Revisiting TFP Dynamics: The Role of Goods Market Search and Capacity Utilization

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Abstract

Frictional goods markets play a crucial role in determining capacity utilization and total factor productivity (TFP). The trade-off between goods prices and household search effort is key to goods market matching, influencing TFP throughout the business cycle. This paper develops a New-Keynesian DSGE model with a capital workweek, worker effort, and fixed cost of production, expanding it to include goods market search-and-matching (SaM). Using Bayesian estimation and capacity utilization survey data, I compare different capacity utilization channels. The results show that incorporating goods market SaM improves the data fit, complementing the worker effort channel, while the capital workweek and fixed cost of production channels are less significant than suggested in previous literature. The share of TFP fluctuations explained by demand and labor shocks increases while it decreases for technology shocks - a pattern that intensifies in the convexity of the endogenous price elasticity of demand as goods market frictions rise. These findings highlight the importance of frictional goods markets in explaining the divergence between technology and TFP over the business cycle.

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

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1. Introduction

Total factor productivity (TFP) is at the core of applied macroeconomics as it measures the efficiency of input factor allocation in the production process. Solow (1957) defines TFP growth as output growth that cannot be attributed to input factor growth. While technological progress is the major driver of TFP growth in the long-run (Basu et al. (2006)), it is driven by dispersion, composition, and variable utilization channels in the short-run. Fluctuations in TFP growth are substantial for output, labor, and investment in the US (Brinca et al. (2016)). The data shows that variable capacity utilization explains large parts of those fluctuations (Fernald (2014); Comin et al. (2025)). Explanations of drivers of capacity utilization focus heavily on mismeasurement in the firm production process. The literature discusses mismeasurement of input factors - e.g. variations in the workweek of capital, of unobserved worker effort, and short-run increasing returns-to-scale due to fixed cost of production - as the determinants of variable capacity utilization (Christiano et al. (2005); Lewis et al. (2019)).

Since the seminal paper of Diamond (1982), there is a strong case that goods market are frictional, potentially adding to fluctuations in short-run TFP. However, most business cycle models abstract from frictional goods market matching, assuming that offered capacity is fully matched at each point in time and household search input has no active role in determining the outcome of trades. In the data, costs associated with search-and-matching on the goods market are a prominent feature. Consumers spend significant effort and cost finding suitable goods (see e.g. XXX). Firms spend significant money and employ many people in advertising their products to consumers (Hall (2012)). Using the American Time-Use Survey, Bai et al. (2025) shows that correlations between GDP, TFP, capacity utilization, and shopping time are positive and significant. During the Great Recession, on average a 1% decline in US GDP per capita conicided with a 1.1% decline in shopping time (Petrosky-Nadeau et al. (2016)). The procyclical behavior of shopping time in the data indicates that search is an aggregate matching input rather than a search for lower prices (as assumed in the New Monetarist literature).

In this paper, I complement the firm perspective of capacity utilization and focus on frictions in the goods market that put a wedge between available production capacity and realized sales. The 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 short-run TFP. Specifically, I ask the following two research questions:

(i) Is unobserved search effort in a NK-DSGE model a significant driver of short-run capacity utilization and TFP fluctuations over the business cycle?

(ii) How does unobserved search effort in a NK-DSGE model change the transmission and variance decompositon of economic shocks for US data?

The paper is based on three strands of literature. The first strand of literature analyzes the concept of total factor productivity and its determinants. Lagos (2006) shows how aggregate TFP is determined by the distribution of idiosyncratic productivities but also by policy determining firm entry and exit. The idea of utilization-adjusted TFP has been put forward by several authors in the literature. A variable workweek of capital has been implemented in many RBC (Burnside et al. (1995)) and NK models (Christiano et al. (2005); Smets and Wouters (2007)). Unobserved variable worker effort has been introduced alongside in RBC (Bils and Cho (1994); Basu and Kimball (1997)) and NK models (Lewis et al. (2019)). Both channels lead to an increase in TFP as existing input factors are more utilized over the business cycle. Fixed cost of production (Christiano et al. (2005); Smets and Wouters (2007)) drive productivity over the business cycle as the share of fixed cost in GDP decreases as the economy expands. Lastly, labor search-and-matching models drive TFP fluctuations if vacancy cost decrease productive capacity as workers are employed to search new works (Blanchard and Gali (2010)). The model in this paper extends the capacity utilization drivers by goods market search-and-matching. This literature is the benchmark for the definition of TFP and its relationship to capacity utilization.

On this theoretical basis, Basu and Fernald (2002); Basu et al. (2006); Fernald (2014); Comin et al. (2025) among others estimate utilization-adjusted TFP for different countries with different estimation methods. Utilization-adjusted TFP is a measure of TFP where the impact of capacity utilization has been subtracted (Fernald (2014)). This strand of papers finds that the differences between TFP and utilization-adjusted TFP varies significantly over the business cycle and that capacity utilization covaries negatively with technology. While there is data for the workweek of capital, unobserved worker effort is often estimated through a set of neoclassical price equations based on the theoretical models above. However, fixed cost of production is normally neglected or assumed to be part of quasi-fixed capital and employment. This strand of literature identifies the two main aggregate objects used in this paper while focusing on the aggregate impact of capacity utilization instead of its different channels.

Third, this paper builds on the search-and-matching literature on the goods market. The literature that started with (Diamond (1982); Diamond and Fudenberg (1989)) focuses on price search along the intensive margin of the goods market with exogenous matching probabilities in most papers. The trade-off between prices and quantities (Burdett and Judd (1983)) is also present in this paper, although all firms choose the same price-quantity point as they are symmetric. Benabou (1988, 1992) describes how conditions for search cost and price adjustment cost frame price setting power of firms. It relates to this paper as markups increase and price adjustment decreases in consumer search cost. Recent additions to this literature shifted towards search effort as an input in market matching of multiple goods. In this literature, the outcome of overall trades is endogenous as the matching probability depends on search effort which in turn depends on prices. Michaillat and Saez (2015); Petrosky-Nadeau and Wasmer (2015); Bai et al. (2025) model costly search effort as an input in "trade production", while Qiu and Rios-Rull (2022) assume that the number of varieties to consume increase in search effort. In any case, households rake an active role in goods markets matching in all of these papers.

In this paper, I combine the three strands of literature the following way: I set up a medium-sized New-Keynesian DSGE model based on Christiano et al. (2010); Smets and Wouters (2007) and implement goods market search-and-matching along the lines of Michaillat and Saez (2015). The model incorporates four channels of variable capacity utilization - workweek of capital, unobserved worker effort, fixed cost of production, and goods market search-and-matching (SaM) - and targets aggregate TFP and utilization-adjusted TFP as in the empirical literature. I fit the model to U.S. data of common macroeconomic aggregates and capacity utilization survey data to specifically target the main determinant of short-run TFP[3]. I use the model to discriminate between the explanatory power of the different channels of capacity utilization and short-run TFP and derive the implications for impulse response functions, the variance decomposition, and TFP multipliers of each exogenous shock process.

In a Bayesian estimation exercise, I find that goods market SaM is one of the two most important capacity utilization channel in explaining short-run TFP fluctuations, complementing worker effort and substituting for the capital workweek and fixed cost of production. The trade-off between household search effort and sticky prices is at the center of short-run TFP fluctuations as it endogeneizes the price elasticity of demand and capacity utilization based on household search input. The data favors a significant impact of search effort as a substitute for goods supply in short-run matching with search effort being less elastic than labor supply. markups and fixed cost of production reduce by 50% compared to a benchmark NK model. Overall, the *variable goods market SaM* model challenges the view that short-run TFP is mostly supply driven.

I use the estimated model to analyze the impact of goods market SaM on the transmission channels of each single shock on TFP fluctuations. Adding *variable goods market* SaM leads to an increase in TFP fluctuations following demand shocks, while it leads to a decrease following technology shocks. Cost-push shocks show a significant decline in explaining both inflation and TFP variation in the data as the endogeneous price elasticity of demand reduces their impact. Labor shocks create a pattern of increasing utilization in a decreasing economy as households have alternative productive uses of their time. These effects are strongest if search effort is inelastic, matching inputs are complements, and prices are sticky. Cumulative TFP multiplicators - TFP flucutations relative to GDP fluctuations - show the same pattern but somewhat muted.

[3]As there is no direct evidence on search effort in business cycle frequency, I use the estimated model and its marginal likelihood to discriminate between the explanatory power of the three differennt capacity utilization channels.

The rest of the paper is organized as follows. Section 2 introduces the model and its dynamics. Section 3 derives a model-based TFP decomposition, sets up the measurement equations, and conducts the estimations. Section 4 shows the estimation results. Section 5 discusses impulse response functions and analyzes the drivers of capacity utilization and TFP across models. Section 6 concludes.

2. Model Setup

The model is based on Christiano et al. (2005) featuring a variable capital workweek extended by a detailed labor market differentiating between employment, hours per worker, and worker effort following Bils and Cho (1994); Cacciatore et al. (2020). It 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. The novel model feature is goods market search-and-matching (SaM) following Michaillat and Saez (2015) paired with Rotemberg (1982) price adjustment costs and directed search following Moen (1997). Households provide costly search effort to match firm production capacity on the goods market. Households balance overall consumption costs. Firms balance markups and capacity utilization when setting prices. A simplified pen-and-paper version of this model can be found in Gantert (2025).

2.1. Labor and Goods Markets

Employment is a long-lasting relationship between workers and firms. Unemployed workers supply their labor inelastically to the labor market. The employment rate[4] on the *labor market* is determined by

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

where $0 < \delta_N \leq 1$ is an exogenous separation rate. New employment relationships are determined by beginning-of-period unemployed workers, u_t, and firm i vacancies, $v_t(i)$ in a

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

Cobb-Douglas matching function given by

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

where $0 < \gamma_N, \psi_{N,t} \leq 1$ with $\psi_{N,t}$ varying due to labor market mismatch shocks. The job-finding probability is defined by $f_{N,t} = \frac{m_{N,t}}{u_t}$. The vacancy-filling probability of firm i is defined by $q_{N,t}(i) = \frac{m_{N,t}}{v_t(i)}$. Labor market tightness is defined by $x_{N,t} = \frac{v_t}{u_t}$.

The *goods market* is segmented along varieties of the differentiated good. Households spend search effort, $D_t(i)$, for each variety i. Each firm i produces one unique variety and supplies its unmatched production capacity, $S_t(i)$, to the goods market. Following Moen (1997), household search is directed towards each variety individually[5]. 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 separation rate. Each trades one unit of one variety of the differentiated good. New customer relationships are determined by a constant-elasticity-of-substitution (CES) matching function

$$m_{T,t}(i) \quad = \quad \psi_{T,t} \left[\gamma_T D_t(i)^{\Gamma} + (1 - \gamma_T)\, S_t(i)^{\Gamma} \right]^{\frac{1}{\Gamma}}, \tag{4}$$

where $-\infty < \Gamma \leq 0$ and $0 \leq \gamma_T, \psi_{T,t} < 1$ with $\psi_{T,t}$ varying due to goods market mismatch shocks[6]. The probability of matching a good i is defined by $f_{T,t}(i) = \frac{m_{T,t}(i)}{D_t(i)}$. The probability of firm i selling its good is defined by $q_{T,t}(i) = \frac{m_{T,t}(i)}{S_t(i)}$. Goods market tightness for good i is defined by $x_{T,t}(i) = \frac{D_t(i)}{S_t(i)}$.

[5]It follows, that there are as many individual goods markets as varieties. Each market contains one firm offering variety i and an infinitely many households search for this variety.

[6]The aggregate goods market matching efficiency varies due to goods market mismatch shocks. These represent exogenous variation in market matching technology but also composition and dispersion effects of unmodeled heterogeneity on the goods market, e.g. geography, type, quality, and timing of goods supply. For instance, goods market matching efficiency can fluctuate over the business cycle as economic activity reallocates to markets with higher average efficiency which increases aggregate goods market efficiency.

2.2. Households

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

$$\mathbb{W}_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t Z_t \frac{(\mathbb{U}_{C,t} - \mathbb{U}_{N,t})^{1-\sigma} - 1}{1-\sigma},$$

where $\sigma \geq 0$, $0 \leq \beta < 1$, and $Z_t \geq 0$ is a discount factor shock. Households derive utility from their stock of durable consumption goods, $C_{S,t}$, as defined in

$$\mathbb{U}_{C,t} = C_{S,t} - \theta_C C_{S,t-1} - \frac{\mu_{D,t}}{1+\nu_D}\left[\left(\int_0^1 D_t(i)di\right)^{1+\nu_D} - \theta_D \left(\int_0^1 D_{t-1}(i)di\right)^{1+\nu_D}\right], \quad (5)$$

where $\nu_D, \mu_{D,t} > 0$ determines search effort disuility[7], with $\mu_{D,t}$ varying due to search effort shocks. Consumption and search effort habits are determined by $0 \leq \theta_C, \theta_D < 1$ following Christiano et al. (2005); Qiu and Rios-Rull (2022). The stock of durable consumption goods is given by $C_{S,t} = (1-\delta_S)C_{S,t-1} + C_t$ where C_t is consumption goods bought this period. Labor supply has three margins - employment, hours per worker, and worker effort. Each worker bargains over their hours and worker effort after the employment match is formed. Labor disutility is modeled following Bils and Cho (1994) and given by

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

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)[8]. $H_t(i)$ is hours per worker at firm i where $\mu_{H,t} > 0$ varies due to hours supply shocks, and $e_{H,t}(i)$ is worker effort at firm

[7]Search effort disutility summarizes a broad measure of search costs as e.g. information costs, shopping costs, traveling costs, and further costs associated with the procurement of the good (Michaillat and Saez, 2015). However, time allocated to gather information is not a substantial part of overall shopping time (Petrosky-Nadeau et al., 2016).

[8]As Cacciatore et al. (2020) show, this approach reconciles the behavior of unemployment and hours per worker together with macroeconomic aggregates. For $\omega = 0$, wealth effects cancel out along the lines of Greenwood et al. (1988)-preferences. For $\omega = 1$, utility is a product of consumption and labor supply.

i with $\mu_e > 0$. The supply elasticities are determined by $\nu_H, \nu_e > 0$, respectively. Workers adjust hours and effort instantaneously while employment is quasi-fixed as in (1).

Aggregate shopping effort is given by $D_t = \left(\int_0^1 D_t(i)di\right)^{1+\nu_D}$[9]. The representative household likes to consume a large variety of goods following Dixit and Stiglitz (1977). Its 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 cost-push shock following Ireland (2004). Each household divides its aggregate goods bundle into consumption goods, C_t, and fixed-capital investment goods, $I_{K,t}$, according to $T_t = C_t + P_{I,t}\left(1 + c_{I,t}\right) I_{K,t}$, where $c_{I,t} = \frac{\kappa_I}{2}\left(\frac{I_{A,t}}{I_{A,t-1}} - 1\right)^2$ are convex fixed-capital investment adjustment costs and $P_{I,t} > 0$ is an investment-specific technology shock. Following Qiu and Rios-Rull (2022), we assume that investment adjustment costs do not apply to investment following from utilization depreciation costs, i.e. $I_{A,t} = I_{K,t} - \delta_K\left(e_{K,t}\right) K_{t-1}$, as they represent maintenance investment. The capital stock is given by

$$K_t \quad = \quad \left(1 - \delta_{K,1} - \delta_K\left(e_{K,t}\right)\right) K_{t-1} + I_{K,t}, \tag{7}$$

where $\delta_K\left(e_{K,t}\right) = \frac{\phi_{K,1}\phi_{K,2}}{2}\left(e_{K,t} - 1\right)^2 + \phi_{K,1}\left(e_{K,t} - 1\right)$ with $\delta_{K,1} > 0$ setting the independent capital depreciation, $\phi_{K,1} \geq 0$ setting the capital depreciation subject to the variable capital workweek costs, and $\phi_{K,2}$ setting the convexity of capital depreciation due to capital utilization. Each household follows its intertemporal budget constraint given by

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

where B_t are one-period nominal bonds, $L_t(i) = N_t(i)H_t(i)e_{H,t}(i)$ is effective labor supply, and $K_{e,t} = e_{K,t}K_{t-1}$ is utilized capital supply. Income is determined by nominal wages[10],

[9] I take the assumption that household search costs are convex in their aggregate level, not in their idiosyncratic level per search for variety i. This has first and foremost quantitative reasons as in the alternative assumption markups explode and the model becomes indeterminate for many calibrations. The alternative modeling assumption is shown in Appendix A.

[10] 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

$W_t(i)$, by unemployment benefits, ub, by capital interest, $P_t r_{K,t}$, by bond interest, $r_{B,t-1}$, and by dividends paid by the firms, Div_t[11]. Expenses are determined by money spend on consumption and investment goods, $\int_0^1 P_t(i)T_t(i)di$, and by lump-sum taxes, Tax_t, charged to pay for unemployment benefits and government spending.

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 function[12]

$$F_t(i) = L_t(i)^{1-\alpha} K_{e,t}(i)^{\alpha}, \tag{9}$$

where $0 \leq \alpha \leq 1$ is the capital elasticity of the production function. Each firm maximizes its intertemporal profits given by

$$\Pi_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta_{0,t} P_t(i) \left[T_t(i) + G_t(i) - \frac{W_t(i)}{P_t(i)} L_t(i) - r_{K,t} K_{e,t}(i) \right],$$

where $0 \leq \beta_{0,t} < 1$ is a stochastic discount factor[13]. Firm revenue is determined by sales on private markets, $T_t(i)$, and by exogenous (government) spending, $G_t(i)$. Each firm i pays nominal wages, $W_t(i)$, for effective labor, $L_t(i)$, and capital interest, $r_{K,t}$, for the effective capital stock, $K_{e,t}(i)$. The available production capacity of a firm is given by

$$\mathcal{Y}_t(i) = (1 - \mathcal{C}_t(i)) A_{H,t} F_t(i) - \vartheta, \tag{10}$$

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history of each household is the same. There is perfect unemployment insurance within each household.

[11] 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.

[12] 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.

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

where $\mathcal{C}_t(i) = c_{P,t}(i) + c_{W,t}(i) + c_{N,t}(i)$ summarizes firm adjustment costs[14]. $c_{P,t}(i) = \frac{\kappa_P}{2}\left(\frac{P_t(i)}{P_{t-1}(i)}(1+\pi)^{\iota_P - 1}(1+\pi_{t-1})^{-\iota_P} - 1\right)^2$ are price adjustment costs with $\kappa_P \geq 0$, and $c_{W,t}(i) = \frac{\kappa_W}{2}\left(\frac{W_t(i)}{W_{t-1}(i)}(1+\pi)^{\iota_W - 1}(1+\pi_{t-1})^{-\iota_W} - 1\right)^2$ are nominal wage adjustment costs with $\kappa_W \geq 0$. Inflation indexation is given by $\iota_P, \iota_W \geq 0$. $c_{N,t}(i) = \frac{\kappa_N}{2}\left(\frac{v_t(i)}{L_t(i)}\right)^2$ are labor matching costs following Merz and Yashiv (2007), where $\kappa_N \geq 0$. Each firm searches for additional workers by posting vacancies, $v_t(i)$. The employment level of firm i is given by (1). $A_{H,t} > 0$ is a Hicks-neutral technology process varying due to exogenous shocks. Firms have fixed operation costs, $\vartheta \geq 0$, identical across all firms.

Matching on the goods market depends on the beginning-of-period available production capacity, $S_t(i)$, given by

$$S_t(i) = \mathcal{Y}_t(i) - G_t(i) - (1-\delta_T)\, T_{t-1}(i) + (1-\delta_I)\, I_{S,t-1}(i), \tag{11}$$

which is total production capacity, $\mathcal{Y}_t(i)$, less production capacity sold to the government, $G_t(i)$, or pledged in long-term contracts, and additional any depreciated end-of-period inventories from the previous period, $I_{S,t-1}(i) = (1 - q_{T,t-1}(i))\, S_{t-1}(i)$. $0 < \delta_I \leq 1$ are inventory depreciation costs. Unmatched production capacity, $S_t(i)$, serves as an input to the matching function following Sun (2024).

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

[14] In previous versions of this paper, I included hours per worker adjustment costs following Cacciatore et al. (2020). As they do not change the results of the research question and concentrate exogenous variation in the hours supply shock, I intenionally left the adjustment costs out in this version. For a robustness check including hours per worker adjustment costs, see APPENDIX XXX.

2.4. General Equilibrium

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

$$Y_t \quad = \quad C_t + G_t + Inv_t, \tag{12}$$

where C_t is the numéraire good, and $Inv_t = I_{K,t} + I_{S,t} - I_{S,t-1} - \delta_K\left(e_{K,t}\right)K_{t-1}$ is private investment. Following Qiu and Rios-Rull (2022), we subtract capital depreciation costs due to capital utilization from real GDP as it is maintenance investment and thus an intermediate input. The government budget is always in equilibrium, $Tax_t = G_t + P_t ub\left(1 - \int_0^1 N_t(i)di\right)$. Aggregate capacity utilization in the data is defined as the share of utilized production capacity of its long-run sustainable capacity[15]. It is given by

$$\bar{cu}_t \; = \frac{Y_t}{\bar{\mathcal{Y}}_t}. \tag{13}$$

where $\bar{\mathcal{Y}}_t$ is the long-run sustainable production capacity given by

$$\bar{\mathcal{Y}}_t \; = \; \left(1 - \mathcal{C}_t\right) A_{H,t}\left(\bar{e}_H \bar{H} N_t\right)^{1-\alpha}\left(\bar{e}_K K_{t-1}\right)^{\alpha} - \vartheta + \left(A_{I,t} - 1\right) T_t,$$

where I follow Morin and Stevens (2004); Michaillat and Saez (2015); Comin et al. (2025) and use the following assumptions: First, the capital stock is measured at the current available capital of a firm. This includes non-utilized capital $e_{K,t}$. Second, the level of employment and vacancy costs are measured at their current level. And third, hours per worker and worker effort are measured at the steady-state, as any deviation is not sustainable over the long-run. $\left(A_{I,t} - 1\right) T_t$ is the correction of production capacity for the investment-good production at the household level with $A_{I,t} = 1 + \left(1 - P_{I,t}\left(1 + c_{I,t}\right)\right)\frac{I_{K,t}}{T_t}$. A related concept is the short-run capacity utilization rate, $e_{M,t} = \frac{Y_t}{\mathcal{Y}_t}$. It is defined as production capacity sold on the market given short-run capital utilization and worker effort. The central bank follows a Taylor (1993)-type rule to determine the nominal interest rate

$$\frac{1 + r_{B,t}}{1 + r_B} \; = \left[\frac{1 + r_{B,t-1}}{1 + r_B}\right]^{i_r}\left[\left(\frac{1 + \pi_t}{1 + \pi}\right)^{i_\pi}\left(\tilde{Y}_t\right)^{i_{gap}}\left(\frac{\tilde{Y}_t}{\tilde{Y}_{t-1}}\right)^{i_{\Delta gap}}\right]^{1-i_r} \cdot M_t, \tag{14}$$

[15]The definition of capacity utilization used in the FED survey questionnaire can be found in APPXXX.

