Three Essays in Macroeconomics

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THREE ESSAYS IN MACROECONOMICS

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This dissertation comprises three chapters, with the first two focusing on the labor market and the third examining the impact of uncertainty on asset prices. These topics are highly relevant to current literature and have significant policy implications.

The primary purpose of the first two chapters is to address the Shimer puzzle, which suggests that technology shocks cannot account for the high variations observed in the labor market. Understanding the underlying sources that can explain this puzzle is crucial as it helps us comprehend factors affecting job creation and the unemployment rate. Moreover, labor market fluctuations play a vital role in predicting business cycles and evaluating interest rates.

Labor market conditions have been emphasized in recent economic policy discussions. They are a key consideration during the process of raising interest rates in 2021 and have been mentioned in every Federal Open Market Committee (FOMC) meeting and public speech since the beginning of 2024 by Federal Reserve Chairman Jerome Powell. Beyond the impact of labor market conditions on monetary policy, research on the labor market also provides insights into other government policies, such as those related to wage rigidities, unemployment benefits, or mismatches between firms and the unemployed.

Given the importance of labor market research and the limitations of previous studies, Chapter One examines the impact of the discount factor in the labor market. We emphasize that this factor can influence both households' decisions and firms' hiring decisions. In Chapter Two, considering that business formation is one of the major driving forces of aggregate fluctuations and that credit constraints limit firms' borrowing capacity to hire, we integrate these two aspects into one real business cycle model. Furthermore, the third chapter is closely related to the preceding two chapters, as variations in the labor market are also a source of uncertainty and both the labor market and asset prices are influenced by monetary policies and business cycles.

In the first chapter, we explore the determinants of co-movements in the labor market and the stock market, moving beyond previous literature focusing on technology shocks. We develop a real business cycle model incorporating labor market frictions. We also employ the Epstein-Zin utility function and convex adjustment costs for capital, standard in the asset pricing literature, to better capture the role of the discount factor. Additional considerations include unemployment benefits and matching efficiency, as well as government spending. To examine the impact of wage rigidities, we compare Nash bargaining and alternative offer bargaining mechanisms. We also examine different ratios of unemployment benefits to wages to address the lack of consensus in the existing literature. Using Bayesian estimation, we quantify the contributions of each source to the variations in the labor market and the stock market. The findings indicate that unemployment benefits are the primary driver of labor market fluctuations, while the discount factor explains most variations in the price-dividend ratio. Our findings also reveal that the impact of these shocks varies depending on the presence of wage rigidities and the ratio of unemployment benefits to wages.

In the second chapter, we integrate credit constraints and firm dynamics into a real business cycle model to explore how these two frictions explain labor market fluctuations. By considering the direct impact of credit constraints on job creation as well as the direct effects of firm dynamics on both job creation and destruction, our study addresses research gaps that have previously focused on analyzing these frictions in isolation. We utilize the enforcement constraint to model credit frictions, while the endogenous number of firms depends on the number of varieties produced. We find that productivity shocks are amplified due to credit frictions and firm dynamics.

In the third chapter, we examine the impact of uncertainty on asset prices using the macroeconomic uncertainty index as a proxy. However, previous literature has focused on investigating these effects in the structural vector autoregressive (VAR) model. Utilizing a structural VAR model to analyze the effects of the uncertainty index is inadequate due to its inability to capture nonlinearity and time-varying variance in the uncertainty index. To address this gap in the literature, we employ a time-varying VAR model with stochastic volatility to determine whether the impacts of uncertainty shocks differ across business cycles and exhibit asymmetric impacts. The findings show adverse effects of uncertainty shocks in both models, with varying magnitudes of rebound and overshoot across different business cycles. Furthermore, the findings do not provide evidence of the asymmetric effects of uncertainty shocks.

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To my past self, my present self, and my future self.

Chapter 1

Discount rates, Business Cycles, and Unemployment: A DSGE Analysis

1.1. Introduction

Exploring the sources of labor market fluctuations has gained more attention in economics, especially after the emergence of the search and matching model based on the seminal work of Merz (1995) and Andolfatto (1996). With search and matching frictions in a real business cycle model, the labor productivity shock is thought to be at the root of the reason accounting for labor market variation; however, existing models are still criticized for failing to replicate labor market moments (Shimer (2005)). This has prompted attempts to find underlying reasons to explain labor market fluctuations, such as Hall (2017), who argues in the context of a partial equilibrium model that discount rates could explain the joint fluctuations in the labor market and asset markets. While the discount factor is extensively researched in the asset pricing literature, its role in explaining labor market volatility has yet to receive much attention. According to Hall (2017), if hiring is viewed as an investment action affected by the discount factor, the present value of hiring is negatively correlated with the discount factor, meaning fewer vacancies will be posted if the discount rate is high. Similar studies are done by Albertini and Poirier (2014), highlighting the significance of the discount factor in explaining labor market variations in a general equilibrium model and Mukoyama (2009).

To address how the labor market and the stock market are correlated, several studies examine the impact of the labor market on asset pricing. Belo et al. (2014) find that firms with higher labor hiring rates have higher future stock returns. Kuehn et al. (2017) show that labor market tightness is a key factor in determining stock returns in a partial equilibrium model. The link is also explored in a general equilibrium model. Some of these studies focus on the explanation of time-varying volatility. For instance, after taking search and matching frictions and firm dynamics into account, Schaal (2017) discovers that a firm's idiosyncratic productivity significantly impacts unemployment fluctuations. Kehoe et al. (2023) find that preferences generating time-varying risk and human capital could explain labor market variations. Kilic and Wachter (2018) show how the probability of an economic disaster affects both the labor market and asset pricing. Moreover, Kuehn et al. (2012) and Bai and Zhang (2022) use labor market frictions to explain financial moments. Although the link between the labor market and the stock market has been extensively studied, some studies, such as Kuehn et al. (2012) and Schaal (2017), fail to consider the role of capital, which is crucial for understanding asset pricing. Furthermore, previous studies are long on the matching moments method and short on Bayesian estimation to explore the other driving forces of joint fluctuations.

Given these concerns, this paper aims to understand whether other possible underlying factors, thoroughly discussed in other studies, drive the joint fluctuations in the labor market and the stock market, and to examine the extent to which these factors contribute to the joint fluctuations in the unemployment rate and stock prices. To address this issue, we build a real business cycle model integrating imperfect competition, recursive utility, physical capital accumulation, and search and matching frictions. Five exogenous shocks are considered, including technology shock, matching efficiency shock, preference shock (known as the discount rate shock), government spending shock, and unemployment benefit shock. To assess the quantitative importance of these shocks, we estimate the model using the Bayesian method based on the work of Smets and Wouters (2007). We also consider the implications of wage rigidities. A large body of literature has examined how wage rigidities contribute to asset pricing and labor market volatility (e.g., Pissarides (2009); Christiano et al. (2016); Hall (2017); Petrosky-Nadeau and Zhang (2021)). Uhlig (2007) shows that wage rigidities generate an equity premium in a DSGE model with external habits. Favilukis and Lin (2016) find that wage rigidities contribute to high equity volatility. To quantify the importance of wage rigidities, we compare the results of two wage determination mechanisms: Nash bargaining and alternative wage bargaining. The former emphasizes that wages are determined by the surplus between firms and workers, while wages in the latter are the result from a continuing bargaining process over a fixed time period, resulting in some wage rigidities.

There is a robust body of literature supporting the five types of shocks chosen in this paper. Albuquerque et al. (2016) and Schorfheide et al. (2018) demonstrate that the time preference shock influences asset pricing moments. Moreover, the rationale for considering the matching efficiency shock stems from the argument that this shock may be connected to the firm's cash flow. Furlanetto and Groshenny (2016) and Zhang (2017) examine the impact of the matching efficiency shock on the unemployment rate, revealing more pronounced effects during recessions. Kuehn et al. (2017) show that the expected stock returns of firms depend on matching efficiency, represented by the different degrees of loadings on labor market tightness. In terms of the government spending shock, previous studies (e.g., Christiano and Eichenbaum (1992); Hansen et al. (1992)), based on the RBC model, show that government spending leads to a fall in consumption due to the negative wealth effect, thus increasing household labor supply. Moreover, the effects of the government spending shock on asset prices vary across different time periods (Dissanayake (2016)). Another strand of studies focuses on how unemployment benefit extensions influence the labor market. Albertini and Poirier (2015) find that benefit extensions increase the unemployment rate outside of the periods with a zero lower bound. Hagedorn et al. (2013) find that benefit extensions cause a fall in job postings and employment. Nakajima (2012) reports that unemployment benefits contribute to 30% of the fluctuations in the unemployment rate after comparing the data before and after 2008. However, no previous evidence supports the impact of benefit extensions on asset pricing. It is worth discussing whether this impact can be achieved through the discount rate channel.

The primary finding of this paper is that the unemployment benefit shock, resembling the labor supply shock, and the discount rate shock are separately the major driving forces of the fluctuations in the labor market, including the unemployment rate and vacancies, and in the price-dividend ratio during the period. Specifically, the unemployment benefit shock accounts for more than 50% of the fluctuations in the labor market, while the discount rate shock contributes over 70% of the fluctuations in the price-dividend ratio in our two wage determination schemes with a 0.42 replacement ratio, the ratio of unemployment benefits to wages. This finding contrasts with the consensus that the discount rate shock or the technology shock primarily affects fluctuations in the labor market. However, wage rigidities modify the effects of both the unemployment benefit shock and the discount rate shock, as their effects are somewhat mitigated by the technology shock. The results, based on our Nash bargaining model without wage rigidities, reveal that the unemployment benefit shock helps explain fluctuations in the unemployment rate and vacancies. In the presence of wage rigidities, the results reveal that the unemployment benefit shock has a persistent effect on the unemployment rate and vacancies. One possible reason is that we assume that at a given wage, households value the unemployment benefits as the monetary value for not working; hence, the unemployment benefit shock can capture the effect of the negative labor supply shock. Unemployment benefits reduce the number of job seekers, making vacancy postings and hiring more expensive, thereby leading to a higher unemployment rate and fewer vacancy postings. Additionally, wage rigidities increase a firm's labor costs, increasing the burden on firms to post fewer vacancies. These two reasons may explain the persistent impact of the unemployment benefit shock on the unemployment rate and vacancies in the presence of wage rigidities. Unlike several studies, we find that the matching efficiency shock has a minor effect on labor market variables. This result contradicts not only the ones emphasizing that the matching efficiency shock affects unemployment fluctuations during recessions, as in Furlanetto and Groshenny (2016) and Zhang (2017), but also Kuehn et al. (2017), showing that the matching efficiency shock affects the expected stock returns. Finally, when we estimate the Nash bargaining model at a replacement ratio of 0.82, the discount rate shock has an important impact and accounts for approximately one-third of the fluctuations in the unemployment rate and vacancies.

The rest of the paper is organized as follows. Section 2 describes the baseline real business cycle model and the two wage mechanisms. Section 3 presents the data and the estimation of the model. Section 4 highlights the quantitative findings of the Nash bargaining model through impulse response, variance decomposition, and historical decomposition. Section 5 concludes. The results for the alternative offer bargaining model and the selective results for the Nash bargaining model with the replacement ratio of 0.82 are presented in the Appendix.

1.2. DSGE model

In this section, we embed monopolistic competition and wage rigidities into the real business cycle model with search and matching frictions. The model provides a theoretical framework for examining the relationship between labor market fluctuations and asset prices. We begin by outlining the optimization problems faced by households and firms. Next, we discuss the labor market, including the framework of Nash bargaining and alternative wage bargaining.

1.2.1. Household

There is a representative household consisting of a continuum of individuals of mass one. The household has Epstein-Zin recursive preferences to maximize its utility over aggregate consumption. Consistent with the utility function in Christiano et al. (2016), the one in our paper has no variables related to the intensive margin of employment. In the budget constraint, unemployment benefits, as one source of household income, provide a channel through which labor market frictions can affect household labor supply. At time t, the household consumes an amount of final goods C_t and purchases stocks of intermediate firms S_{t+1} for future investment by paying the real stock price P_t. Some employed members in the household receive the real wage W_t after selling their labor services N_t to the intermediate firms, while the unemployed receive a fixed unemployment benefit B_t from the government that collects a lump-sum tax τ_t from the household to finance unemployment benefits. The household collects D_t, the real aggregate dividends from holding stock purchased in the last period, as one of its sources of income. The household utility function is given by:

$$J_t^H = \left\{ (1 - \beta\phi_t)\, C_t^{1-\frac{1}{\psi}} + \beta\phi_t \left(\underset{t}{E} \left[J_{t+1}^{H,1-\gamma} \right] \right)^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}, \tag{1.1}$$

where $\beta \in (0,1)$ is the time discount factor, $\gamma \geq 0$ is the relative risk aversion, and $\psi \geq 0$ is the elasticity of intertemporal substitution. The exogenous stochastic process ϕ_t, an intertemporal preference shock, is specified in logs as :

$$log\phi_t = \rho_\phi log\phi_{t-1} + \epsilon_t^\phi, \tag{1.2}$$

where $0 < \rho_\phi < 1$ is the parameter that denotes the persistence of the preference shock ε_t^ϕ, which is assumed to be i.i.d. $N(0,1)$.

The household is subject to the budget constraint:

$$C_t + S_{t+1} P_t^s \leq W_t N_t + (1 - N_t)\, B_t - \tau_t + S_t\,(P_t^s + D_t)\,, \tag{1.3}$$

The discount factor derived from the optimization problem is:

$$M_{t,t+1} = \beta\phi_t \left[\frac{(1 - \beta\phi_{t+1})}{(1 - \beta\phi_t)} \right] \left[\frac{C_{t+1}}{C_t} \right]^{-\frac{1}{\psi}} \left[\frac{J_{t+1}^h}{\underset{t}{E} \left[J_{t+1}^{h,1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right]^{\frac{1}{\psi}-\gamma}, \tag{1.4}$$

The return of stock and the risk-free rate are defined as:

$$R_t = \frac{P_t^s + D_t}{P_{t-1}}, \tag{1.5}$$

$$R_{f,t} = M_{t,t+1}^{-1}. \tag{1.6}$$

where R_t is the stock return and $R_{f,t}$ is the risk-free rate.

1.2.2. Labor market

There is a continuum of mass one workers in the household. At time t, the workers working in the previous period exit from the labor market at a constant exogenous rate $\mu \in (0, 1)$. The number of workers surviving from the separation process is $(1 - \mu) N_{t-1}$. Job-seekers finding a new job after successfully matching with firms, become being productive in the same period t. The number of these new matching job-seekers depends on vacancies, V_t, posted by the firms and the vacancy filling rate, $q(\theta_t)$. The total number of workers evolves according to:

$$N_t = (1 - \mu) N_{t-1} + V_t q(\theta_t), \tag{1.7}$$

The unemployment rate U_t is defined as:

$$U_t = 1 - N_t, \tag{1.8}$$

The number of the unemployed seeking new jobs at the beginning of each period is defined as:

$$u_t = 1 - (1 - \mu) N_{t-1}, \tag{1.9}$$

Note that the standard search and matching model assumes a frictional labor market, and the matching function follows the Cobb-Douglas function is given by:

$$m\left(u_t, V_t\right) = \epsilon_t^M m_0 V_t^{1-\xi} u_t^{\xi}, \tag{1.10}$$

where m_0 is the scale parameter that denotes the aggregate matching efficiency, $\xi \in (0,1)$ is the matching elasticity, and V_t is the number of vacancies posted by firms. ϵ_t^M is an exogenous stochastic process that determines the matching process's efficiency. The stochastic process for matching efficiency in logs, $log\left(\epsilon_t^M\right)$, is:

$$log\epsilon_t^M = \rho_{\epsilon^M} log\epsilon_{t-1}^M + \epsilon_t^{\epsilon^M}, \tag{1.11}$$

where $0 < \rho_{\epsilon^M} < 1$ is the parameter that denotes the persistence of the matching efficiency shock $\epsilon_t^{\epsilon^M}$, which is assumed to be i.i.d. $N(0,1)$.

The probability of a job seeker finding a job is defined as:

$$f\left(\theta_t\right) \equiv \frac{m\left(u_t, V_t\right)}{u_t} = \frac{\epsilon_t^M m_0 V_t^{1-\xi} u_t^{\xi}}{u_t} = \epsilon_t^M m_0 \theta_t^{1-\xi}, \tag{1.12}$$

The vacancy filling rate is defined as:

$$q\left(\theta_t\right) \equiv \frac{m\left(u_t, V_t\right)}{V_t} = \frac{\epsilon_t^M m_0 V_t^{1-\xi} u_t^{\xi}}{V_t} = \epsilon_t^M m_0 \theta_t^{-\xi}. \tag{1.13}$$

1.2.3. Final goods sector

There is a continuum of mass one of identical and competitive final goods firm. The final goods Y_t is produced from intermediate goods $Y_{j,t}$ by a constant elasticity of substitution aggregation.

$$Y_t = \left(\int_0^1 Y_{j,t}^{\frac{\nu_t - 1}{\nu_t}} dj \right)^{\frac{\nu_t}{\nu_t - 1}}, \tag{1.14}$$

where ν_t governs the degree of sustainability among intermediate goods. Given that the final goods firm wants to maximize its profits, the demand function for the intermediate goods firms could be written as:

$$Y_{j,t} = \left(\frac{P_{j,t}}{P_t} \right)^{-\nu_t} Y_t, \tag{1.15}$$

where P_t and $P_{j,t}$ are the price of the final goods and the price of the intermediate input, respectively. Using zero-profit condition: $P_t Y_t = \int_0^1 P_{j,t} Y_{j,t} dj$, the price of the final goods is derived as:

$$P_t = \left(\int_0^1 P_{j,t}^{1-\nu_t} dj \right)^{\frac{1}{1-\nu_t}}. \tag{1.16}$$

where $\frac{\nu_t}{\nu_t - 1}$ is the mark-up.

1.2.4. Intermediate goods sector

There is a continuum of mass one of identical intermediate-goods producers indexed by $j \in (0, 1)$. At time t , the intermediate goods producer j decides to use labor input $N_{j,t}$ and capital input $K_{j,t}$ to produce its output Y_j sold at the relative price $\frac{P_{j,t}}{P_t}$. The producer j rents labor input from households, paying a real cost of $W_{j,t} N_{j,t}$. Besides determining labor and capital input, the intermediate-goods producer j also needs to choose the number of vacancies $V_{j,t}$ to post at the fixed cost per posting κ_t and makes an investment decision $I_{j,t}$. All intermediate firms' decisions are to maximize their real present value of dividends $D_{j,t}$.

The production decision of each intermediate goods producer follows the Cobb-Douglas production technology:

$$Y_{t,j} = e^{z_t} K_{t,j}^{\alpha} \left(L_t N_{t,j} \right)^{1-\alpha}, \tag{1.17}$$

where L_t is labor-augmenting technology, shared by all the intermediate goods firms. The growth rate of labor-augmenting technology is defined as, $\frac{L_t}{L_{t-1}} = g_{L,t}$. The exogenous stochastic process z_t, known as the technology shock, is specified in the following stationary stochastic process:

$$z_t = \rho_z z_t + \epsilon_t^z, \tag{1.18}$$

where $0 < \rho_z < 1$ is the parameter denotes the persistence of the technology shock ε_t^z, which is assumed to be i.i.d. $N(0, 1)$.

The capital of law of motion evolves according to:

$$K_{j,t+1} = (1 - \delta) K_{j,t} + \Phi \left(\frac{I_{j,t}}{K_{j,t}} \right) K_{j,t}, \tag{1.19}$$

where δ refers to the depreciation rate of capital. $K_{j,t}$ is the capital stock in period t, which is determined at time $t-1$. The intermediate-good producer j purchases physical capital $K_{j,t+1}$ to use in the next period. $\Phi \left(\frac{I_{j,t}}{K_{j,t}} \right)$ is the concave adjustment cost function; its specification following Jermann (1998), is given by:

$$\Phi \left(\frac{I_{j,t}}{K_{j,t}} \right) = b_1 + \frac{b_2}{1 - \frac{1}{\chi_k}} \left(\frac{I_{j,t}}{K_{j,t}} \right)^{1-\frac{1}{\chi_k}}, \tag{1.20}$$

where χ_k governs the degree of the concavity of $\Phi \left(\frac{I_{j,t}}{K_{j,t}} \right)$. The value of $b_1 = \frac{(1-g_L-\delta)}{\chi_k - 1}$ and $b_2 = (g_L - 1 + \delta)^{\frac{1}{\chi_k}}$, all of which are determined in the steady state.

The employment law of motion evolves as:

$$N_{j,t} = (1 - \mu) N_{j,t-1} + V_{j,t} q \left(\theta_{j,t} \right), \tag{1.21}$$

Dividends (cash flow) is defined as:

$$D_{j,t} = \frac{P_{j,t}}{P_t} Y_{j,t} - W_{j,t} N_{j,t} - \kappa_t V_{j,t} - I_{j,t}, \tag{1.22}$$

where κ_t is the cost of posting vacancies. Since households own intermediate firms, the real dividends of intermediate goods firm $D_{j,t}$ are discounted by the stochastic discount factor $M_{t,t+1}$. Intermediate goods producers aim to maximize the present discounted value of real cum-dividend:

$$P_t^{sc} = E_t \left[\sum_{s=0}^{\infty} M_{t,t+s} \left(\frac{P_{j,t+s}}{P_{t+s}} Y_{j,t+s} - W_{j,t+s} N_{j,t+s} - \kappa_t V_{j,t+s} - I_{j,t+s} \right) \right], \tag{1.23}$$

The ex-dividend equity value is $P_t = P_t^{sc} - D_t$, and equation (1.23) can be rewritten as a firm's Bellman equation: $P_t^{sc} = max \left\{ D_t + E_t \left[M_{t+1} P_{t+1}^{sc} \right] \right\}$, then the stock returns and the price-dividend ratio can be expressed as $R_t = \frac{P_t^{sc}}{P_{t-1}^{sc} - D_{t-1}}$ and $\frac{P_t^s}{D_t} = \frac{P_t^{sc} - D_t}{D_t}$ respectively. The optimization problem is subject to constraints (1.15), (1.16), (1.17), (1.19), and (1.21). Given that all the intermediate goods producers are identical in a symmetric equilibrium, so that $P_t = P_{j,t}$, $Y_t = Y_{t,j}$, and the first-order conditions can be rewritten in terms of new aggregated variables: $M_t = \int_0^1 M_{j,t} dj$, $V_t = \int_0^1 V_{j,t} dj$, $N_t = \int_0^1 N_{j,t} dj$, $I_t = \int_0^1 I_{j,t} dj$, $K_t = \int_0^1 K_{j,t} dj$, $D_t = \int_0^1 D_{j,t} dj$. Hence, the first-order conditions are:

$$\begin{gathered} Q_t = \underset{t}{E} M_{t+1} \\ \left[Q_{t+1} \left((1-\delta) + b_1 + \frac{b_2}{1 - \frac{1}{\chi_k}} \left(\frac{I_t}{K_t} \right)^{1 - \frac{1}{\chi_k}} - b_2 \left(\frac{I_{t+1}}{K_{t+1}} \right)^{-\frac{1}{\chi_k}} \left(\frac{I_{t+1}}{K_{t+1}} \right) \right) + \frac{\nu_t - 1}{\nu_t} \alpha \frac{Y_{t+1}}{K_{t+1}} \right], \end{gathered} \tag{1.24}$$

where Q_t, one of the Lagrangian multipliers, is the real marginal cost of capital. Equation (1.24) states the relationship between the marginal cost of capital at time t and the marginal benefit of capital at time $t+1$.

$$J_t^F = \frac{\nu_t - 1}{\nu_t}\left(1-\alpha\right)\frac{Y_t}{N_t} - W_t + \left(1-\mu\right)\underset{t}{E} M_{t+1} J_{t+1}^F, \tag{1.25}$$

where J_t^F is the value of a firm's hiring of one worker. Equation (1.25) states that the hiring value comprises the marginal revenue related to one more worker hired, the wage paid by the firm, and the discounted value of hiring one worker at time $t+1$.

Equation (1.26), interpreted as a free entry condition for firms, states that the firm's cost of posting vacancies equals the firm's benefit of filling vacancies.

$$\kappa_t = q\left(\theta_t\right) J_t^F, \tag{1.26}$$

Plugging equation (1.25) into equation (1.26), the value of vacancies is given by:

$$\frac{\kappa_t}{q\left(\theta_t\right)} = \left(1-\alpha\right)\frac{\nu_t - 1}{\nu_t}\frac{Y_t}{N_t} - W_t + \left(1-\mu\right)\underset{t}{E} M_{t+1}\frac{\kappa_{t+1}}{q\left(\theta_{t+1}\right)}. \tag{1.27}$$

1.2.5. Wage bargaining

Both the producers and the households determine the optimal wage bargaining results. The producer's optimal conditions are obtained in section 1.2.4, and the choice of the households depends on the conditions below. At time t, the present value of being employed $H\left(W_t\right)$ relies on the real wage W_t , and the expected discounted value of being employed or being unemployed at time $t+1$, as shown in equation (1.28).

$$H(W_t) = W_t + \underset{t}{E} M_{t+1}\left\{\left[1-\mu(1-f(\theta_{t+1})\right] H\left(W_{t+1}\right) + \mu\left(1-f\left(\theta_{t+1}\right)\right) H(U_{t+1})\right\}, \tag{1.28}$$

The present value of being unemployed $H\left(U_t\right)$ depends on the unemployment benefits received B_t, and the expected discounted value of being successfully employed and being continuously unemployed at time $t+1$.

$$H(U_t) = B_t + \underset{t}{E} M_{t+1} \left[f(\theta_{t+1}) H(W_{t+1}) + (1 - f(\theta_{t+1})) H(U_{t+1}) \right], \tag{1.29}$$

The stochastic process for the total flow of unemployment benefits in logs, $log(B_t)$, is:

$$logB_t = (1 - \rho_B) logB + \rho_B logB_{t-1} + \epsilon_t^B. \tag{1.30}$$

where $0 < \rho_B < 1$ is the parameter denotes the persistence of the unemployment benefit shock ϵ_t^B, which is assumed to be i.i.d. $N(0,1)$.

1.2.5.1. Nash bargaining

The Nash bargaining is given by:

$$W_t = \underset{W_t}{argmax} \left(J_t^F \right)^{1-\eta} \left(H(W_t) - H(U_t) \right)^{\eta}, \tag{1.31}$$

where $0 < \eta < 1$ is the bargaining power of the workers. The first-order condition of equation (1.31) implies that:

$$J_t^F = \frac{1-\eta}{\eta} \left(H(W_t) - H(U_t) \right). \tag{1.32}$$

1.2.5.2. Alternative wage bargaining

This section describes the process of alternative wage bargaining. When the meeting begins, a producer proposes a wage offer first, and then it turns to the job-seekers to accept or reject the offer. By accepting the offer, job-seekers can start working immediately. However, failing to accept an offer results in two options the job-seekers can choose: terminating bargaining or coming back next period with counteroffers. When the job-seekers coming back, both sides of bargaining risk negotiation failure with probability ϱ, leaving them with outside options to terminate bargaining. The job-seekers are still being unemployed and receiving $H(U_t)$. The producer, however, either benefits or loses. Luckily, the negotiation continues with probability $1-\varrho$, when the job-seekers return with their counteroffer, which costs γ. The bargaining process keeps going when the negotiation continues. However, the bargaining process is not endless. Consistent with Christiano et al. (2016), we assume that the maximum number of bargaining rounds, F, is 60. The optimal alternative bargaining equation can be written as:

$$J_t^F = \frac{a_2}{a_1}\left(H\left(W_t\right) - H\left(U_t\right)\right) - \frac{a_3}{a_1}\gamma + \frac{a_4}{a_1}\left(v_t - b_t\right), \tag{1.33}$$

where:

$$a_1 = (1-\varrho) + (1-\varrho)^F,$$

$$a_2 = 1 - (1-\varrho)^F,$$

$$a_3 = a_2\frac{1-\varrho}{\varrho} - a_1,$$

$$a_4 = \frac{1-\varrho}{2-\varrho}\frac{a_2}{F} + 1 - a_2.$$

1.2.6. Market equilibrium

Based on the specification of government spending in Christiano and Eichenbaum (1992), the aggregate resource constraint is:

$$Y_t = C_t + I_t + \kappa V_t + G_t, \tag{1.34}$$

Consumption, investment, the total cost of posting vacancies, and government spending comprise the final output. Adding government spending helps to overcome the singularity problem in estimation. Following the previous literature, we calibrate the ratio of $\frac{G}{Y}$ to equal 0.2. The stochastic process for government spending in logs, $log\,(G_t)$, is:

$$logG_t = (1 - \rho_G)logG + \rho_G logG_{t-1} + \epsilon_t^G. \tag{1.35}$$

where $0 < \rho_G < 1$ is the parameter denotes the persistence of the government spending shock ε_t^G, which is assumed to be i.i.d. $N(0, 1)$.

