

Hwang, Kyuyeon; Han, Junhee

Article

Employment shift in response to a technology shock: An analysis of two rigidities and two agents

Economies

Provided in Cooperation with:

MDPI – Multidisciplinary Digital Publishing Institute, Basel

Suggested Citation: Hwang, Kyuyeon; Han, Junhee (2024) : Employment shift in response to a technology shock: An analysis of two rigidities and two agents, *Economies*, ISSN 2227-7099, MDPI, Basel, Vol. 12, Iss. 11, pp. 1-18,
<https://doi.org/10.3390/economies12110303>

This Version is available at:

<https://hdl.handle.net/10419/329230>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

Article

Employment Shift in Response to a Technology Shock: An Analysis of Two Rigidities and Two Agents

Kyuyeon Hwang ^{1,*}  and Junhee Han ²¹ School of Applied Economics, Renmin University of China, Beijing 100872, China² Centre for Comparative Economic Studies, Seoul National University, Seoul 08826, Republic of Korea

* Correspondence: kyuyeonhwang@ruc.edu.cn

Abstract: This paper examines the relationship between a technology shock and employment, considering price, wage rigidities, and heterogeneous agents. To explore this relationship, we utilized a Dynamic Stochastic General Equilibrium (DSGE) model, incorporating households with varying savings rates. For empirical validation, we conducted a Structural Vector Autoregression (SVAR) analysis using data from two economies with distinct savings patterns—the United States and China. This approach allowed us to assess the impact of technology shocks on employment dynamics across different savings environments. Under these conditions, we observe that the effect of technology on aggregate employment is initially positive. Still, it gradually decreases in the mid-term, eventually switching to a negative impact before slowly recovering to equilibrium. The reason for this phenomenon depends on (i) the magnitude of fluctuations in price and wage, precisely, which variable's fluctuations have a greater magnitude, and (ii) which effect, between income effect and substitute effect, is preferred by restricted and unrestricted households. Due to (i), real wages change, and because of (ii), households make different labor supply decisions, leading to fluctuations in employment in response to technology shocks.

Keywords: employment; two agents NK model; technology shock; fluctuations



Citation: Hwang, Kyuyeon, and Junhee Han. 2024. Employment Shift in Response to a Technology Shock: An Analysis of Two Rigidities and Two Agents. *Economies* 12: 303. <https://doi.org/10.3390/economies12110303>

Academic Editor: Ralf Fendel

Received: 24 September 2024

Revised: 5 November 2024

Accepted: 6 November 2024

Published: 10 November 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

We live in a world where technological advances occur rapidly, and we can readily observe these transformations. Moreover, these innovations enrich our lives and enhance the efficiency of our work. Therefore, technological improvements constitute a crucial source of economic growth. For this reason, technological improvement is an intriguing topic for many economists. Numerous studies delve into various aspects of technology improvement, such as defining it and devising suitable measurement methods.

Additionally, researchers explore the validity of employing the Solow residual to assess technology improvement and how to enhance and understand the origins of technological advancements (Kendrick 1976; Hamilton 2006). Many economists are also exploring the reasons behind the disparities in technology levels across countries and are investigating ways to achieve uniformity or close alignment. Just as research on the origins of technological progress has garnered attention, so has the study of its effects, particularly the changes in macroeconomic variables resulting from technological advancement. The employment-generating impacts of technological progress, in particular, have drawn the interest of economists and economic agents across the board, including households, as it directly impacts their livelihoods.

Technology shocks not only affect employment and productivity but also have a significant impact on household income and consumption. When a technology shock leads to productivity improvements, firms increase their output and, in turn, generate higher revenues. This increase in revenue ultimately translates into higher household income, allowing households to engage in greater consumption. At this point, households face a

choice regarding how to allocate their increased income. Their response can be divided into two primary approaches. First, households may choose to convert the increased income into consumption, thereby immediately improving their standard of living. Second, they may save a portion of their income to prepare for future uncertainties. In this context, the savings rate becomes a crucial factor in determining the broader economic impact of the technology shock. If households channel most of their increased income into consumption, this can stimulate demand, encourage firms to expand production, and generate positive economic effects. Conversely, if households increase their savings rate, it may lead to reduced consumption expenditures, limiting the potential positive impact on economic growth.

In today's rapidly changing technological landscape, understanding the effects of technological advancements on macroeconomic variables is of great importance. From this perspective, the impact on employment has garnered significant attention from scholars, with many studies focusing on whether new technologies can replace existing jobs or labor. However, such a labor substitution by new technologies is only feasible if there is demand for the latest products created by these technologies. This study does not merely analyze labor substitution by technology but investigates the effects of technological changes on employment through its interaction with other macroeconomic variables. It also explores the impact of technological change in countries with different savings rates, which influence consumption, making this a valuable contribution to the field. However, most of the existing literature has focused on the effects of technology shocks from a job creation or replacement perspective. There has been relatively little research examining the impact of technology shocks on employment through changes in output, consumption, and savings. This study examines the effects of external technology shocks on employment through changes in output, prices, wages, and consumption. To assess the impact of technology shocks on employment, it is first necessary to analyze how changes in output influence price, wage inflation, and fluctuations in real wages. In addition to examining the variations in these macroeconomic variables, the study explores how differing savings rates affect consumption and influence changes in consumption and employment in response to technology shocks. To examine employment fluctuations resulting from technology shocks, the DSGE methodology was utilized. Heterogeneous agents were incorporated into the theoretical model to represent different savings rates, allowing the derivation of impulse response functions. On the empirical side, data from the United States and China, which have significantly different savings rates, were used to analyze the employment effects of technology shocks using the SVAR method. This empirical analysis was then compared to the simulations derived from the theoretical model for a comprehensive analysis. We also found that the employment effects of technology shocks varied significantly depending on differences in savings rates under identical conditions. When the savings rate was lower, the increased output from the technology shock was absorbed into consumption, leading to more significant employment gains. However, this also caused real wages to rise, with wage growth outpacing price increases, which began to diminish the positive employment effects of the technology shock. In other words, the critical determinant of the impact of technology shocks on employment is whether the increased output translates into consumption, which is more pronounced under lower savings rates.

In the following section, the existing literature on the impact of technology shocks on employment will be reviewed, along with an explanation of the theoretical background of this study. In Section 3, an empirical analysis will be conducted using the SVAR approach to examine the effects of technology shocks on employment and other macroeconomic variables in two countries with differing savings rates (the United States and China). Section 4 will introduce a DSGE model that incorporates differences in savings rates and derives the system equations to explain the causes of the empirical findings from Section 3, particularly those stemming from variations in savings behavior. In Section 5, parameter values used in the model will be estimated, followed by simulations to explore how savings rates interact with other macroeconomic variables to influence the employment effects of

technology shocks. Finally, Section 6 will conclude by summarizing the results and offering closing remarks based on the findings.

2. Literature Review and Hypotheses Development

2.1. Related Literature

Much of the literature has attempted to explore the relationship between technology shocks and employment through theoretical and empirical approaches. Even though almost all economists agree that technological advancement brings output growth, the direction in which employment changes remains ambiguous, and scholars have no consensus.

One notable contribution (or perhaps the one that started this popular puzzle) is that of [Lucas and Rapping \(1969\)](#), who theoretically investigated the dynamics of labor in response to changes in prices and output through their structural equations. The relationship between technology shocks and employment remains ambiguous. However, in the conventional Real Business Cycle (RBC) model, technology is a driving force for the economy and plays a significant role in explaining economic fluctuation ([Francis and Ramey 2005](#)). With this RBC model, labor becomes procyclical, increasing with the output stimulated by a technology shock. [Wang and Wen \(2011\)](#) show that a technology shock remains a primary factor in explaining fluctuations¹. [Mumtaz and Zanetti \(2012\)](#) discovered that employment increases following technological improvement using a DSGE model with price rigidity and labor market search frictions². For empirical studies focused on the technology effect, [Christiano et al. \(2003\)](#) utilize raw data, differenced data, and detrended data of per capita work hours to find that employment increases in response to a technology shock. [Dupaigne et al. \(2005\)](#) also utilizes different specifications of hours and level data to discover a positive correlation between technology shocks and hours worked. This result aligns with the RBC model's findings. [Choi and Shim \(2022\)](#) identify a positive effect of technology on employment using the Structural VAR model with TFP (Total Factor Productivity) instead of labor productivity, in both developed and developing countries, although this effect is relatively small in developing countries. [Alexopoulos \(2011\)](#) examines new book titles related to technology as a proxy for technology shocks and finds that technology positively impacts employment. Empirical analyses on the impact of technological progress on employment have been actively conducted using various employment indicators and data representing technological advancements. The results often differ depending on the data used in the analysis.

