Automation, Job destruction, and Monetary policy

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Abstract

This paper employs estimated automation-based models with households' heterogeneous disutility of work to examine the short-term effects of firms' automation decisions (henceforth, automation) on economic fluctuations. The findings reveal that automation lowers the threshold disutility for accepting work, leading to procyclical unemployment, downward wage pressures, and a decline in the labor income share—effects not observed in models with homogeneous disutility of work but consistent with empirical evidence. In an environment without nominal frictions, heterogeneous disutility mitigates automation's impact on wage rigidity, vacancy volatility, and unemployment volatility while amplifying its effect on reducing the wage-productivity correlation compared to models with homogeneous disutility of work. This mitigation and amplification result from the simultaneous decline in employment and wages triggered by automation. Moreover, household heterogeneity reshapes shock transmission, enhancing the role of automation-specific shocks in driving economic fluctuations. By integrating nominal rigidities, the model aligns monetary policy shock predictions with observed data and demonstrates that the threat of automation heightens the trade-off between inflation and output volatility. Furthermore, we observe a worse trade-off between inflation and unemployment volatility due to the threat of automation.

Keywords: Automation, Monetary Policy, Procyclical Unemployment, Wage rigidities, Desutility of work, Job destruction, Fluctuations

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

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1 Introduction

The emergence of robotic and labor-saving technologies, revolutionizing production processes, has catalyzed significant research into their long-term effects on the labor market, productivity, and inequality[1]. Moreover, some studies address policies (taxation and fiscal policy, public policy, and governance improvements) that can help policymakers enhance societal welfare by leveraging the productivity gains from automation while mitigating its negative effects (e.g., labor displacement, low wages, and inequality)[2].

However, while automation's long-term effects are well studied, its short-term impacts remain underexplored[3]. Leduc and Liu (2024) analyze the relationship between automation and the labor market within the business cycle, but certain critical dimensions—such as households' heterogeneous disutility of work, endogenous job destruction, and hours of work—have been overlooked. Furthermore, the role of automation in shaping the transmission of monetary policy has not yet been fully addressed in the literature. These omissions limit our understanding of how automation influences labor market over the business cycle.

This paper aims to fill these gaps by providing new insights into the short-term implications of firms' automation decisions for economic fluctuations. By incorporating households' heterogeneous disutility of work, we make two key contributions to the literature: (i) we analyze the impact of firms' automation decisions on economic fluctuations in an economy where households exhibit heterogeneous disutility of work, and (ii) we examine how the threat of automation influences the transmission of monetary policy in such an economy.

The analysis builds on the automation framework of Leduc and Liu (2024), where firms with va-

[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 some exceptions, see Charalampidis (2020a), Charalampidis (2020b), Charalampidis (2023), and Leduc and Liu (2024), Charalampidis and Razafitsiory (2024)

cancies 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)[4]. 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 their model assumes households have homogeneous disutility of work, we extend their framework by incorporating heterogeneous disutility of work into two nested models.

Our first model extends Leduc and Liu (2024)'s automation framework in three key ways. First, we incorporate hours of work and heterogeneous disutility of work, drawing from Trigari (2009). This extension allows for a more comprehensive analysis of labor market dynamics, enabling us to consider labor supply on the intensive margin and analyze how automation threats and monetary policy shape the threshold disutility for accepting work. The threshold disutility for accepting work endogenously affect wage negotiations and firm-worker separations, enabling the model to account for the dynamics of endogenous job destruction. Second, we introduce nominal frictions and monetary policy into the framework, inspired by Trigari (2009). This innovation allows us to investigate how the automation threat affect the transmission of monetary policy. Third, while Leduc and Liu (2024) use four U.S. time series for estimation, we expand our model to include six time series—adding inflation and nominal interest rate data in a Bayesian estimation framework—to broaden the model's scope.

The second model builds on the first but omits nominal frictions and monetary policy to isolate the effects of firms' automation decisions in an economy characterized by households' heterogeneous disutility of work. This approach ensures that the analysis is not confounded by monetary policy effects. To align with Leduc and Liu (2024), this model is estimated using the same four U.S. time series, with a crucial modification: wages are measured using wage rates and hours of work rather than total wages. This adjustment allows for a more detailed investigation of labor market dynamics in the presence of automation, focusing on outcomes in a frictionless monetary environment.

Our estimations suggest that, compared to an economy without automation, automation signifi-

[4]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); and Charalampidis and Razafitsiory (2024); 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.

cantly alters labor market dynamics by creating wage rigidity, amplifying the volatility of vacancies and unemployment, and weakening the correlation between wage growth and productivity growth. These impacts vary with household preferences and economic conditions. In economies with heterogeneous disutility of work, the effect of automation on the wage riditity becomes less prononced, the effect on vacancy and unemployment becomes less pronounced and the effect on the wage-productivity correlation becomes more amplified.

The underlying economic mechanisms help explain these differences. In the automation-based model with homogenous desutility of work, important shocks in the economy increase automation value, which, in turn, increases vacancy value. This induces firms to create vacancies, leading to persistent increases in vacancies, a persistent decrease in unemployment, a persistent increase in productivity, and muted wage fluctuations. However, when households have heterogeneous disutility of work, new mechanisms emerge that alter these effects. The inital threat of automation reduces the firm's surplus with a worker at the margin $(J_t^e(\underline{\chi}_t) - J_t^v)$,[5] turning the total surplus negative. This lowers the threshold disutility for accepting work, triggering endogenous separations. As a result, firms destroy jobs by adopting robots. Consequently, wages decline further, and unemployment rises. Destroyed jobs become vacancies, explaining a large initial increase in vacancies. Hence, wages volatility become more amplified, unemployment become less volatile and the wage-productivity correlation further declines.

Our estimation results reveal significant changes in the relative importance of economic fluctuation sources when households' disutility of work is heterogeneous, assuming the absence of nominal frictions. The contribution of technology shocks to productivity fluctuations diminishes, while automation-specific shocks gain prominence. These automation-specific shocks significantly influence not only automation-related variables but also labor market dynamics, aggregate variables, and those linked to household heterogeneity.

By incorporating nominal rigidities into our heterogeneous model, our estimations suggest that the model aligns well with observed data regarding monetary policy shock predictions. A contractionary monetary policy shock leads to persistent declines in output and inflation in both models, with inflation exhibiting significantly lower volatility compared to output. These results highlight a trade-off

[5] A worker at the margin is one for whom the realized preference shock equals the threshold value $\underline{\chi}_t$.

between output and inflation volatility. Similarly, contractionary monetary policy results in a more pronounced and persistent decline in employment, indicating a trade-off between unemployment and inflation volatility. Furthermore, the threat of automation amplifies the effects of monetary policy shocks on both output and employment (or unemployment). These findings motivate an analysis of these trade-offs, and our results reveal that the threat of automation exacerbates both the output-inflation volatility trade-off and the unemployment-inflation volatility trade-off.

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

First, we advance business cycle models with labor market search by integrating households' heterogeneous disutility of work and the intensive margin of labor supply into a framework that incorporates automation. Seminal contributions, including Mortensen and Pissarides (1994), Christiano and Evans (2005), Walsh (2005), and Trigari (2009), analyze labor market search dynamics but do not account for automation. In contrast, Leduc and Liu (2024) explicitly incorporate automation into the business cycle framework. By introducing heterogeneity in households' disutility of work and incorporating the intensive margin highlighted by Trigari (2009) into the automation model proposed by Leduc and Liu (2024), our study provides a more comprehensive understanding of how automation interacts with labor market dynamics.

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.

Fourth, 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 representative households with homogeneous disutility of work. By introducing heterogeneous disutility into the analysis, our research provides novel insights into how automation influences short-term economic fluctuations and labor market outcomes.