1.3. Estimation

We use the Bayesian method to estimate the key structural parameters in the DSGE model. The model is estimated using five observable quarterly US data sets from 1978Q1 to 2019Q4. These variables include the log difference of real GDP, the log difference of real consumption, the demeaned log value of the unemployment rate, the demeaned log value of the vacancy rate, and the demeaned log value of the price-dividend ratio. For real GDP and real consumption series, we divide these two nominal series by the GDP deflator, and then convert them to per capita terms. Following Cochrane (2011), we calculate the price-dividend ratio using the series of value-weighted returns with and without dividends for all stocks traded on the NYSE, AMEX, and NASDAQ. A detailed description of the data is shown in the appendix. The measurement equation for the variables is given by:

$$
\begin{bmatrix} \Delta GDP_t \\ \Delta CONS_t \\ UNEM_t - \overline{UNEM} \\ VANC_t - \overline{VANC} \\ PD_t - \overline{PD} \end{bmatrix} = \begin{bmatrix} g_L \\ g_L \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \hat{y}_t - \hat{y}_{t-1} \\ \hat{c}_t - \hat{c}_{t-1} \\ \hat{U}_t \\ \hat{V}_t \\ \frac{\hat{P}_t}{D_t} \end{bmatrix} \tag{1.36}
$$

where g_L is the quarterly labor technology growth rate, and all the non-stationary variables in our model, except the unemployment rate and the vacancy rate, are detrended.

1.3.1. Prior and posterior of the parameters

The calibrated values based on the previous studies are shown in Table 1.1. We set the values of capital share α and discount factor β to 0.33 and 0.99, respectively. We fix the value of the depreciation rate at 0.025. The elasticity of substitution between differentiated intermediate goods ν is set to 11, meaning the markup is around 20%. Following previous asset pricing studies, relative risk aversion, γ, and intertemporal substitution elasticity, ψ, are calibrated to standard values of 10 and 1.5. For the calibrated values related to the labor market, following Hall (2017), Christiano et al. (2016), and Leduc and Liu (2016), the mean of the unemployment rate over the sample period, equivalent to 0.062, represents its steady-state value, and the steady-state value of the vacancy filling rate $q(\theta)$is set at 0.7. As in Leduc and Liu (2016), the cost of posting per vacancy is set to $0.02\frac{Y_t}{V_t}$ in each period. In terms of the replacement ratio $\frac{B}{W}$, the previous literature has no consensus on the specific number for this ratio, with numbers ranging from 0.22 to 0.95 being applied. For comparison purposes, we set the ratio at 0.42, as in Shimer (2005), for both baseline Nash and alternative offer bargaining models. This setting requires a higher wage bargaining weight in the baseline Nash bargaining model than the commonly used weight of 0.5. To check the impact of the replacement ratio, we also estimate the Nash bargaining model with a wage bargaining weight of 0.5.

As in Smets and Wouters (2007), the prior of the persistence of each shock follows a beta distribution with a mean of 0.5 and a standard deviation of 0.2; the prior of the volatility parameter of each shock follows an inverse-gamma distribution with a mean of 0.1 and a standard deviation of infinity. In terms of the remaining parameters, the prior of the growth rate of labor-augmenting technology takes a normal distribution with a mean of 0.5, assuming the annual growth rate is 2%, and a standard deviation of 0.025. The prior of the degree of concavity in the adjustment cost function χ_k takes a gamma distribution with a mean of 2 and a standard deviation of 0.5; this distribution is consistent with the one in Rapach and Tan (2020). The priors of job separation μ, and the matching function parameter ξ follow those of Lubik (2009). Specifically, μ and ξ are set as beta distributions with respective means of 0.1 and of 0.5 and standard deviations of 0.02 and of 0.15. Since we have no prior information in terms of the probability of bargaining breakup in the alternative bargaining model, the prior distribution of the scaling probability of bargaining breakup, 100ϱ, is set as a normal distribution with a mean of 10 and a standard deviation of 2.

Table 1.1: Calibrated parameters.

Description	Parameter	Value
Capital share	α	0.33
Discount factor	β	0.99
Depreciation rate	δ	0.025
Relative risk aversion	γ	10
Inter-temporal substitution elasticity	ψ	1.5
Demand elasticity	ν	11
Steady-state unemployment rate	U	0.062
Steady-state vacancy filling rate	$q(\theta)$	0.7
Replacement ratio	$\frac{B}{W}$	0.42

1.4. Results of empirical analysis

This section shows the results of the empirical analysis of the Nash bargaining model. The results of the alternative offer bargaining model are shown in Appendix A.5. We examine the impulse responses and then discuss the variance decomposition and historical decomposition.

1.4.1. Impulse response

Figures 1.1–1.4 show the results of four structural shocks on macroeconomic, labor, and stock variables[1]. The macro variables include GDP, capital, consumption, and investment. Labor market-related variables consist of the unemployment rate, vacancies, and wages. The remaining two asset pricing-related variables are stock return and the price-dividend ratio.

As illustrated in Figure 1.1, a positive technology shock benefits the entire economy, as evidenced by increased GDP and consumption. Companies invest more and post more job openings, reducing unemployment and raising wages. However, the effects of a positive technology shock on investment and vacancies exist only in the short run; consequently, a

[1] Since the values of the matching efficiency shock are too small, no graphs of the impulse response to this shock are included.

Table 1.2: Priors and posterior distributions of parameters based on the Nash bargaining framework with a 0.42 replacement ratio.

		Prior distribution			Posterior distribution		
		Distribution	Mean	St.dev	Mean	5%	95%
	Structural parameters						
g_L	Steady-state growth rate	Normal	0.50	0.025	0.4370	0.3919	0.4833
χ_k	Degree of concavity in cost fun.	Gamma	2.00	0.50	1.8102	1.1982	2.4511
μ	Job separation rate	Beta	0.10	0.02	0.1610	0.1565	0.1636
ξ	Matching function parameter	Beta	0.50	0.15	0.6170	0.5578	0.6705
	Shock processes						
ρ_ϕ	Preference	Beta	0.50	0.20	0.9529	0.9205	0.9808
ρ_z	Technology	Beta	0.50	0.20	0.9920	0.9831	0.9991
ρ_{ϵ^M}	Matching efficiency	Beta	0.50	0.20	0.9570	0.9304	0.9834
ρ_B	Unemployment benefit	Beta	0.50	0.20	0.9905	0.9809	0.9991
ρ_G	Government spending	Beta	0.50	0.20	0.9791	0.9409	0.9998
σ_ϕ	Preference shock	InvGamma	0.01	Inf	0.0935	0.0743	0.1138
σ_z	Technology shock	InvGamma	0.01	Inf	0.5770	0.5149	0.6400
σ_{ϵ^M}	Matching efficiency shock	InvGamma	0.01	Inf	1.5874	1.2990	1.8936
σ_B	Unemployment benefit shock	InvGamma	0.01	Inf	1.5141	1.3431	1.6954
σ_G	Government spending shock	InvGamma	0.01	Inf	10.0638	9.0017	11.2050

positive technology shock decreases stock returns and the price-dividend ratio in the short run through the cash flow channel influenced by higher wages and investments.

Figure 1.2 illustrates the impulse response to a positive preference shock. In our model, a positive preference shock leads to a decrease in the discount rate. Due to changes in the intertemporal trade-off, the household reduces consumption and becomes more inclined to work more, shifting the labor supply. After the initial period, however, the positive responses of real wages and the number of job openings increase gradually, indicating that labor demand shifts further than labor supply, resulting in higher equilibrium wages. Figure A.5.2 in Appendix A.5 demonstrates that in the presence of wage rigidities, the alternative offer bargaining framework generates similar impulse responses for both wages and vacancies to a positive preference shock. Therefore, these findings from both wage bargaining frameworks support the claim in Hall (2017) that a lower discount rate leads to an increase in vacancies. One possible explanation, based on the impulse responses of capital to a preference shock, is that the marginal product of capital decreases as the use of capital increases, leading firms to hire more workers.

Figure 1.3 illustrates the impulse response to an increase in government expenditure. The findings show that a government expenditure shock has a detrimental short-term impact on GDP, consumption, investment, job openings, and real wages. These results are consistent with those in the RBC model, which states that government spending crowds out investment and private consumption. The persistent negative effect on real wages can be attributed to the negative wealth effect, which leads households to work longer hours, shifting labor supply, and reducing equilibrium wages. This persistent effect implies that the shift in labor supply is smaller than the shift in labor demand. Furthermore, the response results indicate that the negative effect of crowding out is more significant in magnitude than the positive effect of the government spending shock, resulting in a decrease rather than an increase in GDP.

Figure 1.4 shows the impulse response to a positive unemployment benefit shock. The positive response of consumption indicates a positive wealth effect, causing the household to be unwilling to work and to demand a higher real wage. Consequently, this higher reservation wage leads to higher opportunity costs for the firm's production, thus reducing their incentive to hire additional workers. As a result, unemployment and vacancies respond oppositely to a positive unemployment benefit shock. Furthermore, due to the decreasing discount factor and reduced cash flows, positive responses of stock returns and price-dividend ratios exist in the initial period.

1.4.2. Variance decomposition

Table 1.3 presents the contribution of each structural shock to the variances of key variables at 40 quarters under the Nash bargaining framework. The decomposition result suggests that the technology shock accounts for 77.07% of output growth fluctuations, consistent with previous studies in the RBC literature emphasizing the role of the technology shock in explaining business cycles. In terms of consumption growth fluctuations, the unemployment benefit shock contributes 66.74% to these variations, while the remaining 33% can be explained by the technology shock, the preference shock, and the government spending shock. Notably, the unemployment benefit shock primarily drives the fluctuations in unemployment and vacancies. However, although the technology shock can explain noticeable fluctuations in labor market variables, our findings do not provide evidence supporting the claim that the technology shock is the main driving force for labor market dynamics. Moreover, the preference shock explains sizable fluctuations in the price-dividend ratio and has a comparable contribution to explaining the fluctuations in the labor market as the technology shock, highlighting the importance of the discount rate channel. While the matching efficiency shock does not play a noticeable role in explaining business cycle and stock market variables, it does explain 23% of the fluctuations in vacancies.

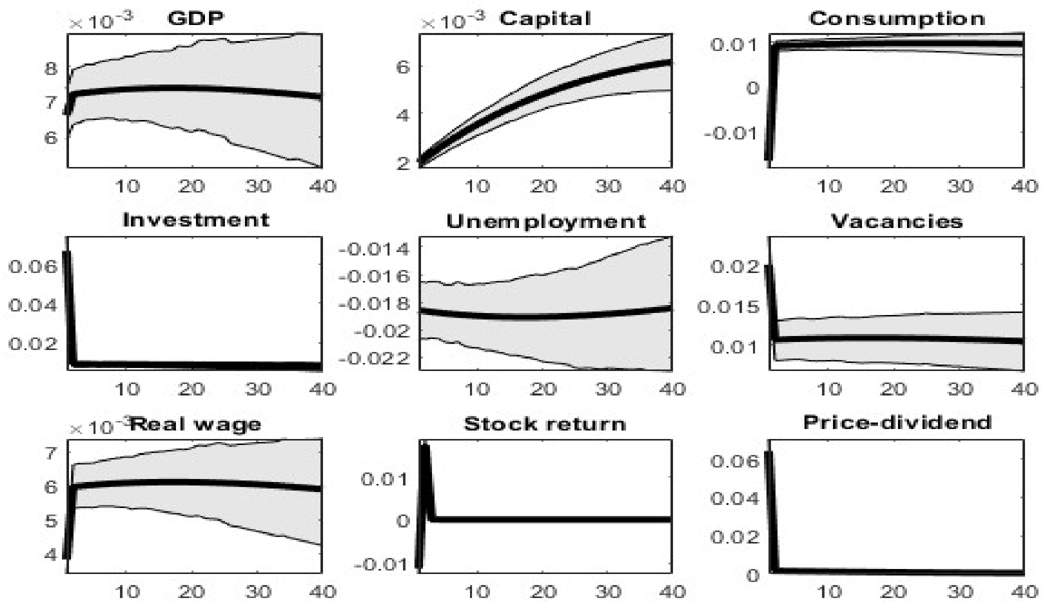


Figure 1.1: Impulse response to a positive technology shock based on the Nash bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

Table A.5.2 presents the contributions of various shocks in the alternative bargaining framework. While accounting for similar fluctuations in output growth as in the Nash bargaining framework, the technology shock generates more fluctuations in other variables. Although wage rigidities reduce the fluctuations in consumption growth, unemployment, and vacancies explained by the unemployment benefit shock, this shock still accounts for over half of the fluctuations in these three variables. Furthermore, our findings reveal that the intertemporal preference shock contributes the most to fluctuations in the price-dividend ratio. The matching efficiency shock only accounts for 4.65% of the fluctuations in the vacancy filling rate; this number is lower than the one observed in the Nash bargaining framework. Moreover, the government spending shock has a negligible effect on the price-dividend ratio and other business cycle variables. Table A.6.2 reports the contributions of various shocks in the Nash bargaining framework without a fixed replacement ratio. With higher unemployment benefits, the fluctuations in unemployment and vacancies are not solely driven by the

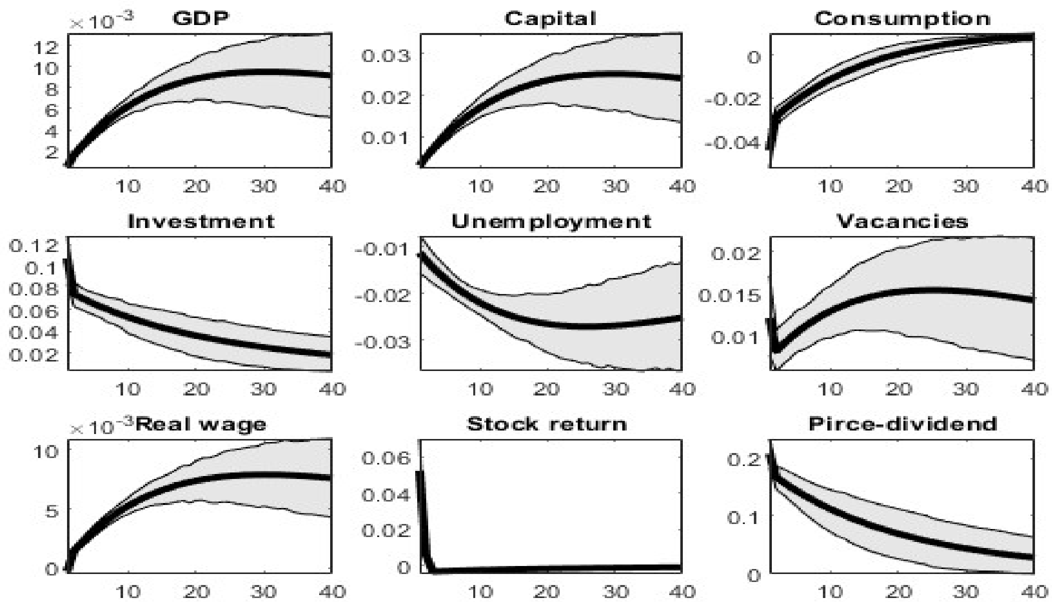


Figure 1.2: Impulse response to a positive preference shock based on the Nash bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

unemployment benefit shock; however, the technology shock, the preference shock, and the unemployment benefit shock share similar contributions to the variations in labor market variables.

1.4.3. Historical decomposition

Figures 1.5-1.7 summarize the historical contribution of the shocks to unemployment, vacancies, and the price-dividend ratio during the sample period 1978Q1-2019Q4. The stacked bar chart shows the contributions of five shocks and initial values to the fluctuations in these three variables, with the black line representing the log deviation of these variables from their scaling mean (scaled by a factor of 100). Figure 1.5 demonstrates that the technology shock plays a vital role in unemployment fluctuations, while the unemployment benefit shock generates significant volatility in unemployment. Prior to the 2008 financial crisis, the

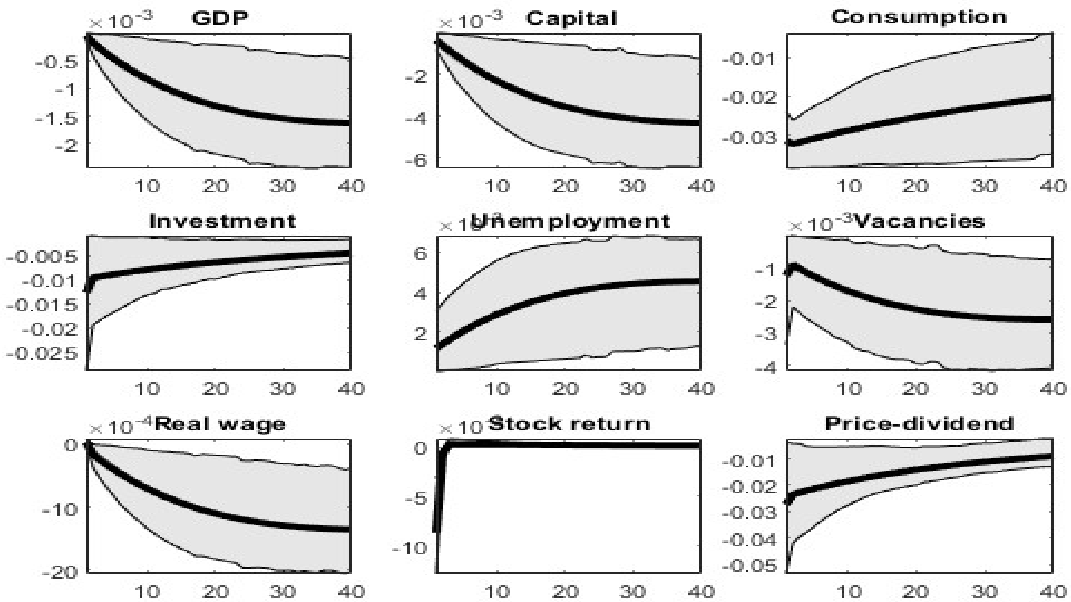


Figure 1.3: Impulse response to a positive government spending shock based on the Nash bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

Table 1.3: Variance decomposition of key variables based on the Nash bargaining framework (in percent) with a 0.42 replacement ratio. The results are the average from 1 million draws of parameters from the posterior.

Shocks/series	$ln(Y_t/Y_{t-1})$	$ln(C_t/C_{t-1})$	$ln(U_t)$	$ln(V_t)$	$ln(P_t/D_t)$
Technology	77.07	7.34	21.56	16.82	1.11
Preference	10.42	17.92	18.82	14.28	87.68
Matching efficiency	0.00	0.00	0.00	21.43	0.00
Unemployment benefit	12.25	66.74	58.70	46.78	7.37
Government spending	0.25	8.00	0.92	0.69	3.85

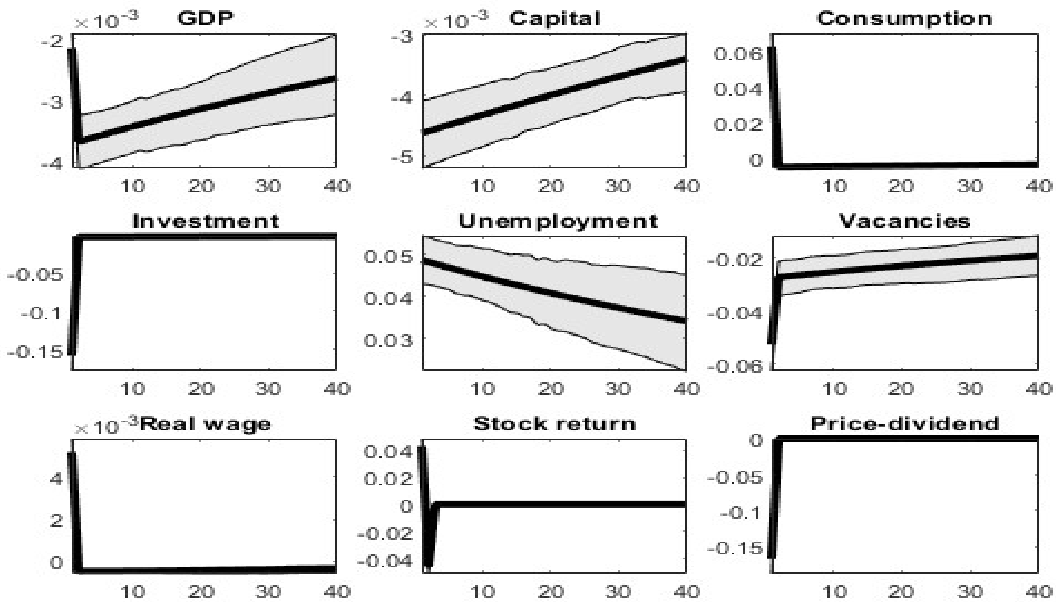


Figure 1.4: Impulse response to a positive unemployment benefit shock based on the Nash bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

technology shock reduces unemployment; however, after the crisis, it worsens unemployment due to a slowdown in productivity growth. The effects of the unemployment benefit shock on the unemployment fluctuations align with business cycles; notably, these effects are amplified after 2008, as they contribute approximately 5-7 percentage points of swing fluctuations. Specifically, if there had been no unemployment benefit shock, the unemployment rate would have been much more stable after 2008.

Figure 1.6 reveals that the fluctuations in vacancies are mainly influenced by the technology, matching efficiency, and unemployment benefit shocks. The effects of the matching efficiency shock mainly happen before 2014, aligning with business cycles. While the unemployment benefit shock explains some fluctuations prior to 2008, its effects become more pronounced in subsequent periods, ranging from 4% to 6% during recessions and economic booms. Importantly, these two figures reveal that the preference shock is not the primary driver of the fluctuations in the labor market. Furthermore, Figure 1.7 demonstrates that until 2008, the preference shock had been the main factor influencing the fluctuations in the price-dividend ratio.

Compared to the historical decomposition of the Nash bargaining framework, the results of the alternative bargaining framework show some noticeable disparities. Firstly, due to wage rigidities, the alternative bargaining framework generates higher levels of labor market volatility, amplifying the contributions of the technology shock and the preference shock to the fluctuations in the labor market. Secondly, the observed effects show that the unemployment benefit shock has a persistent and positive impact on the labor market before 2008.

Figure 1.8 shows the smoothed shocks used in the historical decomposition. The series of these shocks follow a random walk and are not correlated with each other.

1.5. Conclusion

To reassess the underlying factors that contribute to labor market dynamics and asset pricing fluctuations, we employ a RBC model characterized by search and matching frictions. Our findings shed light on the importance of the unemployment benefit shock as it explains most of the fluctuations in the unemployment rate and vacancies in the absence of wage rigidities. Meanwhile, the preference shock contributes considerably to the variations in the unemployment rate and vacancies, though the contributions depend on the presence of wage rigidities and different replacement ratios. With a higher replacement ratio in the Nash bargaining model, the preference shock contributes approximately 30% to variations in the unemployment rate and vacancies. Moreover, our findings also reveal that the preference shock predominantly influences stock market fluctuations. Furthermore, in the presence of wage rigidities, our results show that the technology shock contributes the most to the variations in the labor market rather than the unemployment benefit shock, owing to the

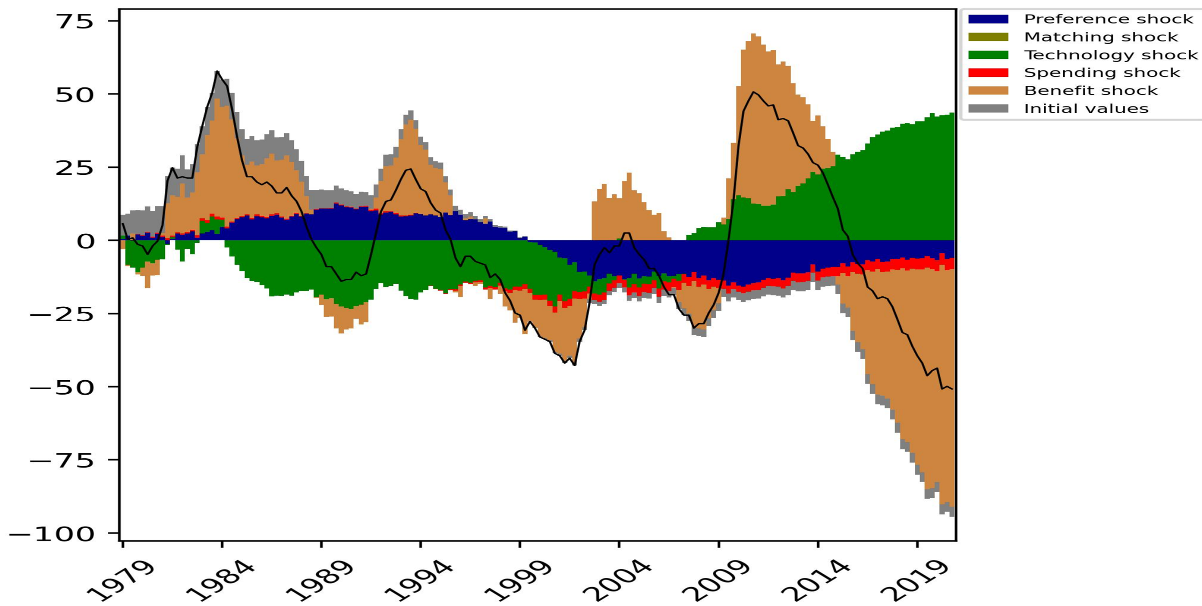


Figure 1.5: Historical decomposition for unemployment:1979-2019. The black line is the log deviation of the unemployment rate from its mean.

