The Impact of Active Aggregate Demand on Utilization-Adjusted TFP

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February 7, 2024

Abstract

Non-clearing goods markets are an important driver of capacity utilization and total factor productivity (TFP). The trade-off between goods prices and household search effort is central to goods market matching and therefore drives TFP over the business cycle. In this paper, I develop a New-Keynesian DSGE model with capital utilization, worker effort, and expand it with *goods market search-and-matching (SaM)* to model non-clearing goods markets. I conduct a horse-race between the different capacity utilization channels using Bayesian estimation and capacity utilization survey data. Models that include goods market SaM improve the data fit, while the capital utilization and worker effort channels are rendered less important compared to the literature. It follows that TFP fluctuations increase for demand and goods market mismatch shocks, while they decrease for technology shocks. This pattern increases as goods market frictions increase and as prices become stickier. The paper shows the importance of non-clearing goods markets in explaining the difference between technology and TFP over the business cycle.

Keywords: Total factor productivity, capacity utilization, search-and-matching, non-clearing goods markets, Bayesian estimation

JEL: E22, E23, E3, J20

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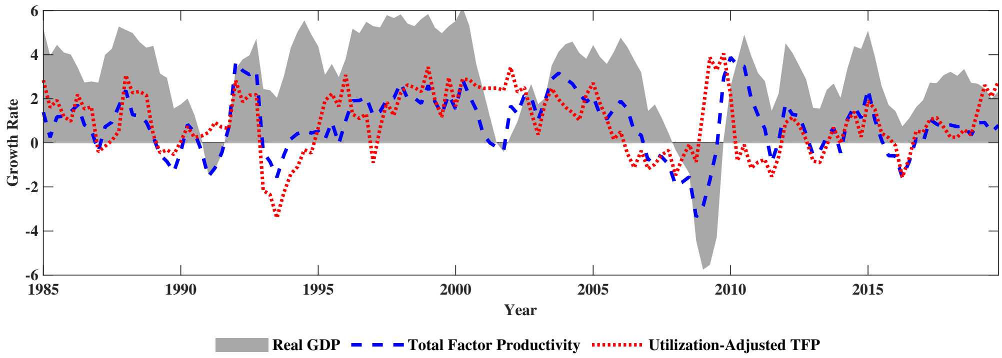
[1] I am thankful for detailed comments by Thomas Steger, Zeno Enders, Gregor von Schweinitz, José-Victor Rios-Rull, and Zhesheng Qiu. Further, I'd like to thank all participants of research seminars at the Dutch Central Bank, the Swedish Central Bank, VfS Conference 2022, Leipzig University, and IWH Halle for their helpful comments.

1. Introduction

Total factor productivity (TFP) is at the core of macroeconomics as it measures the efficiency of input factor allocation and the production process. Solow (1957) defines TFP growth as output growth that cannot be attributed to input factor growth. While TFP growth is driven by technological progress in the long-run (see e.g. Basu et al. (2006)), it is driven by input factor reallocation and capacity utilization in the short-run. The data shows that capacity utilization is incomplete on average and fluctuates significantly over the business cycle. It drives TFP alongside technology. This pattern can be seen in figure 1, which shows quarterly year-on-year growth rates of TFP and *utilization-adjusted TFP* for the U.S. between 1985q1 and 2019q4 as calculated by Fernald (2014).

Figure 1: Year-on-Year TFP Growth Rates



NOTE: The figure shows quarterly data for the U.S. form 1985q1 to 2019q4. It describes year-on-year growth rates for real GDP, TFP, and "utilization-adjusted" TFP. The data is retrieved from Fernald (2014).

Understanding the determinants of TFP and its propagation mechanisms across shocks is essential for fiscal and monetary policy. In order to be able to formulate appropriate policy responses, it is essential to understand whether fluctuations in TFP are driven by technology or demand shocks. It is essential whether an increase in TFP increases potential production or the output gap.

The relationship between capacity utilization and TFP has been analyzed thoroughly in the literature. The drivers of capacity utilization have had less attention though. Is it short-term arbitrage of quasi-fixed input factors or is it imperfect allocation on non-clearing goods market? This paper contributes to the literature by analyzing in depth the determinants of capacity utilization - especially goods market search-and-matching (SaM) - and their impact on TFP. Specifically, I ask the following two research questions:

(i) What are the underlying economic channels that drive short-run capacity utilization and TFP fluctuations?

(ii) How do the different capacity utilization channels affect the transmission of economic shocks on short-run TFP?

I set up a medium-sized New-Keynesian DSGE model, based on Christiano et al. (2005); Smets and Wouters (2007), that incorporates capital utilization, worker effort, and *goods market search-and-matching (SaM)*. I fit the model to U.S. data of capacity utilization and macroeconomic aggregates using Bayesian estimation and discriminate between the explanatory power of the three differennt utilization channels. The estimation setup directly targets the difference between TFP and *utilization-adjusted TFP*. I evaluate the log data density of different model versions using the Bayes factor.

I find that adding goods market SaM improves the data fit of any model version. It adds a trade-off between prices and household search costs that is central to capacity utilization and TFP. Even the simple SaM model, that uses goods market SaM as the only capacity utilization channel, improves the data fit of the model compared to the reference model with capital utilization and worker effort. The parameter posteriors of the full model show the same result. Both the worker effort and capital utilization channel become less important in describing capacity utilization as we add goods market SaM. Therefore, non-clearing goods markets and the trade-off between prices and household search costs play an integral part in explaining capacity utilization in the data.

I use the estimated model to analyze the impact of goods market SaM on the transmission channels of each single shock on TFP fluctuations. The active role of aggregate demand leads to a larger impact of demand and goods market mismatch shocks on TFP fluctuations, while the impact of technology shocks decreases. Cumulative TFP multiplicators - TFP flucutations relative to GDP fluctuations - show the same pattern. Demand shocks show a large increase in the cumulative TFP multiplicators. The goods market SaM channel and the trade-off between prices and household search costs depends heavily on the calibration of the goods market. The impact of demand shocks on TFP fluctuations increases in frictional goods markets with sticky prices.

The paper is based on two strands of literature. First, the idea of *utilization-adjusted TFP* has been thoroughly analyzed in the literature. Capital utilization (Burnside et al., 1995; Christiano et al., 2005) and worker effort (Bils and Cho, 1994; Basu and Kimball, 1997) are common modeling approaches of capacity utilization. On this theoretical basis, many authors (Basu and Fernald, 2002; Basu et al., 2006; Fernald, 2014; Comin et al., 2023) estimate the *utilization-adjusted TFP* for different countries with different estimation methods. They find that the differences between TFP and *utilization-adjusted TFP* are large over the business cycle and that capacity utilization covaries negatively with technology. More recent research (Lewis et al., 2019) shows that it is worker effort instead of capital utilization that drives capacity utilization over the business cycle for EU data. Fernald (2014) is the state-of-the-art approach in estimating *utilization-adjusted TFP*, using both capital utilization and worker effort in his modeling approach.

The second strand of literature (Petrosky-Nadeau and Wasmer, 2015; Michaillat and Saez, 2015; Bai et al., 2017; Qiu and Ríos-Rull, 2022) applies search-and-matching to the goods market. It takes the non-clearing goods market approach on capacity utilization and gives household search effort an active role in the market outcome. The literature focuses on household search as an input factor in goods market matching and hence production - aggregate demand therefore drives TFP. I combine the two strands of literature and analyze the explanatory power of goods market SaM for TFP in the data.

The rest of the paper is organized as follows. Section 2 introduces the model. Section 3 derives the difference between TFP and technology in the model, estimates the model, and compares the data fit of the different model versions. Section 4 shows the impact of different utilization channels on the transmission of economic shocks on the TFP wedge and cumulative TFP multiplicators. Section 5 concludes.

2. Model Setup

The core of the model follows Christiano et al. (2005) with variable capital utilization as in Fernald (2014). The labor market setup follows Cacciatore et al. (2020), who differentiate between employment, hours per worker, and worker effort. The novel feature of the model is goods market search-and-matching (SaM), as described by Michaillat and Saez (2015); Bai et al. (2017). The model has three different types of agents - households, monopolistically competitive firms, and a central bank. Goods and labor markets are subject to search-and-matching (SaM) frictions. The capital market is Walrasian.

2.1. Labor and Goods Markets

The level of employment on the *labor market* is determined by costly vacancy posting and inelastic worker supply. Aggregate employment[2] is given by

$$N_t \quad = \quad (1-\delta_N)\, N_{t-1} + m_{N,t}, \tag{1}$$

where $0 < \delta_N \leq 1$ is an exogenous employment separation rate. New employment relationships are determined by a Cobb-Douglas matching function

$$m_{N,t} \quad = \quad \psi_{N,t} u_t^{\gamma_N} \left(\int_0^1 v_t(i) di \right)^{1-\gamma_N}, \tag{2}$$

where u_t are beginning-of-period unemployed workers, and $v_t(i)$ are vacancies posted by firm i. $0 < \gamma_N \leq 1$ is the matching elasticity with respect to u_t. $\psi_{N,t} > 0$ is the labor market matching efficiency. It fluctuates following an exogenous labor mismatch shock. The job-finding probability of the households is defined as $f_{N,t} = \frac{m_{N,t}}{u_t}$. The aggregate vacancy-filling probability of firm i is defined as $q_{N,t}(i) = \frac{m_{N,t}}{v_t(i)}$. Labor market tightness is defined as demand relative to supply, $x_{N,t} = \frac{v_t}{u_t}$.

The *goods market* is segmented along the varieties of the differentiated good. Households spent search effort $D_t(i)$ for each variety i. Each firm i produces one unique variety and

[2] I normalize the inelastic worker supply to one. Hence, the employment level and the employment rate are to each other. The Cobb-Douglas matching function has constant-returns-to-scale.

supplies its available production capacity $S_t(i)$ to the goods market. Following Moen (1997), search is directed towards each variety individually. It follows, that there are as many individual goods markets as varieties. Customer relationships with firm i form according to

$$T_t(i) \quad = \quad (1-\delta_T)\,T_{t-1}(i) + m_{T,t}(i), \tag{3}$$

where $0 < \delta_T \leq 1$ is an exogenous customer relationship separation rate. New customer relationships are determined by a Cobb-Douglas matching function

$$m_{T,t}(i) \quad = \quad \psi_{T,t} D_t(i)^{\gamma_T} S_t(i)^{1-\gamma_T}, \tag{4}$$

where $0 \leq \gamma_T < 1$ is the matching elasticity with respect to $D_t(i)$. Each customer relationship trades one unit of the good of the respective variety. $\psi_{T,t} > 0$ is the goods market matching efficiency. It fluctuates following an exogenous goods market mismatch shock[3]. The probability of a household finding good i is determined by $f_{T,t}(i) = \frac{m_{T,t}(i)}{D_t(i)}$. The probability of firm i selling its good is determined by $q_{T,t}(i) = \frac{m_{T,t}(i)}{S_t(i)}$. Goods market tightness on the market for good i is determined by demand relative to supply, $x_{T,t}(i) = \frac{D_t(i)}{S_t(i)}$.

2.2. Households

There are infinitely many households on the unit interval. Each household has infinitely many workers, which are inelastically supplied to the labor market. The representative household maximizes her intertemporal utility

$$\mathbb{W}_0 \quad = \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t log\left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right),$$

where $0 \leq \beta < 1$ and instantaneous utility is the difference between additive separable utility out of consumption $\mathbb{U}_{C,t}$ and disutility out of labor supply $\mathbb{U}_{N,t}$. Utility out of consumption is defined as

$$\mathbb{U}_{C,t} \quad = \quad K_{C,t} - \theta K_{C,t-1} - \mu_D \int_0^1 D_t(i)di, \tag{5}$$

[3]Goods market mismatch shocks represent any short-run fluctuations in goods market matching efficiency. It includes dispersion and composition effects of aggregated submarkets. Over the business cycle, economic activity can reallocate to markets with higher or lower than average efficiency. As the model is aggregate, the shock term summarizes those effects.

where $K_{C,t}$ is the stock of durable consumption goods[4]. Households form consumption habits, $0 \leq \theta < 1$, following Christiano et al. (2005). Household search effort creates disutility, $\mu_D > 0$. It summarizes a broad measure of search costs as e.g. information costs, shopping costs, and further costs associated with the procurement of the good (see e.g. Michaillat and Saez (2015); Petrosky-Nadeau et al. (2016)). There is a trade-off between search effort disutility and consumption utility for each household. The stock of durable consumption goods is given by $K_{C,t} = (1 - \delta_H) K_{C,t-1} + C_t$, where $0 < \delta_H \leq 1$ is its depreciation rate and C_t is investment in private consumption.

Labor supply has three margins - employment, hours per worker, and worker effort. Each worker bargains over her hours and her worker effort after the employment match is formed. Disutility out of labor supply is modeled following Bils and Cho (1994) and given by

$$\mathbb{U}_{N,t} = \mu_{N,t} X_t \int_0^1 N_t(i) \left(\frac{\mu_H}{1+\nu_H} H_t(i)^{1+\nu_H} + \frac{\mu_e}{1+\nu_e} H_t(i) e_{H,t}(i)^{1+\nu_e} \right) di, \tag{6}$$

where $X_t = \mathbb{U}_{C,t}^{\omega} X_{t-1}^{1-\omega}$ with $0 \leq \omega \leq 1$ is a flexible parameterization of short-run wealth effects on labor supply following Jaimovich and Rebelo (2009)[5]. $H_t(i)$ is hours per worker at firm i with $\mu_H > 0$, and $e_{H,t}(i)$ is worker effort at firm i with $\mu_e > 0$. ν_H and ν_e determine the respective supply elasticities. $\mu_{N,t} > 0$ is an exogenous labor supply shock. Workers adjust hours and effort instantaneously, while the supply of unemployed workers is quasi-fixed, as given by (1).

Aggregate shopping effort is given by $D_t = \int_0^1 D_t(i) di$. The representative household likes to consume a large variety of goods following Dixit and Stiglitz (1977). Her aggregate goods bundle is given by $T_t = \left(\int_0^1 T_t(i)^{\frac{\epsilon_t - 1}{\epsilon_t}} di \right)^{\frac{\epsilon_t}{\epsilon_t - 1}}$, where $1 \leq \epsilon_t \leq \infty$ is the elasticity of substitution between two varieties. It fluctuates following an exogenous price cost-push shock

[4] I model durable consumption goods out of two reasons. First, I can directly estimate consumption data without adjusting it for durable consumption goods. Second, durable consumption is the counterpart for firm inventories as Bai et al. (2017) show.

[5] This modeling approach allows to reconcile the behavior of unemployment and hours per worker together with macroeconomic aggregates, as Cacciatore et al. (2020) show. For $\omega = 1$, the wealth effects cancel out along the lines of Greenwood et al. (1988)-preferences. For $\omega = 0$, there are short-run wealth effects along the lines of King et al. (1988).

as in Ireland (2004). The household divides her aggregate goods bundle into consumption goods, C_t, and fixed-capital investment goods, $I_{K,t}$, according to $T_t = C_t + P_{I,t}(1 + c_{I,t}) I_{K,t}$, where $c_{I,t} = \frac{\kappa_I}{2}\left(\frac{I_{K,t}}{I_{K,t-1}} - 1\right)^2$ are convex fixed-capital investment adjustment costs and $P_{I,t} > 0$ is an investment-specific technology shock. The household capital stock develops according to

$$K_{I,t+1} = \left(1 - \delta_{K,1} + \delta_{K,2} e_{K,t}^{1+\phi_K}\right) K_{I,t} + I_{K,t}, \tag{7}$$

where I follow Basu and Kimball (1997) and differentiate between "rust and dust" capital depreciation, $0 < \delta_{K,1} \leq 1$, and "wear and tear" capital depreciation, $0 \leq \delta_{K,2} e_{K,t}^{\phi_K} \leq 1$, whith $\phi_K > 0$. Capital depreciation increases in capital utilization, but is not zero for $e_{K,t} = 0$. Each household follows her intertemporal budget constraint

$$\begin{aligned} B_t &= (1 + r_{B,t-1}) B_{t-1} + \int_0^1 W_t(i) L_t(i) di + P_t ub \left(1 - \int_0^1 N_t(i) di\right) \\ &\quad + P_t r_{K,t} K_{e,t} - \int_0^1 P_t(i) T_t(i) di - Tax_t + \Pi_t \end{aligned} \tag{8}$$

where B_t are one-period nominal government bonds, $L_t(i) = N_t(i) H_t(i) e_{H,t}(i)$ is effective labor supply, and $K_{e,t} = e_{K,t} K_{I,t}$ is utilized capital supply. Income is given by nominal wages[6], $W_t(i)$, paid for effective labor, $L_t(i)$, unemployment benefits, ub, capital interest, $P_t r_{K,t}$, bond interest, $r_{B,t-1}$, and dividends paid by the firms, Div_t[7]. Expenses are determined by money spent on consumption and investment goods, $\int_0^1 P_t(i) T_t(i) di$, and by lump-sum taxes, Tax_t, which the government charges to pay for unemployment benefits.

2.3. Firms

There are infinitely many firms on the unit interval. Each firm produces one unique variety i of the differentiated good by employing labor and capital in a Cobb-Douglas production

[6]Aggregate labor of the representative household is the sum over labor supplied to all firms $N_t = \int_0^1 N_t(i) di$. As each household has infinitely many workers and matching on the labor market is random, the employment history of each household is the same. There is perfect unemployment insurance within each household.

[7]I assume that each household owns the same share of a mutual fund owning all firms. Hence, dividends Π_t paid by firms to households are equal across households.

capacity function[8]

$$Y_t(i) = A_t \left[N_t(i) H_t(i) e_{H,t}(i) \left(1 - \frac{\kappa_H}{2} \left(\frac{H_t(i) - \bar{H}(i)}{\bar{H}(i)} \right)^2 \right) \right]^{1-\alpha} \left[e_{K,t} K_{I,t}(i) \right]^{\alpha} , \qquad (9)$$

where $A_t > 0$ is a Hicks-neutral technology shock, and $0 \leq \alpha \leq 1$ is the capital elasticity of production capacity. $\kappa_H \geq 0$ defines hours per worker adjustment costs following Cacciatore et al. (2020), which capture various frictions as e.g. technological constraints due to set up costs and coordination issues, overtime pay, or decreasing returns in hours per worker. Each firm maximizes its intertemporal profits

$$\Pi_t \quad = \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_{0,t} P_t(i) \left[T_t(i) + G_t(i) - \frac{W_t(i)}{P_t(i)} L_t(i) - r_{K,t} K_{e,t}(i) \right] ,$$

where $0 \leq \beta_{0,t} < 1$ is the stochastic period discount rate[9]. The firm revenue is determined by sales on the private market, $T_t(i)$, and by exogenous spending, $G_t(i)$. Each firm i pays wages, $W_t(i)$, for effective labor, $L_t(i)$, and capital interest, $r_{K,t}$, for the rented capital stock, $K_{e,t}$. The available private market beginning-of-period production capacity is given by

$$\begin{aligned} \left(1 + c_{P,t}(i)\right) S_t(i) = \quad & \left(1 - c_{N,t}(i)\right) Y_t(i) - G_t(i) - \left(1 - \delta_T\right) T_{t-1}(i) \\ & + I_{S,t}(i) - c_{W,t} w_t(i) L_t(i), \end{aligned} \qquad (10)$$

where $c_{P,t}(i) = \frac{\kappa_P}{2} \left(\frac{P_t(i)}{P_{t-1}(i)} \left(1+\pi\right)^{\iota_P - 1} \left(1 + \pi_{t-1}\right)^{-\iota_P} - 1 \right)^2$ are convex price adjustment costs with $\kappa_P \geq 0$, and $c_{W,t}(i) = \frac{\kappa_W}{2} \left(\frac{W_t(i)}{W_{t-1}(i)} \left(1+\pi\right)^{\iota_W - 1} \left(1 + \pi_{t-1}\right)^{-\iota_W} - 1 \right)^2$ are convex nominal wage adjustment costs with $\kappa_W \geq 0$. Inflation indexation is given by $\iota_P, \iota_W \geq 0$. Firm inventories are given by $I_{S,t}(i) = \left(1 - \delta_I\right) \left(1 - q_{T,t-1}(i)\right) S_{t-1}(i)$, where $0 < \delta_I \leq 1$ are inventory depreciation costs. $c_{N,t}(i) = \frac{\kappa_N}{2} \left(\frac{v_t(i)}{L_t(i)} \right)^2$ are convex labor matching costs following Merz and Yashiv (2007), where $\kappa_N \geq 0$. Each firm searches for additional workers by posting open vacancies, $v_t(i)$. The employment level of firm i is given by (1).

[8] Burnside et al. (1995); Basu and Kimball (1997) show that any evidence on non-constant-returns-to-scale vanishes as we include variable capacity utilization in the model.

[9] It is equal to the household discount rate as all firms are owned by a mutual fund owned by the representative household.

Each firm supplies its production capacity $S_t(i)$ to the goods market where customer relationships form according to (3). It maximizes its profits by setting the optimal price level in a trade-off with its goods selling probability according to the directed search setup of Moen (1997) and sticky price setup of Rotemberg (1982a). Each firm is a monopolist along the lines of Dixit and Stiglitz (1977). It takes the household search behavior into account when it sets its prices.

2.4. General Equilibrium

To close the model, I define the real gross domestic product of the economy by

$$GDP_t = C_t + G_t + Inv_t, \tag{11}$$

where C_t is the numéraire good, and $Inv_t = (1 + c_{I,t})\, I_{K,t} + I_{S,t} - I_{S,t-1}$ is private investment. The government budget is always in equilibrium, $Tax_t = P_t ub \left(1 - \int_0^1 N_t(i)di\right)$. The central bank follows a Taylor (1993)-type rule to determine the nominal interest rate

$$\frac{1 + r_{B,t}}{1 + r_B} = \left(\frac{1 + r_{B,t-1}}{1 + r_B}\right)^{i_r} \left(\left(\frac{\pi_t}{\pi}\right)^{i_\pi} \tilde{GDP}_t^{i_{gap}}\right)^{1-i_r} \cdot M_t, \tag{12}$$

where r_B and π are steady-state targets set by the central bank, $i_r, i_{gap} \geq 0$ and $i_\pi > 1$ are poliicy coefficients, and M_t is a monetary policy shock. Following Smets and Wouters (2007), the output gap, $\tilde{GDP}_t$, is the deviation of GDP from its level prevailing under flexible prices and wages and absent price and wage cost-push shocks. All shock processes follow an AR(1) process given by

$$\xi_t = \xi^{1-\rho_\xi} \xi_{t-1}^{\rho_\xi} \varepsilon_t^\xi, \quad \varepsilon_t^\xi \sim \mathcal{N}(0,\, \sigma_\xi^2), \tag{13}$$

where $0 \leq \rho_\xi < 1$ is an autocorrelation parameter, and ξ describes the steady-state of the random shock process. There are nine shocks in the model - a Hicks-neutral technology shock A_t, an investment-specific technology shock $P_{I,t}$, a labor supply shock $\mu_{N,t}$, a labor market mismatch shock $\psi_{N,t}$, a price cost-push shock ϵ_t, a wage cost-push shock η_t, a goods market mismatch shock $\psi_{T,t}$, an exogenous spending shock G_t, and a monetary policy shock M_t.

2.5. Dynamic System of the Model Economy

The behavior of households and firms is governed by their first-order conditions. I assume that all firms use the same technology. Hence, I drop the firm index i and summarize all firms by a representative firm.