The remainder of the paper is organized as follows. Section 2 develops the benchmark model. Section 3 describes the data and estimation approach. Section 4 analyzes the effects of automation on economic fluctuations. Section 5 examines the implications of the threat of automation for monetary policy transmission. Section 6 concludes.

2 Model

The model integrates key features of Dynamic Stochastic General Equilibrium (DSGE) models, including nominal rigidities, monetary policy, extensive and intensive margins, households' heterogeneous disutility of work, and firms' automation decisions (referred to as automation). Automation is modeled following the framework of Leduc and Liu (2024), where firms with costly vacancies first decide whether to adopt a robot based on the arrival of a random cost, and then post non-automated vacancies to search for workers in a labor market characterized by search and matching frictions (SAM). The model adapts Trigari (2009) to incorporate intensive margins and heterogeneous disutility of work, elements absent in Trigari (2009). Final consumption goods, produced using both workers and robots, are exchanged in a monopolistically competitive market, where heterogeneous households determine their consumption and saving behaviors.

The timing of the Leduc and Liu (2024) model and the Trigari (2009) model differ. While we aim to maintain the timing of the Leduc and Liu (2024) model as closely as possible, we adapt the timing of the Trigari (2009) model to align with it. In period t, the process begins with a stock of vacancies, workers, and unemployed individuals, followed by aggregate shocks. Workers and job seekers draw their random disutility of work χ_t, and a fraction of vacancies are automated. Exogenous and endogenous separations determine the number of non-separating workers, and those who lose their jobs add to the unemployment pool. Matches are formed between job seekers and vacancies, but only some of them result in productive employment, depending on disutility of work. Values for match and unemployment are defined for households, and employment values for firms are also determined. Production takes place, and final consumption goods are produced using both workers and robots. The 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

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha} \tag{5}$$

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 $E_t \sum_{s=0}^{\infty} \frac{1}{P_{t+s}} D_{t,t+s} F_{t+s}(j)$ (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:

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

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

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

where $q_t^a(1 - q_{t-1}^v \gamma_{t-1})v_{t-1}$ 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 $\epsilon_{z,t} \sim N(0, \sigma_Z^2)$, and ζ_t is a technological shock specific to robots (i.e., a robot productivity shock) that follows the process: $ln\zeta_t = (1 - \rho_\zeta)ln\zeta + \rho_\zeta ln\zeta_{t-1} + \epsilon_{\zeta t}$, $\epsilon_{\zeta t} \sim N(0, \sigma_\zeta^2)$. 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_t^a satisfies the Bellman equation

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

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

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

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_t^e 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:

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

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: $ln(C_t) - \ell(h_t, \chi_t)$, where C_t denotes final consumption goods 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 $\mathbb{E}\sum_{t=0}^{\infty}\beta^t\Theta_t\left(lnC_t - L(h_t,\chi_t)\right)$, 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, Θ_t represents an exogenous shock to the subjective discount factor, and the discount factor shock $\theta_t \equiv \dfrac{\Theta_t}{\Theta_{t-1}}$ 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 representative household chooses consumption C_t and nominal savings B_t to maximize its utility function subject to the sequence of budget constraints:

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

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.

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

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

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

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

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

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

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

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

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

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

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

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

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:

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

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 $\underline{\chi}_t$:

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

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:

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

3 Empirical Approach

Three automation-based models are analyzed in this study:

- **Model 1**: a homogeneous automation-based model, as developed by Leduc and Liu (2024), which assumes uniform disutility of work (a constant disutility-of-work parameter).
- **Model 2**: A heterogeneous automation-based model that incorporates variation in work disutility among households, building on Trigari (2009).
- **Model 3**: A heterogeneous automation-based model that includes nominal frictions and monetary policy, extending Model 2 (i.e., Model 3 = Model 2 + nominal frictions). Model 3 was developed in the previous section.

These models are nested: removing nominal frictions from Model 3 reduces it to Model 2, while further assuming homogeneous preferences simplifies it to Model 1. Each model is linearized around its deterministic steady state and solved under rational expectations. Model 1 is not estimated but relies on the parameter estimates from Leduc and Liu (2024). Model 2 and 3 are estimated using

Bayesian methods, following the approach of An and Schorfheide (2006), on quarterly U.S. data spanning 1985:I to 2018:IV. The primary difference in the sample usage between Models 2 and 3 lies in the specific variables employed for their respective estimations.

3.1 Data and Observation Equations. We fit Model 3 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. Model 2, being smaller in scope, is fitted to only four of these series, excluding inflation and the nominal interest rate.

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). The measurement equation is $\gamma_{R,t}^{data} - \bar{\gamma}_R^{data} = \hat{r}_t^n$, 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.

3.3 Parameter calibration. We present here the calibration of Model 3. The calibration of Model 2 is similar but involves fewer parameters [8]. 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

[8] Model 1 is consistently calibrated using parameters from Leduc and Liu (2024) throughout this paper.

0.535. The rate at which robots become obsolete, ρ^o, is set to 0.03. To ensure consistency in the steady-state automation probability across the models, we adopt the estimated parameter value for the flow cost of operating automation equipment from Leduc and Liu (2024), $\kappa_a = 0.9788$, which implies an automation probability of $q^a = 9.57\%$. 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 discount factor shock implies $\theta = 1$.

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 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 6, and the steady-state inflation, Π, is set to 1, consistent with values commonly used in the literature.

3.4 Steady state equilibrium. In this section, we proceed to solve for the remaining steady-state variables. Given the value of β, the nominal interest rate in the steady state, r^n, is directly determined as $1/\beta$. We sequentially utilize equations (10), (8), (2), (4), (7), (43), (6), (5), and the calibration targets to obtain the following solutions: $\frac{\bar{P}}{P} = 1$, $N = 1 - ur, u = 1 - (1-\delta)N, \gamma = 1 - \frac{\delta^n}{u}, m = \dfrac{\delta N}{\gamma}, Y_n = N, q^u = \dfrac{m}{u}, q^v = \frac{0.71}{\gamma}, v = \dfrac{m}{q^v}, \mu = \dfrac{m}{u^\alpha v^{1-\alpha}}$. We then proceed to solve the flow of new vacancies in the steady state, η, using equations (20), (16), (15), and (3), which allows us to determine the stock of automation equipment in the steady state, $A = \frac{\eta}{\rho^o}$. The steady-sate automation probability is solved from the equation (3), $q^a = \frac{\eta}{(1-q^v\gamma)v}$. Using equation (20), we determine the value of vacancy in the steady state as $J^v = \bar{e}\eta$. From equation (18), we obtain the robot-based production in the steady state, $Y_a = Z\zeta A$. The threshold is solved from

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
Flow cost of automation	κ_a	0.9788
Steady-state, automation probability	q^a	From the value of κ_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	6
Steady state, inflation	Π	1

the equation (16), $x^* = \bar{x}q^a$. Aggregate output in the steady state, Y,is solved from equation (11), $Y = \left[\alpha_n Y_n^{\frac{\sigma-1}{\sigma}} + (1-\alpha_n)Y_a^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$. We derive the steady-state solutions for the two prices of intermediate goods, p_n and p_a, using equation (13). The steady state of the automation value J^a is solved from the Bellman equation (15), yielding $J^a = x^* + J^v$. κ is calibrating from the target $\frac{kv}{Y} = 0.01$. Steady-state consumption is solved from the resource constraint in equation (44). The match value in the steady state, J^e, is derived from the value of vacancy in equation (22), and the equilibrium real wage rate in the steady state, w, is obtained from the Bellman equation for employment in equation (24). The optimality condition of working hours in the equation (36) allows us to solve the steady-state hours disutility shock $\Omega = \frac{p_n Z}{Ch^{\omega}}$. Combining the Nash bargaining equation (35) and the threshold equation (38), we are able to obtain the steady-state upper bound of the disutility of labor. Equation (1) yield the value of the scale parameter for labor disutilities, $\bar{\chi} = \frac{1}{1-\delta^n}\underline{\chi}$. The job creation and destruction steady state comes from the equations (40) and (41).