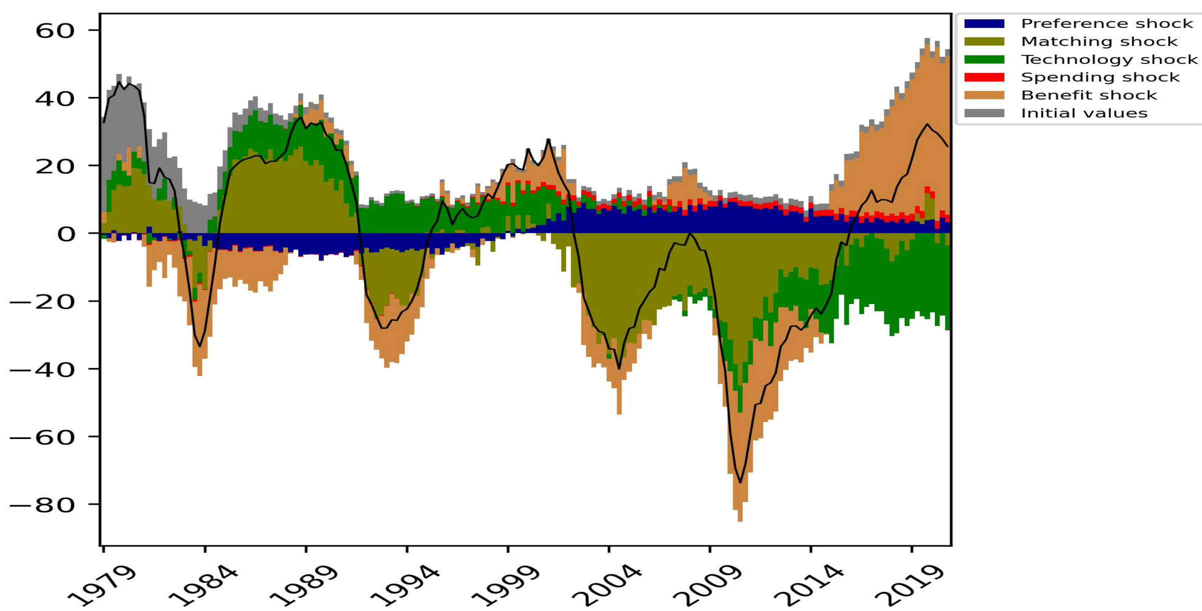


Figure 1.6: Historical decomposition for vacancy:1979-2019. The black line is the log deviation of the vacancy from its mean.

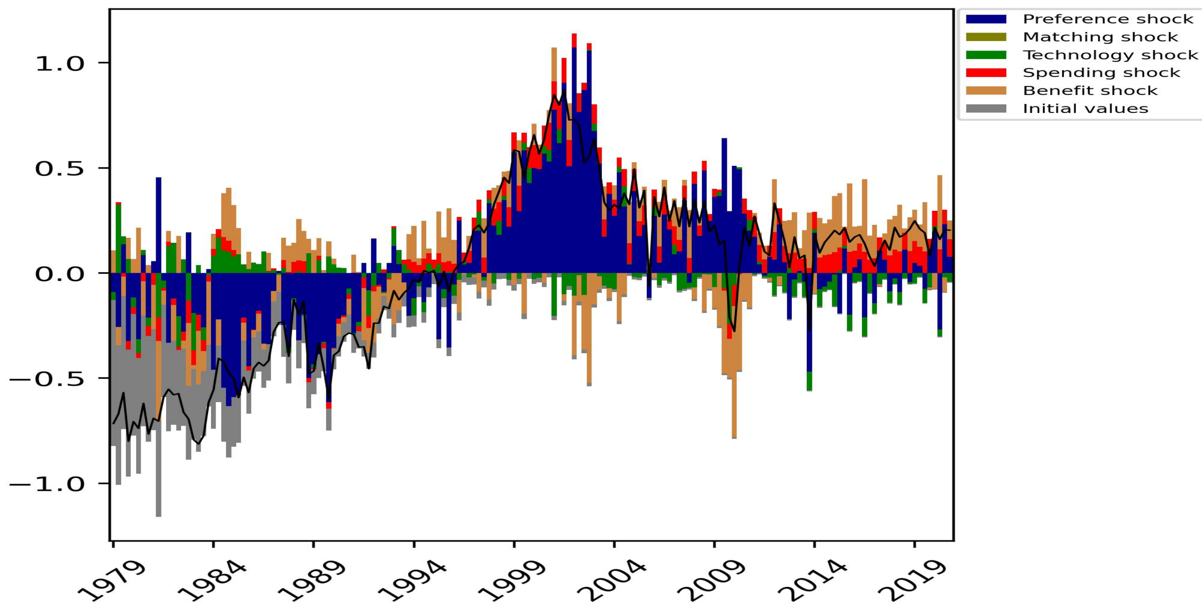


Figure 1.7: Historical decomposition for price-dividend ratio:1979-2019. The black line is the log deviation of the price-dividend ratio from its mean.

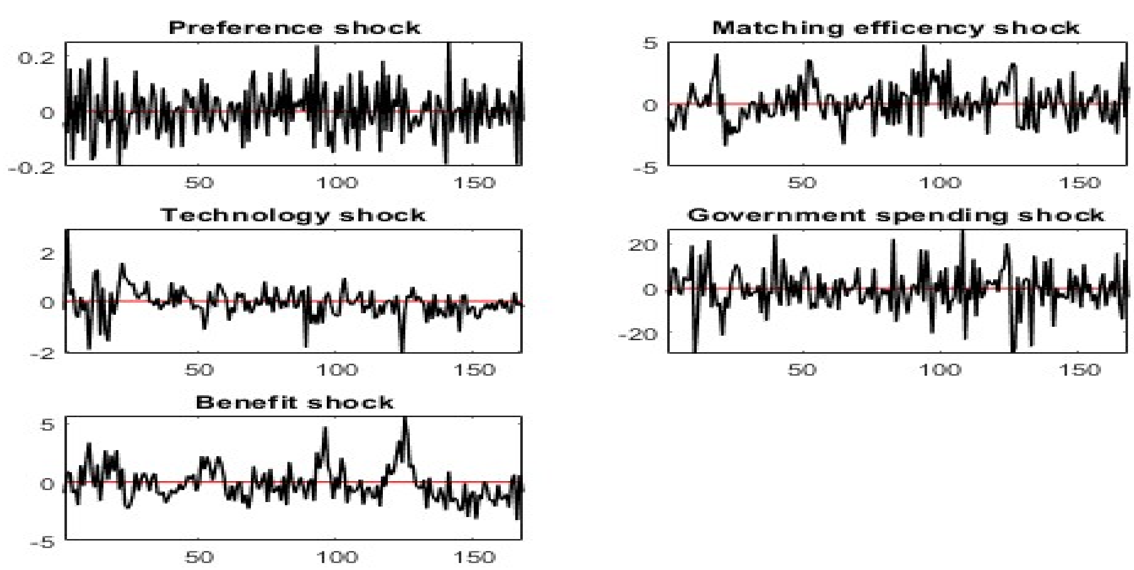


Figure 1.8: Estimated shocks of the historical decomposition:1979-2019. The y-axis represents percentage points the shocks deviate from their steady state value.

stabilizing effect of wage rigidities on household consumption. We also find that the influence of the matching efficiency shock in explaining labor market fluctuations is minimal.

Chapter 2

Credit Frictions, Firm Dynamics, and Unemployment

2.1. Introduction

The dynamic link between firm dynamics and labor market fluctuations is intuitive and documented in empirical studies. After the 2008 Great Recession, it became evident that there was a significant decrease in both job opportunities and the number of firms. Previous studies primarily rely on a standard search and matching model to address the Shimer puzzle, as the traditional labor market model cannot account for the high volatility observed in labor market fluctuations. However, there has been relatively less focus on employing a framework that combines search and matching frictions and firm dynamics to explore the propagation mechanism. Colciago and Rossi (2011) and Bernstein et al. (2021) document that bridging labor market frictions and firm dynamics provides better explanations for labor market volatility. More recently, Bilal et al. (2022) and Elsby and Gottfries (2022) discuss the reallocation of labor in a model featuring firm dynamics and labor market frictions.

Previous studies have extensively explored the significance of financial frictions in understanding labor market dynamics. In order to investigate the impact of financial frictions on the labor market, several studies have assumed frictional labor and credit markets. Petrosky-Nadeau (2014) and Chugh (2013) document that costly external financing affects the labor market. Acemoglu (2001) also supports the notion that credit market frictions influence job creation. Empirical analysis by Corsello and Nispi Landi (2020) reveals the effect of financial shocks on unemployment, particularly in bad times. Shapiro and Olivero (2020) examine how credit spreads affect labor participation. Dong (2023) demonstrates that credit constraints negatively impact matching efficiency. Furthermore, some studies emphasize the effect of wages when firms face financial constraints.(e.g., Michaels et al. (2019); Schoefer (2021); Föll (2021)). Additionally, research has documented the effects of financial frictions on firm dynamics. Mehrotra and Sergeyev (2021) show how credit constraints proxied by house prices affect labor market variables, especially job creation. Ayres and Raveendranathan (2023) find that credit shocks rather than productivity shocks explain the lower entry rate and higher exit rate during the 2008 financial crisis. While previous studies shed light on the importance of financial frictions and firm dynamics in explaining labor market fluctuations, they have yet to focus on the intersections of firm dynamics, financial frictions, and the labor market.

We are interested in the propagation mechanism of a model that incorporates three frictions to explain the fluctuations in the labor market. To achieve this objective, we build a real business cycle model characterized by firm dynamics, financial frictions, and labor market frictions. To embed financial frictions into the model, we follow the approach proposed by Bergin et al. (2018) to introduce a collateral constraint. In their study, debt and equity are utilized to cover entry costs and working capital. The equity payout serves as collateral and is equivalent to incumbent firms' expected production revenue. To ensure that incumbent firms will borrow external financing from costly equity rather than debt when facing default on payment, the household that purchases debt is more patient than the investor that purchases equity. Hence, incumbent firms' borrowing ability is constrained by the collateral constraint, affecting the proportion of equity value used to pay for working capital. This varying proportion reflects the changes in the financial environment's looseness or tightness. Additionally, it is assumed that entrant firms become productive upon entering the market to emphasize the significance of financial frictions for firms' entry. However, labor market frictions are not considered within their framework. We make certain modifications to make search and matching mechanisms tractable within our integrated framework.

In our model with search and matching, we assume that incumbent firms utilize collateral not only to finance working capital but also to cover the costs of posting vacancies. As a result, financial shocks impact the labor market through both labor demand and job creation. Additionally, it is not feasible to apply the same optimization problem faced by entrant firms and incumbent firms as in Bergin et al. (2018) when we incorporate search and matching frictions while assuming entrant firms start production immediately upon entry. This is because entrant firms need to post a greater number of vacancies than incumbent firms and face higher entry costs. Hence, we assume that entrant firms need to hire initial workers and pay their wages when entering, with the number of these initially hired workers being equivalent to the number of workers required for incumbent firms' production. Thus, one period later, surviving entrant firms will encounter the same optimization problem as incumbent firms do. With this modification, we assume that the levels of debts and equity utilized to finance entry costs are based on steady-state values calibrated from incumbent firms' optimization equations. Although our model cannot be utilized to highlight the importance of entry costs or start-up dynamics in explaining labor market fluctuations as explored in a growing literature (e.g., Shao and Silos (2013); Siemer (2014); Cavallari (2015); Gutiérrez et al. (2019); Sedláček (2020)), it can explain how financial shocks affect the labor market.

This paper also contributes to two other strands of literature. Firstly, our work adds to a growing body of literature that documents the importance of firm dynamics in aggregate fluctuations (e.g., Jaimovich and Floetotto (2008); Bilbiie et al. (2012); Clementi and Palazzo (2016)). Secondly, we contribute to the literature that utilizes enforcement constraints to model financial frictions in explaining labor market fluctuations. In line with Kiyotaki and Moore (1997), Jermann and Quadrini (2012) develop a model assuming firms are bound by collateral constraints. In the work of Jermann and Quadrini (2012), bonds and costly equity are the two financing sources. When negative shocks tighten credit frictions, firms need to increase their equity or lay off more workers. Building on the work of Jermann and Quadrini (2012), Zanetti (2019) incorporates search and matching frictions, finding that job destruction shocks contribute significantly to labor market fluctuations. Furthermore, Monacelli et al. (2023) argue that the debt bargaining channel motivates firms to hire more given that firms have a strong position in the bargaining process due to higher debt . Our work is the first to integrate firm dynamics, financial frictions, and labor market frictions within the RBC model. It is closely related to the work of Garin (2015), who finds that credit shocks are vital for explaining volatility in the labor market. The difference between the work of Garin (2015) and ours lies in our utilization of equity as the collateral constraint while incorporating the firm's creation and destruction.

To investigate the amplification mechanism of productivity shocks caused by credit frictions and firm dynamics, we compare the responses to productivity shocks in environments with relaxed financial conditions and higher firm survival rates. We find that at each time period after shocks hit, when we stack the magnitudes of impulse responses of labor market variables to productivity shocks in either of these two environments, the stacking magnitudes are smaller than those observed when both environments change, indicating an amplification effect on productivity shocks. In addition to technology shocks, we also examine the impulse responses to the other four shocks. The positive death shock discourages potential entrant firms from entering the market, leading to a gradual decline in the total number of firms. However, the labor force continuously flows into the surviving firms, driving wages lower. Moreover, the positive entry cost shock also causes labor to move to surviving firms due to the decrease in new entrant firms. Nevertheless, this shock shows different effects on unemployment, aggregate labor, and wages compared to those caused by the death shock. This discrepancy can be attributed to the fact that while firm exit shocks negatively impact all firms, entry cost shocks primarily affect potential entrant firms initially. In terms of the positive credit friction shock, reflecting a relaxation of the collateral constraint, its impact resembles that of a positive technology shock. Furthermore, when workers show a preference for not working, it becomes increasingly challenging for incumbent and potential entrant firms to hire workers for production, resulting in more firms exiting the market. In contrast to the credit friction shock, the disutility of work shock resembles a negative technology shock.

The rest of the paper is organized as follows. Section 2 describes the baseline real business cycle model featuring credit frictions, firm dynamics and labor market frictions. Section 3 summarizes calibrated values and highlights the quantitative findings through impulse responses. Section 4 concludes.

2.2. DSGE model

In this section, we develop a real business cycle (RBC) model that embeds firm dynamics, labor market frictions, and credit frictions. Our model is similar to the framework proposed by Bilbiie et al. (2012) and Bergin et al. (2018). Within our model, the number of varieties depends on the entry and exit flows in each period. Entrant firms become productive in the subsequent period after entering the market. Labor is the only input for production and the creation of new firms. The aggregate labor demand consists of the workers employed by entrant and incumbent firms in each period. Total vacancies comprise vacancies posted by entrant and incumbent firms. At the beginning of each period, the debt is predetermined, leading to a cash flow mismatch that necessitates external financing for working capital and the cost of posting vacancies. Incumbent firms utilize equity as collateral to cover costs when they default on debt repayments. To introduce equity as the costly financing source, we assume that households purchasing debt are more patient than the investors purchasing the equity shares of both entrants and incumbents.

2.2.1. Final goods sector

Each firm produces a single differentiated final good ω. The aggregation of final goods with constant-elasticity combinations of N_t varieties is given by:

$$Y_t = (\int_0^{N_t} y_t(\omega)^{\frac{\epsilon-1}{\epsilon}} d\omega)^{\frac{\epsilon}{\epsilon-1}}, \tag{2.1}$$

where ϵ is the constant elasticity of substitution between differentiated goods and $y_t(\omega)$ is the final good produced by firm ω.

And the aggregate final goods price is:

$$P_t^a = (\int_0^{N_t} P_t(\omega)^{1-\epsilon} d\omega)^{\frac{1}{1-\epsilon}}, \tag{2.2}$$

where $P_t(\omega)$ denotes the nominal price of firm ω and P_t^a denotes final goods price. The real price is given by:

$$\rho_t(\omega) = \frac{P_t(\omega)}{P_t^a}, \tag{2.3}$$

And the demand function for $y_t(\omega)$ can be written as:

$$y_t(\omega) = (\rho_t(\omega))^{-\epsilon} Y_t. \tag{2.4}$$

2.2.2. Labor market and firm dynamics

New entrants start to specialize in final goods production in the next period with one period time lag. All existing firms, both entrants and incumbents, are hit by a death shock $\lambda \in (0,1)$ at the beginning of each period. The dynamic equation of an aggregate number of firms is:

$$N_t = (1 - \lambda\phi_t^\lambda)(N_{t-1} + N_{t-1}^{new}), \tag{2.5}$$

The stochastic process for the death shock in logs, $log\left(\phi_t^\lambda\right)$ is:

$$log\left(\phi_t^{\lambda}\right) = \rho_{\phi^{\lambda}} log\left(\phi_{t-1}^{\lambda}\right) + \epsilon_t^{\phi^{\lambda}}, \tag{2.6}$$

where $0 < \rho_{\phi^{\lambda}} < 1$ is the parameter that denotes the persistence of the death shock $\epsilon_t^{\phi^{\lambda}}$, which is assumed to be i.i.d. $N(0,1)$.

At the beginning of each period, u_t, the number of the unemployed searching for a new job depends on whether firms exit from the market subject to the death shock and whether the employed loses a job due to an exogenous separation rate $s \in (0,1)$. The number of job seekers is given by:

$$u_t = 1 - (1-s)(1-\lambda\phi_t^{\lambda})L_{t-1}, \tag{2.7}$$

At the end of each period, the number of the employed, L_t, depends on the number of the employed still working at the original company and new matches happening at the beginning of each period. The evolution of aggregate employment is given by:

$$L_t = (1-s)(1-\lambda\phi_t^{\lambda})L_{t-1} + m\left(u_t, V_t^{tot}\right), \tag{2.8}$$

The standard matching function follows the Cobb-Douglas function:

$$m\left(u_t, V_t^{tot}\right) = \epsilon^M (V_t^{tot})^{1-\xi} u_t^{\xi}, \tag{2.9}$$

where $\xi \in (0,1)$ denotes the match elasticity of the unemployed, and ϵ^M denotes the scalar parameter for aggregate efficiency. V_t^{tot} denotes the total vacancies posted by all firms in period t. The evolution of total vacancies is given by:

$$V_t^{tot} = N_t^{new} V_t^{new} + N_t V_t^I, \tag{2.10}$$

where V_t^{new} denotes the vacancies posted by entrants. Since we assume that entrants should hire l_t workers in period t for production in the next period $t+1$, so $V_t^{new} = \frac{l_t}{q(\theta_t)}$. V_t^I denotes the vacancies posted by incumbents per firm.

The probability of finding a job $f(\theta_t)$ and filling a vacancy $q(\theta_t)$as follows:

$$f(\theta_t) \equiv \frac{m(u_t, V_t^{tot})}{u_t}, \tag{2.11}$$

$$q(\theta_t) \equiv \frac{m(u_t, V_t^{tot})}{V_t^{tot}}, \tag{2.12}$$

The unemployment rate is:

$$U_t = 1 - L_t. \tag{2.13}$$

2.2.3. Firm entry

When entering the market, in addition to the one-time cost of posting vacancies, entrants also need to pay wages W_t, and the cost related to entry congestion, $K\phi_t^K(\frac{N_t^{new}}{N_{t-1}^{new}})^{\tau}$. In order to cover these entry costs, entrants issue bonds and sell equity. The entry condition implies:

$$\frac{b_{it}}{R_t} + E_t[M_{I,t+1}V_{t+1}(f^E)] = W_t l_t(\omega) + \kappa_t \frac{l_t(\omega)}{q(\theta_t)} + K\phi_t^K(\frac{N_t^{new}}{N_{t-1}^{new}})^{\tau}, \tag{2.14}$$

where κ_t denotes the cost of posting vacancies, $M_{I,t+1}$ denotes the discount rate of the investor, and τ denotes the congestion externality. The stochastic process for the entry cost shock ϕ_t^K in logs, $log\left(\phi_t^K\right)$ is:

$$log\left(\phi_t^K\right) = \rho_{\phi^K} log\left(\phi_{t-1}^K\right) + \epsilon_t^{\phi^K}. \tag{2.15}$$

where $0 < \rho_{\phi^K} < 1$ is the parameter that denotes the persistence of the entry cost shock $\epsilon_t^{\phi^K}$, which is assumed to be i.i.d. $N(0,1)$.

2.2.4. Incumbent firms

There is a continuum of incumbents with mass N_t. These incumbent firms produce one differentiated good denoted by ω and provide final goods for consumption. The production function is given by:

$$y_t(\omega) = A_t l_t(\omega), \tag{2.16}$$

Where $l_t(\omega)$ is the labor demand by one incumbent firm ω. A_t is the technology shock. The stochastic process for the technology shock A_t in logs, $log\,(A_t)$ is:

$$log\,(A_t) = \rho_{\epsilon^A} log\,(A_t) + \epsilon_t^A, \tag{2.17}$$

where $0 < \rho_{\phi^A} < 1$ denotes the persistence of the technology shock ϵ_t^A, which is assumed to be i.i.d. $N(0,1)$.

The incumbent firm surviving from the previous period has the following labor force:

$$l_t(\omega) = (1-s)l_{t-1}(\omega) + V_t^I(\omega) q\,(\theta_t)\,, \tag{2.18}$$

The labor of incumbent firms, $l_t(\omega)$, depends on the number of labor that suffers from an exogenous separation s, and the number of vacancies posted by each firm is $V_t^I(\omega)$. Since the incumbent firm surviving from the last period, equation 2.18 is the same as the one in the standard labor market frictions model without firm dynamics.

The incumbents utilize their expected revenue as collateral to secure financing for wage payments and vacancy costs. To introduce a financial friction, we assume that there is a proportion ς of the collateral value that the incumbents can utilize. An enforcement constraint is given by:

$$\varsigma\phi_t^{\varsigma}E_t[M_{I,t+1}V_{t+1}(f^I)] \geq w_t l_t(\omega) + \kappa_t V_t^I(\omega), \tag{2.19}$$

where $M_{I,}$ denotes the discount factor of the investor, and $V_{t+1}(f^I)$ denotes the firm's value in the next period. The stochastic process for collateral constraint shock ϕ_t^{ς} in logs, $log\,(\phi_t^{\varsigma})$ is:

$$log\,(\phi_t^{\varsigma}) = \rho_{\phi^{\varsigma}} log\left(\phi_{t-1}^{\varsigma}\right) + \epsilon_t^{\phi^{\varsigma}}, \tag{2.20}$$

where $0 < \rho_{\phi^{\lambda}} < 1$ denotes the persistence of the collateral constraint shock $\epsilon_t^{\phi^{\varsigma}}$, which is assumed to be i.i.d. $N(0, 1)$.

The dividend of one incumbent firm is defined as:

$$d_t(\omega) = \frac{P_t(\omega)}{P_t^a} y_t(\omega) - W_t l_t(\omega) - \kappa_t V_t^I(\omega) - (b_{t-1}(\omega) - \frac{b_t(\omega)}{R_t}), \tag{2.21}$$

The present discounted value of the real dividend could be written as a Bellman equation:

$$V_t(f^I) = d_t(\omega) + E_t[M_{t+1}V_{t+1}(f^I)], \tag{2.22}$$

The optimization problems faced by incumbent firms are subject to constraints (2.3), (2.4), (2.16), (2.18), and (2.19). In each period, the incumbents choose $y_t(\omega)$, $\frac{P_t(\omega)}{P_t}$, $b_t(\omega)$, $l_t(\omega)$, and $V_t^I(\omega)$. In the symmetric equilibrium, $P_t(\omega) = P_t$, $\rho_t(\omega) = \rho_t$, $y_t(\omega) = y_t$, $l_t(\omega) = l_t$, $b_t(\omega) = b_t$, $d_t(\omega) = d_t$, and $V_t^I(\omega) = V_t^I$. After imposing symmetry, the real price associated with the number of incumbent firms could be rewritten as:

$$P_t^a = (\int_0^{N_t} P_t(\omega)^{1-\epsilon} d\omega)^{\frac{1}{1-\epsilon}} = N_t^{\frac{1}{1-\epsilon}} P_t, \tag{2.23}$$

Then it's straightforward to express the variety effect associated with relative price:

$$\rho_t = N_t^{\frac{1}{\epsilon-1}}, \tag{2.24}$$

The first-order conditions of the incumbent firm's optimization problem can be simplified into the following three equations:

$$\mu_t = \frac{1/R_t - E_t M_{I,t+1}}{\varsigma \phi_t^{\varsigma} E_t M_{I,t+1}}, \tag{2.25}$$

The Lagrangian multiplier of the enforcement constraint μ_t is inversely related to the financial market condition represented by ς. Specifically, a higher value of ς, indicating better financial condition, leads to a lower value of μ_t, reflecting loosening financial constraints.

$$J_t^F = \frac{\kappa_t}{q\left(\theta_t\right)}(1 + \mu_t), \tag{2.26}$$

where J_t^F is the value of the incumbent firm's hiring of one worker. Equation 2.26 states the free entry condition for firms. The value of hiring one worker equals the cost of posting a vacancy multiplied by the wedge term $(1 + \mu_t)$, which captures the effect of credit frictions on a firm's hiring decision. In the absence of credit frictions, μ_t will be 0. With financial constraints, when the firms pay for the same cost of posting vacancies, the value of hiring one worker, J_t^F, is discounted by $(1 + \mu_t)$. Consequently, tighter credit constraints lead to a greater discounted value of hiring one worker, discouraging firms from hiring more workers.

$$\frac{\kappa_t}{q\left(\theta_t\right)}(1+\mu_t) = (\frac{\epsilon-1}{\epsilon})\frac{P_t}{P_t^a}A_t - (1+\mu_t)W_t + (1-s)\underset{t}{E}M_{I,t+1}(1+\mu_{t+1})\frac{\kappa_{t+1}}{q\left(\theta_{t+1}\right)}. \tag{2.27}$$

Equation 2.27 is the job creation equation. The first two components on the right side of the equation denote the profits from hiring one worker. However, the inclusion of the wedge term, $(1+\mu_t)$, amplifies wage costs, diminishing firm profitability. This equation provides further insight into how credit frictions affect job creation.

2.2.5. Household

A representative household has a continuum of mass one workers. L_t is the labor supplied by the household. The household consumes and purchases debts b_t from entrant and incumbent firms. The household receives a real wage determined by Nash bargaining and unemployment benefits B_t, financed by a lump-sum tax τ_t. Another source of household income comes from revenues from holding debts purchased in the previous period, with the total revenue being $N_t b_{t-1}$. The household maximizes the following utility function:

$$maxE_0 \sum_{t=0}^{\infty} \beta_t [\frac{C_{H,t}^{1-\rho}}{1-\rho} - \gamma\phi_t^{\gamma}\frac{L_t^{1+\varphi}}{1+\varphi}], \tag{2.28}$$

where $\beta \in (0,1)$ denotes the time discount factor, $\rho > 0$ denotes the the relative risk aversion, and φ denotes the inverse Frisch elasticity parameter. C_H is the household consumption. γ is a scale parameter governing the disutility of work, and the stochastic process for disutility of work ϕ_t^{γ} in logs, $log\left(\phi_t^{\gamma}\right)$ is:

$$log\left(\phi_t^{\gamma}\right) = \rho_{\phi^{\gamma}} log\left(\phi_{t-1}^{\gamma}\right) + \epsilon_t^{\phi^{\gamma}}, \tag{2.29}$$

where $0 < \rho_{\phi^{\gamma}} < 1$ denotes the persistence of the disutility of work shock $\epsilon_t^{\phi^{\gamma}}$, which is assumed to be i.i.d. $N(0,1)$.

The household optimization problem is subject to the following constraint:

$$C_{H,t} + \frac{(N_t + N_t^{new})b_t}{R_t} \leq W_t L_t + (1 - L_t)B_t - \tau_t + N_t b_{t-1}, \tag{2.30}$$

In each period, the household chooses b_t, and the first-order condition is:

$$C_{H,t}^{-\rho} = \beta(1 - \lambda\phi_t^{\lambda})E(C_{H,t+1}^{-\rho} R_t). \tag{2.31}$$

2.2.6. Investor

A representative impatient investor consumes, purchases equity shares from entrant and incumbent firms, and receives dividends and revenues from selling equity shares. The impatient investor maximizes the following utility function:

$$maxE_0 \sum_{t=0}^{\infty} \beta_{I,t}, \frac{C_{I,t}^{1-\rho_I}}{1 - \rho_I}, \tag{2.32}$$

where $\beta_I \in (0, 1)$ denotes the discount factor of the investors, ρ_I denotes the the relative risk aversion of the investors. C_I denotes investor consumption.