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

$$\xi_t = \xi^{1-\rho_\xi} \xi_{t-1}^{\rho_\xi} \varepsilon_{\xi,t}, \quad \varepsilon_{\xi,t} \sim \mathcal{N}(0, \sigma_\xi^2), \tag{15}$$

where $0 \leq \rho_\xi < 1$ is an autocorrelation parameter, and ξ describes the steady-state of the AR(1) process. Both cost-push shocks follow an ARMA(1,1) process given by

$$\xi_t = \xi^{1-\rho_\xi} \xi_{t-1}^{\rho_\xi} \varepsilon_{\xi,t} \varepsilon_{\xi,t-1}^{\zeta_\xi}, \quad \varepsilon_{\xi,t} \sim \mathcal{N}(0, \sigma_\xi^2), \tag{16}$$

where ζ_ξ is the MA(1) coefficient. There are eleven shocks of which nine are the main configuration: a Hicks-neutral technology shock $A_{H,t}$, an investment-specific technology shock $P_{I,t}$, an hours supply shock $\mu_{H,t}$, a discount factor shock, Z_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. The labor mismatch shock $\psi_{N,t}$ and the search effort shock $\mu_{D,t}$ are used in robustness exercises and otherwise fixed to their steady-state value.

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 and are summarized by a representative firm.

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

$$\mathbb{U}_{\chi,t} = (\mathbb{U}_{C,t} - \mathbb{U}_{N,t})^{-\sigma} + \omega \frac{\chi_t}{\mathbb{U}_{C,t}}, \tag{17}$$

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

$$\mathbb{W}_{C,t} = \mathbb{U}_{\chi,t} - \beta\theta_C \mathbb{E}_t \frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1} + \beta\,(1-\delta_S)\,\mathbb{E}_t \frac{Z_{t+1}}{Z_t}\mathbb{W}_{C,t+1}, \tag{19}$$

$$\mathbb{W}_{D,t} = \mathbb{U}_{\chi,t} - \beta\theta_D \mathbb{E}_t \frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1}, \tag{20}$$

$$muc_t = \beta\mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}}\frac{Z_{t+1}}{Z_t} muc_{t+1}, \tag{21}$$

where $\mathbb{U}_{\chi,t}$ is the intratemporal marginal utility of the consumption stock corrected for wealth effects by χ_t, and $\mathbb{W}_{C,t}, \mathbb{W}_{D,t}$[16] is the intertemporal marginal (dis-)utility of the consumption stock (search effort). Marginal consumption utility, muc_t, is given by $\mathbb{W}_{C,t}$ net of $\mathbb{W}_{D,t}$. It depends on the current and future states of goods market tightness as customer relationships are potentially long-term. Its value expressed in the numeraire goods is given by

$$P_{T,t} = 1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}, \tag{22}$$

where we define the total price, $P_{T,t} = \frac{\mathbb{W}_{C,t}}{muc_t}$, and the search price, $P_{D,t} = \frac{\mathbb{W}_{D,t}}{muc_t}\frac{\mu_{D,t} D_t^{\nu_D}}{f_{T,t}}$, with the market good as the numeraire good. The price elasticity of demand is given by

$$\Xi_t = (-\epsilon_t)\left[1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}\right]^{-1}, \tag{23}$$

which is determined by endogenous variation in the search price, $P_{D,t}$, and exogenous variation in the elasticity of substitution, ϵ_t. It is inversely related to the overall price, $\Xi_t = \frac{-\epsilon_t}{P_{T,t}}$. We can rewrite (21) using (22) by

$$\mathbb{W}_{C,t} = \beta\mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}}\frac{Z_{t+1}}{Z_t}\frac{P_{T,t}}{P_{T,t+1}}\mathbb{W}_{C,t+1}, \tag{24}$$

[16] I use two separate habit formation parameters for consumption and search effort to be able to estimate them separately as it is not a priori clear whether both consumption and search effort have the same level of habit formation.

which highlights the impact of goods market SaM on the household FOCs through the endogenous variation of the total price determined by variations in the search price $P_{D,t}$. One can interpret $\frac{P_{T,t}}{P_{T,t+1}}$ as a correction for the mismeasurement of overall consumption costs.

Price Setting. The *representative firm* supplies its available production capacity to the goods market to form matches with buyers. The *asset value of production capacity* is given by

$$Q_{Y,t} \;= q_{T,t}Q_{T,t} + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_I\right)\left(1-q_{T,t}\right) Q_{Y,t+1}, \tag{25}$$

which is forward-looking due to the option to hold unsold goods in inventory. It increases in the asset value of matched goods, $Q_{T,t}$, weighted by the probability of matching available production capacity, $q_{T,t}$. Marginal costs[17] (of traded goods) are corrected for short-run capacity utilization by $mc_t = \frac{Q_{Y,t}}{e_{M,t}}$. The asset value of matched goods is given by

$$\left(1+\varphi_t\right) Q_{T,t} \;= 1 + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left[\Big[\left(1-\delta_I\right)\varphi_t - \left(1-\delta_T\right) \Big] Q_{Y,t+1} + \left(1-\delta_T\right) Q_{T,t+1} \right], \tag{26}$$

which is forward-looking due to long-term contracts and determined by goods market frictions and monopolistic competition. $Q_{T,t} < 1$ indicates a markup over the actual costs of matching. The asset value increases in long-term contracts as it reduces search costs per good sold. However, long-term contracts also lower available production capacity tomorrow and thus increase goods markets tightness tomorrow, especially if the asset value of production capacity is expected to be high. Inventories have the opposite effect on expected goods market tightness. The impact of monopolistic competition on the asset value of a matched good is defined by $\varphi_t = \frac{1}{\epsilon_t} \frac{\gamma_T x_{T,t}^{\Gamma}}{1-\gamma_T} \frac{m_{T,t}}{T_t} \frac{P_{T,t}}{P_{D,t}}$ where $\varphi_t \to 0$ as $\epsilon_t \to \infty$ (no monopolistic competition). For $\gamma_T = 0$ (thus $P_{D,t} = 0$), it follows that $\varphi_t = \frac{1}{\epsilon_t}$ (no goods market SaM). The markup is affected by goods market SaM in three ways: First, markups increase in γ_T as search effort is more

[17] The definition of marginal costs follows the assumption in NK models and the formula applied to the data as e.g. in De Loecker et al. (2020). This adjustment makes marginal costs comparable to both the theoretical and empirical markup literature. It corrects marginal costs for the implicit marginal costs of non-utilized goods provided to sell one good on the market (otherwise the markup would imply the proportional costs of unsold capacity).

productive in goods matching. Second, markups increase if the share of newly matched goods to overall sold goods is high, $\frac{m_{T,t}}{T_t}$. And third, markups decrease in $P_{D,t}$ as firms lower prices to attract additional customers in tight goods markets[18].

The representative firm sets prices on the goods market with a markup over marginal costs taking goods market tightness and the household search price into account. The *New-Keynesian Phillips curve* is given by

$$\begin{aligned}\frac{c'_{P,t}}{1-\mathcal{C}_t-\vartheta_{S,t}} &= \frac{\theta_{T,t}}{mc_t} - \frac{\gamma_T x^{\Gamma}_{T,t}}{1-\gamma_T}\frac{\theta_{S,t}}{P_{D,t}}\left(1-\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_I\right)\frac{e_{M,t+1}mc_{t+1}}{e_{M,t}mc_t}\right)\\ &+\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\frac{mc_{t+1}}{mc_t}\frac{Y_{t+1}}{Y_t}\frac{c'_{P,t+1}}{1-\mathcal{C}_{t+1}-\vartheta_{S,t+1}},\end{aligned} \tag{27}$$

where $c'_{P,t}=\frac{\partial c_{P,t}}{\partial P_t}$ and $c'_{P,t+1}=(-1)\frac{\partial c_{P,t+1}}{\partial P_t}$ are marginal price adjustment costs, $\vartheta_{S,t}=\frac{\vartheta}{A_{H,t}F_t}$ are fixed costs as a share of the production function, $\theta_{T,t}=\left(1+\frac{\Delta I_{S,t}}{T_t+G_t}\right)^{-1}$ is the share of GDP traded on markets, and $\theta_{S,t}=1-\frac{G_t+(1-\delta_T)T_{t-1}-(1-\delta_I)I_{S,t-1}}{\mathcal{Y}_t}$ is the share of available production capacity at the beginning of a period. The Phillips curve is forward-looking. High markups, $mp_t=\frac{1}{mc_t}$, allow for high marginal price adjustment costs, $c'_{P,t}$, thus high inflation rates. The impact of markups on inflation is lower in times of substantial inventory build-up as described by $\theta_{T,t}$.

Goods market SaM frictions decrease the equilibrium marginal price adjustment costs - thus inflation - given any equilibrium markup. As γ_T increases, search effort is more productive in matching goods. Hence, any price change induces larger changes in goods market matching which allows for smaller price changes to achieve the same targeted demand. However, an increase in search prices, $P_{D,t}$, has the opposite impact on inflation as it lowers the price elasticity of demand (23). The option to hold inventories has the same impact on prices as the decreasing price elasticity of demand. The option to store a good in times of low prices and sell it in times of high prices increases the market power of a firm. If most of the production capacity is pre-commited, the impact of goods market SaM is lower as a smaller share of overall production has to be matched this period as described by $\theta_{S,t}$. As prices only

[18]Even though the price elasticity of demand (23) decreases in $P_{D,t}$, firms cannot exploit this and raise markups as households are responsive to goods market tightness and their search prices.

adjust gradually due to price adjustment costs, search prices and thus search effort adjust gradually (and sub-optimally), which in turn leads to fluctuations in capacity utilization. The trade-off between sticky posted prices and flexible search prices is central to the results of this paper.

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

$$\begin{aligned} Q_{K,t} &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \Big[r_{K,t+1} e_{K,t+1} + (1-\delta_{K,1}) Q_{K,t+1} \\ &\qquad - (1+c_{I,t+1}) P_{T,t+1} P_{I,t+1} \delta_K (e_{K,t+1}) \Big], \end{aligned} \tag{28}$$

$$Q_{K,t} = P_{T,t} P_{I,t} \left[(1+c_{I,t}) + \frac{I_{K,t} \left\{ c'_{I,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{P_{T,t+1} P_{I,t+1}}{P_{T,t} P_{I,t}} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1} \right\}}{I_{K,t} - \delta_K (e_{K,t}) K_{t-1}} \right], \tag{29}$$

$$r_{K,t} = (1+c_{I,t}) P_{T,t} P_{I,t} (\phi_{K,1} \phi_{K,2} (e_{K,t} - 1) + \phi_{K,1}), \tag{30}$$

where $Q_{K,t}$ is the shadow price of installed capital following Tobin (1969). It increases in investment adjustment costs, but also in search prices through $P_{T,t}$ as obtaining fixed-capital investment goods requires more effort from households. The *representative firm* employs capital according to

$$r_{K,t} = \alpha (1 - \mathcal{C}_t) \frac{A_{H,t} F_t}{e_{K,t} K_{t-1}} e_{M,t} mc_t, \tag{31}$$

where the capital interest rate increases in marginal productivity of capital, marginal costs, and the short-run capacity utilization rate. Therefore, both capital supply and capital demand are determined by goods market frictions through $e_{M,t}$ and $P_{T,t}$. Firms demand less capital and households employ and utilize less capital as both expect a lower utilization rate of employed capacity. Thus, goods market frictions have a direct impact on the variable capital workweek.

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

$$Q_{F,t} = \mathcal{C}'_{N,t} \frac{A_{H,t} F_t}{N_t} e_{M,t} mc_t - w_t e_{H,t} H_t + (1 - \delta_N) \mathbb{E}_t \frac{1 + \pi_{t+1}}{1 + r_{B,t}} Q_{F,t+1}, \tag{32}$$

$$Q_{F,t} = \frac{c'_{N,t}}{q_{N,t}} \frac{A_{H,t} F_t}{e_{H,t} H_t N_t} e_{M,t} mc_t, \tag{33}$$

where $\mathcal{C}'_{N,t} = (1 - \alpha)(1 - \mathcal{C}_t) + 2c_{N,t}$. The asset value of marginal employment to the firm, $Q_{F,t}$, increases in marginal labor productivity and short-run capacity utilization and decreases in labor matching costs and real wages. The value function is forward-looking as employment relationships are long-term. As there is free entry on the labor market, firms post vacancies as long as the marginal labor matching costs, $\frac{c'_{N,t}}{q_{N,t}}$, are lower or equal than the value of marginal employment, $Q_{F,t}$.

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. Latent worker effort is determined by

$$e_{H,t} = \left[\frac{\mu_{H,t}}{\mu_e} \frac{1 + \nu_e}{\nu_e} H_t^{\nu_H} \right]^{\frac{1}{1+\nu_e}}, \tag{34}$$

which increases in hours per worker. The elasticity of worker effort with respect to hours per worker depends on the the relative supply elasticity of hours over effort, $\frac{\nu_H}{1+\nu_e}$. Using (9), we can derive the increasing returns to scale in hours per worker due to the latent worker effort margin by $\phi = 1 + \frac{\nu_H}{1+\nu_e}$ as in Lewis et al. (2019). Real wage bargaining is determined by

$$\begin{aligned} w_t e_{H,t} H_t &= ub + \frac{X_t \frac{\mu_{H,t}}{1+\nu_H} \left(1 + \frac{1+\nu_H}{\nu_e}\right) H_t^{1+\nu_H}}{muc_t \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}} + \frac{\eta_t}{1 - \eta_t} \frac{Q_{F,t}}{\tau_{W,t}} \\ &\quad - (1 - \delta_N) \mathbb{E}_t \frac{1 + \pi_{t+1}}{1 + r_{B,t}} (1 - f_{N,t+1}) \frac{\eta_{t+1}}{1 - \eta_{t+1}} \frac{Q_{F,t+1}}{\tau_{W,t+1}}, \end{aligned} \tag{35}$$

where household bargaining power is given by $0 \leq \eta_t \leq 1$, which fluctuates following an exogenous wage cost-push shock. $\tau_{W,t}$ is a function of sticky wage adjustment with $\tau_W = 1$ which increaes monotonically in wage inflation. 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 marginal productivity. Goods market SaM affects labor demand through short-run capacity utilization, $e_{M,t}$, implicitly given through $Q_{F,t}$ as shown by (32) and (33), and labor supply through the impact of search prices on muc_t as shown by (22). Marginal productivity of all three labor margins (thus the firm's value of labor) increases in short-run capacity utilization. However, if search prices increase with capacity utilization, muc_t decreases and counteracts labor expansion through higher wages.

3. Estimation Setup: Capacity Utilization as a Driver of TFP

In this section, I derive the *efficiency wedge* in the model as the difference between total factor productivity (TFP) and technology shocks and show its identification through capacity utilization and potential biases of this strategy. I set up the full information Bayesian estimation procedure[19] and outline the benchmark for the model comparison. Henceforth, all variables are denoted as percentage deviations from their deterministic steady-state. The percentage deviation variables are indicated by a hat, e.g. $\hat{gdp}_t = \frac{GDP_t - GDP}{GDP}$. 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[20]. TFP fluctuations in the model are given by

$$\hat{TFP}_t \quad = \quad \hat{GDP}_t - (1-\alpha)\left(\hat{N}_t + \hat{H}_t\right) - \alpha \hat{K}_{t-1}, \tag{36}$$

which decompose into *utilization-adjusted TFP* fluctuations, $\hat{\hat{A}}_t$, and *efficiency wedge* flucutations, $\hat{\Phi}_t$. Fluctuations in *utilization-adjusted TFP* follow from exogenous "technology" shocks[21] that impact the resource constraints - i.e. Hicks-neutral technology shocks, $\hat{A}_{H,t}$,

[19] I use the Dynare toolbox (Adjemian et al. (2024)) in order to linearize, solve, and estimate the model.

[20] 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 (Basu et al., 2006; Fernald, 2014).

[21] The utilization-adjusted term also includes TFP channels not modeled in this paper - i.e. reallocation across sectors over the business cycle (see e.g. Basu et al. (2006)). Its impact on TFP is similar to the impact

investment-specific technology shocks, $\hat{P}_{I,t}$, and goods market efficiency shocks, $\hat{\psi}_{T,t}$[22]. The *efficiency wedge* - the variation in TFP that is explained by endogenous propagation of shocks in the model - is calculated as the difference between TFP and utilization-adjusted TFP. It is given by

$$\hat{\Phi}_t \quad = \quad \hat{\Phi}_{\vartheta,t} + \hat{\Phi}_{Labor,t} + \hat{\Phi}_{Capital,t} + \hat{\Phi}_{SaM,t}, \tag{37}$$

which decomposes into a fixed costs of production channel, $\hat{\phi}_{\vartheta,t}$, a labor market channel, $\hat{\Phi}_{Labor,t}$, a capital market channel, $\hat{\Phi}_{Capital,t}$, and a goods market SaM channel, $\hat{\Phi}_{SaM,t}$[23]. All four channels increase the *efficiency wedge* as capacity utilization increases while utilization-adjusted TFP is constant[24]. Neglecting capacity utilization leads to an overestimation of utilization-adjusted TFP fluctuations in the data.

The challenge to identify the determinants of the *efficiency wedge* is that we do not observe any of them directly. However, we observe survey data on aggregate capacity utilization[25] which we use to identify the *efficiency wedge*. Its decomposition into the four channels of the model follows from the identifying restrictions of matching eight further macroeconomic aggregates simultaneously. Using (13), we start by deriving the relationship between capacity

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of capacity utilization. In a boom, input factors are reallocated to more productive industries. Hence, TFP increases. For that reason, I use the term "utilization-adjusted TFP" instead of "technology".

[22]It is ambiguous whether the goods market efficiency shock, $\hat{\psi}_{T,t}$, is a technology shock, as it can also contain market dispersion and composition fluctuations. I define a lower and upper bound in the decomposition of TFP to take this ambiguity into account. They are identified by $\hat{\hat{A}}_{Low,t}$ and $\hat{\hat{A}}_{Up,t}$, respectively. The benchmark case used in the main part of the paper is the upper bound of technology shocks, $\hat{\hat{A}}_{Up,t}$. The lower bound can be derived symmetrically and is shown in Appendix B.

[23]The model framework nests Fernald (2014); Comin et al. (2025) where the variable capital workweek and variable worker effort are the determinants of capacity utilization.

[24]The efficiency wedge channels decompose as follows: (1) $\hat{\Phi}_{\vartheta,t}$: $\frac{\partial \hat{\Phi}_{\vartheta,t}}{\partial GDP_t} > 0$; (2) $\hat{\Phi}_{Labor,t}$: $\frac{\partial \hat{\Phi}_{Labor,t}}{\partial \hat{e}_{H,t}} > 0$ and $\frac{\partial \hat{\Phi}_{Labor,t}}{\partial \hat{c}_{N,t}} < 0$; (3) $\hat{\Phi}_{Capital,t}$: $\frac{\partial \hat{\Phi}_{Capital,t}}{\partial \hat{e}_{K,t}} > 0$; (4) $\hat{\Phi}_{SaM,t}$: $\frac{\partial \hat{\Phi}_{SaM,t}}{\partial \hat{x}_{T,t}} > 0$, $\frac{\partial \hat{\Phi}_{SaM,t}}{\partial \hat{T}_{t-1}} > 0$, and $\frac{\partial \hat{\Phi}_{SaM,t}}{\partial \hat{I}_{S,t}} > 0$. Detailed derivations of the TFP decomposition are given in Appendix B.

[25]In Appendix C, I show how to calculate an economy wide capacity utilization measure from industry data and some evidence on service sector capacity utilizaiton rates.

utilization and the *efficiency wedge* given by

$$\hat{\Phi}_t = \underbrace{\frac{\hat{\boldsymbol{cu}}_{\boldsymbol{t}} - \vartheta_S cu \hat{\boldsymbol{\vartheta}}_{\boldsymbol{S,t}}}{1+\vartheta_S cu} - \frac{c_N \hat{\boldsymbol{c}}_{\boldsymbol{N,t}}}{1-c_N} - (1-\alpha)\,\hat{\boldsymbol{H}}_{\boldsymbol{t}}}_{=\hat{\Phi}_{cu,t}} - \underbrace{\left[\varphi_{AI}\hat{\boldsymbol{A}}_{\boldsymbol{I,t}} + \varphi_\psi \hat{\boldsymbol{\psi}}_{\boldsymbol{T,t}}\right]}_{=\hat{\Phi}_{Bias,t}}, \tag{38}$$

where $\varphi_{AI} = \frac{1-cu}{(1+\vartheta_S cu)\delta_T \delta_I}$ and $\varphi_\psi = \frac{1-cu(1-(1-g_S)\delta_T\delta_I)}{(1+\vartheta_S cu)\delta_I}$. The *efficiency wedge* is determined by observables - capacity utilization corrected for fixed cost of production, hours per worker and labor matching cost - summarized by $\hat{\Phi}_{cu,t}$, and by two latent variables - investment-specific technology and goods market efficiency shocks - summarized by $\hat{\Phi}_{Bias,t}$. If the bias of the latent variables, $\hat{\Phi}_{Bias,t}$, is small, the model and estimation setup in this paper is in line with Fernald (2014); Comin et al. (2025) and their estimates of "utilization-adjusted TFP" are directly connected to this model. However, the underlying determinants might differ due to the introduction of goods market search-and-matching.