3.5 Priors. The third column of Table 2 presents the prior distributions in the model 2 and 3. For both models, the priors closely align with those used by Leduc and Liu (2024). The priors for the structural parameters, $\bar{e}$, $\bar{x}$, follow a gamma distribution with a mean of 5 and a standard deviation of 1. The persistence parameters for each shock are modeled using a beta distribution with a mean of 0.8 and a standard deviation of 0.1, while the volatility parameters for the shocks follow an inverse gamma distribution with a mean of 0.01 and a standard deviation of 0.1. The parameter ω, related to hours of work, is not specified in Leduc and Liu (2024); for this parameter, we assume a normal distribution with a mean of 10 and a standard deviation of 1.

For the priors specific to Model 3 with nominal rigidities, parameters such as the price adjustment cost (ξ), the indexation parameter (γ), and the Taylor rule coefficients—interest rate smoothing (ψ_r), responsiveness to inflation (ψ_π), and responsiveness to output (ψ_y)—are set in line with the literature.

3.6 Posteriors. Table 2 presents the estimation results for the two models (Models 2 and 3), including posterior means and 90 percent probability intervals for the posterior distributions.

The posterior mean estimates for Model 2 reveal that the scale of vacancy creation cost is $\bar{e} = 5$, the automation cost parameter is $\bar{x} = 1.98$, and the inverse of the elasticity of substitution for leisure is $\omega = 4.66$. The 90 percent probability intervals indicate that the data are informative for $\bar{x}$ and ω but not for $\bar{e}$. By comparison, the homogeneous automation-based model (Model 1) in Leduc and Liu (2024) reports posterior means of $\bar{e} = 3.07$ and $\bar{x} = 4.95$.

Regarding the shock processes, the posterior estimates suggest that all shocks are persistent, with separation and automation-specific shocks being particularly volatile. The 90 percent probability intervals confirm that the data provide substantial information about these shock processes.

For Model 3, the posterior mean estimates indicate a vacancy creation cost scale of $\bar{e} = 5.80$, an automation cost parameter of $\bar{x} = 1.69$, and an inverse elasticity of substitution for leisure of $\omega = 9.82$. Similar to Model 2, the 90 percent probability intervals suggest that the data are informative for $\bar{x}$, $\bar{e}$ and ω.

The estimates also suggest small price adjustment costs (ξ) and moderate indexation to past inflation (γ). The policy parameter estimates align with those found in the literature. For nominal rigidities and monetary policy, the data provide strong evidence supporting these parameter values.

In terms of shock dynamics, automation-specific and exogenous separation shocks exhibit high persistence, whereas technology, discount factor, and price markup shocks are less persistent. Among these, separation shocks display the highest volatility, while the discount factor, monetary policy, and price markup shocks exhibit the least. The 90 percent probability intervals indicate that the data are informative for these shock processes.

4 Implications of Automation on Economic Fluctuations

This section evaluates the implications of firms' automation decisions (automation, henceafter) on economic fluctuations in an economy where households have heterogeneous disutility of work. By comparing the effects of automation across the three models mentionned in the previous section, we explore how automation impacts an economy characterized by households' heterogeneous disutility of work.

4.1 Automation and labor market volatilities This subsection examines the impact of firms' automation decisions (henceforth, Automation) on labor market fluctuations, focusing on household

Table 2: Estimated parameters

Parameter		Prior	Model 2	Model 3
Scale, Vacancy creation	$\bar{e}$	$G(5.00, 1)$	4.9992 [3.3339, 6.6103]	5.8044 [5.7573, 5.8530]
Scale, Robot adoption	$\bar{x}$	$G(5.00, 1)$	1.9771 [1.9131, 2.0371	1.6924 [1.6424, 1.7403]
Parameter, Hours	ω	$N(10, 1)$	4.6556 [3.6387, 6.3352]	9.8244 [9.7 845, 9.8541]
Price adjustment cost	ξ	$N(100, 25)$	—	27.7987 [27.1614, 28.5112]
Indexation, Inflation	γ	$B(0.5, 0.15)$	—	0.4300 [0.4252, 0.4339]
Taylor rule, Interest rate	ψ_r	$B(0.75, 0.10)$	—	0.9064 [0.9049, 0.9083]
Taylor rule, Inflation	ψ_π	$G(1.75, 0.3)$	—	2.1286 [2.1236, 2.1349]
Taylor rule, Output	ψ_y	$G(0.12, 0.05)$	—	0.0810 [0.0796, 0.0823]
AR(1), Separation shocks	ρ_δ	$B(0.80, 0.10)$	0.9594 [0.9365, 0.9825]	0.9293 [0.9269, 0.9314]
AR(1), Technology shocks	ρ_z	$B(0.80, 0.10)$	0.9553 [0.9335, 0.9775]	0.8776 [0.8757, 0.8798]
AR(1), Automation shocks	ρ_ζ	$B(0.80, 0.10)$	0.9682 [0.9498, 0.9875]	0.9932 [0.9894, 0.9977]
AR(1), Discount factor shocks	ρ_θ	$B(0.80, 0.10)$	0.9855 [0.9755, 0.9966]	0.7622 [0.7580, 0.7676]
AR(1), Price markup shocks	ρ_π	$B(0.80, 0.10)$		0.6642 [0.6607, 0.6683]
SD, Separation shocks	σ_δ	$IG(0.01, 0.10)$	0.0928 [0.0828, 0.1026]	0.1154 [0.1103, 0.1197]
SD, Technology shocks	σ_z	$IG(0.01, 0.10)$	0.0136 [0.0120, 0.0151]	0.0187 [0.0180, 0.0196]
SD, Automation shocks	σ_ζ	$IG(0.01, 0.10)$	0.0484 [0.0427, 0.0537]	0.0367 [0.0345, 0.0392]
SD, Discount factor shocks	σ_θ	$IG(0.01, 0.10)$	0.0322 [0.0276, 0.0366]	0.0141 [0.0128, 0.0153]
SD, Monetary policy shocks	σ_r	$IG(0.01, 0.10)$	—	0.0058 [0.0055, 0.0063]
SD, Price markup shocks	σ_π	$IG(0.01, 0.10)$	—	0.0051 [0.0048, 0.0052]

Note: "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 the heterogeneous automation-based model (Model 2), and the heterogeneous automation-based model that includes nominal frictions (Model 3). B, G, IG, and N denote the Beta, Gamma, Inverse Gamma, and Normal distributions, respectively.

preferences with homogeneous or heterogeneous disutility of work. The analysis compares the three models: homogeneous automation-based model (1), heterogeneous automation-based model (2), and heterogeneous automation-based with nominal frictions model (3), against their counterfactuals without automation.[9]

Table (3) presents key metrics: (i) Volatility of the real wage (wh) relative to output volatility (Y), (ii) Volatility of vacancies (v), (iii) Volatility of unemployment (ur), and (iv) Correlation between real wage growth (Δwh) and productivity growth ($\Delta \frac{Y}{N}$). For each metric, counterfactual values are expressed as ratios relative to the automation-based models (Comparison ratio=no automation/automation).

Automation creates wage rigidity in Model 2 but less so than in Model 1. The comparison ratio (no automation/automation) is 1.85 in Model 1, higher than 1.59 in Model 2. This may result from automation-induced endogenous separations in Model 2, which destruct jobs and amplify wage volatility by pushing wages downward. A similar pattern appears in Model 3, where the comparison ratio is 1.32, still lower than in Model 1.

Automation increases vacancies volatility in Model 2 but less than in Model 1. The comparison ratio (no automation/automation) is 0.56 in Model 1 and 0.79 in Model 2. A similar pattern appears in Model 3, where the comparison ratio is 0.73, still greater than in Model 1.