The investor is subject to the following budget constraint:

$$C_{I,t} + (N_t + N_t^{new})q_t x_t \leq N_t x_{t-1}(q_t + d_t), \tag{2.33}$$

where q_t denotes the firm's value of share, s_t denotes the shares invested in each firm, d_t denotes the dividends received from each surviving firm.

And the Euler equation of holding shares is:

$$C_{I,t}^{-\rho_I} q_t = \beta_{I,t}(1 - \lambda\phi_t^{\lambda})E[C_{I,t+1}^{-\rho_I}(q_{t+1} + d_{t+1})]. \tag{2.34}$$

2.2.7. Wage bargaining

We assume that the real wage is determined by the Nash bargaining between households and firms. In period t, the employed receives real wage W_t, while also bearing the cost of disutility of work. In period $t+1$, the expected discounted values of being employed and unemployed are conditional on the exogenous separation rate s, the firm's surviving rate λ, and the probability that the employed being laid off at the beginning of each period will find a job. The value of being employed is given as:

$$H(W_t) = W_t - \frac{\gamma\phi_t^{\gamma}L_t^{\varphi}}{C_{H,t}^{-\rho}} + \underset{t}{E}M_{H,t+1}\{\left[(1-\lambda\phi_{t+1}^{\lambda})(1-s+sf(\theta_{t+1})) + \lambda\phi_{t+1}^{\lambda}f(\theta_{t+1})\right]H(W_{t+1})$$
$$+\left[s(1-\lambda\phi_{t+1}^{\lambda})(1-f(\theta_{t+1})) + \lambda\phi_{t+1}^{\lambda}(1-f(\theta_{t+1})\right]H(U_{t+1})\}, \tag{2.35}$$

where M_h denotes the discount factor of the household.

The value of being unemployed relies on the unemployment benefits B_t received in period t, and the discounted expected values of finding a job and remaining being unemployed.

$$H(U_t) = B_t + \underset{t}{E}M_{H,t+1}\left[f(\theta_{t+1})H(W_{t+1}) + (1-f(\theta_{t+1})H(U_{t+1})\right], \tag{2.36}$$

The equilibrium wage W_t determined by the Nash bargaining is given by:

$$W_t = \underset{W_t}{argmax}(J_t^F)^{1-\eta}(H(W_t) - H(U_t))^{\eta}, \tag{2.37}$$

where $\eta \in (0,1)$ denotes the bargaining power.

The first-order condition of equation 2.37 is given by:

$$J_t^F = \frac{1-\eta}{\eta}(H(W_t) - H(U_t)). \tag{2.38}$$

2.2.8. Market clearing

In the aggregate economy, the total output could be expressed as:

$$Y_t = y_t N_t^{\frac{\epsilon}{\epsilon-1}}, \tag{2.39}$$

The labor market clearing condition states that aggregate labor demand is :

$$L_t = (N_t + N_t^{new}) l_t, \tag{2.40}$$

The resource constraint condition[1] is given by:

$$Y_t = C_{I,t} + C_{H,t} + \kappa_t V_t^{tot} + N_t^{new} \left[K \phi_t^K (\frac{N_t^{new}}{N_{t-1}^{new}})^\tau \right]. \tag{2.41}$$

The last component of equation 2.41 represents the aggregate entry cost paid by entrant firms; nevertheless, it can also be interpreted as the investment in creating new entrants.

[1] Appendix C shows the way to obtain resource constraint.

2.3. Implications of the DSGE model

2.3.1. Calibration

The calibrated values are summarized in Table 2.1, with parameter values calibrated at the quarterly frequency. Specifically, we set the household discount factor β and investor discount factor β_I to be 0.995 and 0.985, respectively. Moreover, the household relative risk aversion and the investor relative risk aversion are set at 2 and 1 correspondingly. The choice of different values for discount factors and relative risk aversion aligns with previous studies by Garin (2015) and Bergin et al. (2018). Additionally, we select $\varphi = 10$ as the inverse Frisch elasticity[2]. Moreover, we calculate the value of disutility of work, γ, to be 1.45.

For the enforcement constraint, we set $\varsigma = 0.1634$, consistent with values utilized in Jermann and Quadrini (2012) and Bergin et al. (2018). The elasticity of substitution, ϵ, and exit rate, λ, are calibrated to 3.8 and 0.025, respectively, following Bilbiie et al. (2012). In the search and matching part, we assign a value of 0.09 to the separation rate s, ensuring that the total separation rate equals 0.1, as commonly utilized in the previous studies. For other labor market parameters, our target steady-state unemployment rate U is 0.062. We also target the vacancy filling rate $q(\theta) = 0.7$, in line with the calibration of Christiano et al. (2016). Following Blanchard and Galí (2010), we set the cost of posting per vacancy at $0.01\frac{Y_t}{V_t}$ in each period. Furthermore, in terms of the replacement ratio,$\frac{B}{W}$, and Nash bargaining weight,η, we set the values at 0.42 and 0.5, respectively. By calculation, we obtain unemployment benefit $B = 0.287$ and matching efficiency $\epsilon^M = 0.664$.

For the entry costs part, we target the value of congestion externality at 2.42. We also normalize the number of firms N and relative price ρ to 1. After calibrating other parameters,

[2]Previous studies typically assume the value of the inverse Frisch elasticity between 0 and 1. However, this range fails to satisfy the Blanchard-Kahn condition in our model. To address this issue, we set $\varphi = 10$, assuming the labor supply to be highly inelastic in our benchmark model.

we determine the entry cost, K, to be 7.17. Additionally, we set the persistence and standard deviations of the stochastic AR(1) processes as 0.95 and 0.01, respectively.

Table 2.1: Calibrated parameters.

Description	Parameter	Value
Household discount	β	0.996
Investor discount factor	β_I	0.985
Household relative risk aversion	ρ	2
Investor relative risk aversion	ρ_I	1
Inverse Frisch elasticity	φ	10
Disutility of work	γ	1.45
Enforcement parameter	ς	0.1634
Elasticity of substitution	ϵ	3.8
Exit rate	λ	0.025
Entry cost	K	7.17
Congestion externality	τ	2.42
Separation rate	s	0.09
Steady-state unemployment rate	U	0.062
Steady-state vacancy filling rate	$q(\theta)$	0.7
Replacement ratio	$\frac{B}{W}$	0.42
Bargaining power	η	0.5

2.3.2. Impulse responses to the technology shock

To illustrate the transmission mechanism in our model, we calculate the impulse responses of key variables to five exogenous shocks. Figure 2.1 shows the impulse responses of key variables to a 1 percent productivity increase. The shock leads to a persistent increase in output, consumption, and dividends. Moreover, it has a positive and enduring impact on the labor market by increasing aggregate labor demand and wages while reducing unemployment. Additionally, the creation of more vacancies increases job-finding rates. With persistent increases in the number of entrants, the number of firms grows gradually because it is a predetermined variable. Consequently, incumbent firms experience a reallocation of labor towards entrant firms as these entrant firms need to hire more workers, leading to a persistent decline in firm-level labor. This finding is consistent with empirical observations in Bilbiie et al. (2012), who differentiate labor utilization for entrant firms' creation and incumbents' production, although our model assumes that entrant and incumbent firms hire labor at the same level. The result also reveals that the positive technology shocks contribute to loosening financial constraints as measured by the Lagrange multiplier on the collateral constraint.

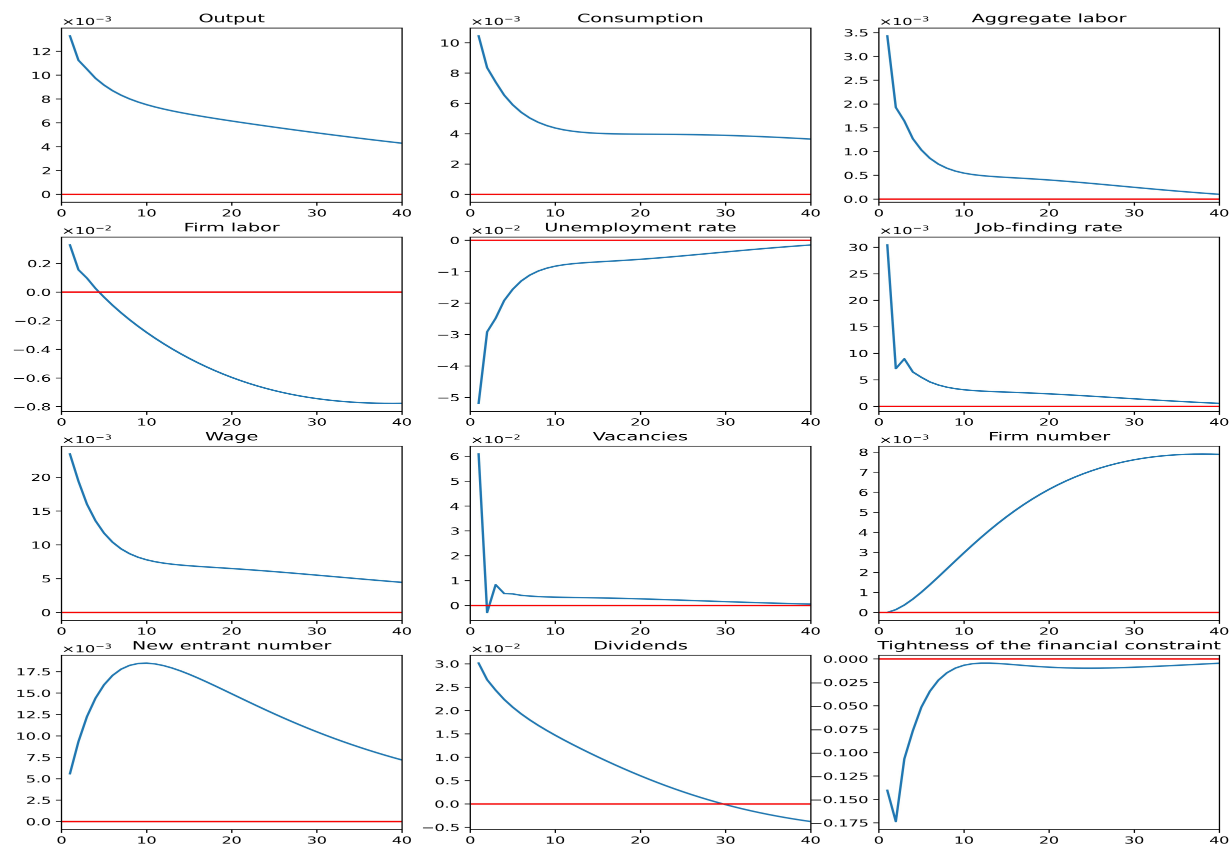


Figure 2.1: Impulse responses to a positive technology shock.

To investigate the importance of a less tight financial constraint and a higher number of surviving firms, we compare the impulse responses of our baseline model with either one of these two environments or both.[3] We set the new death rate $\lambda = 0.02$ and introduce a new enforcement parameter $\varsigma = 0.25$. Figure 2.2 displays the impulse responses of labor market and firm variables to a 1 percent productivity increase based on four scenarios. Under our benchmark parameters, the technology shock (depicted by the blue line) has minimal impact on output and other labor market variables, echoing the lowest magnitude of the initial responses. However, when the credit market is less tightened and there are more firms (represented by the orange line), we observe significant positive effects on the labor market and firm number variables. Lowering the death rate or loosening credit conditions also leads to technology shocks (shown by the green and red lines) impacting labor market and the firm numbers more than the responses with benchmark parameters. These two individual effects are still smaller than those resulting from credit frictions and firm dynamics combined, highlighting an amplification mechanism in our model. As potential entrant firms observe a high success rate in their business over time and an increased likelihood to borrow funds to expand operations in a less financially constrained environment, in response to a technology shock, more resources are allocated to help these entrants enter the market[4].

2.3.3. Impulse responses to other shocks

Figure 2.3 presents the impulse responses to a positive death shock. A higher death rate leads to persistent declines in the number of firms and entrants, resulting in fewer hiring opportunities and increased unemployment rates. Similarly, there is a decline in the demand for aggregate labor. However, the reduced competition and prospects of higher dividends incentivize surviving firms to expand their businesses, leading to an increased demand for labor at the firm level and more aggregate job vacancies. Due to the continuous firm exits and weaker labor demand at the aggregate level, workers are placed at a disadvantage when

[3] This comparison is still based on our benchmark model with different calibrated values. It is not the comparison between a model with credit frictions and firm dynamics and a model without either one of these two frictions or both. To compare the results of models without these two frictions, calibrated values and steady-state conditions need adjustment.

[4] This result is shown in the subplot on the bottom right corner of Figure 3.2

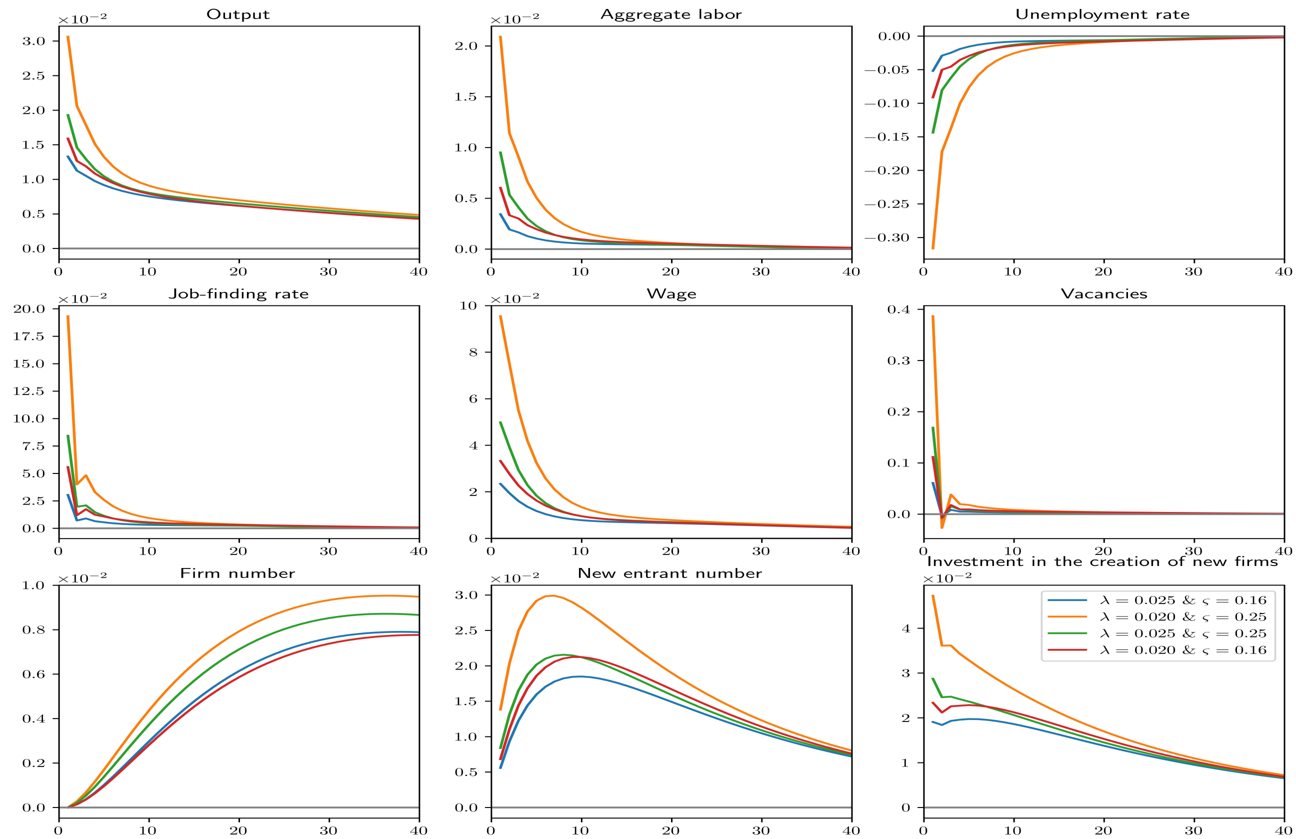


Figure 2.2: Impulse responses to a positive technology shock based on four scenarios.

bargaining with firms, resulting in lower wages. Reduced wages and a high unemployment rate result in contractions in both consumption and output, leading to heightened financial constraints.

Figure 2.4 shows the impulse responses to a positive collateral constraint shock, reflecting the relaxation of the collateral constraint. The impact of such a shock resembles that of a positive technology shock. In an environment where firms can utilize a higher proportion of their collateral, represented by the negative impact on reducing the tightness of the finance constraint, to finance working capital and vacancy costs, there is an increase in labor demand at the aggregate and firm levels, resulting in reduced unemployment rates and increased job finding rates, vacancies, and wages. The rise in aggregate labor leads to more production and consumption.

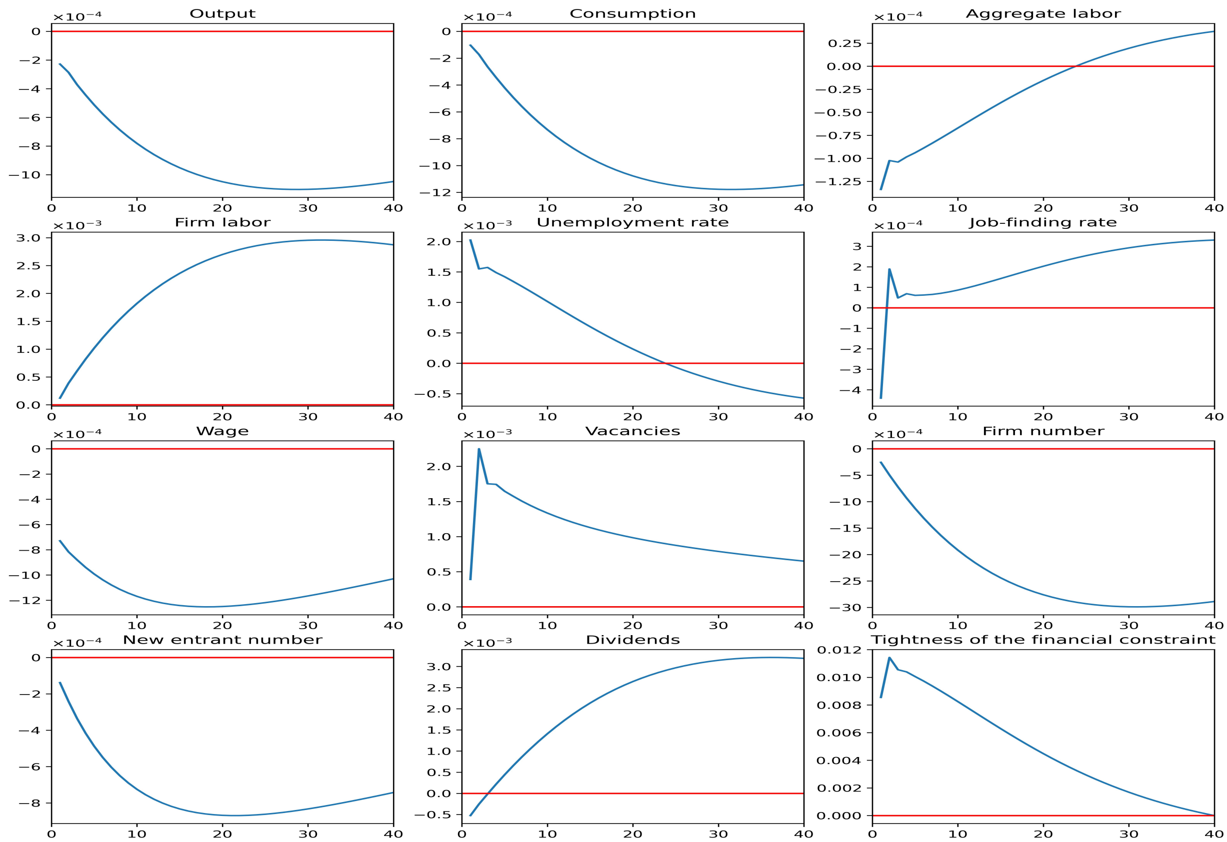


Figure 2.3: Impulse responses to a positive death shock.

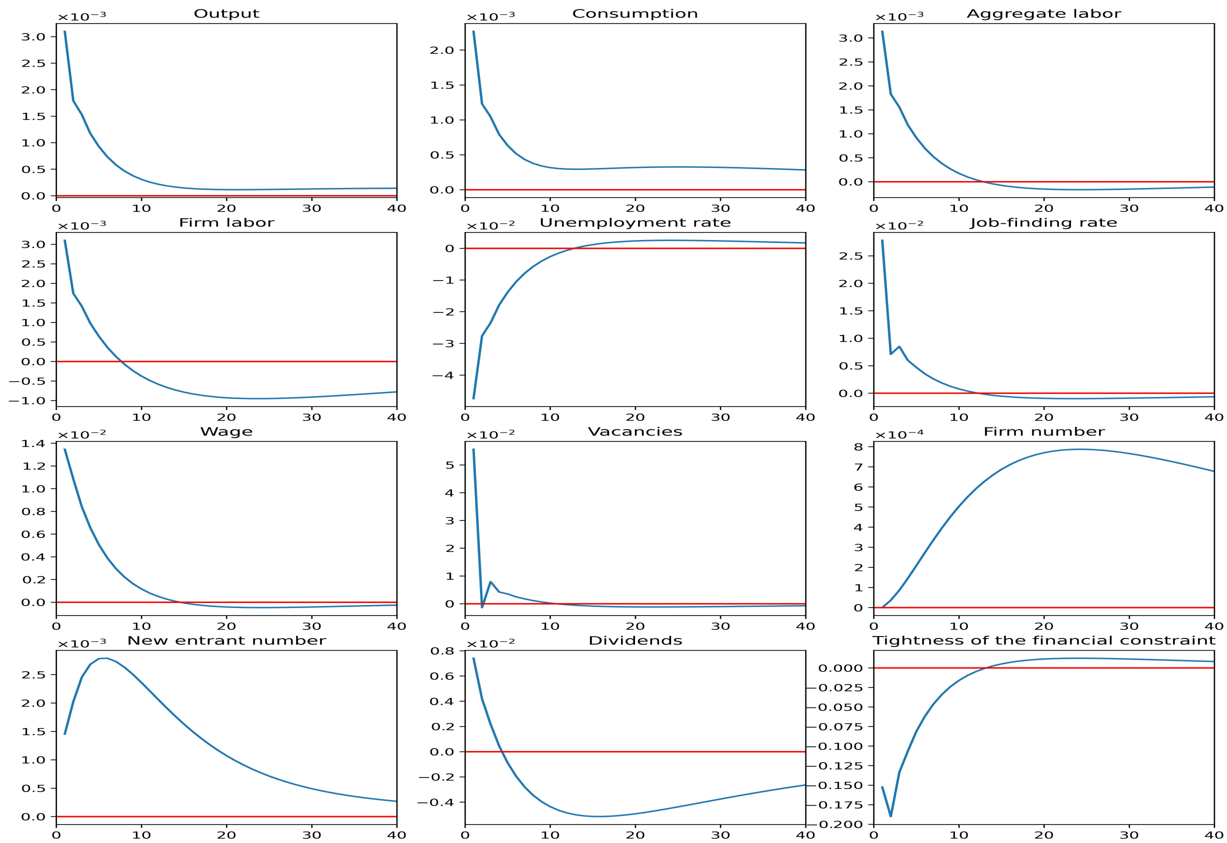


Figure 2.4: Impulse responses to a positive collateral constraint shock.

Figure 2.5 shows the impulse responses to a positive entry cost shock. A higher entry cost acts as a barrier to creating new firms, gradually decreasing the number of firms. As less labor is reallocated to create new firms and less competition is faced by incumbent firms, more workers flow into incumbent firms, consequently increasing labor at both firm and aggregate levels while reducing unemployment rates. However, due to the continuous decline in entrant firms, the positive impact of the shock on job finding rates, wages, and vacancies diminishes approximately 10 quarters after the initial shocks hit. Although death shocks and entry cost shocks show similarities in their effects on firm-level labor and aggregate vacancies, they differ in their effects on unemployment rates, wages, and aggregate labor. This disparity arises because death shocks negatively affect the numbers of entrant and incumbent firms directly. In contrast, entry cost shocks primarily influence the number of firms through their impact on entrant firms first. Furthermore, the positive effects of entry cost shocks on output and consumption eventually diminish after 10-15 quarters.

Figure 2.6 demonstrates the impulse responses to a positive disutility of work shock. As an increasing number of individuals opt to withdraw from the labor market, both incumbent and entrant firms encounter difficulties in recruiting sufficient workers for production, discouraging incumbents from staying in the market and deterring new entrants. As a result, the increased disutility leads to a decline in aggregate labor and job finding rates. The disincentives for household labor supply and firms' willingness to hire have a persistent negative effect on wages.

2.4. Conclusion

This study examines the effect of credit frictions and firm dynamics on labor market variables. The ability of firms to borrow by utilizing collateral to finance working capital and vacancy posting is constrained by changes in financial conditions; firms exit the market with a pre-assumed probability. Our findings indicate that reducing financial frictions and increasing firm longevity cause technology shocks to have longer effects on the fluctuations in the labor market compared to our benchmark calibrated model. Additionally, we find that death shocks and entry cost shocks impact the concentration of the labor force through distinct channels. Furthermore, positive collateral constraint shocks act like positive technology shocks, while positive disutility of work shocks resemble negative technology shocks.

Our analysis can be further extended by applying Bayesian estimation to explore the contributions of the five shocks discussed in our model in explaining labor market dynamics and to echo previous studies that underscore the importance of entry costs. Another potential extension of our study is to investigate the effect of Artificial Intelligence or robots, given their strong interconnection with start-ups and the labor market.

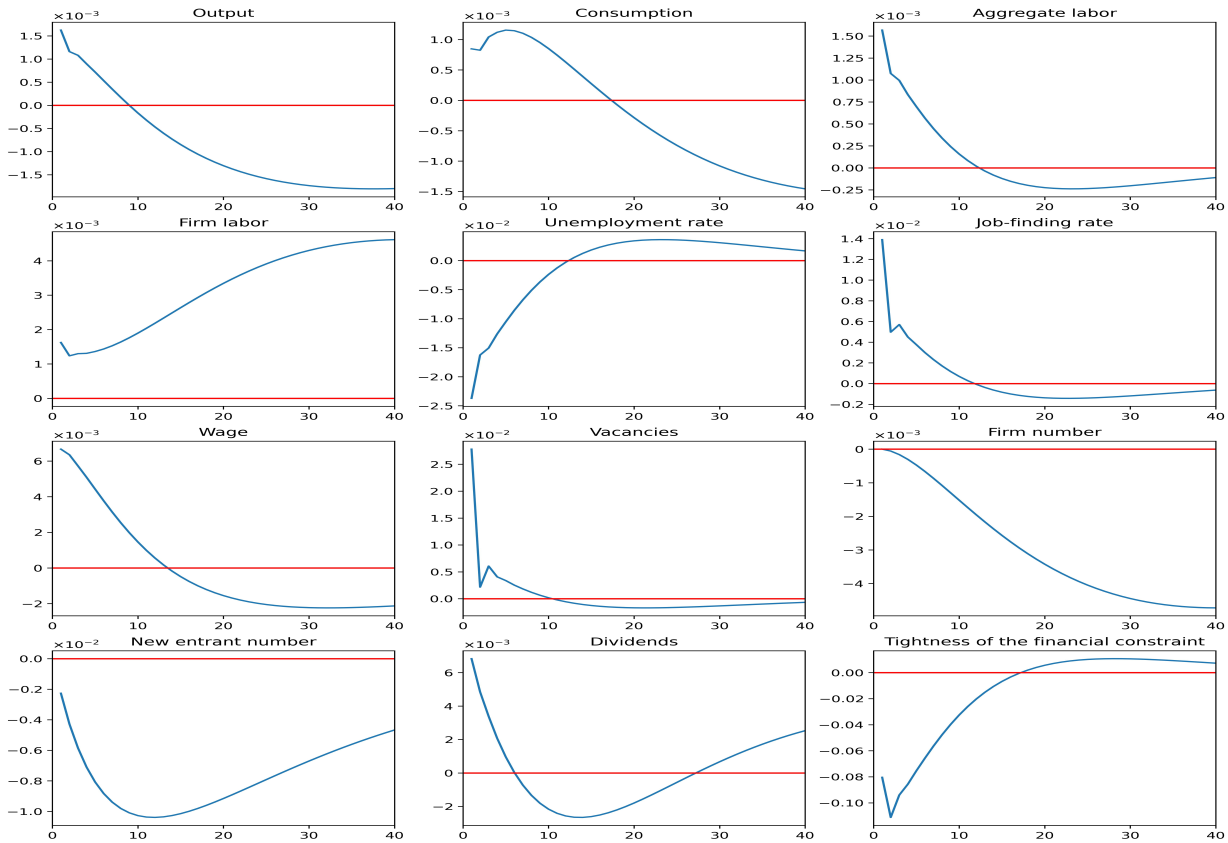


Figure 2.5: Impulse responses to a positive entry cost shock.