However, advocates of New Keynesian models see it differently. [Galí \(1999\)](#) revealed a negative long-run effect on employment due to labor productivity, using data from G7 countries. Furthermore, the negative impact of labor productivity on employment is attributed to price rigidity. [Shea \(1998\)](#) also found a negative effect of technology improvement on employment using R&D spending and patent activity data. [Francis and Ramey \(2005\)](#) extended Galí's identification scheme and concluded a negative effect on employment due to technology shock exists³. [Smets and Wouters \(2005\)](#) show the impact of technology on European countries using a New Keynesian model with price and wage rigidities and VARs analysis. Their conclusion indicates that a positive productivity shock gradually increases output, consumption, investment, and the real wage. However, it also negatively impacts employment, which aligns with the findings documented for the United States ([Galí 1999](#)). [Basu et al. \(2006\)](#) also attempted to isolate non-technological effects from the TFP (Total Factor Productivity) and used pure-technological effects as a technology indicator. They found that technology shocks significantly reduce employment and non-residential investment in the short run. For empirical studies, [Bertinelli et al. \(2022\)](#) examine the effect of technology on employment by dividing the open economy model into the traded goods part and the non-traded goods part. Using data from OECD countries between 1970 and 2013, they found that a technology shock hurts the traded goods sector, thus, it has a negative impact on employment in the traded goods sector. Similarly, [Collard and Dellas \(2004\)](#) and [Collard and Dellas \(2007\)](#) also concluded that technological improvement decreases employment if domestic and foreign goods are complementary⁴.

As one can see, researchers report different results depending on how they structure this problem. To overcome this matter, instead of taking a dichotomous view of which direction employment moves when there is a positive technology shock, studies are taking a broader perspective by looking at sectors (industries) and seeing how employment responds differently. [Chang and Hong \(2006\)](#) used the VAR model to investigate the impact of technology shocks on employment within the US manufacturing industry. The results revealed that out of 458 4-digit industries, only 133 industries showed a significant increase in employment due to a technology shock. In comparison, only 25 industries substantially decreased employment due to a technology shock. They found no significant relationship between employment and price rigidity. In other words, there must be a reason why the impact of a technology shock varies from one company to another. [Kim and Chun \(2011\)](#) suggest that firms' varying responses to technology shocks are attributed to production-related costs. Using US manufacturing firm data, they analyzed the short-term impact of technology shocks on employment. Their findings revealed that firms with a low inventory ratio experience a more significant increase in employment when technology shocks occur, while firms with a high inventory ratio show a relatively minor increase in employment. This relationship is associated with the cost of storing inventory, and the study confirms that technology shocks, regardless of their magnitude, positively affect employment. [Chang et al. \(2006\)](#) examined the impact of technology shocks on employment decisions through a simple model of industry employment. They found that factors related to production and sales significantly influence a company's employment response to technology shocks. Differences in inventory storage cost, demand elasticity, and price rigidity among industries were crucial determinants of employment.

Consequently, industries with lower inventory management costs, higher demand elasticity, and greater price flexibility experienced increased employment when exposed to technology shocks. [Malley and Muscatelli \(1997\)](#), using a semi-structural vector autoregressive model, revealed that technological innovation leads to the capitalization effect, eliminating jobs with low productivity and creating jobs in many new industries with high productivity. Concerned with the creation of new employment reacting to technical progress, [Autor et al. \(2003\)](#) conducted an empirical analysis using data from 1960 to 1998, which confirmed that technological advancements, particularly in automation and computerization, led to a reduction in employment in industries with many simple and repetitive tasks while increasing employment in industries with irregular and complex tasks. In other words, the study revealed that technological development can act as substitute and complement employment in a sector-level analysis. Through prior studies, the focus has gradually shifted from analyzing the overall impact of technology shocks on total employment to examining their effects on employment by sector. This shift stems from the ambiguous effects of technology shocks on total employment. In this study, we confirm that the impact of technology shocks on total employment does not simply take the form of a straightforward increase or decrease. Rather, the response of total employment can exhibit both patterns—an initial increase followed by a decrease or vice versa—depending on changes in other macroeconomic variables such as output, inflation, and wages. Furthermore, we will show that the cause of these results lies in the fluctuations in output driven by technology shocks, which are amplified by changes in consumption and wages due to households' saving behavior.

2.2. Theoretical Background

One of the main theoretical frameworks for studying macroeconomic volatility caused by external shocks is the Real Business Cycle (RBC) model, which was developed by [Kydland and Prescott \(1977, 1982\)](#). This theory explains economic fluctuations through real factors, particularly productivity shocks. The central idea is that business cycles are primarily driven by exogenous technology shocks, which affect productivity, leading to changes in the allocation of resources across the economy, thereby causing economic fluctuations. However, in reality, the immediate attainment of market equilibrium, as

suggested by the RBC model, may only sometimes occur. To address this limitation, the New Keynesian Economics school introduced the DSGE model, which incorporates various market frictions observed in the real world. In DSGE models, market inefficiencies like price, wage stickiness, and financial frictions prevent an immediate market equilibrium, causing macroeconomic variables to respond differently to shocks. These frictions delay price and wage adjustments and constrain firms' ability to secure external funding, making the economy more sensitive to shocks. As a result, DSGE models provide a more realistic representation of economic responses and are valuable for analyzing the effects of policy measures. [Christiano et al. \(2005\)](#), in their research, suggest that models incorporating the assumption of wage rigidity offer a reasonable explanation for the variation in macroeconomic variables in response to external shocks. Similarly, [Blanchard and Galí \(2007\)](#) noticed that the New Keynesian model with real wage rigidities provides a better description of the real economy compared to one solely based on price rigidity. A limitation of the NK model is the assumption of a representative household, which means all households behave identically within the model. It is recommended that heterogeneous features are incorporated into the model to better understand aggregate issues by analyzing households with different characteristics ([Guvenen 2011](#); [Kaplan et al. 2018](#)). Modeling the real economy is challenging due to its complexity and broad scope. As demonstrated above, integrating a range of characteristics among economic agents can bridge the gap between the model and the real economy, facilitating a better understanding of the impact of external shocks on the macroeconomy. In this context, the primary challenge lies in identifying the sources of heterogeneity. Recent studies increasingly examine fluctuations in macroeconomic variables by introducing heterogeneity or broadening the diversity of economic agents. However, this research primarily emphasizes amplifying external shocks through heterogeneity or financial frictions. In contrast, this study focuses on the impact of technology shocks on output, household consumption behavior, and employment dynamics by incorporating the savings rate into the model, thus capturing the effects of price and wage adjustments on these variables.

As previous literature has shown, the direction of employment fluctuations in response to technology shocks remains ambiguous. This paper establishes a DSGE model with price and wage rigidities and heterogeneous households, including "rule-of-thumb" households that do not save at all. We will show that for economies with higher ratios of the rule-of-thumb households (lower savings rate), employment initially experiences an enormous increase compared to when this rate is low when a positive technology shock occurs. We evaluate the predictive accuracy of the estimated DSGE model against Vector Autoregressions (VARs) and Structural VARs (SVAR) using the same data set. The estimated model also analyzes the factors influencing business cycle fluctuations in two economies with significantly different savings rates (the United States and China). Our empirical findings from these two countries support our theoretical results, indicating that changes in aggregate technology remain a significant driver of business cycles.

3. Empirical Analysis

In this section, we use SVAR to analyze the impact of technological change on the model we developed and examine real-world data from the US and China using five variables (Technology, GDP, Employment, Wage, and Inflation). [Figure 1](#) illustrates the difference in savings rates between the United States and China. In this study, to examine the impact of savings rate differences on employment fluctuations caused by technology shocks, we used data from the United States and China, which exhibit a relatively significant difference in savings rates. Since it is challenging to find discrete differences in savings rates within a single country at a specific time, the empirical analysis was conducted to investigate how technology shocks affect the macroeconomic variables of these two economies. The US data include the GDP, inflation rate, real wage, employment, and total factor productivity (TFP). Most data are derived from FRED, while employment data are obtained from the US Bureau of Labor Statistics. The data on China's GDP, inflation rate,

real wage, and employment are obtained from the National Bureau of Statistics of China. Furthermore, we utilize China’s TFP data from Penn World Table 10.01. When selecting technological improvement data, it is essential to consider the measures researchers use, as emphasized by (Christiano et al. 2003).

