of all firms to obtain:

$$Y_t = C_t + \kappa_a A_t + \kappa v_t + (1 - q^v_{t-1}\gamma_{t-1})v_{t-1} \int_0^{x_t^*} x dG(x) + \int_0^{J_t^v} e dF(e) + \frac{\xi}{2}\left(\frac{\Pi_t}{\Pi_{t-1}^{\gamma}} - 1\right)^2 Y_t \tag{44}$$

3 Empirical Approach

Two types of economies are analyzed in this study: one without nominal and rigidity frictions, and one with such frictions. In the frictionless case, we consider two models: the original model from Leduc and Liu (2024), in which job destruction is treated as exogenous, and an extended version referred to as the "Endogenous Job Destruction" model, in which job destruction is modeled endogenously. The extended model modifies only the job destruction mechanism, excluding other features such as nominal rigidities, habit formation in consumption, and the risk premium shock.[8] The original Leduc and Liu (2024) model is drawn directly from their paper.

In contrast, when nominal and real rigidity frictions are introduced, we rely on our "benchmark" model, as presented in the previous section. This model incorporates nominal and rigidity frictions (including habit formation in consumption), and features a risk premium shock[9].

[8]The complete derivation of this extended model is provided in the online appendix. In this specification, we use a discount factor shock as in Leduc and Liu (2024) instead of a risk premium shock.

[9]The complete derivation of the benchmark model is provided in the online appendix.

Each model is log-linearized around its deterministic steady state and solved under rational expectations. The Leduc and Liu (2024) model is not re-estimated; instead, we use the authors' reported parameter values. The Endogenous Job Destruction model and the Benchmark model are both estimated using Bayesian methods, following the approach of An and Schorfheide (2006), and are fitted to quarterly U.S. data from 1985:I to 2018:IV. The main difference between the two estimations lies in the specific observable variables used, reflecting differences in the number of shocks present in each model.

3.1 Data and Observation Equations. We fit the benchmark model to six U.S. quarterly time series, several of which were also used in Leduc and Liu (2024): the unemployment rate, the job vacancy rate, the growth rate of the real wage, the growth rate of average labor productivity in the nonfarm business sector, inflation, and the nominal interest rate. The endogenous job destruction model, being smaller in scope, is fitted to only four of these series, excluding inflation and the nominal interest rate. These four series are also those used in Leduc and Liu (2024).

1. Similar to Leduc and Liu (2024), we use the unemployment rate (civilian aged 16 years and over) from the Bureau of Labor Statistics (BLS). The measurement equation is $ur_t^{data} - \bar{ur}^{data} = \hat{ur}_t$, where ur_t^{data} is 100 times the logarithm of the unemployment rate, and $\bar{ur}_t^{data}$ is the mean of ur_t^{data}. $\hat{ur}_t$ denotes the log deviations of the unemployment rate in the model from its steady-state value.

2. We employ data for job vacancies similar to Leduc and Liu (2024). For periods before 2001, we use the vacancy rate constructed by Barnichon (2010) based on the Help Wanted Index. For periods starting in 2001, we utilize the job openings rate from the Job Openings and Labor Turnover Survey (JOLTS). The measurement equation is $v_t^{data} - \bar{v}^{data} = \hat{v}_t$, where v_t^{data} is 100 times the logarithm of the vacancy rate, and $\bar{v}_t^{data}$ denotes the mean of v_t^{data}. $\hat{v}_t$ indicates the log deviations of the vacancy rate in the model from its steady-state value.

3. We measure labor productivity in the data by real output per Worker in the nonfarm business sector (PRS85006163 from FRED). The measurement equation is $\gamma_{p,t}^{data} - \bar{\gamma_p}^{data} = (\hat{Y}_t - \hat{N}_t) - (\hat{Y}_{t-1} - \hat{N}_{t-1})$, where $\gamma_{p,t}^{data}$ represents 100 times the log growth rate of real labor productivity in the data, $\bar{\gamma}_p$ denotes the mean of $\bar{\gamma_p}^{data}$, and $\hat{Y}_t$ and $\hat{N}_t$ indicate the log deviations of

aggregate output and employment from their steady-state levels in the model.

4. We measure the real wage rate in the data by real compensation per worker in the nonfarm business sector. Initially, we compute the nominal wage rate as the ratio of labor compensation of all workers in the nonfarm business sector (PRS85006063 from FRED) to the product of employment in the nonfarm business sector (PRS85006013 from FRED). We then deflate it using the implicit price deflator in the nonfarm business sector (IPDNBS from FRED). The measurement equation is $\gamma_{w,t}^{data} - \bar{\gamma_w}^{data} = \hat{w}_t + \hat{h}_t - \hat{w}_{t-1} - \hat{h}_{t-1}$, where $\gamma_{w,t}^{data}$ represents 100 times the log growth rate of the real wage rate in the data, $\bar{\gamma_w}$ denotes the mean of $\bar{\gamma_w}^{data}$, $\hat{w}_t$ indicates the log deviations of real wages from the steady-state in the model, and $\hat{h}_t$ indicates the log deviations of hours from the steady-state in the model.

5. We measure the inflation in the data by the GDP Implicit Price Deflator (GDPDEF from FRED). The measurement equation is $\gamma_{\pi,t}^{data} - \bar{\gamma_\pi}^{data} = \hat{\Pi}_t$, where $\gamma_{\pi,t}^{data}$ represents 100 times the log growth rate of the GDP Implicit Price Deflator, $\bar{\gamma_\pi}$ denotes the mean of $\bar{\gamma_\pi}^{data}$, and $\hat{\Pi}_t$ indicates the log deviations of inflation from its steady-state in the model.

6. We measure the nominal interest rate in the data by the Federal Funds effective Rate (FEDFUNDS from FRED)[10]. The measurement equation is $\gamma_{R,t}^{data} - \bar{\gamma}_R^{data} = 4 * \hat{r}_t^n$, where $\gamma_{R,t}^{data}$ represents the federal fund rate, $\bar{\gamma_R}$ denotes the mean of $\bar{\gamma_R}^{data}$, and $\hat{r}_t^n$ indicates the deviations of the nominal interest rate from its steady-state in the model.

3.2 Functional Forms Consistent with Leduc and Liu (2024) and following Fujita and Ramey (2007) for the vacancy creation and robot adoption costs, we assume uniform distributions for robot adoption costs and entry costs: $F(e) = e/\bar{e}$ and $G(x) = x/\bar{x}$, with $\bar{e}, \bar{x} > 0$.

Similarly, we assume that the distribution of labor disutilities follows a uniform distribution, denoted as $H(\chi_t) = \chi_t/\bar{\chi}$, with $\bar{\chi} > 0$. This distribution differs from the log-normal distribution assumed in Trigari (2009), providing greater tractability in steady-state calculations.

[10]The period of the zero lower bound falls in our sample. During the period of the binding zero lower bound (2009.I-2015.IV), we use the shadow rate of Wu and Xia (2016) as done in Charalampidis (2020b).

3.3 Parameter calibration. We present here the calibration of the benchmark model. The calibration of the endogenous job destruction model is similar but involves fewer parameters[11]. We undertake the calibration of several parameters as outlined in Table (1).

We refer to Leduc and Liu (2024) for some parameter values. Specifically, the discount factor β is set to 0.99. The unemployment benefit ϕ is set to 0.25. The elasticity of the matching function α is fixed at 0.5. Additionally, the Nash bargaining weight b is set to 0.50, the elasticity of substitution between intermediate goods σ to 3, and the share of worker-produced intermediate goods α_n to 0.535. The rate at which robots become obsolete, ρ^o, is set to 0.03. We set the parameters $\bar{e}$ and $\bar{x}$—which represent the scale of the fixed cost of vacancy creation and the scale of the fixed cost of automation, respectively—at 3.0703 and 4.9483, consistent with their estimated values in the Leduc and Liu (2024) model.

In line with Leduc and Liu (2024), we set the steady-state automation probability at $q^a = 9.6\%$ which implies the flow cost of operating automation equipment to $\kappa_a = 0.9788$ in line with Leduc and Liu (2024). Furthermore, we fix the steady-state value of the technology shock, Z, and the steady-state value of the automation-specific shock, ζ, at 1 and 1.5, respectively. The stochastic process of the risk premium shock implies $\theta = 1$. For the endogenous job destruction model without the nominal frictions, we also set the steady-state level of the discount factor shock to $\theta = 1$.[12]

In line with Trigari (2009), we normalize steady-state hours of work to $h = 1$. We also adopt the steady-state endogenous job separation rate computed by Trigari (2009), $\delta^n = 2.74\%$. Furthermore, consistent with Leduc and Liu (2024) and Hall and Robert (1995), we target a steady-state overall job separation rate of $\delta = 10\%$. This target enables us to determine the steady-state exogenous job separation rate, which is, $\delta^x = 7.46\%$. These values subsequently help in solving for the labor disutility parameter $\bar{\chi}$ in the steady-state calculation.