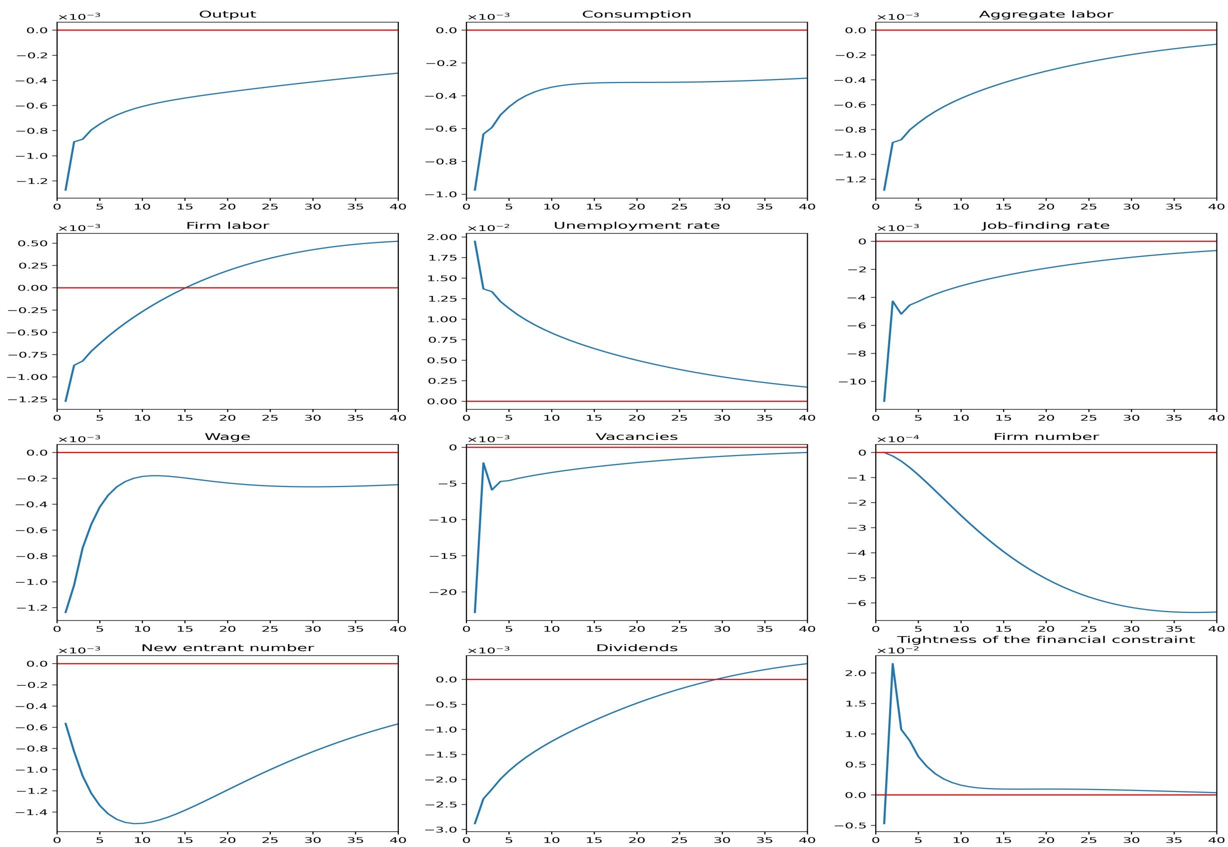


Figure 2.6: Impulse responses to a positive disutility of work shock.

Chapter 3

Macroeconomic Uncertainty and Asset Prices

3.1. Introduction

Research on the macroeconomic consequences of uncertainty gained traction after the 2008 financial crisis. Within this body of research, some studies examine the empirical results of uncertainty (e.g., Bloom (2009)), while others incorporate uncertainty into theoretical models to analyze its effect (e.g., Leduc and Liu (2016); Basu and Bundick (2017); Balke et al. (2021)). Although the relationship between uncertainty shocks and asset prices is extensively examined (e.g., Lettau et al. (2008); Bekaert et al. (2009); Paye (2012); Boguth and Kuehn (2013); Engle et al. (2013); Bansal et al. (2014); Segal et al. (2015)), some studies question whether the impact of uncertainty shocks varies across different economic environments. Caggiano et al. (2020) and Nalban and Smădu (2021) emphasize the asymmetric effects of uncertainty shocks on macroeconomic variables in different periods. Building on these findings in terms of asymmetric effects, certain studies have explored the influence of uncertainty shocks on housing prices (e.g., Christou et al. (2019); Balcilar et al. (2022)). These previous studies, however, do not consider the variables that are highly related to the stock market. To fill this void, our research aims to contribute to the literature by investigating the time-varying impact of uncertainty shocks on various asset prices. Addressing this issue could provide insights into whether the impulse responses to uncertainty shocks differ across business cycles and reveal the impact of uncertainty shocks in good and bad times.

Previous empirical studies have employed several measures of uncertainty of the stock market, including the widely used VIX and VXO indices which capture volatility based on the S&P 500 and S&P 100 indexes, respectively. The economic policy uncertainty index (hereafter EPU) proposed by Baker et al. (2016) is calculated using three equally weighted components: media coverage, federal tax code provisions, and disagreement among forecasters. An alternative, the economic uncertainty index calculated by Jurado et al. (2015) (hereafter JLN), represents the macroeconomic environment as it is derived from a wide range of economic variables. These indices have been extensively utilized in previous literature in asset pricing models to predict stock returns. Bali et al. (2017) highlight the significance of JLN in accurately forecasting stock returns, while Brogaard and Detzel (2015) use EPU as a proxy for VIX and find a negative relationship between EPU and market returns and that EPU impacts the discount rate. Lee et al. (2022) compare the performance of JLN, EPU, and VIX in predicting stock returns; however, their findings indicate that VIX remains the most accurate predictor.

Previous studies have primarily focused on analyzing the impact of uncertainty shocks on individual assets, neglecting a comprehensive understanding of their effects on various asset prices. To address this gap, we investigate the influence of uncertainty shocks on consumption growth, real stock returns, small minus big (hereafter SMB)[1], real oil prices, and three-month interest rates. The presence of uncertainty significantly influences agents' behavior in terms of consumption choices, investment decisions, and firm borrowing constraints through the precautionary saving channel. Our analysis incorporates consumption growth as it directly affects the discount rate. Additionally, we include SMB as a representative factor in the Fama-French portfolios, as it is commonly used in predicting stock returns in the Capital Asset Pricing Model (CAPM). Furthermore, the three-month rate can also be considered as an interest rate that has a relationship with the oil market and exchange rate (Kilian and Zhou (2022)), and it is used to calculate excess returns.

[1] A factor in the Fama-French stock pricing model where small companies outperform larger ones over the long term

In terms of the remaining variables, it is noteworthy that previous literature attributes business cycle fluctuations to oil prices rather than considering oil prices as a financial asset price. However, given their significant impact on both firms' production decisions and households' consumption patterns, oil prices can be considered a financial asset. Moreover, there exists an extensive body of literature investigating the relationship between oil prices and the stock market (e.g., Kilian and Park (2009); Kang and Ratti (2013); Bastianin and Manera (2018)) and the relationship between oil prices and exchange rates (e.g., Reboredo (2012); Reboredo and Rivera-Castro (2013); Beckmann et al. (2020)). Basher et al. (2012) examine these three macroeconomic aggregates in emerging markets. Roubaud and Arouri (2018) extend the previous research examining the trilateral relationship between oil prices and the stock market by incorporating the exchange rate. Their rationale for doing so is based on considering the US dollar as the predominant currency for worldwide transactions. The findings reveal strong relationships among these variables, which become even more solidified in times of greater uncertainty.

Despite the lack of consensus on the superiority of alternative uncertainty indices, we employ JLN as a proxy for uncertainty in our analysis. In comparison to other indices, JLN possesses some advantages. Firstly, JLN has distinct effects on consumption. Based on survey data, Nam et al. (2021) investigate the impact of both JLN and VIX on household consumption and find that JLN has a more prolonged influence on consumption volatility than on financial-related volatility. Secondly, the credibility of VIX as a proxy to represent the macroeconomic environment is challenged due to its sensitivity to unpredictable events (Jurado et al. (2015)). Lastly, our primary objective is to analyze the impact of macroeconomic uncertainty on asset prices. As the JLN index incorporates macroeconomic uncertainty indicators, it is more attractive than asset price indicators such as VIX.

While a large body of empirical uncertainty research mainly relies on fixed-coefficient VAR models, Lubik and Matthes (2015) argue that these models may fail to capture the nonlinearity in macroeconomic series caused by structural changes, favoring a time-varying VAR model with stochastic volatility (hereafter TVP-VAR-SV) instead. Most uncertainty indices are associated with fluctuations in the conditional variance of the data-generating process. In situations with a high level of uncertainty, the conditional variance will also be higher, suggesting that the empirical analysis should consider drifting coefficients and shocks with stochastic volatility (e.g., Uhlig (1997); Cogley and Sargent (2005)). The previous literature has already established the time-varying effects of uncertainty indices. For example, Kurasawa (2017) demonstrates a time-varying relationship between economic policy uncertainty and exchange rates. By applying a threshold VAR model, Van Robays (2016) shows that the macroeconomic uncertainty index plays an important role in driving oil prices, particularly during recessions characterized by elevated levels of macroeconomic uncertainty.

To address the questions posed at the outset of this paper, we employ a benchmark structural VAR model and an alternative TVP-VAR-SV model to examine the impact of uncertainty shocks on asset prices, taking into account the dynamic nature of economic relationships over time. Our study builds upon prior literature that has analyzed the time-varying effects of various shocks (e.g., Baumeister and Peersman (2013a,b); Mumtaz and Zanetti (2013); Kang et al. (2015); Bastianin and Manera (2018); Tian et al. (2021)). To investigate whether uncertainty shocks have diverse impacts across different business cycles, we estimate the impulse responses after five months of NBER announcing business cycle beginning dates to provide more precise estimates. Our findings indicate that uncertainty shocks have adverse effects in both the structural VAR model and the TVP-VAR-SV model. However, the magnitude of the rebound and overshoot varies across different dates. Specifically, our results highlight higher persistence in variable responses during 2008 compared to other years, except for the three-month rate. Furthermore, we find no asymmetric effects of uncertainty shocks on asset prices in good and bad times. Notably, our findings are robust to changes in the order of the variables and different lags.

This paper is organized as follows: Section 2 discusses the data and the results of the baseline VAR model. The time-varying model and its results are presented in Section 3. Section 4 discusses robustness checks. Section 5 concludes the paper.

3.2. Data and baseline VAR model

3.2.1. Data

We collect monthly data covering the sample period from January 1973 to December 2018. We use a three-month ahead macroeconomic uncertainty index, sourced from Ludvigson's website. Consumption is quantified by the growth rate of personal consumption expenditure. Oil prices are measured in dollars per barrel using spot market prices traded on West Texas Intermediate crude oil. Exchange rates are measured using a trade-weighted exchange rate index, which is a weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies; a higher exchange rate value means the U.S. dollar's appreciation. The real interest rate is defined as the three-month nominal U.S. Treasury rate, adjusted for the one-month inflation rate over the preceding month. The stock market return is the monthly aggregate return for the S&P 500 index, and the data are collected from The Center for Research in Security Prices (CRSP). The data for SMB are available from Kenneth French's data library. The Federal Reserve Bank of St. Louis provides access to data on oil prices, exchange rates, the three-month Treasury bill rate, personal consumption expenditure, and the consumer price index. All variables, except for SMB, are converted to real values by deflating them with the U.S. CPI. For modeling purposes, real consumption, real exchange rate index, real stock returns, and real oil prices are expressed in natural logarithms; the SMB and real interest rates are expressed in levels.

3.2.2. VAR specification

Our benchmark structural VAR model is defined as:

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + \varepsilon_t.$$

where $\varepsilon_t \sim iidN(0, \Omega)$ and where A_0 is a lower triangular matrix.

Our benchmark analysis depends on a vector of variables $Y_t = (u_t, c_t, sr_t, smb_t, op_t, ex_t, r_t)$, where u_t denotes the normalized JLN index, c_t denotes the percentage change in real consumption, sr_t denotes the percentage change in real stock return, smb_t denotes the small minus big factor, op_t denotes the percentage change in real oil price, ex_t denotes the percentage change in the exchange rate, and r_t denotes the real interest rate.

Figure 3.1 shows the impulse responses to normalized uncertainty shocks based on the structural VAR model with two lags, as determined by the AIC criteria. The results reveal that positive normalized uncertainty shocks lead to a sharp collapse in consumption growth, stock returns, SMB, and the (invested) exchange rate, followed by a subsequent recovery; these responses are consistent with existing empirical literature. The adverse impacts on these four variables reach their minimum after one month. However, the initial responses of oil prices and the three-month interest rate are positive but diminish quickly. The adverse responses of oil prices and the exchange rate reach their minimum after one month and three months, respectively. One possible explanation for the response of the exchange rate is associated with one of the exchange rate puzzles, referring to the weak relationship between the exchange rate and macroeconomic aggregates in the short run. Another possible explanation is that investors buy U.S. bonds as a safety asset against the underlying risks in the future, leading to an appreciation of the U.S. dollar.

Although the magnitudes of the impact of normalized uncertainty shocks on these variables reach their minimum or maximum within the first four months, the subsequent rebound rates vary across different variables. Notably, rebounds and overshoots are more pronounced for SMB and oil prices. The rebound effect in the responses of consumption growth is characterized by a protracted duration of approximately three years, while stock returns, exchange rates, and three-month rates exhibit a shorter duration of around fifteen months. These results indicate that investors in the stock market and foreign exchange market are more sensitive to uncertainty news, and that agents' consumption decisions are more cautious.

3.3. Time-varying analysis

3.3.1. Time-varying VAR analysis

Following Primiceri (2005) and Nakajima et al. (2011), the structural VAR model is defined as:

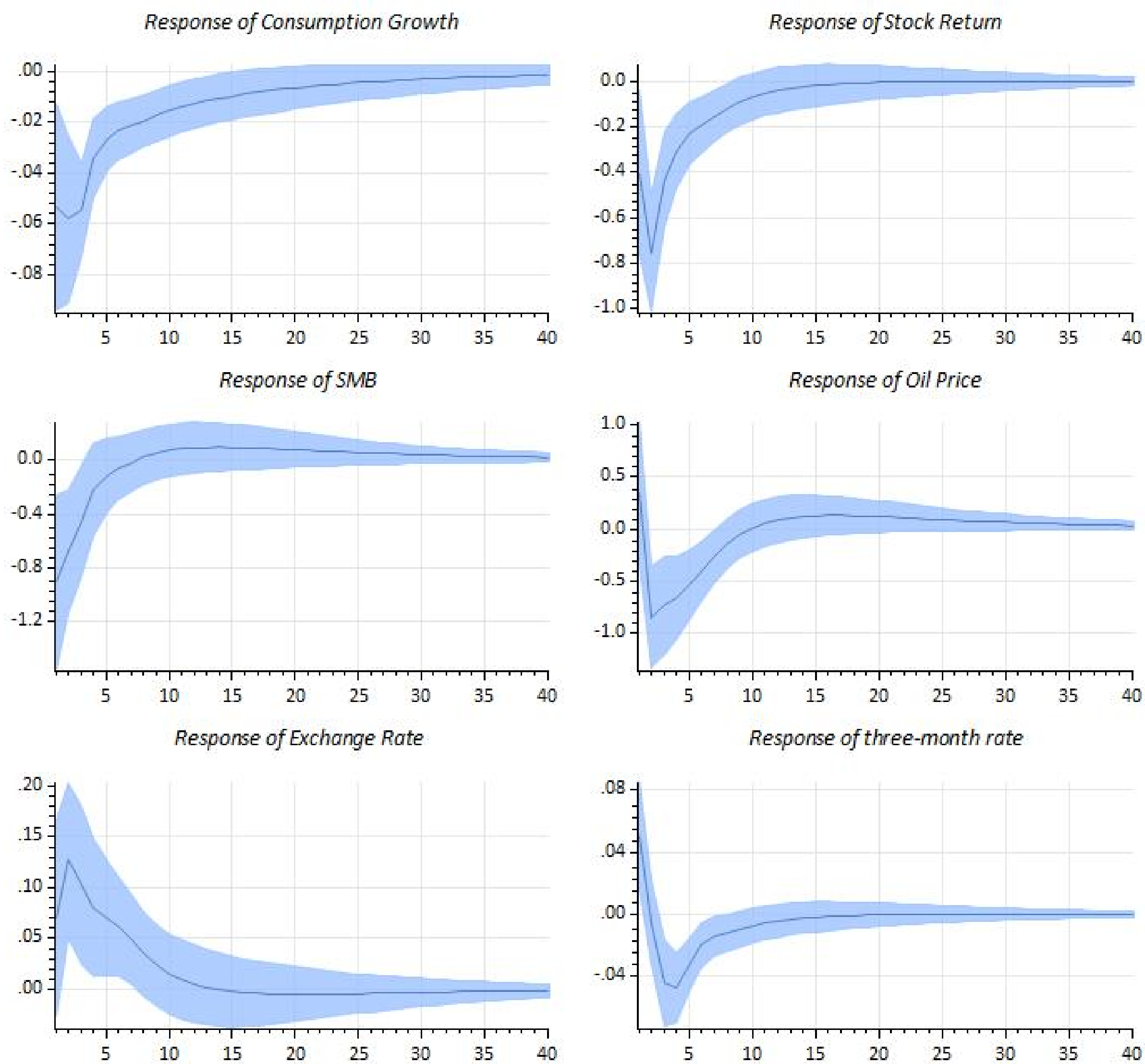
$$A\mathbf{y}_t = F_1\mathbf{y}_{t-1} + ... + F_s\mathbf{y}_{t-s} + u_t, t = s+1, ...n.$$

Where $\mathbf{y}_t$ is an $k \times 1$vector of observed endogenous variables; and $A, F_1, ..., F_s$ are $k \times k$ matrices of coefficients. The disturbance u_t is a $n \times 1$ structural shock, and we assume that $u_t \sim N(0, \Sigma\Sigma)$, where

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}.$$

In order to obtain the structural shocks, we assume that A is lower-triangular,

Figure 3.1: Impulse responses of asset prices to one normalized macroeconomic uncertainty shock.



$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix}.$$

Then rewrite the VAR model as:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_s y_{t-s} + \Sigma \varepsilon_t.$$

where $\varepsilon_t \sim N(0, I_k)$. $B_i = A^{-1}F$, for $i = 1, ..., s$. Then stacking the elements in the rows of the B_is to form $\beta(k^2 s \times 1 vector)$, and define $X_t = I_k \otimes (\mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-s})$, the model can be written as:

$$\mathbf{y}_t = X_t \beta + \Sigma \varepsilon_t.$$

By allowing the parameters to change over time, we could extend the structural VAR model to the TVP-VAR model, and the new model could be written as:

$$\mathbf{y}_t = X_t \beta_t + \Sigma_t \varepsilon_t, t = s + 1, ..., n.$$

where β_t, A_t and Σ_t are the time varying matrices. Let $\boldsymbol{a}_t = (a_{21}, a_{31}, a_{32}, a_{41}, ..., a_{k,k-1})'$ be a stacked vector of the lower-triangular elements in A_t and $\boldsymbol{h}_t = (h_{1t}, ..., h_{kt})'$with $h_{jt} = log\sigma_{jt}^2$ for $j = 1, ..., k$,$t = s + 1, ..., n$.

We then assume that all the parameters follow a random walk process as follows:

$$\beta_{t+1} = \beta_t + u_{\beta t}, \boldsymbol{a}_{t+1} = \boldsymbol{a}_t + u_{at}, \boldsymbol{h}_{t+1} = \boldsymbol{h}_t + u_{ht}.$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right), t = s+1, ..., n.$$

where $\beta_{s+1} \sim N(u_{\beta 0}, \Sigma_{\beta 0})$, $\boldsymbol{a}_{s+1} \sim N(u_{a0}, \Sigma_{a0})$, and $\boldsymbol{h}_{s+1} \sim N(u_{h0}, \Sigma_{h0})$.

The estimation procedure uses the Markov Chain Monte Carlo algorithm and we assume that Σ_h and Σ_a are diagonal matrices.

The priors are assumed for the i-th diagonals of the covariance matrices:

$(\Sigma_\beta)_i^2 \sim Gamma(8, 0.02), (\Sigma_a)_i^2 \sim Gamma(8, 0.02), (\Sigma_h)_i^2 \sim Gamma(8, 0.02).$

And the priors for the initial state of the time-varying parameters are decided as:

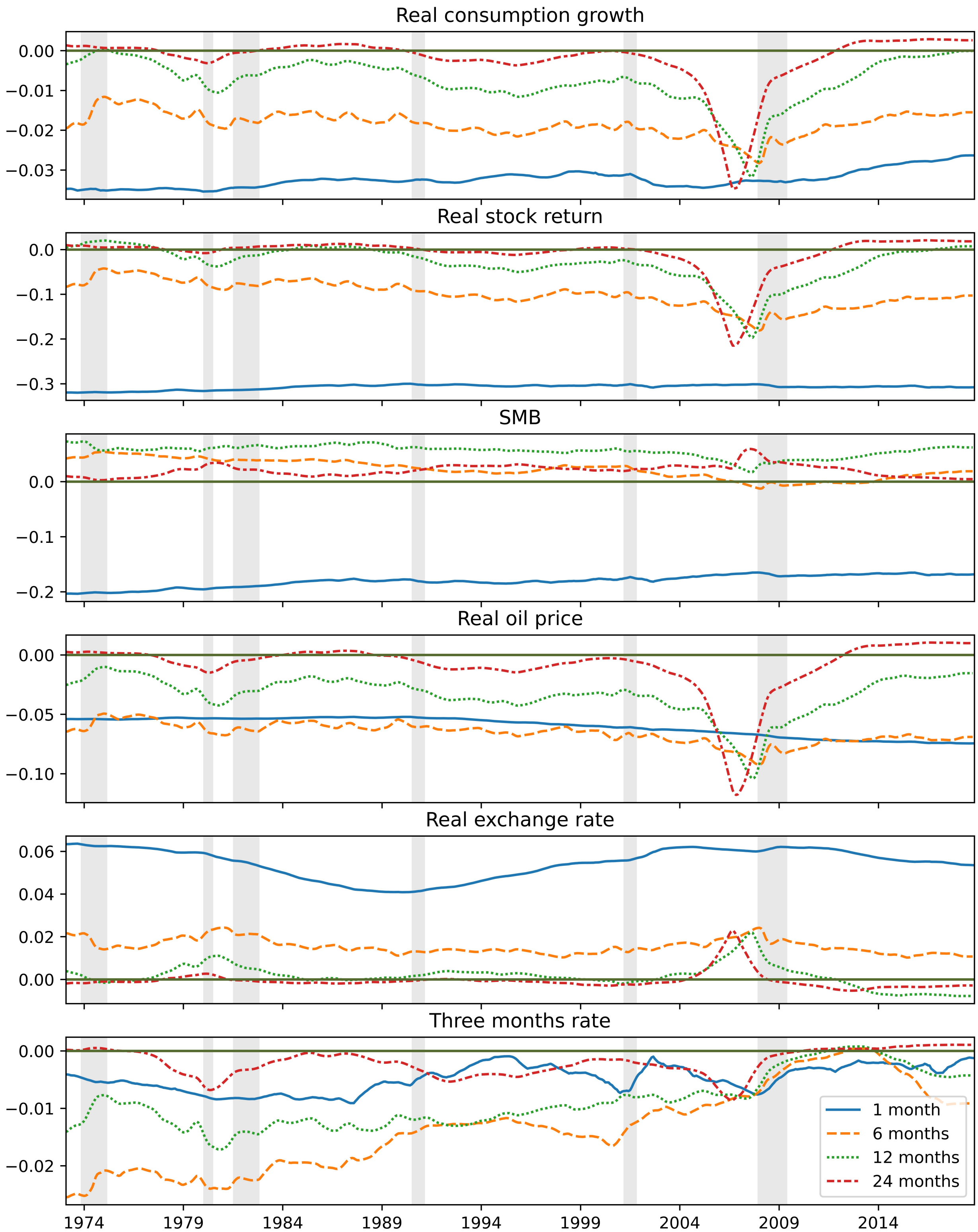
$\mu_{\beta 0} = \mu_{a0} = \mu_{h0} = 0$ and $\Sigma_\beta = \Sigma_a = \Sigma_h = 10 \times I$.

We follow Primiceri (2005) in using two lags. The impulse responses for each specification in the following sections are calculated based on the posterior mean of parameters using 50,000 draws with 10,000 burn-in.

3.3.1.1. Time-varying effect analysis

Figure 3.2 presents the impulse responses of consumption growth, real stock returns, SMB, real oil prices, exchange rate, and the three-month rate to positive normalized uncertainty shocks at 1, 6, 12, and 24 months after the uncertainty shocks hit. The results confirm the adverse impact of positive normalized uncertainty shocks on all variables one month after shocks hit; however, there is limited variation over time. At longer horizons, from 6 to 24

Figure 3.2: Impulse responses of real consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-month rate at 1, 6, 12, 24 months after initial positive normalized uncertainty shocks hit. The impulse responses are calculated based on the posterior mean of parameters. The grey-shaded regions represent business cycle periods.