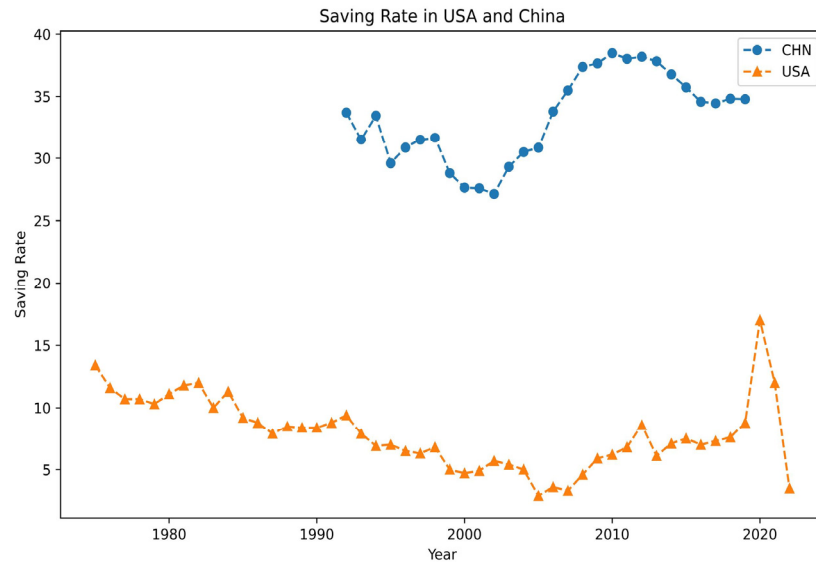


Figure 1. Savings rate in the US and China.

This empirical investigation uses TFP data to represent technological changes instead of labor productivity. This choice is made because labor productivity includes not only the input mix but also reflects the property of improved efficiency. Therefore, the TFP is considered a purer measure for explaining technological changes (Chang and Hong 2006). Figure 2 shows the distribution of the time series variables for both economies, which have been smoothed and standardized using the HP filter. This allows us to assess the validity of analyzing these time series data.

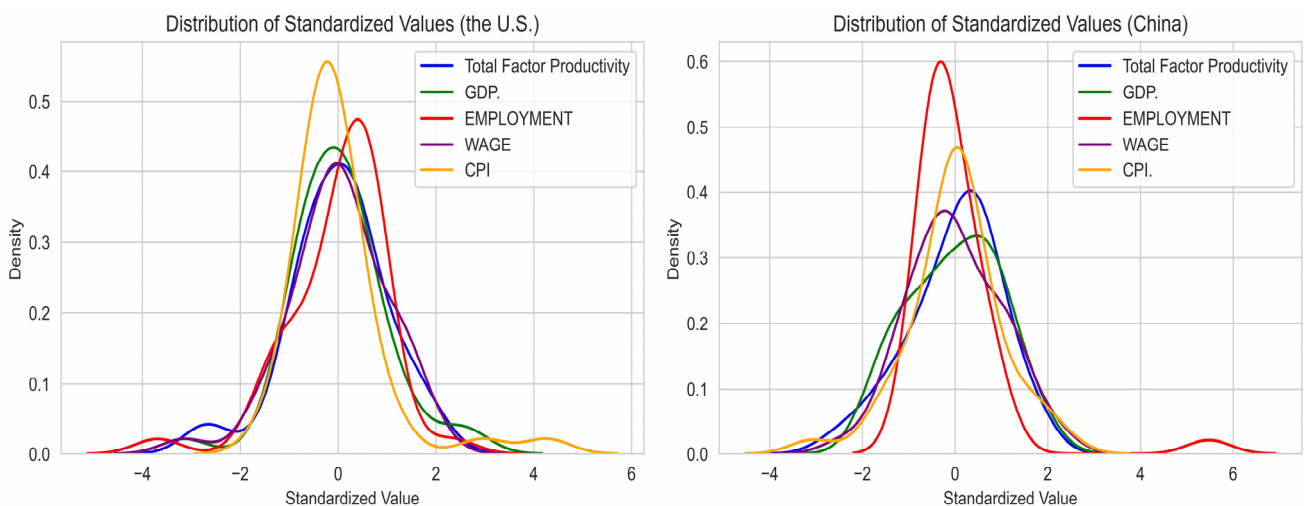


Figure 2. Distribution of standardized variables.

We empirically examine the effect of technology from 1979 to 2019 on the US and China. Although the periods for the two countries differ, this does not pose a problem, as our objective is not to directly compare the effect of technological changes between the countries. Instead, we aim to understand this effect in the real world and compare it with the outcomes from the model we developed. We undertake empirical analysis to

compare the fluctuations between the developed model and the actual economy. Before conducting the empirical analysis, we initially apply data differencing to stabilize the time series and standardize the data to achieve a uniform distribution. Following these procedures, we use VAR and SVAR analyses using a 5-dimensional vector time series denoted as $X_t = (TFP, GDP, Employment, Wage, Inflation)$. Here, β is a lower triangular matrix with a diagonal of 1, obtained using Cholesky decomposition, and i, j represents the dimensions. Lastly, ε_t is a white noise error term consisting of five dimensions.

The structural VAR model is outlined below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ E & 1 & 0 & 0 & 0 \\ E & E & 1 & 0 & 0 \\ E & E & E & 1 & 0 \\ E & E & E & E & 1 \end{bmatrix} \begin{bmatrix} TFP \\ GDP \\ Employment \\ Wage \\ Inflation \end{bmatrix} = C + \sum_{j=1}^i \beta_j X_j + \begin{bmatrix} E & 0 & 0 & 0 & 0 \\ 0 & E & 0 & 0 & 0 \\ 0 & 0 & E & 0 & 0 \\ 0 & 0 & 0 & E & 0 \\ 0 & 0 & 0 & 0 & E \end{bmatrix} \varepsilon_t$$

As illustrated in Figure 3, these two observations identified using the orthogonalized VAR model also manifest in our structural VAR analysis.

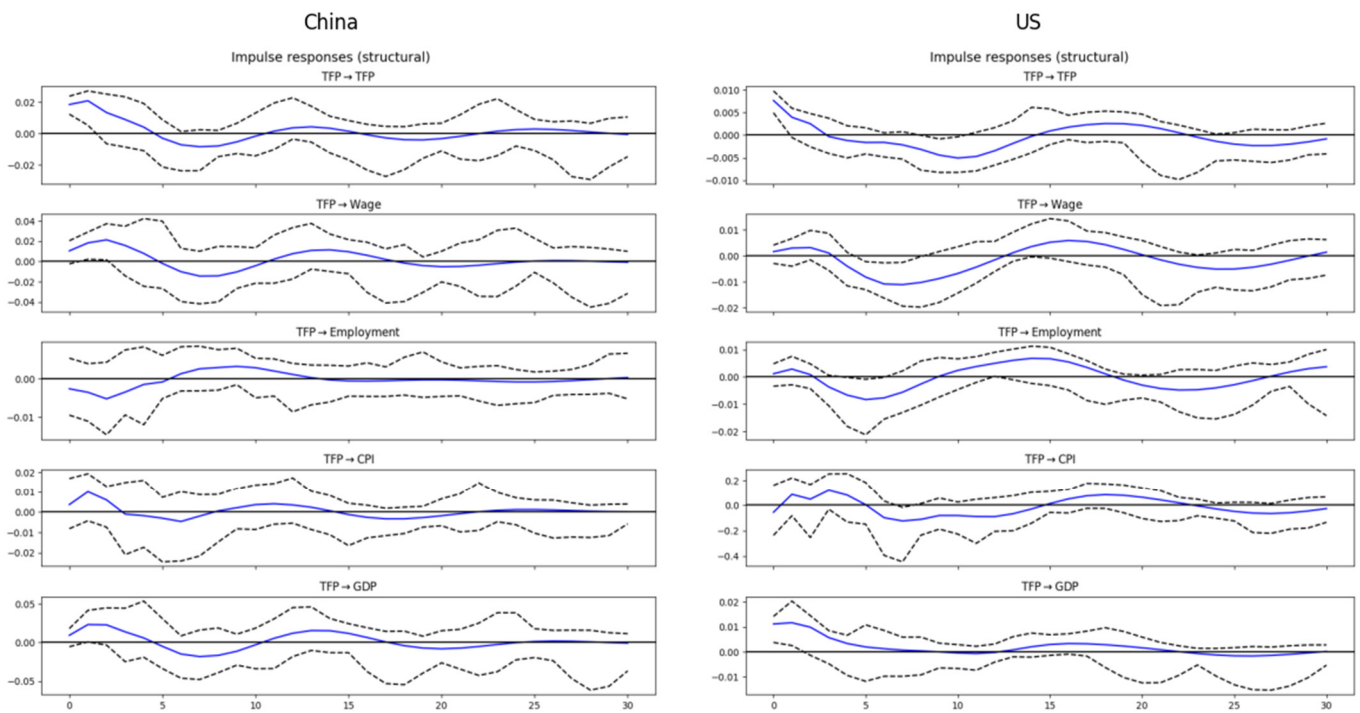


Figure 3. Impulse response function to TFP shock (structural VAR).