3.2. Data Description and Estimation Setup

I estimate the model to replicate U.S. business cycle data from 1984q1 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, hours per worker, the employment rate, the GDP deflator, the growth rate of real labor compensation, and the federal funds effective 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. There is no service sector capacity utilization rate for the U.S. We approximate it using EU survey data as follows: First, we observe that industry and service sector capacity utilization rates correlation is high for the observation period. Second, we derive the economy-wide capacity utilization rate by correcting the industry capacity utilization rate with the standard deviation of the service sector capacity utilization rate, weighting both by their share of GDP across time. I adjust the federal funds effective rate for the effective lower bound period by

Table 1: Calibrated Parameters of the Model

Parameter	Value	Description	Reference
ub	$(N = 0.94)$	Unemployment benefits	FRED data: UNRATE
μ_H	$(H = 1)$	Hours supply disutility	Normalization
μ_e	$(e_H = 1)$	Worker effort supply disutility	Normalization
ψ_N	$(q_N = 0.7)$	Labor matching efficiency	Blanchard and Gali (2010)
γ_N	0.6	Labor matching elasticity	Petrongolo and Pissarides (2001)
δ_N	0.12	Employment separation rate	Blanchard and Gali (2010)
κ_N	$(\frac{c_N Y}{GDP} = 0.01)$	Vacancy posting cost	Blanchard and Gali (2010)
η	0.5	Wage bargaining weight	Blanchard and Gali (2010)
ψ_T	$(cu = 0.86)$	Goods matching efficiency	Calculation based on FRED data: TCU
Ω	0.27	Industry share of GDP	FRED data: PCES
μ_D	$(x_T = 1)$	Search effort disutility	Normalization
ϑ	$(\Pi = 0)$	Fixed cost of production	Christiano et al. (2010)
G	$(g_S = 0.2)$	Government spending share of GDP	Christiano et al. (2010)
β	$(r = 0.01)$	Discount factor	FRED data: FEDFUNDS
α	$(ls = 0.6)$	Capital elasticity of production	FRED data: LABSHPUSA156NRUG
σ	1.5	Elasticity of intertemporal substitution	Smets and Wouters (2007)
$\delta_{K,1}$	$\left(1 - \delta_{K,2}^{share}\right) 0.025$	Capital depreciation rate	Christiano et al. (2010)
σ_K	$(e_K = 1)$	Variable capital workweek cost exponent	Normalization

NOTE: Capacity utilization is corrected for service capacity utilization as shown in Appendix B.

using the shadow rate of Wu and Xia (2016). As Wu and Zhang (2019) show, this accounts for quantitative easing in the data and its non-linear impact that is not present in a linear New-Keynesian model. Growth rates are demeaned by the average real GDP growth rate. The capacity utilization rate, inflation rate, and interest rate are demeaned by their own sample mean. The employment rate and hours per worker are detrended using a linear trend as in Cacciatore et al. (2020). Details on the data sources and construction can be found in Appendix C.

Table 1 shows the calibrated parameters of the model. I use a combination of values from the literature and steady-state targets. The calibrated parameters are in line with the literature, e.g. Blanchard and Gali (2010); Christiano et al. (2010). Table 2 shows the prior setup and posterior estimates of the main model specifications. A complete overview of the calibration and estimation strategy is given in Appendix D.

I estimate several parameters indirectly through proxies to improve the stability of the estimation or constrain the interval of permissible values for a parameter. ϵ is set by the steady-state markup, $\frac{1}{mc}$, which in turn is estimated with a prior mean of 0.2 and standard deviation 0.1. There is no closed-form solution for ϵ based on steady-state markups. ϵ increases in γ_T for any level of $\frac{1}{mc}$. Hence, the same markup can lead to different elsaticities of substitution depending on the level of goods market search-and-matching frictions determined by γ_T.

I set $\nu_e = \frac{\nu_H}{\phi-1} - 1$ by estimating the parameter determining increasing returns to scale in hours worked due to unobserved variable worker effort (see Lewis et al. (2019)). The prior mean of ϕ is set to 1.5 with a standard deviation of 0.1. Given the estimate of ν_H, the prior for ν_e falls in its common range, $\nu_e \in [2\ 3]$, in the literature (see e.g. Bils and Cho (1994)). I set the prior mean of $\delta_{K,2}^{share}$ to 0.6 with a standard deviation of 0.1 (see e.g. Basu and Kimball (1997)). It determines $\delta_{K,2} = \delta_{K,2}^{share}\delta_K$ where the overall capital depreciation rate is given by 2.5% per quarter. Both priors contain sufficient information from the literature but also use rather large standard deviations to account for a possible trade-off with variable goods market SaM.

The novel feature in this paper - variable goods market SaM - is described by five parameters. The search elasticity of goods market matching is estimated by $\gamma_T \in [0.11\ 0.33]$ in the literature (see e.g. Michaillat and Saez (2015); Bai et al. (2025); Huo and Rios-Rull (2020); Qiu and Rios-Rull (2022)). I limit the permissible parameter range to that interval and estimate the proxy $\gamma_T^{prox} = 3 \cdot \gamma_T$ with a prior mean of 0.5, a standard deviation of 0.2, and a beta-distribution to determine the point estimate of γ_T on that interval. Next, I estimate the elasticity of substituiton of the goods market matching function, Γ, using the same approach. I limit permissible values to $\Gamma \in [-5\ 0]$[26] and estimate $\Gamma^{prox} = \frac{-1}{5}\Gamma$ with a prior mean of 0.1, a standard deviation of 0.075, and a beta-distribution. Hence, the prior assumes a goods

[26] The permissible interval for Γ allows for light complements to a unit elasticity (Cobb-Douglas). I exclude strong complements and strong substitutes for the goods market matching function. This interval is based on the literature, see e.g. Michaillat and Saez (2015); Bai et al. (2025); Huo and Rios-Rull (2020); Qiu and Rios-Rull (2022).

Table 2: Steady-State Targets and Parameterization

		Estimation				
		Prior			Posterior	
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	SaM-VWE (90% HDP)	Full (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.38 (0.14 – 0.63)	0.18 (0.00 – 0.61)	0.09 (0.00 – 0.19)
θ_H	Beta	0.7	0.1	0.77 (0.69 – 0.84)	0.82 (0.75 – 0.90)	0.85 (0.79 – 0.90)
ν_H	Gamma	2	0.5	2.23 (1.63 – 2.80)	2.44 (1.77 – 3.10)	2.24 (1.66 – 2.81)
$\frac{1}{mc} - 1$	Beta	0.2	0.1	0.37 (0.24 – 0.49)	0.19 (0.14 – 0.25)	0.20 (0.14 – 0.26)
κ_I	Gamma	4	1.5	1.88 (1.38 – 2.36)	2.69 (2.08 – 3.31)	2.79 (2.12 – 3.44)
κ_W	Gamma	30	5	27.0 (19.4 – 34.4)	23.1 (15.6 – 30.5)	23.7 (16.1 – 31.1)
κ_P	Gamma	180	20	179 (162 – 195)	175 (158 – 191)	178 (162 – 194)
ι_W	Beta	0.5	0.15	0.44 (0.20 – 0.67)	0.46 (0.21 – 0.69)	0.46 (0.22 – 0.70)
ι_P	Beta	0.5	0.15	0.07 (0.02 – 0.11)	0.05 (0.02 – 0.08)	0.05 (0.02 – 0.08)
i_π	Gamma	1.8	0.1	1.70 (1.56 – 1.85)	1.68 (1.55 – 1.82)	1.61 (1.48 – 1.75)
i_{gap}	Gamma	0.12	0.05	0.02 (0.01 – 0.03)	0.02 (0.01 – 0.04)	0.02 (0.27 – 0.57)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.33 (0.21 – 0.45)	0.33 (0.16 – 0.48)	0.42 (0.00 – 0.19)
i_r	Beta	0.75	0.05	0.75 (0.71 – 0.79)	0.63 (0.55 – 0.70)	0.60 (0.53 – 0.67)
Benchmark Utilization Parameters						
ϕ	Gamma	1.5	0.1	1.76 (1.59 – 1.92)	1.76 (1.60 – 1.92)	1.79 (1.63 – 1.95)
$\delta_{K,2}^{share}$	Beta	0.6	0.1	0.30 (0.20 – 0.39)	–	0.28 (0.18 – 0.38)
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.89 (0.79 – 0.98)	0.90 (0.81 – 0.99)
ν_D^{mult}	Gamma	1	0.5	–	1.48 (0.57 – 2.37)	1.69 (0.60 – 2.74)
Γ^{prox}	Beta	0.5	0.2	–	0.07 (0.00 – 0.14)	0.05 (0.00 – 0.10)
θ_D	Beta	0.5	0.2	–	–	0.22 (0.04 – 0.39)
δ_I	Beta	0.15	0.05	–	–	0.93 (0.89 – 0.97)
δ_T	Beta	0.25	0.15	–	–	0.84 (0.74 – 0.94)

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) SaM-VWE model, and (3) full model. The 90% HDP intervals are given in paranthesis. The posterior mean is computed with four chains of the Metropolis-Hastings algorithm on a sample of 2,000,000 draws.

market matching function close to the Cobb-Douglas case. Next, I estimate ν_D as a multiple of ν_H with a prior mean of 1 and a standard deviation of 0.5. This prior follows the rationale that supplying one hour of search effort or one hour of labor supply should roughly create the same amount of disutility. Next, the depreciation rate of inventories δ_I is estimated with a prior mean of 0.15 and a standard deviation of 0.05. It follows the estimates of Khan and Thomas (2007) for manufacturing, while $\delta_{S,I} = 1$ for the service sector is taken into account by setting Ω - the share of goods that can be stored in inventories. Lastly, data on δ_T is scarce. I follow Mathä and Pierrard (2011) who calculate the mean duration of business-to-business contracts and set its prior to 0.25 with a large standard deviation of 0.15 as we model household-firm contracts instead of business-to-business contracts.

I conduct a horse-race between variable capital workweek (VCW), variable worker effort (VWE), fixed cost of production (FCP), and variable goods market search-and-matching (SaM) in explaining total factor productivity and capacity utilization data, while also being in line with eight other macroeconomic aggregates. In the baseline setup, fixed cost of production is a part of every model specification. While I explore different combinations of the utilization margins, it is useful to frame the model specifications into three main versions:

1. **Benchmark Model:** A model with variable capital workweek, $\delta_{K,2}^{share} > 0$, variable worker effort, $\nu_e < \infty$, and fixed cost of production, $\vartheta > 0$, but no goods market search-and-matching, $\gamma_T = \Gamma = \nu_D = 0$, and $\delta_T = \delta_I = 1$.
2. **SaM Model:** A simplified model only containing goods market search-and-matching and fixed cost of production as drivers of capacity utilization: $\nu_e = \infty$, $\delta_{K,2} = 0$, $\vartheta > 0$.
3. **Full Model:** The model presented in section 2 which is a combination of the benchmark and SaM models with $0 < \gamma_T < 1$, $\Gamma \leq 0$, $\nu_D > 0$ and $0 < \delta_T = \delta_I \leq 1$.

In the estimation and model comparison, I analyze different combinations of the four channels. Each model specification is identified by the codes defined, i.e. VCW, VWE, FCP, and SaM. The analysis determines the combination of capacity utilization channels that has the highest probability in explaining the efficiency wedge as it is identified by (38) 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 are available from the author.

4. Estimation Results

In this section, I show how the log data density changes for different versions of the model featuring the different capacity utilization channels. I analyze the posterior densities of the main parameters showing the structure of its channels. And lastly, I derive the (conditional) variance decomposition of the main model versions showing how the sources of business cycle fluctuations change as we add *variable goods market SaM*.

4.1. Analyzing the Explanatory Power

Adding *variable goods market SaM* improves the explanatory power of the model for different model setups. It is one of two the most important capacity utilization channels of the model, rendering variable capital workweek less important and complementing variable worker effort. Table 3 shows the log data densities for the main model versions and its elements. I replicate the results of Lewis et al. (2019) for the US. Adding *variable worker effort* to a model with a *variable capital workweek* increases the likelihood of the model in explaining the data decisively with a log Bayes factor following Kass and Raftery (1995) of 100. In fact, a model featuring only variable worker effort compared to the benchmark model is favored by the data with a log Bayes factor of 14.

Using *variable goods market SaM* instead of both benchmark channels of variable capital workweek and worker effort shows a strong, but not decisive improvement of the log data density. Using it as a single utilization margin does about as well as only using *variable worker effort* with a slight but not decisive preference by the data for the second channel. When comparing *variable goods market SaM* to *variable capital workweek* alone, it shows a decisive increase in the log data density with a Bayes factor of 96, which is in line with the results of Qiu and Rios-Rull (2022). In contrast to their results, the log data density decreases as we combine the two margins. Hence, the *variable capital workweek* is not favored by the

Table 3: Log data density of different model setups in explaining US data

Model Setup	Log data density	2ln Bayes factor
Capital Workweek	5124	−86
Worker Effort	5174	14
Benchmark	5167	0
Search-and-Matching (SaM)	5171	8
SaM & Capital Workweek	5155	−24
SaM & Worker Effort	5211	88
Full Model	5197	60
Full Model (intertemporal search)	5183	32

NOTE: Log data densities are calculated by the modified harmonic mean following Geweke (1999). To compare different versions of the model, I use the $2ln$ Bayer factor as described by Kass and Raftery (1995).

data as an important margin to explain variable capacity utilization. However, combining *variable goods market SaM and worker effort* leads to the highest log data density in this paper with a log Bayes factor of 88 compared to the benchmark model. This result reinforces the findings of Lewis et al. (2019) while at the same time supports the modeling of fritional goods markets and the active but unobserved input of household search effort.

The full model - the combination of the benchmark and SaM models - shows a decisive improvement in log data density over the benchmark model with a log Bayes factor of 60. This log Bayes factor is about 28 points smaller than for the model featuring *variable goods market SaM and worker effort*. Hence, a *variable capital workweek* is also not favored in a model with all capacity utilization margins. Adding *intertemporal search-and-matching margins* - habit formation in search effort, long-term contracts, and inventories - decreases the log data density of the model decisively with a reduction in the Bayes factor of 28 points. As the posterior estimates show (see table 2 and figure 1), the parameters of all three margins indicate that neither one is improving the log data density of the model.

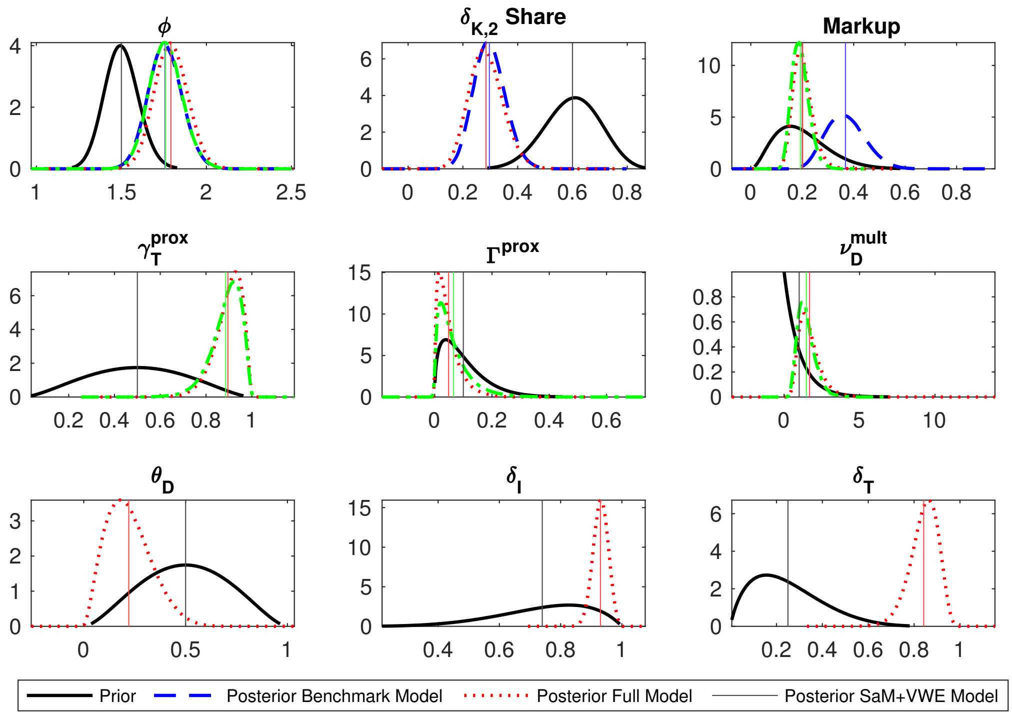
The results presented in this section are in line with a variety of robustness checks: (1) using the full available data sample 1967q1 to 2019q4, (2) excluding data post-2006q4 to exclude the zero lower bound period and the Wu and Xia (2016) shadow rate estimates, (3) fixing $\epsilon = 6$ and $\alpha = 0.2$ as in Comin et al. (2025) instead of estimating the steady-state markup, (4) dropping capacity utilization data and goods market mismatch shocks from the estimation, and (5) assuming zero fixed cost of production. 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 benchmark model especially improves the correlations between inflation, capacity utilization, and TFP. The results are given in Appendix D.2. In the following analysis, I compare the benchmark model, the SaM & worker effort (SaM-VWE) model, and the full model including intertemporal SaM margins. This set of models includes the benchmark model of the literature, the most likely model in this estimation, as well as the model including all prior information.

4.2. Parameter Posteriors of the Utilization Margins

The results of the log data density analysis in section 4.1 are confirmed by the posterior densities of the SaM-VWE and full models given in figure 1. The data is informative on the parameters of the utilization margins. The posterior estimates of the parameters are all well within their prior intervals, except for the esitmate for δ_T. Most of the parameters are similar across the three models. The differences are discussed below.

Figure 1 shows the prior and posterior densities of the parameters defining the capacity utilization channels in the benchmark and full model. A full overview of the parameters is given in table 2. The returns to scale parameter $\phi = 1 + \frac{\nu_H}{1+\nu_e}$ - indicating the elasticity of *variable worker effort* - is estimtated to be higher in all three models compared to its prior. Its estimate ranges between 1.76 to 1.79 across the models, which implies nu_e in the range of 1.84 to 2.21 given ν_H of the respective models. These results imply a worker effort supply elasticity at the lower bound proposed by the literature (e.g. Bils and Cho (1994)) with a slightly more elastic margin as we add *variable goods market SaM*. The posterior standard deviation is close to its prior counterpart indicating low data information on this parameter. The share of capital depreciation determined by the *variable capital workweek* is about 50% lower than its prior mean across the benchmark and full models with a slightly lower value for

Figure 1: Prior-Posteriors of the Utilization Parameters



NOTE: The figure shows the prior and posterior distribution for the benchmark and full model. The estimation follows the description in Appendix D.

the full model. Its posterior standard deviation decreases significantly indicating high data information on this parameter. Steady-state markup posterior estimates - indicating the fixed cost of production - are higher in the benchmark model compared to the prior mean while they are close to the prior mean for the SaM-VWE and full models. Steady-state markups almost double for the benchmark model with a value of 37%, which implies significantly higher fixed cost of production in the benchmark model. This pattern is also shown by Qiu and Rios-Rull (2022) in a complementing analysis. The posterior standard deviations of all three models decrease compared to the prior standard deviation. However, for the SaM-VWE and full models the parameter is tightly identified while for the benchmark model posterior standard deviation only slighlty decreases. The posterior densities indicate that *variable worker effort* is favored by the data while *variable capital workweek* is less important and well identified. For a higher prior standard deviation, it converges to zero. Goods market

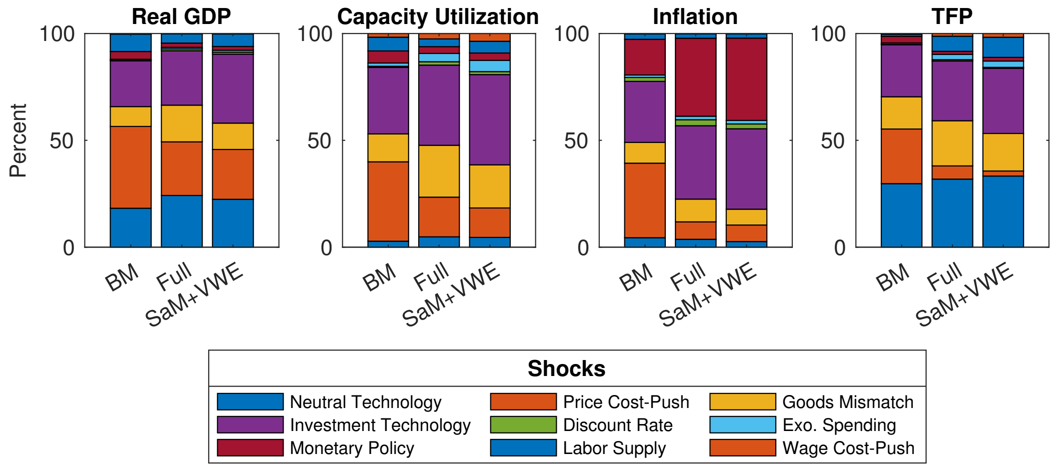
SaM partially substitutes for the capital workweek and worker effort channels.