Automation increases unemployment volatility in Model 2, though to a lesser extent than in Model 1. The comparison ratio of unemployment volatility (no automation/automation) is 0.56 in Model 1 and 0.79 in Model 2. This difference may be attributed to automation-induced endogenous separations in Model 2, which lead to a rise in unemployment rather than the significant decrease observed in Model 1. In Model 3, which incorporates nominal rigidities, automation amplifies the effect even further, resulting in a comparison ratio of 0.15.

Automation reduces the wage-productivity correlation more in Model 2 than in Model 1. The comparison ratio (no automation/automation) is 1.33 in Model 1, lower than 1.97 in Model 2. The

[9] We compare the three automation-based models with their respective counterfactual models in which automation is excluded. The homogeneous automation-based model (1) is calibrated using parameters from Leduc and Liu (2024), while the heterogeneous automation-based model (2) and the heterogeneous automation-based model with nominal frictions (3) are calibrated using their respective estimated parameters. Counterfactual models without automation are presented in the appendix, where each uses the parameterization of its respective benchmark model.

reason may be the fact that Automation creates endogenous separations in the Model 2, pushing wages down while productivity increases, weakening their correlations. A similar pattern appears in Model 3, where the comparison ratio is 1.67, still greater than in Model 1.

Table 3: Automation and labor market volatility (Comparison ratio)

	$\frac{\sigma(wh)}{\sigma(Y)}$	$\sigma(v)$	$\sigma(ur)$	$\varrho\Big(\Delta wh, \Delta(\frac{Y}{N})\Big)$
(1) Homogenous model	1.85	0.56	0.50	1.33
(2) Heterogenous model	1.59	0.79	0.76	1.97
(3) Heterogenous model with nominal rigidities	1.32	0.73	0.15	1.67

Note: Standard deviation, $\sigma(\cdot)$, and correlation, $\varrho(\cdot)$ of variables in the three contrefactual linearized models without automation. All measures are expressed relative to their corresponding values in the models with automation. The homogeneous automation-based model (1) is calibrated using parameters from Leduc and Liu (2024), while the heterogeneous automation-based model (2) and the heterogeneous automation-based model with nominal frictions (3) are calibrated using their respective estimated parameters. Each counterfactual models without automation uses the parameterization of its respective benchmark model.

4.2 Economic transmissions This subsection examines how firms' automation decisions (henceforth referred to as Automation) are transmitted to labor market fluctuations in an economy with heterogeneous disutility of work, serving as a supporting factor for the effects summarized in Table (3). The analysis compares two models: the homogeneous automation-based model (1) and the heterogeneous automation-based model (2)[10].

Figure 1 illustrates the responses to a one-standard-deviation increase in technology shocks in both models. In both cases, a technology shock raises firm profitability for both worker-based production (J_t^e) and robot-based production (J_t^a), driving persistent increases in vacancy value (J_t^v) and vacancies (v_t). Firms use these vacancies to create jobs (jc_t), which persistently reduces unemployment (ur_t) and boosts worker-based output (Y_t^n) [11]. At the same time, firms use vacancies to adopt robots, which persistently increases robot-based output (Y_t^a), leading to a sustained rise in productivity (Y_t/N_t). As robots are more productive than workers, Y_t^a grows faster than Y_t^n, causing the relative price of robot-based output (p_t^a) to decline, which reduces J_t^a and the automation probability (q_t^a) after about nine quarters. The threat of automation dampens wages, and the combined effect of wage dampening and increased productivity reduces the labor income share (LIS_t).

[10]The homogeneous automation-based model (1) is calibrated using parameters from Leduc and Liu (2024), while the heterogeneous automation-based model (2) is calibrated using the estimated parameters.

[11]The initial increase in employment in the Model 2 will be explain in the next paragraph.

With heterogenous desutility of work (Model 2), new mechanisms emerge. The initial increase in automation value that increases the vacancy value further reduces the firm's surplus with a worker at the margin ($J_t^e(\underline{\chi}_t) - J_t^v$),[12] turning the total surplus negative. This lowers the threshold disutility for accepting work ($\underline{\chi}_t$), triggering endogenous separations (δ_t^n). Firms then destroy jobs (jd_t) by adopting robots. Consequently, wages and the labor income share decline further, and unemployment rises by 2% initially, followed by smaller reductions over time. Destroyed jobs become vacancies, which explains the peak in vacancies observed in the second quarter. These effects diminish as the threat of automation subsides.

Figure 2 shows responses to a one-standard-deviation increase in automation-specific shocks in both models. The transmission mechanism here follows the one described above. This shock leads to a significant increase in automation value in both models, creating a strong automation threat, with the automation probability initially rising to around 40% (compared to 15% under technology shocks). The responses are more pronounced in the heterogeneous model (Model 2). This amplifies job destruction, wage reductions, and labor income decreases. Unemployment initially increases by 12%, and destroyed jobs subsequently become vacancies, leading to a sharp vacancy peak in the second quarter.

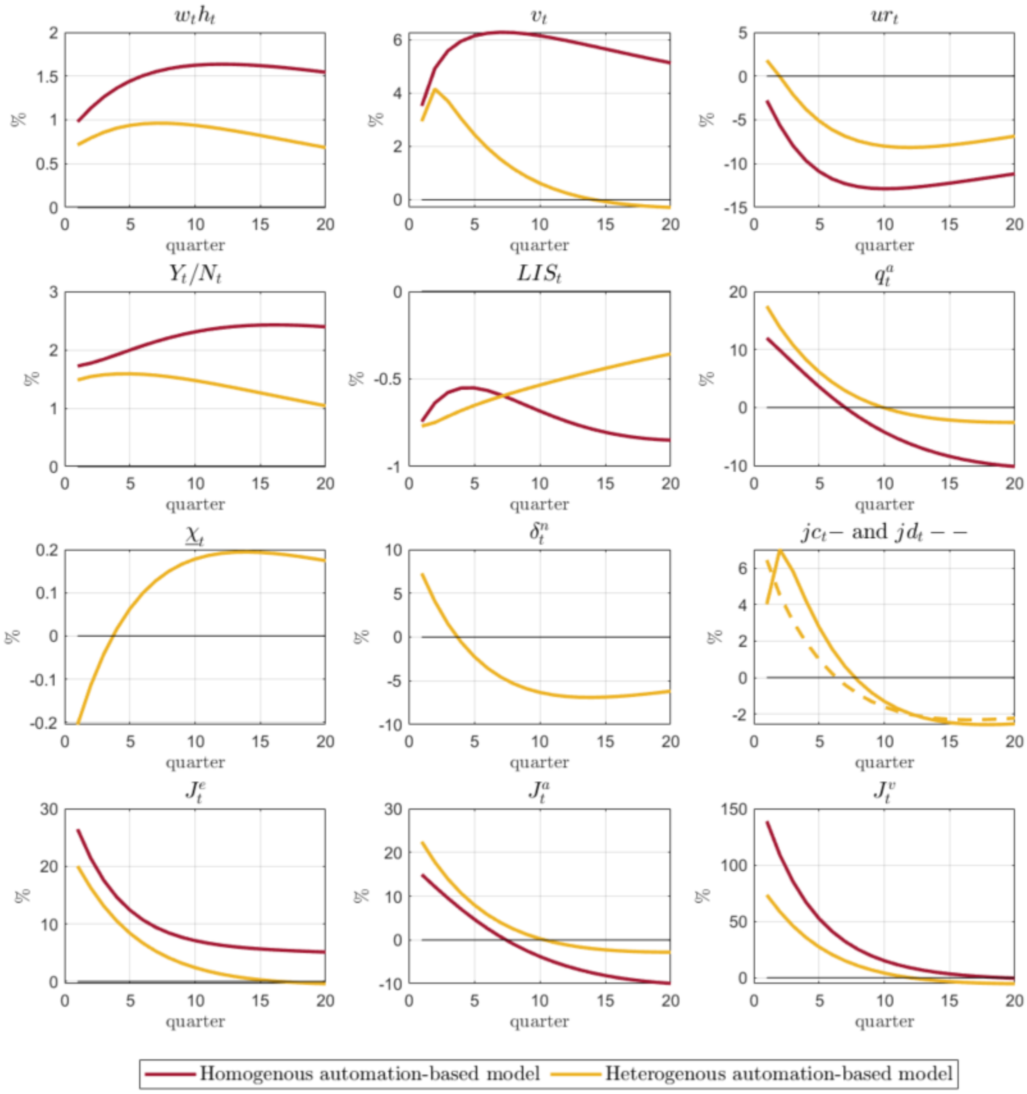
Several mechanisms are noteworthy when disutilities of work are heterogeneous. Automation creates procyclical unemployment, downward wage pressures, and greater reductions in the labor income share. These results are better than the results in the model with homogenous desutility of work because they square well with the earlier studies [13].