In Figure 3, the blue line represents the variation of the respective variable in response to an external shock, while the dashed line indicates the 95% confidence interval. As depicted in Figure 1, the United States has the lowest savings rate among these two countries. In other words, when an exogenous technology shock occurs, its impact will be most significant in the U.S. This is because the savings rate can influence consumption in response to an external shock that increases output. Specifically, if the savings rate is low, higher consumption of the increased output will lead to greater fluctuations in macroeconomic variables in response to the technology shock. Conversely, if the savings rate is high, additional consumption remains relatively limited, resulting in smaller fluctuations in these variables. As shown in Figure 3, in China, where the savings rate is high, the employment effects of a technology shock appear to diminish slightly. In contrast, in the United States, where the savings rate is lower, the effects show a slight increase, with fluctuations between increases and decreases. These results align with previous studies, such as Francis and Ramey (2005); Blanchard and Galí (2010); Riggi and Tancioni (2010); and Barnichon (2010), which found

that in economies with high savings rates, market inefficiencies cause technology shocks to have a negative impact on employment. Similarly, the findings for low-savings-rate economies are consistent with the studies by [Basu et al. \(2006\)](#); [Smets and Wouters \(2007\)](#); and [Mnif et al. \(2018\)](#), which demonstrated that technology shocks have a positive effect on employment in such economies. However, it would be somewhat ambiguous to make a direct comparison in our empirical analysis, even though the DSGE model trends and empirical results exhibit similar directions.

Therefore, we propose that the results display slight deviations from the model, possibly arising due to nuanced variations in each country's economic conditions and specific circumstances. It is indisputable that discrepancies in household savings rates play a substantial role in influencing the fluctuations of macroeconomic variables in response to external shocks, even when all other conditions are consistent within the model.

4. The Model Economy

For simplicity, we consider an economy without capital following ([McCallum and Nelson 1999](#)). This economy consists of heterogeneous, infinitely lived households indexed by $j \in [0, 1]$. Households can adjust their nominal wage in the labor market, and there is a perfectly competitive final goods firm. Similarly to households, firms have the flexibility to set their prices freely. The probability of being unable to change the price in any given period is θ_p . This represents the proportion of all firms that maintain their prices from the previous period, while the rest of the firms $(1 - \theta_p)$ reset their prices. Apart from including heterogeneous households and the absence of capital, our model structure resembles a standard DSGE model following ([Blanchard and Galí 2007](#)). The derivation methods for the model equations presented in this chapter are detailed in the Supplementary Material.

4.1. Firm Sector

There is a perfectly competitive final goods firm in this economic setting, but households possess monopoly power in the labor market. This creates a two-dimensional problem for firms to navigate. First, firms must determine the optimal combination of labor that maximizes output for any given level of labor costs. Second, firms must set prices to maximize profits after obtaining the optimal labor vector.

Firms must first solve the following problem to identify the output-maximizing combination of labor:

$$\max_{N_{ijt}} \left(\int_0^1 N_{ijt}^{\frac{\varepsilon_w - 1}{\varepsilon_w}} dj \right)^{\frac{\varepsilon_w}{\varepsilon_w - 1}} \equiv N_t \quad (1)$$

$$\text{s.t.} \int_0^1 W_{jt} N_{ijt} dj \leq Z_t \quad (2)$$

$$\mathcal{L} = \left(\int_0^1 N_{ijt}^{\frac{\varepsilon_w - 1}{\varepsilon_w}} dj \right)^{\frac{\varepsilon_w}{\varepsilon_w - 1}} + \left(Z_t - \int_0^1 W_{jt} N_{ijt} dj \right) \quad (3)$$

where W_{jt} represents the wage of worker type j in period t , N_{ijt} is the quantity of type j labor employed by firm i , and N_{it} denotes total labor used by firm i . The elasticity of substitution among labor types is denoted ε_w .

Upon solving Equation (3), we obtain $N_{ijt} = \left(\frac{W_{jt}}{W_{kt}} \right)^{\varepsilon_w} \cdot N_{ikt}$, and subsequently, we can derive the nominal wage for a type j worker in period t by substituting N_{ijt} into Equation (1), as follows:

$$W_t = \left(\int_0^1 W_{jt}^{1 - \varepsilon_w} dj \right)^{\frac{1}{1 - \varepsilon_w}} \quad (4)$$

By utilizing equation $N_{ijt} = \left(\frac{W_{jt}}{W_{kt}} \right)^{\varepsilon_w} \cdot N_{ikt}$ and Equation (4), we can determine the labor demand for firm i , as follows:

$$N_{ijt} = \left(\frac{W_{jt}}{W_t} \right)^{-\varepsilon_w} N_{it} \tag{5}$$

Next, given this optimal labor vector, firms must set prices to maximize profit. We assume a Cobb–Douglas production function like $Y_{it} = A_t N_{it}^{1-\alpha}$, where Y_{it} is the output produced by firm i , A_t represents the economy’s technology level, and α represents the proportion of the production process allocated to the respective production factor. In this economy, labor is used at a proportion of $1 - \alpha$ in the production process. The profit maximization process unfolds as follows:

$$\max_{P_t^*} \left\{ \sum_{k=0}^{\infty} \theta_p^k E_t \left[Q_{t,t+k} \left(P_t^* Y_{it+k|t} - TC_{it+k|t}^n \left(Y_{it+k|t} \right) \right) \right] \right\} \tag{6}$$

$$\text{s.t. } Y_{it+k|t} = \left(\frac{P_t^*}{P_{t+k}} \right)^{-\varepsilon_p} C_{t+k} \tag{7}$$

The parameter θ_p represents the price stickiness in the goods market, while ε_p denotes the elasticity of substitution between consumption goods. The term $Q_{t,t+k}$ refers to the stochastic discount factor for nominal payoffs in period $t + k$, and P_t^* represents the optimal price that is renewed to maximize the current market value of the profits generated while that price remains effective.

The term $Y_{it+k|t}$ denotes the output in period $t + k$ for a firm that last set its price in period t , and TC^n represents the total cost in period $t + k$ as a function of this output.

By solving this problem, we can determine the optimal price P_t^* as follows:

$$P_t^* = \frac{\varepsilon_p}{(\varepsilon_p - 1)(1 - \lambda)} \frac{E_t \sum_{k=0}^{\infty} \theta_p^k \beta^k C_{t+k}^{1-\sigma} P_{t+k}^{\varepsilon_p} MC_{t+k|t}^r}{E_t \sum_{k=0}^{\infty} \theta_p^k \beta^k C_{t+k}^{1-\sigma} P_{t+k}^{\varepsilon_p - 1}} \tag{8}$$

where $MC_{t+k|t}^r$ represents the real marginal cost at time $t + k$, as forecasted at time t . After log-linearization, we can express Equation (8) as follows:

$$\hat{\pi}_t^p = \beta E_t \hat{\pi}_{t+1}^p + \lambda_p \hat{w}_t + \kappa_p \hat{y}_t - \lambda_p \frac{1}{1 - \alpha} \hat{a}_t \tag{9}$$

$$\left(\because \lambda_p = \frac{(1 - \theta\beta)}{\theta} \cdot \frac{(1 - \alpha)}{1 - \alpha + \alpha\varepsilon_p}, \kappa_p = \frac{\alpha}{1 - \alpha} \cdot \lambda_p \right)$$

We define $\hat{p}_t^* - \hat{p}_{t-1}$ as π_t , and the hat symbol denotes the linear version of the variables and \hat{a}_t is the log-linearized expression of the technology level A_t .

4.2. Household Sector

We divide households into the following two agents: unrestricted households, represented by the share of λ , who can save their money; and rule-of-thumb households, represented by the share of $(1 - \lambda)$, who cannot save their money. We assume that unconstrained households maximize their inter-temporal utility function while maintaining a lifetime budget constraint. Conversely, ROT households (rule-of-thumb or hand-to-mouth) consume all their resources in each period.