Consumption Allocation. The *representative household* allocates intertemporal consumption according to

$$muc_{N,t} = \beta \mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}} muc_{N,t+1}, \tag{14}$$

$$muc_{N,t} = muc_{G,t} - c'_{D,t} \mathbb{W}_{C,t} + \beta (1-\delta_T) \mathbb{E}_t c'_{D,t+1} \mathbb{W}_{C,t+1}, \tag{15}$$

$$muc_{G,t} = \mathbb{W}_{C,t} - \beta\theta \mathbb{E}_t \mathbb{W}_{C,t+1} + \beta (1-\delta_H) \mathbb{E}_t muc_{G,t+1}, \tag{16}$$

$$\mathbb{W}_{C,t} = \frac{1}{\mathbb{U}_{C,t} - \mathbb{U}_{N,t}} - \omega \frac{\chi_t}{\mathbb{U}_{C,t}}, \tag{17}$$

$$\chi_t = \frac{\mathbb{U}_{N,t}}{\mathbb{U}_{C,t} - \mathbb{U}_{N,t}} + \beta (1-\omega) \mathbb{E}_t \chi_{t+1}, \tag{18}$$

where $muc_{G,t}$ and $muc_{N,t}$ are gross and net marginal utility out of consumption. $\mathbb{W}_{C,t}$ is contemporaneous marginal utility out of consumption, which depends on the labor wealth effect, χ_t. The difference between gross and net marginal utility out of consumption is determined by marginal household search costs, $c'_{D,t} = \frac{\mu_D}{f_{T,t}}$, which is the level of disutility necessary to find one consumption good. It depends on the current state of goods market tightness.

Capital Allocation. The *representative household* allocates intertemporal fixed-capital investment according to

$$Q_{K,t} = \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(e_{K,t+1} r_{K,t+1} + \left(1 - \delta_{K,1} - \delta_{K,2} e_{K,t+1}^{1+\phi_K}\right) Q_{K,t+1} \right), \tag{19}$$

$$Q_{K,t} = \frac{muc_{G,t}}{muc_{N,t}} P_{I,t} \left(1 + c_{I,t} + c'_{I,t}\right) - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{muc_{G,t+1}}{muc_{N,t+1}} P_{I,t+1} c'_{I,t+1} \frac{I_{K,t+1}}{I_{K,t}}, \tag{20}$$

$$e_{K,t} = \left(\frac{r_{K,t}}{(1+\phi_K)\, \delta_{K,2} Q_{K,t}} \right)^{\frac{1}{\phi_K}}, \tag{21}$$

where $Q_{K,t}$ defines the shadow price of installed capital according to Tobin (1969). Both investment adjustment costs and goods market frictions lead to higher investment costs. The fraction $\frac{muc_{G,t}}{muc_{N,t}}$ determines the impact of household search costs on its investment decision. The *representative firm* employs capital according to

$$r_{K,t} \quad = \quad \alpha \frac{Y_t}{e_{K,t} K_t} \left(1 - c_{N,t}\right) mc_t, \tag{22}$$

where goods market frictions drive marginal costs, mc_t, and thus capital allocation. Both capital supply and capital demand are determined by goods market frictions. Therefore, capital utilization and goods market SaM are directly connected and impact each other.

Labor Allocation. The *representative firm* follows the setup in Merz (1995); Andolfatto (1996) and employs labor according to

$$\begin{aligned} Q_{F,t} \quad &= \quad \left[\left(1-\alpha\right) + \left(1+\alpha\right) c_{N,t}\right] \frac{Y_t}{N_t} mc_t - \left(1 + mc_t c_{W,t}\right) w_t H_t e_{H,t} \\ &\quad + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_N\right) Q_{F,t+1}, \end{aligned} \tag{23}$$

$$Q_{F,t} \quad = \quad \frac{c'_{N,t}}{q_{N,t}} \frac{Y_t}{N_t H_t e_{H,t}} mc_t, \tag{24}$$

where the value of marginal employment of the firm, $Q_{F,t}$, depends on the difference between marginal labor productivity, net of idle production capacity and labor matching costs, and real wage costs. The value function is forward-looking as employment relationships are long-term. Firms post vacancies as long as the marginal labor matching costs, $\frac{c'_{N,t}}{q_{N,t}}$, are lower or equal to the value of marginal employment, $Q_{F,t}$. Hence, there is free-entry on the labor market.

Each worker-firm match *bargains over the conditions of work* following a Nash (1950)-protocol. Each match maximizes the joint surplus by bargaining over the *real wage*, *hours per worker*, and *worker effort* jointly. The first-order conditions are given by

$$\begin{aligned} w_t H_t e_{H,t} \quad &= \quad ub + \frac{\frac{\partial \mathbb{U}_{N,t}}{\partial N_t}}{muc_{N,t}\left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)} \\ &\quad + \frac{\eta_t}{1-\eta_t} \frac{Q_{F,t}}{\tau_{W,t}} - \mathbb{E}_t \frac{\eta_{t+1}}{1-\eta_{t+1}} \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_N\right)\left(1-f_{N,t+1}\right) \frac{Q_{F,t+1}}{\tau_{W,t+1}}, \end{aligned} \tag{25}$$

$$w_t e_{H,t} \Gamma_{W,t} \quad = \quad \tau_{W,t} \frac{\frac{\partial^2 \mathbb{U}_{N,t}}{\partial N_t \partial H_t}}{muc_{N,t}\left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)} - \alpha\left(c'_{H,t}; c_{N,t}\right) mc_t \frac{Y_t}{H_t N_t}, \tag{26}$$

$$w_t H_t \Gamma_{W,t} \quad = \quad \tau_{W,t} \frac{\frac{\partial^2 \mathbb{U}_{N,t}}{\partial N_t \partial e_{H,t}}}{muc_{N,t}\left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)} - \alpha\left(c_{N,t}\right) mc_t \frac{Y_t}{e_{H,t} N_t}, \tag{27}$$

where $0 \leq \eta_t \leq 1$ is the household bargaining power. It fluctuates following an exogenous wage cost-push shock. $\tau_{W,t}$ and $\Gamma_{W,t}$ are functions of sticky wage adjustment with $\tau_W = 1$ and $\Gamma_W = 0$. They increase monotonically in wage inflation. $\alpha\left(c'_{H,t}; c_{N,t}\right)$ and $\alpha\left(c_{N,t}\right)$ determine the marginal productivity of labor. They decrease monotonically in hours per worker adjustment costs and labor matching costs. A full description can be found in Appendix A. All three margins - real wages, hours per worker, and worker effort - are determined by opportunity costs equalizing their marginal productivity. The goods selling probability, $q_{T,t}$, has a direct impact through marginal costs, mc_t, on all three marginal productivities. An increase in the goods selling probability leads to higher marginal labor productivity and has a positive impact on worker effort. The two utilization margins - worker effort and the goods selling probability - are therefore positively correlated on the firm side of the economy.

Price Setting. The *representative firm* sets prices on the goods market with a markup over marginal costs, mc_t, given by the process

$$
\begin{aligned}
mc_t &= \frac{q_{T,t} pr_t + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_I\right)\left(1-q_{T,t}\right) mc_{t+1}}{1+c_{P,t}}, && (28)\\
pr_t &= \frac{1 + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left[\left(1-\delta_T\right)\left(pr_{t+1} - mc_{t+1}\right) + \left(1-\delta_I\right)\Omega_t mc_{t+1}\right]}{1+\Omega_t}, && (29)\\
\Omega_t &= \frac{1}{\epsilon} \frac{\gamma_T}{1-\gamma_T} \frac{q_{T,t} S_t}{T_t} \frac{muc_{G,t}}{c'_{D,t} \mathbb{W}_{C,t}}, && (30)
\end{aligned}
$$

where markups combine the profit channel, pr_t, with its monopolistic competition channel, Ω_t, and the costs of idle capacity determined by $q_{T,t}$.The New-Keynesian Phillips curve is given by

$$
\begin{aligned}
c'_{P,t} = \; & \frac{T_t + G_t}{S_t mc_t} - \frac{\gamma_T}{1-\gamma_T} \frac{muc_{N,t}}{c'_{D,t} \mathbb{W}_{C,t}} \left[1 + c_{P,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_I\right) \frac{mc_{t+1}}{mc_t}\right] \\
& + c_{W,t} w_t \frac{L_t}{S_t} + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{mc_{t+1} S_{t+1}}{mc_t S_t} c'_{P,t+1},
\end{aligned} \quad (31)
$$

where $c'_{P,t} = \frac{\partial c_{P,t}}{\partial P_t}$. Inflation is forward-looking and determined by firm marginal costs and household marginal search costs. The two determinants describe the trade-off between sticky prices and household search effort. Inflation increases as the price elasticity of demand decreases in marginal household search costs $c'_{D,t}$. Households trade higher prices for lower search costs and firms use the decrease in price elasticity to increase their markups. The impact on the price elasticity increases in γ_T. Prices adjust only gradually due to price adjustment costs. This leads to a suboptimal household search effort, which drives capacity utilization. The trade-off between sticky prices and household search effort is central to the paper. An in-depth analysis of the impact goods market SaM on the Phillips curve can be found in Gantert (2021).

3. Variable Capacity Utilization as a Driver of Total Factor Productivity

In this section, I decompose total factor productivity (TFP) in the model into its technology and capacity utilization channels. I show how capacity utilization identifies the wedge between TFP and technology and use Bayesian estimation[10] to assess changes in the overall data fit and parameter posteriors when adding goods market SaM to the model. Henceforth, all variables are denoted as percentage deviations from the deterministic steady-state indicated by a hat. Details on the estimation are given in Appendix D.

3.1. Deriving Technology and Total Factor Productivity in the Model

Total factor productivity (TFP) is measured as output deviations that cannot be explained by input factor deviations (Solow, 1957), given an appropriate production function[11]. In the model, it is given by

$$T\hat{F}P_t = G\hat{D}P_t - (1-\alpha)\left(\hat{N}_t + \hat{H}_t\right) - \alpha\hat{K}_{I,t}. \tag{32}$$

To derive the share of TFP that is driven by technology, I solve for the technology parameters in the model - Hicks-neutral technology, $\hat{A}_t$, and investment-specific technology, $\hat{P}_{I,t}$. I

[10] I use the Dynare toolbox (Adjemian et al. (2022)) in order to linearize, solve, and estimate the model.

[11] In the literature, an appropriate production function implies a Cobb-Douglas function, as its properties reflect the (mainly) constant shares of labor and capital income in the data. See e.g. Basu et al. (2006); Fernald (2014).

summarize technology fluctuations as utilization-adjusted TFP fluctuations[12], $\hat{TFP}_{util,t}$, and calculate the difference to $\hat{TFP}_t$. The difference is defined as the *TFP wedge*

$$\hat{\Phi}_t = \hat{\Phi}_{SAM,t} + \hat{\Phi}_{Labor,t} + \hat{\Phi}_{Capital,t}, \tag{33}$$

which decomposes into a goods market channel, $\hat{\Phi}_{SAM,t}$, a labor market channel, $\hat{\Phi}_{Labor,t}$, and a capital market channel, $\hat{\Phi}_{Capital,t}$. All three channels increase the TFP wedge as capacity utilization increases. It follows that all three channels drive TFP without fluctuations in technology. Therefore, neglecting capacity utilization leads to an overestimation of technology fluctuations in the data.

We can further decompose the three channels of the TFP wedge. First, the goods market channel, $\hat{\Phi}_{SAM,t}$, is driven by non-clearing goods markets, $\frac{\partial \hat{\Phi}_{SAM,t}}{\partial \hat{q}_{T,t}} > 0$, long-term customer relationships, $\frac{\partial \hat{\Phi}_{SAM,t}}{\partial \hat{T}_{t-1}} > 0$, and firm inventories, $\frac{\partial \hat{\Phi}_{SAM,t}}{\partial \hat{I}_{S,t}} > 0$. Second, the labor market channel, $\hat{\Phi}_{Labor,t}$, is driven by worker effort, $\frac{\partial \hat{\Phi}_{Labor,t}}{\partial \hat{e}_{H,t}} > 0$, and labor matching costs, $\frac{\partial \hat{\Phi}_{Labor,t}}{\partial \hat{c}_{N,t}} < 0$. And third, the capital market channel, $\hat{\Phi}_{Capital,t}$, is driven by capital utilization, $\frac{\partial \hat{\Phi}_{Capital,t}}{\partial \hat{e}_{K,t}} > 0$. The derivations of the TFP decomposition are given in detail in Appendix B.

An increase of capacity utilization leads to an increase in the TFP wedge for all three channels. For the measurement of TFP and the TFP wedge, it does not matter whether utilization originates on the goods, labor, or capital market. The model framework is flexible and nests the approach of Fernald (2014), where capital utilization and variable worker effort are the determinants of capacity utilization. In this setup, the challenge of identifying the determinants of the TFP wedge is that we do not observe any of the capacity utilization channels directly. Instead, we observe survey data on overall capacity utilization. Therefore, I reformulate the model using the definition of capacity utilization in the data.

I follow Morin and Stevens (2004); Michaillat and Saez (2015); Comin et al. (2023) and define capacity utilization[13] with the following assumptions: 1) The capital stock is measured

[12] In this paper, I concentrate on the capacity utilization channels of TFP_t. Another channel analyzed in the literature is input factor reallocation between industries. Basu et al. (2006) show that its impact on TFP is similar to the impact of capacity utilization. In a boom, input factors are reallocated to more productive industries. Hence, TFP increases.

[13] The definition of capacity utilization used in the FED survey questionnaire can be found in Appendix C.

at the current available capital of a firm. This includes non-utilized capital $e_{K,t}$. 2) The level of employment and vacancy costs are measured at their current level. 3) Hours per worker and worker effort are measured at the steady-state, as any deviation is not sustainable over the long-run. The capacity utilization rate is defined as real GDP relative to production capacity and given by

$$\hat{cu}_t = G\hat{D}P_t + \Theta_{cn}\hat{c}_{N,t} - (1-\alpha)\hat{N}_t - \alpha\hat{K}_{I,t} - \hat{A}_t - \Theta_{AI}\hat{A}_{I,t}, \tag{34}$$

where $\Theta_{cn} = \frac{c_N}{1-c_N} > 0$ and $\Theta_{AI} = \frac{1}{1-c_N}\frac{T}{N^{1-\alpha}K_I^{\alpha}} > 0$. Using (34) to substitute for real GDP in (32) leads to

$$\hat{\Phi}_t = \Theta\hat{c}_{N,t} + (1-\alpha)\hat{H}_t - \hat{cu}_t, \tag{35}$$

where the TFP wedge is determined by capacity utilization corrected for hours per worker and labor matching costs. Therefore, capacity utilization summarizes the impact of the goods, labor, and capital market channels of the TFP wedge. The model setup supports the results of Comin et al. (2023), regardless of whether goods market SaM is a determinant of capacity utilization in the data. The estimated "utilization-adjusted TFP" of both Fernald (2014) and Comin et al. (2023) are directly connected to the model, but its determinants might differ. I use the identified TFP wedge (35) and discriminate between the capacity utilization channels by evaluating their explanatory power of the other eight macroeconomic time series used in the estimation.

3.2. Data Description and Estimation Setup

I estimate the model to replicate U.S. business cycle data from 1985q1 to 2019q4 using full information Bayesian estimation. Time is in quarters. The estimation contains nine time series - real GDP growth, real private investment growth, real private consumption growth, the capacity utilization rate, total hours worked, the unemployment rate, price inflation (GDP deflator), wage inflation (nominal labor compensation), and the FED funds rate - and the nine model shocks.

The economy wide capacity utilization rate is constructed by combining industry and service sector data. The industry sector capacity utilization rate is based on physical data where available and on the U.S. Census Bureau's Quarterly Survey of Plant Capacity Utilization. Due to lack of data, the service sector capacity utilization rate is approximated by using the variance of EU survey data and the high correlation between industry and service sector capacity utilization rates. The economy wide capacity utilization rate is based on industry data adjusted for the service sector variance. I adjust the FED funds rate for the zero lower bound period by using the shadow rate of Wu and Xia (2016). This accounts for the non-linearity in the data that is not present in a linear New-Keynesian model, as Wu and Zhang (2019) show. All the data is detrended using a one-sided HP filter following Stock and Watson (1999) to demean the data and account for structural breaks. An overview of the data sources and construction can be found in Appendix C.

Table 1 shows the calibration and prior setup of the model parameters. A complete overview of the calibration and estimation strategy can be found in Appendix D. I set $\epsilon = 11$ and $\alpha = 0.3$ directly, instead of targeting steady-state price markups as e.g. in Comin et al. (2023). Targeting steady-state price markups leads to significantly different values for ϵ and α between model versions, as adding goods market SaM adds a second price markup channel. Different values for ϵ and α imply different levels of market concentration and production setup. Here, I focus to keep both constant across model versions.

I set the prior mean of ν_e to 2 with a standard deviation of 1, as the literature shows a wide range of parameters between 0.35 and 3 (see e.g. Bils and Cho (1994); Lewis et al. (2019)). I set the prior mean of $\delta_{K,2}$ to 60% of δ_K (see e.g. Basu and Kimball (1997)) with a standard deviation of 15%. Both priors have large standard deviations to account for the possible trade-off with goods market SaM. This approach lets the data decide on the importance of each capacity utilization channel.

The novel feature in this paper - goods market SaM - is described by three parameters. I set the prior mean of γ_T to 0.17 with a standard deviation of 0.1. The setup follows Bai et al. (2017) who estimate γ_T between 0.11 and 0.23 using the American Time-Use Survey. I set the prior mean of δ_I to 0.74 with a standard deviation of 0.05. It is a combination of $\delta_{M,I} = 0.15$ for the manufacturing sector, as calculated by Khan and Thomas (2007), and

Table 1: Steady-State Targets and Parameterization

Calibration		Estimation			
Variable	Value	Variable	Distribution	Prior Mean	Prior Std.Dev.
Labor markets		*Labor markets*			
$repl$	$(N = 0.94)$	ν_e	Gamma	2	1
μ_H	$(H = 1)$	κ_H	Gamma	4	1.5
μ_e	$(e_H = 1)$	κ_W	Gamma	10	3
γ_N	0.6	ι_W	Beta	0.5	0.15
δ_N	0.12	*Goods markets*			
ψ_N	$(q_N = 0.7)$	θ	Beta	0.5	0.15
η	0.5	δ_H	Beta	0.5	0.15
κ_N	$(c_N cu = 0.015)$	δ_I	Beta	0.5	0.15
ν_H	1	γ_T	Beta	0.17	0.1
ω	0.01	κ_P	Gamma	60	20
Goods markets		ι_P	Beta	0.5	0.15
ψ_T	$(cu = 0.86)$	*Capital markets*			
μ_D	$(f_T = q_T)$	i_π	Gamma	1.7	0.1
ϵ	11	i_{gap}	Gamma	0.2	0.1
G	$(g_S = 0.2)$	i_r	Beta	0.5	0.15
Capital markets		κ_I	Gamma	4	1.5
β	$(r = 0.01)$	$\frac{\delta_{K,2}}{\delta_K}$	Beta	0.6	0.15
α	0.3				
ϕ_K	$(e_K = 1)$				
δ_K	0.025				
$\delta_{K,1}$	$(\delta_K - \delta_{K,2})$				

NOTE: Default calibration of the model. Values in parentheses are steady-state targets.

$\delta_{S,I} = 1$ for the service sector, weighted by the respective value-added. Data on δ_T is scarce, hence I set its prior to 0.5 with a standard deviation of 0.15.

I conduct a horse-race between capital utilization, worker effort, and goods market SaM in explaining the capacity utilization data, while also being in line with eight other macroeconomic aggregates. The different model versions can be framed into three setups. First, the reference model, as is common in the literature (see e.g. Fernald (2014)), that describes an economy with capital utilization and worker effort, $\delta_{K,2} > 0, \nu_e < \infty, \gamma_T = 0, \delta_T, \delta_I = 1$. Second, the SaM model that describes an economy with non-clearing goods markets, but fully utilized input factors, $\delta_{K,2} = 0, \nu_e = \infty, \gamma_T > 0, \delta_T, \delta_I < 1$. And third, the full model that describes the combination of the reference and SaM models, $\delta_{K,2} > 0, \nu_e < \infty, \gamma_T > 0, \delta_T, \delta_I < 1$.

The analysis determines the combination of capacity utilization channels that has the highest probability in explaining the TFP wedge, as the TFP wedge is completely identified by (35) and the data used. I use the modified harmonic mean following Geweke (1999) and compare the likelihood of the different model versions in explaining the data. The model comparison is based on the Bayes factor as described by Kass and Raftery (1995). Convergence diagnostics can be found in Appendix D.3.

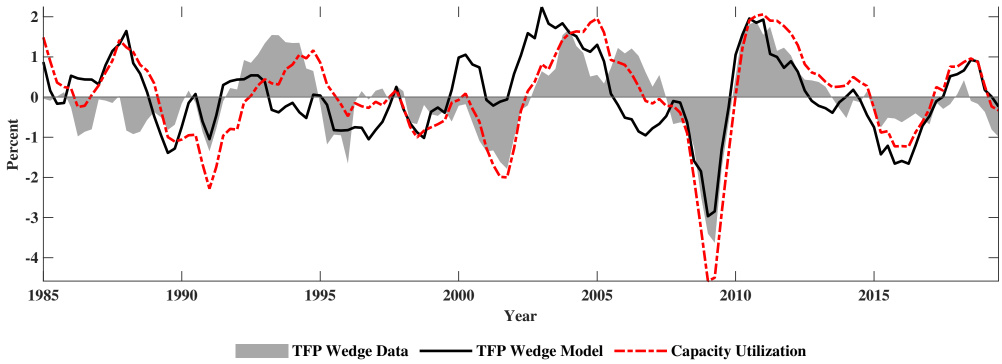
3.3. Decomposing Total Factor Productivity in the Data

The TFP wedge across model versions is completely described by (35) and the data used in the estimation. Before analyzing the likelihood of the different model versions, we can therefore derive the TFP wedge implied by the model for US data and compare it to the TFP wedge in the literature, as given by Fernald (2014). There are two distinct differences taken by assumption compared to the approach of Fernald (2014). First, I use investment data instead of capital stock data. Second, I use direct evidence on capacity utilization data. The TFP time series for the US and its decomposition implied by the model are strongly connected to the results of Fernald (2014), but also show some distinct differences that depend on the definition of capacity utilization. The time series for TFP growth are highly correlated with the data, $Corr(TFP_{Model}, TFP_{Fernald}) = 0.75$. The model results are based on the full model, but can be interchangeably based on the reference model. Figures for TFP growth and its decomposition are given in Appendix D.4.

Figure 2 shows the TFP wedge and capacity utilization percentage deviations[14] from its deterministic steady-state (long-run value) for the model and the data. The corrseponding second moments are given in Appendix D.4. The estimated model TFP wedge shows a correlation of $Corr(\Phi_{Model}, \Phi_{Fernald}) = 0.54$ with the data TFP wedge. We observe a split in

[14] I use percentage deviations from the deterministic steady-state instead of growth rates for better visibility. The results are nevertheless close to each other.