As discussed in Table (3), Automation induces wage rigidity in Model 2, though to a lesser extent than in Model 1. This finding is corroborated here, as Automation in Model 2 amplifies wage volatility by pushing wages downward. Additionally, Automation increases unemployment volatility in Model 2, though less than in Model 1. This result is confirmed here, as Automation raises unemployment, which in turn limits its volatility. Finally, Automation weakens the wage-productivity correlation more significantly in Model 2 than in Model 1. This occurs because, in Model 2, Automation drives wages downward during procyclical fluctuations.

[12] A worker at the margin is one for whom the realized preference shock equals the threshold value $\underline{\chi}_t$.

[13] The increase in unemployment squares well with Acemoglu and Restrepo (2018b), Acemoglu, Anderson, et al. (2022), and with Charalampidis (2020b). However the decrease in unemployment align with Leduc and Liu (2024).

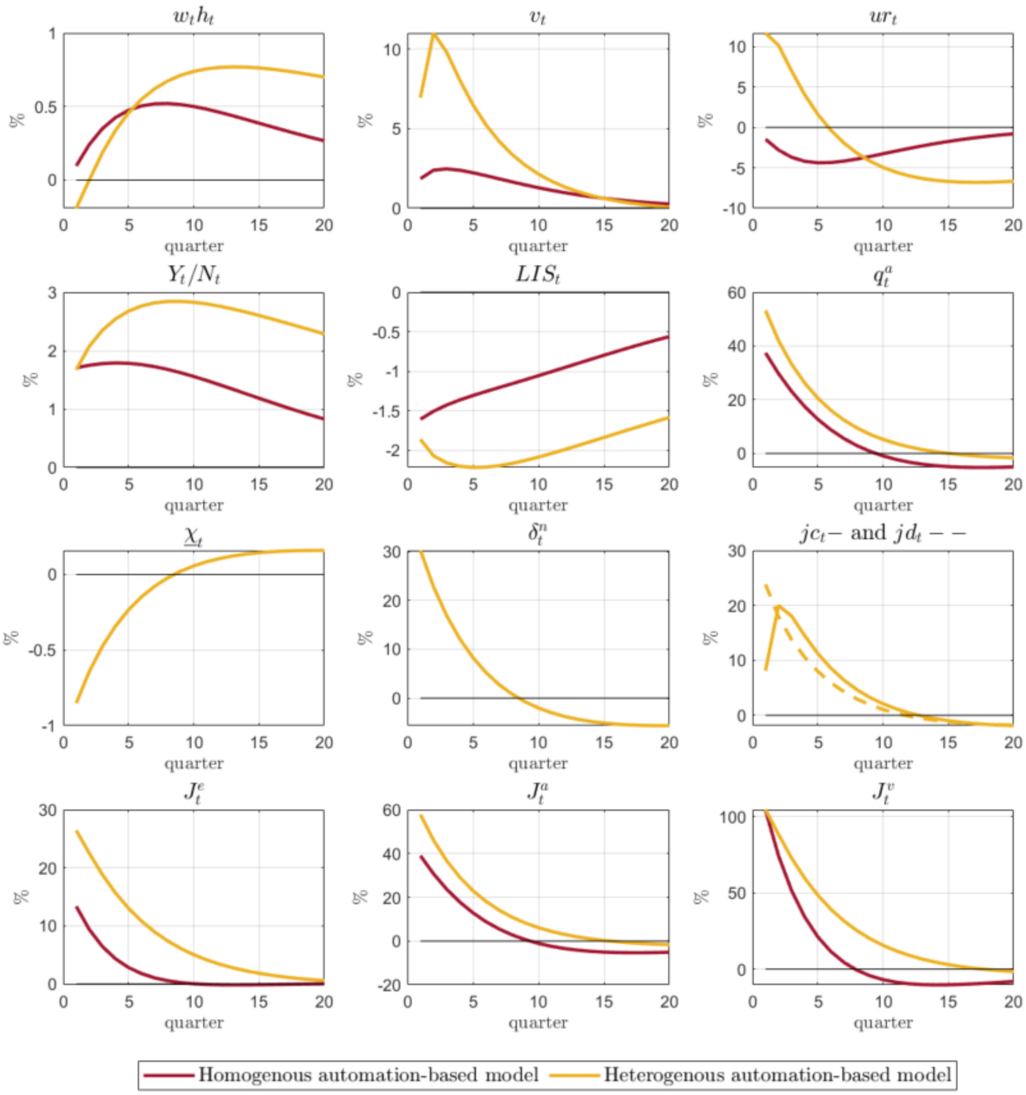
Figure 1: Aggregate Implications of Changes in Productivity



Note: Propagation of a one-standard-deviation increase in technology in the two linearized models. Both models are evaluated using the parameters from the Leduc and Liu (2024) model. For parameters not specified in the Leduc and Liu (2024) model, we apply our own estimated parameters in the Heteregenous automation-based model (Model 2), ensuring alignment in the steady state and shock configurations. Notably, neither model incorporates nominal rigidities, allowing us to focus exclusively on the real impacts of the heterogeneity.

4.3 Business Cycle Sources This section investigates how the relative importance of shocks driving business cycle fluctuations is affected by the inclusion of households with heterogeneous disutility of work. Specifically, we compare the sources of these fluctuations (Table 4) across two setups: an automated economy with homogeneous disutility of work, represented by Model 1 cali-

Figure 2: Aggregate Implications of Automation-specific Productivity



Note: Propagation of a one-standard-deviation increase in automation-specific shocks in the two linearized models. Both models are evaluated using the parameters from the Leduc and Liu (2024) model. For parameters not specified in the Leduc and Liu (2024) model, we apply our own estimated parameters in the Heteregenous automation-based model (Model 2), ensuring alignment in the steady state and shock configurations. Notably, neither model incorporates nominal rigidities, allowing us to focus exclusively on the real impacts of the heterogeneity.

brated according to Leduc and Liu (2024), and an automated economy with heterogeneous disutility of work, represented by Model 2, using our estimated parameters. It is important to note that neither model incorporates nominal rigidities.

4.3.1 Automation-Related Variables

With homogeneous disutility of work, technological shocks are the dominant driver of automation-related variables. They account for 41% of automation probability (q^a) fluctuations, 40% of automation value (J^a), 38% of relative prices of robot-based intermediate goods (p^a), and 50% of the labor income share (LIS). Discount factor shocks explain 31% of automation probability and value, 35% of relative prices, and 17% of the labor income share. Automation shocks contribute 28%, 29%, 27%, and 34% to fluctuations in these variables, respectively.

With heterogenous disutility of work, automation-specific shocks become the primary driver of automation-related variables, contributing 84% to automation probability, 80% to automation value, 92% to intermediate goods prices, and 94% to the labor income share. Technological shocks, by contrast, lose significance, contributing only 10%, 12%, 4%, and 6% to fluctuations in automation probability, automation value, intermediate goods prices, and the labor income share, respectively.