4.2.1. Unrestricted Household

Unrestricted households (represented by the share of λ) maximize their lifetime utility while discounting the future with a factor $\beta \in (0, 1)$. The subscript “ s ” is used to distinguish them from restricted households.

$$\max_{C_{t,s}, N_{t,s}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t u(C_{t,s}, N_{t,s}) \right\} \tag{10}$$

$$\text{s.t.} \int_0^1 P_t C_{t,s} + Q_t B_{t,s} \leq B_{t-1,s} + W_t N_{t,s} + T_t \tag{11}$$

where $C_{t,s}$ is the sum of consumption of all goods i , it is given by $C_{jt} \equiv \left(\int_0^1 C_{ijt}^{\frac{\varepsilon_p - 1}{\varepsilon_p}} di \right)^{\frac{\varepsilon_p}{\varepsilon_p - 1}}$, Here, j represents each household. Therefore, C_{ijt} refers to the quantity of good i consumed by household j , N_{jt} denote labor. In this setup, B_{t-1} is the number of bonds purchased in the last period or it can be expressed as savings in the last period, and $Q_t \equiv \frac{1}{1+i_t}$ is the price per bond bought or saved today. We assume the specified utility function follows a specific form: $u(C_{t,s}, N_{t,s}) = \frac{C_{t,s}^{1-\sigma}}{1-\sigma} - \frac{N_{t,s}^{1+\varphi}}{1+\varphi}$. Here, σ and φ denote inter-temporal elasticity of substitution and the inverse of Frisch elasticity of labor supply, respectively.

By utilizing Equations (10) and (11) to solve the utility maximization problem for unrestricted households, we can obtain the first-order conditions (F.O.C.s) as follows:

$$1 = \beta Q_t^{-1} E_t \left\{ \left(\frac{C_{t+1,s}}{C_{t,s}} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right\} \tag{12}$$

$$C_{t,s}^\sigma N_{t,s}^\varphi = \frac{W_t}{P_t} \tag{13}$$

Log-linearization yields the following:

$$\widehat{c}_{t,s} = E_t \widehat{c}_{t+1,s} - \frac{1}{\sigma} (\widehat{i}_t - E_t \widehat{\pi}_{t+1}) \tag{14}$$

$$\sigma \widehat{c}_{t,s} + \varphi \widehat{n}_{t,s} = \widehat{\omega}_t \tag{15}$$

where \widehat{i}_t is the log-linearized form of Q_t . ω_t indicates a real wage $\frac{W_t}{P_t}$ and $\widehat{\omega}_t$ denotes a linear form of real wage.

4.2.2. Rule-of-Thumb Household

ROT households (represented by the share of $1 - \lambda$) also maximize their lifetime utility like unrestricted households. However, their budget constraint differs because they do not consider inter-temporal problems. The subscript “ h ” denotes restricted households. Thus, restricted households face a trade-off problem as follows,

$$\max_{C_{t,h}, N_{t,h}} E_0 \left\{ \sum_{t=0}^{\infty} \beta^t u(C_{t,h}, N_{t,h}) \right\} \tag{16}$$

$$\text{s.t.} \int_0^1 P_t C_{t,h} \leq W_t N_{t,h} + T_t \tag{17}$$

Due to their inability to maximize consumption inter-temporally, we can deduce the following:

$$C_{t,h} = \frac{1}{P_t} (W_t N_{t,h} + T_t) \tag{18}$$

$$C_{t,h}^\sigma N_{t,h}^\varphi = \frac{W_{t,h}}{P_t} \tag{19}$$

Log-linearized yields are as follows:

$$\widehat{c}_{t,h} = \widehat{\omega}_t + \widehat{n}_{t,h} \tag{20}$$

$$\sigma \widehat{c}_{t,h} + \varphi \widehat{n}_{t,h} = \widehat{\omega}_t \tag{21}$$

4.2.3. Optimal Wage Selection by Households

As we can observe in the preceding section, household j seeks to maximize lifetime utility, and we assumed that households can set their wage. This means that households have some monopoly power in the labor market given by $\varepsilon_w > 1$. A fixed proportion θ_w of households cannot adjust their wages from the previous period. In contrast, the remaining $1 - \theta_w$ households have the flexibility to reoptimize the price of their labor services. Through this optimization process, households may adjust their wages based on prevailing economic conditions, expectations of future wage changes, and the overall economic environment. Thus, if a household intends to reset its wage in period t , it will choose W_t^* to maximize the following:

$$E_t \left\{ \sum_{k=0}^{\infty} (\beta\theta_w)^k u(C_{t+k|t}, N_{t+k|t}) \right\} \tag{22}$$

$$\text{s.t. } P_{t+k}C_{t+k|t} + E_{t+k}Q_{t+k,t+k+1}D_{t+k+1|t} \leq D_{t+k|t} + W_t^*N_{t+k|t} + T_{t+k} \tag{23}$$

Flow budget constraints are effective while W_t^* remains in place. $C_{t+k|t}$ and $N_{t+k|t}$ indicate consumption and labor at time $t + k$ for a household that last set the wage at time t , respectively. Although wage rigidity is possible, households will eventually reset their optimal wage in the long run since $\beta\theta_w < 1$. $E_{t+k}Q_{t+k,t+k+1}D_{t+k+1|t}$ represents the market values of bonds purchased or savings made during period $t + k$, evaluated as the same period $t + k$, with a random payoff $D_{t+k+1|t}$. By solving this problem, we can derive the equation for the optimal wage as follows:

$$w_t^* = \frac{\varepsilon_w}{(\varepsilon_w - 1)} \frac{E_t \sum_{k=0}^{\infty} (\beta\theta_w)^k W_{t+k}^{\varepsilon_w} N_{t+k} \cdot u_c(C_{t+k|t}, N_{t+k|t}) MRS_{t+k|t}}{E_t \sum_{k=0}^{\infty} (\beta\theta_w)^k W_{t+k}^{\varepsilon_w} N_{t+k} \cdot u_c(C_{t+k|t}, N_{t+k|t}) \frac{N_{t+k}}{P_{t+k}}} \tag{24}$$

After log-linearization, we can obtain the following:

$$\hat{\pi}_t^w = \beta E_t \hat{\pi}_{t+1}^w - \lambda_w \hat{w}_t + \kappa_w \hat{y}_t - \lambda_w \frac{\varphi}{1 - \alpha} \hat{a}_t \tag{25}$$

where $\lambda_w = \frac{(1-\theta_w)(1-\beta\theta_w)}{\theta_w(1+\varepsilon_w\varphi)}$ and $\kappa_w = \lambda_w \cdot \frac{(\varphi+\sigma(1-\alpha))}{1-\alpha}$. And we can also derive the dynamic equation for real wages as follows:

$$\hat{w}_t = \hat{w}_{t-1} + \hat{\pi}_t^w - \hat{\pi}_t^p \tag{26}$$

By analyzing Equation (26), we observe that wage inflation positively correlates with future wage inflation and current output, but it exhibits negative relationships with wage level and technology level. Additionally, we can deduce that the real wage level is related to the difference between wage and price inflation.

4.3. Market Equilibrium and Shock Process

In the labor market, equilibrium is achieved when the labor demand from final goods firms, denoted as $N_t = \int N_{it} di$, equals the labor services workers supply. Similarly, in the goods market, equilibrium is attained when the demand for products by consumers, represented as $Y_t = \int Y_{it} di$, matches the product supply by firms. As the previous section states, our model does not include capital, so the equality $Y_t = C_t$ holds true. Additionally, we assume an exogenous technology shock is present in our analysis. Thus, a technology improvement \hat{a}_t follows an AR(1) stochastic process, where the persistence of a technology shock $\rho_a \in [0, 1]$.

$$\hat{a}_t = \rho_a \hat{a}_{t-1} + \varepsilon_t^a \tag{27}$$

4.4. Aggregation

The aggregate level of any household-specific variable $\widehat{x}_{i,t}$, where $i \in [s, h]$, is determined by the weighted measure of $\widehat{x}_{t,h}$ and $\widehat{x}_{t,s}$, with λ representing the ratio of the rule-of-thumb households who do not save, and $(1 - \lambda)$ representing the ratio of unrestricted households who can save their income. Thus, it can be expressed as $\widehat{x}_t = \lambda \widehat{x}_{t,h} + (1 - \lambda) \widehat{x}_{t,s}$.

$$C_t = \lambda C_{t,h} + (1 - \lambda) C_{t,s} \tag{28}$$

$$N_t = \lambda N_{t,h} + (1 - \lambda) N_{t,s} \tag{29}$$

Utilizing the assumptions employed, Table 1 presents the log-linearized equations essential for analyzing the impulse response function⁵. Employing these linear functions and their associated parameters, we proceed with implementing the Schur decomposition.