Figure 2: The TFP Wedge in the Data and the Model



NOTE: The figure shows percentage deviations from the deterministic steady-state (long-term trend) for the model TFP wedge, the data TFP wedge, and capacity utilization. It shows US data from 1985q1 to 2019q4.

the sample in 1995[15]. We observe that before 1995 $Corr(\Phi_{Model,Pre1995}, \Phi_{Fernald,Pre1995}) = 0.00$ and after 1995 $Corr(\Phi_{Model,Post1995}, \Phi_{Fernald,Post1995}) = 0.66$. Therefore, the model and the data are closer connected since the methodological adjustment of the capacity utilization data in 1995.

The average share of TFP fluctuations explained by TFP wedge fluctuations in the model is close to the data throughout the sample, though. I calculate the share of TFP fluctuations explained by TFP wedge flucutations by $\Phi_{Share,t} = \frac{Abs(\hat{\Phi}_t)}{Abs(\hat{\Phi}_t)+Abs(T\hat{F}P_{Util,t})}$. The results are $\Phi_{Share,Model,t} = 47\%$ and $\Phi_{Share,Data,t} = 50\%$. Using growth rates instead leads to the same conclusion, as $d\Phi_{Share,Model,t} = 49\%$ and $d\Phi_{Share,Data,t} = 44\%$.

There is an obvious difference in the approaches of calculating the TFP wedge between Fernald (2014) and this paper. As can be seen in figure 2, we can recover a large part of the difference to the data by using capacity utilization fluctuations directly as a proxy of the TFP wedge. The correlation for the full sample is $Corr(cu_{Model}, \Phi_{Fernald}) = 0.79$. The correlations of the pre- and post-1995 sub-samples are $Corr(cu_{Model,Pre1995}, \Phi_{Fernald,Pre1995}) = 0.37$, and $Corr(cu_{Model,Post1995}, \Phi_{Fernald,Post1995}) = 0.89$, respectively.

[15]Following Morin and Stevens (2004), there has been a methodological adjustment in the capacity utilization survey data in 1995.

The difference between capacity utilization and the TFP wedge in the model depends on whether capacity utilization is defined at long-run or short-run hours per worker. The default option taken in this paper is the long-run definition. The option closer to Fernald (2014) is the short-run definition. The correlations between the model TFP wedge and capacity utilization are $Corr(\Phi_{Model}, cu_{Model}) = 0.73$, $Corr(\Phi_{Model,Pre1995}, cu_{Model,Pre1995}) = 0.56$, and $Corr(\Phi_{Model,Post1995}, cu_{Model,Post1995}) = 0.77$, respectively. In order to use capacity utilization data to estimate the TFP wedge correctly, it is therefore essential to use the correct definition. We find both in the literature. See also section 3.1. Nevertheless, all three time series shown here are closer aligned to each other since 1995.

3.4. Analyzing the Explanatory Power of Non-Clearing Goods Markets

Adding goods market SaM improves the explanatory power of the model for different estimation setups. In fact, it is the single most important capacity utilization channel of the model, rendering capital utilization and worker effort less important. Table 2 shows the log data densities for the main model versions. I can replicate the results of Lewis et al. (2019) who show that worker effort is more important than capital utilization in explaining variable capacity utilization. In contrast to their results, I find that the worker effort model also explains the data better than the reference model, which combines both channels.

The simple SaM model, which excludes long-term customer relationships and firm inventories, shows decisive improvement in the data fit compared to the reference model with an increase of 56 points in the Bayes factor following Kass and Raftery (1995). This is in line with the results of Qiu and Ríos-Rull (2022). Goods market SaM is the single most important channel in explaining capacity utilization data and TFP in this setup. The results support the non-clearing goods market approach in general, and in an otherwise textbook New-Keynesian model in specific, as shown in the companion paper Gantert (2021). In the companion paper, I derive a three-equation New-Keynesian model with variable capacity utilization and demand-driven TFP. It allows for a parsimonious modeling approach of capacity utilization while only showing minor deviations from the textbook New-Keynesian model as e.g. in Gali (2015).

Table 2: Model fit comparison (One-sided HP filter)

	Log data density	2ln Bayes factor
Capital Utilization Model	4801	−20
Worker Effort Model	4814	6
Simple SaM Model	4839	56
Reference Model (VWE & VCU)	4811	0
SaM Model	4845	68
SaM & Capital Utilization Model	4835	48
SaM & Worker Effort Model	4839	56
Full Model (VWE, VCU & SaM)	4829	36

NOTE: Log data densities are calculated by the modified harmonic mean following Geweke (1999). For model comparison, I use $2ln$ Bayer factor as described by Kass and Raftery (1995). Model Abbreviations: 1) Variable Worker Effort (VWE), 2) Variable Capital Utilization (VCU), and 3) Goods Market Search-and-Matching (SaM). The simple SaM Model excludes long-term customer relationships and firm inventories.

Adding long-term customer relationships and firm inventories in the SaM model further improves the data fit decisively by 12 points in the Bayes factor statistic. Both channels lead to an intertemporal disconnect between production and consumption (see (33)), and therefore have to be taken into account when calculating utilization-adjusted TFP. Adding either capital utilization or worker effort to the SaM model leads to a decisively worse data fit. Hence, in contrast to Qiu and Ríos-Rull (2022) I find that the SaM model shows a better data fit than the SaM & capital utilization model.

The full model - the combination of the reference and SaM model - shows a decisive improvement in the data fit as well. It shows an increase by 36 points compared to the reference model in the Bayes factor following Kass and Raftery (1995). This increase is about 32 points smaller than the increase in the data fit of the SaM model. Therefore, also the combination of capital utilization and worker effort is rendered obsolete by the likelihood of the data once we add goods market SaM.

In the following analysis, I take the full model as the preferred model nevertheless. Even though the SaM model is better in explaining the data from a technical point of view, it takes dogmatic priors for capital utilization and worker effort into account. The dogmatic priors are in contrast to the beliefs of myself and much of the literature.

The results presented in this section are in line with a variety of robustness checks: 1) using demeaned instead of HP filtered data, 2) using $\epsilon = 6, \alpha = 0.2$ as in Comin et al. (2023), 3) using different approaches of setting the price adjustment costs parameter κ_P[16], 4) using an alternative definition[17] of capacity utilization as discussed in section 3.3, and 5) dropping capacity utilization data and goods market mismatch shocks from the estimation. Reducing the sample size to 1985q1-2008q4 to exclude the zero lower bound period and thus the Wu and Xia (2016) shadow rate leads to almost the same results with the exception that the full model is only preferred to the reference model when we exclude long-term customer relationships and firm inventories. The sensitivity results of the estimation can be found in Appendix D. The analysis of the second moments of the different models is delegated to the appendix. The correlograms show that the full model compared to the reference model especially improves the correlations between inflation, capacity utilization, and TFP. The results are given in Appendix D.6.

3.5. The Impact of Non-Clearing Goods Markets on Parameter Posteriors

Adding goods market SaM renders capital utilization and worker effort less important in the full model, while the demand elasticity of goods market matching is well identified and significant. The long-term margins of goods market SaM are of secondary importance.

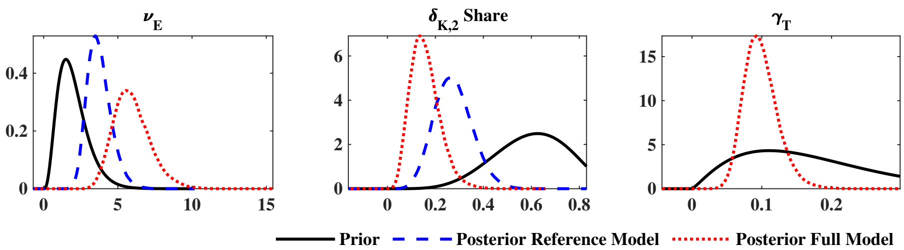
The data is informative on the parameters of interest. The posterior estimates of the parameters are all well within their prior intervals. There are some differences in the

[16] As Ireland (2004) shows, the price adjustment costs parameter can become very large in a maximum-likelihood estimation, which is not in line with the data. In the appendix, I therefore show the results of setting two alternative dogmatic priors and estimating the model. Setting κ_P to replicate empirical Phillips curve slopes and setting κ_P to replicate empirical price adjustment costs leads to the same results as presented in this section.

[17] If we define capacity utilization at short-run instead of long-run hours per worker, the resulting TFP wedge time series for the U.S. is closer to the data calculated by Fernald (2014).

posteriors, but most of the parameters are close to each other across the reference, SaM, and full model. The price adjustment cost parameter decreases as we add goods market SaM. It is 198 in the reference model, 139 in the full model, and goes as low as 104 for the SaM model. Although the parameter size is generally higher than the calculations of Gantert (2021), the difference between the models matches the calculations well[18]. The result is also in line with the robustness analysis of the price adjustment cost parameter given in Appendix D.5. It follows that the price cost-push shock has a larger standard deviation for the reference model.

Figure 3: Prior-Posteriors of the Utilization Parameters



NOTE: The figure shows the prior and posterior distribution for the reference and full model. The estimation follows the description in Appendix D. ν_e follows a prior Gamma-distribution. $\delta_{K,2} - share$ and γ_T follow a prior Beta-distribution.

Figure 3 shows the priors and posteriors of the parameters defining the capacity utilization channels for the reference and full model. The parameters of the reference model show a higher $\nu_e = 3.73$ compared to its prior, and a lower $\delta_{K,2} = 0.27$ compared to its prior. The posterior standard deviations for both $\delta_{K,2}$ and ν_e decrease, indicating well identified parameters. The data indicates that the reference model leads to large variations in both capital utilization and worker effort.

Adding goods market SaM - given by the full model - leads to a significant increase in $\nu_e = 5.93$, and a significant decrease in $\delta_{K,2} = 0.16$ compared to the priors and to the reference model posteriors. $\delta_{K,2}$ shows a 41% decrease and ν_e a 59% increase relative to the reference model. Goods market SaM partially substitutes for the capital utilization and

[18]The goods market SaM channel reduces price adjustment cost significantly and puts them closer to a more realistic range of adjustment cost of 1.2% of GDP on average, as e.g. calculated by Zbaracki et al. (2004).

worker effort channels.

The posterior mean of γ_T decreases compared to its prior, but is well within the estimated interval of Bai et al. (2017) with $\gamma_T = 0.10$. Its posterior standard deviation is less than half of the prior standard deviation, hence γ_T is well identified by the data. Firm inventories and long-term customer relationships show rather a minor role in the model as their parameters are estimated at $\delta_I = 0.84$ and $\delta_T = 0.81$, respectively. Overall, the parameter posteriors of the full model show the importance of goods market SaM in explaining capacity utilization data as well. A complete overview of the prior setup, posterior estimates, and their 90% HPD intervals for all parameters can be found in Appendix D.

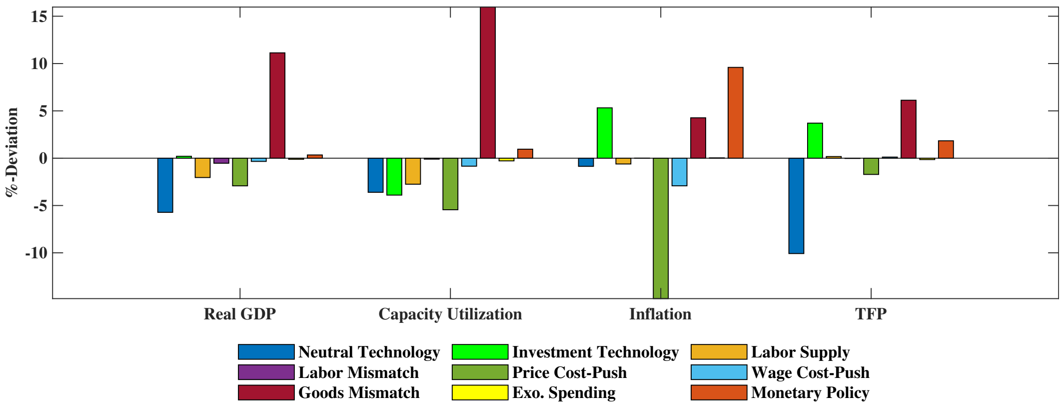
4. Drivers of TFP over the Business Cycle

In this section, I show the shock decomposition for US macroeconomic aggregates and TFP as we introduce goods market SaM to the model. Demand shocks become more important relative to supply shocks. The change in the shock decomposition pattern occurs although TFP and the TFP wedge are set by the data across models. Therefore, any change follows from the changes in the propagation mechanisms of the models. I show the impact of goods market SaM on the impulse responses of the TFP wedge and decompose its determinants. Further, I show cumulative TFP multiplicators that put TFP fluctuations in perspective to GDP fluctuations of the model economy.

4.1. Shock Decomposition: The Determinants of the TFP Wedge

As we add goods market SaM to the model, the propagation mechanism of the model changes, which in turn changes the underlying shocks that drive the economy and replicate the macroeconomic time series. The dominant driving forces in both the reference and full model are technology and goods market mismatch shocks. Technology shocks explain $42 - 55\%$, and goods market mismatch shocks $24 - 45\%$ of variation in real GDP. In contrast, labor, cost-push, and monetary policy shocks explain about $4 - 10\%$ of variation in real GDP each. A complete (historical) variance decomposition is given in Appendix D.7. Figure 4 shows the change in the historical variance decomposition as we move from the reference to

Figure 4: Shock Decomposition Difference between the Reference and Full Model



NOTE: The figure shows the percentage point change of the variance decomposition for the model shocks and across models. An increase indicates a larger variance share for the respective shock in the full model compared to the reference model.

the full model. A positive deviation shows a percentage point increase in the variance share of a shock for the full model. The comparison for the SaM model is given in Appendix D.7. There is a general pattern in the change of real GDP, capacity utilization, inflation, and TFP variance decomposition as we move from the reference to the full model. The share of variation explained by neutral technology and cost-push shocks decreases, while the share of variation explained by investment-specific technology and goods market mismatch shocks increases, although investment-specific technology shocks show lower variation in capacity utilization. This pattern indicates a shift to aggregate demand and market heterogeneity as drivers of the economy: Investment-specific technology shocks affect household income besides technology and therefore drives the household search effort upwards. Goods market mismatch shocks affect household search disutility, but also summarize goods market composition and dispersion effects. They capture unmodeled market heterogeneity. Similar effects have been shown for input factor reallocation to more productive firms over the business cycle by e.g. Basu et al. (2006); Baqaee et al. (2021). In contrast, neutral technology and cost-push shocks are drivers of the supply side of the economy.

For capacity utilization, the increase in the variance share of goods market mismatch shocks is with over $15\% - points$ especially large. At the same time, the variance share of technology and cost-push shocks show a quantitatively similar decrease. Therefore, adding goods market

SaM leads to a much larger role of aggregate demand, and goods market composition and dispersion effects for the fluctuations of capacity utilization. In contrast, technology and cost-push shocks that drive firm marginal costs have a larger impact on capital utilization and worker effort in the reference model. Exogenous changes in marginal costs have a smaller impact on the full model economy, as there is a trade-off between prices and search effort.

For inflation, the general pattern of change applies with two differences. First, the variance share of price cost-push shocks decreases significantly, and second the variance share of monetary policy shocks increases, as we move from the reference to the full model. This pattern further underlines the importance of the trade-off between prices and search effort. Adding goods market SaM leads to a stronger incomplete pass-through of marginal costs to prices. Their allocative role decreases (see also e.g. Abbritti and Trani (2020); Abbritti et al. (2021)). Exogenous shifts in costs alone do not suffice to move aggregate demand if household search effort is rigid.

The general pattern also applies for TFP. Non-technology shocks increase their variance share as the decrease in neutral technology is larger than the increase in investment-specific technology. Goods market mismatch shocks explain a larger variance share of TFP[19] as we move from the reference to the full model. Hence, aggregate demand, and goods market composition and dispersion effects play a larger role as a driver of TFP (see again e.g. Basu et al. (2006); Baqaee et al. (2021)). Further, monetary policy shocks - although small in the overall picture of variance decomposition - show a sizeable increase in the variance share of TFP. This pattern is additional evidence on the increased importance of aggregate demand for TFP in the full model. Whether the change in the variance decomposition of TFP just follows the change in real GDP variance decomposition or a change in the propagation mechanism, is the topic of the next sections.

[19] Generally, goods market mismatch shocks also contain market technology shocks. Here, the shock is essentially a black-box containing different goods market shocks. As market technology is more of a medium to long-term development though, I do not interpret the goods market mismatch shock as a technology shock. To differentiate between market technology and market dispersion and composition effects is a task for future research.

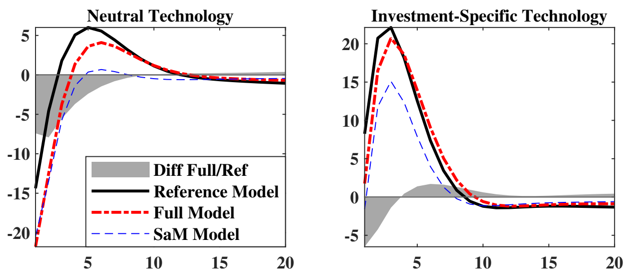
4.2. The Impact of the TFP Wedge on Measuring Technology

How large is the TFP wedge between TFP and utilization-adjusted TFP for the different shocks over the business cycle? A positive TFP wedge indicates that TFP overestimates the underlying utilization-adjusted TFP, vice-versa. I analyze the differences of the TFP wedge impulse response functions (IRFs), as we move from the reference model to the full model.

Technology shocks. The defining feature of neutral and investment-specific technology shocks is that they have some inherent technology component. Figure 5 shows TFP wedge IRFs to expansionary technology shocks for the reference, SaM, and full model. The TFP wedge IRF to the neutral technology shock shows a significant initial decrease. Hence, technology innovations are underestimated by TFP deviations. The initial decrease in capacity utilization leads to a smaller increase in TFP than in technology. Because prices are sticky, aggregate demand only adjusts gradually. Firms decrease their capital utilization, workers decrease their effort, and TFP increases by 15% less than technology. As prices adjust, the TFP wedge turns positive over the medium-run. Aggregate demand increases as prices drop and income is high. We observe an overshooting of TFP as capacity utilization increases above its steady-state. By comparing the results to the SaM model, we see that the overshooting process is driven by capital utilziation and worker effort, as it is not present in the SaM model. In the long-run, the TFP wedge turns slightly negative again, as capital utilization decreases to increase the life-span of the increased capital stock and increase the persistence of the impact of the neutral technology shock.

Adding goods market SaM (full model) amplifies the initial negative IRF of the TFP wedge. Its initial decrease of 22% in the full model is therefore 50% larger than in the reference model. The trade-off between sticky prices and household search effort leads to a stronger decrease in capacity utilization, as the additional production capcacity of firms is only picked up as prices decrease. The medium to long-run pattern is identical to the reference model, but shows a lower variation in the TFP wedge. Therefore, goods market SaM amplifies the initial impact of capacity utilization on TFP compared to the reference model, as can also be seen by comparing it to the SaM model IRFs.

Figure 5: The Cyclical TFP Wedge for the Technology Shocks

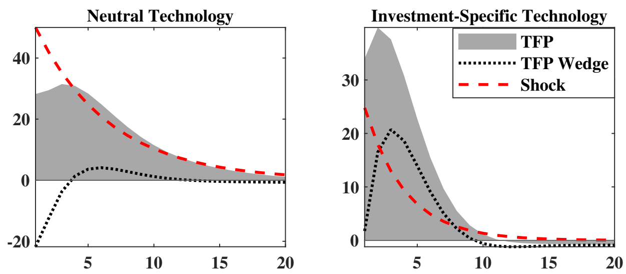


NOTE: The figure shows impulse response functions of the TFP wedge to technology shocks according to (33). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the reference (black curves), full (red dashed curves), and SaM (blue curves) model.

The TFP wedge IRF to the investment-specific technology shock shows positive deviations over the short and medium-run. Small initial deviations due to the pre-determined capital stock increase significantly and show TFP wedge deviations of up to 23% for the reference model. Hence, technology innovations are overestimated by TFP deviations. The investment-specific technology shock shows larger fluctuations in TFP than in technology. The shock has two components. First, an increase in production capacity as the capital stock increases exogenously. Second, an increase in household income as they hold a larger capital stock. As sticky prices only adjust gradually, the income (aggregate demand) channel is larger than the production capacity (aggregate supply) channel. Hence, capacity utilization and the TFP wedge increase. As prices increase, the TFP wedge decreases and converges back to its steady-state. In the long-run, the TFP wedge turns negative as capital utilization decreases to increase the life-span of the additional capital stock.

Adding goods market SaM amplifies the production capacity channel over the income channel in the short-run, as additional aggregate demand requires additional household search effort. Hence, the positive TFP wedge deviations are smaller compared to the reference model. The peak of TFP wedge deviations for the full model is 21%, hence $2\% - points$ smaller than in the reference model. The peak of the TFP wedge deviations for the SaM model is 15%, in line with the previous results. The IRFs of the full model quickly converge to the IRFs of the reference model as prices adjust.

Figure 6: Decomposing TFP into Wedge and Shock for the Technology Shocks

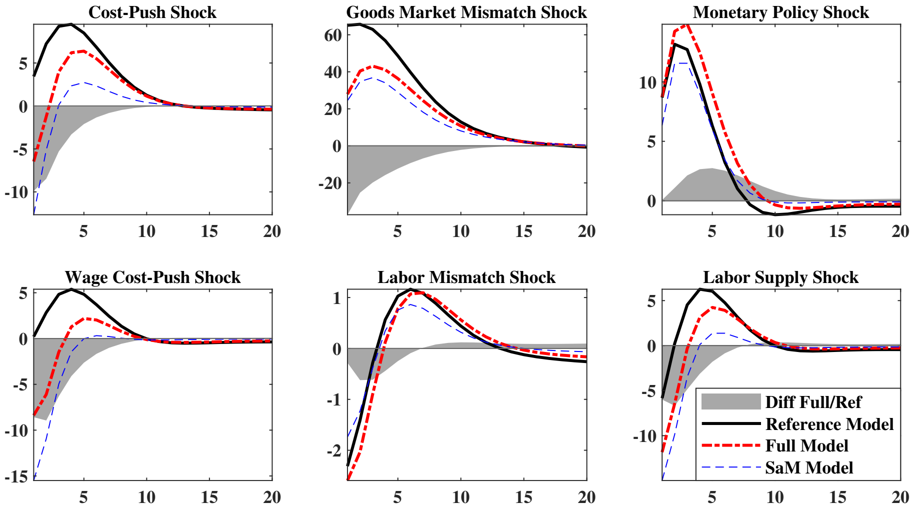


NOTE: The figure shows the decomposition of the impulse response functions of the TFP wedge to technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. TFP IRFs (grey areas) are decomposed into the TFP wedge (black dotted curves) and the exogenous shock (red dashed curves).

The decomposition of the TFP IRFs into a technology and TFP wedge component can be seen in figure 6 for the full model. TFP underestimates technology for the neutral technology shock, and overestimates technology for the investment-specific technology shock. I find that the shock component shows larger and more persistent deviations for both technology shocks. The shock component dominates TFP deviations for the Hicks-neutral technology shock. In contrast, the shock component shows about the same deviations as the TFP wedge for the investment-specific technology shock. Its initial deviation is somewhat higher, but lower over the medium-run. The investment-specific technology shock shows a consistent disconnect between the technology shock and TFP deviations. Therefore, we have to be especially careful about decomposing technology and capacity utilization deviations for investment-specific technology shocks. The figures for the reference and SaM models are qualitatively identical, but quantitatively different, as described by the difference in the TFP wedges shown in figure 5.