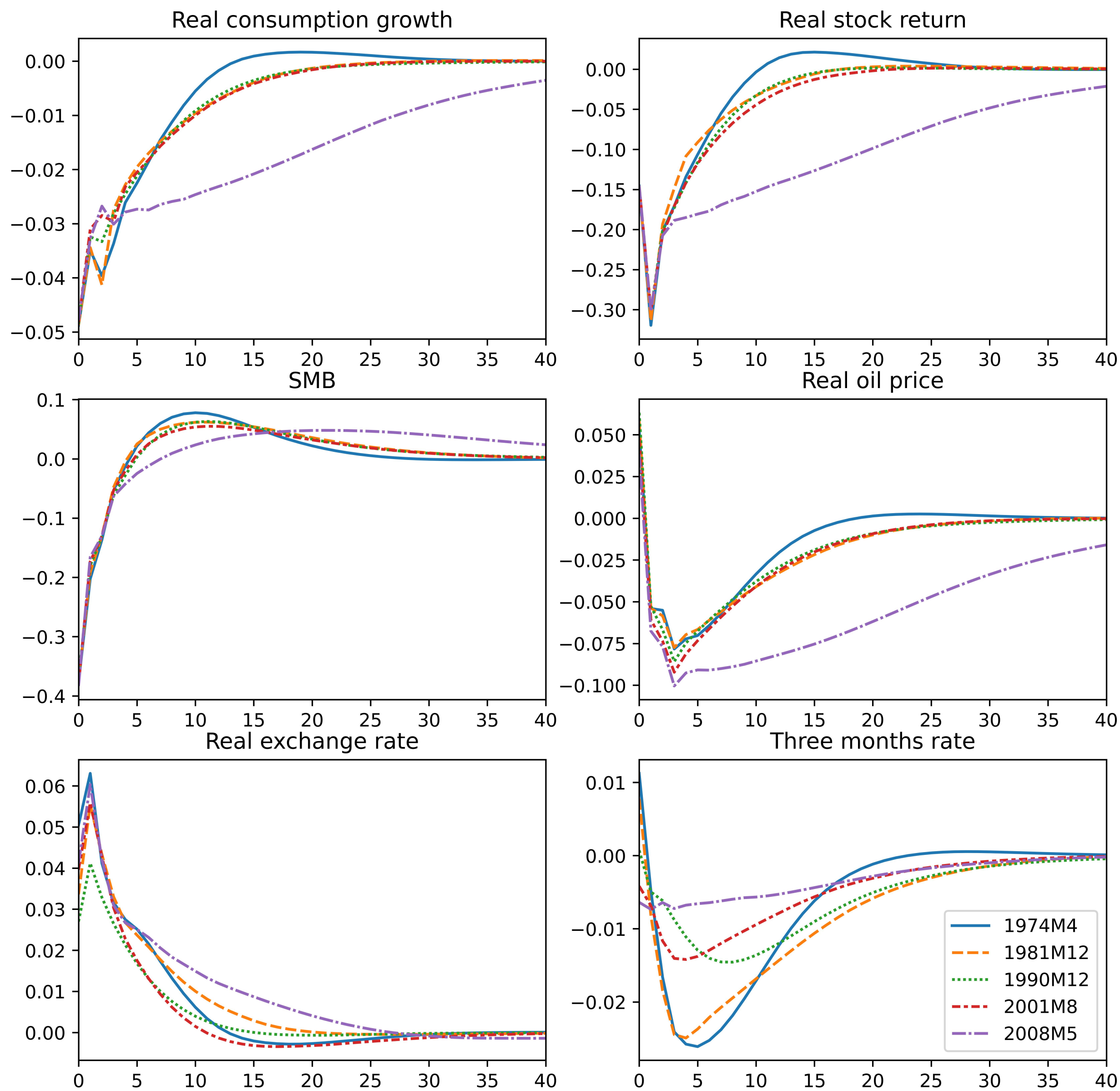


months, the effects on these variables present different pictures. Firstly, the long-run effects (at 24 months) of the uncertainty shocks on consumption growth and other asset prices are minimal, with fluctuations around zero. Specifically, the impulse response of consumption growth is positive from 1984 to 1989 and after 2003 but negative from 1990 to 1999. A similar pattern of long-run effects can also be observed for other asset prices. Secondly, the uncertainty shocks cause a greater negative effect on variables in two business cycle periods: one around 1980 and another during the 2008 Great Recession. However, the greatest adverse effects caused by the uncertainty shocks occur before the 2008 NBER announcement date in our results; this may be attributed to the forward-looking of impulse responses as the uncertainty index relies on a three-month ahead forecast error. Additionally, we do not find robust evidence to support the claim that uncertainty shocks have asymmetric effects on asset prices within our sample periods, as the magnitudes of these impulse responses are not higher during good times compared to bad times. For example, six months after the uncertainty shock hits, there is a limited impact on stock returns from 1983 to 1990 as the impulse response fluctuates around zero; however, from 1990 to 2000, the impulse responses are negative.

3.3.1.2. Impulse responses at different time points

We analyze the impulse responses at five specific dates within the business cycles instead of the dates at the onset of a recession to better understand the effects of uncertainty shocks. In Figure 3.3, when positive uncertainty shocks hit, the impulse responses of consumption growth and asset prices reach their minimum values within the initial five months. When comparing the impulse responses in Figure 3.1, we observe that while the impulse responses are consistent, there are discernible variations at different time points, indicating the presence of a time-varying effect. Specifically, although the magnitudes of the impulse responses of the first five variables in 2008 initially decrease to the minimum, after a few months, the

Figure 3.3: Impulse responses of consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-month rate to positive normalized uncertainty shocks at five different dates. Responses are calculated based on the posterior mean of parameters.



rebound effects of these impulse responses are weaker than those observed in other years, demonstrating the sluggish recovery characteristic of the Great Recession. In contrast, the impulse responses in 1974 show a faster rebound compared to other years. Furthermore, the impulse responses in 1990 indicate that uncertainty shocks have relatively smaller effects on the U.S. dollar, with their magnitudes reaching maximum levels lower than those observed in other years despite reaching the maximum simultaneously. Moreover, noticeable differences exist among the magnitudes and speeds of rebound for the three-month rates at different time points. Notably, during the business cycles of 1974 and 1981, uncertainty shocks have the most significant impact on the three-month rate.

3.4. Robustness analysis

Ludvigson et al. (2021) suggest that uncertainty shocks exhibit an endogenous response to business cycles rather than an exogenous one. Given the recursive identification scheme employed in the TVP-VAR model, we are concerned about the significance of the ordering of the uncertainty index. In addition to checking the ordering, we also compare the results obtained from the baseline TVP-VAR model and those with different numbers of lags to check the robustness of the results. We apply a new vector of variables $Y_t = (c_t, sr_t, smb_t, op_t, ex_t, r_t, u_t)$ in the first robustness check. Figures 3.4 and 3.5 present the results based on the new ordering. The time-varying effects displayed in Figure 3.4 are consistent with those presented in Figure 3.2, while the magnitudes of impulse responses range from one-third to half of those in the benchmark order. Figure 3.5 illustrates a similar pattern of impulse responses at five different time points. The impulse responses in 2008 recover faster than those in Figure 3.2. These findings do not support the idea that recessions cause uncertainty proposed by Bachmann et al. (2013). Furthermore, the impact of positive uncertainty shocks on the exchange rate in 1990 is comparable to that observed in other years, which is different from the result in the baseline TVP-VAR model.

Figure 3.4: Impulse responses of real consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-month rate at 1, 6, 12, 24 months after initial positive normalized uncertainty shocks hit. The impulse responses are calculated based on the posterior mean of parameters. The grey-shaded regions represent business cycle periods.

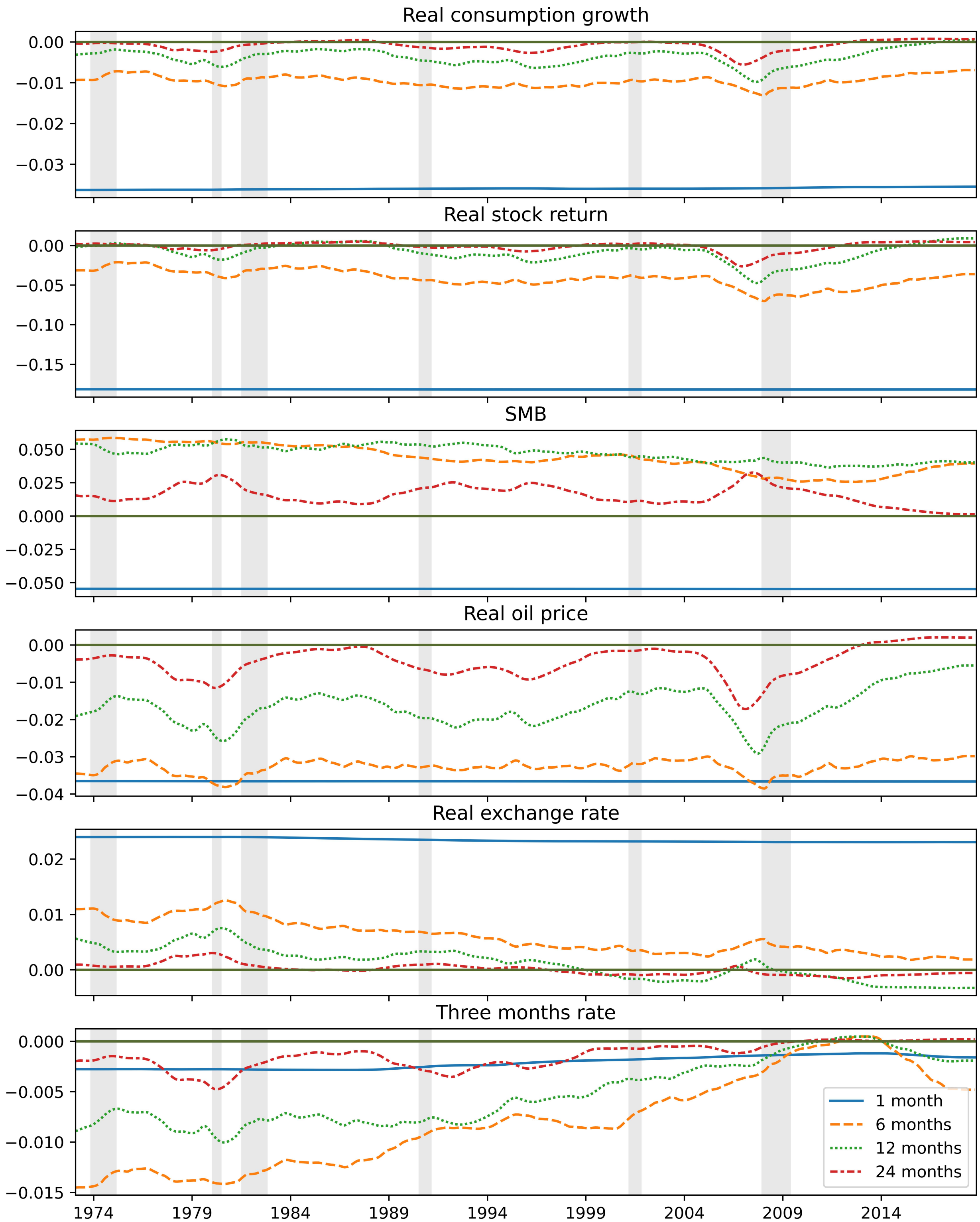
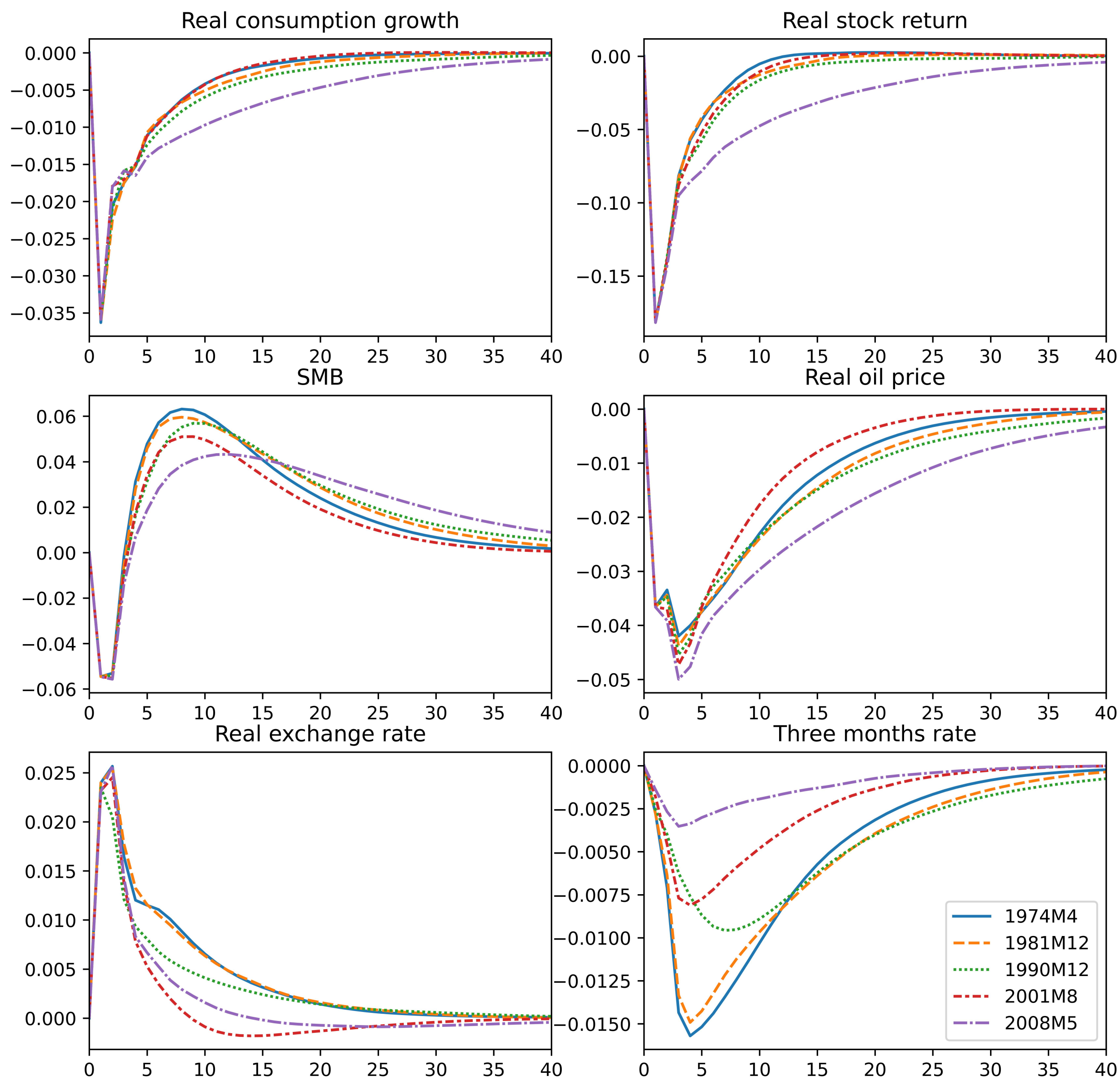


Figure 3.5: Impulse responses of consumption growth, real stock return, SMB, real oil price, exchange rate, and the three months rate to positive normalized uncertainty shocks at four different dates. Responses are calculated based on the posterior mean of parameters.



Figures C.1.1 to C.1.4 (presented in Appendix C) display results obtained from the baseline TVP-VAR model with three and four lags, respectively. These findings show similarity to those in the model with two lags, indicating that our results from the baseline model are robust to the model with different lags.

3.5. Conclusion

This study presents empirical evidence of the time-varying effects of uncertainty shocks on asset prices by employing the time-varying VAR model with stochastic volatility. Uncertainty shocks are identified using a macroeconomic uncertainty index as a proxy variable. We analyze the impulse responses at five different time points in the business cycles and examine time-varying impulse responses over the sample period. Our findings show that positive uncertainty shocks have time-varying effects on consumption growth and asset prices at 6 months, 12 months, and 24 months after the uncertainty shocks hit. However, our findings do not support the previously highlighted asymmetric impact of uncertainty shocks in good and bad times. Additionally, we find that uncertainty shocks have a long-lasting adverse impact on asset prices in 2008 due to a sluggish recovery.

Appendix A

Appendix of Chapter 1

A.1. Dynamic equations

The system of equilibrium conditions can be reduced to the following equations:

$$J_t^H = \left\{ (1 - \beta\phi_t) C_t^{1-\frac{1}{\psi}} + \beta\phi_t \left(\underset{t}{E} \left[J_{t+1}^{H,1-\gamma} \right] \right)^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}} \tag{1.1}$$

$$M_{t,t+1} = \beta\phi_t \left[\frac{(1 - \beta\phi_{t+1})}{(1 - \beta\phi_t)} \right] \left[\frac{C_{t+1}}{C_t} \right]^{-\frac{1}{\psi}} \left[\frac{J_{t+1}^H}{\underset{t}{E} \left[J_{t+1}^{H,1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right]^{\frac{1}{\psi}-\gamma} \tag{1.2}$$

$$Y_t = e^{z_t} K_t^{\alpha} (L_t N_t)^{1-\alpha} \tag{1.3}$$

$$K_{t+1} = (1 - \delta) K_t + \Phi \left(\frac{I_t}{K_t} \right) K_t \tag{1.4}$$

$$\Phi \left(\frac{I_t}{K_t} \right) = b_1 + \frac{b_2}{1 - \frac{1}{\chi_k}} \left(\frac{I_t}{K_t} \right)^{1-\frac{1}{\chi_k}} \tag{1.5}$$

$$Q_{t+1} = \frac{1}{b_2 \left(\frac{I_{j,t}}{K_{j,t}} \right)^{-\frac{1}{\chi_k}}} \tag{1.6}$$

$$Q_t = \underset{t}{E} M_{t+1} \left[Q_{t+1} \left((1-\delta) + b_1 + \frac{b_2}{1-\frac{1}{\chi_k}} \left(\frac{I_t}{K_t} \right)^{1-\frac{1}{\chi_k}} - b_2 \left(\frac{I_{t+1}}{K_{t+1}} \right)^{-\frac{1}{\chi_k}} \left(\frac{I_{t+1}}{K_{t+1}} \right) \right) + \frac{\nu-1}{\nu} \alpha \frac{Y_{t+1}}{K_{t+1}} \right] \tag{1.7}$$

$$J_t^F = (1-\alpha) \frac{\nu-1}{\nu} \frac{Y_t}{N_t} - W_t + (1-\mu) \underset{t}{E} M_{t+1} J_{t+1}^F \tag{1.8}$$

$$U_t = 1 - N_t \tag{1.9}$$

$$u_t = 1 - (1-\mu) N_t \tag{1.10}$$

$$m(u_t, V_t) = \epsilon_t^M m_0 V_t^{1-\xi} u_t^{\xi} \tag{1.11}$$

$$f(\theta_t) \equiv \frac{m(u_t, V_t)}{u_t} \tag{1.12}$$

$$q(\theta_t) \equiv \frac{m(u_t, V_t)}{V_t} \tag{1.13}$$

$$N_t = (1-\mu) N_{t-1} + V_t q(\theta_t) \tag{1.14}$$

$$\kappa_t = q(\theta_t) J_t^F \tag{1.15}$$

$$H(W_t) = W_t + \underset{t}{E} M_{t+1} \left\{ [1 - \mu(1 - f(\theta_{t+1})] H(W_{t+1}) + \mu (1 - f(\theta_{t+1})) H(U_{t+1}) \right\} \tag{1.16}$$

$$H(U_t) = b_t + \underset{t}{E} M_{t+1} \left[f(\theta_t) H(W_{t+1}) + (1 - f(\theta_t)) H(U_{t+1}) \right] \tag{1.17}$$

$$H(W_t) - H(U_t) = W_t - b_t + \underset{t}{E} M_{t+1} \left[(1 - \mu - f(\theta_t)) (H(W_{t+1}) - H(U_{t+1})) \right] \tag{1.18}$$

Nash sharing:

$$\eta \left(H(W_t) - H(U_t) + J_t^F \right) = H(W_t) - H(U_t) \tag{1.19}$$

AOB:

$$a_1 J_t^F = a_2 (H(W_t) - H(U_t)) - a_3 \gamma + a_4 (\upsilon_t - b_t) \tag{1.20}$$

$$Y_t = C_t + I_t + \kappa_t V_t \tag{1.21}$$

$$log\phi_t = \rho_\phi log\phi_{t-1} + \sigma_t^\phi \varepsilon_t^\phi \tag{1.22}$$

$$log\epsilon_t^M = \rho_M log\epsilon_{t-1}^M + \varepsilon_t^\epsilon \tag{1.23}$$

$$logA_t = \rho_A logA_{t-1} + \varepsilon_t^A \tag{1.24}$$

$$D_t = Y_t - W_t N_t - \kappa_t V_t - I_t \tag{1.25}$$

$$R_{t+1} = \frac{S_{t+1}}{S_t - D_t} \tag{1.26}$$

$$S_t = D_t + M_{t+1} S_{t+1} \tag{1.27}$$

$$R_{f,t+1} = \left[\underset{t}{E}(M_{t,t+1}) \right]^{-1} \tag{1.28}$$

A.2. Detrended equations

We detrend the endogenous variables J_t^H, C_t, Y_t, I_t, K_t, J_t^F,W_t, J_t, υ_t^p, W_t^p, υ_t, κ_t, $H\left(W_t\right)$, $H\left(U_t\right)$, S_t, D_t. The detrended variable is expressed as $\tilde{X}_t$, and the gross growth rate of technology is $g_{L,t}$=$\frac{L_t}{L_{t-1}}$.

$$\tilde{J}_t^H = \left\{(1-\beta\phi_t)\tilde{C}_t^{1-\frac{1}{\psi}} + \beta\phi_t(\underset{t}{E}\left[\tilde{J}_{t+1}^H g_{L,t+1}\right]^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}}\right\}^{\frac{1}{1-1/\psi}} \tag{1.29}$$

$$M_{t,t+1} = g_{L,t+1}^{-\frac{1}{\psi}}\beta\phi_t\left[\frac{(1-\beta\phi_{t+1})}{(1-\beta\phi_t)}\right]\left[\frac{\tilde{C}_{t+1}}{\tilde{C}_t}\right]^{-\frac{1}{\psi}}\left[\frac{\tilde{J}_{t+1}^H}{\underset{t}{E}\left[\tilde{J}_{t+1}^{H,1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right]^{\frac{1}{\psi}-\gamma} \tag{1.30}$$

$$\tilde{Y}_t = e^{z_t}\tilde{K}_t^{\alpha}\left(N_t\right)^{1-\alpha} \tag{1.31}$$

$$\tilde{K}_{t+1} = \left(1-\delta\right)\tilde{K}_t g_{L,t+1}^{-1} + \Phi\left(\frac{\widetilde{I}_t}{\widetilde{K}_t}\right)\tilde{K}_t g_{L,t+1}^{-1} \tag{1.32}$$

$$\Phi\left(\frac{\tilde{I}_t}{\tilde{K}_t}\right) = b_1 + \frac{b_2}{1-\frac{1}{\chi_k}}\left(\frac{\tilde{I}_t}{\tilde{K}_t}\right)^{1-\frac{1}{\chi_k}} \tag{1.33}$$

$$Q_{t+1} = \frac{1}{b_2\left(\frac{\tilde{I}_{j,t}}{\tilde{K}_{j,t}}\right)^{-\frac{1}{\chi_k}}} \tag{1.34}$$

$$Q_t = \underset{t}{E}M_{t+1}$$
$$\left[Q_{t+1}\left((1-\delta)+b_1+\frac{b_2}{1-\frac{1}{\chi_k}}\left(\frac{\widetilde{I}_t}{\widetilde{K}_t}\right)^{1-\frac{1}{\chi_k}} - b_2\left(\frac{\widetilde{I}_{t+1}}{\widetilde{K}_{t+1}}\right)^{-\frac{1}{\chi_k}}\left(\frac{\widetilde{I}_{t+1}}{\widetilde{K}_{t+1}}\right)\right) + \frac{\nu_t-1}{\nu_t}\alpha\frac{\widetilde{Y}_{t+1}}{\widetilde{K}_{t+1}}\right] \tag{1.35}$$

$$\widetilde{J}_t^F = (1-\alpha)\frac{\nu_t - 1}{\nu_t}\frac{\widetilde{Y}_t}{N_t} - \widetilde{W}_t + (1-\mu)\underset{t}{E} M_{t+1}\widetilde{J}_{t+1}^F g_{L,t+1} \tag{1.36}$$

$$U_t = 1 - N_t \tag{1.37}$$

$$u_t = 1 - (1-\mu) N_{t-1} \tag{1.38}$$

$$m(u_t, V_t) = \epsilon_t^M m_0 V_t^{1-\xi} u_t^{\xi} \tag{1.39}$$

$$f(\theta_t) \equiv \frac{m(u_t, V_t)}{u_t} \tag{1.40}$$

$$q(\theta_t) \equiv \frac{m(u_t, V_t)}{V_t} \tag{1.41}$$

$$N_t = (1-\mu) N_{t-1} + V_t q(\theta_t) \tag{1.42}$$

$$\widetilde{\kappa}_t = q(\theta_t)\widetilde{J}_t^F \tag{1.43}$$

$$\widetilde{H(W_t)} = \widetilde{W}_t + \underset{t}{E} M_{t+1} g_{L,t+1}\left[(1-\mu)\widetilde{H(W_{t+1})} + \mu\widetilde{H(U_{t+1})}\right] \tag{1.44}$$

$$\widetilde{H(U_t)} = b_t + \underset{t}{E} M_{t+1} g_{L,t+1}\left[f(\theta_t)\widetilde{H(W_{t+1})} + (1 - f(\theta_t))\widetilde{H(U_{t+1})}\right] \tag{1.45}$$

$$Nash: \eta\left(\widetilde{H(W_t)} - \widetilde{H(U_t)} + \widetilde{J}_t^F\right) = \widetilde{H(W_t)} - \widetilde{H(U_t)} \tag{1.46}$$

$$AOB: a_1 \widetilde{J}_t^F = a_2 \left(\widetilde{H\left(W_t\right)} - \widetilde{H\left(U_t\right)} \right) - a_3 \gamma_t + a_4 \left(\widetilde{\upsilon}_t - b_t \right) \tag{1.47}$$

$$\widetilde{D}_t = \widetilde{Y}_t - \widetilde{W}_t N_t - \widetilde{\kappa}_t V_t - \widetilde{I}_t \tag{1.48}$$

$$\widetilde{Y}_t = \widetilde{C}_t + \widetilde{I}_t + \widetilde{\kappa}_t V_t \tag{1.49}$$

$$R_{t+1} = \frac{\widetilde{S}_{t+1}}{\tilde{S}_t - \widetilde{D}_t} g_{L,t+1} \tag{1.50}$$

$$\tilde{S}_t = \tilde{D}_t + M_{t+1} \tilde{S}_{t+1} g_{L,t+1} \tag{1.51}$$

$$R_{f,t+1} = \left[\underset{t}{E}(\widetilde{M}_{t,t+1}) \right]^{-1} \tag{1.52}$$

$$r_t^d - r_t^f = log(R_t) - log(R_{t+1}^f) \tag{1.53}$$

$$log\phi_t = \rho_\phi log\phi_{t-1} + \sigma_{t-1}^\phi \varepsilon_t^\phi \tag{1.54}$$

$$log\epsilon_t^M = \rho_M log\epsilon_{t-1}^M + \varepsilon_t^\epsilon \tag{1.55}$$

$$logA_t = \rho_A logA_{t-1} + \sigma_{t-1}^A \varepsilon_t^A \tag{1.56}$$

$$log\nu_t = \rho_\nu log\nu_{t-1} + \varepsilon_t^\nu \tag{1.57}$$

$$logb_t = \rho_b logb_{t-1} + \varepsilon_t^b \tag{1.58}$$

A.3. Steady state

$$\phi = \epsilon^M = A = \nu = b = Q = 1 \tag{1.59}$$

$$\frac{\tilde{J}^H}{\tilde{C}} = \left(\frac{1-\beta\phi}{1-\beta\phi g_L^{1-1/\psi}}\right)^{\frac{1}{1-1/\psi}} \tag{1.60}$$

$$M = \beta\phi g_L^{-\frac{1}{\psi}} \tag{1.61}$$

$$\tilde{Y}_t = e^{z_t}\tilde{K}_t^{\alpha}\left(N_t\right)^{1-\alpha} \tag{1.62}$$

$$g_L = \Lambda \tag{1.63}$$

$$\frac{\widetilde{I}}{\widetilde{K}} = g_L - 1 + \delta \tag{1.64}$$

$$b_1 = \frac{(1-g_L-\delta)}{\chi_k - 1} \tag{1.65}$$

$$b_2 = \left(g_L - 1 + \delta\right)^{\frac{1}{\chi_k}} \tag{1.66}$$

$$\frac{\widetilde{K}}{\widetilde{Y}} = \left[\left(\frac{1}{M} - 1 + \delta\right)\frac{\nu}{(\nu-1)\alpha}\right]^{-1} \tag{1.67}$$

$$\frac{\widetilde{N}}{\widetilde{Y}} = \left[\left(\left(1-\left(1-\mu\right)Mg_L\right)\widetilde{J}^F + \widetilde{W}\right)\frac{\nu}{\left(\nu-1\right)\left(1-\alpha\right)}\right]^{-1} \tag{1.68}$$

$$u = U + \mu N \tag{1.69}$$

$$m = \epsilon^M m_0 V^{1-\xi} u^{\xi} \tag{1.70}$$

$$f(\theta) \equiv \frac{m}{u} \tag{1.71}$$

$$q(\theta) \equiv \frac{m}{V} \tag{1.72}$$

$$\mu N = V q(\theta) \tag{1.73}$$

$$\widetilde{\kappa} = q(\theta) J^F \tag{1.74}$$

$$(1 - (1-\mu) M g_L) \widetilde{H(W)} = \widetilde{W} + M \mu g_L \widetilde{H(U)} \tag{1.75}$$

$$(1 - (1 - f(\theta)) M g_L) \widetilde{H(U)} = b g_L + M g_L f(\theta) \widetilde{H(W)} \tag{1.76}$$

$$\eta \left(\widetilde{H(W)} - \widetilde{H(U)} + \widetilde{J}^F \right) = \widetilde{H(W)} - \widetilde{H(U)} \tag{1.77}$$

$$a_1 \widetilde{J}^F = a_2 \left(\widetilde{H(W)} - \widetilde{H(U)} \right) - a_3 \gamma + a_4 (\widetilde{\upsilon} - b) \tag{1.78}$$

$$\widetilde{D} = \widetilde{Y} - \widetilde{W} N - \widetilde{\kappa} V - \widetilde{I} \tag{1.79}$$

$$\widetilde{Y} = \widetilde{C} + \widetilde{I} + + \widetilde{\kappa} V \tag{1.80}$$

$$R = \frac{\tilde{S}}{\tilde{S} - \widetilde{D}} g_L \tag{1.81}$$

$$\tilde{S} = \frac{\widetilde{D}}{1 - M g_L} \tag{1.82}$$

$$R_f = \beta^{-1} g_L^{\frac{1}{\psi}} \tag{1.83}$$

A.4. Data sources

This section describes the detailed information in terms of the data used in the estimation and the base year is 1975.