Table 1. Log-linearized equations.

| Name | System Equations |
|---------------------|---|
| Production | $\widehat{y}_t = \widehat{a}_t + (1 - \alpha) \widehat{n}_t$ |
| Resource constraint | $\widehat{y}_t = \widehat{c}_t = \lambda \widehat{c}_{t,h} + (1 - \lambda) \widehat{c}_{t,s}$ |
| Labor demand | $\widehat{n}_t = \frac{1}{1-\alpha} (\widehat{y}_t - \widehat{a}_t) = \lambda \widehat{n}_{t,h} + (1 - \lambda) \widehat{n}_{t,s}$ |
| Phillips curve | $\widehat{\pi}_t^p = \beta E_t \widehat{\pi}_{t+1}^p + \lambda_p \widehat{\omega}_t + \kappa_p \widehat{y}_t - \lambda_p \frac{1}{1-\alpha} \widehat{a}_t$ |
| Wage Phillips curve | $\widehat{\pi}_t^w = \beta E_t \widehat{\pi}_{t+1}^w - \lambda_w \widehat{\omega}_t + \kappa_w \widehat{y}_t - \lambda_w \frac{\varphi}{1-\alpha} \widehat{a}_t$ |
| Real wage | $\widehat{\omega}_t = \widehat{\omega}_{t-1} + \widehat{\pi}_t^w - \widehat{\pi}_t^p$ |
| Output gap | $\widetilde{y}_t = E_t \widetilde{y}_{t+1} - \frac{(1-\lambda)}{\sigma(1-\lambda\chi)} (\widehat{a}_t - E_t \widehat{\pi}_{t+1}) + \iota(\rho_a - 1) \widehat{a}_t$ |
| Technology process | $\widehat{a}_t = \rho_a \widehat{a}_{t-1} + \varepsilon_t^a$ |

5. Calibration and Simulation Result

5.1. Calibrated Parameters

In this section, we will examine the impact of technological change using the model we developed. The parameter values in this study are calibrated using prior research and real-world economic data. We chose the calibration method for three key reasons. First, this study focuses on analyzing the employment response to technology shocks under different savings rates rather than investigating fluctuations in macroeconomic variables of a specific country, which is why we opted not to estimate parameters using Bayesian methods. Second, calibration provides a quicker and more efficient approach despite being less accurate than estimation. Our goal is to compare savings rate differences in response to technology shocks rather than to create a precise simulation of the real economy. Finally, the results and policy mechanisms of the DSGE model rely more on the initial model structure than on slight differences in parameter values, making calibration a more appropriate choice for this analysis. To simulate the effect of a technology shock, we set the parameters according to the existing literature, as outlined in Table 2. [Smets and Wouters \(2005\)](#) assumed a 1 percent annual discount rate, following a gamma distribution. They estimated the posterior distribution for the discount factor to be 0.65 using the Metropolis–Hastings algorithm. However, most studies took the range of discount factor as 0.95–0.99, and this indicates a steady-state real interest rate of approximately 4 percent. As shown in Table 2, we set the discount factor at $\beta = 0.99$, which is the standard value based on previous analyses ([Galí and Rabanal 2004](#); [Galí 2015](#); [Mandelman and Zanetti 2014](#)). The elasticity of consumption and labor on utility falls within a range denoted as $\sigma \in [1.16, 1.59]$ and $\varphi \in [0.91, 2.78]$, respectively, because in most previous studies, modeling assumes a neutral substitution relationship between consumption and labor to achieve equilibrium, so the elasticity of substitution between consumption and leisure is typically set to 1 to maintain a constant trade-off between the two. Thus, following [Smets and Wouters \(2005\)](#),

in this study, we set them at 1 and 1, respectively. To specify the value of the capital share, we rely on long-term historical averages and set $\alpha = 0.33$. The monetary policy rule parameters are derived from a standard Taylor rule, where $\phi_\pi = 1.5$ and $\phi_y = 0$ represent the long-run reactions to inflation and the output gap, respectively. Moreover, ϕ_w is set to 0. The persistence of technology improvement is determined by assuming it follows a normal distribution with a mean of 0.9 and a standard deviation of 0.1. Technology shocks significantly impact productivity, and in this model, firms and households can set product and wage prices. Since the consumption space varies according to the savings rate, we set the price and wage elasticity to 6 to model a situation where demand is highly responsive to changes in prices or wages. This setting allows for convenient analysis of demand responses to changes in productivity and savings rates while reflecting the flexibility of the demand and labor markets. Additionally, price and wage stickiness are set at 2/3 and 3/4, respectively. This is based on findings from Altig et al. (2011) and Erceg et al. (2000), which have shown that prices and wages do not frequently adjust in real-world economies. And finally, we vary the value of λ , representing the ratio of rule-of-thumb households, from 0 to 4 to examine the effects caused by changes in the ratio of rule-of-thumb households in response to a technology shock. This is because the actual savings rates observed in the empirical analysis of the two economies (the United States and China) show that the U.S. has a savings rate of around 3–4%, while China's is approximately 40%. To replicate a similar scenario, the proportion of rule-of-thumb households was set accordingly in the model.

Table 2. Parameter values.

| Parameter | Descriptions | Value | Source |
|-----------------|--|----------|--|
| β | Discount factor | 0.99 | Galí (2015) |
| σ | Elasticity of consumption on utility | 1 | Smets and Wouters (2005) |
| α | Capital ratio in product function | 1/3 | See text |
| φ | Elasticity of labor on the utility | 1 | Smets and Wouters (2005) |
| θ_p | Probability of being unable to change the price | 2/3 | Erceg et al. (2000); Altig et al. (2011) |
| θ_w | Probability of being unable to change the wage | 3/4 | Erceg et al. (2000); Altig et al. (2011) |
| ϕ_y | Federal funds rate (Output Gap Coefficient) | 0 | See text |
| ϕ_p | Federal funds rate (Inflation Response Coefficient) | 1.5 | Galí (2015) |
| ϕ_w | Federal funds rate (Wage Inflation Response Coefficient) | 0 | See text |
| ρ_a | Persistency of technology shocks | 0.9 | Galí (2015) |
| ε_p | Price elasticity of demand | 6 | See text |
| ε_w | Wage elasticity of demand | 6 | See text |
| λ | Constant share of hand-to-mouth households | [0, 0.4] | See text |

5.2. Impulse Response Function

We will examine the simulation results for the model mentioned above and compare them with the analysis based on actual data from two economies (the United States and China).

As shown in Figure 4, we can observe varying increases in output in response to a technology shock for the two different economies, each characterized by a distinct ratio of the rule of thumb, and also observe a positive short-term response of employment, which later turns negative. The magnitude of macroeconomic variables' response to technology shocks varies as the rule-of-thumb ratio differs. For the former reason, it is related to price and wage inflation, which affect fundamental wage changes. Despite our assumption of nominal wage stickiness, however, as shown in Equation (26), real wages are influenced by the disparity between wage and price inflation. The simulation results indicate that decreases in price inflation exceed wage inflation, leading to an increase in real wages. But, as price inflation returns to equilibrium faster than wage inflation, the growth rate in real wages diminishes, resulting in a gradual return of employment to equilibrium. And its effect is more significant in economies with a higher rule-of-thumb ratio. If a

positive shock occurs, economies with a higher rule-of-thumb ratio experience a more substantial positive impact, and vice versa. This phenomenon can be attributed to the rule of thumb of household characteristics. Since the rule-of-thumb household does not save and spends all of its income on consumption, a higher ratio of the rule of thumb in households leads to more significant consumption. As a result, production experiences a considerable increase, leading to a substantial rise in employment. Nevertheless, because rule-of-thumb households are less prepared for future uncertainties, adverse external shocks lead to a more pronounced economic downturn than other economies. The differences in savings rates cause variations in output, employment, and wage responses to technology shocks, yielding outcomes that diverge from the simple employment increases or decreases noted in previous studies. This suggests that the impact of technology shocks on employment is more nuanced and complex than previously thought.