Non-technology shocks. Most of the economic shocks in the model are not driven by technology. They drive TFP, in contrast to the technology shocks, only by fluctuations in capacity utilization. Figure 7 shows TFP wedge IRFs to expansionary price and wage cost-push, goods and labor market mismatch, labor supply, and monetary policy shocks. We observe positive TFP wedge deviations over the short and medium-run for the reference model for all shocks except the labor mismatch and supply shocks. The two shocks show an initial

Figure 7: The Cyclical TFP Wedge for Price Cost-Push, Goods Market Mismatch, and Monetary Policy Shocks



NOTE: The figure shows impulse response functions of the TFP wedge to non-technology shocks according to (33). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the reference (black curves), full (red dashed curves), and SaM (blue curves) model.

decline in the TFP wedge as additional labor increases the production capacity, which only matches gradually due to sticky prices. As prices decline, both shocks show positive TFP wedge deviations as well. The slight negative deviations of the TFP wedge in the long-run follow again from the underutilization of capital to increase its life-span. Therefore, expansionary non-technology shocks generally imply an increase in capacity utilization and hence technology deviations being overestimated by TFP deviations.

Adding goods market SaM (full model) decreases the TFP wedge deviations for all six shocks except the monetary policy shock (although it also decreases slightly for the SaM model). The cost-push shocks decrease marginal costs of the firm, the labor shocks increase labor allocation to the firm, and the goods market mismatch shock decreases idle capacity of the firm. In order to pass the lower marginal costs or larger production capacity through to the market, aggregate demand has to increase as well. As goods market SaM adds the trade-off between sticky prices and household search effort, the pass-through becomes more difficult. The shocks affect the supply side of the economy, but do not stimulate the demand side enough to pick up the additional production capacity. Capacity utilization and therefore TFP do not increase as much in the full model compared to the reference model, as can be seen by the negative IRFs of the difference between the full and reference model. The effect is even more pronounced in the SaM model. The maximum TFP wedge deviations decrease from 9.5% to 6.4% for the price cost-psuh shock, from 5.4% to 2.2% for the wage cost-push shock, and from 65.7% to 43.1% for the goods market mismatch shock. For the labor mismatch and supply shocks, the initial TFP wedge deviations decrease from −2.3% to −2.6%, and from −5.8% to −11.8%, respectively. The differences generally become larger if we look at the SaM model, excluding capital utilization and worker effort from the analysis. In contrast, the monetary policy shock directly affects aggregate demand and household search effort through the consumption Euler equation. Lower interest rates stimulate contemporaneous aggregate demand. As prices adjust slowly, the trade-off between sticky prices and search costs lead to higher household search effort, which in turn increases capacity utilization and TFP. The maximum TFP wedge deviation increases from 13.2% for the reference model to 14.9% for the full model. Across all shocks to the economy, it is the trade-off between sticky prices and household search effort that is central to the changes in the propgation mechanisms as we add goods market SaM. Active aggregate demand becomes an important driver of capacity utilization.

Capacity Utilization Channel Decomposition. The fluctuations in the TFP wedge are driven by capacity utlization fluctuations on the labor, capital, and goods market, as shown in (33). Adding goods market SaM shifts the TFP wedge drivers from labor and capital markets to goods markets, as also shown in section 3.5. In this section, I analyze the impact of adding goods market SaM on the TFP wedge decomposition for each single shock. The TFP wedge variance share of each channel is given by the share of absolute fluctuations in labor, capital, and goods market capacity utilization. The results are shown in table 3.

In line with the prior-posterior analysis of the parameters, I find that in the reference model the labor channel (50 − 70%) is significantly more important than capital utilization (20 − 40%) in driving the TFP wedge fluctuations across shocks. The result is in line with Lewis et al.

Table 3: Decomposition of the TFP Wedge Fluctuations

		eA	eI	eP	eW	eT	eN	eH	eM
Labor Channel	Reference Model	53%	49%	57%	68%	16%	54%	58%	63%
	SaM Model	22%	15%	33%	22%	5%	50%	12%	10%
	Full Model	28%	32%	39%	42%	10%	48%	37%	25%
Capital Channel	Reference Model	26%	38%	33%	23%	8%	22%	31%	28%
	SaM Model	0%	0%	0%	0%	0%	0%	0%	0%
	Full Model	12%	22%	19%	4%	5%	14%	10%	9%
SaM Channel	Reference Model	21%	14%	11%	9%	76%	24%	12%	9%
	SaM Model	78%	85%	67%	78%	95%	50%	88%	91%
	Full Model	59%	46%	42%	54%	85%	38%	53%	66%

NOTE: The TFP wedge variance share of each channel is given by the share of absolute fluctuations in labor, capital, and goods market capacity utilization. Shock abbreviations: eA: Neutral technology shock, eH: Labor supply shock, eI: Investment-specific technology shock, eM: Monetay policy shock, eN: Labor mismatch shock, eP: Price cost-push shock, eT: Goods market mismatch shock, eW: Wage cost-push shock.

(2019). The goods market SaM channel represents $10-20\%$ of TFP wedge fluctuations in the reference model. This follows from a constant 86% capacity utilization on the private goods market and a varying share of GDP traded on the private goods market. I find that the capital utilization channel is somewhat more important for the investment-specific technology shock, and that the worker effort channel is somewhat more important for the wage cost-push shock. Overall, both channels are important across shocks in the reference model, except the goods market matching shock, which is by definition driven by the goods market SaM channel.

Adding the variable goods market SaM channel (full model) reduces the variance share of the TFP wedge explained by capital utilization and worker effort across shocks and increases the variance share of goods market SaM significantly. For most shocks it increases to over $40-60\%$. Along the results found in section 3.5, the decrease is especially pronounced for the capital utilization channel, while the worker effort channel also becomes less important, but still explains a sizeable share of TFP wedge fluctuations. For the monetary policy shock, the shift from the reference model to the full model is the largest across shocks with an increase of the SaM channel variance share from 9% to 66%. The result emphasizes the significant impact of goods market SaM on demand shocks.

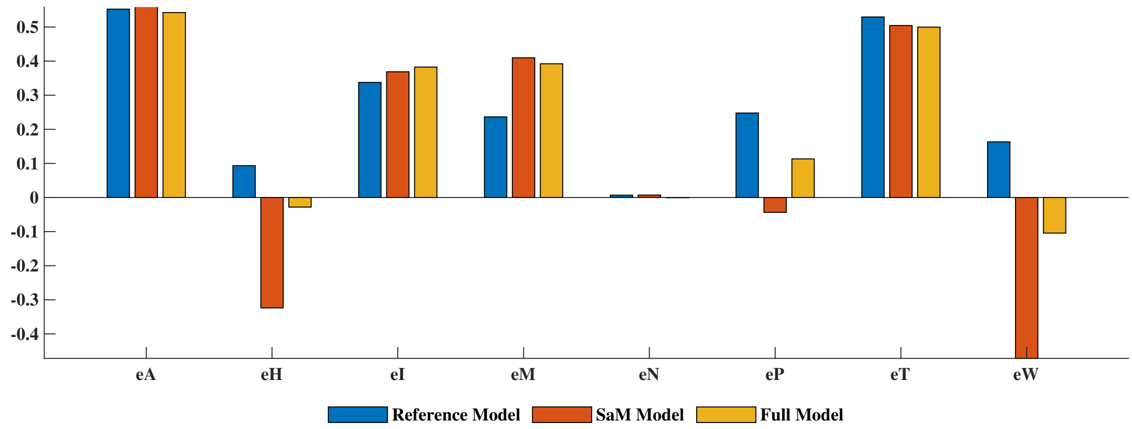
Goods market SaM puts the trade-off between household search effort and sticky prices to the center of the TFP wedge analysis. The trade-off has a distinct impact on capacity utilization and the mismeasurement of technology by TFP. It leads to a larger underestimation of technology by TFP following technology shocks and to a larger overestimation of technology by TFP following non-technology shocks. The investment-specific technology shock is the exception in this setup, as it has both an income and production capacity channel. The TFP wedge decomposition shows, that goods market SaM is the dominant driver of the TFP wedge across all shocks in the full model, while worker effort and to a lesser extent capital utilization are the drivers across shocks in the reference model. Adding goods market SaM decreases especially the importance of capital utilization in driving the TFP wedge.

The trade-off between household search effort and sticky prices increases in the price adjustment costs, κ_P, and the demand elasticity of goods market matching, γ_T, leading to stronger variation in capacity utilization, while it decreases in long-term customer relationships, $(1-\delta_T)$, and firm inventories, $(1-\delta_I)$. Therefore, the mismeasurement of technology by TFP increases in $\kappa_P, \gamma_T, \delta_T$, and δ_I. In this framework, "demand shocks look like supply shocks" (Bai et al., 2017) if prices are sticky and goods markets are demand-driven. The robustness results can be found in Appendix E.

4.3. Cumulative TFP Multiplicators

As we add goods market SaM, the business cycle fluctuations of TFP relative to GDP increase significantly for demand and policy shocks, but not for technology shocks. So far, we have derived the impact of goods market SaM on TFP fluctuations. But, in a dynamic general equilibrium model, it also has an impact on the entire economy. I derive the cumulative TFP multiplicator as an indicator of the impact of the capacity utilization channels on TFP

Figure 8: Cumulative TFP Multiplicators



NOTE: The figure shows cumulative TFP and TFP wedge multiplicators for the reference, SAM, and full model according to (36). Shock abbreviations: eA: Neutral technology shock, eH: Labor supply shock, eI: Investment-specific technology shock, eM: Monetay policy shock, eN: Labor mismatch shock, eP: Price cost-push shock, eT: Goods market mismatch shock, eW: Wage cost-push shock.

fluctuations relative to GDP fluctuations. It is given by

$$\Lambda_{TFP,cum} \quad = \quad \frac{\sum_{t=1}^{20} T\hat{F}P_t}{\sum_{t=1}^{20} G\hat{D}P_t}, \tag{36}$$

where I use the first 20 quarters of each IRF which represents about the average period of a business cycle. A large cumulative TFP multiplicator indicates large increases in TFP relative to increases in GDP, vice-versa. A negative cumulative TFP multiplicator indicates negative correlations between TFP and GDP deviations. Figure 8 shows the cumulative TFP multiplicators for all shocks except the exogenous spending shock[20].

We observe cumulative TFP multiplicators that are clearly dominated by technology shocks for the reference model. The neutral technology and goods market matching[21] shocks show

[20]The exogenous spending shock is dropped for visibility reasons, as its cumulative TFP multiplicator for the reference model becomes very large with a value of -11. This pattern follows from GDP IRFs that show cumulative values of close to zero. The cumulative TFP multiplicator decreases for the SAM model (-0.56) and the full model (-0.90).

[21]In the reference model, the goods market matching shock is indistinguishable from the neutral technology shock as there is no active aggregate demand.

cumulative TFP multiplicators of about 0.55, and the investment-specific technology shock of about 0.35[22]. The monetary policy and price cost-push shocks show cumulative TFP multiplicators of about 0.25, while the wage cost-push shock shows a cumulative TFP multiplicator of 0.2. Both the labor supply and mismatch shocks show cumulative TFP multiplicators close to zero. Supplying more labor in the model therefore does not affect productivity significantly.

Compared to the refrence model, the SaM and full model cumulative TFP multiplicators for the neutral technology and goods market mismatch shocks do not show any significant change. Although adding goods market SaM leads to smaller fluctuations in the TFP wedge, the impact on GDP fluctuations is similar for the two shocks. Nevertheless, both shocks show the largest fluctuations in TFP relative to GDP in the full model.

Compared to the reference model, the SaM and full model cumulative TFP multiplicators for the labor supply and cost-push shocks decrease significantly and even turn negative. The full model shows a more muted response compared to the SaM model. All three shocks decrease marginal costs and therefore supply additional production capacity. Prices do not fall fast enough, and it takes time to match the additional production capacity. This pattern is especially strong with the trade-off between goods prices and household search effort. Nevertheless, GDP increases, which in turn leads to negative cumulative TFP multiplicators. The labor mismatch shock shows no significant cumulative TFP multiplicators across models.

Compared to the reference model, the SaM and full model cumulative TFP multiplicators increase for the monetary policy and investment-specific technology shocks. Especially the cumulative TFP multiplicator of monetary policy shocks shows a strong increase with values of up to 0.4 and thus close to the cumulative TFP multiplicator of neutral technology shocks. Therefore, active aggregate demand leads to a strong response of productivity relative to GDP as household search effort becomes an input factor into production. Adding the trade-off between sticky prices and household search costs leads to demand shocks that increasingly look like technology shocks - also in relation to GDP.

[22]Given that the investment-specific technology shock only affects about 20% of the economy, its impact on overall productivity is significant.

Compared to the analysis of the TFP wedge IRFs before, we see that the impact of the goods market SaM channel on the economy is less pronounced when we set it relative to GDP. It shows a similar impact on both TFP and GDP for the neutral technology and goods market mismatch shocks, hence the TFP multiplicators are similar across models. The cumulative TFP multiplicator for the investment-specific technology shock increases in the full model even though the TFP wedge IRFs decrease. Hence, the impact of goods market SaM on GDP is larger than on TFP. The cumulative TFP multiplicators of the cost-push and monetary policy shocks are along the results found for their TFP wedge IRFs. We find that adding goods market SaM leads to smaller TFP fluctuations relative to GDP fluctuations for both cost-push shocks, and to larger TFP fluctuations relative to GDP fluctuations for the monetary policy shock. Therefore, the two shocks that contain some sort of demand component - investment-specific technology and monetary policy - show larger fluctuations in TFP relative to GDP as we add goods market SaM.

The impact of the price adjustment cost parameter κ_P on the cumulative TFP multiplicators is rather limited, except for the cost-push shocks. Price stickiness shows an almost proportional impact on fluctuations of both TFP and GDP. In contrast, an increase in γ_T leads to larger cumulative TFP multiplicators for demand shocks and lower TFP multiplicators for supply shocks. It has a distinct impact on the variation of capacity utilization and TFP as markets become more demand-driven, while the impact on GDP is muted. The robustness results for δ_T and δ_I follow γ_T. The robustness results are shown in Appendix E.

5. Discussion and Concluding Remarks

Total factor productivity (TFP) is at the core of macroeconomics as it describes the efficiency of an economy. This paper shows that goods market search-and-matching (SaM) is an important channel in explaining the differences between TFP and utilization-adjusted TFP in a New-Keynesian model.

What are the underlying economic channels that drive short-run capacity utilization and TFP fluctuations? In a Bayesian estimation exercise, I find that goods market SaM is the single most important capacity utilization channel in explaining short-run TFP fluctuations.

Worker effort and especially capital utilization are largely substituted by the introduction of goods market SaM. The trade-off between active aggregate demand (household search effort) and sticky prices is at the center of short-run TFP fluctuations and thus challenges the view that it is mostly supply driven.

How do the different capacity utilization channels affect the transmission of economic shocks on short-run TFP? Adding goods market SaM leads to an increase in TFP fluctuations following demand shocks, while it leads to a decrease following supply and cost-push shocks. This pattern especially applies if markets are demand-driven and show sticky prices.

The paper shows the importance of variable capacity utilization for TFP fluctuations. In its approach, it is in line with the literature, but emphasizes the trade-off between active aggregate demand and sticky prices. The paper shows that variations in TFP are much more driven by imperfect markets than by utilization decisions of households and firms. Efficient markets are therefore a driver of TFP and welfare. Furthermore, modeling goods market SaM allows to analyze the impact of goods market features, as e.g. household search heterogeneity and idiosyncratic market features. Neglecting non-clearing goods markets can lead to biased estimates of the drivers of TFP over the business cycle.

References

Abbritti, M., Aguilera-Bravo, A., Trani, T., 2021. Long-term business relationships, bargaining and monetary policy. Economic Modelling 101, 105551.

Abbritti, M., Trani, T., 2020. On price dynamics with search and bargaining in the product market. Macroeconomic Dynamics , 1–34.

Adjemian, S., Bastani, H., Juillard, M., Karamé, F., Mihoubi, F., Mutschler, W., Pfeifer, J., Ratto, M., Rion, N., Villemot, S., 2022. Dynare: Reference Manual Version 5. Dynare Working Papers 72. CEPREMAP.

Andolfatto, D., 1996. Business cycles and labor-market search. American Economic Review , 112–132.

Bai, Y., Rios-Rull, J.V., Storesletten, K., 2017. Demand shocks as technology shocks.

Baqaee, D., Farhi, E., Sangani, K., 2021. The Supply-Side Effects of Monetary Policy. Technical Report.

Basu, S., Fernald, J.G., 2002. Aggregate productivity and aggregate technology. European Economic Review 46, 963–991.

Basu, S., Fernald, J.G., Kimball, M.S., 2006. Are technology improvements contractionary? American Economic Review 96, 1418–1448.

Basu, S., Kimball, M.S., 1997. Cyclical productivity with unobserved input variation. Technical Report.

Bils, M., Cho, J.O., 1994. Cyclical factor utilization. Journal of Monetary Economics 33, 319–354.

Blanchard, O., Gali, J., 2010. Labor markets and monetary policy: A new keynesian model with unemployment. American Economic Journal: Macroeconomics 2, 1–30.

Brooks, S.P., Gelman, A., 1998. General methods for monitoring convergence of iterative simulations. Journal of computational and graphical statistics 7, 434–455.

Burnside, C., Eichenbaum, M., Rebelo, S., 1995. Capital utilization and returns to scale. NBER Macroeconomics Annual 10, 67–110.

Cacciatore, M., Fiori, G., Traum, N., 2020. Hours and employment over the business cycle: A structural analysis. Review of Economic Dynamics 35, 240–262.

Christiano, L.J., Eichenbaum, M., Evans, C.L., 2005. Nominal rigidities and the dynamic effects of a shock to monetary policy. Journal of Political Economy 113, 1–45.

Comin, D.A., Quintana, J., Schmitz, T.G., Trigari, A., 2023. Revisiting Productivity Dynamics in Europe: A New Measure of Utilization-Adjusted TFP Growth. Technical Report. National Bureau of Economic Research.

Dixit, A.K., Stiglitz, J.E., 1977. Monopolistic competition and optimum product diversity. American Economic Review 67, 297–308.

Fernald, J.G., 2014. A quarterly, utilization-adjusted series on total factor productivity, Federal Reserve Bank of San Francisco.

Gali, J., 2015. Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications. Princeton University Press.

Gantert, K., 2021. Non-Clearing Goods Markets and the Capacity Utilization Phillips Curve. Technical Report.

Geweke, J., 1999. Using simulation methods for bayesian econometric models: inference, development, and communication. Econometric Reviews 18, 1–73.

Greenwood, J., Hercowitz, Z., Huffman, G.W., 1988. Investment, capacity utilization, and the real business cycle. American Economic Review , 402–417.

Ireland, P.N., 2004. Technology shocks in the new keynesian model. Review of Economics and Statistics 86, 923–936.

Jaimovich, N., Rebelo, S., 2009. Can news about the future drive the business cycle? American Economic Review 99, 1097–1118.

Kass, R.E., Raftery, A.E., 1995. Bayes factors. Journal of the American Statistical Association 90, 773–795.

Keane, M., Rogerson, R., 2012. Micro and macro labor supply elasticities: A reassessment of conventional wisdom. Journal of Economic Literature 50, 464–76.

Khan, A., Thomas, J.K., 2007. Inventories and the business cycle: An equilibrium analysis of (s, s) policies. American Economic Review 97, 1165–1188.

King, R.G., Plosser, C.I., Rebelo, S.T., 1988. Production, growth and business cycles: I. the basic neoclassical model. Journal of Monetary Economics 21, 195–232.

Lewis, V., Villa, S., Wolters, M.H., 2019. Labor productivity, effort and the euro area business cycle .

Merz, M., 1995. Search in the labor market and the real business cycle. Journal of Monetary Economics 36, 269–300.

Merz, M., Yashiv, E., 2007. Labor and the market value of the firm. American Economic Review 97, 1419–1431.

Michaillat, P., Saez, E., 2015. Aggregate demand, idle time, and unemployment. Quarterly Journal of Economics 130, 507–569.

Moen, E.R., 1997. Competitive search equilibrium. Journal of Political Economy 105, 385–411.

Morin, N.J., Stevens, J.J., 2004. Estimating capacity utilization from survey data .

Nash, J.F., 1950. The bargaining problem. Econometrica 18, 155–162.

Petrongolo, B., Pissarides, C.A., 2001. Looking into the black box: A survey of the matching function. Journal of Economic Literature 39, 390–431.

Petrosky-Nadeau, N., Wasmer, E., 2015. Macroeconomic dynamics in a model of goods, labor, and credit market frictions. Journal of Monetary Economics 72, 97–113.

Petrosky-Nadeau, N., Wasmer, E., Zeng, S., 2016. Shopping time. Economics Letters 143, 52–60.

Pfeifer, J., 2018. A guide to specifying observation equations for the estimation of dsge models , 1–150.

Qiu, Z., Ríos-Rull, J.V., 2022. Procyclical Productivity in New Keynesian Models. Technical Report. National Bureau of Economic Research.

Rotemberg, J.J., 1982a. Monopolistic price adjustment and aggregate output. Review of Economic Studies 49, 517–531.

Rotemberg, J.J., 1982b. Sticky prices in the united states. Journal of Political Economy 90, 1187–1211.

Smets, F., Wouters, R., 2007. Shocks and frictions in us business cycles: A bayesian dsge approach. American Economic Review 97, 586–606.

Solow, R.M., 1957. Technical change and the aggregate production function. Review of Economics and Statistics , 312–320.

Stock, J.H., Watson, M.W., 1999. Forecasting inflation. Journal of Monetary Economics 44, 293–335.

Taylor, J.B., 1993. Discretion versus policy rules in practice, in: Carnegie-Rochester conference series on public policy, Elsevier. pp. 195–214.

Tobin, J., 1969. A general equilibrium approach to monetary theory. Journal of Money, Credit and Banking 1, 15–29.

Wohlrabe, K., Wollmershäuser, T., 2017. Zur konstruktion einer gesamtwirtschaftlichen ifo kapazitätsauslastung. ifo Schnelldienst 70, 26–30.

Wu, J.C., Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking 48, 253–291.

Wu, J.C., Zhang, J., 2019. A shadow rate new keynesian model. Journal of Economic Dynamics and Control 107, 103728.

Zbaracki, M.J., Ritson, M., Levy, D., Dutta, S., Bergen, M., 2004. Managerial and customer costs of price adjustment: direct evidence from industrial markets. Review of Economics and Statistics 86, 514–533.