4.3.2 Heterogeneity-Related Variables

With heterogeneous disutility of work, discount factor shocks (θ) become the main driver of fluctuations in heterogeneity-related variables, explaining 57% of endogenous separations (δ^n) fluctuations, 52% of hours (h) fluctuations, 31% of job creation (jc) fluctuations, and 30% of job destruction (jd) fluctuations. Automation-specific shocks (ζ) also play a significant role, accounting for 30% of endogenous separations, 21% of hours, 53% of job creation, and 56% of job destruction fluctuations. Technological shocks (Z) are relevant for fluctuations in hours of work (h), explaining 22%.

4.3.3 Labor Market Variables

With homogeneous disutility of work, technological shocks (Z) are the primary drivers of labor market fluctuations. They account for 56% of unemployment (ur) fluctuations, 53% of vacancy (v) fluctuations, 57% of labor market tightness (the v–ur ratio), and 84% of real wage (wh) fluctuations. Discount factor shocks (θ) also contribute significantly, explaining 41% of unemployment fluctuations, 39% of vacancy fluctuations, 41% of labor market tightness, and 14% of real wage fluctuations.

In contrast, with heterogeneous disutility of work, the influence of technological shocks (Z) diminishes. They explain only 15% of unemployment fluctuations, 7% of vacancy fluctuations, 18% of labor market tightness, and 44% of real wage fluctuations. Meanwhile, discount factor shocks (θ) gain prominence, contributing 66% to unemployment fluctuations, 65% to labor market tightness, and 20% to real wage fluctuations. Furthermore, automation shocks (ζ) become important, explaining 17% of unemployment, 48% to vacancy, 17% of labor market tightness, and 36% of real wages fluctuations. Exogenous separation shocks (δ^x) become important to explain 43% of vacancy fluctuations.

4.3.4 Aggregate Variables

With homogeneous disutility of work, aggregate variables are primarily driven by technological shocks (Z), which account for 72% of productivity (Y/N) fluctuations and 87% of consumption (C) fluctuations. However, with heterogenous disutility of work, the influence of technological shocks decreases significantly, explaining only 19% and 46% of productivity and consumption fluctuations, respectively. Automation-specific shocks gain importance, accounting for 79% of productivity and 38% of consumption fluctuations.

4.3.5 Summary

These findings highlight how incorporating households with heterogeneous disutility of work fundamentally transforms the propagation of shocks across key variables. Automation-specific shocks become more prominent, surpassing the role of technological shocks, which are more significant under homogeneous disutility. This shift reshapes business cycle dynamics, impacting not only automation-related variables but also the broader economy.

5 Implication of the automation threat on monetary policy

This section evaluates the implications of the automation threat for monetary policy. Specifically, it compares two linearized models that incorporate nominal rigidities and monetary policy: the heterogeneous automation-based model with nominal frictions (Model 3) and a counterfactual version without an automation threat. In the latter, all features of Model 3 are preserved, but the

Table 4: Sources of Fluctuations (in percentage)

		Homogenous model				Heterogenous model			
		θ_t	δ_t^x	ζ_t	Z_t	θ_t	δ_t^x	ζ_t	Z_t
Automation related	q^a	31	1	28	41	4	1	84	10
	J^a	31	1	29	40	7	1	80	12
	p^a	35	0	27	38	4	0	92	4
	LIS	17	0	34	50	0	0	94	6
Heterogeneity related	δ_n	-	-	-	-	57	0	30	12
	h	-	-	-	-	52	5	21	22
	jc	-	-	-	-	31	5	53	11
	jd	-	-	-	-	30	5	56	8
Labor market	ur	41	1	2	56	66	2	17	35
	v	39	6	2	53	3	43	48	7
	v/ur	41	0	2	57	65	0	17	18
	wh	14	0	3	84	20	0	36	44
Aggregates	Y/N	2	0	12	72	2	0	79	19
	C	5	0	7	87	30	5	56	8

Note: The variance decomposition of forecast errors for key variables is presented for two linearized models: the homogeneous automation-based model (Model 1), calibrated using parameters from Leduc and Liu (2024), and the heterogeneous automation-based model (Model 2), calibrated using its estimated parameters. All values are expressed as percentages (%). The shocks analyzed are defined as follows: θ_t represents discount factor shocks, δ_t^x represents exogenous separation shocks, ζ_t represents robotic technology shocks, and Z_t represents productivity shocks. It is important to note that neither model incorporates nominal rigidities.

automation probability is fixed at its steady-state level ($q_t^a = q_a$), thereby removing fluctuations around the steady state in this variable. First, we examine the transmission of monetary policy in both models, comparing the cases with and without the automation threat. Next, we assess how the automation threat affects the government's capacity to stabilize economic fluctuations.

5.1 Economic transmissions This subsection analyzes the transmissions of monetary policy shocks in two models with and without the automation threat, benchmarking their responses against empirical evidence and the findings of Trigari (2009), a framework renowned for its ability to replicate observed data. The objective is to uncover the mechanisms of monetary policy in both models and to evaluate the capacity of both models to reproduce the empirical responses to monetary policy shocks.

Figure (3) illustrates the dynamic responses of key variables to a one-standard-deviation monetary policy shock (equivalent to a 0.58% increase) in both models. A contractionary monetary policy shock generates persistent declines in output (Y_t) and inflation (Π_t) in both models, with inflation displaying significantly lower volatility compared to output. These dynamics are consistent with empirical evidence and the predictions of Trigari (2009). The reduction in output is more pronounced than in inflation, with a decline of approximately 0.12% for inflation in both models, whereas output falls by about 0.40% without the automation threat and 0.50% with the automation threat.

The lower inflation volatility relative to output and the greater persistence of output are attributed to smaller fluctuations in real marginal costs ($\bar{p}_t$) in both models. Contractionary shocks reduce aggregate demand, which directly affects output and the demand for intermediate goods. Consequently, the relative prices of intermediate goods decrease, leading to a decline in real marginal costs of less than 0.5% in both models. These mechanisms align with the findings of Trigari (2009), which emphasize that search-and-matching frictions dampen real marginal cost volatility by enabling labor inputs to adjust at both intensive and extensive margins.

The output decline is more pronounced in the model with the automation threat than in the model without it, driven by reductions in the automation probability. Contractionary monetary policy diminishes the threat of automation, leading to a persistent decline in the automation probability (q_t^a) in the model incorporating this threat. As a result, the production of intermediate goods by robots (Y_t^a) decreases in the presence of the automation threat, whereas it increases in the absence of such a threat [14]. Consequently, output declines more sharply when the threat of automation diminishes compared to the scenario where it is absent.

In both models, contractionary monetary policy leads to a more pronounced and persistent decline in employment (N_t) compared to hours of work (h_t). Employment effects are long-lasting, while hours adjustments are transitory. These findings are consistent with empirical evidence and the predictions of Trigari (2009).