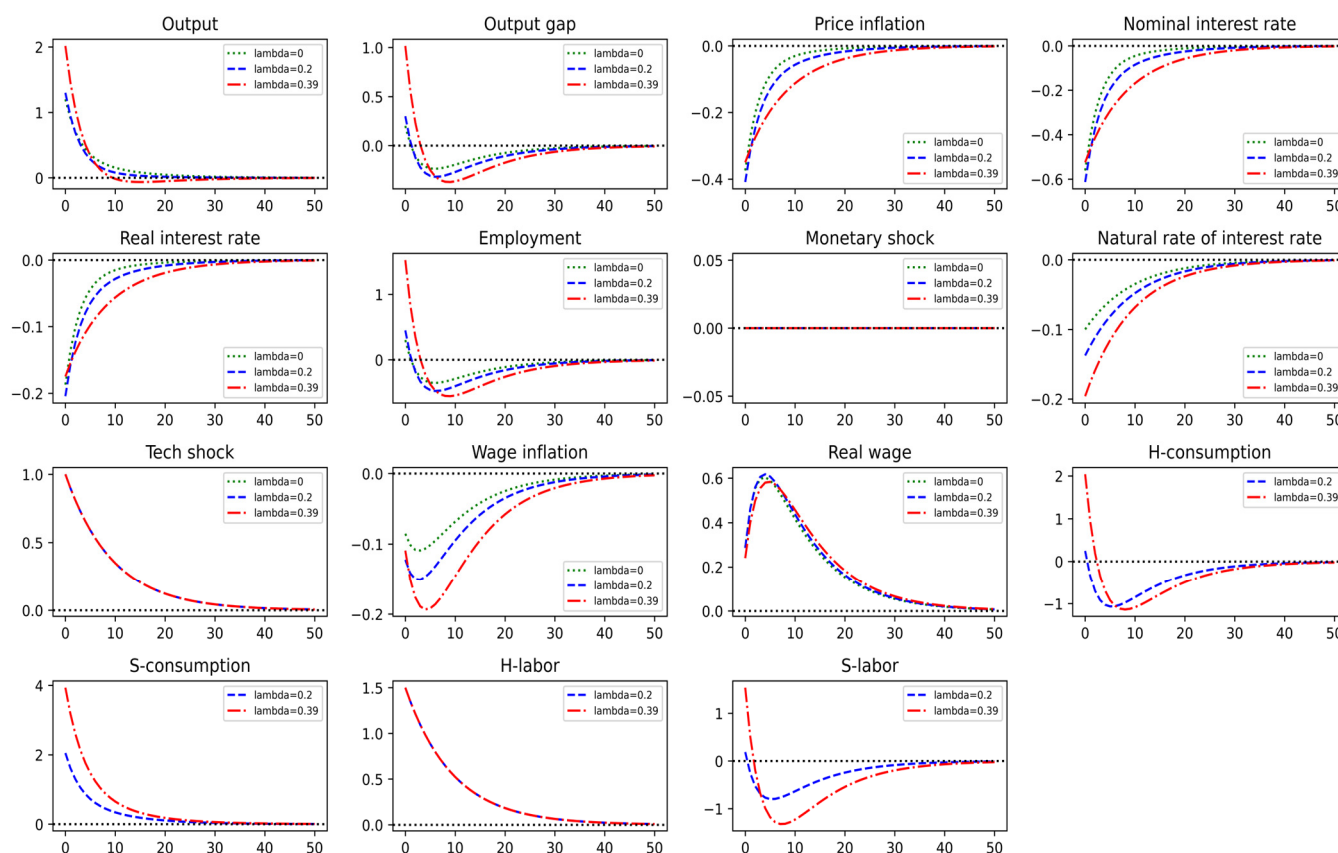


Figure 4. IRF (Impulse Response Function) of variables to technology shock.

Another noteworthy point is the differing responses of restricted and unrestricted agents to technology shocks. In restricted households, we observed a substitution effect, wherein an increase in real wage growth led to reduced consumption and increased labor supply. In contrast, decreased real wage growth increased consumption and reduced labor supply. On the other hand, we observed an income effect in unrestricted households, where they reduced the labor supply when the real wage growth rate increased, and the labor supply increased when the real wage growth decreased. This conclusion aligns with the empirical research results presented by Saijo (2019), who also observed that when faced with a technology shock, restricted households exhibit a decrease in labor supply, while unrestricted households demonstrate an increase in labor supply, as indicated by data from a consumer expenditure survey. Hence, this study has contributed in the following ways. Firstly, it has been confirmed that a positive external shock exerts a more pronounced influence during economic downturns characterized by a higher share of the rule of thumb. Secondly, through an empirical analysis employing TFP data instead of labor productivity

and utilizing employment data derived from hourly labor, we have established that a technology shock leads to short-term employment growth, followed by medium-term contraction, which ultimately stabilizes in the long term. This phenomenon is interpreted as a manifestation of employment fluctuations driven by changes in real wages resulting from variations in prices and wages within the model. Thirdly, notable disparities in consumption and labor activity responses were observed between households that save and those that do not, particularly in the context of increasing real wages.

6. Conclusions and Policy Recommendations

In today's world, where the pace and scale of technological innovation are far greater than ever before, and technological advancements are quickly integrated into everyday life, understanding the impact of technology on macroeconomic variables has become critically important. Among these, the effects of technology on employment have produced mixed results in previous studies, with many showing varying outcomes and even conflicting directions. The purpose of this study is to explore the reasons behind these discrepancies and to understand how technology impacts employment through key mediating factors. To achieve this, this study examines how technology influences productivity and, through changes in output, how it interacts with consumption and savings behavior to affect employment. This research identifies several key findings.

First, in the short term, employment increases following a positive technology shock. This is largely due to real wage growth driven by slower price inflation relative to wage inflation. This result aligns with much of the existing empirical and theoretical literature. For instance, the studies by [Mumtaz and Zanetti \(2012\)](#) and [Christiano et al. \(2003\)](#) found similar short-term employment increases after a technology shock, consistent with the RBC model.

Second, the positive employment response diminishes over the mid-term and eventually turns negative. This decline can be attributed to decelerating real wage growth as price inflation catches up with wage inflation. This finding aligns more with New Keynesian models, where wage and price rigidities cause temporary labor market disruptions, as discussed by [Galí \(1999\)](#) and [Francis and Ramey \(2005\)](#). The results also echo the findings of [Basu et al. \(2006\)](#), who observed that technology shocks reduce employment in sectors affected by real wage adjustments in the short run.

Third, the savings rate significantly shapes the magnitude of the impact of technology shock. This is a notable contribution to the literature, as many previous studies have yet to emphasize household savings rates as a determinant of employment fluctuations.

Fourth, the study highlights that restricted (rule-of-thumb) and unrestricted households respond differently to technology shocks. Restricted households tend to increase their consumption and labor supply, while unrestricted households reduce their labor supply as wages rise. This finding contributes to the ongoing discussion about heterogeneous household behavior in response to technology shocks, reflecting similar conclusions drawn by [Autor et al. \(2003\)](#) and [Saijo \(2019\)](#), who examined how technological change affects households differently based on their consumption and savings patterns. The observed differences between restricted and unrestricted households provide new insights into how savings rates and labor supply decisions influence employment dynamics.

Furthermore, this study has identified that while technology shocks initially have a positive impact on employment, there is a tendency for employment to decline in the mid-to-long term. To address this issue, several policy solutions are proposed. This negative response is largely due to rising real wages caused by price and wage rigidity. Specifically, restricted (rule-of-thumb) households experience limited changes in labor supply, while unrestricted households reduce their labor supply as wages rise, leading to an overall decline in employment over time. To mitigate this long-term employment decline, policymakers can implement several key strategies. First, strengthening labor market flexibility is crucial, as wage rigidity is one of the primary drivers of employment reduction following technology shocks. When wages do not adjust in line with technological progress, real wages

rise, which in turn reduces labor demand. Increasing wage flexibility could help ease this long-term employment decline. This could be achieved through reforms to labor market institutions, such as allowing more flexible wage negotiations, loosening legal restrictions on wage adjustments, or restructuring the bargaining processes between employers and workers. Additionally, governments could offer incentives to encourage businesses to adopt more flexible wage policies, such as tax benefits for firms that implement wage structures linked to productivity.

In addition, enhancing education and retraining programs is essential, as technological shocks often bring structural changes to the labor market, resulting in job displacement. Investing in education and retraining programs, particularly for workers in industries at risk of automation or technological displacement, is vital. Governments should support reskilling initiatives that allow workers in declining sectors to acquire new skills and transition into growing industries. Additionally, it is important to promote digital and IT skills, as much of today's technological advancement occurs in these fields. Narrowing the digital skills gap will enable more workers to take advantage of new opportunities created by technological change. Equally important is the strengthening of social safety nets, particularly for workers in industries with high wage rigidity or low labor market flexibility, who are at greater risk of job loss due to technological changes. Expanding unemployment benefits and income support programs will help workers maintain a basic standard of living while they search for new employment. Additionally, discussions around implementing basic income could be important, as ongoing automation and technological advancements may continue to impact employment levels over the long term. Basic income could serve as a tool for equitably distributing the benefits of technological progress.

This study models heterogeneity primarily through variations in savings rates. In future research, incorporating additional dimensions of heterogeneity, such as household debt, as well as integrating capital and multiple production agents (e.g., housing), could provide a more detailed analysis of how technology shocks impact productivity and employment through capital-related channels. While this study centers on the immediate employment effects and simplifies the model by excluding capital, we believe this approach offers clear insights into the interactions between consumption, savings, and labor dynamics.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/economics12110303/s1>. An Online Appendix for this article can be found at *Economics* online.