ONLINE APPENDIX

Appendix A. Model Derivations

Appendix A.1. Household Optimization Problem

The household utility maximization (MAX: $K_{C,t}$, C_t, $D_t(i)$, X_t, B_t, $T_t(i)$, $e_{K,t}$, $K_{I,t+1}$, $I_{K,t}$, $N_t(i)$) given the necessary constraints is given by

$$
\begin{aligned}
\mathcal{L} \;=\; & \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ log \Bigg[K_{C,t} - \theta K_{C,t-1} - \mu_D \int_0^1 D_t(i)di \\
& \qquad - \mu_{N,t} X_t \int_0^1 N_t(i) \left(\frac{\mu_H}{1+\nu_H} H_t(i)^{1+\nu_H} + H_t(i) \frac{\mu_e}{1+\nu_e} e_{H,t}(i)^{1+\nu_e} \right) di \Bigg] \\
& \lambda_{1,t} \Bigg[B_t - (1 + r_{B,t-1}) B_{t-1} - \int_0^1 W_t(i) e_{H,t}(i) H_t(i) N_t(i) di - P_t ub \left(1 - \int_0^1 N_t(i) di \right) \\
& \quad + \int_0^1 P_t(i) T_t(i) di - P_t r_{K,t} e_{K,t} K_{I,t} + Tax_t - \Pi_t \Bigg] \\
& - \lambda_{2,t} \left[X_t - \left(K_{C,t} - \theta K_{C,t-1} - \mu_{D,t} \int_0^1 D_t(i) di \right)^{\omega} X_{t-1}^{1-\omega} \right] \\
& - \lambda_{3,t} \left[\int_0^1 T_t(i) di - (1 - \delta_T) \int_0^1 T_{t-1}(i) di - \int_0^1 f_{T,t}(i) D_t(i) di \right] \\
& - \lambda_{4,t} \left[\int_0^1 N_t(i) di - (1 - \delta_N) \int_0^1 N_{t-1}(i) di - f_{N,t} \left(1 - (1 - \delta_N) \int_0^1 N_t(i) di \right) \right] \\
& - \lambda_{5,t} \left[K_{I,t+1} - \left(1 - \delta_{K,1} - \delta_{K,2} e_{K,t}^{1+\phi_K} \right) K_{I,t} - I_{K,t} \right] \\
& - \lambda_{6,t} \left[\left(\int_0^1 T_t(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} - C_t - P_{I,t} \left(1 + \frac{\kappa_I}{2} \left(\frac{I_{K,t}}{I_{K,t-1}} - 1 \right)^2 \right) I_{K,t} \right] \\
& - \lambda_{7,t} \left[K_{C,t} - (1 - \delta_H) K_{C,t-1} - C_t \right] \Bigg\},
\end{aligned}
$$

where it is assumed that the no-Ponzi scheme condition $\lim_{T \to \infty} B_T \geq 0$ holds.

First-order conditions.

$$\begin{aligned}\mathcal{L}_{K_{C,t}}: \quad \lambda_{7,t} = &\left(\frac{1}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}} + \frac{\omega X_t \lambda_{2,t}}{\mathbb{U}_{C,t}}\right) \\ &- \beta\theta\mathbb{E}_t\left(\frac{1}{\mathbb{U}_{C,t+1}-\mathbb{U}_{N,t+1}} + \frac{\omega X_{t+1}\lambda_{2,t+1}}{\mathbb{U}_{C,t+1}}\right) + \beta\left(1-\delta_H\right)\lambda_{7,t+1}\end{aligned} \tag{A.1}$$

$$\mathcal{L}_{C,t}: \quad (-1)\lambda_{6,t} = \lambda_{7,t} \tag{A.2}$$

$$\mathcal{L}_{D_t(i)}: \quad \lambda_{3,t} = \frac{\mu_D}{f_{T,t}(i)}\left[\frac{1}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}} + \frac{\omega X_t\lambda_{2,t}}{\mathbb{U}_{C,t}}\right] \tag{A.3}$$

$$\mathcal{L}_{X_t}: \quad \lambda_{2,t}X_t = \frac{(-1)\mathbb{U}_{N,t}}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}} + \beta\left(1-\omega\right)\mathbb{E}_t X_{t+1}\lambda_{2,t+1} \tag{A.4}$$

$$\mathcal{L}_{B_t}: \quad \lambda_{1,t} = \beta\left(1+r_{B,t}\right)\mathbb{E}_t\lambda_{1,t+1} \tag{A.5}$$

$$\mathcal{L}_{T_t(i)}: \quad \lambda_{1,t}P_t(i) = (-1)\lambda_{6,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon}} - \lambda_{3,t} + \beta\left(1-\delta_T\right)\mathbb{E}_t\lambda_{3,t+1} \tag{A.6}$$

$$\mathcal{L}_{e_{K,t}}: \quad \lambda_{5,t} = \frac{\lambda_{1,t}P_t r_{K,t}}{\left(1+\phi_K\right)\delta_{K,2}e_{K,t}^{\phi_K}} \tag{A.7}$$

$$\mathcal{L}_{K_{I,t+1}}: \quad \lambda_{5,t} = \beta\mathbb{E}_t\left(\lambda_{1,t+1}P_{t+1}e_{K,t+1}r_{K,t+1} + \left(1-\delta_{K,1}-\delta_{K,2}e_{K,t+1}^{1+\phi_K}\right)\lambda_{5,t+1}\right) \tag{A.8}$$

$$\mathcal{L}_{I_{K,t}}: \quad \lambda_{5,t} = (-1)\lambda_{6,t}P_{I,t}\left(1+c_{I,t}+c'_{I,t}\right) - \beta\mathbb{E}_t(-1)\lambda_{6,t+1}P_{I,t+1}\frac{I_{K,t+1}}{I_{K,t}}c'_{I,t+1} \tag{A.9}$$

$$\begin{aligned}\mathcal{L}_{N_t(i)}: \quad \lambda_{4,t} = &\lambda_{1,t}\left(W_t(i)e_{H,t}(i)H_t(i) - P_t ub\right) - \frac{\frac{\partial\mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}}, \\ &+ \beta\left(1-\delta_N\right)\mathbb{E}_t\left(1-f_{N,t+1}\right)\lambda_{4,t+1}\end{aligned} \tag{A.10}$$

where

$$\begin{aligned}\mathbb{U}_{C,t} &= K_{C,t} - \theta K_{C,t-1} - \mu_D\int_0^1 D_t(i)di, \\ \mathbb{U}_{N,t} &= \mu_{N,t}X_t\int_0^1 N_t(i)\left(\frac{\mu_H}{1+\nu_H}H_t(i)^{1+\nu_H} + H_t(i)\frac{\mu_e}{1+\nu_e}e_{H,t}(i)^{1+\nu_e}\right)di, \\ c_{I,t} &= \frac{\kappa_I}{2}\left(\frac{I_{K,t}}{I_{K,t-1}}-1\right)^2, \\ c'_{I,t} &= \kappa_I\left(\frac{I_{K,t}}{I_{K,t-1}}-1\right).\end{aligned}$$

Define $muc_{N,t} = \lambda_{1,t}P_t$, $muc_{G,t} = \lambda_{7,t}$, and $\chi_t = (-1)\lambda_{2,t}X_t$. Further, summarize contemporaneous utility by $\mathbb{W}_{C,t} = \frac{1}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}} - \omega\frac{\chi_t}{\mathbb{U}_{N,t}}$. The wealth effects equation (A.4), the gross marginal consumption utility of the household (A.1), and the Euler equation (A.5) are then given by

$$\chi_t = \frac{\mathbb{U}_{N,t}}{\mathbb{U}_{C,t} - \mathbb{U}_{N,t}} + \beta(1-\omega)\mathbb{E}_t\chi_{t+1}, \tag{A.11}$$

$$muc_{G,t} = \mathbb{W}_{C,t} - \beta\theta\mathbb{E}_t\mathbb{W}_{C,t+1} + \beta(1-\delta_H)\mathbb{E}_t muc_{G,t+1}, \tag{A.12}$$

$$muc_{N,t} = \beta\mathbb{E}_t\frac{1+r_{B,t}}{1+\pi_{t+1}} muc_{N,t+1}, \tag{A.13}$$

where $(1+\pi_{t+1}) = \frac{P_{t+1}}{P_t}$. We can derive the net marginal consumption utility of the household by substituting (A.2) and (A.3) in (A.6)

$$muc_{N,t} = \frac{P_t}{P_t(i)}\left[muc_{G,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon}} - \frac{\mu_D}{f_{T,t}(i)}\mathbb{W}_{C,t} + \beta(1-\delta_T)\mathbb{E}_t\frac{\mu_D}{f_{T,t+1}(i)}\mathbb{W}_{C,t+1}\right]. \tag{A.14}$$

Define $Q_{K,t} = \frac{\lambda_{5,t}}{muc_{N,t}}$ and substitute (A.2) in (A.9) to solve for the capital market equations (A.7)-(A.9) denominated in the numéraire good

$$Q_{K,t} = \frac{r_{K,t}}{(1+\phi_K)\delta_{K,2}e_{K,t}^{\phi_K}}, \tag{A.15}$$

$$Q_{K,t} = \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_t}\left(e_{K,t+1}r_{K,t+1} + \left(1-\delta_{K,1}-\delta_{K,2}e_{K,t+1}^{1+\phi_K}\right)Q_{K,t+1}\right), \tag{A.16}$$

$$Q_{K,t} = \frac{muc_{G,t}}{muc_{N,t}}P_{I,t}\left(1+c_{I,t}+c'_{I,t}\right) - \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\frac{muc_{G,t+1}}{muc_{N,t+1}}P_{I,t+1}\frac{I_{K,t+1}}{I_{K,t}}c'_{I,t+1}, \tag{A.17}$$

where $\mathbb{E}_t\beta\frac{muc_{N,t+1}}{muc_{N,t}} = \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}$ follows from the Euler equation (A.13). Define $Q_{NH,t} = \frac{\lambda_{4,t}}{muc_{N,t}}$ and plug it into (A.10) to derive the value function of marginal employment of the household denominated in the numéraire good

$$\begin{aligned} Q_{H,t}(i) = & \left(\frac{W_t(i)}{P_t}e_{H,t}(i)H_t(i) - ub\right) - \frac{\frac{\partial\mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{muc_{N,t}(\mathbb{U}_{C,t}-\mathbb{U}_{N,t})} \\ & + \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}(1-\delta_N)(1-f_{N,t+1})Q_{H,t+1}(i), \end{aligned} \tag{A.18}$$

where $\mathbb{E}_t\beta\frac{muc_{N,t+1}}{muc_{N,t}} = \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}$ follows from the Euler equation (A.13), and

$$\frac{\partial\mathbb{U}_{N,t}(i)}{\partial N_t(i)} = \mu_{N,t}X_t\left(\frac{\mu_H}{1+\nu_H}H_t(i)^{1+\nu_H} + H_t(i)\frac{\mu_e}{1+\nu_e}e_{H,t}(i)^{1+\nu_e}\right)$$

is the marginal disutility of working for one specific firm i.

Household Consumption Demand Equation. For any two varieties (i, j) of the differentiated consumption good, we can use (A.14) to derive the household consumption

$$\frac{P_t(i)}{P_t(j)} = \frac{\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon}} muc_{G,t} - c'_{D,t}(i)\mathbb{W}_{C,t} + \beta\left(1-\delta_T\right)c'_{D,t+1}(i)\mathbb{W}_{C,t+1}}{\left(\frac{T_t}{T_t(j)}\right)^{\frac{1}{\epsilon}} muc_{G,t} - c'_{D,t}(j)\mathbb{W}_{C,t} + \beta\left(1-\delta_T\right)c'_{D,t+1}(j)\mathbb{W}_{C,t+1}},$$

where $c'_{D,t}(i) = \frac{\mu_D}{f_{T,t}(i)}$.

Appendix A.2. Firm Optimization Problem

The firm profit maximization (MAX: $T_t(i)$, $S_t(i)$, $x_{T,t}(i)$, $P_t(i)$, $N_t(i)$, $v_t(i)$, $K_{e,t}(i)$) given the necessary constraints is given by

$$\begin{aligned}
\mathcal{L} = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_{0,t} \{ & [P_t(i)T_t(i) + P_t(i)G_t(i) - W_t(i)e_{H,t}(i)H_t(i)N_t(i) - P_t(i)r_{K,t}K_{e,t}(i)] \\
& - \phi_{1,t}\left[\left(1 + c_{P,t}(i)\right)S_t(i) + \left(1-\delta_T\right)T_{t-1}(i) + G_t(i) \right.\\
& \quad - \left(1-\delta_I\right)\left(1 - \psi_{T,t-1}x_{T,t-1}(i)^{\gamma_T}\right)S_{t-1}(i) \\
& \quad \left. - \left(1 - c_{N,t}(i)\right)Y_t(i) + c_{W,t}(i)\frac{W_t(i)}{P_t(i)}e_{H,t}(i)H_t(i)N_t(i)\right] \\
& - \phi_{2,t}\left[T_t(i) - \left(1-\delta_T\right)T_{t-1}(i) - \psi_{T,t}x_{T,t}(i)^{\gamma_T}S_t(i)\right] \\
& - \phi_{3,t}\left[N_t(i) - \left(1-\delta_N\right)N_{t-1}(i) - q_{N,t}v_t(i)\right] \\
& - \phi_{4,t}\left[muc_{N,t}\frac{P_t(i)}{P_t} - \left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon}} muc_{G,t} + \frac{\mu_D}{\psi_{T,t}}x_{T,t}(i)^{1-\gamma_T}\mathbb{W}_{C,t} \right.\\
& \quad \left.\left. -\beta\left(1-\delta_T\right)\frac{\mu_D}{\psi_{T,t+1}}x_{T,t+1}(i)^{1-\gamma_T}\mathbb{W}_{c,t+1}\right]\right\}
\end{aligned}$$

where

$$\begin{aligned}
K_{e,t}(i) &= e_{K,t}K_{I,t}(i), \\
Y_t(i) &= A_t\left[\left(1 - \frac{\kappa_H}{2}\left(\frac{H_t(i) - \bar{H}(i)}{\bar{H}(i)}\right)^2\right)e_{H,t}(i)H_t(i)N_t(i)\right]^{1-\alpha} K_{e,t}(i)^{\alpha}, \\
c_{P,t}(i) &= \frac{\kappa_P}{2}\left(\frac{P_t(i)}{P_{t-1}(i)}\left(1+\pi\right)^{\iota_P - 1}\left(1+\pi_{t-1}\right)^{-\iota_P} - 1\right)^2, \\
c_{W,t}(i) &= \frac{\kappa_W}{2}\left(\frac{W_t(i)}{W_{t-1}(i)}\left(1+\pi\right)^{\iota_W - 1}\left(1+\pi_{t-1}\right)^{-\iota_W} - 1\right)^2, \\
c_{N,t}(i) &= \frac{\kappa_N}{2}\left(\frac{v_t(i)}{e_{H,t}(i)H_t(i)N_t(i)}\right)^2.
\end{aligned}$$

First-order conditions.

$$\mathcal{L}_{T_t(i)}: \quad \phi_{2,t} = P_t(i) - \phi_{4,t}\frac{1}{\epsilon}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon}}\frac{muc_{G,t}}{T_t(i)} + \mathbb{E}_t\beta_{t,t+1}\left(1-\delta_T\right)\left(\phi_{2,t+1}-\phi_{1,t+1}\right) \tag{A.19}$$

$$\begin{aligned}\mathcal{L}_{S_t(i)}: \quad \phi_{1,t}\left(1+c_{P,t}(i)\right) &= \phi_{2,t}\left(1-\gamma_T\right)q_{T,t}(i) + \phi_{4,t}\left(1-\gamma_T\right)\frac{c'_{D,t}(i)\mathbb{W}_{C,t}}{S_t(i)} \\ &\quad + \mathbb{E}_t\beta_{t,t+1}\left(1-\delta_I\right)\phi_{1,t+1}\left(1-\left(1-\gamma_T\right)q_{T,t}(i)\right)\end{aligned} \tag{A.20}$$

$$\mathcal{L}_{x_{T,t}(i)}: \quad \phi_{4,t} = \frac{\gamma_T}{1-\gamma_T}\frac{f_{T,t}(i)D_t(i)}{c'_{D,t}(i)\mathbb{W}_{C,t}}\left(\phi_{2,t}+\mathbb{E}_t\beta_{t,t+1}\left(1-\delta_I\right)\phi_{1,t+1}\right) \tag{A.21}$$

$$\begin{aligned}\mathcal{L}_{P_t(i)}: \quad c'_{P,t}(i)S_t(i)\frac{\phi_{1,t}}{P_t(i)} &= T_t(i) + G_t(i) - \phi_{4,t}muc_{N,t}\frac{1}{P_t} \\ &\quad + \frac{\phi_{1,t}}{P_t(i)}c_{W,t}(i)\frac{W_t(i)}{P_t(i)}e_{H,t}(i)H_t(i)N_t(i) \\ &\quad + \mathbb{E}_t\beta_{t,t+1}\frac{P_{t+1}(i)}{P_t(i)}S_{t+1}(i)\frac{\phi_{1,t+1}}{P_{t+1}(i)}c'_{P,t+1}(i)\end{aligned} \tag{A.22}$$

$$\begin{aligned}\mathcal{L}_{N_t(i)}: \quad \phi_{3,t} &= \phi_{1,t}\left[\left(1-\alpha\right)\left(1-c_{N,t}(i)\right)+2c_{N,t}(i)\right]\frac{Y_t(i)}{N_t(i)} \\ &\quad - W_t(i)e_{H,t}(i)H_t(i)\left(1-c_{W,t}(i)\frac{\phi_{1,t}}{P_t(i)}\right) + \mathbb{E}_t\beta_{t,t+1}\left(1-\delta_N\right)\phi_{3,t+1}\end{aligned} \tag{A.23}$$

$$\mathcal{L}_{v_t(i)}: \quad \phi_{3,t} = \phi_{1,t}2c_{N,t}(i)\frac{Y_t(i)}{q_{N,t}v_t(i)} \tag{A.24}$$

$$\mathcal{L}_{K_{e,t}(i)}: \quad P_t(i)r_{K,t} = \phi_{1,t}\left(1-c_{N,t}(i)\right)\alpha\frac{Y_t(i)}{K_{e,t}(i)} \tag{A.25}$$

Define marginal costs as $mc_t(i) = \frac{\phi_{1,t}}{P_t(i)}$, and the inverse of marginal profits as $pr_t(i) = \frac{\phi_{2,t}}{P_t(i)}$. Substitute (A.21) in (A.19), and (A.20) for the marginal costs equations

$$\begin{aligned}pr_t(i) &= \frac{1+\mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_T\right)\left(pr_{t+1}(i)-mc_{t+1}(i)\right)}{1+\frac{1}{\epsilon}\frac{\gamma_T}{1-\gamma_T}\frac{q_{T,t}(i)S_t(i)}{T_t(i)}\frac{muc_{G,t}}{c'_{D,t}(i)\mathbb{W}_{C,t}}} \\ &\quad + \frac{\mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_I\right)\frac{1}{\epsilon}\frac{\gamma_T}{1-\gamma_T}\frac{q_{T,t}(i)S_t(i)}{T_t(i)}\frac{muc_{G,t}}{c'_{D,t}(i)\mathbb{W}_{C,t}}mc_{t+1}(i)}{1+\frac{1}{\epsilon}\frac{\gamma_T}{1-\gamma_T}\frac{q_{T,t}(i)S_t(i)}{T_t(i)}\frac{muc_{G,t}}{c'_{D,t}(i)\mathbb{W}_{C,t}}}\end{aligned} \tag{A.26}$$

$$mc_t(i) = \frac{q_{T,t}(i)pr_t(i)+\mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_I\right)\left(1-q_{T,t}(i)\right)mc_{t+1}(i)}{1+c_{P,t}(i)} \tag{A.27}$$

Substitute (A.21) in (A.22) for the New-Keynesian Phillips Curve

$$\begin{aligned} c'_{P,t}(i) &= \frac{T_t(i)+G_t(i)}{S_t(i)mc_t(i)} + c_{W,t}(i)\frac{W_t(i)}{P_t(i)}\frac{e_{H,t}(i)H_t(i)N_t(i)}{S_t(i)} \\ &\quad - \frac{\gamma_T}{1-\gamma_T}\frac{muc_{N,t}}{c'_{D,t}(i)\mathbb{W}_{C,t}}\left[q_{T,t}(i)\frac{pr_t(i)}{mc_t(i)} - \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_I\right)q_{T,t}(i)\frac{mc_{t+1}(i)}{mc_t(i)}\right] \\ &\quad + \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\frac{mc_{t+1}(i)S_{t+1}(i)}{mc_t(i)S_t(i)}c'_{P,t+1}(i), \end{aligned} \tag{A.28}$$

where I use (A.27) to substitute for $q_{T,t}(i)\frac{pr_t(i)}{mc_t(i)}$ to get

$$\begin{aligned} c'_{P,t}(i) &= \frac{T_t(i)+G_t(i)}{S_t(i)mc_t(i)} + c_{W,t}(i)\frac{W_t(i)}{P_t(i)}\frac{e_{H,t}(i)H_t(i)N_t(i)}{S_t(i)} \\ &\quad - \frac{\gamma_T}{1-\gamma_T}\frac{muc_{N,t}}{c'_{D,t}(i)\mathbb{W}_{C,t}}\left[1+c_{P,t}(i) - \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_I\right)\frac{mc_{t+1}(i)}{mc_t(i)}\right] \\ &\quad + \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\frac{mc_{t+1}(i)S_{t+1}(i)}{mc_t(i)S_t(i)}c'_{P,t+1}(i). \end{aligned} \tag{A.29}$$

Define the value of marginal employment for the firm as $Q_{NF,t}(i) = \frac{\phi_{3,t}}{P_t(i)}$ and rewrite the input factor demand equations (A.23)-(A.25) by

$$\begin{aligned} Q_{F,t}(i) &= \left[(1-\alpha)\left(1-c_{Nt}(i)\right)+2c_{N,t}(i)\right]mc_t(i)\frac{Y_t(i)}{N_t(i)} \\ &\quad - w_t(i)e_{H,t}(i)H_t(i)\left(1-c_{W,t}(i)mc_t(i)\right) \\ &\quad + \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_N\right)Q_{F,t+1}(i), \end{aligned} \tag{A.30}$$

$$Q_{F,t}(i) = 2c_{N,t}(i)mc_t(i)\frac{Y_t(i)}{q_{N,t}v_t(i)}, \tag{A.31}$$

$$r_{K,t} = \left(1-c_{N,t}(i)\right)mc_t(i)\alpha\frac{Y_t(i)}{K_{e,t}(i)}. \tag{A.32}$$

Appendix A.3. Nash Bargaining: Real Wages, Hours per Worker, and Worker Effort

Each worker-firm match maximizes its joint surplus by solving a Nash bargaining problem

$$\max_{W_t(i);H_t(i);e_{H,t}(i)} \quad \left(Q_{H,t}(i)\right)^{\eta_t}\left(Q_{F,t}(i)\right)^{1-\eta_t},$$

where $0 \leq \eta_t \leq 1$.