1. Nominal Gross Domestic Product. Billions of Dollars, Seasonally Adjusted at Annual Rate. Source: Bureau of Economic Analysis, National Income and Product Accounts Table 1.1.5.

2. Real Gross Domestic Product. Billions of Chained 2009 Dollars, Seasonally Adjusted at Annual Rate. Source: Bureau of Economic Analysis, National Income and Product Accounts Table 1.1.6.

3. Personal Consumption Expenditures, Nondurable Goods. Billions of Dollars, Seasonally Adjusted at Annual Rate. Source: Bureau of Economic Analysis, National Income and Product Accounts Table 1.1.5.

4. Personal Consumption Expenditures, Services. Billions of Dollars, Seasonally Adjusted at Annual Rate. Source: Bureau of Economic Analysis, National Income and Product Accounts Table 1.1.5.

5. Unemployment Rate, Seasonally Adjusted. Source: Bureau of Labor Statistics.

6. Civilian Labor Force. 16 years and over, thousands. Series label LNS11000000Q. Source: Bureau of Labor Statistics.

7. Index of Help-Wanted Advertising, Seasonally Adjusted. Source: Composite Help-Wanted Index by Regis Barnichon.

8. Series of value-weighted returns with and without dividends for all the stocks traded on NYSE, AMEX, and NASDQ. Source: CRSP database and WRDS.

9. GDP Deflator= (2)/(1).

10. Real Per Capita Output, Y_t= (2)/(6).

11. Real Per Capita Consumption, C_t= [(3)+(4)]/(6)/(9).

12. Vacancy, V_t= (7)/(6).

A.5. Empirical results of alternative offer bargaining

Table A.5.1: Priors and posterior distributions of parameters based on the alternative offer bargaining framework and a 0.42 replacement ratio.

		Prior distribution			Posterior distribution		
		Distribution	Mean	St.dev	Mean	5%	95%
	Structural parameters						
g_L	Steady-state growth rate	Normal	0.50	0.025	0.4125	0.3717	0.4539
χ_k	Degree of concavity in cost fun.	Gamma	2.00	0.50	1.9278	1.3143	2.5684
μ	Job separation rate	Beta	0.10	0.02	0.1623	0.1599	0.1636
ξ	Matching function parameter	Beta	0.50	0.15	0.6185	0.5609	0.6727
100ϱ	Prob of bargaining breakup	Normal	10.00	2.00	0.7109	0.7043	0.7142
	Shock processes						
ρ_ϕ	Preference	Beta	0.50	0.20	0.8681	0.7760	0.9422
ρ_z	Technology	Beta	0.50	0.20	0.9895	0.9784	0.9988
ρ_{ϵ^M}	Matching efficiency	Beta	0.50	0.20	0.9567	0.9286	0.9824
ρ_B	Unemployment benefit	Beta	0.50	0.20	0.9922	0.9839	0.9993
ρ_G	Government spending	Beta	0.50	0.20	0.9723	0.9246	0.9998
σ_ϕ	Preference shock	InvGamma	0.01	Inf	0.0799	0.0647	0.0955
σ_z	Technology shock	InvGamma	0.01	Inf	0.5723	0.5128	0.6386
σ_{ϵ^M}	Matching efficiency shock	InvGamma	0.01	Inf	1.5770	1.2953	1.8817
σ_B	Unemployment benefit shock	InvGamma	0.01	Inf	1.0144	0.8954	1.1325
σ_G	Government spending shock	InvGamma	0.01	Inf	10.2591	9.1219	11.5016

Table A.5.2: Variance decomposition of key variables based on the alternative offer bargaining framework with a 0.42 replacement ratio.The results are the average from 1 million draws of parameters from the posterior.

Shocks/series	$ln(Y_t/Y_{t-1})$	$ln(C_t/C_{t-1})$	$ln(U_t)$	$ln(V_t)$	$ln(P_t/D_t)$
Technology	74.52	40.08	47.34	45.16	21.88
Preference	6.79	9.16	11.11	10.45	48.87
Matching efficiency	0.00	0.00	0.00	4.65	0.00
Unemployment benefit	18.43	49.18	39.44	37.77	25.21
Government spending	0.26	1.58	2.11	1.97	4.03

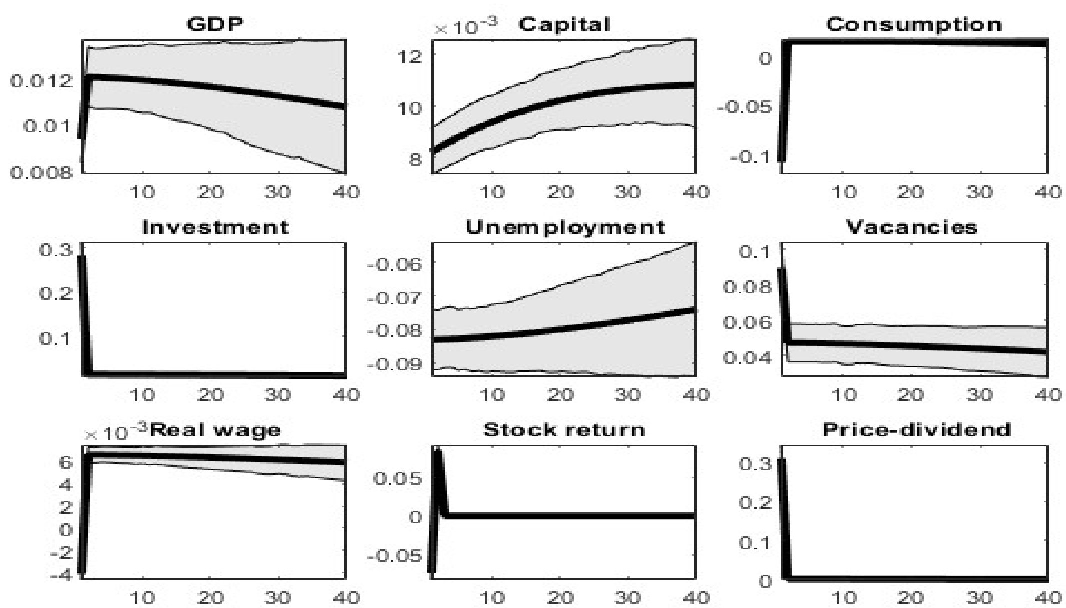


Figure A.5.1: Impulse response to a positive technology shock based on the alternative offer bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

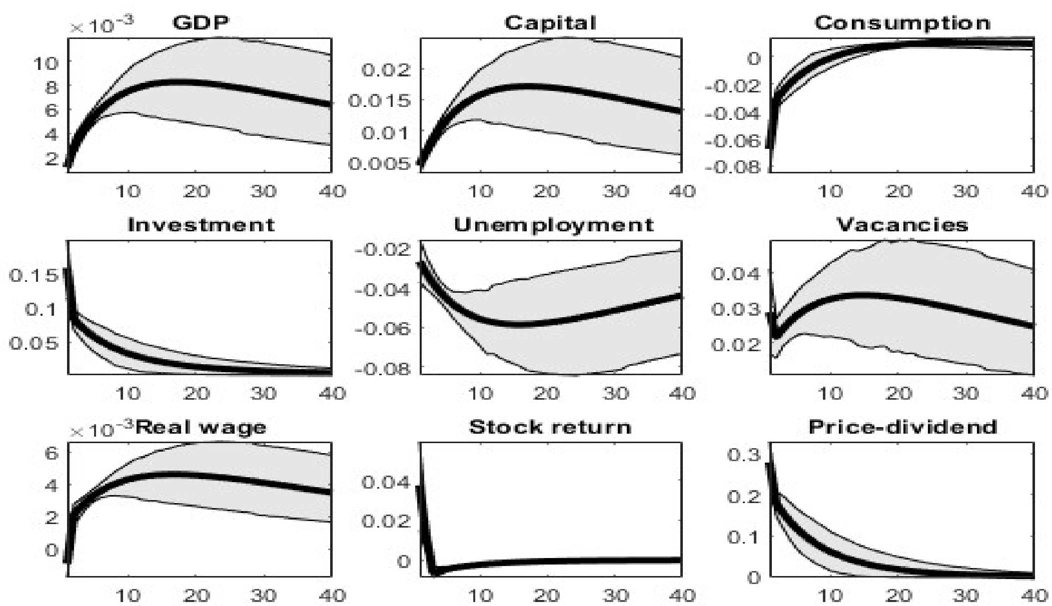


Figure A.5.2: Impulse response to a positive preference shock based on the alternative offer bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

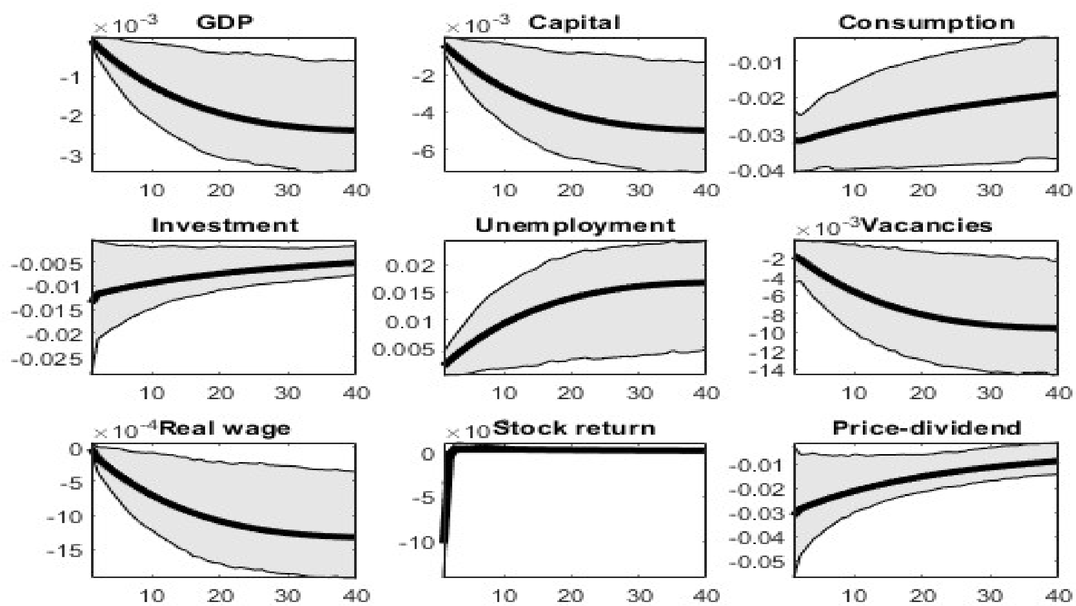


Figure A.5.3: Impulse response to a positive government spending shock based on the alternative offer bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

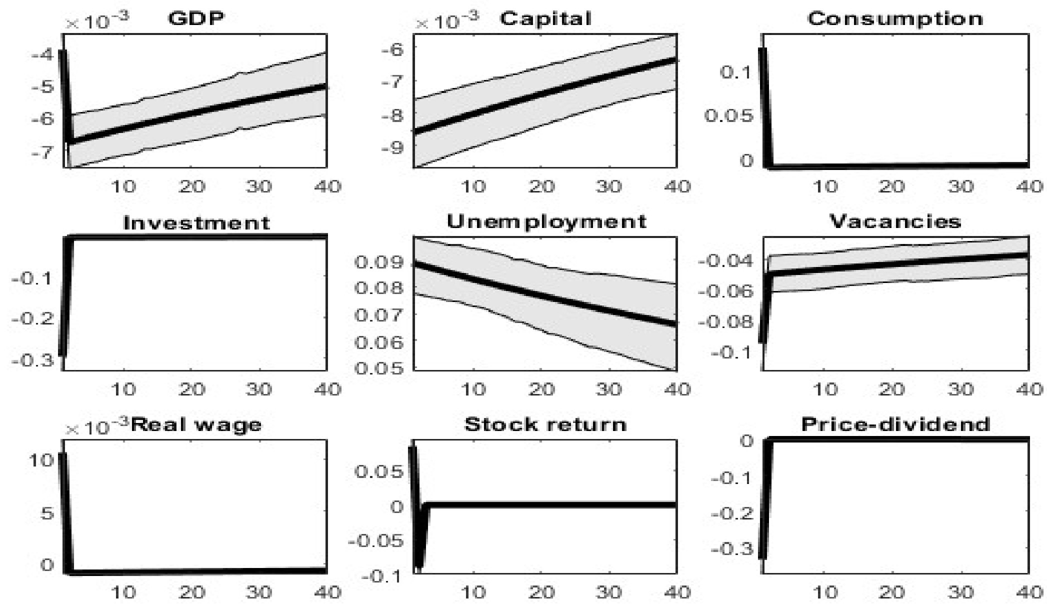


Figure A.5.4: Impulse response to a positive unemployment benefit shock based on the alternative offer bargaining framework with a 0.42 replacement ratio. The shaded areas provide the 95% posterior density intervals. The horizontal axis represents the time period, and the vertical axis represents log-deviations from the steady state.

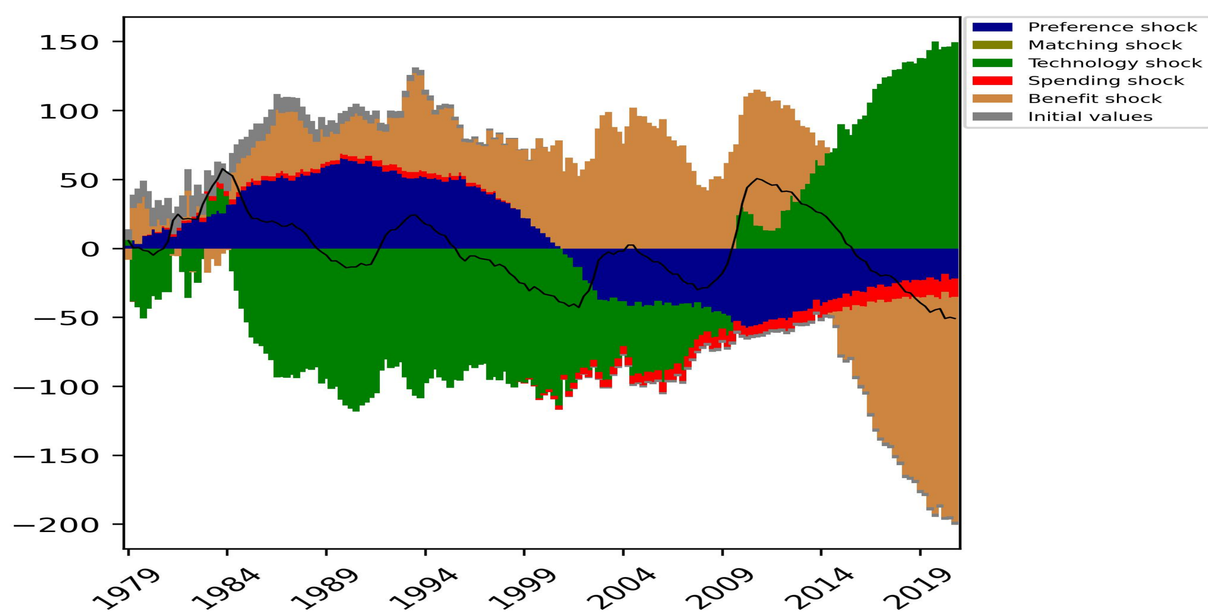


Figure A.5.5: Historical decomposition for unemployment:1979-2019 based on the alternative bargaining framework with a 0.42 replacement ratio. The black line is the log deviation of the unemployment from its mean.

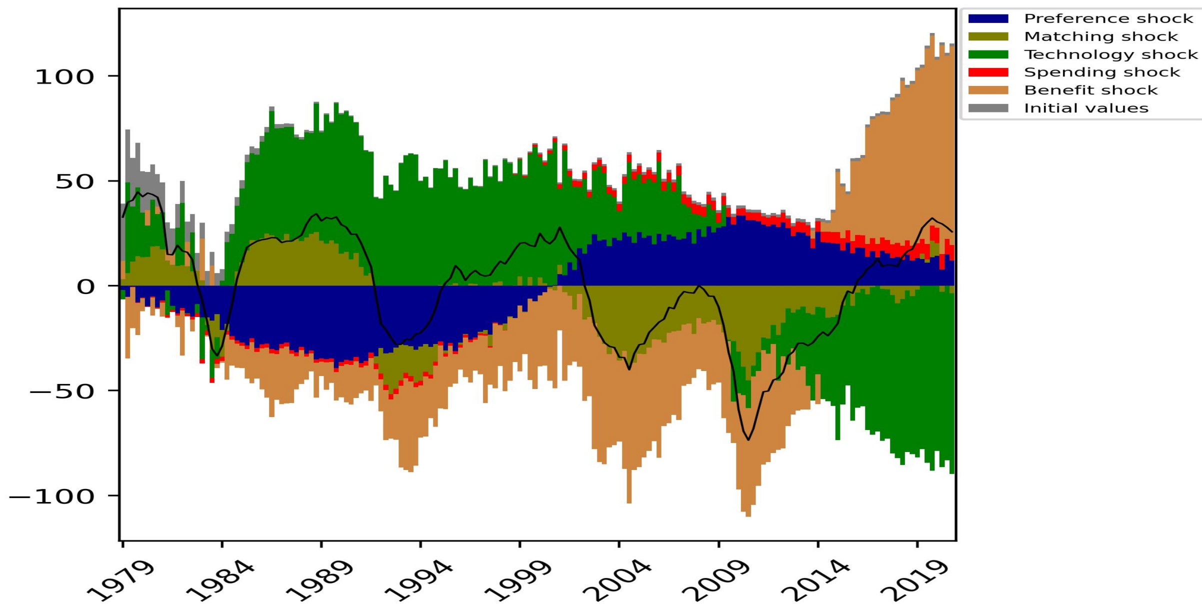


Figure A.5.6: Historical decomposition for vacancy:1979-2019 based on the alternative bargaining framework with a 0.42 replacement ratio. The black line is the log deviation of the vacancy from its mean.

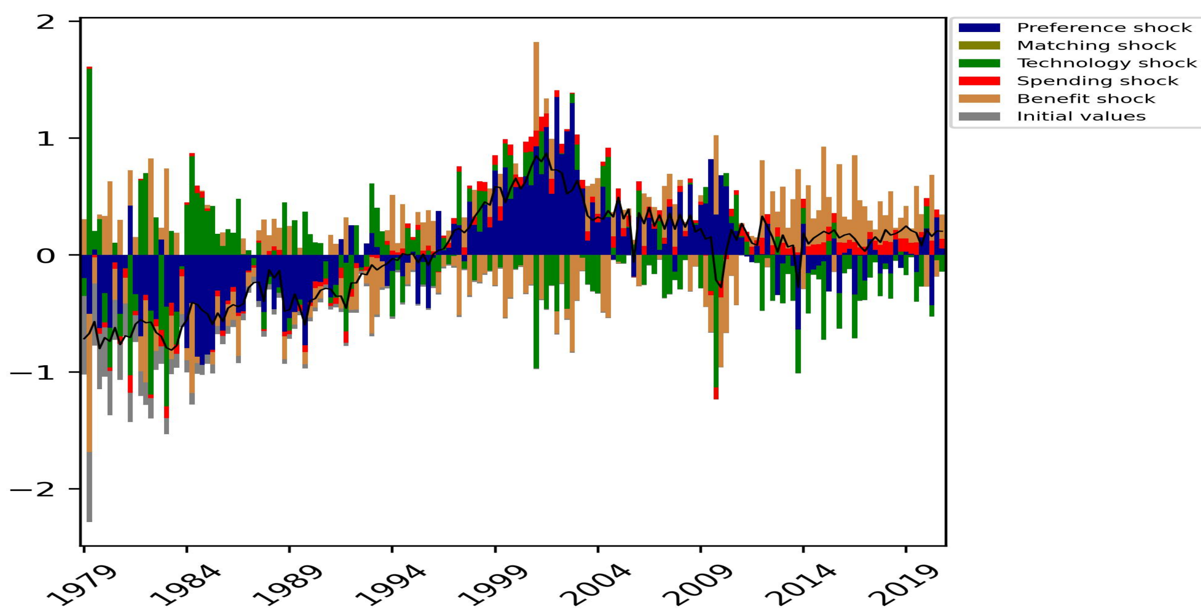


Figure A.5.7: Historical decomposition for price-dividend ratio:1979-2019 based on alternative bargaining framework and 0.42 replacement ratio. The back line is the log deviation of the price-dividend ratio from its mean.

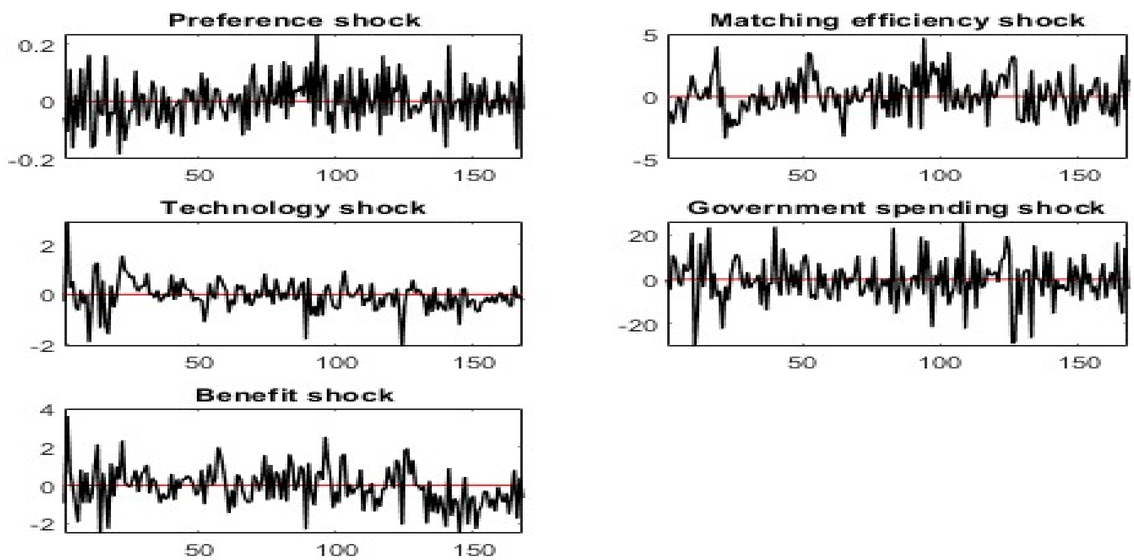


Figure A.5.8: Estimated shocks of the historical decomposition:1979-2019 based on the alternative bargaining framework with a 0.42 replacement ratio. The y-axis represents percentage points the shocks deviate from their steady state value.

A.6. Selective empirical results of the Nash bargaining model without a fixed replacement ratio

Table A.6.1: Priors and posterior distribution of parameters based on the Nash bargaining framework without a fixed replacement ratio.

		Prior distribution			Posterior distribution		
		Distribution	Mean	St.dev	Mean	5%	95%
	Structural parameters						
g_L	Steady-state growth rate	Normal	0.50	0.025	0.4060	0.3671	0.4453
χ_k	Degree of concavity in cost fun.	Gamma	2.00	0.50	1.3282	0.8084	1.9032
μ	Job separation rate	Beta	0.10	0.02	0.1422	0.1297	0.1554
ξ	Matching function parameter	Beta	0.50	0.15	0.5743	0.502	0.6432
	Shock processes						
ρ_ϕ	Preference	Beta	0.50	0.20	0.9519	0.9211	0.9802
ρ_z	Technology	Beta	0.50	0.20	0.9876	0.9750	0.9983
ρ_{ϵ^M}	Matching efficiency	Beta	0.50	0.20	0.9546	0.9262	0.9824
ρ_B	Unemployment benefit	Beta	0.50	0.20	0.9908	0.9814	0.9989
ρ_G	Government spending	Beta	0.50	0.20	0.9578	0.9189	0.9938
σ_ϕ	Preference shock	InvGamma	0.01	Inf	0.0951	0.0767	0.1143
σ_z	Technology shock	InvGamma	0.01	Inf	0.5752	0.5127	0.6394
σ_{ϵ^M}	Matching efficiency shock	InvGamma	0.01	Inf	1.8282	1.4580	2.2323
σ_B	Unemployment benefit shock	InvGamma	0.01	Inf	0.5810	0.5162	0.6497
σ_G	Government spending shock	InvGamma	0.01	Inf	8.3294	7.3207	9.3574

Table A.6.2: Variance decomposition of key variables based on the Nash Bargaining framework (in percent) without a fixed replacement ratio. The results are the average from 1 million draws of parameters from the posterior.