Following Leduc and Liu (2024), we set the steady-state unemployment rate, ur, at 5.95% and the job filling probability, γq^v, at the often-used value of 71%. This setting enables us to derive the matching efficiency μ and the scale of labor desutility, Ω. Vacancy posting costs amount to 1% of

[11] Leduc and Liu (2024) model is consistently calibrated using parameters from Leduc and Liu (2024) throughout this paper.

[12] We use the notation θ_t to denote the risk premium shock in the benchmark model, and, with slight abuse of notation, also use θ_t to represent the discount factor shock in the endogenous job destruction model.

output and permit the retrieval of the flow cost κ.

Specific to nominal rigidities, the elasticity of substitution between two varieties, Υ, is set to 10, and the steady-state inflation, Π, is set to 1, consistent with values commonly used in the literature.

Table 1: Calibrated Parameters

Parameter	Symbol	Value
Discount factor	β	0.99
Unemployment benefit	ϕ	0.25
Elasticity of matching function	α	0.50
Nash bargaining weight	b	0.50
EOS between intermediate goods	σ	3
Automation obsolescence	ρ^o	0.03
Share of worker-produced intermediate goods	α_n	0.535
Scale for fixed cost of vacancy creation	$\bar{e}$	3.0703
Scale for fixed cost of automation	$\bar{x}$	4.9483
Automation probability	q^a	0.096
Flow cost of operating automation equipment	κ_a	From the value of q^a
Steady-state, discount factor shock	θ	1
Steady-state, technology shock	Z	1
Steady-state, robot-specific shock	ζ	1.5
Steady-state, hours	h	1
Steady-state, Endogenous job separation	δ^n	0.0274
Steady-state, Overall job separation	δ	0.1
Steady-state, exogenous job separation	δ^x	0.0746
Steady-state, unemployment rate	ur	0.0595
Steady-state, job filling probability	γq^v	0.71
Matching efficiency	μ	from $ur = 0.0595$ and $\gamma q^v = 0.71$
Vacancy posting cost	κ	from $\kappa v/Y = 0.01$
Scale for labor disutilities	$\bar{\chi}$	from the value of δ^n
Scale, labor disutility	Ω	from $\gamma q^v = 0.71$
EOS between two varieties	Υ	10
Steady state, inflation	Π	1

3.4 Steady state equilibrium. In this section, we solve for the remaining steady-state variables of the model. Given the value of the discount factor β, the steady-state nominal interest rate r^n is directly determined as $1/\beta$. We then sequentially solve the steady-state system using the following equations: (10), (8), (2), (4), (7), (43), (6), (5), and the calibration targets. From these, we obtain the following steady-state expressions: $\frac{\bar{P}}{P} = 1$, $N = 1 - ur, u = 1 - (1-\delta)N, \gamma = 1 - \frac{\delta^n}{u}, m = \dfrac{\delta N}{\gamma}, Y_n = N, q^u = \dfrac{m}{u}, q^v = \frac{0.71}{\gamma}, v = \dfrac{m}{q^v}, \mu = \dfrac{m}{u^\alpha v^{1-\alpha}}$.

We use the law of motion for vacancies, equation (3), to solve for the steady-state inflow of new vacancies, η. The steady-state stock of automated positions, A, is obtained from equation (17). The automation threshold in steady state is derived from equation (16), which gives $x^* = \bar{x}q^a$.

Using equation (20), we compute the value of a vacancy in steady state: $J^v = \bar{e}\eta$. The steady-state value of automation, J^a, is obtained from the Bellman equation (15), yielding $J^a = x^* + J^v$. Robot-based production in steady state is computed from equation (18) as $Y_a = Z\zeta A$.

Aggregate output, Y, is then derived using the CES aggregator in equation (11):

$$Y = \left[\alpha_n Y_n^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n)Y_a^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The prices of intermediate goods, p_n and p_a, are computed from the demand system in equation (13). The fixed operating cost flow κ_a is calibrated using the steady-state value of automation from equation (19). The fixed cost of vacancy creation, κ, is calibrated to match the target ratio $\frac{\kappa v}{Y} = 0.01$.

Steady-state consumption, C, is solved from the resource constraint in equation (44). The match value, J^e, is obtained from the vacancy value using equation (22), and the equilibrium real wage, w, is determined from the Bellman equation for employment, equation (24).

Using the optimality condition for hours worked, equation (36), we solve for the steady-state hours disutility shock: $\Omega = \frac{p_n Z}{C(1-\gamma_c)h^\omega}$.

Finally, the steady-state upper bound of labor disutility, $\underline{\chi}$, is derived from the Nash bargaining condition (35), while the scale parameter for disutility, $\bar{\chi}$, is obtained from equation (1) as: $\bar{\chi} = \frac{1}{1-\delta^n}\underline{\chi}$. Steady-state job creation and destruction rates are computed from equations (40) and (41), respectively.

3.5 Priors. The third column of Table 2 in Appendix A presents the prior distributions for the two models without nominal frictions: the Endogenous Job Destruction model and its No Automation Threat counterpart, in which the probability of robot adoption is fixed ($q_t^a = q^a$). In both cases, the priors are consistent with those used by Leduc and Liu (2024). Specifically, the persistence parameters for each shock follow a beta distribution with a mean of 0.8 and a standard deviation of 0.1. The standard deviations of the shocks are modeled using an inverse gamma distribution with a mean of 0.01 and a standard deviation of 0.1. The parameter ω, which governs the disutility of hours worked and is not specified in Leduc and Liu (2024), is assigned a normal distribution with a mean of 10 and a standard deviation of 1.

The third column of Table 3 in Appendix A presents the prior distributions for the two models with nominal frictions: the Benchmark model and its No Automation Threat counterpart. The priors are identical across both models for each parameter. The persistence parameters for the separation shocks and the disutility parameter ω follow the same distributions as those used in the models without nominal frictions.

For the persistence of the risk premium and price markup shocks, we assume a beta distribution with a mean of 0.8 and a standard deviation of 0.1, in line with standard practice in the literature. The persistence of the neutral technology shock is modeled with a beta distribution as well, centered at 0.85 with a standard deviation of 0.1 and a lower bound of 0.82. For the automation-specific technology shock, we specify a beta distribution with a mean of 0.8, a standard deviation of 0.1, and an upper bound of 0.9.

The standard deviation of each shock is assumed to follow an inverse gamma distribution with a mean of 0.05 and a standard deviation of 0.5. An exception is made for the automation-specific technology shock, for which we impose an upper bound of 0.08 on its standard deviation.

Additional structural parameters—including habit persistence in consumption (γ_c), price adjustment cost (ξ), the indexation parameter (γ), and the Taylor rule coefficients for interest rate smoothing (ψ_r), inflation responsiveness (ψ_π), and output responsiveness (ψ_y)—are assigned priors consistent with the existing literature.

3.6 Posteriors. Table 2 in Appendix A presents the estimation results, including posterior means and 90 percent probability intervals, for the posterior distributions of the two models without nominal frictions. We focus on interpreting the results of the endogenous job destruction model; its counterfactual version without the automation threat is used solely for assessing model fit.

The inverse of the elasticity of substitution for leisure is estimated at $\omega = 11.10$, and the 90 percent probability interval indicates that the data are not informative for this parameter. With the exception of the discount factor shock, all shocks are persistent and consistent with the findings of Leduc and Liu (2024). The standard deviations of the separation and discount factor shocks are higher than those reported in Leduc and Liu (2024). The increased volatility of the separation shock may stem from the integration of endogenous separation into the model, while the higher variance of the discount factor shock may be explained by its low persistence. The standard deviations of the technology and automation shocks are broadly consistent with those in Leduc and Liu (2024).

Table 3 in Appendix A presents the estimation results for the two models with nominal frictions, again including posterior means and 90 percent probability intervals. We interpret only the results for the benchmark model; its counterfactual version without the automation threat is used solely for model comparison purposes.

In the benchmark model, the posterior mean estimate of the inverse of the elasticity of substitution for leisure is $\omega = 10.67$. The 90 percent probability interval suggests that the data are informative for this parameter. Nevertheless, the estimate remains close to that obtained in the model without nominal frictions. All shocks are persistent and consistent with the literature. The data are informative about the persistence of each shock. The standard deviation of the separation shock remains relatively high, echoing the results from the endogenous job destruction model. The standard deviations of the technology and automation shocks align with those in Leduc and Liu (2024). In contrast, the standard deviations of the risk premium, monetary policy, and price markup shocks are relatively low, with the data being informative.