The *variable goods market SaM* parameters are all well identified with posterior standard deviations lower than their prior counterpart. The search-and-matching process is determined by search effort with a significant weight in the matching function close to its imposed boundary of $\gamma_T = 0.33$, which is in line with Qiu and Rios-Rull (2022); Bai et al. (2025). The goods market matching function is close to Cobb-Douglas with Γ between 0.05 to 0.07 showing almost unit elasticity between search effort and goods supply. This estimate implies that search effort significantly drives capacity utilization fluctuations as it can substitute for (insufficient) goods supply. If the two would be greater complements, search effort would mainly drive marginal search cost but not capacity utilization over the business cycle. The search effort supply elasticity is about 50% to 70% lower than the Frisch elasticity of labor supply which is in line with Bai et al. (2025) but at stark contrast to $\nu_D = 0$ as in Qiu and Rios-Rull (2022). All three intertemporal search-and-matching margins converge to their insignificance, supporting the lower log data density for the model featuring those margins. Overall, the parameter posteriors of the SaM-VWE and full models show the importance of *variable goods market SaM* in explaining capacity utilization data. The posterior estimates further seem to be robust as they are close between those two models even though with drop the *variable capital workweek* and the intertemporal search-and-matching margins in the SaM-VWE model. A complete overview of the prior setup, posterior estimates, and their 90% HDP intervals for all parameters is given in table 2.

4.3. Variance Decomposition: The Determinants of the Efficiency 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. Figure 2 shows the variance decomposition for four variables - real GDP, capacity utilization, inflation, and TFP - for our three main models. The dominant driving forces of the business cycle are the Hicks-neutral technology shock explaining between 18% to 24% of variation in GDP, the price cost-push shock explaining bteween 23% to 38% of variation in GDP, and the investment-specific technology shock explaining between 21% to

Figure 2: Variance Decomposition of Benchmark and Full Model



NOTE: The figure shows the variance decomposition of the three main models: (1) Benchmark model (BM), (2) full model (Full), and (3) the search-and-matching + variable worker effort (SaM+VWE) model. The share of the variance of a variable explained by a certain shock is indicated by color and ordered from the bottom of the top of the figure with the bottom shock representing the first shock in the legend.

32% of variation in GDP. To a smaller extent, the goods market mismatch and hours supply shocks explaining between 9% to 17% and 6% to 8%, respectively. The remaining shocks are only marginally important to explain real GDP fluctuations in this model economy.

There is a general pattern in the variance decomposition as we add *variable goods market SaM*. The share of Hicks-neutral technology shocks explaining business cycle fluctuations slightly increases. A similar pattern can be observed for goods market mismatch shocks. The share of variation explained by price cost-push shocks decreases significantly, while the share of investment-specific technology shocks increases significantly. These patterns indicate a shift from supply shocks to demand shocks in explaining business cycle fluctuations in the model 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[27].

For capacity utilization, Hicks-neutral technology shocks do not matter with a variance share

[27]Similar effects have been shown for input factor reallocation to more productive firms over the business cycle by e.g. Basu et al. (2006).

of up to 1.5% across all models. This follows from the negative correlation between real GDP and capacity utilization of the shock, which is not a common feature of the data. Goods market mismatch shocks on the other hand show a significant increase of up to 11%-points in explaining the variance of capacity utilization. This pattern follows from the unconstrained impact on this shock on capacity utilization while frictional goods markets decrease the propagation of other shocks. Investment-specific technology shocks show a similar increase in explaining the variation of capacity utilization by up to 11%-points as we add *variable goods market SaM*. This pattern results from the strong demand component of this shock increasing the wealth of households and hence their search effort on the goods market. Price cost-push shocks on the other hand show a strong decrease by up to 23%-points, which is in line with its decrease in explaining real GDP variations. Adding *variable goods market SaM* creates an endogenous price elasticity of demand which increases in marginal search cost as demand expands after an expansionary price cost-push shock, leading to a significantly lower overall propagation. Monetary policy shocks, although overall less important, show a symmetric pattern for capacity utilization. Exogenous spending shocks show an increase in explaining capacity utilization as they indicate the shift to a more efficient markets (no search frictions) as we add *variable goods market SaM*.

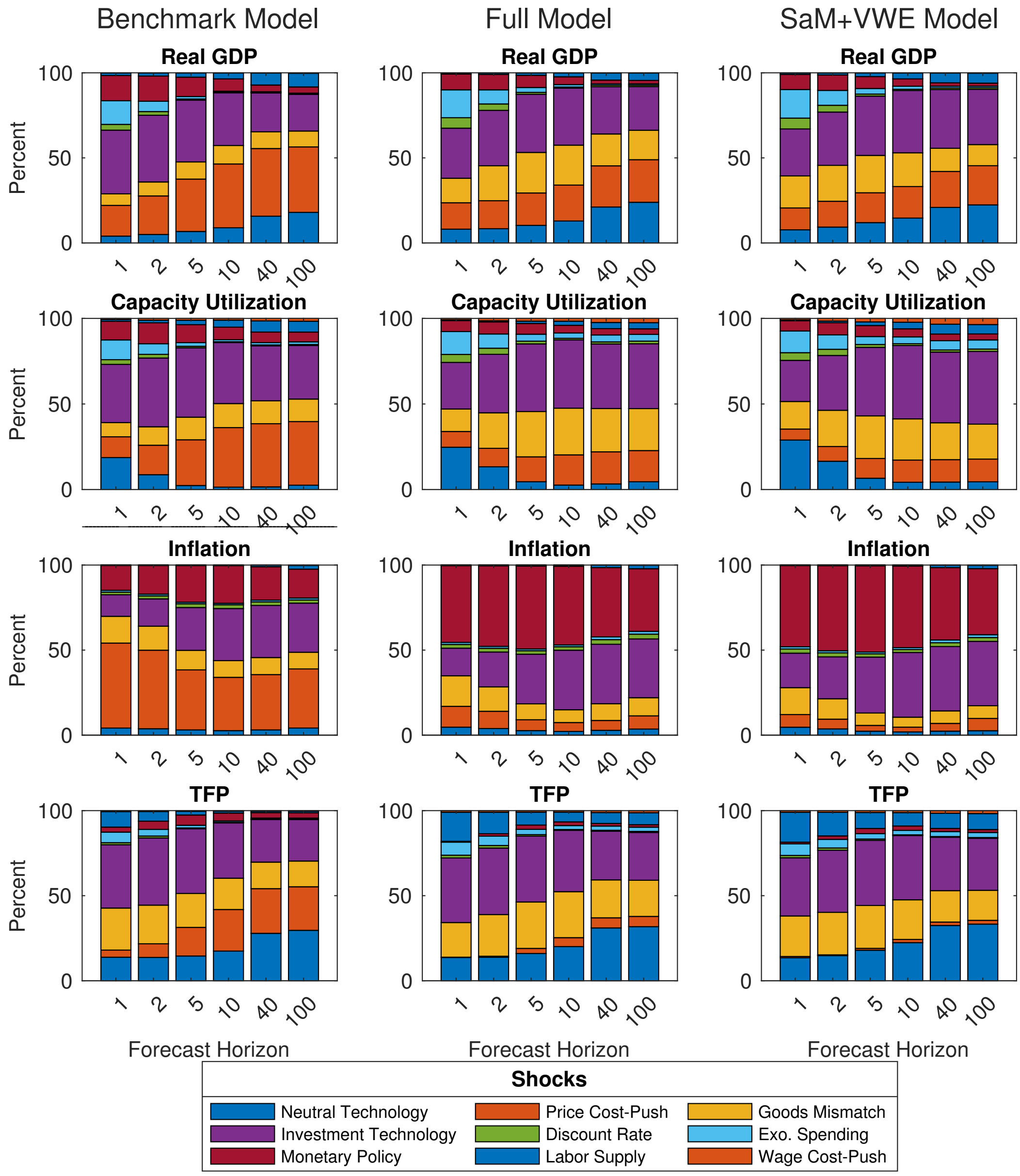
The variance decomposition of inflation shows generally the same pattern as capacity utilization with one stark difference: While price cost-push shocks explain very little of inflation variation as we add *variable goods market SaM*, monetary policy shocks seem to pick up the difference, becoming the main determinant of inflation variation besides investment-specific technology shocks. This pattern underlines the importance of the trade-off between sticky prices and search effort, i.e. the endogenous price elasticity of demand. 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 goods markets are frictional and trades require household search effort.

The general pattern of the variance decomposition of capacity utilization also applies for TFP with one difference: TFP variations are explained up to 33% in all three models due to the exogenous component of Hicks-neutral technology shocks. As capacity utilization does not have a significant impact on measured TFP following a Hicks-neutral technology shock, the shock propagates directly to TFP. Price cost-push shocks decrease and goods market mismatch and investment-specific technology shocks increase the share of TFP variation they explain due to their changed propagation of capacity utilization. Hours supply shocks become a significant determinant of TFP fluctuations increasing their share from 1% up to 9% as we add *variable goods market SaM*. The shock decreases labor disutility and thus labor supply. Households exert more search effort to match the additional production capacity available. As hours worked depend on other quasi-fixed production inputs, it does not increase significantly, leaving room to expand search effort beyond what is necessary to keep capacity utilization constant.

Figure 3 shows the conditional variance decomposition of 1, 2, 5, 10, 40 and 100 quarters ahead for the three main models. The first column of figures shows the benchmark model, the second column shows the full model, and the third column shows the SaM+VWE model. Building on the analysis of figure 2, this allows us to identify dynamic patterns in the variance decomposition.

The dynamic patterns of the real GDP, capacity utilization, and inflation variance decomposition are consistent across all three models with the quantitative differences in shocks as described in figure 2. Aggregate demand shocks like monetary policy and exogenous spending shocks explain up to 25% of real GDP in business cycle frequencies. At longer time horizons, technology shocks become more prominent. Hicks-neutral technology and exogenous spending shocks drive capacity utilization in the short-run but less so in the longer-run. Monetary policy shows a constant impact on capacity utilization over time. And the main drivers of capacity utilization - goods market mismatch and investment-specific technology shocks - explain about 50% of short-run variation in capacity utilization and increase their share for longer forecast horizons as other short-run effects die out. For inflation, price cost-push, goods market mismatch, and investment-specific shocks are strong drivers of the short-run, while monetary policy shocks explains up to 50% of inflation variation as we add *variable goods market SaM*. In the longer-run, monetary policy and investment-specific technology

Figure 3: Conditional Variance Decomposition of Benchmark and Full Model



NOTE: The figure shows the conditional variance decomposition of 1, 2, 5, 10, 40 and 100 quarters ahead for the three main models: (1) Benchmark model (BM), (2) full model (Full), and (3) the search-and-matching + variable worker effort (SaM+VWE) model. The share of the variance of a variable explained by a certain shock is indicated by color and ordered from the bottom of the top of the figure with the bottom shock representing the first shock in the legend.

shocks explain more than 80% of inflation in the economy.

The dynamic pattern of the TFP variance decomposition is mostly consistent across the three main models with one difference: Hours supply shocks have a longer-run impact on TFP instead only affecting short-run TFP variation as in the benchmark model. Both goods market mismatch and investment-specific technology shocks explain a significant part of short-run TFP variation which decreases over the longer-run as Hicks-neutral technology shocks become a more prominent driver of TFP. Exogenous spending shocks explain some of the TFP variation over the first two years but than decrease consistently. All these results show an initial impact of capacity utilization on TFP variation, which dies out in the longer-run leading shocks with a technology component to be the main determinants.

Overall, we see a shift from supply to demand and labor shocks in explaining variation in TFP over the business cycle. This pattern is driven by the variation of capacity utilization in the short-run which depends on search effort being a productive and substitutable input to the goods market matching function. Price cost-push shocks become insignificant for both inflation and TFP as the price elasticity of demand becomes endogenous due to marginal search cost. Marginal production cost are complemented by marginal search cost determined by unobserved household search effort changing the pattern of capacity utilization. The overall assessment of the change of TFP variance decomposition across models does not depend on whether we include goods market mismatch shocks as supply or demand shocks. 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.

5. Drivers of TFP over the Business Cycle

In this section, I show the impact of *variable goods market SaM* on the impulse responses of the efficiency wedge and decompose its determinants. Further, I show cumulative TFP multiplicators that put TFP fluctuations in perspective to GDP fluctuations of the model economy.

5.1. The Impact of the Efficiency Wedge on Measuring Technology

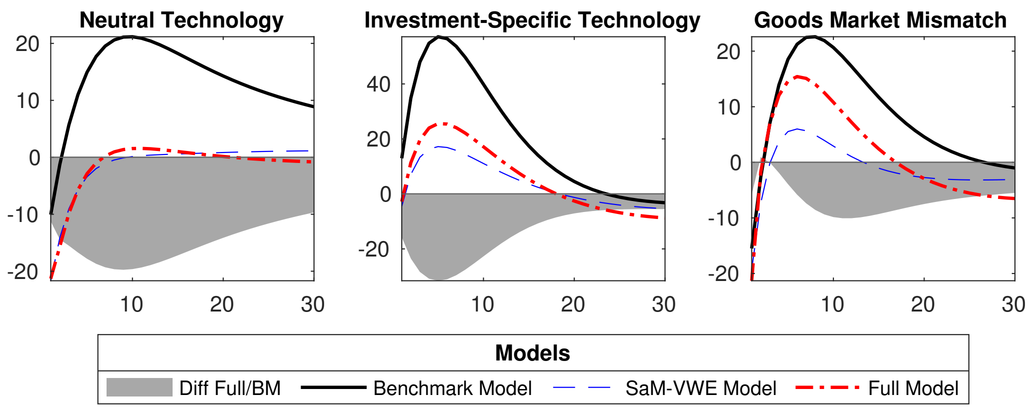
How large is the efficiency wedge between TFP and utilization-adjusted TFP for the different shocks over the business cycle? A positive efficiency wedge indicates that TFP overestimates the underlying utilization-adjusted TFP, vice-versa. I analyze the differences of the efficiency wedge impulse response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

Technology shocks. The defining feature of Hicks-neutral technology shock, investment-specific technology shock, and goods market mismatch shock is that they drive TFP both through the exogenous shock and endogenous propagation - they have some inherent technology component. Figure 4 shows efficiency wedge IRFs to expansionary technology shocks for the becnhmark, SaM-VWE, and full model.

The efficiency wedge IRF to the Hicks-neutral technology shock of the benchmark model shows a significant initial decrease - technology innovations are underestimated by TFP deviations. Prices are sticky, aggregate demand only adjusts gradually, thus capacity utilization is below its steady-state. Firms decrease their capital utilization, workers decrease their effort, and TFP increases by 10% less than technology. As prices adjust, the efficiency wedge turns positive over the medium-run. Aggregate demand increases as prices drop and income is high. We observe an overshooting of TFP by up to 20% as capacity utilization increases above its steady-state. Adding *variable goods market SaM* (either model) amplifies the initial negative impulse response of the efficiency wedge up to twice the impulse response of the benchmark 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. After about 7 quarters, the impulse response converges back to its steady-state. By comparing the results to the benchmark model, we see that the overshooting process in the benchmark model is driven by capital utilziation and worker effort, as it is not present in either model including *variable goods market SaM.*

The efficiency 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

Figure 4: The Cyclical Efficiency Wedge for the Technology Shocks

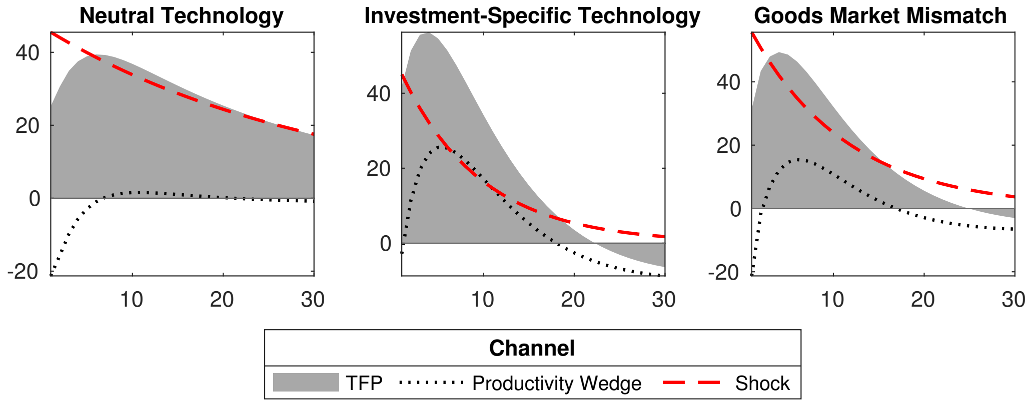


NOTE: The figure shows impulse response functions of the efficiency wedge to technology shocks according to (37). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the benchmark (black curves), SaM-VWE (blue curves), and full (red dashed curves) model.

stock increase significantly and show efficiency wedge deviations of up to 50% for the benchmark model - technology innovations are overestimated by TFP deviations. 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 efficiency wedge increase. As prices increase, the efficiency wedge decreases and converges back to its steady-state. In the long-run, the efficiency wedge turns negative as a capital stock above steady-state leads to production capacity above steady-state, both of which only slowly depreciate.

Adding *variable 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 efficiency wedge deviations are smaller compared to the benchmark model. The peak of efficiency wedge deviations for either model adding *variable goods market SaM* is about half compared to the benchmark model. The IRFs of all three models converge to each other as prices adjust and the short-run effect of search effort on capacity utilization declines.

Figure 5: Decomposing TFP into Wedge and Shock for the Technology Shocks

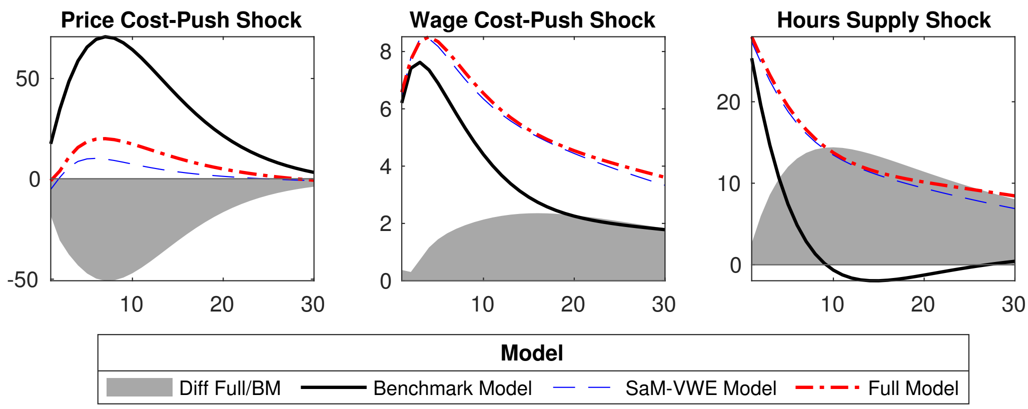


NOTE: The figure shows the decomposition of the impulse response functions of the efficiency wedge to technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. TFP IRFs (grey areas) are decomposed into the efficiency wedge (black dotted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

The efficiency wedge IRF to the goods market mismatch shock shows a similar pattern as the investment-specific technology shock. It shows a stronger initial decline of the efficiency wedge across models due to declining search effort as goods markets become more efficient. The decomposition of the TFP IRFs into a technology and efficiency wedge component can be seen in figure 5 for the full model. TFP underestimates technology for the Hicks-neutral technology shock, and overestimates technology for the investment-specific technology shock. For the goods market mismatch shock we find an initial underestimation of the efficiency gains by TFP but an overestimation in the medium run. The shock component shows larger and more persistent deviations for all three technology shocks. The shock component dominates TFP deviations for the Hicks-neutral technology and goods market mismatch shocks. In contrast, it shows about the same deviations as the efficiency wedge for the investment-specific technology shock in the medium-run. The investment-specific technology shock shows a consistent amplification of TFP deviations over its technology shock. It is a prime example why TFP and technology fluctuations should be considered as two distinct margins.

Labor 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 6: The Cyclical Efficiency Wedge for Labor Shocks

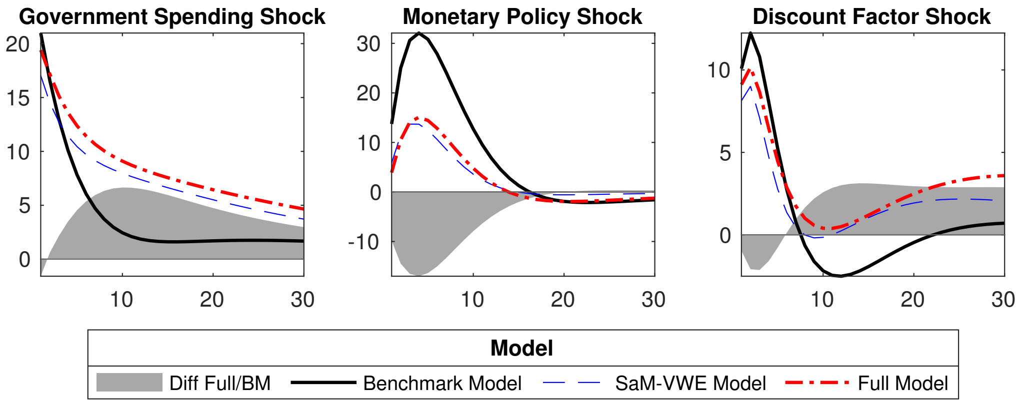


NOTE: The figure shows impulse response functions of the efficiency wedge to labor shocks according to (37). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the benchmark (black curves), SaM-VWE (blue curves), and full (red dashed curves) model.