Shocks/series	$ln(Y_t/Y_{t-1})$	$ln(C_t/C_{t-1})$	$ln(U_t)$	$ln(V_t)$	$ln(P_t/D_t)$
Technology	75.09	43.73	37.53	36.62	14.59
Preference	6.74	6.00	31.27	29.83	68.07
Matching efficiency	0.00	0.00	0.00	3.01	0.00
Unemployment benefit	17.98	48.86	30.14	29.53	15.17
Government spending	0.19	1.42	1.05	1.00	2.17

Appendix B

Appendix of Chapter 2

B.1. Dynamic equations

$$Y_t = y_t N_t^{\frac{\epsilon}{\epsilon-1}} \tag{2.1}$$

$$\rho_t = N_t^{\frac{1}{\epsilon-1}} \tag{2.2}$$

$$N_t = (1 - \lambda\phi_t^{\lambda})(N_{t-1} + N_{t-1}^{new}) \tag{2.3}$$

$$\varsigma\phi_t^{\varsigma} E_t[M_{I,t+1}V_{t+1}(f^I)] \geq w_t l_t + \kappa_t V_t^I \tag{2.4}$$

$$M_{I,t+1} = \beta_I(1 - \lambda\phi_t^{\lambda})\frac{C_{I,t+1}^{-\rho_I}}{C_{I,t}^{-\rho_I}} \tag{2.5}$$

$$M_{H,t+1} = \beta(1 - \lambda\phi_t^{\lambda})\frac{C_{h,t+1}^{-\rho_I}}{C_{H,t}^{-\rho_I}} \tag{2.6}$$

$$y_t = A_t l_t \tag{2.7}$$

$$d_t = \frac{P_t}{P_t^a} y_t - W_t l_t - \kappa_t V_t^I - (b_{t-1} - \frac{b_t}{R_t}) \tag{2.8}$$

$$V_t(f^I) = d_t + E_t[M_{t+1}V_{t+1}(f^I)] \tag{2.9}$$

$$\mu_t = \frac{1/R_t - E_t M_{I,t+1}}{\varsigma \phi_t^{\varsigma} E_t M_{I,t+1}} \tag{2.10}$$

$$J_t^F = \frac{\kappa_t}{q(\theta_t)}(1+\mu_t) \tag{2.11}$$

$$\frac{\kappa_t}{q(\theta_t)}(1+\mu_t) = -(1+\mu_t)W_t + (1-s)\underset{t}{E} M_{I,t+1}\frac{\kappa_{t+1}}{q(\theta_{t+1})}(1+\mu_{t+1}) + (\frac{\epsilon-1}{\epsilon})\frac{P_t}{P_t^a}A_t \tag{2.12}$$

$$\frac{b_{it}}{R_t} + E_t[M_{I,t+1}V_{t+1}(f^E)] = W_t l_t + \kappa_t \frac{l_t}{q(\theta_t)} + K\phi_t^K(\frac{N_t^{new}}{N_{t-1}^{new}})^{\tau} \tag{2.13}$$

$$C_{H,t}^{-\rho} = \beta(1-\lambda\phi_t^{\lambda})E(C_{H,t+1}^{-\rho}R_t) \tag{2.14}$$

$$C_{I,t} + (N_t + N_t^{new})q_t x_t = N_t x_{t-1}(q_t + d_t) \tag{2.15}$$

$$C_{I,t}^{-\rho_I} q_t = \beta_I(1-\lambda\phi_t^{\lambda})E[C_{I,t+1}^{-\rho_I}(q_{t+1}+d_{t+1})] \tag{2.16}$$

$$U_t = 1 - L_t \tag{2.17}$$

$$u_t = 1 - (1-s)(1-\lambda\phi_t^{\lambda})L_{t-1} \tag{2.18}$$

$$m\left(u_t, V_t^{tot}\right) = \epsilon^M (V_t^{tot})^{1-\xi} u_t^{\xi} \tag{2.19}$$

$$f\left(\theta_{t}\right) \equiv \frac{m\left(u_{t}, V_{t}^{tot}\right)}{u_{t}} \tag{2.20}$$

$$q\left(\theta_{t}\right) \equiv \frac{m\left(u_{t}, V_{t}^{tot}\right)}{V_{t}} \tag{2.21}$$

$$L_{t} = (1-s)(1-\lambda\phi_{t}^{\lambda})L_{t-1} + m_{t} \tag{2.22}$$

$$V_{t}^{tot} = N_{t}^{new}\frac{l_{t}}{q\left(\theta_{t}\right)} + N_{t}V_{t}^{I} \tag{2.23}$$

$$H(W_{t}) = W_{t} - \frac{\gamma\phi_{t}^{\gamma}L_{t}^{\varphi}}{C_{H,t}^{-\rho}} + \underset{t}{E}M_{H,t+1}\{\left[(1-\lambda\phi_{t+1}^{\lambda})(1-s+sf(\theta_{t+1})) + \lambda\phi_{t+1}^{\lambda}f(\theta_{t+1})\right]H(W_{t+1})$$
$$+ \left[s(1-\lambda\phi_{t+1}^{\lambda})(1-f(\theta_{t+1})) + \lambda\phi_{t+1}^{\lambda}(1-f(\theta_{t+1})\right]H(U_{t+1})\}$$

$$H(U_{t}) = B_{t} + \underset{t}{E}M_{H,t+1}\left[f(\theta_{t+1})H(W_{t+1}) + (1-f(\theta_{t+1})H(U_{t+1})\right] \tag{2.24}$$

$$\eta\left(H\left(W_{t}\right) - H\left(U_{t}\right) + J_{t}^{F}\right) = H\left(W_{t}\right) - H\left(U_{t}\right) \tag{2.25}$$

$$log\left(\phi_{t}^{\lambda}\right) = \rho_{\phi^{\lambda}}log\left(\phi_{t-1}^{\lambda}\right) + \epsilon_{t}^{\phi^{\lambda}} \tag{2.26}$$

$$log\left(\phi_{t}^{K}\right) = \rho_{\phi^{K}}log\left(\phi_{t-1}^{K}\right) + \epsilon_{t}^{\phi^{K}} \tag{2.27}$$

$$log\left(A_{t}\right) = \rho_{\epsilon^{A}}log\left(A_{t}\right) + \epsilon_{t}^{A} \tag{2.28}$$

$$log\left(\phi_t^{\gamma}\right) = \rho_{\phi^{\gamma}} log\left(\phi_{t-1}^{\gamma}\right) + \epsilon_t^{\phi^{\gamma}} \tag{2.29}$$

$$log\left(\phi_t^{\varsigma}\right) = \rho_{\phi^{\varsigma}} log\left(\phi_{t-1}^{\varsigma}\right) + \epsilon_t^{\phi^{\varsigma}} \tag{2.30}$$

$$L_t = (N_t + N_t^{new}) l_t \tag{2.31}$$

$$Y_t = C_{I,t} + C_{H,t} + \kappa_t V_t^{tot} + N_t^{new} K \phi_t^K \left(\frac{N_t^{new}}{N_{t-1}^{new}}\right)^{\tau} \tag{2.32}$$

B.2. Analytic steady state

This section summarizes the steady-state equations in our model. We normalize the number of firms and the number of labor, so $N = 1$, and $L = 1 - U$. The relative price ρ=1, and the number of shares $x = 1$. The remaining steady-state equations below follow the order used in Dynare.

$$N^{new} = \frac{\lambda}{1-\lambda} \tag{2.33}$$

$$u = 1 - (1-s)(1-\lambda)L \tag{2.34}$$

$$m\left(u, V\right) = (1 - (1-s)(1-\lambda))L \tag{2.35}$$

$$l = (1-\lambda)L \tag{2.36}$$

$$V^{tot} = \frac{m\left(u, V\right)}{q\left(\theta\right)} \tag{2.37}$$

$$\epsilon^{M} = \frac{m\left(u, V\right)}{(V^{tot})^{1-\xi} u^{\xi}} \tag{2.38}$$

$$f\left(\theta\right) = \frac{m\left(u_t, V^{tot}\right)}{u} \tag{2.39}$$

$$V^{I} = V^{tot} - \frac{\lambda}{1-\lambda} \frac{l}{q\left(\theta\right)} \tag{2.40}$$

$$y = Al \tag{2.41}$$

$$Y = N^{\frac{\epsilon}{\epsilon-1}} y \tag{2.42}$$

$$\kappa = 0.01(\frac{Y}{V^{tot}}) \tag{2.43}$$

$$M_I = \beta_I(1 - \lambda) \tag{2.44}$$

$$M_H = \beta(1 - \lambda) \tag{2.45}$$

$$R = \frac{1}{\beta(1 - \lambda)} \tag{2.46}$$

$$\mu = \frac{1/R - M_I}{\varsigma M_I} \tag{2.47}$$

$$B = 0.42W \tag{2.48}$$

From the enforcement constraint, we then can get the steady-state value of dividends.

$$d = \frac{(Wl + \kappa V^I)(1 - M_I)}{\varsigma M_I} \tag{2.49}$$

$$q = \frac{M_I}{1 - M_I} d \tag{2.50}$$

$$V(f^I) = \frac{d}{1 - M_I} \tag{2.51}$$

$$b = \frac{y - d - Wl - \kappa V^I}{(1 - 1/R)} \tag{2.52}$$

$$c_I = (1 - \frac{\lambda}{1-\lambda}\frac{M_I}{1-M_I})d \tag{2.53}$$

After plugging in the resource constraint equation to replace the entry cost K and equation 2.52 into the entry condition. Then, household consumption is given by:

$$c_H = \frac{\lambda}{1-\lambda}Wl + \frac{\lambda}{1-\lambda}\frac{l}{q(\theta)} + Y - \kappa V^{tot} - d - \frac{1}{larr}(y - d - Wl - \kappa V^I) \tag{2.54}$$

where $larr = \frac{(R-1)(1-\lambda)}{\lambda}$. After knowing c_H, then the steady state value of disutility of work γ could be obtained.

Finally, we could obtain the steady-state value of the entry cost.

$$K = (Y - c_H - c_I - \kappa V^{tot})\frac{1-\lambda}{\lambda} \tag{2.55}$$

B.3. Resource constraint

This section shows how to get the resource constraint. Following four equations are needed.

$$C_{H,t} + \frac{(N_t + N_t^{new})b_t}{R_t} \leq W_t L_t + (1 - L_t)B_t - \tau_t + N_t b_{t-1} \tag{2.56}$$

$$C_{I,t} + (N_t + N_t^{new})q_t x_t \leq N_t x_{t-1}(q_t + d_t) \tag{2.57}$$

$$d_t = \frac{P_t}{P_t^a} y_t - W_t l_t - \kappa_t V_t^I - (b_{t-1} - \frac{b_t}{R_t}) \tag{2.58}$$

$$\frac{b_{it}}{R_t} + E_t[M_{I,t+1} V_{t+1}(f^E)] = W_t l_t + \frac{\kappa_t l_t}{q\left(\theta_t\right)} + K\phi_t^K (\frac{N_t^{new}}{N_{t-1}^{new}})^\tau \tag{2.59}$$

After combing equation 2.56 and equation 2.57, replacing L_t with $(N_t + N_t^{new})l_t$, and aggregating equation 2.58 with N_t and equation 2.59 with N_t^{new}, the new equation could be written as:

$$\begin{aligned} C_{H,t} + C_{I,t} + N_t(\frac{b_t}{R_t} + q_t) + N_t^{new}(\frac{b_t}{R_t} + q_t) = \\ W_t(N_t + N_t^{new})l_t + (Y_t - W_t l_t N_t - \kappa_t V_t^I N_t - b_{t-1} N_t + \frac{b_t}{R_t} N_t) - N_t b_{t-1} \end{aligned} \tag{2.60}$$

After canceling out same patterns on the both side of equation and applying aggregated equation 2.59, equation 2.60 could be simplified as:

$$C_{H,t} + C_{I,t} + N_t^{new}(W_t l_t + \kappa_t l_t + K\phi_t^K (\frac{N_t^e}{N_{t-1}^e})^\tau) = W_t N_t^{new} l_t + Y_t - \kappa_t V_t^I N_t \tag{2.61}$$

Finally, applying $V_t^{tot} = N_t^{new}\frac{l_t}{q(\theta_t)} + N_t V_t^I$, the resource constraint is given by:

$$Y_t = C_{I,t} + C_{H,t} + \kappa_t V_t^{tot} + N_t^{new} K \phi_t^K (\frac{N_t^{new}}{N_{t-1}^{new}})^{\tau} \tag{2.62}$$

Appendix C

Appendix of Chapter 3

C.1. Additional robustness analysis

Figure C.1.1: Impulse responses of real consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-month rate at 1 ,6, 12, 24 months after initial positive normalized uncertainty shocks hit. The impulse responses are calculated based on the posterior mean of parameters. The grey-shaded regions represent business cycle periods. The results are based on the TVP model with three lags.

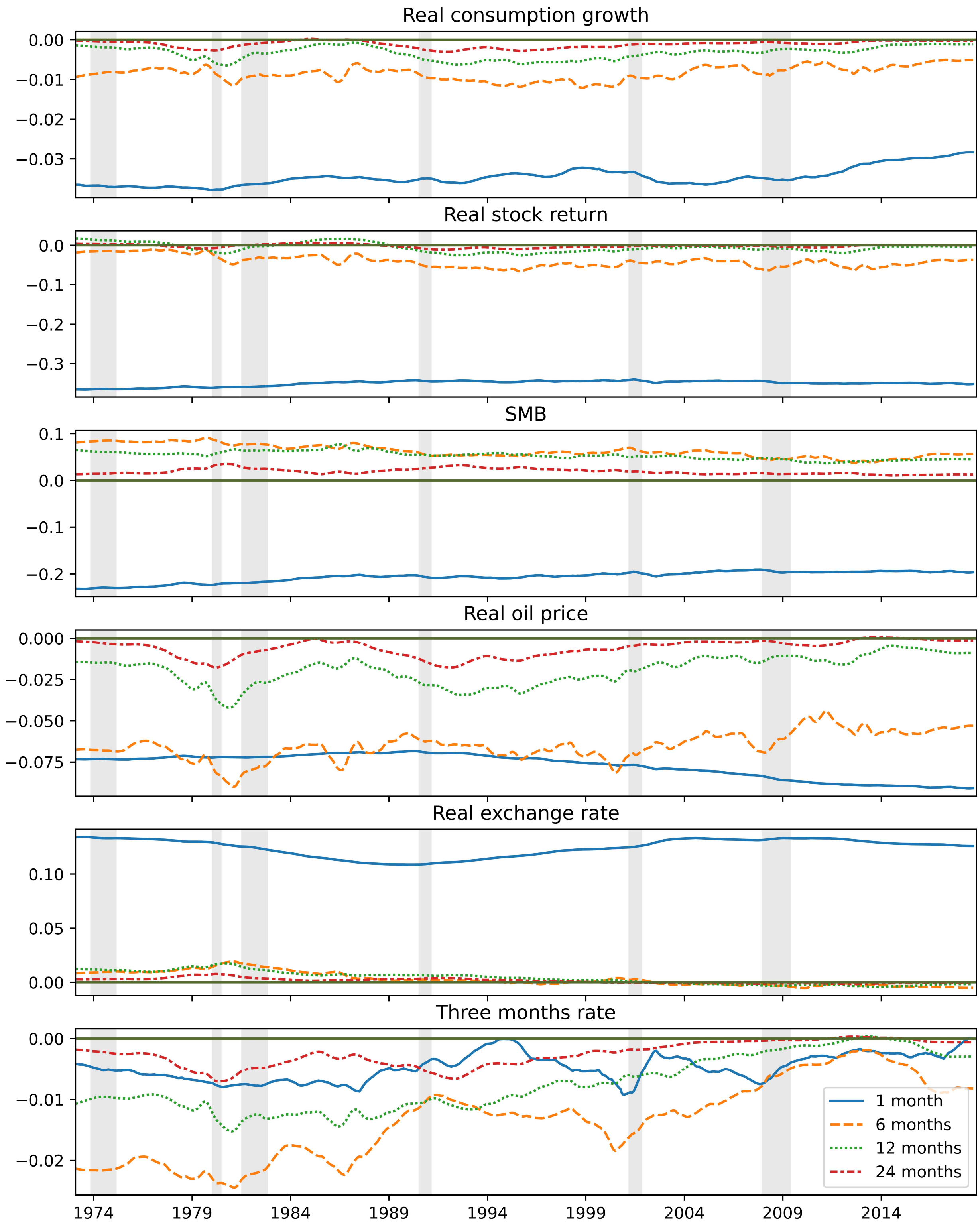


Figure C.1.2: Impulse responses of consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-months rate to positive normalized uncertainty shocks at four different dates. Responses are calculated based on the posterior mean of parameters. The results are based on the TVP model with three lags.

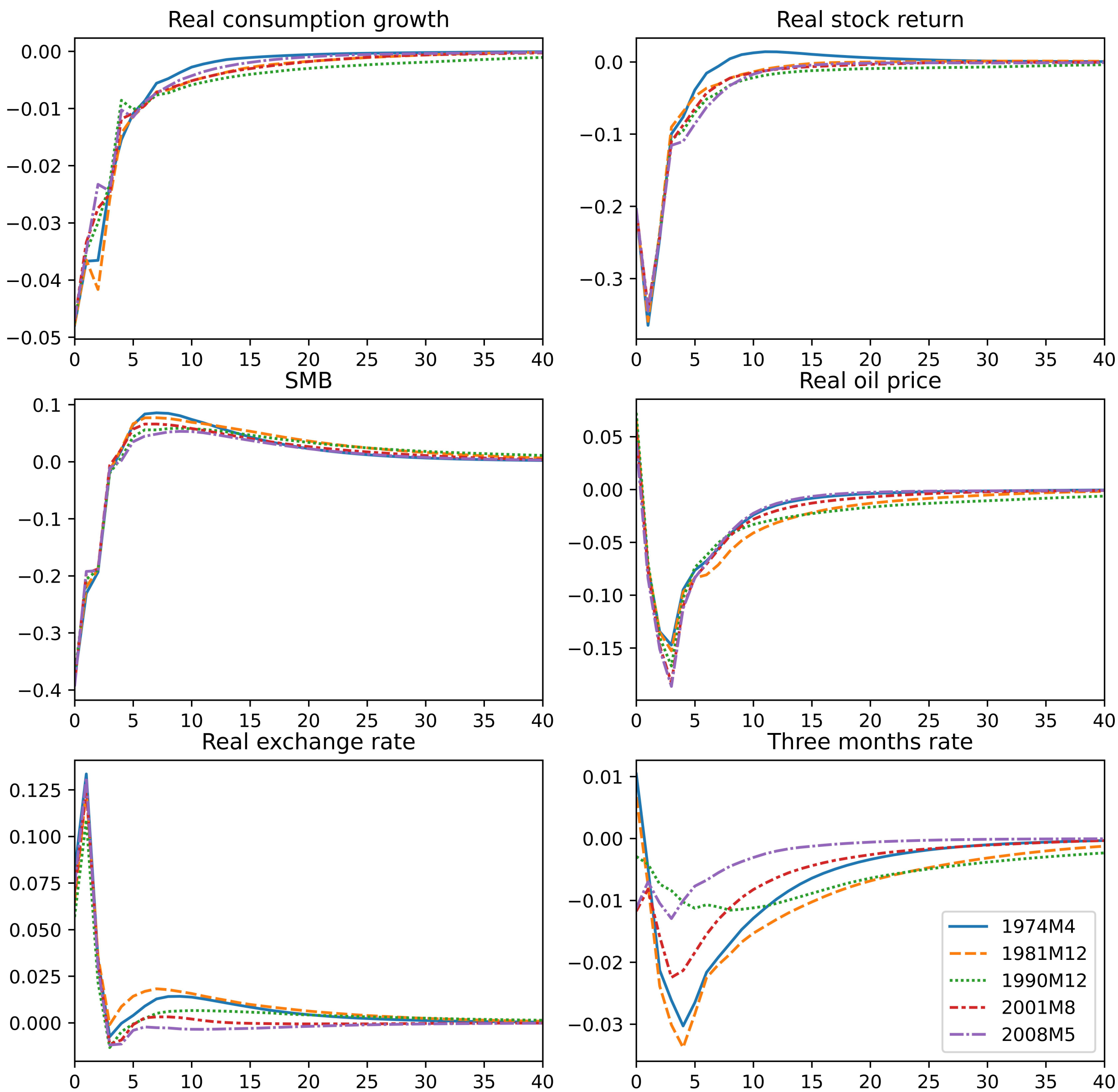


Figure C.1.3: Impulse responses of real consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-months rate to positive normalized uncertainty shocks after 1, 6, 12, 24 months based on the posterior mean of parameters. The grey-shaded regions represent business cycle periods. The results are based on the TVP model with four lags.

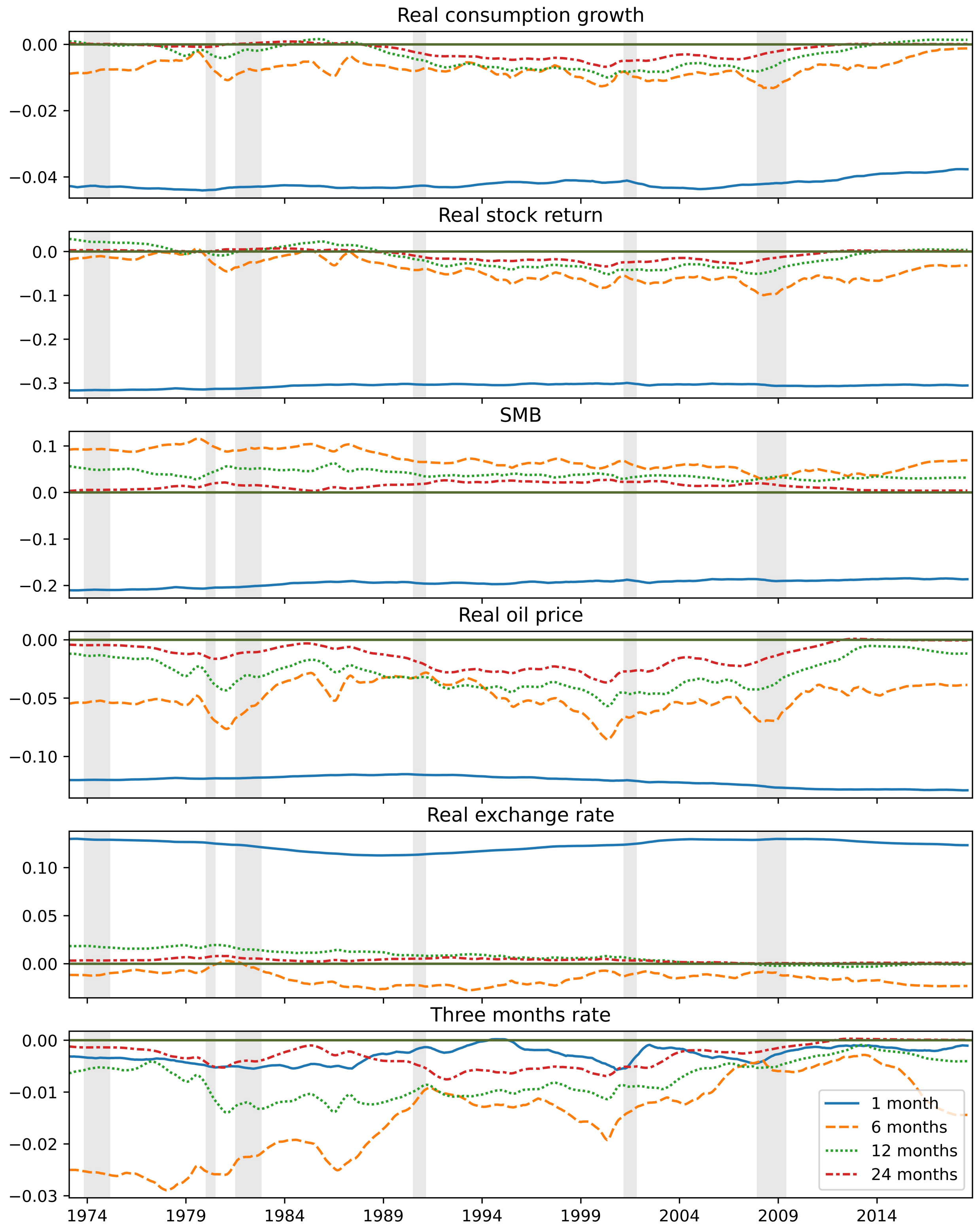
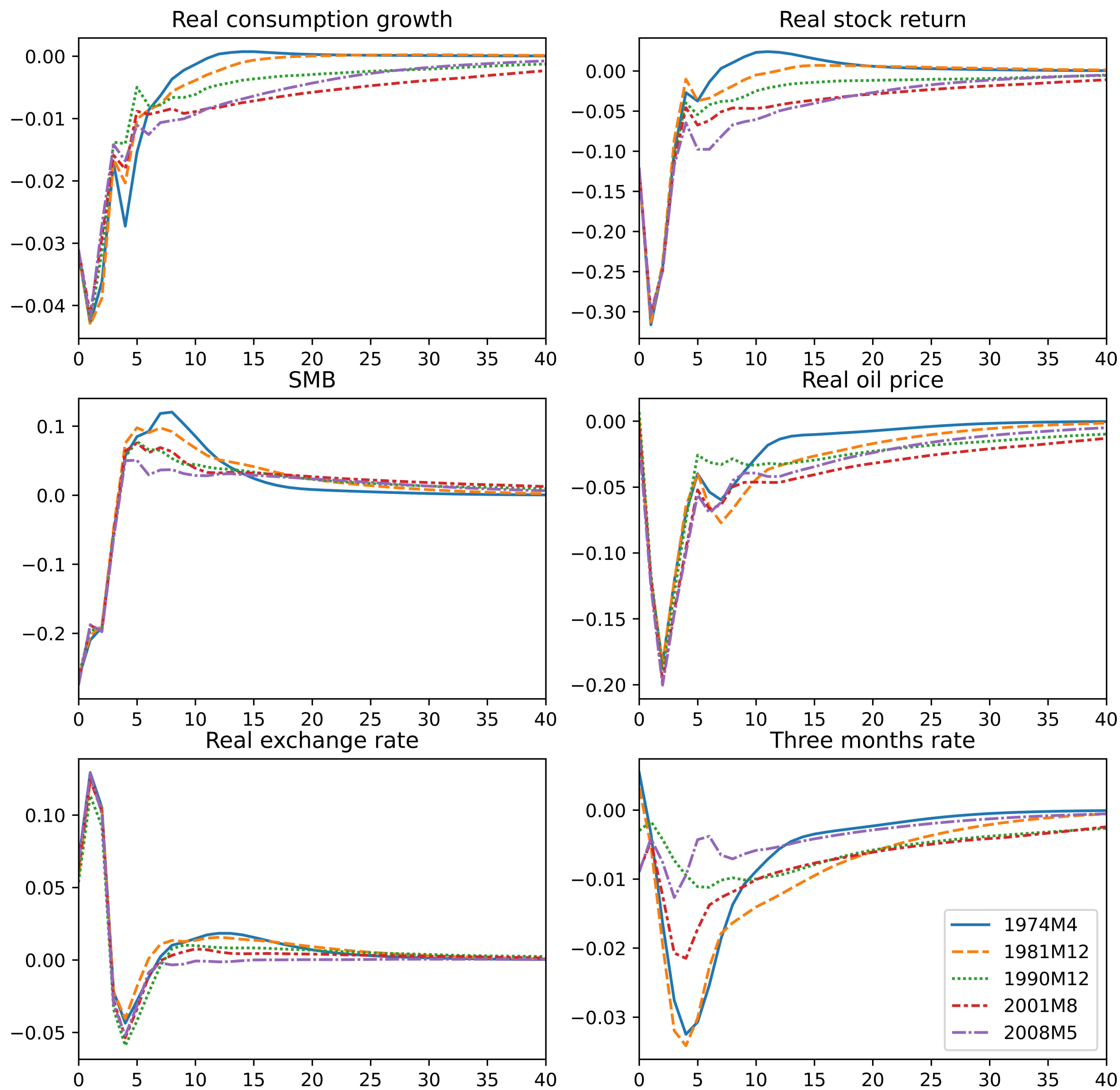


Figure C.1.4: Impulse responses of consumption growth, real stock return, SMB, real oil price, exchange rate, and the three-months rate to positive normalized uncertainty shocks at four different dates. Responses are calculated based on the posterior mean of parameters. The results are based on the TVP model with four lags.



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