The posterior estimates for habit persistence in consumption (γ_c), price adjustment cost (ξ), indexation parameter (γ), and the Taylor rule coefficients for interest rate smoothing (ψ_r), inflation responsiveness (ψ_π), and output responsiveness (ψ_y) are all consistent with values commonly found in the literature.

3.7 Model Fits Table 2 in Appendix A presents the estimation results, including the log data densities for the two models without nominal frictions. The Endogenous Job Destruction model yields a log data density of –1352, which is higher than that of its No Automation Threat counterpart, estimated at –1366. This result indicates that, in the absence of nominal frictions, the model featuring endogenous automation decisions provides a better fit to the data than the version in which the probability of automation is fixed ($q_t^a = q^a$).

Similarly, Table 3 in Appendix A reports the log data densities for the two models with nominal frictions. The benchmark model achieves a log data density of –2624, substantially higher than that of its fixed-automation counterpart, which has a log data density of –7285. This confirms that, in the presence of nominal frictions, the benchmark model with endogenous automation also fits the data significantly better than its counterfactual specification with fixed robot adoption probability.

3.8 Variance decomposition This subsection presents the sources of fluctuations in the models analyzed in this paper. The results indicate that, in many cases, our estimated models preserve the variance decomposition patterns found in Leduc and Liu (2024).

Tables 4 and 5 in Appendix B display the sources of fluctuations in the Leduc and Liu (2024) model and the endogenous job destruction model, respectively. Both models are estimated without nominal rigidities. In the Leduc and Liu (2024) model, the main driver of vacancy stock fluctuations is the neutral technology shock, followed by the discount factor shock. However, in the endogenous job destruction model, the separation shock emerges as the dominant driver, possibly due to the inclusion of endogenous separation. The separation shock also remains the main driver of hiring fluctuations in both models. The neutral technology shock is the primary driver of unemployment, real wages, productivity, consumption, and the probability of automation in both models. Specifically, in the endogenous job destruction model, the main source of fluctuations in endogenous separation and hours worked is the neutral technology shock.

Tables 6 and 7 in Appendix B show the variance decomposition for the benchmark model and its counterfactual version in which the probability of automation is held constant. Both models incorporate nominal rigidities. In both cases, the cost-push shock is the primary source of output gap fluctuations. Moreover, the neutral technology shock is the dominant driver of inflation, nominal interest rate, aggregate output, unemployment, job destruction, job creation, vacancy stock, real wages, and worker-based production. The robot-based production is mainly driven by the automation-specific shock in the benchmark model, but by the neutral technology shock in the counterfactual model. Notably, in the benchmark model, the automation-specific shock is the main driver of fluctuations in the probability of automation.

4 Transmission of automation-specific productivity shocks

This section assesses whether automation-specific productivity shocks destroy more jobs than they create in the short run. We show that this outcome arises only when job destruction is endogenous. The result holds in both types of economies: with and without nominal frictions.

4.1 Economies without Nominal Frictions: Exogenous Versus Endogenous Job Destruction Figure 1 presents the responses to a one-standard-deviation increase in automation-specific productivity shocks under two model specifications: the original Leduc and Liu (2024) model, in which job destruction is treated as exogenous, and an extended version in which job destruction is modeled endogenously. The extended model alters only the job destruction mechanism, omitting other features such as nominal rigidities, habit formation in consumption and the risk premium shock[13]. This controlled comparison allows us to isolate and evaluate the specific role of endogenous job destruction.

Introducing endogenous job destruction gives rise to new and important dynamics. The shock boosts robot productivity and thereby increases both the value of automation and the value of vacancies, which in turn reduces firms' surplus from matching with workers, as robots become a more attractive alternative. This diminishes firms' willingness to pay high wages, resulting in lower equilibrium wages. In response, only workers with relatively low disutility of work are willing to accept job offers, effectively lowering the disutility threshold required for employment. As a result, the matching process weakens, and endogenous separations arise as firms and workers no longer find it mutually beneficial to maintain employment relationships—particularly for workers with high disutility. Robots consequently destroy jobs and reduce real wages.

In the exogenous job destruction model, the increases in automation and vacancy values are more pronounced, likely due to greater volatility of the shock in that specification. This leads to a stronger

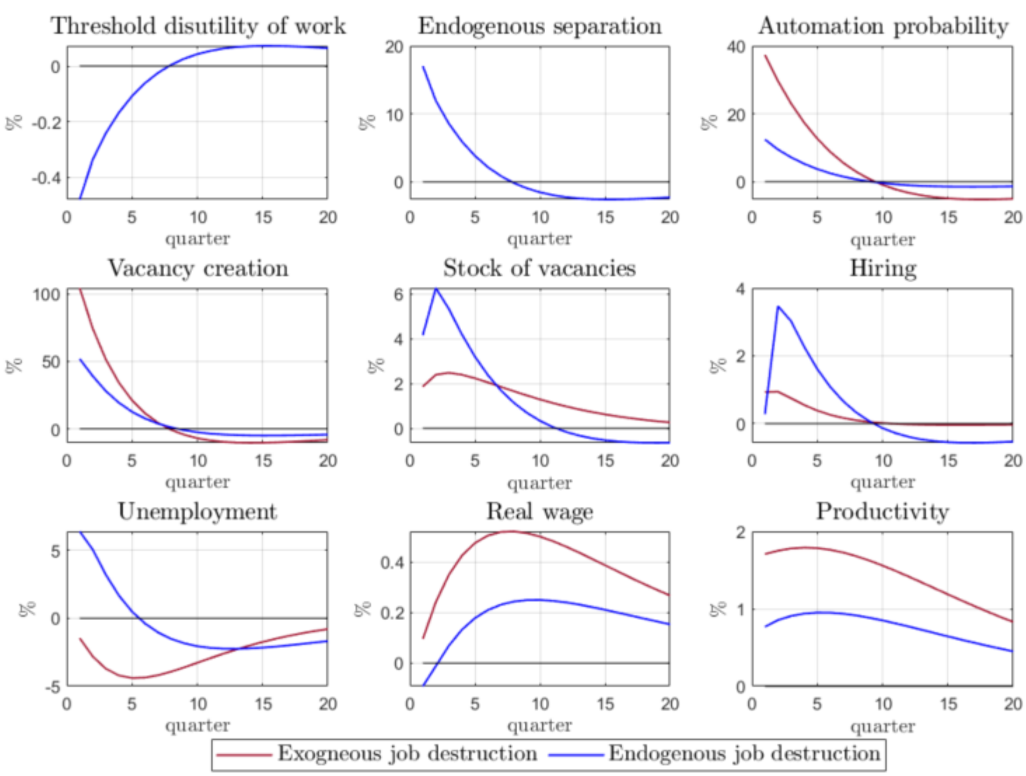
[13] The complete derivation of the extended model is presented in the appendix. In this specification, a discount factor shock replaces the risk premium shock.

rise in automation probability and vacancy creation. However, because a larger share of vacancies is automated, the net increase in the stock of vacancies is limited, which constrains hiring. In the absence of endogenous separations, unemployment tends to decline due to the rise in hiring alone.

In contrast, in the endogenous job destruction model, a portion of employment from the previous period is endogenously separated, and these job positions are reallocated as vacancies. This process amplifies the increase in the stock of vacancies and, subsequently, in hiring. Despite this stronger hiring response, unemployment increases due to the simultaneous rise in endogenous separations.

As a result, the automation-specific productivity shock leads to job losses through endogenous separation mechanisms, resulting in higher unemployment and lower real wages. These outcomes differ from those predicted by the exogenous separation model of Leduc and Liu (2024), and are more consistent with empirical evidence on the short-run labor market effects of automation.

Figure 1: Implications of Automation-specific Productivity



Note: One-standard-deviation increase in the innovation of the automation-specific productivity shock. Variables in % deviations around the steady state. "Exogenous job destruction": Leduc and Liu (2024) model with the parameters at their posterior mean. "Endogenous job destruction" refers to an extended version of the Leduc and Liu (2024) model that incorporates endogenous job destruction, with parameters calibrated at their posterior mean under this new specification.

4.2 Economies with nominal frictions: Benchmark Model Versus No Automation Threat Model Figure 2 presents the impulse responses to a one-standard-deviation increase in automation-specific productivity shocks under two model specifications: the benchmark model and a counterfactual version referred to as the no automation threat model, in which the probability of robot adoption is held constant ($q_t^a = q^a$). Both models are calibrated using the same set of posterior mean parameters from the benchmark specification. This comparison allows us to assess the role of the threat of automation—that is, the endogenous variation in robot adoption probability—in the transmission of robot productivity shocks.