The first-order conditions for the real wage, hours per worker, and worker effort are given by

$$\frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial W_t(i)}}{\frac{\partial Q_{H,t}(i)}{\partial W_t(i)}} \tag{A.33}$$

$$\frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial H_t(i)}}{\frac{\partial Q_{H,t}(i)}{\partial H_t(i)}} \tag{A.34}$$

$$\frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial e_{H,t}(i)}}{\frac{\partial Q_{H,t}(i)}{\partial e_{H,t}(i)}} \tag{A.35}$$

Deriving the first-order conditions of (A.18) and (A.30) with respect to $W_t(i)$ and plugging them into (A.33) gives the sticky wage horizon equation that determines the impact of sticky wages on the wage setting process

$$\begin{aligned}\tau_{W,t}(i) &= \frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial W_t(i)}}{\frac{\partial Q_{H,t}(i)}{\partial W_t(i)}} \\ &= \left(1+mc_t(i)\left(c_{W,t}(i)+c'_{W,t}(i)\right)\right) \\ &\quad -\mathbb{E}_t\frac{1+\pi_{W,t+1}(i)}{1+r_t}\left(1-\delta_N\right)mc_{t+1}(i)\frac{H_{t+1}(i)e_{H,t+1}(i)}{H_t(i)e_{H,t}(i)}c'_{W,t+1}(i).\end{aligned}$$

Plugging (A.33) into (A.18) gives the real wage bargaining equation from the point of view of the household for each match

$$\begin{aligned}&w_t(i)e_{H,t}(i)H_t(i) - ub - \frac{1}{muc_{N,t}}\frac{\frac{\partial \mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}} \\ &= \frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{\tau_{W,t}(i)} - \mathbb{E}_t\frac{\eta_{t+1}}{1-\eta_{t+1}}\frac{1+\pi_{t+1}}{1+r_t}\left(1-\delta_N\right)\left(1-f_{N,t+1}\right)\frac{Q_{F,t+1}(i)}{\tau_{W,t+1}(i)}.\end{aligned}$$

Deriving the first-order conditions of (A.18) and (A.30) with respect to $H_t(i)$ and plugging them into (A.34) gives the optimality condition of hours per worker for each match

$$\begin{aligned}&\left(1+mc_t(i)c_{W,t}(i)\right)w_t(i)e_{H,t}(i) - \tau_{W,t}(i)\left[w_t(i)e_{H,t}(i) - \frac{1}{muc_{N,t}}\frac{\frac{\partial^2 \mathbb{U}_{N,t}(i)}{\partial N_t(i)\partial H_t(i)}}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}}\right] \\ &= \left[(1-\alpha)^2\left(1-\frac{c'_{H,t}(i)}{1-c_{H,t}(i)}\right) + (1+\alpha)\,c_{N,t}(i)\left((1-\alpha)\left(1-\frac{c'_{H,t}(i)}{1-c_{H,t}(i)}\right)-2\right)\right]mc_t(i)\frac{Y_t(i)}{H_t(i)N_t(i)}\end{aligned}$$

Deriving the first-order conditions of (A.18) and (A.30) with respect to $e_{H,t}(i)$ and plugging them into (A.35) gives the optimality condition of worker effort for each match

$$(1+mc_t(i)c_{W,t}(i))\, w_t(i)H_t(i) - \tau_{W,t}(i)\left[w_t(i)H_t(i) - \frac{1}{muc_{N,t}}\frac{\frac{\partial^2 \mathbb{U}_{N,t}(i)}{\partial N_t(i)\partial e_{H,t}(i)}}{\mathbb{U}_{C,t}-\mathbb{U}_{N,t}}\right]$$
$$= \left[(1-\alpha)^2 + (1+\alpha)\, c_{N,t}(i)\left((1-\alpha)-2\right)\right] mc_t(i)\frac{Y_t(i)}{e_{H,t}(i)N_t(i)}.$$

Appendix B. Utilization-adjusted TFP and TFP wedge

Definition of the aggregate investment-specific technology shock.

$$\begin{aligned} \frac{C_t + I_{K,t}}{T_t} &= \frac{T_t - P_{I,t}\left(1+c_{I,t}\right)I_{K,t} + I_{K,t}}{T_t} \\ &= 1 + \left(1 - P_{I,t}\left(1+c_{I,t}\right)\right)\frac{I_{K,t}}{T_t} \quad = \quad A_{I,t}. \end{aligned} \tag{B.1}$$

where I use the household resource constraint $C_t = T_t - P_{I,t}\left(1 + c_{I,t}I_{K,t}\right)$ to substitute for C_t. The aggregate investment-specific technology shock $A_{I,t}$ depends on fluctuations in $P_{I,t}$ and is weighted by the share of fixed-capital investment relative to private market consumption T_t. In the steady-state $A_I = 1$ as $P_I = 1$ by normalization and $c_I = 0$.

Calculating the utilization-adjusted TFP. Total factor productivity is defined as the gross domestic product divided by the input factors in an appropriate production function. It is given by

$$TFP_t = \frac{GDP_t}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}^{\alpha}} = \frac{C_t + I_{K,t} + I_{S,t} - I_{S,t-1} + G_t}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}}, \tag{B.2}$$

$$= \frac{A_{I,t}T_t + I_{S,t} - I_{S,t-1} + G_t}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}}, \tag{B.3}$$

where I use (B.1) to substitute for private consumption C_t and fixed-capital investment $I_{K,t}$. Further, using the customer relationship law of motion $T_t = \left(1-\delta_T\right)T_{t-1} + q_{T,t}S_t$ and substitute for T_t, we get

$$TFP_t = \frac{A_{I,t}\left[\left(1-\delta_T\right)T_{t-1} + q_{T,t}S_t\right] + I_{S,t} - I_{S,t-1} + G_t}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}},$$

and substitute for S_t with the firm resource constraint (10), we get

$$TFP_t = \frac{A_{I,t}\frac{q_{T,t}}{1+c_{P,t}}\left(\left(1-c_{N,t}\right)Y_t + I_{S,t-1} - \left(1-\delta_T\right)T_{t-1} - G_t - c_{W,t}L_t\right)}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}},$$
$$+ \frac{A_{I,t}\left(1-\delta_T\right)T_{t-1} + I_{S,t} - I_{S,t-1} + G_t}{\left(N_tH_t\right)^{1-\alpha}K_{I,t}}.$$

Substituting for Y_t with the production capacity function (9) and expanding the right side with $\frac{GDP_t}{GDP_t}$ we get

$$\begin{aligned} TFP_t &= A_{I,t}\frac{\psi_{T,t}x_{T,t}^{\gamma_T}}{1+c_{P,t}}\left(1-c_{N,t}\right)A_t\left(e_{H,t}\left(1-c_{H,t}\right)\right)^{1-\alpha}\left(e_{K,t}\right)^{\alpha} \\ &\quad + TFP_t A_{I,t}\left(1-\frac{\psi_{T,t}x_{T,t}^{\gamma_T}}{1+c_{P,t}}\right)\left(1-\delta_T\right)\frac{T_{t-1}}{GDP_t} \\ &\quad + TFP_t\left(1-\left(1-A_{I,t}\frac{\psi_{T,t}x_{T,t}^{\gamma_T}}{1+c_{P,t}}\right)\frac{I_{S,t-1}}{I_{S,t}}\right)\frac{I_{S,t}}{GDP_t} \\ &\quad + TFP_t\left(1-A_{I,t}\frac{\psi_{T,t}x_{T,t}^{\gamma_T}}{1+c_{P,t}}\right)\frac{G_t}{GDP_t} - TFP_t A_{I,t}\frac{\psi_{T,t}x_{T,t}^{\gamma_T}}{1+c_{P,t}}\frac{\Gamma_{W,t}}{GDP_t} \end{aligned} \tag{B.4}$$

Linearization. I linearize (B.4) around its deterministic steady-state and group all variables to their respective channel. Linearized total factor productivity can be summarized as

$$T\hat{F}P_t = \hat{\Phi}_{SAM,t} + \hat{\Phi}_{Labor,t} + \hat{\Phi}_{Capital,t} + T\hat{F}P_{Util,t}, \tag{B.5}$$

where $\hat{\Phi}_{SAM,t}$ summarizes the goods market search-and-matching impact on TFP, $\hat{\Phi}_{Labor,t}$ summarizes the labor market impact on TFP, $\hat{\Phi}_{Capital,t}$ summarizes the capital market impact on TFP, and $T\hat{F}P_{Util,t}$ summarizes all technology shocks. The linearized impact of the single channels is given by

$$\begin{aligned} \hat{\Phi}_{SAM,t} &= \hat{q}_{T,t} + \frac{TFP}{1-c_N}\frac{I_S}{GDP}\left[\frac{1}{q_T}\left(\hat{I}_{S,t}-\left(1-q_T\right)\hat{I}_{S,t-1}\right) - G\hat{D}P_t + \hat{q}_{T,t}\right] \\ &\quad + \frac{TFP}{1-c_N}\frac{1-q_T}{q_T}\left(1-\delta_T\right)\frac{T}{GDP}\left[\hat{T}_{t-1} - G\hat{D}P_t - \frac{q_T}{1-q_T}\hat{q}_{T,t}\right] \\ &\quad + \frac{TFP}{1-c_N}\frac{1-q_T}{q_T}\frac{G}{GDP}\left[\hat{G}_t - G\hat{D}P_t - \frac{q_T}{1-q_T}\hat{q}_{T,t}\right], \end{aligned} \tag{B.6}$$

$$\hat{\Phi}_{Labor,t} = \left(1-\alpha\right)\hat{e}_{H,t} - \frac{c_N}{1-c_N}\hat{c}_{N,t}, \tag{B.7}$$

$$\hat{\Phi}_{Capital,t} = \alpha\hat{e}_{K,t}, \tag{B.8}$$

$$T\hat{F}P_{Util,t} = \hat{A}_t + \frac{TFP}{1-c_N}\frac{T}{q_T GDP}\hat{A}_{I,t}, \tag{B.9}$$

where I assume that $q_T = 1$ in B.9. This assumption states that the investment-specific technology shock only applies to matched goods, not to unmatched goods. It states that investment-specific technology only applies to actual investment goods. Otherwise, it is applied to all unmatched goods as a markup, also to goods that could become consumption goods.

The Utilization-Adjusted TFP and Capacity Utilization. Instead of solving for the private goods market and its determinants, we can use the definition of capacity utilization

$$cu_t = \frac{GDP_t}{(1 - c_{N,t})\, A_t \left(N_t \bar{H} \bar{e}_H\right)^{1-\alpha} K_{I,t}^{\alpha} + (A_{I,t} - 1)\, T_t}, \tag{B.10}$$

where $(A_{I,t} - 1)\, T_t$ corrects for the additional production capacity of fixed-capital investment on the household side of the economy. Substituting (B.10) in (B.3) and linearizing around its deterministic steady-state results in

$$T\hat{F}P_t = \hat{cu}_t - \frac{c_N}{1 - c_N} \hat{c}_{N,t} - (1 - \alpha)\, \hat{H}_t + T\hat{F}P_{Util,t}, \tag{B.11}$$

where the TFP wedge is defined by capacity utilization, labor matching costs, and hours per worker. We have direct data on those variables except labor matching costs, which is set by a steady-state target. Therefore, we can directly estimate the TFP wedge.

Appendix C. Connecting the Model with the Data

Appendix C.1. Calibration of the Model Parameters

Table C.4: Steady-State Targets and Parameterization

Variable	Value (Target)	Description	Source
Labor markets			
$repl$	$(N = 0.94)$	Steady-state replacement rate	FRED St Louis
μ_H	$(H = 1)$	Hours per worker disutility	Normalization
μ_e	$(e_H = 1)$	Worker effort disutility	Normalization
γ_N	0.6	Labor matching elasticity	Petrongolo and Pissarides (2001)
δ_N	0.12	Labor separation rate	Blanchard and Gali (2010)
ψ_N	$(q_N = 0.7)$	Labor matching efficiency	Blanchard and Gali (2010)
κ_N	$(c_N cu = 0.015)$	Labor matching costs	Merz and Yashiv (2007)
ν_H	1	Frisch labor supply elasticity	Keane and Rogerson (2012)
ω	0.01	Wealth effect parameter	Cacciatore et al. (2020)
Goods markets			
ψ_T	$(cu = 0.86)$	Steady-state capacity utilization rate	FRED St Louis
μ_D	$(f_T = q_T)$	Household search effort disutility	
ϵ	11	Steady-state price markup	
G	$(g_S = 0.2)$	Steady-state government spending	FRED St Louis
Capital markets			
β	$(r = 0.01)$	Period discount rate	FRED St Louis
α	0.3	Capital elasticity w.r.t. production capacity	Own calculations
ϕ_K	$(e_K = 1)$	Capital utilization costs	
δ_K	0.025	Capital depreciation rate	Christiano et al. (2005)

The Production Capacity Elasticity. In order to reduce the bias in the estimation of TFP and technology, the capital elasticity with respect to production capacity α has to be set correctly[23]. If α is not set correctly, it biases the impact of labor and capital have on production and TFP. Comin et al. (2023) show that neglecting e.g. price markups in U.S. data can lead to a biased α, where the impact of capital on production and TFP is overestimated. I follow the approach of Solow (1957); Fernald (2014); Comin et al. (2023)

[23]For a constant-returns-to-scale production function, the labor elasticity with respect to production capacity is given by $(1 - \alpha)$. Burnside et al. (1995); Basu and Kimball (1997) show that any evidence on increasing-returns-to-scale vanishes as we include utilization margins in the model.

and solve for the steady-state of the employment demand equation[24] (23) and its free-entry condition (24) given by

$$\alpha = 1 - \frac{wNHe_H}{GDP} \frac{1}{mc} \Theta_G - \Theta_L, \tag{C.1}$$

$$= 1 - LaborShare \cdot Markup \cdot \Theta_G - \Theta_L \tag{C.2}$$

where

$$\Theta_G = \frac{1}{1 + \delta_T \frac{1-q_T}{q_T} \frac{T}{GDP} + \frac{I_S}{GDP}},$$

$$\Theta_L = \frac{2c_N}{1-c_N} \left(\frac{1-\beta(1-\delta_N)}{\delta_N} - 1 \right),$$

are a goods and labor market search-and-matching wedge on the production capacity elastcities, respectively. The labor market wedge Θ_L increases in labor market frictions. The goods market wedge Θ_G decreases in goods market frictions. One has to take both frictions into account when setting α in order to have an unbiased labor and capital impact on TFP.

The Substitution Elasticity of Differentiated Goods. If we choose to target steady-state price markups, we in turn set ϵ endogenously. In the full model, it is determined by

$$\epsilon = \frac{1}{1-\frac{G}{GDP}} \left[1 + \frac{(1-\beta(1-\delta_T)) \left(1 + \delta_T \frac{\gamma_T}{1-\gamma_T} \left(1 - \frac{G}{GDP}\right) \left(1 - \frac{\beta q_T (1-\delta_I)}{1-\beta(1-\delta_I)(1-q_T)}\right)\right) + \frac{\beta q_T (1-\delta_T)}{1-\beta(1-\delta_I)(1-q_T)}}{Markup - 1 + \beta(1-\delta_T) - \frac{\beta q_T(1-\delta_T)}{1-\beta(1-\delta_I)(1-q_T)}} \right],$$

where goods market characteristics as e.g. steady-state capacity utilization, long-term contracts, and inventory depreciation are its determinants. Setting $\delta_T = \delta_I = 1$, the equation simplifies to

$$\epsilon = \frac{1}{1-g_S} \left[1 + \frac{1 + \frac{\gamma_T}{1-\gamma_T}(1-g_S)}{Markup - 1} \right],$$

[24] In contrast to the literature, α represents the elasticity of the production capacity function, not the production function. But, production is always a share of production capacity. Hence, there is a linear relationship between production and production capacity, independent of capital and labor shares. It follows, that the production capacity elasticities are applicable to the production elasticities.

where goods market search-and-matching is still a determinant of ϵ. Further, setting $\gamma_T = 0, \psi_T = 1$, the equation simplifies to

$$\epsilon = \frac{1}{1 - g_S} \frac{Markup}{Markup - 1},$$

where the substitutability of differentiated goods is mainly determined by the steady-state target of price markups. Therefore, we can see that targeting the same price markup can lead to significantly different values for ϵ in models with and without goods market search-and-matching. At the same time, ϵ determines the goods market structure by setting the competitiveness of the market, besides setting the steady-state price markup. One has to take the trade-off between steady-state price markup and goods market competitiveness targeting into account when calibrating ϵ.

Table C.5: Calculated Values for α and ϵ

	α	ϵ
Reference Model	0.21	5.4
Goods Market SAM Model	0.32	19.6
Full Model	0.40	18.1

NOTE: Targeting a steady-state price markup $\frac{1}{mc} =$ 1.3 and calculating α and ϵ using the steady-state model as described above.

Table C.5 shows some results for targeting steady-state price markups and the implications for α and ϵ. First, the low value of α implied by high price markups (see also e.g. Comin et al. (2023)) vanishes as we introduce goods market search-and-matching. Second, the monopolistic competition channel becomes less important in targeting the price markup and ϵ increases, as we introduce goods market search-and-matching. As we introduce long-term customer relationships and firm inventories, ϵ decreases again. Therefore, the model in this paper shows that both parameters are highly dependent on the model setup. As different values for α and ϵ imply different deep model characteristics, I set α and ϵ directly instead of targeting steady-state price markups.

Appendix C.2. Data Sources and Data Construction

Real GDP. Nominal GDP is constructed as the sum of private consumption (BEA Account Code: DPCERC), private investment (BEA Account Code: A006RC), and government expenditures (BEA Account Code: W068RC). The current account is excluded as the model replicates a closed economy. Real GDP growth is

$$100\left[ln\left(\frac{GDP_t}{Defl_t \cdot Pop_t}\right) - ln\left(\frac{GDP_{t-1}}{Defl_{t-1} \cdot Pop_{t-1}}\right)\right],$$

where $Defl_t$ is the GDP deflator and Pop_t is non-institutional population over 16 years (U.S. Bureau of Labor Statistics, Population Level [CNP16OV]).

Real Consumption. Nominal consumption is calculated as nominal private consumption (BEA Account Code: DPCERC). Contrary to the literature, I do not subtract nominal durable private consumption (BEA Account Code: DDURRC), as I estimate a model with explicit durable consumption goods. Real Consumption growth is

$$100\left[ln\left(\frac{Cons_t}{Defl_t \cdot Pop_t}\right) - ln\left(\frac{Cons_{t-1}}{Defl_{t-1} \cdot Pop_{t-1}}\right)\right],$$

where $Defl_t$ is the GDP deflator and Pop_t is non-institutional population over 16 years (U.S. Bureau of Labor Statistics, Population Level [CNP16OV]).

Real Investment. Nominal investment is calculated as nominal private investment (BEA Account Code: A006RC). Contrary to the literature, I do not add nominal durable private consumption (BEA Account Code: DDURRC), as I estimate a model with explicit durable consumption goods. Real investment is

$$100\left[ln\left(\frac{I_t}{Defl_t \cdot Pop_t}\right) - ln\left(\frac{I_{t-1}}{Defl_{t-1} \cdot Pop_{t-1}}\right)\right],$$

where $Defl_t$ is the GDP deflator and Pop_t is non-institutional population over 16 years (U.S. Bureau of Labor Statistics, Population Level [CNP16OV]).

Total Hours Worked. Total Hours Worked is the total of hours worked of all persons employed in the non-farm business sector. Data is retrieved from U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Hours of All Persons [HOANBS]. Total hours worked is

$$100 \cdot ln\left(\frac{TH_t}{Pop_t}\right),$$

where Pop_t is non-institutional population over 16 years (U.S. Bureau of Labor Statistics, Population Level [CNP16OV]).

Unemployment Rate. The unemployment rate is the U-3 measure of labor underutilization. Data is retrived from U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE]. The unemployment rate is

$$100 \cdot UE_t.$$

Capacity Utilization Rate Definition. The survey questionnaires of capacity utilization follows a clear-cut definition. The aim of this definition is that each survey respondent has the same interpretation of capacity utilization, such that the data is comparable. To connect the data and the model, I use the definition of production capacity given by the Federal Reserve to derive a model-based definition of capacity utilization. It defines capacity utilization as the output index divided by the capacity index[25]. The Federal Reserve Board defines production capacity as follows:

> *"The Federal Reserve Board's capacity indexes attempt to capture the concept of sustainable maximum output—the greatest level of output a plant can maintain within the framework of a realistic work schedule, after factoring in normal downtime and assuming sufficient availability of inputs to operate the capital in place."*

[25] Both time series are regularly calculated by the Federal Reserve Board and published as the "Industrial Production and Capacity Utilization - G.17", which can be found online: https://www.federalreserve.gov/releases/g17/.

Capacity Utilization Rate Construction. There is no economy-wide capacity utilization rate for the US. Survey data is available on US industry capacity utilization. In order to get an economy-wide capacity utilization rate, we have to construct it. I follow in principle Wohlrabe and Wollmershäuser (2017), who show the high correlation between industry and service capacity utilization measures and use business sentiment indicators to estimate capacity utilization data where necessary. I use the high correlation of industry and service capacity utilization and the average difference in variation to construct an economy-wide capacity utilization measure. Neglecting the agriculture, forestry, fishing, and hunting sector[26], economy-wide capacity utilization is given by

$$cu_t = \frac{GDP_t}{Y_t} = \frac{GDP_{ind,t} + GDP_{ser,t}}{Y_{ind,t} + Y_{ser,t}},$$

where variables with subscript "ind" represent industry sector variables and with subscript "ser" represent service sector variables. As we are interested in the cyclical deviations of capacity utilization, I take a first-order Taylor approximation around the deterministic steady-state of the economy-wide capacity utilization rate given by

$$\hat{cu}_t = \frac{GDP_{ind}}{Y} G\hat{D}P_{ind,t} + \frac{GDP_{ser}}{Y} G\hat{D}P_{ser,t} - \frac{GDP}{Y^2}\left(Y_{ind}\hat{Y}_{ind,t} + Y_{ser}\hat{Y}_{ser,t}\right),$$

where variables without a time subscript represent the deterministic steady-state. Sector-specific production capacity $\hat{Y}_{ind,t}$ and $\hat{Y}_{ser,t}$ can be approximated by sector capacity utilization rates and sector real GDP given by

$$\hat{cu}_{ind,t} = cu_{ind}\left(G\hat{D}P_{ind,t} - \hat{Y}_{ind,t}\right) \Leftrightarrow \hat{Y}_{ind,t} = G\hat{D}P_{ind,t} - \frac{\hat{cu}_{ind,t}}{cu_{ind}},$$
$$\hat{cu}_{ser,t} = cu_{ser}\left(G\hat{D}P_{ser,t} - \hat{Y}_{ser,t}\right) \Leftrightarrow \hat{Y}_{ser,t} = G\hat{D}P_{ser,t} - \frac{\hat{cu}_{ser,t}}{cu_{ser}},$$

where capacity utilization is given as percentage point deviation from its deterministic steady-state. Using those definitions to substitute for sector-specific production capacity, the

[26]There is no data on the capacity utilization of agriculture, forestry, fishing, and hunting sector. Also, not for other economies similar to the US. As this sector comprises about 1% of the U.S. economy we neglect it in the analysis of economy-wide capacity utilization.

economy-wide capacity utilization is given by

$$\hat{cu}_t = cu\frac{GDP_{ind}}{GDP}\left(1-\frac{cu}{cu_{ind}}\right)G\hat{D}P_{ind,t} + cu\frac{GDP_{ser}}{GDP}\left(1-\frac{cu}{cu_{ser}}\right)G\hat{D}P_{ser,t} + \frac{GDP_{ind}}{GDP}\left(\frac{cu}{cu_{ind}}\right)^2 \hat{cu}_{ind,t} + \frac{GDP_{ser}}{GDP}\left(\frac{cu}{cu_{ser}}\right)^2 \hat{cu}_{ser,t},$$

where we have reduced the number of unknowns to the deterministic steady-states of GDP_{ser}, cu, and cu_{ser} and to the cyclical fluctuations of $GDP_{ser,t}$, and $\hat{cu}_{ser,t}$. Service-sector and industry-sector GDP are calculated using the BEA Value Added GDP-by-industry tables. For service-sector capacity utilization we only have indirect approximations. For the European Union there is survey data for service-sector capacity utilization. I use the data to approximate service-sector capacity utilization using industry-sector capacity utilization as the correlations between both sector-specific real GDP and sector-specific capacity utilization is very high for the European Union. I approximate U.S. service-sector capacity utilization by U.S. industry-sector capacity utilization using the relative standard deviation of EU service-sector to industry-sector capacity utilization as the slope. Therefore, U.S. service-sector capacity utilization is approximated by

$$\hat{cu}_{serUS,t} = \frac{std(\hat{cu}_{serEU,t})}{std(\hat{cu}_{indEU,t})}\hat{cu}_{indUS,t} = \gamma_{CU,EU}\hat{cu}_{indUS,t},$$

where $\gamma_{CU,EU}$ is the slope parameter of the approximation equation. Plugging everything back into the economy-wide capacity utilization measure, we get

$$\hat{cu}_t = cu\left[\left(1-\frac{cu}{cu_{ser}}\right)G\hat{D}P_t + \frac{GDP_{ind}}{GDP}\left(\frac{cu}{cu_{ser}}-\frac{cu}{cu_{ind}}\right)G\hat{D}P_{ind,t}\right] + \left[\frac{GDP_{ind}}{GDP}\left(\frac{cu}{cu_{ind}}\right)^2 + \left(1-\frac{GDP_{ind}}{GDP}\right)\left(\frac{cu}{cu_{ser}}\right)^2\gamma_{CU,EU}\right]\hat{cu}_{ind,t}.$$

The economy-wide capacity utilization growth rate is given by

$$100\cdot\hat{cu}_t.$$

GDP Deflator. The GDP deflator is the log difference of nominal GDP (BEA Account Code: A191RC) and real GDP (BEA Account Code: A191RX). Price Inflation is

$$100\left[ln\left(\frac{GDP_{nom,t}}{GDP_{real,t}}\right) - ln\left(\frac{GDP_{nom,t-1}}{GDP_{real,t-1}}\right)\right].$$

Nominal Labor Compensation. Nominal labor compensation is given by the non-farm business sector labor compensation per hour. Data is retrived from U.S. Bureau of Labor Statistics, Nonfarm Business Sector: Compensation Per Hour [COMPNFB]. Nominal wage inflation is

$$100\left[ln\left(W_t\right) - ln\left(W_{t-1}\right)\right].$$

FED Funds Rate. The FED funds rate is given by the Federal Reserve Bank of New York, Effective Federal Funds Rate [EFFR]. For the period of binding zero lower bound, I use the shadow rate of Wu and Xia (2016) as the model does not incorporate a lower bound on its nominal interest rate. I follow Wu and Zhang (2019), who show that the shadow rate is a good representation of the interest rate in a New-Keynesian model. The constructed time series shows annual interest rates. I therefore calculate the quarterly interest rate by

$$int_{quarter,t} \quad = \quad \left(1 + int_{year,t}\right)^{\frac{1}{4}} - 1.$$

All time series are detrended using a one-sided HP filter following Stock and Watson (1999). This approach takes structural breaks into account, as are e.g. present in the capacity utilization rate, unemployment rate, and nominal interest rate.