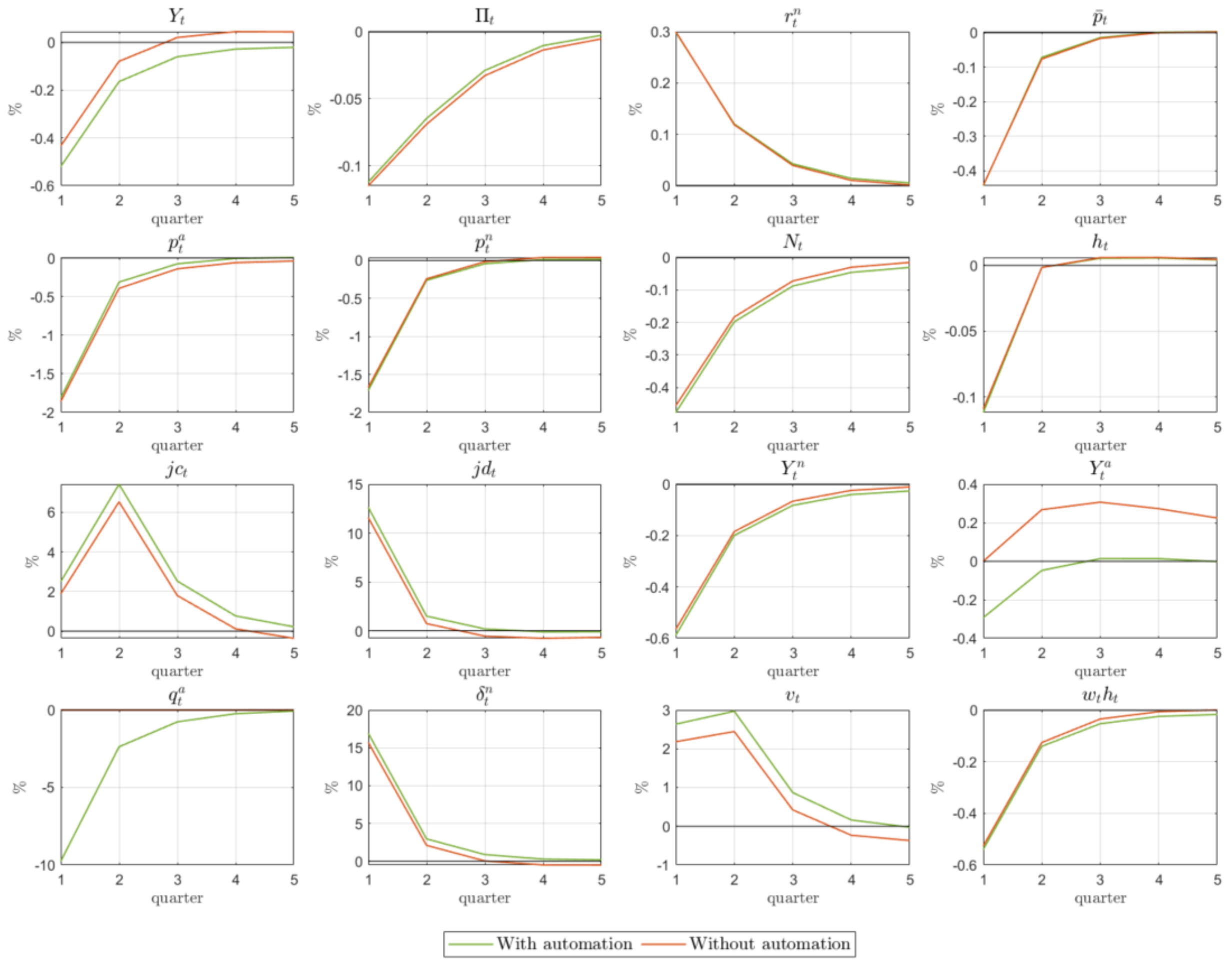
In both models, the economic slowdown leads to a reduction in hours of work. Employment reductions are primarily driven by increased job destruction (jd_t), a result that aligns with empirical data and Trigari (2009). Job destruction rises more significantly than job creation (jc_t) in both models. This is a direct consequence of contractionary shocks reducing aggregate demand, which subsequently lowers the demand for intermediate goods, reduces firms' profits from production using workers and robots. Lower profits in both models generate endogenous separations between firms and workers (δ_t^n) and reduce the number of firms opening new vacancies (η_t). This dynamic increases job destruction, decreases wages ($w_t h_t$), and limits the rise in job creation. The presence of the threat of automation intensifies these separations, leading to a significantly larger increase in job destruction, employment and a more pronounced decline in wages.

Overall, the dynamics observed in both models closely mirror empirical evidence, validating their use for analyzing monetary policy responses in environments with and without automation.

5.2 Optimal Monetary policy design The previous section demonstrated how the automation threat amplifies the effects of monetary policy shocks on output and unemployment (or employment). These shocks induce a positive correlation between output and inflation, compelling the central bank to navigate a trade-off between output and inflation volatility. Similarly, shocks generate a negative correlation between unemployment and inflation, forcing the central bank to address a trade-off between unemployment and inflation volatility. This naturally raises the question of how the automation threat influences these trade-offs.

[14]Note that in the absence of the automation threat, automation still occurs; however, the automation probability remains constant.

Figure 3: Aggregate Implications of Changes in monetary policy shocks



Note: Propagation of a one-standard-deviation increase in monetary policy shocks in two linearized models with nominal rigidities: the heterogeneous automation-based model that includes nominal frictions (Model 3) and its counterfactual without the automation threat. Both models are calibrated from the estimated parameter values of the model 3.

To explore this, we compute inflation-output volatility frontiers for alternative parameterizations of a central bank loss function, assuming that output and inflation volatility are the sole objectives of monetary policy. These policy frontiers are derived for both models under consideration.

The central bank's optimal policy is ad hoc and minimizes a quadratic loss function:

$$W_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t (\hat{\Pi}_t^2 + \lambda_y \hat{Y}_t^2) \tag{45}$$

where $\hat{\Pi}_t$ is the inflation rate, $\hat{Y}_t$ is the output, and $\lambda_y > 0$ reflects the relative importance of stabilizing output fluctuations compared to inflation. For simplicity, we consider the limiting case of this objective when β goes to unity, transforming the loss function into the following form:

$$W_0 = var(\hat{\Pi}_t) + \lambda_y var(\hat{Y}_t) \tag{46}$$

Given calibrated and estimated parameters, the policymaker selects λ_y and optimizes the coefficients $(\psi_r, \psi_\pi, \psi_y)$ in the Taylor-type rule:

$$\hat{r}_t^n = \psi_r \hat{r}_{t-1}^n + (\psi_\pi \hat{\Pi}_t + \psi_y \hat{Y}_t) + \hat{\epsilon}_t^{mp} \tag{47}$$

where the nominal interest rate reacts to inflation, the output, the vacancy-to-unemployment ratio, and its own lag. Optimal coefficients reveal key differences in monetary policy responses with and without automation.

5.3 Optimal simple rules Table (5) summarizes the results of the optimal simple rule analysis for models with and without automation, evaluated under five distinct objective functions that vary the weight assigned to output stabilization (λ_y). This comparison highlights how automation influences the formulation and effectiveness of optimal simple rules.

In both models, when output stabilization is assigned no weight $\lambda_y = 0$, the optimal simple rule corresponds to the coefficients $(\psi_r, \psi_\pi, \psi_y) = (0.91, 10, 0)$, i.e a maximum role for inflation and no role for the output. As the weight on output stabilization increases ($\lambda_y \to 1$), the optimal simple rule adjusts to reflect a decline in the inflation coefficient (ψ_π) and an increase in the output coefficient (ψ_y). This pattern is consistent with the framework of flexible inflation targeting (Svensson and O. (1997, 1999)). The shift in the policy rule is accompanied by an increase in the standard deviation of inflation and a decrease in the standard deviation of output, mapping a policy trade-off. This inflation-output stabilization trade-off is visualized in Figure (4), which depicts the policy frontier for both models. We also observe a trade-off between the inflation-unemployment stabilization in Figure (5).