The transmission mechanism in both models mirrors the dynamics outlined in subsection 4.1. An increase in robot productivity raises both the value of automation and the value of vacancies. As firms perceive robots as increasingly attractive substitutes for labor, the surplus from matching with workers declines. This reduces firms' willingness to offer high wages, leading to a fall in real wages in equilibrium. Consequently, only workers with lower disutility from working accept job offers, thereby lowering the disutility threshold required for employment. The matching process deteriorates, and endogenous separations occur as high-disutility workers and firms find continued employment relationships unprofitable. Thus, increased robot productivity leads to both job destruction and wage reductions.

In parallel, a portion of employment from the previous period is endogenously separated, and these job positions are reallocated as vacancies. This results in a sharp increase in the stock of vacancies and job creation. However, despite strong job creation dynamics, unemployment rises due to the simultaneous increase in job destruction.

In the no automation threat model, where the probability of robot adoption is fixed, the response of robot-based production is more muted than in the benchmark model. In the benchmark case, the shock increases the probability of automation, resulting in a larger rise in the stock of robots and a more persistent expansion in robot-based production. As a result, while the price of robot-produced goods is lower than that of worker-produced goods in both models, the no automation threat model features relatively higher prices for robot-produced goods and relatively lower prices for worker-produced goods. This relative price shift makes robot production more valuable and worker production less valuable in the no automation threat model. Consequently, the increase in the value of a vacancy is smaller in the no automation threat model, leading to a more modest rise in the number of newly created vacancies.

However, because the gap between the value of employment and the value of a vacancy evolves similarly in both models, the decline in firms' surplus from matching with workers is proportionally the same. Therefore, job destruction and real wage responses are nearly identical across the two specifications.

Despite the lower creation of new vacancies in the no automation threat model, the stock of vacancies evolves similarly in both models. This is because a larger share of vacancies is automated in the benchmark model. As a result, the number of vacancies actively seeking workers is the same in both models, which leads to similar job creation dynamics. Considering both job creation and destruction, net job losses dominate in both models, resulting in the same rise in unemployment. Accordingly, worker-based production declines at a similar pace in both models.

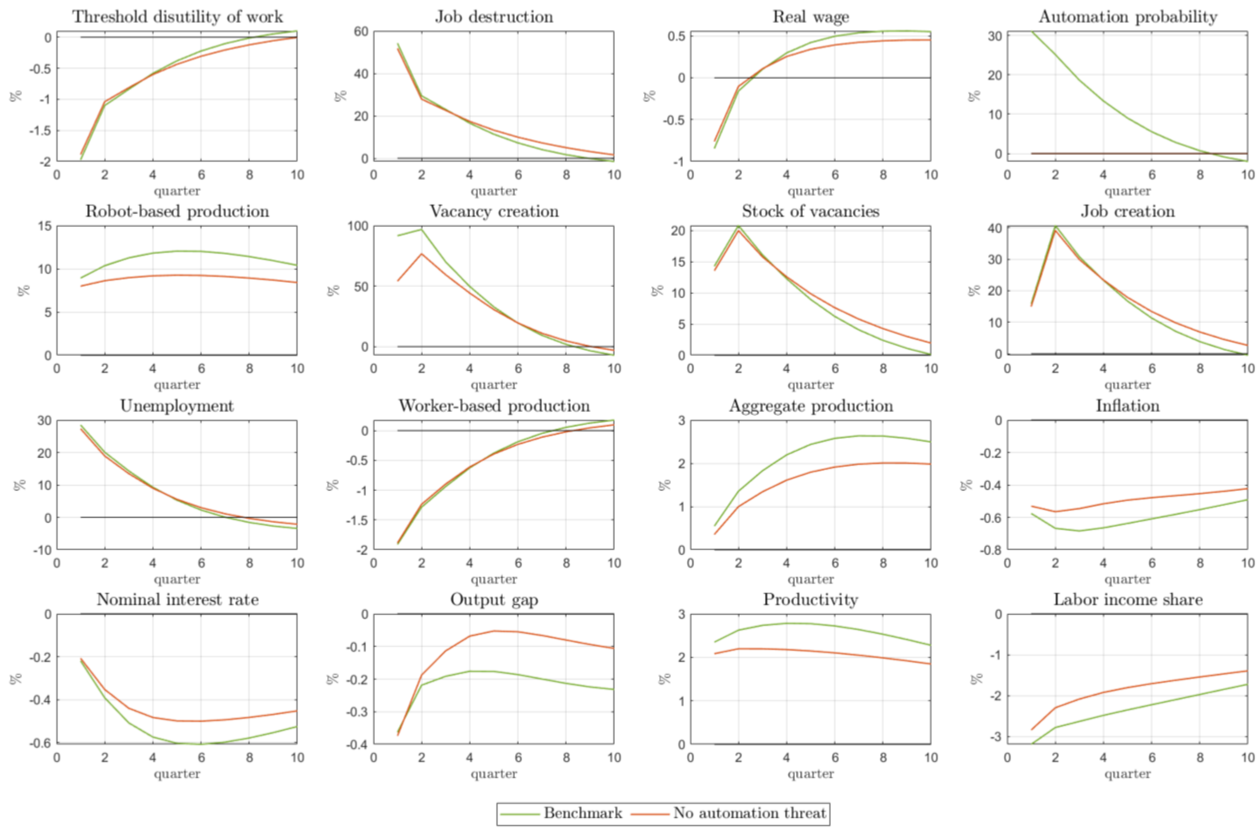
The increase in robot-based production outweighs the decrease in worker-based production in both models, leading to a persistent rise in aggregate output. This effect is stronger in the benchmark model due to the larger response in robot-based production. Since unemployment responds similarly in both cases, productivity rises more in the benchmark model. Consequently, the labor income share declines more in the benchmark model. The stronger output response in this model also explains the larger fall in inflation, which in turn leads to a greater decrease in the nominal interest rate.

In both models, the automation-specific productivity shock initially generates a negative output gap, with a larger magnitude in the benchmark model. When the probability of robot adoption is endogenous, the resulting supply shock induces greater output inefficiency than in the fixed-probability case.

5 Implication of the automation threat on optimal monetary policy

This section explores how monetary policy should be optimally conducted by comparing two model frameworks: the benchmark model and a counterfactual "no automation threat" model, where the

Figure 2: Implications of Automation-specific Productivity



Note: One-standard-deviation increase in the innovation of the automation-specific technology shock. Variables in % deviations around the steady state. “Benchmark”: benchmark model with the parameters at their posterior mean. “No Automation Threat” model in which the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark specification.

probability of robot adoption is fixed ($q_t^a = q^a$). Both models are calibrated using the posterior mean parameters from the benchmark. The comparison highlights the role of endogenous automation decisions—referred to as the "threat of automation"—in shaping optimal monetary policy.

5.1 Transmission of monetary policy shocks Before analyzing optimal monetary policy responses, it is important to understand how monetary policy shocks propagate in both models. Figure 3 shows the responses to a one-standard-deviation contractionary monetary policy shock (a 0.8% increase) under two model specifications: the benchmark model and a counterfactual “no automation threat” model, in which the probability of robot adoption is fixed ($q_t^a = q^a$).

In both models, the shock raises the nominal interest rate, reducing aggregate demand and lowering inflation, as well as the prices of robot- and worker-based production. These price declines reduce the profitability of using both inputs.