Author Contributions: Conceptualization, J.H.; Data curation, K.H. and J.H.; Investigation, K.H. and J.H.; Methodology, K.H.; Writing—original draft, K.H. and J.H.; Writing—review & editing, K.H. and J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

- ¹ According to their research, technological improvement plays a role in increasing employment in the mid to long run, using a perfectly competitive flexible-price RBC model with firms' entry and exit. They also emphasize that the number of firms serves as a critical propagation mechanism of aggregate technology shocks.
- ² This result contrasts with other models that incorporate labor market frictions and predict a decrease in employment following a technology shock.
- ³ Furthermore, they obtain the same result by establishing a model that assumes a Leontief function with habit formation in consumption, even in the absence of price rigidity. This indicates that employment is countercyclical in response to a positive technology shock. This phenomenon seems to be consistent in other countries as well.

- ⁴ Moreover, technology shock yields a decrease in output when the degree of complementarity is more substantial. They suggest that if the degree of substitution between domestic and foreign products is low, it becomes challenging to substitute foreign products even if the production increases due to the increased productivity of domestic products. In this situation, they have no choice but to accept unfavorable terms of trade for market clearing, which can cause a decrease in employment. Although they succeed in finding a negative relationship, the fact that employment is counter-cyclical implies that technology improvement is no longer the main driver of fluctuations.
- ⁵ See the Supplementary Material for a more comprehensive derivation of the log-linearized equations utilized in this model.

References

- Alexopoulos, Michelle. 2011. Read all about it!! What happens following a technology shock? *American Economic Review* 101: 1144–79. [\[CrossRef\]](#)
- Altig, David, Lawrence J. Christiano, Martin Eichenbaum, and Jesper Linde. 2011. Firm-specific capital, nominal rigidities and the business cycle. *Review of Economic Dynamics* 14: 225–47. [\[CrossRef\]](#)
- Autor, David H., Frank Levy, and Richard J. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics* 118: 1279–333. [\[CrossRef\]](#)
- Barnichon, Regis. 2010. Productivity and unemployment over the business cycle. *Journal of Monetary Economics* 57: 1013–25. [\[CrossRef\]](#)
- Basu, Susanto, John G. Fernald, and Miles S. Kimball. 2006. Are technology improvements contractionary? *American Economic Review* 96: 1418–48. [\[CrossRef\]](#)
- Bertinelli, Luisito, Olivier Cardi, and Romain Restout. 2022. Labor market effects of technology shocks biased toward the traded sector. *Journal of International Economics* 138: 103645. [\[CrossRef\]](#)
- Blanchard, Olivier, and Jordi Galí. 2007. Real wage rigidities and the New Keynesian model. *Journal of Money, Credit and Banking* 39: 35–65. [\[CrossRef\]](#)
- Blanchard, Olivier, and Jordi Galí. 2010. Labor markets and monetary policy: A new keynesian model with unemployment. *American economic journal: Macroeconomics* 2: 1–30. [\[CrossRef\]](#)
- Chang, Yongsung, and Jay H. Hong. 2006. Do technological improvements in the manufacturing sector raise or lower employment? *American Economic Review* 96: 352–68. [\[CrossRef\]](#)
- Chang, Yongsung, Andreas Hornstein, and Pierre-Daniel G. Sarte. 2006. *Understanding How Employment Responds to Productivity Shocks in a Model with Inventories*. Richmond: Federal Reserve Bank of Richmond. [\[CrossRef\]](#)
- Choi, Sangyup, and Myungkyu Shim. 2022. Labor Market Dynamics under Technology Shocks: The Role of Subsistence Consumption. *Macroeconomic Dynamics* 26: 1965–93. [\[CrossRef\]](#)
- Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy* 113: 1–45. [\[CrossRef\]](#)
- Christiano, Lawrence J., Martin S. Eichenbaum, and Robert J. Vigfusson. 2003. *What Happens After a Technology Shock?* Cambridge, MA: National Bureau of Economic Research.
- Collard, Fabrice, and Harris Dellas. 2004. Supply shocks and employment in an open economy. *Economics Letters* 82: 231–37. [\[CrossRef\]](#)
- Collard, Fabrice, and Harris Dellas. 2007. Technology shocks and employment. *The Economic Journal* 117: 1436–59. [\[CrossRef\]](#)
- Dupaigne, Martial, Patrick Fève, and Julien Matheron. 2005. *Technology Shock and Employment: Do We Really Need DSGE Models with a Fall in Hours?* Paris: Banque de France. [\[CrossRef\]](#)
- Erceg, Christopher J., Dale W. Henderson, and Andrew T. Levin. 2000. Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics* 46: 281–313. [\[CrossRef\]](#)
- Francis, Neville, and Valerie A. Ramey. 2005. Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. *Journal of Monetary Economics* 52: 1379–99. [\[CrossRef\]](#)
- Galí, Jordi. 1999. Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review* 89: 249–71. [\[CrossRef\]](#)
- Galí, Jordi. 2015. *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications*, 2nd ed. Economics Books. Princeton: Princeton University Press.
- Galí, Jordi, and Pau Rabanal. 2004. Technology shocks and aggregate fluctuations: How well does the real business cycle model fit postwar US data? *NBER Macroeconomics Annual* 19: 225–88. [\[CrossRef\]](#)
- Guvenen, Fatih. 2011. *Macroeconomics with Heterogeneity: A Practical Guide*. Cambridge, MA: National Bureau of Economic Research. [\[CrossRef\]](#)
- Hamilton, Kirk. 2006. *Where Is the Wealth of Nations?: Measuring Capital for the 21st Century*. World Bank Publications. Washington, DC: World Bank.
- Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. 2018. Monetary policy according to HANK. *American Economic Review* 108: 697–743. [\[CrossRef\]](#)
- Kendrick, John. 1976. *The Formation and Stocks of Total Capital*. Columbia: National Bureau of Economic Research. Columbia: Columbia University Press.
- Kim, Jung-Wook, and Hyunbae Chun. 2011. Technology Shocks and Employment: Evidence from US Firm-Level Data. *The BE Journal of Macroeconomics* 11: 1–23. [\[CrossRef\]](#)

- Kydland, Finn E., and Edward C. Prescott. 1977. Rules rather than discretion: The inconsistency of optimal plans. *Journal of Political Economy* 85: 473–91. [\[CrossRef\]](#)
- Kydland, Finn E., and Edward C. Prescott. 1982. Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society* 50: 1345–70. [\[CrossRef\]](#)
- Lucas, Robert E., Jr., and Leonard A. Rapping. 1969. Real wages, employment, and inflation. *Journal of Political Economy* 77: 721–54. [\[CrossRef\]](#)
- Malley, Jim, and V. Anton Muscatelli. 1997. Productivity shocks and employment: Evidence from US industrial data. *Economics Letters* 57: 97–105. [\[CrossRef\]](#)
- Mandelman, Federico S., and Francesco Zanetti. 2014. Flexible prices, labor market frictions and the response of employment to technology shocks. *Labour Economics* 26: 94–102. [\[CrossRef\]](#)
- McCallum, Bennett T., and Edward Nelson. 1999. Performance of operational policy rules in an estimated semiclassical structural model. In *Monetary Policy Rules*. Chicago: University of Chicago Press.
- Mnif, Sirine, Chiraz Feki, and Ines Abdelkafi. 2018. Effects of technological shock on employment: Application of structural approach VECM. *Journal of the Knowledge Economy* 9: 1138–53. [\[CrossRef\]](#)
- Mumtaz, Haroon, and Francesco Zanetti. 2012. Neutral technology shocks and the dynamics of labor input: Results from an agnostic identification. *International Economic Review* 53: 235–54. [\[CrossRef\]](#)
- Riggi, Marianna, and Massimiliano Tancioni. 2010. Nominal vs real wage rigidities in New Keynesian models with hiring costs: A Bayesian evaluation. *Journal of Economic Dynamics and Control* 34: 1305–24. [\[CrossRef\]](#)
- Saijo, Hikaru. 2019. Technology shocks and hours revisited: Evidence from household data. *Review of Economic Dynamics* 31: 347–62. [\[CrossRef\]](#)
- Shea, John. 1998. What do technology shocks do? *NBER Macroeconomics Annual* 13: 275–310. [\[CrossRef\]](#)
- Smets, Frank, and Raf Wouters. 2005. Comparing shocks and frictions in US and euro area business cycles: A Bayesian DSGE approach. *Journal of Applied Econometrics* 20: 161–83. [\[CrossRef\]](#)
- Smets, Frank, and Rafael Wouters. 2007. Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review* 97: 586–606. [\[CrossRef\]](#)
- Wang, Pengfei, and Yi Wen. 2011. Understanding the effects of technology shocks. *Review of Economic Dynamics* 14: 705–24. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.