Appendix D. Bayesian Estimation and Posterior Results

Appendix D.1. Estimation Procedure

I estimate the model using Bayesian inference methods for the model described in this paper with the data and calibration given in section Appendix C and the prior distribution given in table D.6. The posterior distribution is a combination of the prior density for the parameters and the likelihood function, evaluated using the Kalman filter. I compute the mode of the posterior distribution using Marco Ratto's NewRat. The scale parameter of the jumping distribution's covariance matrix is set using Dynare's automatic tuner such that the overall acceptance ratio is close to the desired level. I draw four chains with 200,000 draws each from the posterior distribution using the random walk Metropolis-Hastings algorithm. I drop half of the draws before calculating model statistics. Table D.6 shows the posterior estimates of the reference, SaM, and full model. All include nine shocks and nine observables. The observables are linked to the model following Pfeifer (2018) and given by

$$\begin{bmatrix} GDP_t \\ Cons_t \\ Inv_t \\ \pi_t \\ \pi_{W,t} \\ r_{B,t} \\ TH_t \\ UE_t \\ CU_t \end{bmatrix} = \begin{bmatrix} log\left(\frac{GDP_t}{GDP_{t-1}}\right) \\ log\left(\frac{C_t}{C_{t-1}}\right) \\ log\left(\frac{Inv_t}{Inv_{t-1}}\right) \\ \pi_t - \bar{\pi} \\ (\pi_{W,t} - \bar{\pi}_W)\,\frac{e_{H,t}}{e_{H,t-1}} \\ r_{B,t} - \left(\frac{1}{\beta} - 1\right) \\ log\left(\frac{N_t H_t}{\bar{N}\bar{H}}\right) \\ ue_t - (1 - \bar{N}) \\ cu_t - \bar{cu} \end{bmatrix} \approx \begin{bmatrix} \hat{gdp}_t - \hat{gdp}_{t-1} \\ \hat{c}_t - \hat{c}_{t-1} \\ \hat{inv}_t - \hat{inv}_{t-1} \\ \hat{\pi}_t \\ \hat{\pi}_{W,t} + \hat{e}_{H,t} - \hat{e}_{H,t-1} \\ \hat{r}_{B,t} \\ \hat{n}_t + \hat{h}_t \\ \hat{ue}_t \\ \hat{cu}_t \end{bmatrix}$$

I estimate different model versions of the capacity utilization channel. They can be summarized as follows:

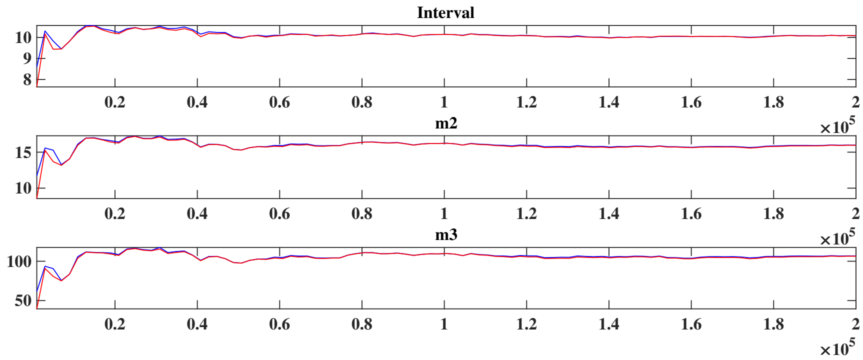
1. **Capital utilization (VCU):** This channel is fine-tuned by setting $0 \leq \delta_{K,2} \leq \delta_K$. There is no capital utilization in the model for $\delta_{K,2} = 0$.
2. **Worker effort (VWE):** This channel is fine-tuned by setting the worker effort supply elasticity ν_E. There is no variable worker effort if $\nu_e = \infty$.
3. **Goods market search-and-matching (SaM):** This channel is fine-tuned by setting $0 \leq \gamma_T < 1$. If $\gamma_T = 0$, aggregate demand plays no role in goods market matching, which becomes a linear function of available supply. This channel opens up the possibility to analyze the impact of long-term customer relationships $0 < \delta_T \leq 1$, and inventories $0 < \delta_I \leq 1$.

Table D.6: Prior-Posteriors for the Reference and Full Model

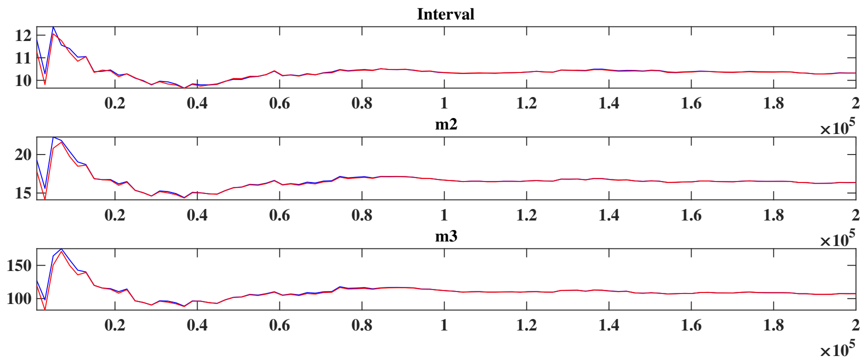
Prior				Posterior								
				Reference Model			SaM Model			Full Model		
Parameter	Distribution	Mean	StdDev	Mean	90% HPD		Mean	90% HPD		Mean	90% HPD	
θ	Beta	0.5	0.15	0.63	0.56	0.70	0.61	0.54	0.68	0.65	0.59	0.71
δ_H	Beta	0.74	0.05	0.77	0.70	0.84	0.75	0.68	0.83	0.77	0.70	0.84
κ_P	Gamma	60	20	198	147	248	104	78	131	139	105	171
ι_P	Beta	0.5	0.15	0.20	0.07	0.32	0.14	0.05	0.22	0.14	0.05	0.23
κ_W	Gamma	10	3	17.9	12.5	23.2	14.5	7.9	20.8	17.7	12.1	23.2
ι_W	Beta	0.5	0.15	0.49	0.25	0.73	0.52	0.28	0.76	0.51	0.26	0.75
κ_H	Gamma	4	1.5	1.47	0.96	1.97	3.99	3.13	4.87	2.07	1.44	2.65
κ_I	Gamma	4	1.5	0.52	0.37	0.66	0.48	0.32	0.63	0.64	0.46	0.81
i_π	Gamma	1.7	0.1	1.74	1.58	1.91	1.72	1.56	1.87	1.70	1.55	1.86
i_{gap}	Gamma	0.2	0.1	0.19	0.17	0.20	0.19	0.17	0.21	0.19	0.17	0.20
i_r	Beta	0.5	0.15	0.80	0.76	0.83	0.75	0.71	0.80	0.78	0.74	0.82
ν_E	Gamma	2	1	3.74	2.47	4.99	–	–	–	5.93	3.95	7.85
$\delta_{K2,S}$	Beta	0.6	0.15	0.27	0.15	0.40	–	–	–	0.16	0.06	0.25
γ_T	Beta	0.17	0.05	–	–	–	0.14	0.09	0.19	0.10	0.06	0.14
δ_I	Beta	0.74	0.05	–	–	–	0.79	0.74	0.83	0.84	0.80	0.88
δ_T	Beta	0.5	0.15	–	–	–	0.74	0.62	0.87	0.81	0.71	0.92
σ_A	InvGamma	0.01	2	0.0037	0.0042	0.0052	0.0047	0.0042	0.0052	0.0050	0.0044	0.0055
σ_I	InvGamma	0.01	2	0.0148	0.0118	0.0178	0.0141	0.0107	0.0174	0.0166	0.0132	0.0199
σ_H	InvGamma	0.01	2	0.0234	0.0188	0.0278	0.0265	0.0216	0.0315	0.0268	0.0219	0.0315
σ_N	InvGamma	0.01	2	0.0127	0.0114	0.0140	0.0122	0.019	0.0135	0.0121	0.0108	0.0133
σ_P	InvGamma	0.01	2	0.1412	0.1011	0.1816	0.0858	0.0721	0.0991	0.0896	0.0743	0.1041
σ_W	InvGamma	0.01	2	0.1357	0.1011	0.1686	0.1381	0.0966	0.1787	0.1409	0.1036	0.1768
σ_T	InvGamma	0.01	2	0.0064	0.0057	0.0072	0.0119	0.0096	0.0142	0.0112	0.0090	0.0132
σ_G	InvGamma	0.01	2	0.0071	0.0063	0.0078	0.0066	0.0058	0.0072	0.0066	0.0059	0.0073
σ_M	InvGamma	0.001	2	0.0009	0.0008	0.0010	0.0010	0.0009	0.0012	0.0010	0.0008	0.0011
ρ_A	Beta	0.5	0.15	0.85	0.80	0.89	0.85	0.80	0.89	0.84	0.79	0.88
ρ_I	Beta	0.5	0.15	0.67	0.61	0.74	0.68	0.61	0.75	0.72	0.66	0.79
ρ_H	Beta	0.5	0.15	0.48	0.38	0.58	0.48	0.37	0.59	0.43	0.33	0.53
ρ_N	Beta	0.5	0.15	0.82	0.75	0.89	0.74	0.65	0.83	0.82	0.74	0.89
ρ_P	Beta	0.5	0.15	0.68	0.57	0.80	0.77	0.70	0.83	0.77	0.71	0.83
ρ_W	Beta	0.5	0.15	0.19	0.08	0.29	0.44	0.28	0.61	0.24	0.11	0.36
ρ_T	Beta	0.5	0.15	0.79	0.74	0.84	0.81	0.76	0.87	0.79	0.74	0.84
ρ_G	Beta	0.5	0.15	0.89	0.85	0.93	0.88	0.84	0.93	0.89	0.85	0.93
ρ_M	beta	0.5	0.15	0.42	0.32	0.51	0.51	0.41	0.61	0.55	0.45	0.65

Figure D.9: Multivariate Convergence Diagnostics of the Bayesian Estimation

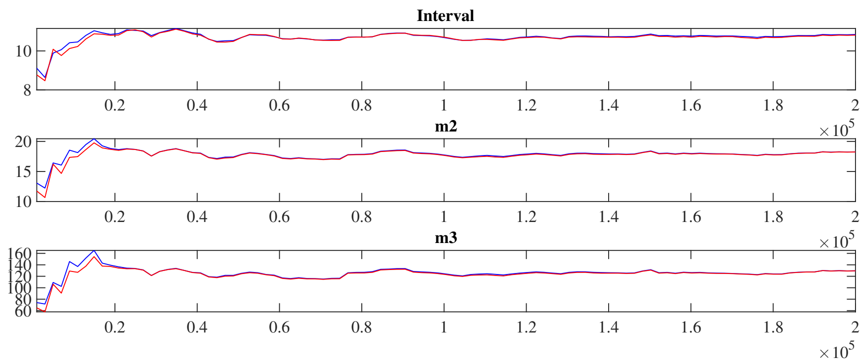
Reference Model



SaM Model



Full Model



NOTE: Multivariate convergence diagnostics following Brooks and Gelman (1998) for the reference, SaM, and full models calculated using Dynare.

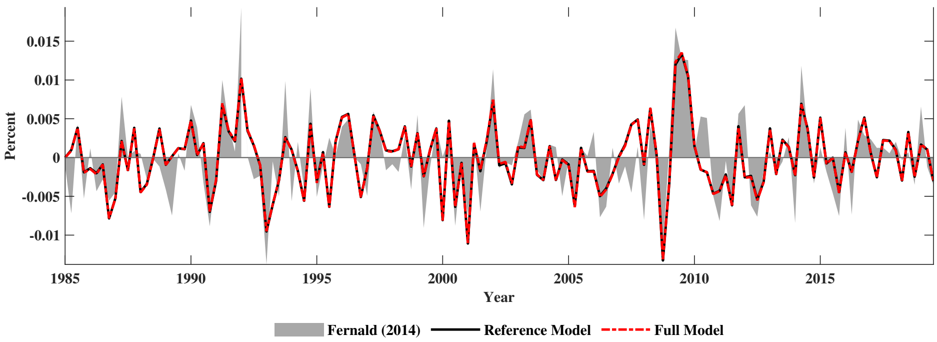
Appendix D.4. The TFP and TFP Wedge: Second Moments and Decomposition

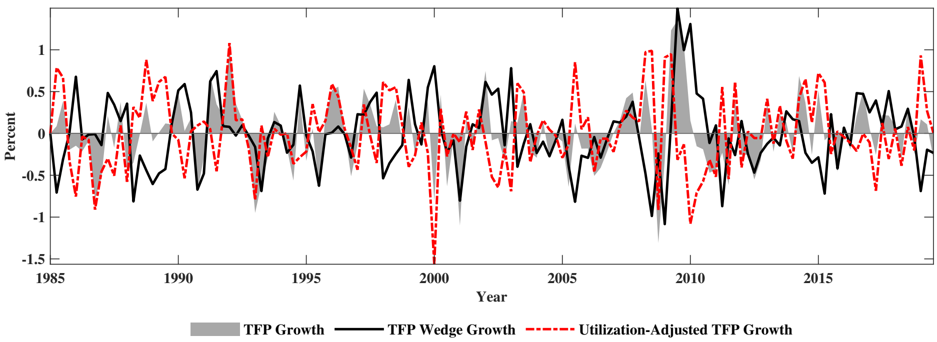
Table D.7: Second Moments of the TFP Process

	RelStd	Correlation			
		$dGDP_t$	$dTFP_t$	$d\Phi_t$	$dTFP_{Util,t}$
$dGDP_t$	1.00(1.00)	1.00(1.00)	0.71(0.60)	0.31(0.62)	0.23(0.05)
$dTFP_t$	0.77(0.98)	–	1.00(1.00)	0.34(0.32)	0.45(0.66)
$d\Phi_t$	0.89(0.85)	–	–	1.00(1.00)	−0.68(−0.50)
$dTFP_{Util,t}$	0.93(1.08)	–	–	–	1.00(1.00)

NOTE: The table shows second moments the model and for the data calculated by Fernald (2014) (parentheses). The relative standard deviations are with respect to standard deviations of real GDP.

Figure D.10: TFP (Wedge) in the Data and the Model





NOTE: The first figure shows TFP growth data from 1985q1-2019q4 for the Fernald (2014)-data, the reference model, and the full model. The second figure shows the TFP growth decomposition for the full model (identical to the reference model).

Appendix D.5. Model Fit of the Data

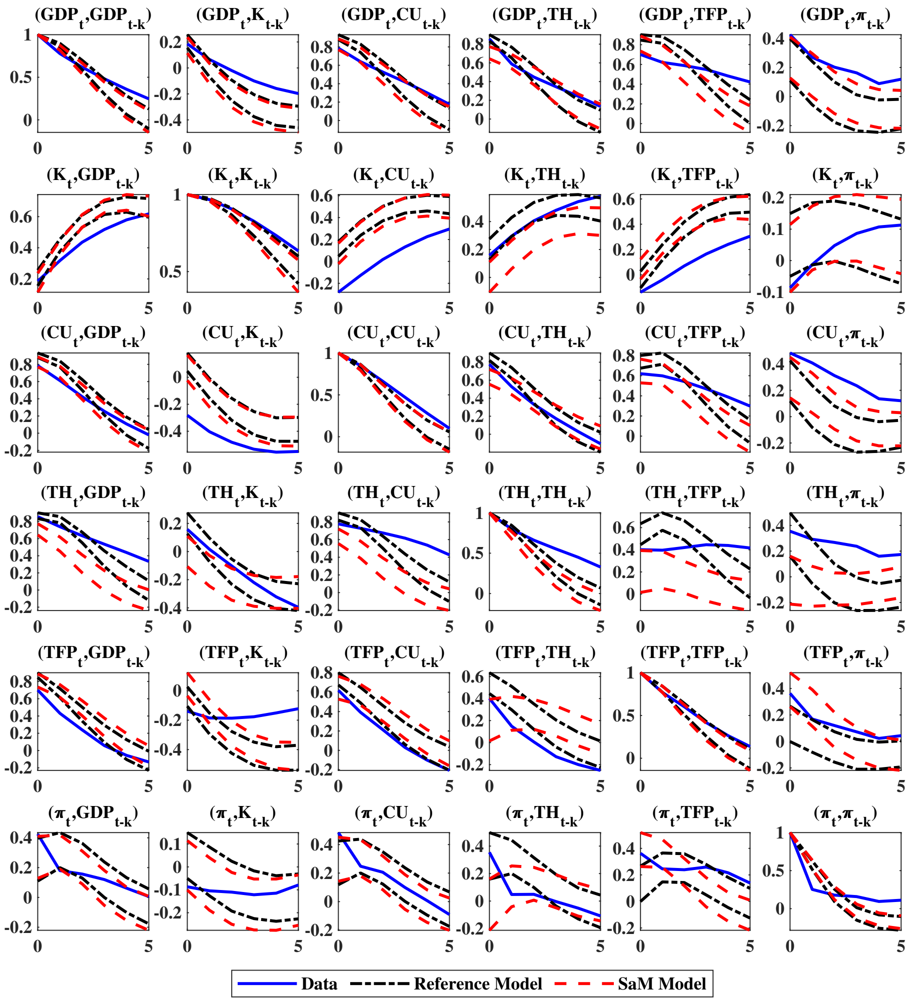
Table D.8: Model fit comparison sensitivity analysis

	Log data density	2ln Bayes factor	Log data density	2ln Bayes factor
	Demeaned data		$\epsilon = 6$ & $\alpha = 0.2$	
Reference Model	4385	0	4795	0
Simple SaM Model	4436	102	4782	−26
SaM Model	4436	102	4779	−32
Simple Full Model	4431	92	4799	8
Full Model	4430	90	4784	−22
	Targeting price adjustment costs			
Reference Model $\kappa_P = 47$	4782	−42		
Reference Model $\kappa_P = 96$	4803	0		
Full Model $\kappa_P = 47$	4809	12		
Full Model $\kappa_P = 96$	4828	50		
	No SAM shock & no CU data		*Alt. Capacity Utilization Definition*	
Reference Model	4293	0	4802	0
Simple SaM Model	4321	56	4810	16
SaM Model	4323	60	4814	24
Simple Full Model	4312	38	4820	36
Full Model	4187	−212	4820	36
	Data 1985q1 - 2008q4			
Reference Model	2919	0		
Simple SaM Model	2947	56		
SaM Model	2944	50		
Simple Full Model	2930	22		
Full Model	2922	6		

NOTE: Log data densities are calculated by the modified harmonic mean following Geweke (1999). For model comparison, I use Bayes factor according to Kass and Raftery (1995). The exercise targeting price adjustment costs follows Gantert (2021), where I calculate the parameter in a Rotemberg (1982b) setup for both the reference and SaM models targeting a Phillips curve slope of 0.1. The simple SaM and simple full models are without long-term customer relationships and firm inventories.

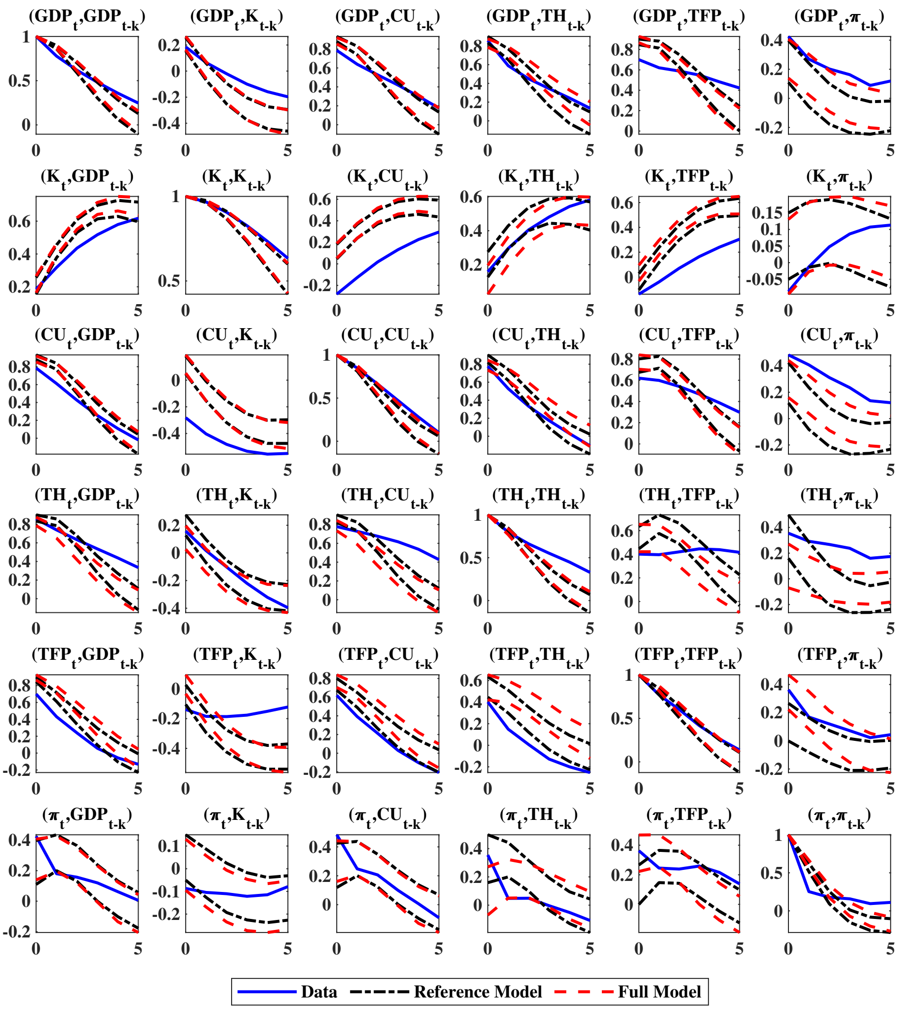
Appendix D.6. Correlograms

Figure D.11: Correlogram for the Reference and SaM Model



NOTE: The figure shows correlograms of GDP, the capital stock, capacity utilization, total hours worked, TFP, and inflation with five lags for the data, the reference model, and the SaM model. The correlograms for the models show the 90% HPD intervals of their posterior estimates. All data is detrended with a one-sided HP filter before calculating the correlations.