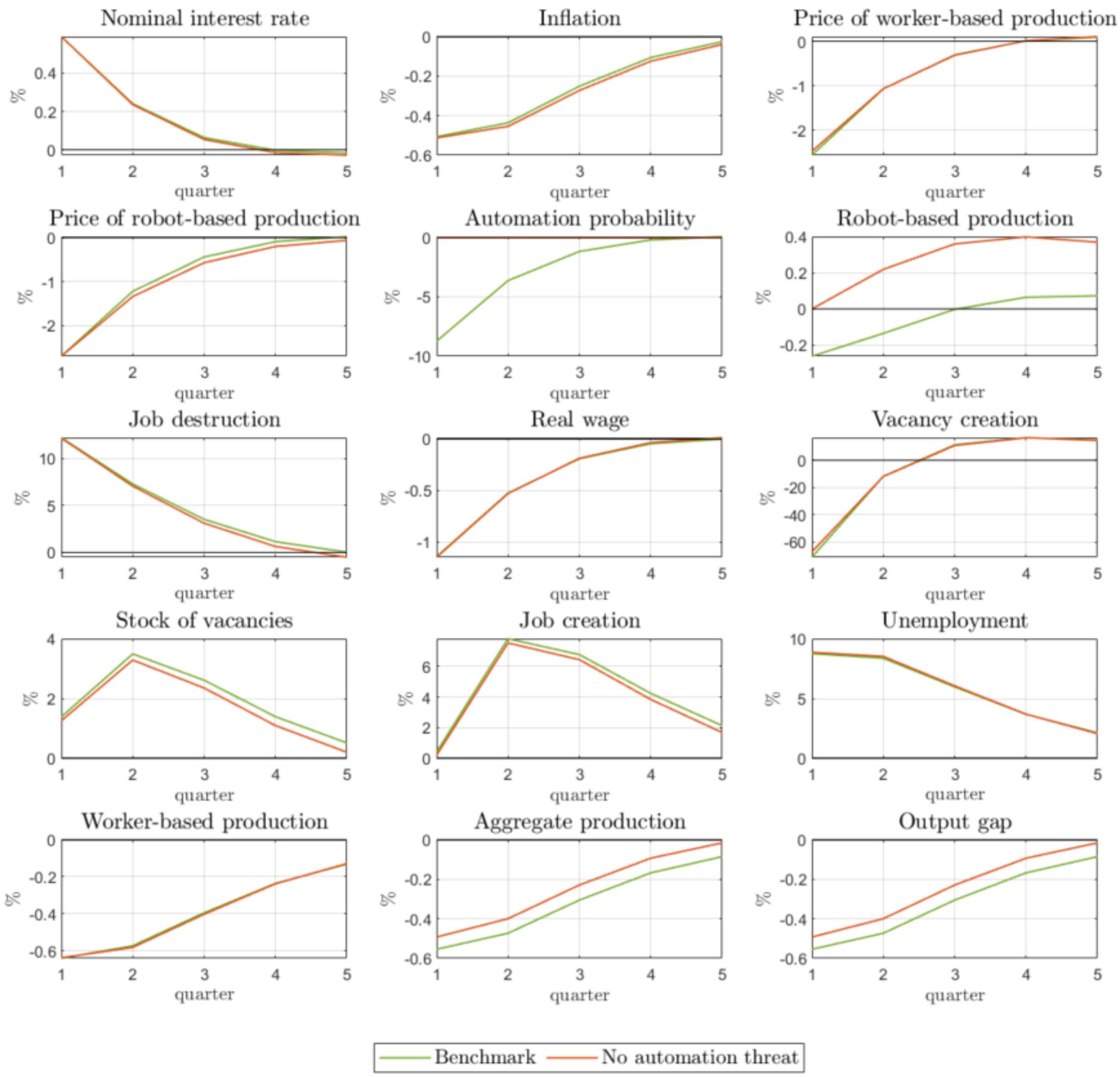
In the benchmark model, lower profitability in robot-based production decreases the probability of robot adoption, reducing robot-based output. Simultaneously, reduced profitability in worker-based production lowers firms' matching surplus, resulting in job destruction and declining real wages. Profitability losses also reduce the value of posting vacancies, decreasing vacancy creation. However, the overall stock of vacancies still rises due to unautomated vacancies from the previous period and destroyed jobs being converted into vacancies. This larger stock contributes to increased job creation, although not all destroyed jobs are re-matched, which raises unemployment and further reduces worker-based production. The combined decline in robot- and worker-based production leads to a drop in aggregate output that exceeds the fall in inflation, consistent with empirical evidence and the predictions of Trigari (2009).

In the no automation threat model, the fixed probability of robot adoption prevents the decline in robot-based output despite reduced profitability. While the monetary shock still lowers inflation, prices, profits, and real wages, the responses of job destruction, vacancy creation, unemployment, and worker-based production remain broadly similar to those in the benchmark model due to the relatively modest size of the shock. However, because the probability of automating a vacancy is non-negative in this model, the overall stock of vacancies increases slightly less than in the benchmark model, leading to a marginally weaker response in job creation. These differences, although present, are quantitatively small.

Since natural output remains unchanged following the monetary policy shock in both models, the decline in actual output translates directly into a fall in the output gap. This gap is larger in the benchmark model due to the additional contraction in robot-based production. Overall, the rise in the nominal interest rate stabilizes inflation but creates a larger inefficiency in output, highlighting the trade-off between output gap and inflation stabilization.

5.2 Transmission of the cost-push shock Following the analysis of monetary policy shocks, it is also important to examine the transmission of cost-push shocks, as they are the main drivers of the output gap in our model. Figure 4 presents the impulse responses to a one-standard-deviation increase in the cost-push shock under two model specifications: the benchmark model and a coun-

Figure 3: Implications of monetary policy shocks



Note: One-standard-deviation increase in the innovation of the monetary policy shock. Variables in % deviations around the steady state. "Benchmark": benchmark model with the parameters at their posterior mean. "No Automation Threat" model in which the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark specification.

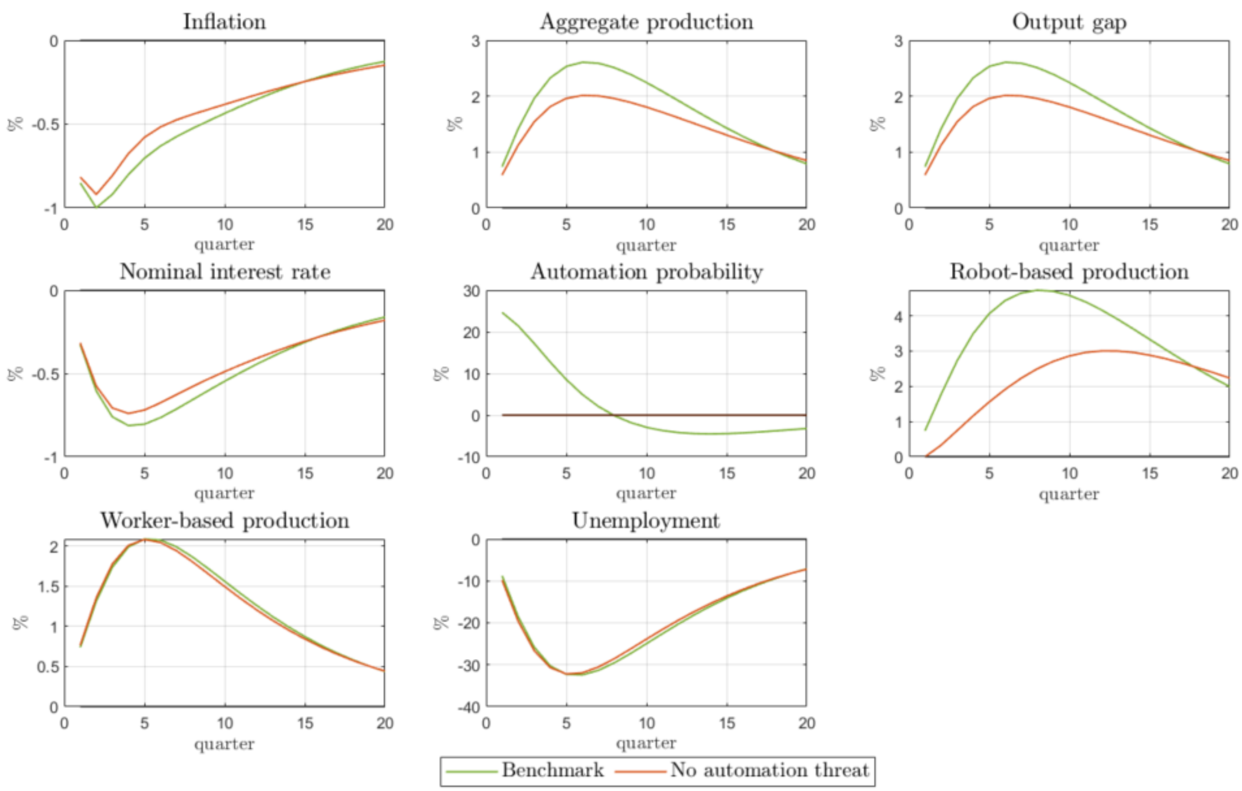
terfactual no automation threat model, in which the probability of robot adoption is fixed ($q_t^a = q^a$).

In the benchmark model, the shock leads to a decline in inflation due to higher price adjustment costs. The fall in inflation increases real demand, which in turn raises aggregate output. To meet this higher demand, firms increase production using both workers and robots. As inflation and output respond, the nominal interest rate adjusts downward.

In contrast, when the probability of automation is fixed, the expansion in robot-based production is more limited. This constraint reduces the overall increase in aggregate output, although the nominal interest rate still declines in response to lower inflation.

The key takeaway is the amplification of the aggregate output response when the probability of automation is endogenous. Since cost-push shocks operate only in the presence of nominal rigidities, the output gap coincides with actual output. We therefore conclude that the benchmark model exhibits a stronger amplification of the output gap.

Figure 4: Implications of cost-push shocks



Note: One-standard-deviation increase in the innovation of the monetary policy shock. Variables in % deviations around the steady state. "Benchmark": benchmark model with the parameters at their posterior mean. "No Automation Threat" model in which the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark specification.