Figure 6 shows efficiency wedge IRFs to price cost-push, wage cost-push, and hours supply shocks. The price cost-push shock is expansionary as markups decrease. The two labor shocks are contractionary as wage bargaining power of household or hours supply disutility increase. We observe positive efficiency wedge deviations for all three shocks in the benchmark model. Lower product prices or lower labor supply lead to higher search effort, thus higher demand and utilization given quasi-fixed production inputs.

Adding *variable goods market SaM* decreases the efficiency wedge deviations for the price cost-push shock. Additional aggregate demand requires additional search effort. As this is costly, households ask for lower prices to increase aggregate demand by the same amount as in the benchmark model. This trade-off leads to a lower expansion of aggregate demand, thus of the efficiency wedge. In contrast, adding *variable goods market SaM* increases efficiency wedge deviations for both labor shocks. Production capacity declines as labor becomes more expensive. In the trade-off between labor and search effort supply, households increase search effort as the relative price has decreased. The peak efficiency wedge deviations decrease from 70% to 20% for the price cost-psuh shock, increase from 7.5% to 8.5% for the wage cost-push shock, and from 25% to 28% for the hours supply shock. The persistence of the hours supply shock increases as well.

Figure 7: The Cyclical Efficiency Wedge for Demand Shocks



The figure shows impulse response functions of the efficiency wedge to demand shocks according to (37). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the benchmark (black curves), SaM-VWE (blue curves), and full (red dashed curves) model.

Demand shocks. Demand shocks, like labor shocks, have no inherent technology component. Thus, TFP following a demand shock is only driven by fluctuations in capacity utilization. Figure 7 shows efficiency wedge IRFs to government spending, monetary policy, and discount factor shocks. All three shocks are expansionary as the government buys more goods, monetary policy decreases its interest rate, or households are less inclined to save. We observe positive efficiency wedge deviations for all three shocks in the benchmark model. Higher aggregate demand leads to higher utilization of quasi-fixed inputs in the benchmark model. However, after an initial increase for the discount rate shock, both aggregate demand and the efficiency wedge show negative deviations from the steady-state as the initial increase in demand lead to underinvestment into the capital stock.Adding *variable goods market SaM* increases efficiency wedge deviations for the government spending shock, decreases them for monetary policy shocks, and shows an ambiguous pattern for the discount factor shock. Government spending (or exogenous spending to avoid the label) is a more efficient trading arrangement in this economy as it does not require search effort. As it increases, it directly increases utilization and thus the efficiency wedge. At the same time, it decreases available production capacity without lowering revenue for firms. Goods market tightness increases leading to an increase in TFP. The decrease in efficiency wedge deviations for monetary policy shocks follow the same reason as for price cost-push shocks: Lower prices alone do not increase aggregate demand, search effort also has to increase. This lowers the overall change in aggregate demand and thus the increase in utilization, the efficiency wedge, and TFP. The discount factor shock shows the same pattern. Yet, with *variable goods market SaM* it does not show a negative deviation in the efficiency wedge. The peak efficiency wedge deviations decrease from 21% to 19.5% for the government spending shock. However, efficiency wedge deviations show a much more persistent deviation from steady-state. For monetary policy shocks, the peak efficiency wedge decreases from 31% to 15% keeping its general persistency pattern. For the discount factor shock, the peak efficiency wedge deviation decreases from 12% to 10%. However, its throught efficiency wedge deviation increases from -2.2% to 0.2%, showing a persistent positive efficiency wedge deviation over the medium-run.

General pattern. 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 propagation mechanisms as we add *variable goods market SaM*. It is determined by the impact of marginal search cost on the price elasticity of demand and the variation of goods market tightness (determined by the substitutability of search effort and goods supply) that can alleviate otherwise strong increases in marginal search cost. The active household search effort channel becomes an important driver of capacity utilization.

5.2. Capacity Utilization Channel Decomposition

The fluctuations in the efficiency wedge are driven by the labor, capital, goods market, and fixed cost channel as shown in (37). Adding goods market SaM shifts the efficiency wedge drivers from fixed production cost to goods markets fricitons while the labor channel has a similar impact across models and the capital channel decreases somewhat in goods market SaM (if it is part of the model). This pattern is confirmed in section 4.2 which shows high and significant goods market SaM parameters and a strong reduction in steady-state markups as we add *variable goods market SaM*. In this section, I analyze the impact of adding goods market SaM on the efficiency wedge decomposition for each shock. The efficiency wedge variance share of each channel is given by the share of absolute fluctuations in the

Table 4: Decomposition of the Efficiency wedge Fluctuations

		eA	eP	eT	eI	eZ	eG	eM	eH	eW
	Benchmark model	11	20	18	21	24	24	30	47	70
Labor channel	SaM-VWE model	7	23	23	23	28	28	36	52	74
	Full model	9	21	23	21	22	23	40	50	73
	Benchmark model	9	20	16	21	29	16	20	6	3
Capital channel	SaM-VWE model	0	0	0	0	0	0	0	0	0
	Full model	7	13	17	20	23	17	16	5	2
	Benchmark model	3	5	6	5	4	30	4	4	2
SaM channel	SaM-VWE model	47	44	42	37	49	55	40	31	17
	Full model	43	38	26	29	36	47	20	28	16
	Benchmark model	77	55	60	53	43	31	46	43	24
Fixed cost channel	SaM-VWE model	46	33	35	40	23	16	24	17	9
	Full model	41	27	34	30	19	13	23	16	8

NOTE: The efficiency wedge variance share of each channel is given by the share of absolute fluctuations in labor, capital, goods market, and fixed cost efficiency wedge. Shock abbreviations: eA: Hicks-neutral technology shock, eP: Price cost-push shock, eT: Goods market mismatch shock, eI: Investment-specific technology shock, eZ: Discount factor shock, eG: Government spending shock, eM: Monetay policy shock, eH: Hours supply shock, eW: Wage cost-push shock.

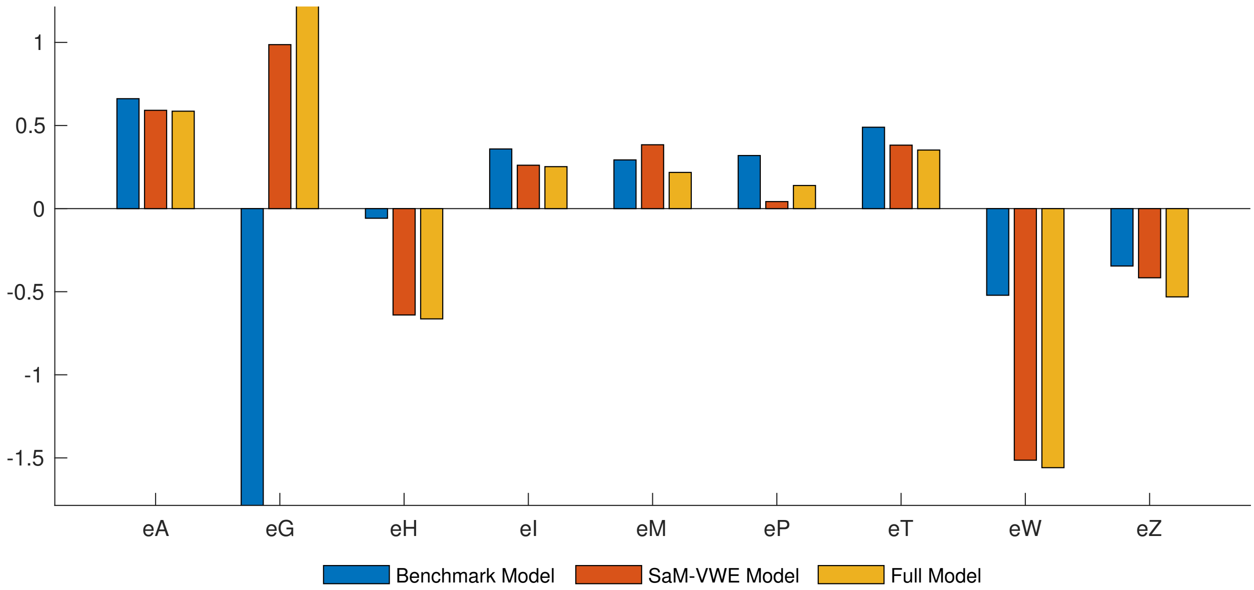
efficiency wedge due to labor, capital, goods market, and fixed cost. The results are shown in table 4.

In line with the prior-posterior analysis of the parameters, I find that in the benchmark model the labor channel ($70 - 74\%$) is significantly more important than capital utilization ($9 - 29\%$) in driving the efficiency wedge fluctuations across shocks. The result is in line with Lewis et al. (2019). The goods market SaM channel represents $3 - 6\%$ of efficiency wedge fluctuations in the benchmark model (with the discount factor shock being an outlier that amounts almost no variance share in the decomposition). 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 *variable capital workweek* channel is somewhat more important for non-labor shocks, while the *variable worker effort* channel is especially

important for the two labor shocks. The fixed cost of production channel is especially important in explaining the efficiency wedge variation for all technology shocks and the price cost-push shock. Overall, the most important channel for efficiency wedge variation appears to be the fixed cost of production channel (explaining the estimated steady-state markup of 37%, see 2), followed second by the *variable worker effort channel*.
Adding the *variable goods market SaM* channel reduces the variance share of the efficiency wedge explained by *variable capital workweek and worker effort*, but not consistently so across shocks. The *variable goods market SaM* channel accounts for 17% to 55% of efficiency wedge variation, with only one shock showing a share below 30%. This is the largest single share of any channel for six shocks, while the efficiency wedge of two shocks is mainly explained by *variable worker effort* (hours supply and wage cost-push shocks) and for one shock by fixed cost of production (investment-specific technology shock). Along the results found in section 4.2, the decrease is especially pronounced for the capital utilization channel and fixed cost of production, while the worker effort channel also becomes less important, but still explains a sizeable share of efficiency wedge fluctuations. The result emphasizes the significant impact of the *variable goods market SaM* channel across all shocks, but especially on demand shocks in the SaM-VWE model.

Summary. Goods market SaM puts the trade-off between household search effort and sticky prices to the center of the efficiency 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 efficiency wedge decomposition shows, that goods market SaM is the dominant driver of the efficiency wedge across most shocks. Adding goods market SaM decreases especially the importance of the variabble capital workweek and fixed cost of production in driving the efficiency wedge. In this framework, "demand shocks look like supply shocks" (Bai et al., 2025) if prices are sticky and goods markets are demand-driven.

Figure 8: Cumulative TFP Multiplicators



NOTE: The figure shows cumulative TFP and efficiency wedge multiplicators for the benchmark, SaM-VWE, and full model according to (39). Shock abbreviations: eA: Hicks-neutral technology shock, eG: Government spending shock eH: Hours supply shock, eI: Investment-specific technology shock, eM: Monetay policy shock, eP: Price cost-push shock, eT: Goods market mismatch shock, eW: Wage cost-push shock, eZ: Discount factor shock.

5.3. Cumulative TFP Multiplicators

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 fluctuations relative to GDP fluctuations. It is given by

$$\Lambda_{TFP,cum} \quad = \quad \frac{\sum_{t=1}^{50} T\hat{F}P_t}{\sum_{t=1}^{50} G\hat{D}P_t}, \tag{39}$$

where I use the first 50 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.

We observe cumulative TFP multiplicators that are clearly dominated by technology shocks for the benchmark model. The Hicks-neutral technology and goods market matching shocks show cumulative TFP multiplicators of about 0.5 to 0.6, and the investment-specific technology shock of about 0.4[28]. The monetary policy and price cost-push shocks show cumulative TFP multiplicators of about 0.25. The labor and discount factor shocks show a negative cumulative TFP multiplicator as GDP increases mainly through the use of more inputs rather than higher utilization of those.

Compared to the benchmark model, the SaM-VWE and full model cumulative TFP multiplicators for the three technology shocks show decreases of up to 30% for the full model. The cost-push shock shows an even stronger decrease in the cumulative TFP multiplicator to basically zero for the SaM-VWE model and less than half for the full model. Thus, the impact of *variable goods market SaM* is stronger on the efficiency wedge than on GDP (though both decrease in their variation). Compared to the benchmark model, the SaM-VWE and full model cumulative TFP multiplicators for the labor and discount factor shocks decrease significantly. This shows the opportunity of households to substitute search effort for labor supply if labor supply becomes relatively more expensive to the household. GDP decreases, but due to an increase in unobserved search effort, utilization of the production capacity increases. As figure 8 shows, this leads to (negative) cumulative TFP multiplicators that compete in absolute size with the multiplicators of the technology shocks.

Compared to the benchmark model, the SaM-VWE cumulative TFP multiplicators increase for monetary policy shocks while they decrease for the full model. For the SaM-VWE model, monetary policy shows cumulative TFP multiplicators similar to 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.

Compared to the analysis of the efficiency wedge IRFs before, we see that the impact of the *variable goods market SaM* channel on the economy is less pronounced when we set it

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

relative to GDP. It shows a similar impact on both TFP and GDP for the technology shocks, hence the TFP multiplicators are similar across models. The cumulative TFP multiplicator for monetary policy shocks shows a similar picture as for its efficiency wedge IRF for the full model, however not for the SaM-VWE model where productivity is amplified. The price cost-push shock replicates is close to zero variation of the efficiency wedge in the cumultaive TPF multiplicators. The labor shocks show highly negative cumulative TFP multiplicators reflecting their strong increase in efficiency wedge variation as shown by their IRFs. Therefore, demand and labor shocks show stronger amplification of productivity over GDP (both positive and negative) as we add *variable goods market SaM*. Technology shocks show a general decline in their cumulative TFP multiplicators.

6. 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 *variable 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 one of the two most important capacity utilization channel in explaining short-run TFP fluctuations, complementing worker effort and substituting for the capital workweek and fixed cost of production. The trade-off between household search effort and sticky prices is at the center of short-run TFP fluctuations as it endogeneizes the price elasticity of demand and capacity utilization based on household search input. The data favors a significant impact of search effort as a substitute for goods supply in short-run matching with search effort being less elastic than labor supply. markups and fixed cost of production reduce by 50% compared to a benchmark NK model. Overall, the *variable goods market SaM* model challenges the view that short-run TFP is mostly supply driven.

How do the different capacity utilization channels affect the transmission of economic shocks on short-run TFP? Adding *variable goods market* SaM leads to an increase in TFP fluctuations following demand shocks, while it leads to a decrease following technology shocks. Cost-push shocks show a significant decline in explaining both inflation and TFP variation in the data as the endogeneous price elasticity of demand reduces their impact. Labor shocks create a pattern of increasing utilization in a decreasing economy as households have alternative productive uses of their time. These effects are strongest if search effort is inelastic, matching inputs are complements, and prices are sticky. Cumulative TFP multiplicators - TFP flucutations relative to GDP fluctuations - show the same pattern but somewhat muted.

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 household search effort and sticky prices. The paper shows that variations in TFP are driven much more by goods market frictions than by utilization decisions of 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 *variable goods market SaM* can lead to biased estimates of the drivers of TFP over the business cycle.

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Appendix A. Model Setup and Derivations

Appendix A.1. Household Optimization Problem

The household maximizes its utility by choosing $C_{S,t}$, C_t, $D_t(i)$, X_t, B_t, $T_t(i)$, $e_{K,t}$, K_t, $I_{A,t}$, $I_{K,t}$, and $N_t(i)$. Its constrained utility maximization problem is given by

$$
\begin{aligned}
\mathcal{L} \ &= \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t Z_t \Bigg\{ \frac{\Big[\mathbb{U}_C \left(C_{S,t}; C_{S,t-1}; D_t(i); D_{t-1}(i)\right) - \mathbb{U}_N \left(X_t; N_t(i); H_t(i); e_{H,t}(i)\right)\Big]^{1-\sigma} - 1}{1-\sigma} \\
&- \lambda_{1,t} \Bigg[B_t - \left(1 + r_{B,t-1}\right) B_{t-1} - \int_0^1 W_t(i) e_{H,t}(i) H_t(i) N_t(i) di - P_t ub \left(1 - \int_0^1 N_t(i) di\right) \\
&\qquad + \int_0^1 P_t(i) T_t(i) di - P_t r_{K,t} e_{K,t} K_{t-1} + Tax_t - \Pi_t \Bigg] \\
&- \lambda_{2,t} \left[X_t - \Big[\mathbb{U}_C \left(C_{S,t}; C_{S,t-1}; D_t(i); D_{t-1}(i)\right)\Big]^{\omega} X_{t-1}^{1-\omega} \right] \\
&- \lambda_{3,t} \left[C_t + P_{I,t} I_{K,t} \left(1 + c_I \left(I_{A,t}; I_{A,t-1}\right)\right) - \left(\int_0^1 T_t(i)^{\frac{\epsilon_t - 1}{\epsilon_t}} di \right)^{\frac{\epsilon_t}{\epsilon_t - 1}} \right] \\
&- \int_0^1 \lambda_{4,t}(i) \Big[T_t(i) - \left(1 - \delta_T\right) T_{t-1}(i) - f_{T,t}(i) D_t(i) \Big] di \\
&- \lambda_{5,t} \left[\int_0^1 N_t(i) di - \left(1 - \delta_N\right) \int_0^1 N_{t-1}(i) di - f_{N,t} \left(1 - \left(1 - \delta_N\right) \int_0^1 N_{t-1}(i) di\right) \right] \\
&- \lambda_{6,t} \left[K_t - \left(1 - \delta_{K,1} - \delta_K \left(e_{K,t}\right)\right) K_{t-1} - I_{K,t} \right] \\
&- \lambda_{7,t} \left[C_{S,t} - \left(1 - \delta_S\right) C_{S,t-1} - C_t \right] \\
&- \lambda_{8,t} \left[I_{A,t} - I_{K,t} + \delta_K \left(e_{K,t}\right) K_{t-1} \right] \Bigg\},
\end{aligned}
$$

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

First-order conditions.

$$
\begin{aligned}
\mathcal{L}_{C_{S,t}}: \lambda_{3,t} =& \left(\frac{1}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^{\sigma}}+\frac{\omega X_t \lambda_{2,t}}{\mathbb{U}_{C,t}}\right)\frac{\partial \mathbb{U}_{C,t}}{\partial C_{S,t}}+\beta\left(1-\delta_S\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{3,t+1} \\
&+\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\left(\frac{1}{\left(\mathbb{U}_{C,t+1}-\mathbb{U}_{N,t+1}\right)^{\sigma}}+\frac{\omega X_{t+1}\lambda_{2,t+1}}{\mathbb{U}_{C,t+1}}\right)\frac{\partial \mathbb{U}_{C,t+1}}{\partial C_{S,t}}
\end{aligned} \tag{A.1}
$$

$$
\begin{aligned}
\mathcal{L}_{D_t(i)}: \lambda_{4,t} =& (-1)\left[\frac{1}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^{\sigma}}+\frac{\omega X_t\lambda_{2,t}}{\mathbb{U}_{C,t}}\right]\frac{\frac{\partial \mathbb{U}_{C,t}}{\partial D_t(i)}}{f_{T,t}(i)} \\
&-\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\left[\frac{1}{\left(\mathbb{U}_{C,t+1}-\mathbb{U}_{N,t+1}\right)^{\sigma}}+\frac{\omega X_{t+1}\lambda_{2,t+1}}{\mathbb{U}_{C,t+1}}\right]\frac{\frac{\partial \mathbb{U}_{C,t+1}}{\partial D_t(i)}}{f_{T,t}(i)}
\end{aligned} \tag{A.2}
$$

$$
\mathcal{L}_{X_t}: \lambda_{2,t}X_t = \frac{(-1)\mathbb{U}_{N,t}}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^{\sigma}}+\beta\left(1-\omega\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{2,t+1}X_{t+1} \tag{A.3}
$$

$$
\mathcal{L}_{B_t}: \lambda_{1,t} = \beta\left(1+r_{B,t}\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{1,t+1} \tag{A.4}
$$

$$
\mathcal{L}_{T_t(i)}: \lambda_{1,t}P_t(i) = \lambda_{3,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}}-\lambda_{4,t}+\beta\left(1-\delta_T\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{4,t+1} \tag{A.5}
$$

$$
\begin{aligned}
\mathcal{L}_{N_t(i)}: \lambda_{5,t} =& \lambda_{1,t}\left(W_t(i)e_{H,t}(i)H_t(i)-P_t ub\right)-\frac{\frac{\partial \mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^{\sigma}}, \\
&+\beta\left(1-\delta_N\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\left(1-f_{N,t+1}\right)\lambda_{5,t+1}
\end{aligned} \tag{A.6}
$$

$$
\begin{aligned}
\mathcal{L}_{e_{K,t}}: \lambda_{6,t}\frac{\partial \delta_K\left(e_{K,t}\right)}{\partial e_{K,t}}K_{t-1} =& \lambda_{1,t}P_t r_{K,t}-\lambda_{3,t}P_{I,t}I_{K,t}\frac{\partial c_{I,t}}{\partial e_{K,t}} \\
&-\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{3,t+1}P_{I,t+1}I_{K,t+1}\frac{\partial c_{I,t+1}}{\partial e_{K,t}}
\end{aligned} \tag{A.7}
$$

$$
\begin{aligned}
\mathcal{L}_{K_t}: \lambda_{6,t} =& \beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\left(\lambda_{1,t+1}P_{t+1}e_{K,t+1}r_{K,t+1}+\left(1-\delta_K(e_{K,t})\right)\lambda_{6,t+1}\right) \\
&-\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\left[P_{I,t+1}I_{K,t+1}\frac{\partial c_{I,t+1}}{\partial K_t}\lambda_{3,t+1}+\beta\frac{Z_{t+2}}{Z_{t+1}}P_{I,t+2}I_{K,t+2}\frac{\partial c_{I,t+2}}{\partial K_t}\lambda_{3,t+2}\right]
\end{aligned} \tag{A.8}
$$

$$
\mathcal{L}_{I_{K,t}}: \lambda_{6,t} = \lambda_{3,t}P_{I,t}\left(1+c_{I,t}+\frac{\partial c_{I,t}}{\partial I_{K,t}}\right)+\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\lambda_{3,t+1}P_{I,t+1}I_{K,t+1}\frac{\partial c_{I,t+1}}{\partial I_{K,t}} \tag{A.9}
$$