Figure D.12: Correlogram for the Reference and Full Model



NOTE: The figure shows correlograms of GDP, the capital stock, capacity utilization, total hours worked, TFP, and inflation with five lags for the data, the reference model, and the full model. The correlograms for the models show the 90% HPD intervals of their posterior estimates. All data is detrended with a one-sided HP filter before calculating the correlations.

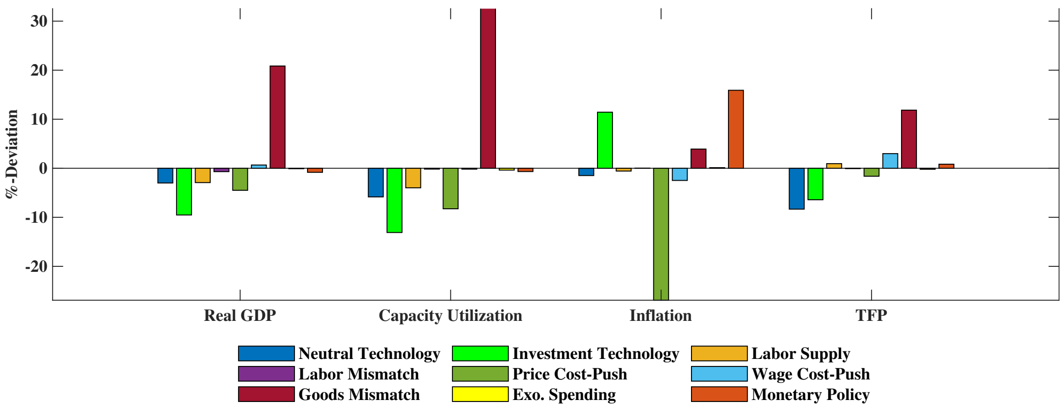
Appendix D.7. Historical Variance Decomposition U.S. Data 1985q1-2019q4

Table D.9: Variance Decomposition

Reference Model	*eA*	*eI*	*eH*	*eN*	*eP*	*eW*	*eT*	*eG*	*eM*
GDP	27.7	26.9	4.4	2.3	7.8	2.1	24.2	0.5	4.2
Capital	32.4	25.9	7.8	2.1	2.5	0.7	25.7	2.4	0.7
Total Hours	12.0	25.8	7.3	8.3	17.0	6.0	13.0	0.5	10.1
Capacity Utilization	8.4	25.2	4.8	0.4	12.1	3.4	37.7	0.7	7.3
Inflation	6.3	17.2	2.9	0.2	37.9	12.3	8.8	0.3	14.3
TFP	37.3	22.1	0.9	0.1	2.7	0.4	34.6	0.4	1.5
SaM Model	*eA*	*eI*	*eH*	*eN*	*eP*	*eW*	*eT*	*eG*	*eM*
GDP	24.7	17.4	1.5	1.6	3.3	2.8	45.1	0.4	3.4
Capital	24.7	21.6	4.0	1.1	1.6	0.6	43.9	2.0	0.6
Total Hours	5.1	8.1	5.7	6.7	20.0	35.3	14.2	0.2	4.9
Capacity Utilization	2.6	12.1	0.9	0.2	3.9	3.2	70.2	0.3	6.7
Inflation	4.8	28.6	2.3	0.2	11.0	9.8	12.7	0.4	30.2
TFP	29.0	15.7	1.8	0.1	1.1	3.4	46.5	0.2	2.3
Full Model	*eA*	*eI*	*eH*	*eN*	*eP*	*eW*	*eT*	*eG*	*eM*
GDP	21.9	27.1	2.3	1.7	4.9	1.8	35.4	0.4	4.6
Capital	23.0	32.1	4.7	1.4	1.9	0.4	34.0	1.6	0.9
Total Hours	7.8	17.7	5.7	7.9	21.5	14.6	16.9	0.2	7.6
Capacity Utilization	4.8	21.3	2.1	0.3	6.7	2.5	53.6	0.4	8.3
Inflation	5.4	22.5	2.3	0.2	23.1	9.3	13.1	0.3	23.9
TFP	27.2	25.8	1.1	0.1	1.0	0.6	40.8	0.3	3.3

NOTE: The variance shares are given in percent. Rounding errors can lead to cumulative variance not equal to 100%.

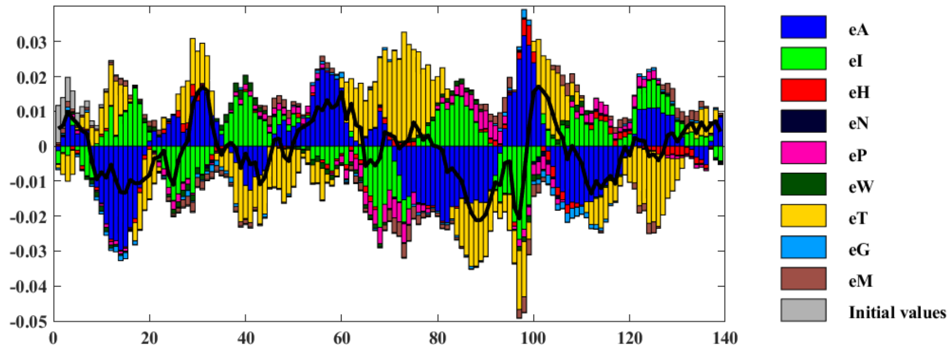
Figure D.13: Shock Decomposition Difference between the Reference and SaM Model



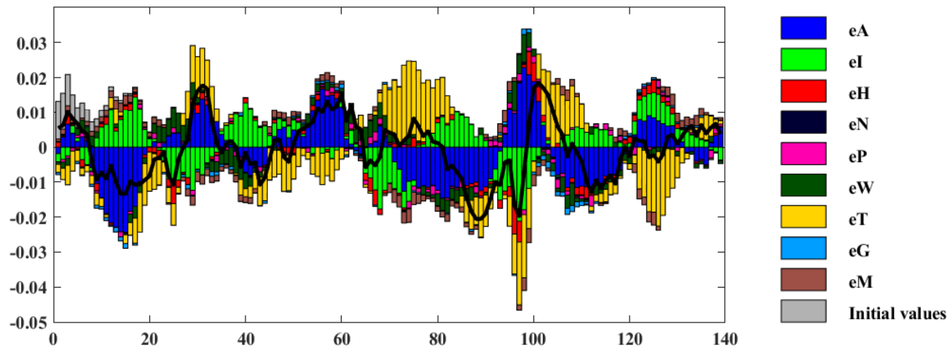
NOTE: The figure shows the percentage point change of the variance decomposition for the model shocks and across models. An increase indicates a higher variance share for the respective shock in the SaM model compared to the reference model. Hence, a positive value indicates a larger share of variance of a variable being explained by the shock in the SaM model compared to the reference model.

Figure D.14: Historical Variance Decomposition U.S. Data 1985q1-2019q4 (Time Series)

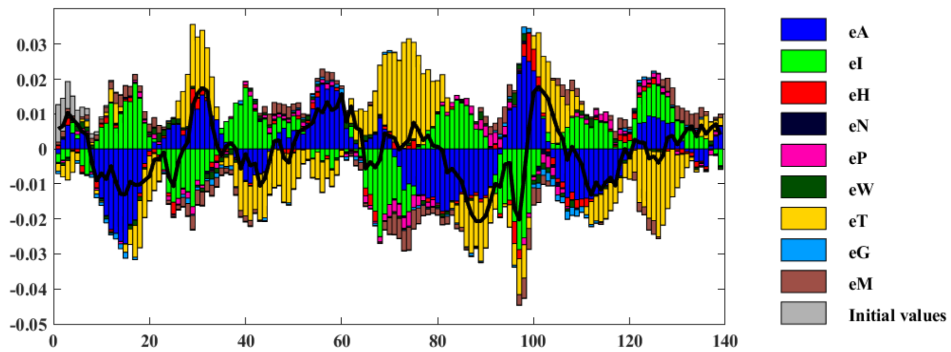
Reference Model



SaM Model



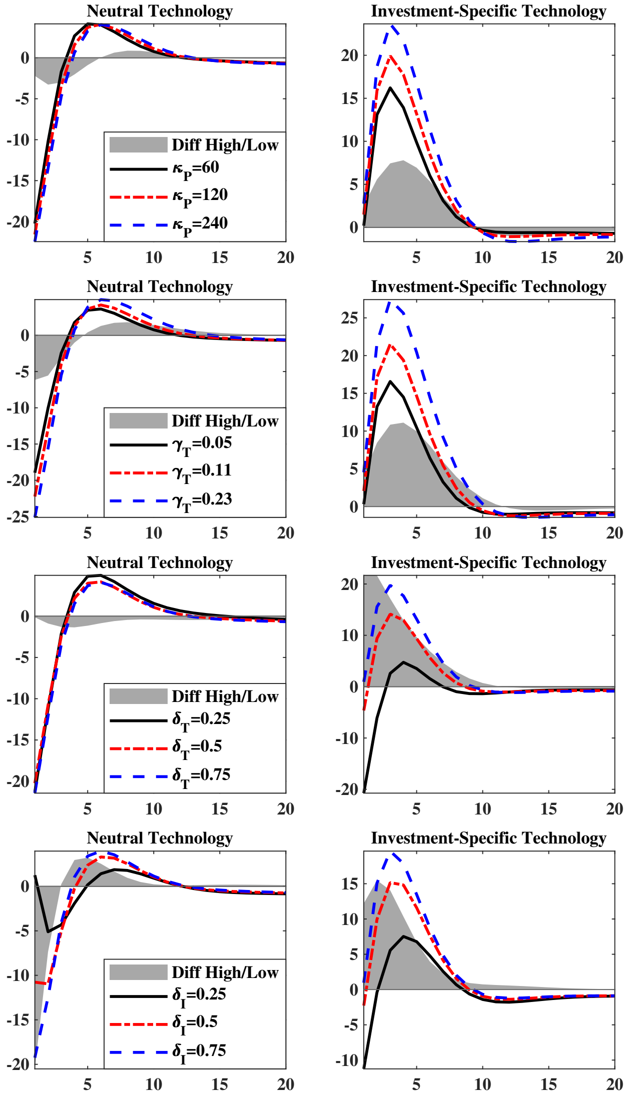
Full Model



NOTE: The upper figure shows the historical variance decomposition for the reference model. The lower figure shows the historical variance decomposition for the full model.

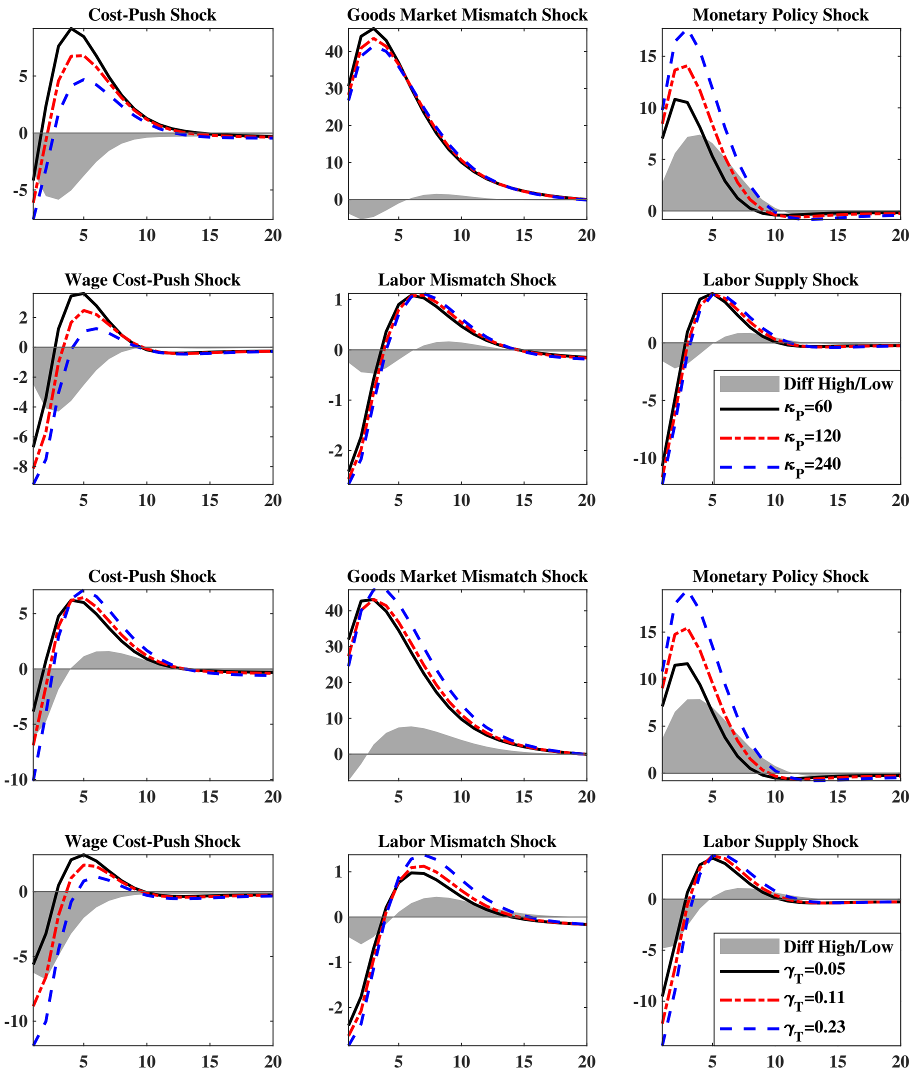
Appendix E. TFP Bias and Multiplicators Sensitivity Analysis

Figure E.15: Robustness: TFP Wedge Fluctuations for Technology Shocks



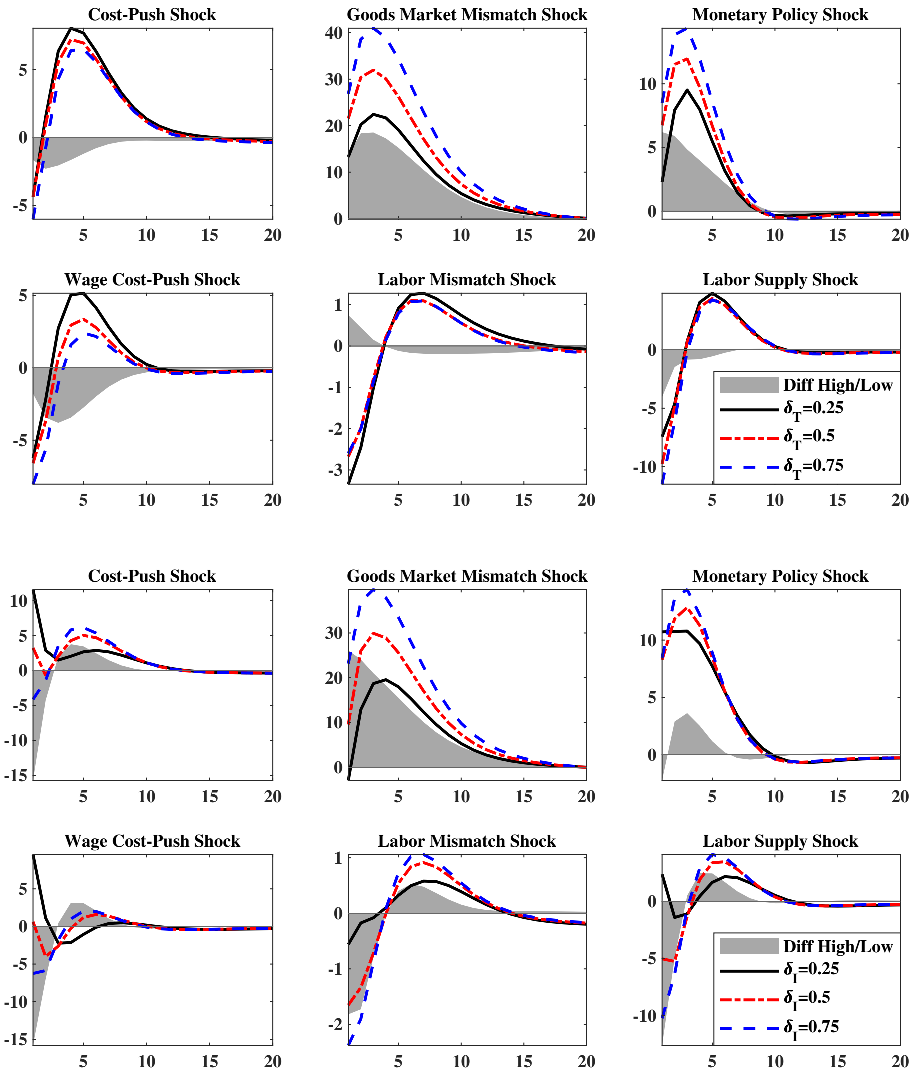
NOTE: The figure shows impulse response functions of the TFP wedge to technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. It shows a robustness analysis for the parameters of price stickiness, κ_P, demand elasticity of goods market matching, γ_T, long-term customer separation rate δ_T, and inventory depreciation rate, δ_I. The curves show low (black curves), medium (red dashed curves), and high (blue dashed curves) values for the respective parameters.

Figure E.16: Robustness: TFP Wedge Fluctuations for Non-Technology Shocks (1/2)



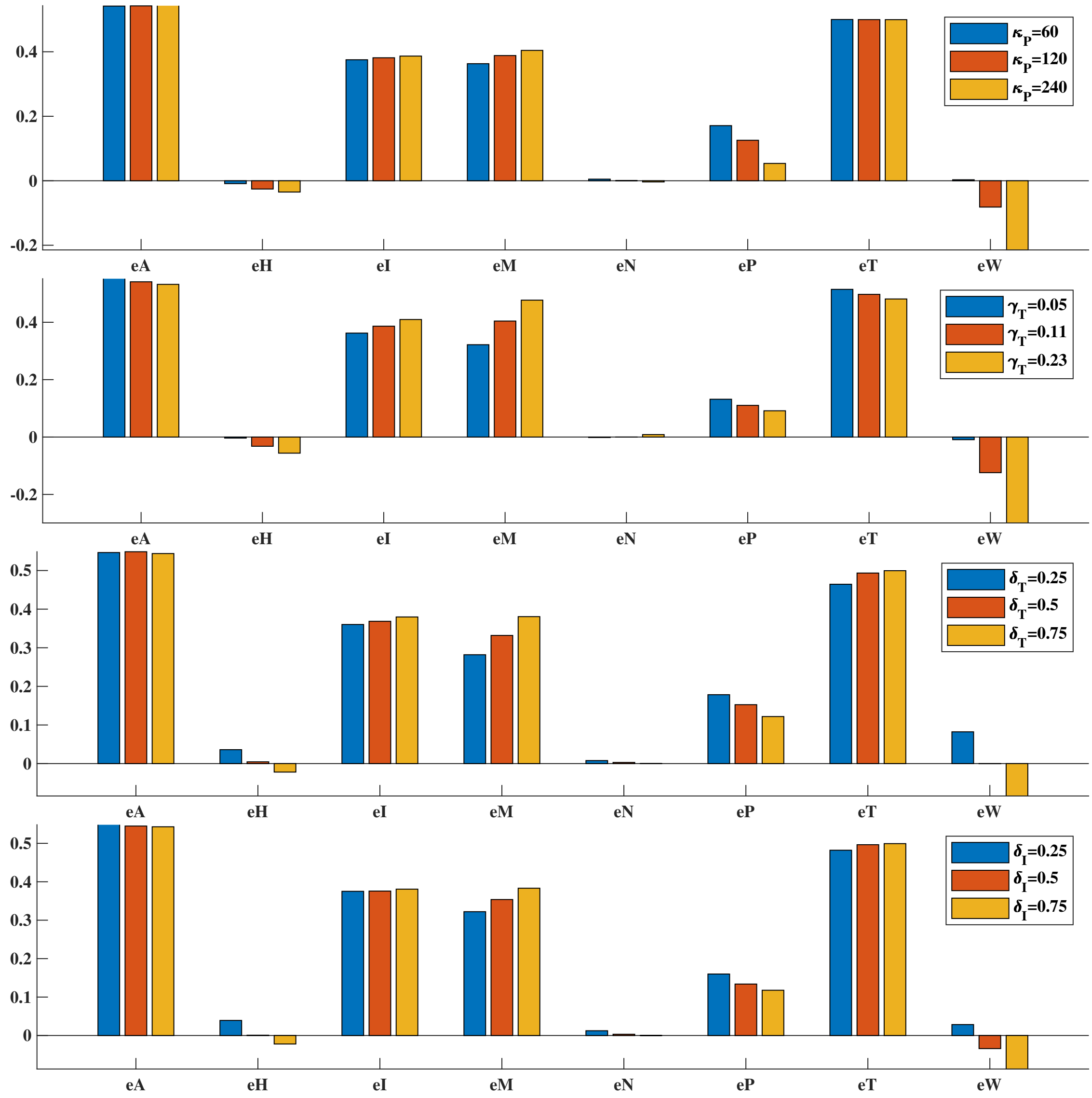
NOTE: The figure shows impulse response functions of the TFP wedge to non-technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. It shows a robustness analysis for the parameters of price stickiness, κ_P, and demand elasticity of goods market matching, γ_T. The curves show low (black curves), medium (red dashed curves), and high (blue dashed curves) values for the respective parameters.

Figure E.17: Robustness: TFP Wedge Fluctuations for Non-Technology Shocks (2/2)



NOTE: The figure shows impulse response functions of the TFP wedge to non-technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. It shows a robustness analysis for the parameters of long-term customer separation rate δ_T, and inventory depreciation rate, δ_I. The curves show low (black curves), medium (red dashed curves), and high (blue dashed curves) values for the respective parameters.

Figure E.18: Robustness: Cumulative TFP Multiplicators



NOTE: The figure shows cumulative TFP multiplicators to all shocks for the full model. It shows a robustness analysis for the parameters of price stickiness, κ_P, demand elasticity of goods market matching, γ_T, long-term customer separation rate δ_T, and inventory depreciation rate, δ_I. The bars show low (blue bars), medium (red bars), and high (yellow bars) values for the respective parameters.