5.3 Optimal Monetary policy design As demonstrated by Gali (2008), monopolistic competition and nominal rigidities are key sources of inefficiency in an economy. Accordingly, we consider both of our economic frameworks—the benchmark model and the no automation threat model—as inefficient due to their inclusion of these features. Their respective counterfactual versions, which exclude monopolistic competition and nominal rigidities, are treated as efficient and represent the allocation targets of the central bank.[14] In our analysis, these efficient counterfactuals are calibrated using the posterior mean parameters from the benchmark model, and their allocations are referred to as "natural allocations". This section first examines the welfare loss function associated with deviations from the natural allocation and then analyzes how the central bank implements the optimal monetary policy in our framework.

5.3.1 Welfare loss function

Assuming that the natural allocation is efficient, the presence of monopolistic competition and nominal rigidities generates welfare losses. The welfare loss function is derived from a second-order approximation of the deviation in household utility—expressed in terms of consumption—from its steady state. While the approach is ad hoc, it aligns with the microfounded welfare criterion in the New Keynesian framework developed by Gali (2008), where the average welfare loss per period is a linear combination of the variances of the output gap and inflation.[15]

In the linearized version of the model, the output gap $\hat{X}_t$ is defined as the difference between actual aggregate output $\hat{Y}_t$ and output under the natural allocation, $\hat{Y}_t^n$:

$$\hat{X}_t = \hat{Y}_t - \hat{Y}_t^n \tag{45}$$

Let $U_t \equiv U(C_t, N_t, h_t, \chi_t)$ denote household utility at time t, and $U \equiv U(C, N, h, \chi)$ the utility at the steady state. The welfare loss function $\mathbb{W}_0$ (ad hoc) is given by:

$$\begin{aligned} \mathbb{W}_0 &\approx -\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{U_t - U}{U_c C} \right] \\ &\approx \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\hat{\Pi}_t^2 + \lambda_x \hat{X}_t^2 \right] \end{aligned} \tag{46}$$

where β is the household discount factor and λ_x is the relative weight of the output gap. The

[14] These counterfactual models differ from those in subsection 4.1 in both shock specifications and calibration, as they use a risk premium shock instead of a discount factor shock. The only change introduced here is the removal of monopolistic competition and nominal rigidities, while the calibration remains identical to that of the model with frictions.

[15] The analysis based on a micro-founded welfare loss function in models with automation is left for future research.

average welfare loss per period, $\mathbb{L}$, is then:

$$\mathbb{L} \approx var(\hat{\Pi}_t) + \lambda_x var(\hat{X}_t) \tag{47}$$

where $var(\hat{\Pi}_t)$ and $var(\hat{X}_t)$ denote the variances of the log-deviations (in percentage terms) from the steady state of inflation and the output gap, respectively.

5.3.2 Optimal simple rule design

The optimal central bank policy is determined by selecting the monetary policy coefficients $\{\psi_r, \psi_\pi, \psi_y\}$ that minimize the welfare loss function (46) subject to the following Taylor rule:[16]

$$\hat{r}_t^n = \psi_r \hat{r}_{t-1}^n + (1 - \psi_r)(\psi_\pi \hat{\Pi}_t + \psi_y \hat{Y}_t) \tag{48}$$

In this rule, the nominal interest rate responds to inflation, output and its own lag. All variables are expressed as percentage deviations from their steady state values.

The analysis is carried out in both the benchmark model, calibrated using the posterior mean of its parameters, and the No Automation Threat model, in which the probability of robot adoption is fixed at $q_t^a = q^a$, using the same parameter values as the benchmark. During the optimization process, only the policy rule coefficients are adjusted; all other parameters remain unchanged. For tractability, we focus on minimizing the average welfare loss per period, $\mathbb{L}$, in Equation (47). Thus, it is assumed that the central bank follows a quadratic loss function, stabilizing inflation and the output gap, with $\lambda_x > 0$ indicating the weight of the stabilization of the output gap relative to inflation.

5.4 Optimal simple rules Tables 8 and 9 in Appendix C summarize the results of the optimal simple rule analysis for the two linearized models: the Benchmark model and the No Automation Threat model. Both are calibrated using the same posterior mean parameters, with the only difference being that the probability of robot adoption is fixed at $q_t^a = q^a$ in the latter. The models are evaluated under eleven different objective functions, each corresponding to a different value of the output gap weight: $\lambda_x \in 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5$.

[16] We follow the standard methodology commonly used in the literature on estimated structural models.

In both models, when no weight is assigned to output gap stabilization ($\lambda_x = 0$), the optimal policy corresponds to strict inflation targeting, with coefficients $(\psi_r, \psi_\pi, \psi_y) = (0, 10, 0)$. This reflects a rule where monetary policy responds exclusively to inflation. As λ_x increases (i.e., greater emphasis on output gap stabilization), the coefficient on output, ψ_y, rises, while ψ_r remains at 0 and ψ_π stays at 10. In the benchmark model, ψ_y increases from 0 to 0.91, while in the No Automation Threat model, it rises from 0 to 0.66.

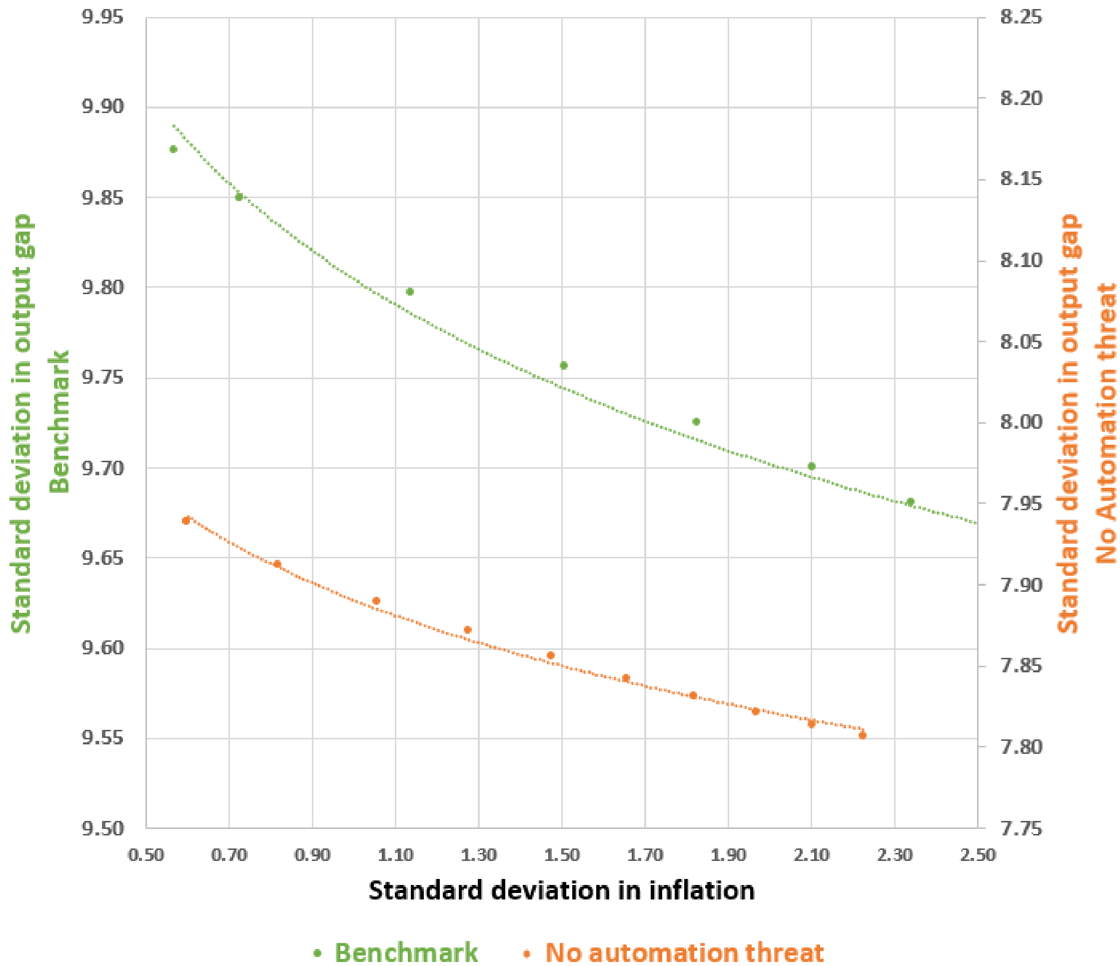
These results indicate that in both models, the optimal simple rule primarily targets inflation but gradually incorporates output stabilization as λ_x increases. The response to output is consistently stronger in the benchmark model. This is intuitive, as the benchmark model features greater output and output gap volatility—driven by the endogenous probability of automation—which calls for a stronger policy response to mitigate the resulting inefficiencies in output.

5.5 Trade-off in stabilization Tables 8 and 9 in Appendix C show that in both models, increasing the weight on output gap stabilization (λ_x) reduces the standard deviation of the output gap, while increasing the standard deviation of inflation. This reflects the classic trade-off between inflation and output gap stabilization. The presence of the automation threat exacerbates this trade-off, as both output gap and inflation volatility are consistently higher in the benchmark model.