Applying functional forms. We use the following functional forms for the utility function, investment adjustment costs, and capital utilization costs given by

$$\begin{aligned}
\mathbb{U}_{C,t} &= C_{S,t} - \theta_C C_{S,t-1} - \frac{\mu_{D,t}}{1+\nu_D}\left(\left(\int_0^1 D_t(i)di\right)^{1+\nu_D} - \theta_D\left(\int_0^1 D_{t-1}(i)di\right)^{1+\nu_D}\right),\\
\mathbb{U}_{N,t} &= X_t\int_0^1 N_t(i)\left(\frac{\mu_{H,t}}{1+\nu_H}H_t(i)^{1+\nu_H} + H_t(i)\frac{\mu_e}{1+\nu_e}e_{H,t}(i)^{1+\nu_e}\right)di,\\
I_{A,t} &= I_{K,t} - \delta_K\left(e_{K,t}\right)K_{t-1},\\
c_{I,t} &= \frac{\kappa_I}{2}\left(\frac{I_{A,t}}{I_{A,t-1}}-1\right)^2,\\
\delta_K\left(e_{K,t}\right) &= \frac{\phi_{K,1}\phi_{K,2}}{2}\left(e_{K,t}-1\right)^2 + \phi_{K,1}\left(e_{K,t}-1\right).
\end{aligned}$$

Further, we define $muc_t = \lambda_{1,t}P_t$, $\mathbb{W}_{C,t} = \lambda_{3,t}$, $\mathbb{W}_{D,t} = \lambda_{4,t}$, $\mathbb{U}_{\chi,t} = \frac{1}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^\sigma} + \frac{\omega X_t\lambda_{2,t}}{\mathbb{U}_{C,t}}$, and $\chi_t = \lambda_{2,t}X_t$ to rewrite (A.1), (A.2), (A.3), and (A.4) as follows

$$\mathbb{W}_{C,t} = \mathbb{U}_{\chi,t} - \beta\theta_C\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1} + \beta\left(1-\delta_S\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\mathbb{W}_{C,t+1}, \tag{A.10}$$

$$\mathbb{W}_{D,t} = \mathbb{U}_{\chi,t} - \beta\theta_D\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1}, \tag{A.11}$$

$$\chi_t = \beta\left(1-\omega\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\chi_{t+1} - \frac{\mathbb{U}_{N,t}}{\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^\sigma}, \tag{A.12}$$

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

where $(1+\pi_{t+1}) = \frac{P_{t+1}}{P_t}$ and $\beta\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\frac{muc_{t+1}}{muc_t} = \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}$ follows from the Euler equation (A.13). Marginal consumption utility is derived from (A.5) and given by

$$muc_t = \frac{P_t}{P_t(i)}\left[\mathbb{W}_{C,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} - \mathbb{W}_{D,t}c'_{D,t}(i) + \beta\left(1-\delta_T\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\mathbb{W}_{D,t+1}c'_{D,t+1}(i)\right],$$

$$\Leftrightarrow \frac{P_t(i)}{P_t} = P_{T,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} - P_{D,t}(i) + \left(1-\delta_T\right)\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}P_{D,t+1}(i) \tag{A.14}$$

where $P_{T,t} = \frac{\mathbb{W}_{C,t}}{muc_t}$, $P_{D,t}(i) = \frac{c'_{D,t}(i)\mathbb{W}_{D,t}}{muc_t}$, and $c'_{D,t}(i) = \mu_{D,t}\frac{D_t(i)^{\nu_D}}{f_{T,t}(i)}$. Define $Q_{H,t} = \frac{\lambda_{5,t}}{muc_t}$ and plug it into (A.6) to derive the value function of marginal employment of the household denominated in the numéraire good

$$\begin{aligned}
Q_{H,t}(i) = &\left(\frac{W_t(i)}{P_t}e_{H,t}(i)H_t(i) - ub\right) - \frac{\frac{\partial\mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{muc_t\left(\mathbb{U}_{C,t}-\mathbb{U}_{N,t}\right)^\sigma}\\
&+\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_N\right)\left(1-f_{N,t+1}\right)Q_{H,t+1}(i),
\end{aligned} \tag{A.15}$$

where $\frac{\partial \mathbb{U}_{N,t}(i)}{\partial N_t(i)} = X_t \left(\frac{\mu_{H,t}}{1+\nu_H} H_t(i)^{1+\nu_H} + H_t(i) \frac{\mu_e}{1+\nu_e} e_{H,t}(i)^{1+\nu_e} \right)$ is the marginal disutility of working for one specific firm i. Define $Q_{K,t} = \frac{\lambda_{6,t}}{muc_t}$ and rewrite the capital market equations (A.7)-(A.9) denominated in the numéraire good

$$
\begin{aligned}
r_{K,t} &= (1 + c_{I,t}) P_{T,t} P_{I,t} \left(\phi_{K,1} \phi_{K,2} (e_{K,t} - 1) + \phi_{K,1} \right), && \text{(A.16)} \\
Q_{K,t} &= P_{T,t} P_{I,t} \left[(1 + c_{I,t}) + \frac{I_{K,t} \left\{ c'_{I,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{P_{T,t+1} P_{I,t+1}}{P_{T,t} P_{I,t}} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1} \right\}}{I_{K,t} - \delta_K (e_{K,t}) K_{t-1}} \right], && \text{(A.17)} \\
Q_{K,t} &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \Big[r_{K,t+1} e_{K,t+1} + (1 - \delta_{K,1}) Q_{K,t+1} \\
&\qquad - (1 + c_{I,t+1}) P_{T,t+1} P_{I,t+1} \delta_K (e_{K,t+1}) \Big], && \text{(A.18)}
\end{aligned}
$$

where $c'_{I,t} = \kappa_I \left(\frac{I_{A,t}}{I_{A,t-1}} - 1 \right) \frac{I_{A,t}}{I_{A,t-1}}$. If we instead assume $I_{A,t} = I_{K,t}$, which implies that capital utilization costs affect investment adjustment costs through their impact on capital investments, the household capital FOCs are given by

$$
\begin{aligned}
Q_{K,t} &= \frac{r_{K,t}}{\phi_{K,1} \phi_{K,2} (e_{K,t} - 1) + \phi_{K,1}}, && \text{(A.19)} \\
Q_{K,t} &= P_{T,t} P_{I,t} \left(1 + c_{I,t} + c'_{I,t} \right) - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{T,t+1} P_{I,t+1} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1}, && \text{(A.20)} \\
Q_{K,t} &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_t} \left[e_{K,t+1} r_{K,t+1} + (1 - \delta_{K,1} - \delta_K (e_{K,t})) Q_{K,t+1} \right]. && \text{(A.21)}
\end{aligned}
$$

Price Elasticity of Demand. For any two varieties (i, j) of the differentiated consumption good, we can use (A.14) to derive the household consumption demand equation by

$$
\begin{aligned}
\frac{P_t(i)}{P_t(j)} &= \frac{\left(\frac{T_t}{T_t(i)} \right)^{\frac{1}{\epsilon_t}} \mathbb{W}_{C,t} - c'_{D,t}(i) \mathbb{W}_{D,t} + \beta (1 - \delta_T) \mathbb{E}_t \frac{Z_{t+1}}{Z_t} c'_{D,t+1}(i) \mathbb{W}_{D,t+1}}{\left(\frac{T_t}{T_t(j)} \right)^{\frac{1}{\epsilon_t}} \mathbb{W}_{C,t} - c'_{D,t}(j) \mathbb{W}_{D,t} + \beta (1 - \delta_T) \mathbb{E}_t \frac{Z_{t+1}}{Z_t} c'_{D,t+1}(j) \mathbb{W}_{D,t+1}}, \\
&= \frac{\left(\frac{T_t}{T_t(i)} \right)^{\frac{1}{\epsilon_t}} P_{T,t} - P_{D,t}(i) + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}(i)}{\left(\frac{T_t}{T_t(j)} \right)^{\frac{1}{\epsilon_t}} P_{T,t} - P_{D,t}(j) + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}(j)},
\end{aligned}
$$

where we use the definitions for search prices, $P_{D,t}(i) = \frac{c'_{D,t}(i) \mathbb{W}_{D,t}}{muc_t}$, and overall prices, $P_{T,t} = \frac{\mathbb{W}_{C,t}}{muc_t}$. The price elasticity of demand is defined by

$$
\Xi_t(i) = \frac{\partial T_t(i)}{\partial P_t(i)} \frac{P_t(i)}{T_t i},
$$

where we use (A.14) to derive the first-order condition. This results in

$$\begin{aligned}
\Xi_t(i) &= (-\epsilon_t)\frac{muc_t}{\mathbb{W}_{C,t}}\left(\frac{T_t(i)}{T_t}\right)^{\frac{1}{\epsilon_t}}\frac{P_t(i)}{P_t} \;=\; (-\epsilon_t)P_{T,t}^{-1}\left(\frac{T_t(i)}{T_t}\right)^{\frac{1}{\epsilon_t}}\frac{P_t(i)}{P_t}, \\
&= \frac{(-\epsilon_t)\frac{P_t(i)}{P_t}}{\frac{P_t(i)}{P_t} + P_{D,t}(i) - \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}P_{D,t+1}(i)}
\end{aligned}$$

which decreases in $P_{T,t}$ and thus in $P_{D,t}(i)$.

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

$$\begin{aligned}
\mathcal{L} &= \mathbb{E}_0\sum_{t=0}^{\infty}\beta_{0,t}\Bigg\{\Big[P_t(i)\left[T_t(i)+G_t(i)\right] - W_t(i)e_{H,t}(i)H_t(i)N_t(i) - P_t(i)r_{K,t}K_{e,t}(i)\Big] \\
&\quad - \phi_{1,t}\Big[S_t(i) - \left[1 - c_{N,t}(i) - c_{P,t}(i) - c_{W,t}(i) - c_{H,t}(i)\right]A_{H,t}F_t(i) + \vartheta \\
&\qquad + G_t(i) + (1-\delta_T)\,T_{t-1}(i) - (1-\delta_I)\,(1-q_{T,t-1}(i))\,S_{t-1}(i)\Big] \\
&\quad - \phi_{2,t}\Big[T_t(i) - (1-\delta_T)\,T_{t-1}(i) - q_{T,t}(i)S_t(i)\Big] \\
&\quad - \phi_{3,t}\Big[N_t(i) - (1-\delta_N)\,N_{t-1}(i) - q_{N,t}v_t(i)\Big] \\
&\quad - \phi_{4,t}\left[\frac{P_t(i)}{P_t} - P_{T,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} + P_{D,t}(i) - \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}P_{D,t+1}(i)\right]\Bigg\}
\end{aligned}$$

where

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

First-order conditions.

$$\mathcal{L}_{T_t(i)}:\phi_{2,t}=P_t(i)-\phi_{4,t}\frac{1}{\epsilon_t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}}\frac{P_{T,t}}{T_t(i)}+\mathbb{E}_t\beta_{t,t+1}\left(1-\delta_T\right)\left(\phi_{2,t+1}-\phi_{1,t+1}\right) \tag{A.22}$$

$$\begin{aligned}\mathcal{L}_{S_t(i)}:\phi_{1,t}=\phi_{2,t}\frac{\partial m_{T,t}(i)}{\partial S_t(i)}-\phi_{4,t}\frac{\partial P_{D,t}(i)}{\partial S_t(i)}\\ +\mathbb{E}_t\beta_{t,t+1}\left(1-\delta_I\right)\phi_{1,t+1}\left(1-q_{T,t}(i)-S_t(i)\frac{\partial q_{T,t}(i)}{\partial S_t(i)}\right)\end{aligned} \tag{A.23}$$

$$\mathcal{L}_{x_{T,t}(i)}:\phi_{4,t}\frac{\partial P_{D,t}(i)}{\partial x_{T,t}(i)}=\phi_{2,t}\frac{\partial m_{T,t}(i)}{\partial x_{T,t}(i)}-\mathbb{E}_t\beta_{t,t+1}\left(1-\delta_I\right)S_t(i)\frac{\partial q_{T,t}(i)}{\partial x_{T,t}(i)}\phi_{1,t+1} \tag{A.24}$$

$$\begin{aligned}\mathcal{L}_{P_t(i)}:\frac{\partial c_{P,t}(i)}{\partial P_t(i)}A_{H,t}F_t(i)\phi_{1,t}=T_t(i)+G_t(i)-\phi_{4,t}\frac{1}{P_t}\\ -\mathbb{E}_t\beta_{t,t+1}\phi_{1,t+1}A_{H,t+1}F_{t+1}(i)\frac{\partial c_{P,t+1}(i)}{\partial P_t(i)}\end{aligned} \tag{A.25}$$

$$\begin{aligned}\mathcal{L}_{N_t(i)}:\phi_{3,t}=\phi_{1,t}\frac{A_{H,t}F_t(i)}{N_t(i)}\left[\left(1-\alpha\right)\left(1-\mathcal{C}_t(i)\right)-\frac{\partial c_{N,t}(i)}{\partial N_t(i)}N_t(i)\right]\\ -W_t(i)e_{H,t}(i)H_t(i)+\mathbb{E}_t\beta_{t,t+1}\left(1-\delta_N\right)\phi_{3,t+1}\end{aligned} \tag{A.26}$$

$$\mathcal{L}_{v_t(i)}:\phi_{3,t}=\phi_{1,t}\frac{A_{H,t}F_t(i)}{q_{N,t}}\frac{\partial c_{N,t}(i)}{\partial v_t(i)} \tag{A.27}$$

$$\mathcal{L}_{K_{e,t}(i)}:P_t(i)r_{K,t}=\phi_{1,t}\left(1-\mathcal{C}_t(i)\right)\alpha\frac{A_{H,t}F_t(i)}{K_{e,t}(i)} \tag{A.28}$$

Define the asset value of production capacity as $Q_{Y,t}(i)=\frac{\phi_{1,t}}{P_t(i)}$, and the asset value of matched goods as $Q_{T,t}(i)=\frac{\phi_{2,t}}{P_t(i)}$. Marginal costs are given by $mc_t(i)=\frac{Q_{Y,t}(i)}{e_{M,t}(i)}$ where $e_{M,t}(i)=\frac{Y_t(i)}{\mathcal{Y}_t(i)}$ is short-run capacity utilization. Substitute (A.24) in (A.22), and (A.23) for the marginal costs equations

$$\begin{aligned}Q_{T,t}(i)&=\frac{\frac{P_t(i)}{P_t}+\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_T\right)\left(Q_{T,t+1}(i)-Q_{Y,t+1}(i)\right)}{1+\frac{1}{\epsilon_t}\varphi_{\mathbb{W},t}(i)\varphi_{\Gamma,t}(i)}\\ &\quad+\frac{\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_I\right)\frac{1}{\epsilon_t}\varphi_{\mathbb{W},t}(i)\varphi_{\Gamma,t}(i)Q_{Y,t+1}(i)}{1+\frac{1}{\epsilon_t}\varphi_{\mathbb{W},t}(i)\varphi_{\Gamma,t}(i)},\end{aligned} \tag{A.29}$$

$$\begin{aligned}Q_{Y,t}(i)&=q_{T,t}(i)Q_{T,t}(i)\frac{1+\varphi_{\Gamma,t}(i)}{1+\frac{\gamma_T x_{T,t}(i)^{\Gamma}}{1-\gamma_T}}\\ &\quad+\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_I\right)\left(1-q_{T,t}(i)\frac{1+\varphi_{\Gamma,t}(i)}{1+\frac{\gamma_T x_{T,t}(i)^{\Gamma}}{1-\gamma_T}}\right)Q_{Y,t+1}(i),\end{aligned} \tag{A.30}$$

where

$$\begin{aligned}\varphi_{\mathbb{W},t}(i)&=\frac{P_{T,t}}{P_{D,t}(i)}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}}\frac{q_{T,t}(i)S_t(i)}{T_t(i)},\\ \varphi_{\Gamma,t}(i)&=\frac{\gamma_T x_{T,t}(i)^{\Gamma}}{\left(1-\gamma_T\right)}.\end{aligned}$$

Substitute (A.24) in (A.25) for the New-Keynesian Phillips Curve

$$\begin{aligned} c'_{P,t}(i) &= \frac{T_t(i)}{A_{H,t}F_t(i)Q_{Y,t}(i)} \left[\left(1+\frac{G_t(i)}{T_t(i)}\right) - \frac{q_{T,t}(i)S_t(i)}{T_t(i)P_{D,t}(i)}\varphi_{\Gamma,t}(i)\left(Q_{T,t}(i) - \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_I\right)Q_{Y,t+1}(i)\right)\right] \\ &+ \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\frac{Q_{Y,t+1}(i)A_{H,t+1}F_{t+1}(i)}{Q_{Y,t}(i)A_{H,t}F_t(i)}c'_{P,t+1}(i). \end{aligned} \tag{A.31}$$

Define the value of marginal employment for the firm as $Q_{F,t}(i) = \frac{\phi_{3,t}}{P_t(i)}$ and rewrite the input factor demand equations (A.26)-(A.28) by

$$\begin{aligned} Q_{F,t}(i) &= \left[(1-\alpha)\left(1-\mathcal{C}_t(i)\right) + 2c_{N,t}(i)\right]\frac{A_{H,t}F_t(i)}{N_t(i)}Q_{Y,t}(i) - w_t(i)e_{H,t}(i)H_t(i) \\ &\quad + \mathbb{E}_t\frac{1+\pi_{t+1}(i)}{1+r_{B,t}}\left(1-\delta_N\right)Q_{F,t+1}(i), \end{aligned} \tag{A.32}$$

$$Q_{F,t}(i) = 2c_{N,t}(i)\frac{A_{H,t}F_t(i)}{q_{N,t}v_t(i)}Q_{Y,t}(i), \tag{A.33}$$

$$r_{K,t} = \left(1-\mathcal{C}_t(i)\right)\alpha\frac{A_{H,t}F_t(i)}{K_{e,t}(i)}Q_{Y,t}(i). \tag{A.34}$$

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

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

where $0 \leq \eta_t \leq 1$.
The first-order conditions for the real wage, hours per worker, and worker effort are given by

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

$$\frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial H_t(i)}}{\frac{\partial Q_{H,t}(i)}{\partial H_t(i)}} \tag{A.36}$$

$$\frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial e_{H,t}(i)}}{\frac{\partial Q_{H,t}(i)}{\partial e_{H,t}(i)}} \tag{A.37}$$

Deriving the first-order conditions of (A.15) and (A.32) with respect to $W_t(i)$ and plugging them into (A.35) gives the sticky wage horizon equation that determines the impact of sticky wages on the wage setting process

$$\tau_{W,t}(i) = \frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{Q_{H,t}(i)} = (-1)\frac{\frac{\partial Q_{F,t}(i)}{\partial W_t(i)}}{\frac{\partial Q_{H,t}(i)}{\partial W_t(i)}} \tag{A.38}$$

$$\begin{aligned} &= 1 + (1-\alpha)\frac{A_{H,t}F_t(i)}{e_{H,t}(i)H_t(i)N_t(i)}Q_{Y,t}(i)P_t\frac{\partial c_{W,t}(i)}{\partial W_t(i)} \\ &+ \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}(1-\delta_N)(1-\alpha)\frac{A_{H,t+1}F_{t+1}(i)}{N_{t+1}(i)}\frac{Q_{Y,t+1}(i)}{e_{H,t}(i)H_t(i)}P_t\frac{\partial c_{W,t+1}(i)}{\partial W_t(i)}. \end{aligned} \tag{A.39}$$

where $\frac{\partial c_{W,t}(i)}{\partial W_t(i)} = c'_{W,t}(i)\frac{1}{W_t(i)}$ and $\frac{\partial c_{W,t+1}(i)}{\partial W_t(i)} = (-1)c'_{W,t+1}(i)\frac{1}{W_t(i)}$ with

$$c'_{W,t}(i) = \kappa_W\left[\frac{W_t(i)}{W_{t-1}(i)}(1+\pi)^{\iota_W-1}(1+\pi_{t-1})^{\iota_W}-1\right]\frac{W_t(i)}{W_{t-1}(i)}(1+\pi)^{\iota_W-1}(1+\pi_{t-1})^{\iota_W}.$$

Plugging (A.35) into (A.15) gives the real wage bargaining equation from the point of view of the household for each match

$$\begin{aligned} &w_t(i)e_{H,t}(i)H_t(i) - ub - \frac{1}{muc_t}\frac{\frac{\partial \mathbb{U}_{N,t}(i)}{\partial N_t(i)}}{(\mathbb{U}_{C,t}-\mathbb{U}_{N,t})^{\sigma}} \\ &= \frac{\eta_t}{1-\eta_t}\frac{Q_{F,t}(i)}{\tau_{W,t}(i)} - \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_t}(1-\delta_N)(1-f_{N,t+1})\frac{\eta_{t+1}}{1-\eta_{t+1}}\frac{Q_{F,t+1}(i)}{\tau_{W,t+1}(i)}. \end{aligned} \tag{A.40}$$

Deriving the first-order conditions of (A.15) and (A.32) with respect to $H_t(i)$ and plugging them into (A.36) gives the optimality condition of hours per worker for each match

$$\begin{aligned} &w_t(i)e_{H,t}(i)\Gamma_{W,t}(i) \\ &= \frac{\tau_{W,t}(i)}{muc_t}\frac{\frac{\partial^2 \mathbb{U}_{N,t}(i)}{\partial N_t(i)\partial H_t(i)}}{(\mathbb{U}_{C,t}-\mathbb{U}_{N,t})^{\sigma}} \\ &- \left[(1-\alpha)^2(1-\mathcal{C}_t(i)) - 4\alpha c_{N,t}(i) - (1-\alpha)c'_{H,t}(i)\right]\frac{A_{H,t}F_t(i)}{H_t(i)N_t(i)}Q_{Y,t}(i), \end{aligned} \tag{A.41}$$

where $\Gamma_{W,t}(i) = \tau_{W,t}(i) - 1$ and $c'_{H,t}(i) = \kappa_H\left(\frac{H_t(i)-\bar{H}(i)}{\bar{H}(i)}\right)\frac{1}{\bar{H}(i)}$. Deriving the first-order conditions of (A.15) and (A.32) with respect to $e_{H,t}(i)$ and plugging them into (A.37) gives the optimality condition of worker effort for each match

$$\begin{aligned} &w_t(i)H_t(i)\Gamma_{W,t}(i) \\ &= \frac{\tau_{W,t}(i)}{muc_t}\frac{\frac{\partial^2 \mathbb{U}_{N,t}(i)}{\partial N_t(i)\partial e_{H,t}(i)}}{(\mathbb{U}_{C,t}-\mathbb{U}_{N,t})^{\sigma}} - \left[(1-\alpha)^2(1-\mathcal{C}_t(i)) - 4\alpha c_{N,t}(i)\right]\frac{A_{H,t}F_t(i)}{e_{H,t}(i)N_t(i)}Q_{Y,t}(i). \end{aligned} \tag{A.42}$$

Appendix B. Utilization-adjusted TFP and TFP wedge

Definition of the aggregate investment-specific technology shock.