5.4 Trade-off The automation threat adversely affects the trade-off between output and inflation volatility compared to the model without the automation threat. Under all optimized simple

Table 5: Optimal simple rules

		With the Automation threat						Without the Automation threat				
		Relative weight on output (λ_y)						Relative weight on output (λ_y)				
		0	0.25	0.50	0.75	1		0	0.25	0.50	0.75	1
Taylor rule coefficients	Model	Optimal coefficients					Model	Optimal coefficients				
ψ_r	0.91	–	–	–	–	–	0.91	–	–	–	–	–
ψ_π	2.13	10	1.01	1.01	1.01	1.13	1.01	10	1.01	1.01	1.01	1.01
ψ_y	0.08	0.00	0.11	0.22	0.34	0.45	0.08	0.00	0.09	0.20	0.31	0.42
Loss		0	650	1236	1762	2234		0	600	1,152	1,654	2,111
Standard deviation	Model	Optimized					Model	Optimized				
Nominal interest rate (r_t^n)	2.51	1.60	5.88	11.30	16.36	20.98	2.43	1.59	5.11	10.01	14.79	19.30
Inflation (Π_t)	2.07	0.08	5.74	11.24	16.35	21.00	1.98	0.08	4.95	9.92	14.74	19.26
Output (Y_t)	51.36	52.22	49.69	47.11	44.64	42.35	49.20	49.96	48.00	45.90	43.78	41.71
Output growth (ΔY_t)	2.94	2.83	2.92	2.64	2.46	2.34	2.38	2.29	2.46	2.27	2.12	2.02
Productivity (Y_t/N_t)	34.02	34.33	33.43	32.50	31.61	30.78	32.57	32.84	32.13	31.38	30.62	29.88
Unemployment (ur_t)	278.06	286.92	261.49	235.68	211.46	189.29	267.82	275.62	255.74	234.57	213.62	193.71

Note: Optimal simple rules are derived for two linearized models with nominal rigidities: (1) the heterogeneous model without automation, and (2) the heterogeneous model with automation. Both models are optimized using the same parameter set, based on the estimated parameter values from the model with automation.

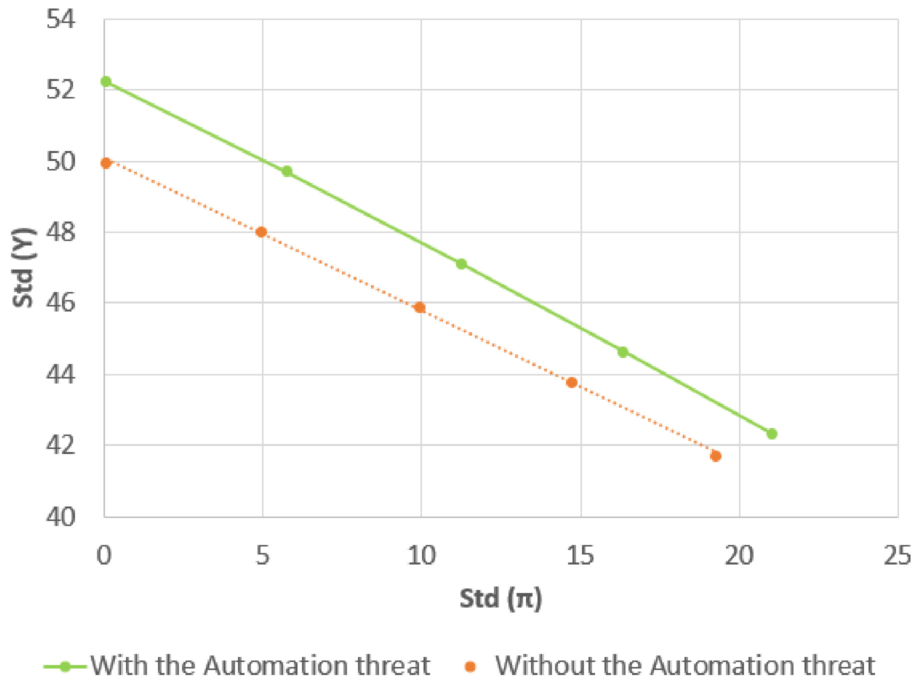
interest rate rules, the model with the automation threat consistently exhibits greater volatility in both output and inflation. The same mechanism applies to the trade-off between inflation and unemployment volatility, highlighting the broader destabilizing impact of the automation threat on macroeconomic fluctuations.

6 Conclusion

This paper analyzed the short-term effects of firms' automation decisions on economic fluctuations and the implications of the threat of automation for monetary policy transmission. Departing from the standard assumption of homogeneous disutility of work, we introduced heterogeneous disutility among households to capture endogenous job destruction, offering a richer framework for understanding labor market dynamics. Using two automation-based models—one with nominal frictions and one without—estimated on U.S. data, we explored these effects.

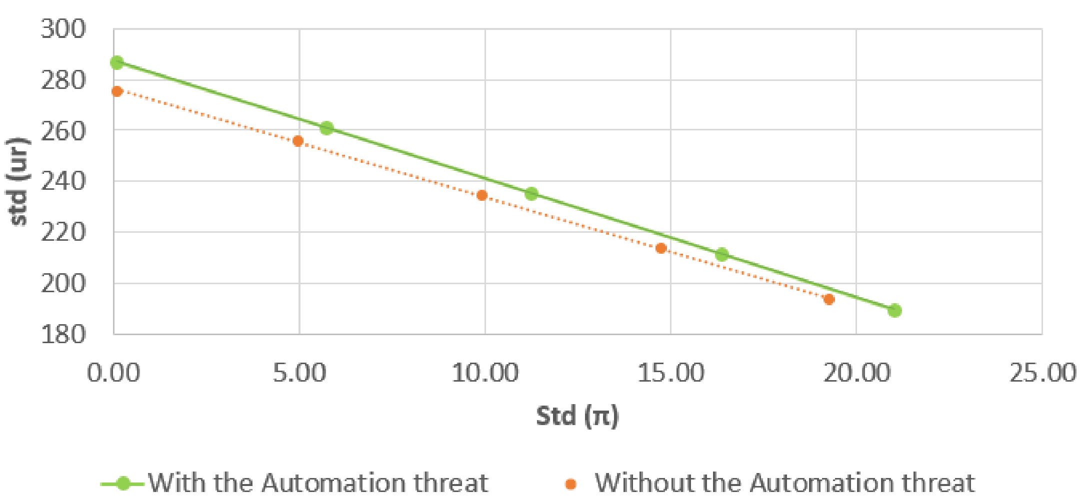
Our findings underscore the significant impact of automation on labor market outcomes and macroeconomic dynamics. Specifically, automation reduces the threshold disutility required for accepting work, resulting in procyclical unemployment, downward wage pressures, and a decline in the labor income share. These effects, which align with empirical evidence, are absent in models assuming homogeneous disutility of work. In the absence of nominal frictions, the incorporation of heterogeneous

Figure 4: Policy Frontiers (Output-Inflation)



Note: The figure illustrates the trade-offs between the standard deviation of inflation (horizontal axis) and the standard deviation of output (vertical axis), under optimal simple rules in Table (5). The model incorporating the automation threat is represented by the green line, while the model without the automation threat is shown in orange.

Figure 5: Policy Frontiers (Unemployment-Inflation)



Note: The figure illustrates the trade-offs between the standard deviation of inflation (horizontal axis) and the standard deviation of output (vertical axis), under optimal simple rules in Table (5). The model incorporating the automation threat is represented by the green line, while the model without the automation threat is shown in orange.

disutility mitigates automation's influence on wage rigidity, vacancy volatility, and unemployment volatility but amplifies its effect on reducing the wage-productivity correlation. This dual effect arises from the simultaneous decline in employment and wages driven by automation.

Moreover, the inclusion of nominal rigidities enhances the model's ability to replicate observed macroeconomic responses to monetary policy shocks. Notably, the threat of automation exacerbates the trade-off between inflation and output volatility, as well as the trade-off between inflation and unemployment volatility. These findings highlight the complex interplay between automation and monetary policy, underscoring the necessity for policymakers to account for automation's pervasive effects when designing monetary interventions.

Overall, this study emphasizes the critical role of automation in shaping economic fluctuations. Future research could extend this analysis by examining the role of fiscal policy in mitigating automation's effects over the business cycle. Investigating optimal policy decisions, such as the design of unemployment benefits (Enders and Vespermann (2021); Birinci and See (2020)) or the implementation of robot taxes (Guerreiro, Rebelo, and Teles (2021)), represents a promising avenue for further exploration. These considerations could offer valuable insights into balancing productivity gains with equitable labor market outcomes in the age of automation.

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