These policy trade-offs are further illustrated in Figure (5), which displays the policy frontiers for both models. The frontiers highlight the non-linear, inverse relationship between output gap and inflation volatility. Notably, the automation threat results in a less favorable trade-off: the policy frontier of the benchmark model lies farther from the origin, indicating greater macroeconomic volatility and, consequently, higher welfare losses.

The output gap–inflation volatility trade-off observed in both models is intuitive when considering the effects of a contractionary monetary policy shock, as shown in Figure (3). As discussed in subsection 5.1, this shock reduces inflation, output, and the output gap simultaneously. As a result, efforts to stabilize inflation inherently generate output inefficiencies. The worsening of this trade-off in the presence of the automation threat is also intuitive: when the probability of automation is endogenous, it amplifies output gap volatility. This can be seen, for instance, in the responses to a cost-push shock in Figure 4. In contrast, inflation dynamics remain broadly similar across the two models.

Figure 5: Policy Frontiers (Output gap-Inflation)



Note: The figure illustrates the trade-offs between the standard deviation of inflation (horizontal axis) and the standard deviation of the output gap under optimal simple rules. For the benchmark model, the standard deviation of the output gap is shown on the left vertical axis, as reported in Table (8). For the no automation threat model, the corresponding values—reported in Table (9)—are plotted against the right vertical axis.

6 Conclusion

This paper examined the short-term effects of automation-specific productivity shocks on job creation and destruction, as well as the implications of the automation threat for monetary policy transmission.

Our analysis reveals that when job separation is modeled as purely exogenous—consistent with earlier studies—an automation-specific productivity shock leads to more job creation than destruction, resulting in a decline in unemployment. This outcome occurs because higher profits from automatable vacancies encourage firms to create more job openings, which can either be automated or filled by workers.

However, when we incorporate endogenous separation between firms and workers, the same shock leads to rising unemployment, aligning with empirical evidence on the labor market consequences of automation. In this case, the shock raises the profitability of robot-based production, prompting firms to substitute robots for labor and offer lower wages. As a result, some workers choose not to participate in the labor market, generating endogenous separation and increasing unemployment. Under this configuration, automation destroys more jobs than it creates.

The threat of automation—defined as the endogenous decision to automate rather than relying on a fixed automation probability—has important implications for monetary policy. It exacerbates the trade-off between inflation and output gap stabilization, leading to greater welfare losses due to the presence of nominal and real rigidity frictions. This mechanism necessitates a stronger policy response to output fluctuations within the optimal monetary policy framework. The worsening of this trade-off stems from the fact that the threat of automation amplifies output gap volatility, particularly in response to cost-push shocks. These findings suggest that policymakers should account for the macroeconomic fluctuations induced by automation when designing monetary policy.

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Appendix

A Estimation Results

Table 2: Estimation Results: Models Without Nominal frictions

Parameter		Prior	Endogenous job destruction	Without the automation threat
Parameter, Hours	ω	$N(10, 1)$	11.1010 [9.5740, 12.5829]	10.7489 [9.2400, 12.2794]
AR(1), Separation shocks	ρ_δ	$B(0.80, 0.10)$	0.9383 [0.9105, 0.9684]	0.9490 [0.9177, 0.9791]
AR(1), Technology shocks	ρ_z	$B(0.80, 0.10)$	0.9661 [0.9476, 0.9860]	0.9750 [0.9590, 0.9912]
AR(1), Automation shocks	ρ_ζ	$B(0.80, 0.10)$	0.9126 [0.8817, 0.9447]	0.9283 [0.9003, 0.9553]
AR(1), Discount factor shocks	ρ_θ	$B(0.80, 0.10)$	0.6970 [0.6726, 0.7219]	0.7350 [0.7053, 0.7659]
SD, Separation shocks	σ_δ	$IG(0.01, 0.10)$	0.1667 [0.1493, 0.1839]	0.1832 [0.1618, 0.2033]
SD, Technology shocks	σ_z	$IG(0.01, 0.10)$	0.0107 [0.0096, 0.0119]	0.0105 [0.0093, 0.0115]
SD, Automation shocks	σ_ζ	$IG(0.01, 0.10)$	0.0261 [0.0229, 0.0291]	0.0352 [0.0305, 0.0394]
SD, Discount factor shocks	σ_θ	$IG(0.01, 0.10)$	0.2774 [0.2395, 0.3138]	0.2410 [0.2096, 0.2716]
Log data density			-1352	-1366

Note:"Endogenous job destruction" refers to an extended version of the Leduc and Liu (2024) model that incorporates endogenous job destruction. "Without the automation threat" refers to its version in which the probability of robot adoption is held constant ($q_t^a = q^a$). "Prior" refers to the shape, mean, and standard deviation of the prior distribution. The last two columns present the mean and the 90% HPD interval of the posterior distributions for both models, and B, G, IG, and N denote the Beta, Gamma, Inverse Gamma, and Normal distributions, respectively.

Table 3: Estimation Results: Models With Nominal frictions

Parameter		Prior	Benchmark	Without the automation threat
Parameter, Hours	ω	$N(10,1)$	10.6752 [10.6736, 10.6772]	10.0770 [10.0767, 10.0774]
Habits	γ_c	$B(0.6,0.1)$	0.6239 [0.6238, 0.6241]	0.7678 [0.7677, 0.7681]
Price adjustment cost	ξ	$N(75,10)$	75.1903 [75.1803, 75.2025]	74.9858 [74.9857, 74.9859]
Indexation, Inflation	γ	$B(0.5,0.1)$	0.5400 [0.5398, 0.5403]	0.5184 [0.5183, 0.5184]
Taylor rule, Interest rate	ψ_r	$B(0.75,0.15)$	0.7427 [0.7426, 0.7429]	0.8154 [0.8151, 0.8156]
Taylor rule, Inflation	ψ_π	$G(1.75,0.25)$	1.6100 [1.6095, 1.6104]	1.7244 [1.7243, 1.7244]
Taylor rule, Output	ψ_y	$G(0.15,0.05)$	0.1395 [0.1395, 0.1396]	0.1890 [0.1889, 0.1892]
AR(1), Separation shocks	ρ_δ	$B(0.80,0.10)$	0.8198 [0.8196, 0.8200]	0.9222 [0.9219, 0.9225]
AR(1), Technology shocks	ρ_z	$B(0.85,0.10,0.82,1)$	0.8310 [0.8307, 0.8312]	0.8201 [0.8200, 0.8201]
AR(1), Automation shocks	ρ_ζ	$B(0.80,0.10,0,0.9)$	0.8998 [0.8996, 0.9000]	0.9000 [0.9000, 0.9000]
AR(1), Risk premium shocks	ρ_θ	$B(0.80,0.10)$	0.7826 [0.7825, 0.7827]	0.7967 [0.7965, 0.7969]
AR(1), Price markup shocks	ρ_π	$B(0.80,0.10)$	0.8362 [0.8361, 0.8363]	0.8318 [0.8317, 0.8318]
SD, Separation shocks	σ_δ	$IG(0.05,0.5)$	0.4081 [0.4067, 0.4097]	0.3660 [0.3653, 0.3667]
SD, Technology shocks	σ_z	$IG(0.05,0.5)$	0.0857 [0.0852, 0.0863]	0.1066 [0.1065, 0.1068]
SD, Automation shocks	σ_ζ	$IG(0.05,0.5,0,0.08)$	0.0799 [0.0798, 0.0800]	0.0800 [0.0800, 0.0800
SD, Risk premium shocks	σ_θ	$IG(0.05,0.5)$	0.0061 [0.0059, 0.0063]	0.0063 [0.0062, 0.0064]
SD, Monetary policy shocks	σ_r	$IG(0.05,0.5)$	0.0082 [0.0081, 0.0083]	0.0059 [0.0059, 0.0060]
SD, Price markup shocks	σ_π	$IG(0.05,0.5)$	0.0441 [0.0437, 0.0443]	0.1135 [0.1134, 0.1136]
Log data density			-2624	-7285

Note: "Benchmark" refers to the benchmark model with nominal frictions. "Without the automation threat" refers to the version of this model in which the probability of robot adoption is held constant ($q_t^a = q^a$). "Prior" indicates the shape, mean, and standard deviation of the prior distribution. In some cases, the prior also includes a lower and upper bound. For example, $B(0.85, 0.10, 0.82, 1)$ indicates a Beta distribution with a mean of 0.85, a standard deviation of 0.10, a lower bound of 0.82, and an upper bound of 1. The last two columns present the mean and the 90% HPD interval of the posterior distributions for both models, and B, G, IG, and N denote the Beta, Gamma, Inverse Gamma, and Normal distributions, respectively.