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

where I use the household resource constraint $C_t = T_t - P_{I,t}\left(1 + c_{I,t}\right) I_{K,t}$ 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

$$TFP_t = \frac{GDP_t}{\left(N_t H_t\right)^{1-\alpha} \left(K_{t-1}\right)^{\alpha}} = \frac{A_{I,t} T_t + I_{S,t} - I_{S,t-1} + G_t - \delta_K\left(e_{K,t}\right) K_{t-1}}{\left(N_t H_t\right)^{1-\alpha} \left(K_{t-1}\right)^{\alpha}}, \tag{B.2}$$

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

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

and substitute for S_t with the firm resource constraint (11), we get

$$\begin{aligned}TFP_t = &\frac{A_{I,t} q_{T,t}\left\{\left(1 - \mathcal{C}_t\right) A_{H,t} F_t - \vartheta - G_t - \left(1 - \delta_T\right) T_{t-1} + I_{S,t}\right\}}{\left(N_t H_t\right)^{1-\alpha} \left(K_{t-1}\right)^{\alpha}}, \\ &+ \frac{A_{I,t}\left(1 - \delta_T\right) T_{t-1} + I_{S,t} - I_{S,t-1} + G_t - \delta_K\left(e_{K,t}\right) K_{t-1}}{\left(N_t H_t\right)^{1-\alpha} \left(K_{t-1}\right)^{\alpha}}.\end{aligned}$$

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

$$\begin{aligned}&q_{T,t}\left(1 - \mathcal{C}_t\right) \frac{A_{H,t} A_{I,t}}{TFP_t} e_{H,t}^{1-\alpha} e_{K,t}^{\alpha} \\ &= 1 - \left(1 - q_{T,t} A_{I,t}\right)\left(g_{S,t} + i_{S,t}\right) + i_{S,t-1} + q_{T,t} A_{I,t} \vartheta_{S,t} \\ &\quad + \delta_K\left(e_{K,t}\right) k_{t-1} - \left(1 - q_{T,t}\right)\left(1 - \delta_T\right) A_{I,t} t_{t-1}\end{aligned} \tag{B.3}$$

where $g_{S,t} = \frac{G_t}{GDP_t}$, $i_{S,t} = \frac{I_{S,t}}{GDP_t}$, $i_{S,t-1} = \frac{I_{S,t-1}}{GDP_t}$, $\vartheta_{S,t} = \frac{\vartheta}{GDP_t}$, $k_{t-1} = \frac{K_{t-1}}{GDP_t}$, and $t_{t-1} = \frac{T_{t-1}}{GDP_t}$. Further, $q_{T,t} = \psi_{T,t}\left[\gamma_T x_{T,t}^{\Gamma} + \left(1 - \gamma_T\right)\right]^{\frac{1}{\Gamma}}$ contains endogenous reactions to goods market tightness and to goods market mismatch shocks.

Linearization. I linearize (B.3) around its deterministic steady-state and group all variables to their respective channel. However, there is an ambiguity in the goods market mismatch shock, $\psi_{T,t}$, as it can be either a market technology shock or composition and dispersion shock. Therefore, I derive an lower and upper bound of the following decomposition by either assuming goods market mismatch shocks have no technology component or they are only technology shocks. Linearizing (B.3) leads to

$$T\hat{F}P_t \;= \hat{\Phi}_{\vartheta,t} + \hat{\Phi}_{Labor,t} + \hat{\Phi}_{Capital,t} + \hat{\Phi}_{SaM,t} + \tilde{A}_t, \tag{B.4}$$

where $\hat{\Phi}_{\vartheta,t}$ summarizes the impact of fixed cost of production on creating short-run increasing returns-to-scale, $\hat{\Phi}_{Labor,t}$ summarizes the labor market impact on TFP, $\hat{\Phi}_{Capital,t}$ summarizes the capital market impact on TFP, $\hat{\Phi}_{SaM,t}$ summarizes the goods market search-and-matching impact on TFP, and $\tilde{A}_t$ summarizes all technology shocks. The channels unaffected by the definition of goods market mismatch shocks and technology are given by

$$\boldsymbol{\Phi_{\vartheta,t}} \;= (-1)\,\frac{\vartheta_S cu}{1+\vartheta_S cu}\boldsymbol{\hat{\vartheta}_{S,t}}, \tag{B.5}$$

$$\boldsymbol{\Phi_{Labor,t}} \;= (1-\alpha)\,\boldsymbol{\hat{e}_{H,t}} - \frac{c_N}{1-c_N}\boldsymbol{\hat{c}_{N,t}}, \tag{B.6}$$

$$\boldsymbol{\Phi_{Capital,t}} \;= \left[\alpha - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,(1-g_S)\,\delta_T\delta_I}k\phi_{K,1}\right]\boldsymbol{\hat{e}_{K,t}}. \tag{B.7}$$

The lower bound for $\Phi_{SaM,t}$ and $\tilde{A}_t$ is identified by no technology component for the goods market mismatch shock and given by

$$\begin{aligned}\boldsymbol{\Phi^{Low}_{SaM,t}} \;&= \frac{(1-cu)\,g_S}{(1+\vartheta_S cu)\,(1-g_S)\,\delta_T\delta_I}\boldsymbol{\hat{g}_{S,t}} - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,(1-g_S)\,\delta_T\delta_I}i_S\boldsymbol{\hat{i}_{S,t-1}}\\ &+\left(\frac{cu}{1+\vartheta_S cu} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,(1-cu)\,\delta_T\delta_I}\right)i_S\boldsymbol{\hat{i}_{S,t}} + \frac{(1-cu)\,(1-\delta_T)}{(1+\vartheta_S cu)\,\delta_T\delta_I}\boldsymbol{\hat{t}_{t-1}}\\ &+\frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,\delta_I}\boldsymbol{\hat{q}_t},\end{aligned} \tag{B.8}$$

$$\boldsymbol{\tilde{A}_{Low,t}} \;= \boldsymbol{\hat{A}_{H,t}} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+cu\vartheta_S)\,\delta_T\delta_I}\boldsymbol{\hat{A}_{I,t}}. \tag{B.9}$$

The upper bound for $\Phi_{SaM,t}$ and $\tilde{A}_t$ is identified by all technology component for the goods market mismatch shock and given by

$$\begin{aligned}
\boldsymbol{\Phi^{Up}_{SaM,t}} &= \frac{(1-cu)\,g_S}{(1+\vartheta_S cu)\,(1-g_S)\,\delta_T\delta_I}\boldsymbol{\hat{g}_{S,t}} - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,(1-g_S)\,\delta_T\delta_I} i_S\boldsymbol{\hat{i}_{S,t-1}} \\
&+ \left(\frac{cu}{1+\vartheta_S cu} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,(1-cu)\,\delta_T\delta_I}\right) i_S\boldsymbol{\hat{i}_{S,t}} + \frac{(1-cu)\,(1-\delta_T)}{(1+\vartheta_S cu)\,\delta_T\delta_I}\boldsymbol{\hat{t}_{t-1}} \\
&+ \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,\delta_I}\gamma_S\boldsymbol{\hat{x}_{T,t}},
\end{aligned} \tag{B.10}$$

$$\boldsymbol{\tilde{A}_{Up,t}} = \boldsymbol{\hat{A}_{H,t}} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+cu\vartheta_S)\,\delta_T\delta_I}\boldsymbol{\hat{A}_{I,t}} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+cu\vartheta_S)\,\delta_I}\boldsymbol{\hat{\psi}_{T,t}}. \tag{B.11}$$

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

$$cu_t = \frac{GDP_t}{(1-\mathcal{C}_t)\,A_{H,t}\left(\bar{e}_H\bar{H}N_t\right)^{1-\alpha}(\bar{e}_K K_{t-1})^{\alpha} - \vartheta + (A_{I,t}-1)\,T_t}, \tag{B.12}$$

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.12) in (B.2) and linearizing around its deterministic steady-state results in

$$\begin{aligned}
\boldsymbol{T\hat{F}P_t} &= \boldsymbol{\hat{A}_{H,t}} + \frac{cu\,(1-g_S)}{1+\vartheta_S cu}\boldsymbol{\hat{A}_{I,t}} \\
&+ \frac{1}{1+\vartheta_S cu}\left[\boldsymbol{\hat{cu}_t} - \vartheta_S cu\boldsymbol{\hat{\vartheta}_{S,t}}\right] - \frac{c_N}{1-c_N}\boldsymbol{\hat{c}_{N,t}} - (1-\alpha)\,\boldsymbol{\hat{H}_t}.
\end{aligned} \tag{B.13}$$

Using (B.4) and (B.12) to substitute for $(T\hat{F}P_t - \hat{A}_{H,t})$ and solving for the efficiency wedge results in

$$\boldsymbol{\Phi}^{Low}_{SaM,t} = \frac{1}{1+\vartheta_S cu}\left[\boldsymbol{\hat{cu}_t} - \vartheta_S cu\boldsymbol{\hat{\vartheta}_{S,t}}\right] - \frac{c_N}{1-c_N}\boldsymbol{\hat{c}_{N,t}} - (1-\alpha)\,\boldsymbol{\hat{H}_t} - \frac{1-cu}{(1+\vartheta_S cu)\,\delta_T\delta_I}\boldsymbol{\hat{A}_{I,t}} \tag{B.14}$$

$$\boldsymbol{\Phi}^{Up}_{SaM,t} = \boldsymbol{\Phi}^{Low}_{SaM,t} - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_S cu)\,\delta_I}\boldsymbol{\hat{\psi}_{T,t}} \tag{B.15}$$

where the efficiency wedge is determined by the observables capacity utilization, fixed cost of production share of GDP, labor matching cost, and hours per worker. However, they overestimate the efficiency wedge for investment-specific technology shocks and goods market mismatch shocks (technology definition). The actual efficiency wedge is lower than what the observables predict. The quantitative impact depends on the estimated parameters and shock processes. While capacity utilization data is invariant to Hicks-neutral technology shocks, it is biased by other technology processes in the model. Hence, the efficiency wedge is not directly identified by capacity utilization data.

Appendix C. Connecting the Model with the Data

Appendix C.1. Calibration of the Model Parameters

Table 1 in the main text gives an overview of all calibrated parameters in the model. Those parameters are either not well identified by the data and a good micro estimate exists or they can be determined by a clear steady-state relationship of an endogenous variable. There are some steady-state targets worth discussing as their derivation might not be straight forward. First, the vacancy posting cost as a share of GDP is commonly set to 1% in the literature. As vacancy posting cost are a share of production capacity, we have to derive the relation to realized GDP. It follows that

$$
\begin{aligned}
c_{N,GDP} &= \frac{c_N AF}{GDP} \\
\Leftrightarrow \quad cuY &= \frac{c_N AF}{c_{N,GDP}} \\
\Leftrightarrow \quad c_N &= c_{N,GDP} cu \left[(1 - c_N) - \frac{\vartheta}{AF} \right] \\
\Leftrightarrow \quad c_N &= \frac{c_{N,GDP} cu \left[1 - \frac{\vartheta}{AF} \right]}{1 + c_{N,GDP} cu},
\end{aligned}
$$

where the vacancy posting cost share of production capacity can be derived from the vacancy posting cost share of GDP by correcting for capacity utilization and fixed cost of production.

Next, we set the capital elasticity with respect to production capacity, α, by matching the labor share of income in the data to prevent any bias in input factors in the estimation of TFP and technology. If α is set incorrectly, it biases the impact of labor and capital have on production and TFP. Comin et al. (2025) show that neglecting e.g. 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. (2025) and solve for the steady-state of the employment demand equation[29] and its free-entry condition to to retrieve

[29] 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.

a steady-state equation for α as follows

$$\begin{aligned}
ls &= \frac{we_H HN}{GDP} \\
\Leftrightarrow \quad ls\frac{GDP}{AF}\frac{1}{mc_Y} &= (1-c_N) - \alpha(1-c_N) + 2c_N - 2\frac{c_N}{\delta_N}(1-\beta(1-\delta_N)) \\
\Leftrightarrow \quad ls \cdot cu\left[(1-c_N) - \frac{\vartheta}{AF}\right] &= (1-c_N) - \alpha(1-c_N) + 2c_N - 2\frac{c_N}{\delta_N}(1-\beta(1-\delta_N)) \\
\Leftrightarrow \quad \alpha &= 1 - \frac{2c_N}{1-c_N}\frac{(1-\beta)(1-\delta_N)}{\delta_N} - ls\frac{cu}{mc_Y}\left(1 - \frac{\frac{\vartheta}{AF}}{1-c_N}\right),
\end{aligned}$$

where the labor demand FOCs determines real wages and thus in turn the labor share. The output elasticity α depends on vacancy posting cost, the employment separation rate, and the targeted labor share corrected for capacity utilization and fixed cost of production.

Next, we set the elasticity of substitution of differentiated goods, ϵ, such that the markup target is matched. The target condition is

$$\bar{\mu} = \frac{e_T}{mc_Y} = \frac{1}{mc},$$

where the gross markup is the inverse of the marginal production cost, mc, or the marginal production capacity cost, mc_Y, corrected for short-run capacity utilization, $e_T = \frac{T+G}{Y} = cu$, which is equal to long-run capacity utilization in steady-state. We use the firm FOCs to substitute for mc_Y and the goods market matching conditions to substitute for cu. The resulting condition is given by

$$\begin{aligned}
&\frac{1-\beta\theta_H}{1-\beta\theta_D}\frac{\gamma_T}{1-\gamma_T}\frac{1}{\epsilon c_D'} \\
&= \frac{\delta_T\delta_I(1-g_S)\,cu}{1-cu\left[g_S+(1-g_S)(1-\delta_T\delta_I)\right]}\left[\frac{\frac{\bar{\mu}}{cu}}{1-\beta(1-\delta_I)} - \beta(1-\delta_T) - \frac{\beta(1-\delta_I)}{1-\beta(1-\delta_I)}\right] \\
&\quad - (1-\beta(1-\delta_T)),
\end{aligned}$$

which does not have a closed-form solution in ϵ as c_D' depends inversely and non-linear on ϵ. Hence, we solve for ϵ numerically targeting $\bar{\mu}$ while simultaneously solving for the goods market block. To get some intuition how ϵ depends on goods market frictions and the markup target, I derive a simplified version setting $\delta_T = \delta_I = 1$ which offers a closed-form solution.

It is given by

$$\epsilon \;=\; \frac{1}{1-g_S}\left[1+\frac{\left(1-g_S cu\right)\left(1+\left(1-g_S\right)\frac{\gamma_T}{1-\gamma_T}\right)}{\left(\bar{\mu}-1\right)-g_S\left(\bar{\mu}-cu\right)}\right] \overset{g_S=0}{=} \frac{\bar{\mu}+\frac{\gamma_T}{1-\gamma_T}}{\bar{\mu}-1},$$

which shows that ϵ is increasing in γ_T and g_S. Hence, in this economy, markups increase in goods market frictions and the government spending share. When targeting the steady-state markup, goods markets become more competitive in goods market frictions and the government spending share.

Lastly, we derive the steady-state relationship for fixed cost of production from the firm profit condition given by

$$\begin{aligned}
& \Pi && = GDP - we_H HN - r_K e_K K \\
\Leftrightarrow\quad & \frac{\Pi}{GDP} && = 1-\left[\left(1-\alpha\right)\left(1-c_N\right)+2c_N-2\frac{c_N}{\delta_N}\left(1-\beta\left(1-\delta_N\right)\right)\right]\frac{AF}{GDP}mc_Y \\
& && \quad -\alpha\left(1-c_N\right)\frac{AF}{GDP}mc_Y \\
\Leftrightarrow\quad & \bar{\Pi}_{GDP} && = 1-\left[\left(1-c_N\right)-2c_N\frac{\left(1-\beta\right)\left(1-\delta_N\right)}{\delta_N}\right]\frac{AF}{GDP}mc_Y \\
\Leftrightarrow\quad & \left(1-\bar{\Pi}_{GDP}\right) && = \left[\left(1-c_N\right)-2c_N\frac{\left(1-\beta\right)\left(1-\delta_N\right)}{\delta_N}\right]\left[1-c_N-\frac{\vartheta}{AF}\right]^{-1}\frac{mc_Y}{cu} \\
\Leftrightarrow\quad & \frac{\vartheta}{AF} && = \left(1-c_N\right)\left[1-\left(1-\frac{2c_N}{1-c_N}\frac{\left(1-\beta\right)\left(1-\delta_N\right)}{\delta_N}\right)\frac{mc_Y}{cu}\frac{1}{1-\bar{\Pi}_{GDP}}\right],
\end{aligned}$$

where we target the profit share of GDP, $\bar{\Pi}_{GDP}$. The fixed cost of production increases in vacancy posting cost and markups, and decrease in the steady-state profit share. A common assumption in the literature also taken here is a zero profit condition, $\bar{\Pi}_{GDP} = 0$, which indicates that markups pay for fixed cost of production but no additional profit is made by the firm. The previous four steady-state conditions all depend on each other. Hence, we solve them numerically in one block when solving for the steady-state of the model and thereby setting the parameter values determined by the steady-state targets.

Appendix C.2. Data Sources and Data Construction

Real GDP. Output growth is given by

$$\Delta GDP_{data,t} \;=\; ln\left(\frac{GDP_t}{Defl_t \cdot Pop_t}\right)-ln\left(\frac{GDP_{t-1}}{Defl_{t-1}\cdot Pop_{t-1}}\right),$$

where GDP_t is nominal GDP (BEA Account Code: A191RC), $Defl_t$ 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). I subtract nominal durable private consumption (BEA Account Code: DDURRC) following Justiniano et al. (2010), as I do not estimate a model with durable consumption goods. Real Consumption growth is

$$\Delta C_{data,t} = ln\left(\frac{Cons_t - Cons_{dur,t}}{Defl_t \cdot Pop_t}\right) - ln\left(\frac{Cons_{t-1} - Cons_{dur,t-1}}{Defl_{t-1} \cdot Pop_{t-1}}\right).$$

Real Investment. Nominal investment is calculated as nominal private investment (BEA Account Code: A006RC). I add nominal durable private consumption (BEA Account Code: DDURRC) following Justiniano et al. (2010), as I do not estimate a model with durable consumption goods. Real investment is

$$\Delta I_{data,t} = ln\left(\frac{Inv_t + Cons_{dur,t}}{Defl_t \cdot Pop_t}\right) - ln\left(\frac{Inv_{t-1} + Cons_{dur,t-1}}{Defl_{t-1} \cdot Pop_{t-1}}\right).$$

Total Hours Worked. Total Hours Worked is the total of hours worked of all persons employed in the non-farm business sector (BLS code: HOANBS). Data is retrieved from U.S. Bureau of Labor Statistics. Total Hours Worked is calculated by

$$TH_{data,t} = ln\left(\frac{TotHours_t}{Pop_t}\right),$$

where I follow Cacciatore et al. (2020) and linearily detrend this series to retrieve business cycle fluctuations in the total hours worked.

Employment Rate. The employment rate is based on the number of total non-farm employees (FRED code: PAYEMS). It is calculated by

$$N_{data,t} = \frac{TotEmp_t}{Pop_t},$$

where I follow Cacciatore et al. (2020) and linearily detrend this series to retrieve business cycle fluctuations in the employment rate.

Capacity Utilization. The survey questionnaire 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[30]. 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."*

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[31], economy-wide capacity utilization is given by

$$CU_t = \frac{GDP_t}{CP_t} = \frac{GDP_{ind,t} + GDP_{ser,t}}{CP_{ind,t} + CP_{ser,t}},$$

[30] 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/.