B Variance decompositions

Table 4: Sources of Fluctuations in the exogenous job destruction model

	Shocks			
Variables	discount factor	separation	automation	neutral tech.
Unemployment	41	2	2	56
Stock of vacancies	39	6	2	53
Real wages	14	0	3	84
Hiring	13	70	1	16
Productivity	16	0	12	73
Consumption	5	0	7	87
Automation prob.	31	1	28	41
Endogenous separation	-	-	-	-
Hours	-	-	-	-

NOTES: Forecast error variance decomposition in %. "Exogenous job destruction model": Leduc and Liu (2024) model with the parameters at their posterior mean.

Table 5: Sources of Fluctuations in the endogenous job destruction model

	Shocks			
Variables	discount factor	separation	automation	neutral tech.
Unemployment	32	9	4	55
Stock of vacancies	14	61	12	12
Real wages	9	0	4	87
Hiring	6	86	3	4
Productivity	5	0	21	73
Consumption	6	2	5	87
Automation prob.	75	2	13	10
Endogenous separation	37	0	22	42
Hours	17	16	3	63

NOTES: Forecast error variance decomposition in %. "Endogenous job destruction model" refers to an extended version of the Leduc and Liu (2024) model that incorporates endogenous job destruction, with parameters calibrated at their posterior mean under this new specification.

Table 6: Sources of Fluctuations in the benchmark model

	Shocks					
Variables	risk premium	separation	automation	neutral tech.	monetary	cost-push
Output gap	0	0	1	30	1	68
Inflation	1	0	9	78	1	11
Nom. Interest	1	0	9	77	1	12
Output	0	0	17	70	0	13
Unemployment	0	1	5	64	1	29
Job destruction	0	0	9	87	0	3
Job creation	0	0	11	81	0	6
Stock of vacancies	0	12	12	73	0	3
Real wages	1	0	4	63	1	30
Worker-based prod.	0	0	3	77	0	18
Robot-based prod.	0	0	49	45	0	7
Automation prob.	1	1	43	21	2	32

NOTES: Forecast error variance decomposition in %. Benchmark model with the parameters at their posterior mean.

Table 7: Sources of Fluctuations in the no automation threat model

	Shocks					
Variables	risk premium	separation	automation	neutral tech.	monetary	cost-push
Output gap	0	0	1	29	1	69
Inflation	1	0	7	82	1	9
Nom. Interest	1	0	7	80	1	10
Output	0	0	13	77	0	10
Unemployment	0	1	5	65	1	29
Job destruction	0	0	9	87	0	2
Job creation	0	0	12	82	0	5
Stock of vacancies	0	13	13	72	0	2
Real wages	1	0	3	65	1	29
Worker-based prod.	0	0	3	78	0	17
Robot-based prod.	0	0	40	56	0	4
Automation prob.	-	-	-	-	-	-

NOTES: Forecast error variance decomposition in %. "No Automation Threat model" in which the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark specification.

C Optimal simple rule analysis

Table 8: Optimal simple rules in the benchmark model

		Relative weight on output gap (λ_x)										
		0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
Taylor rule coefficients	Model	Optimal coefficients										
Interest rate, ψ_r	0.74	0	0	0	0	0	0	0	0	0	0	0
Inflation, ψ_π	10	10	10	10	10	10	10	10	10	10	10	10
Output, ψ_y	1.61	0.00	0.07	0.23	0.36	0.48	0.57	0.66	0.73	0.80	0.86	0.91
Loss		0	49	97	145	193	240	287	333	380	427	473
Standard deviation	Model	Optimized										
Nominal interest rate (r_t^n)	6.90	5.65	5.81	6.15	6.44	6.70	6.92	7.12	7.29	7.44	7.58	7.70
Output gap (X_t)	10.30	9.88	9.85	9.80	9.76	9.73	9.70	9.68	9.66	9.65	9.64	9.63
Inflation (Π_t)	7.36	0.57	0.72	1.14	1.51	1.83	2.10	2.34	2.55	2.73	2.89	3.03
Output (Y_t)	23.22	27.47	27.37	27.16	26.99	26.84	26.71	26.60	26.50	26.42	26.34	26.28
Unemployment (ur_t)	181.68	172.48	171.70	170.01	168.61	167.43	166.43	165.57	164.83	164.18	163.61	163.10

Note: Optimal simple rules are derived from policy optimization in the Benchmark model, calibrated at the posterior mean of its parameters.

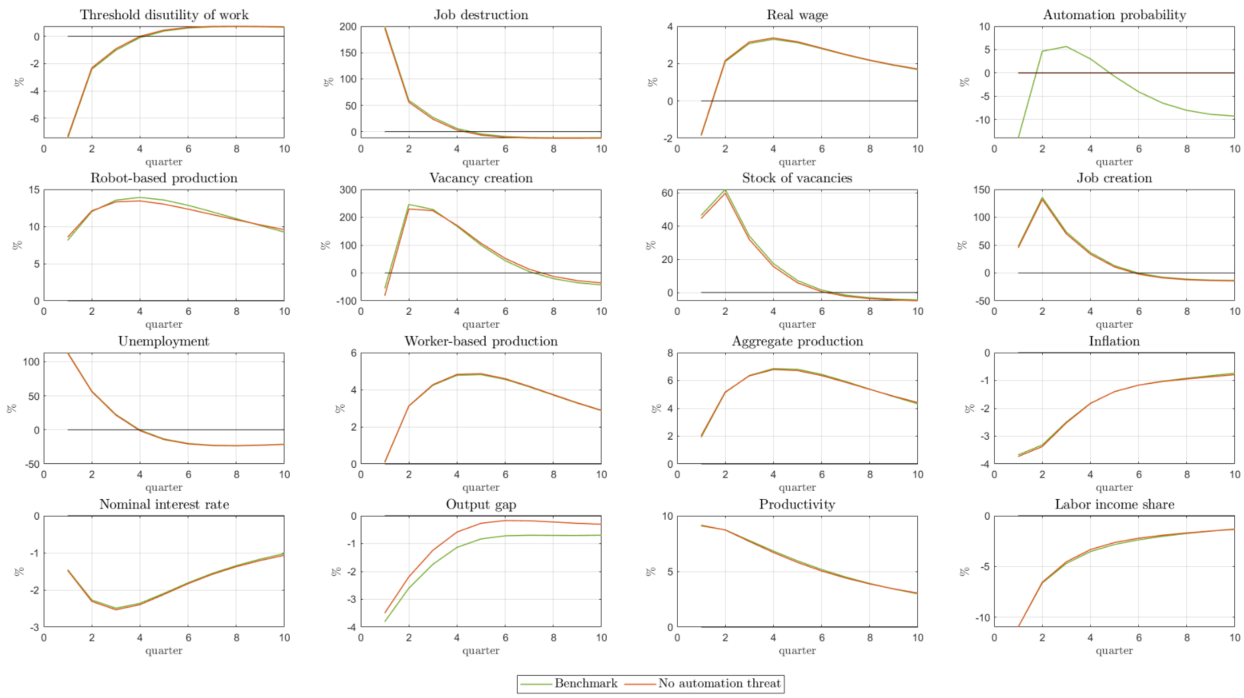
Table 9: Optimal simple rules in the no automation threat model

		Relative weight on output gap (λ_x)										
		0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
Taylor rule coefficients	Model	Optimal coefficients										
Interest rate, ψ_r	0.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Inflation, ψ_π	10	10	10	10	10	10	10	10	10	10	10	10
Output, ψ_y	0.14	0.00	0.00	0.11	0.21	0.29	0.37	0.44	0.50	0.56	0.61	0.66
Loss		0	32	63	94	126	156	187	218	249	279	310
Standard deviation	Model	Optimized										
Nominal interest rate (r_t^n)	6.93	6.00	6.00	6.20	6.40	6.57	6.73	6.87	7.00	7.11	7.22	7.32
Output gap (X_t)	8.49	7.94	7.94	7.91	7.89	7.87	7.86	7.84	7.83	7.82	7.81	7.81
Inflation (Π_t)	7.34	0.60	0.60	0.82	1.06	1.28	1.48	1.66	1.82	1.97	2.10	2.23
Output (Y_t)	22.51	25.28	25.28	25.17	25.07	24.98	24.91	24.84	24.78	24.72	24.67	24.62

Note: Optimal simple rules are derived from policy optimization in the "No Automation Threat" model, where the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark.

D Additionnal figures

Figure 6: Implications of neutral technology



Note: One-standard-deviation increase in the innovation of the neutral technology shock. Variables in % deviations around the steady state. "Benchmark": benchmark model with the parameters at their posterior mean. "No Automation Threat" model in which the probability of robot adoption is held constant ($q_t^a = q^a$), using the same posterior mean parameters as in the benchmark specification.