[31] 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.

where CP_t is aggregate production capacity and variables with subscript "ind" represent industry sector variables and with subscript "ser" represent service sector variables. I take a first-order Taylor approximation around the deterministic steady-state of the economy-wide capacity utilization rate given by

$$\hat{CU}_t \quad = \quad \frac{GDP_{ind}}{CP}\hat{GDP}_{ind,t} + \frac{GDP_{ser}}{CP}\hat{GDP}_{ser,t} - \frac{GDP}{CP^2}\left(CP_{ind}\hat{CP}_{ind,t} + CP_{ser}\hat{CP}_{ser,t}\right),$$

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

$$\begin{aligned}
\hat{CU}_{ind,t} &= CU_{ind}\left(\hat{GDP}_{ind,t} - \hat{CP}_{ind,t}\right) \quad \Leftrightarrow \quad \hat{CP}_{ind,t} = \hat{GDP}_{ind,t} - \frac{\hat{CU}_{ind,t}}{CU_{ind}}, \\
\hat{CU}_{ser,t} &= CU_{ser}\left(\hat{GDP}_{ser,t} - \hat{CP}_{ser,t}\right) \quad \Leftrightarrow \quad \hat{CP}_{ser,t} = \hat{GDP}_{ser,t} - \frac{\hat{CU}_{ser,t}}{CU_{ser}},
\end{aligned}$$

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

$$\begin{aligned}
\hat{CU}_t \quad = \quad & CU\frac{GDP_{ind}}{GDP}\left(1 - \frac{CU}{CU_{ind}}\right)\hat{GDP}_{ind,t} + CU\frac{GDP_{ser}}{GDP}\left(1 - \frac{CU}{CU_{ser}}\right)\hat{GDP}_{ser,t} \\
& + \frac{GDP_{ind}}{GDP}\left(\frac{CU}{CU_{ind}}\right)^2\hat{CU}_{ind,t} + \frac{GDP_{ser}}{GDP}\left(\frac{CU}{CU_{ser}}\right)^2\hat{CU}_{ser,t},
\end{aligned}$$

where the number of unknowns reduce 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. Service sector capacity utilization is not available for the US.

Therefore, I approximate it using survey data on service sector capacity utilization from the

Table C.5: Correlation of industry and service sector capacity utilization in the European Union

	2011q1 - 2019q4	2011q1 - 2024q3
Corr(CU_{ind}, CU_{ser})	0.86	0.67

European Commission[32]. The idea is as follows: First, check the correlation between industry and service sector capacity utilization in Europe. Table C.5 shows that it is high when we exclude the Covid-19 period, which represents the unsual twin shock closing many service firms but increasing demand for industry produce. Second, 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. U.S. service-sector capacity utilization is approximated by

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

where $\gamma_{CU,EU}$ is the slope parameter of the approximation equation. Plugging everything back into aggregate capacity utilization measure results in

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

The economy-wide capacity utilization growth rate is given by

$$cu_{data,t} \;=\; \hat{CU}_t.$$

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

$$\pi_{data,t} \;=\; ln\left(\frac{GDP_{nom,t}}{GDP_{real,t}}\right)-ln\left(\frac{GDP_{nom,t-1}}{GDP_{real,t-1}}\right).$$

Real Labor Compensation. Nominal labor compensation is given by the non-farm business sector labor compensation per hour (BLS code: COMPNFB). Data is retrived from U.S. Bureau of Labor Statistics. Real wage inflation is

$$\pi_{W,data,t} \;=\; ln\left(\frac{W_t}{Defl_t}\right)-ln\left(\frac{W_{t-1}}{Defl_{t-1}}\right).$$

[32] https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en

FED Funds Rate. The FED funds rate is given by the Federal Reserve Bank of New York, Effective Federal Funds Rate (Code: 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 quarterly annualized interest rates. I calculate the quarterly interest rate by

$$r_{data,t} = (1 + int_{year,t})^{\frac{1}{4}} - 1.$$

Connecting the Data to the Model. As the model is stationary we have to de-trend the data accordingly. I follow Smets and Wouters (2007) and de-mean the growth rates of real GDP, real investment, real consumption, and real labor compensation by the mean growth rate of real GDP. This approach follows the idea of a balanced growth path driven by one unit-root process in technology. I de-mean the GDP deflator, the FED funds rate, the unemployment rate, and capacity utilization by their respective mean rates. For hours per worker, I use a log-linear de-trending approach following Cacciatore et al. (2020). The connection between the structural DSGE model and the observation equations can be summarized by

$$\begin{bmatrix} \Delta GDP_{data,t} \\ \Delta C_{data,t} \\ \Delta I_{data,t} \\ TH_{data,t} \\ N_{data,t} \\ cu_{data,t} \\ \pi_{data,t} \\ \pi_{W,data,t} \\ r_{data,t} \end{bmatrix} - \begin{bmatrix} \overline{\Delta GDP_{data,t}} \\ \overline{\Delta GDP_{data,t}} \\ \overline{\Delta GDP_{data,t}} \\ TH_{trend,t} \\ N_{trend,t} \\ \overline{cu_{data,t}} \\ \overline{\pi_{data,t}} \\ \overline{\Delta GDP_{data,t}} \\ \overline{r_{data,t}} \end{bmatrix} = \begin{bmatrix} \Delta log\left(gdp_t\right) \\ \Delta log\left(C_t\right) \\ \Delta log\left(Inv_t\right) \\ log\left(th_t\right) - log\left(\bar{th}\right) \\ N_t - \bar{N} \\ cu_t - \bar{cu} \\ \pi_t - \bar{\pi} \\ \frac{1+\pi_{W,t}}{1+\pi_t} \cdot \frac{e_{H,t}}{e_{H,t-1}} - 1 \\ r_{B,t} - \bar{r}_B \end{bmatrix},$$

where variables with a bar indicate the mean in the data and the steady-state in the model. $TH_{trend,t}$ and $N_{trend,t}$ represent the linear trend applied to total hours worked and the employment rate following Cacciatore et al. (2020). To calculate growth rates in the model, I apply logs before taking the differences. For variables already in percentage units, I simply subtract their mean. For the real wage inflation rate, I adjust for worker effort growth in the model as real wages are paid on labor efficiency units in the model but on hours per worker in the data.

Appendix D. Bayesian Estimation and Posterior Results

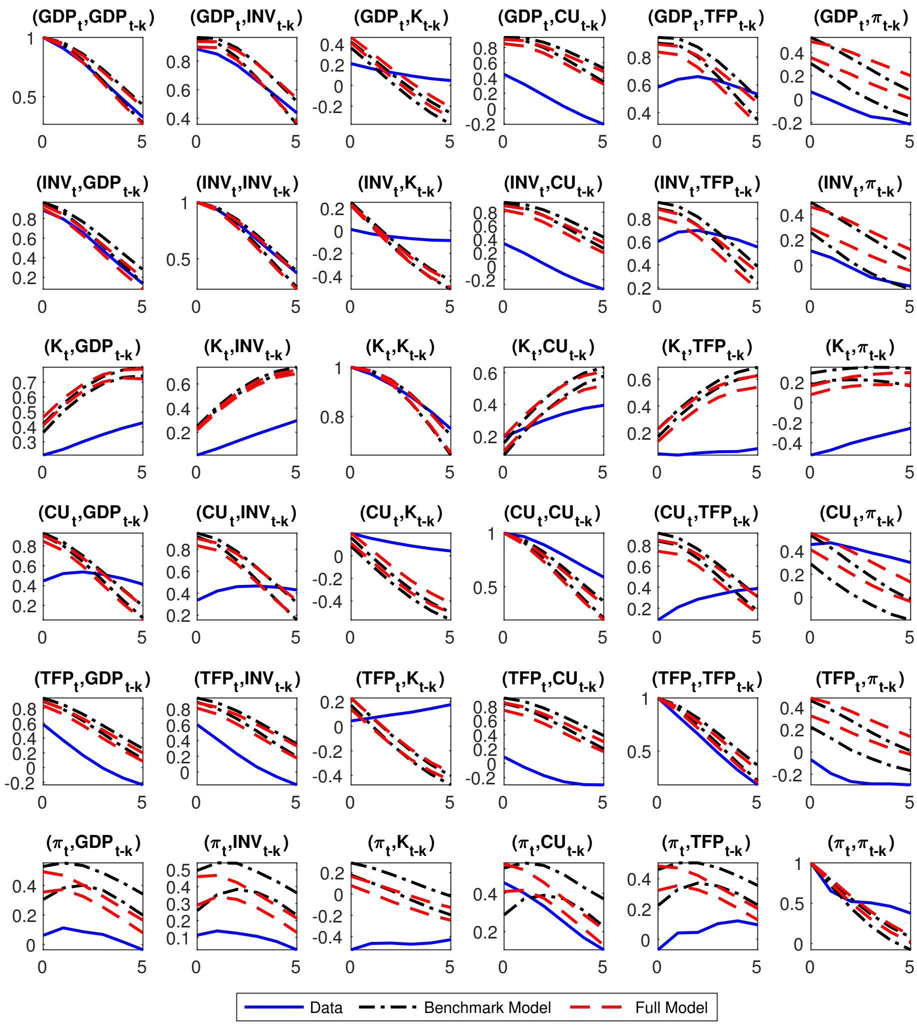
Appendix D.1. Estimation Procedure

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 **??**. 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 2,000,000 draws each from the posterior distribution using the random walk Metropolis-Hastings algorithm and drop half of the draws before calculating model statistics. The posterior densities have converged using the usual statistics (Brooks and Gelman (1998); Geweke (1999)). **??** shows the posterior estimates of the benchmark, SaM-VWE, and full models. All include nine shocks and nine observables. The observables are linked to the model following Pfeifer (2018) and given by

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

Appendix D.2. Correlograms

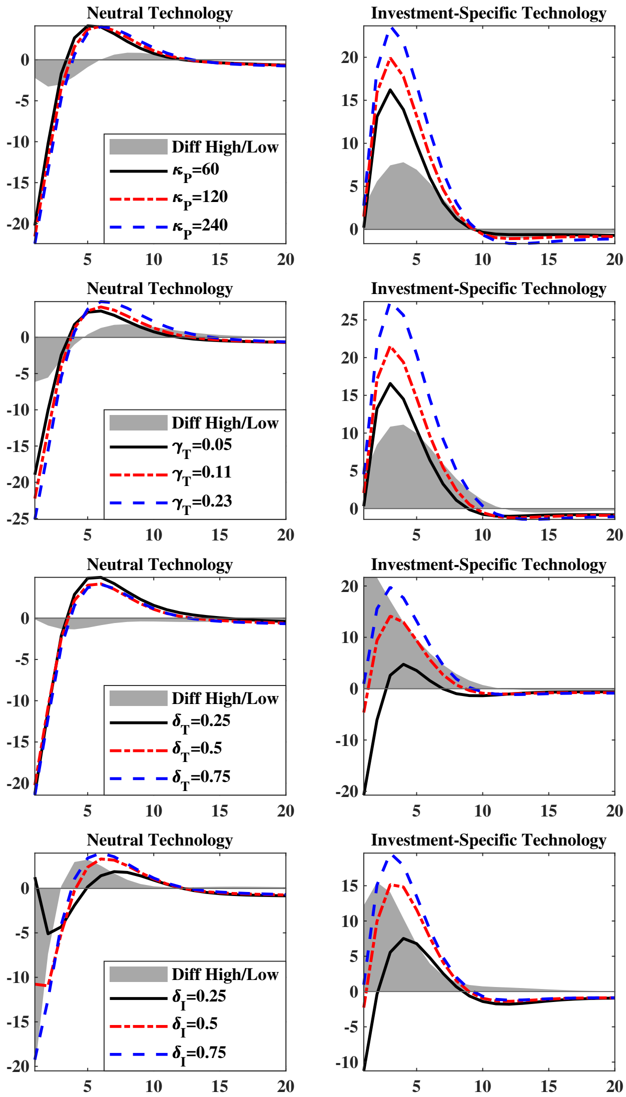
Figure D.9: Correlogram for the Benchmark and Full Model



NOTE: The figure shows correlograms of GDP, capital investment, the capital stock, capacity utilization, 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.

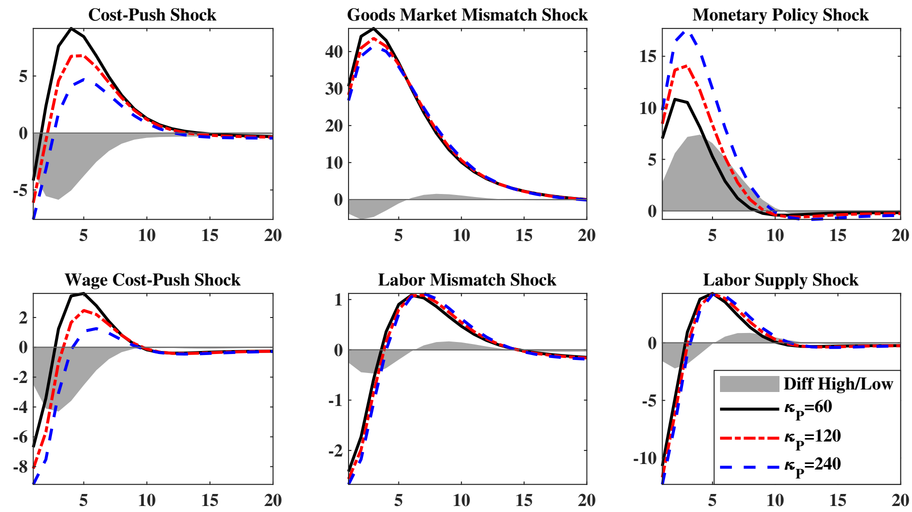
Appendix E. TFP Bias and Multiplicators Sensitivity Analysis

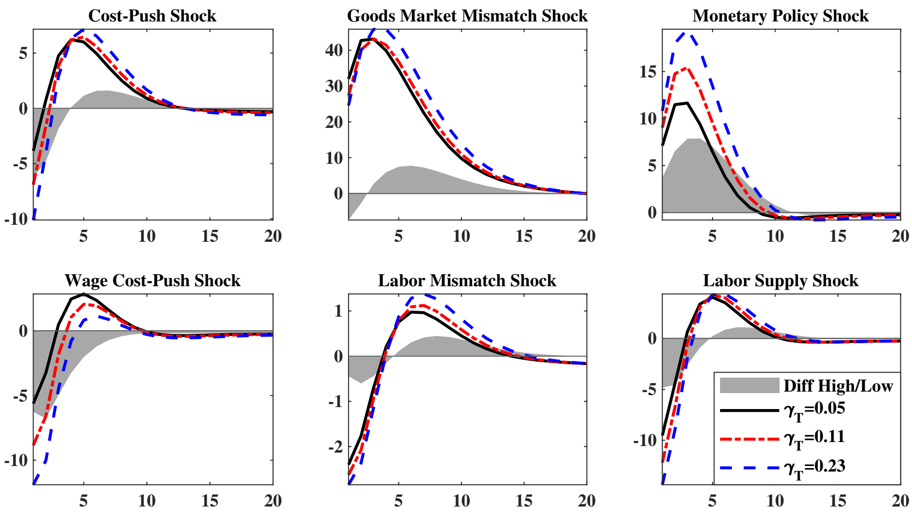
Figure E.10: Robustness: TFP Wedge Fluctuations for Technology Shocks



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.

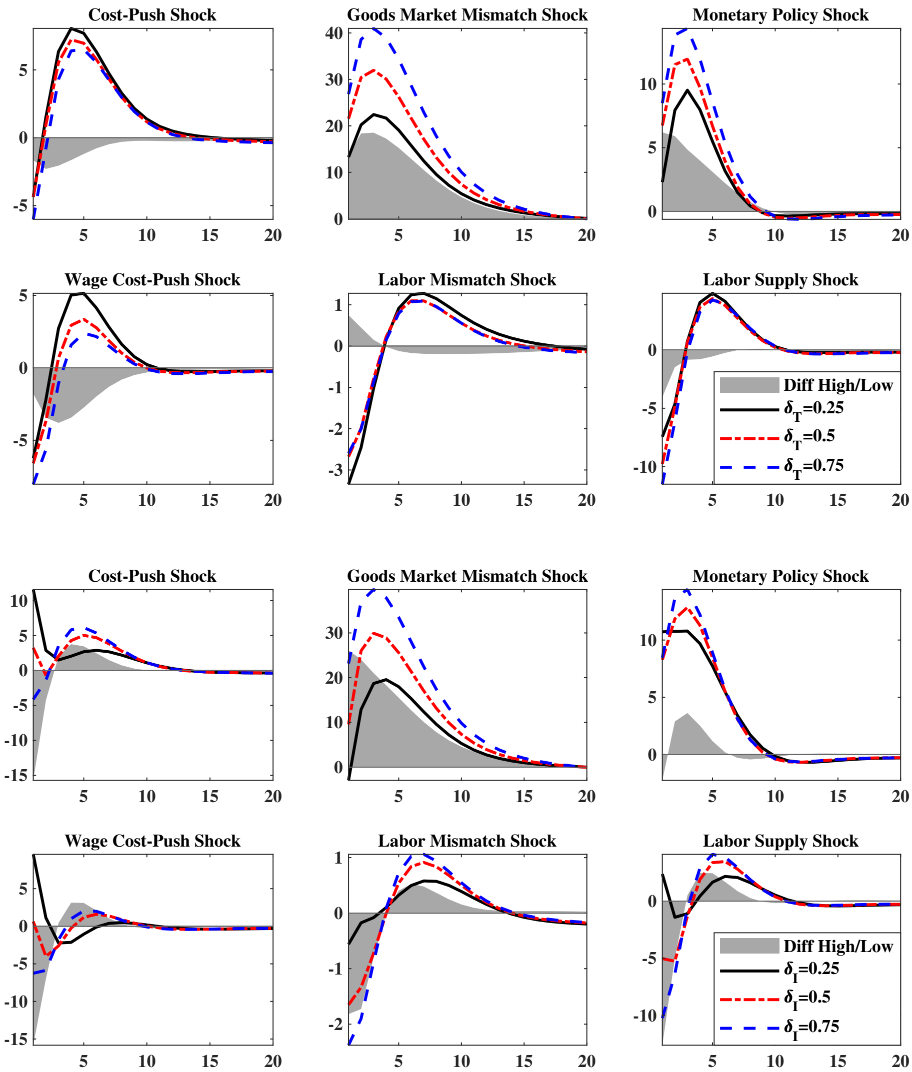
Figure E.11: Robustness: TFP Wedge Fluctuations for Non-Technology Shocks (1/2)





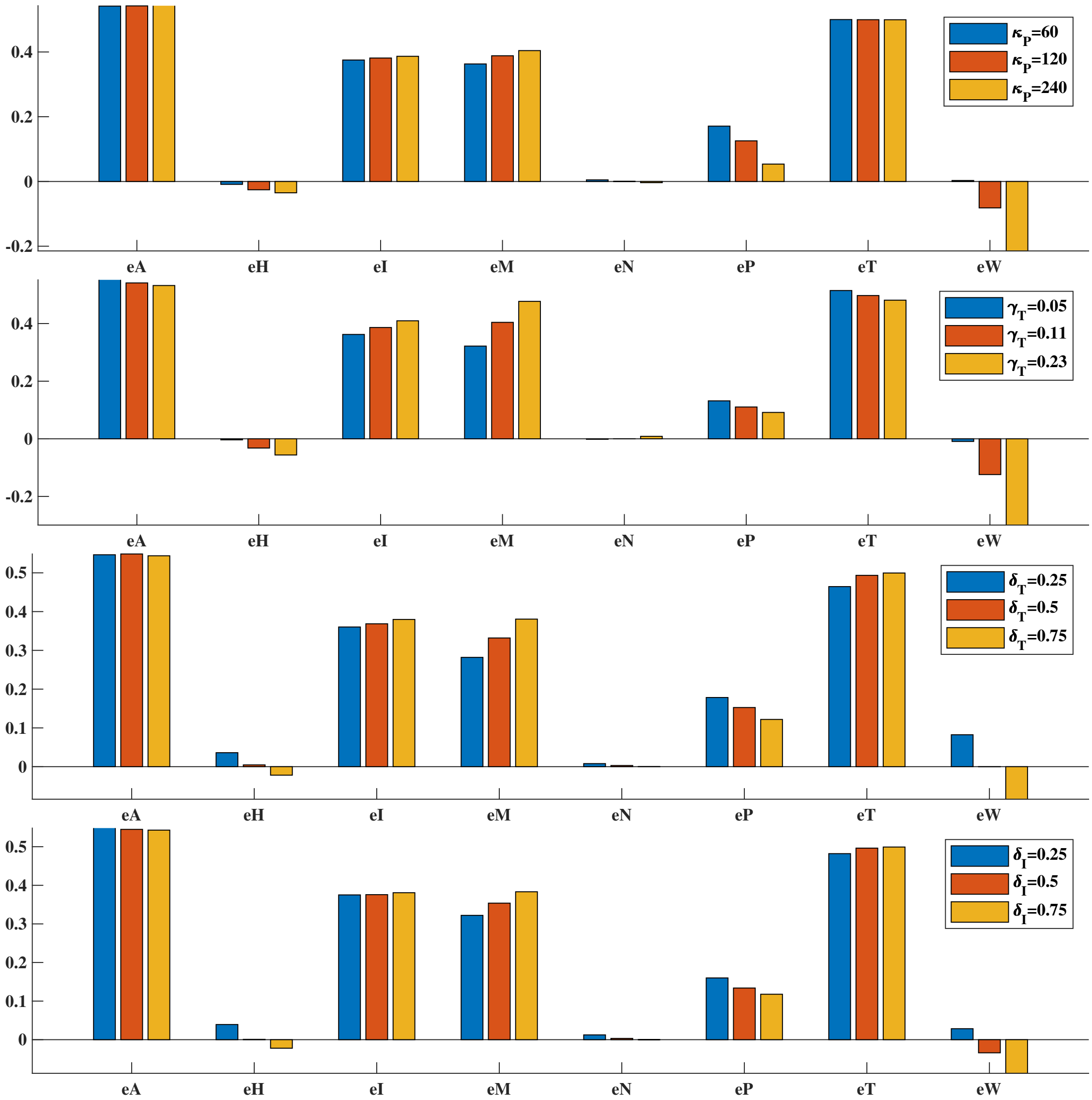
NOTE: The figure shows impulse response functions of the TFP wedge to non-technology shocks for the full model. The deviations are measured in percentage deviations from the deterministic steady-state. It shows a robustness analysis for the parameters of price stickiness, κ_P, and demand elasticity of 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.12: 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.13: 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.