Revisiting TFP Fluctuations: The Role of Goods Market Search and Time Allocation

Job Market Paper

(newest version)

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Abstract

Measured productivity fluctuates far more than technology. This paper shows that these swings largely reflect coordination failures in the goods market rather than technological change. I develop a New Keynesian DSGE model in which households devote time to searching for goods and firms invest resources in reaching customers. The efficiency of this matching process determines capacity utilization and, with it, total factor productivity (TFP). Bayesian estimation on U.S. and Euro Area data demonstrates that incorporating goods market search-and-matching (SaM) markedly improves model fit — especially for capacity utilization — and shifts business cycle variation from supply to demand shocks as the price elasticity of demand becomes endogenous. Excess demand amplifies TFP through productive search effort, while excess supply dampens it, reflecting the household time-allocation trade-off between work and search. The framework explains key macroeconomic puzzles: the "missing-deflation" episode after 2008 arises as a classical-unemployment regime with weak goods market matching efficiency, whereas the post-COVID inflation surge reflects a repressed-inflation regime with excessive tightness. These results imply that short-run productivity fluctuations are coordination-driven and that monetary policy operates in a state-dependent environment where stabilizing market efficiency is as crucial as managing aggregate demand.

Keywords: Total factor productivity, capacity utilization, search-and-matching, supply-determined equilibrium, household time-allocation, Bayesian estimation

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1. Introduction

Periods of expansion and recession reveal a recurring puzzle: factories, offices, and workers often stand idle in downturns, even though the underlying production technology remains intact. In booms, by contrast, buyers queue up for scarce goods, delivery times lengthen, and firms struggle to meet demand. These fluctuations in resource use appear in measured total factor productivity (TFP), yet technology itself changes far less.

Standard measures of productivity treat the process of matching buyers and sellers as instantaneous and costless. But in reality, this process consumes time, information, and organizational resources. Consumers search for products and queue; firms advertise, hold inventories, and staff marketing. When matching becomes less efficient, productive capacity goes idle; when it improves, the same inputs yield more output[3]. Therefore, fluctuations in measured productivity may reflect shifts in *market coordination*, not technology.

This idea suggests that part of "production" takes place not inside factories but in the *interaction between buyers and sellers*. The act of matching supply with demand is itself productive: it transforms available production capacity into actual sales. When either side cuts back its search effort — firms reducing their supply or households reducing shopping — output falls even if machines, labor, and ideas remain unchanged[4] - what macroeconomists label a productivity shock may thus be a coordination shock.

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[3]Shopping time increases by $1.1 - 1.5\%$ in GDP (Petrosky-Nadeau et al., 2016); advertisement is salient and procyclical (slope in real GDP above one) for US data (Hall, 2012); inventory investment explains up to one-fourth of real GDP growth (Den Haan and Sun, 2024) and the inventory-sales ratio is countercyclical (Bils and Kahn, 2000). Capacity utilization is procyclical, has a long-term average $82 - 89\%$, and shows a standard deviation of $1.87 - 2.93$ in a data sample of the US (1984q1-2019q4), Spain, Germany, and France (1998q1-2019q4). Survey data from the European Commission shows that this is the result of "lack of demand" for firms rather than of "lack of input factors". See Appendix C for their description and sources.

[4]Additional to the procyclical shopping (Petrosky-Nadeau et al., 2016) effort which is positively correlated with TFP and capacity utilization (Bai et al., 2025), there is also evidence that firms employ excess capacity to attract additional customers (Sun, 2024).

This view helps reconcile an inconsistency at the heart of the New-Keynesian paradigm (Barro, 2025). By construction, those models assume that firms must supply any quantity demanded at posted prices. But the economy frequently exhibits both excess supply and excess demand - e.g. the 1970s oil shocks or 2008 Great Recession. A framework that allows output to be *either demand-determined or supply-determined*, depending on how efficiently markets match buyers and sellers, can better capture these episodes (Barro and Grossman, 1971) — and provide a richer account of why TFP fluctuates over the business cycle.

Varying matching efficiency has a behavioral dimension: At the household level, the search for goods competes with work, leisure, and home production. When households devote less time to finding goods and firms scale back sales effort, transactions slow and capacity goes unused. From a policy perspective, such shifts in time use and coordination can appear as technological shocks: measured productivity falls even though the underlying technology has not changed. Treating such coordination failures as "TFP shocks" risks overstating the role of technology and understating the role of market functioning[5].

Traditional mechanisms — capital utilization, labor effort, or fixed production costs (Christiano et al., 2005) — operate within the production process, altering how intensively inputs are used, while goods market search-and-matching governs how goods are exchanged. TFP co-moves with sales, inventories, shopping time, and capacity utilization (Bai et al., 2025; Den Haan and Sun, 2024) — indicators of market efficiency. By linking household time allocation and firms' sales effort to aggregate output, the model provides a behavioral foundation for cyclical productivity that existing channels cannot capture.

To study this mechanism, we develop a New Keynesian DSGE model (Cacciatore et al., 2020; Christiano et al., 2010; Smets and Wouters, 2007) in which households allocate time not only to work but also to *searching for goods*, and firms face frictions in selling their output (Bai et al., 2025; Michaillat and Saez, 2015; Qiu and Rios-Rull, 2022). Matching efficiency, and thus effective productivity, vary endogenously with the state of the economy. The model is

[5] Diamond (1982); Diamond and Fudenberg (1989) have shown that search models and their trade-off between search and work allow for multiple equilibria where the equilibrium path depends on sentiment, thus demand management.

estimated on U.S. and Euro Area data using Bayesian methods and survey-based measures of capacity utilization to elicit the explanatory power of goods market search-and-matching (SaM) and compare it with the literature. The central question of this paper is therefore:

> *Can fluctuations in the efficiency with which buyers and sellers find each other explain the cyclical behavior of measured total factor productivity — and with it, key features of the business cycle?*

The paper shows that goods-market search-and-matching (SaM) and household time allocation are fundamental sources of macroeconomic inefficiency. They shape how resources are used, how demand and supply interact, and how monetary policy should interpret the shocks driving the cycle. Incorporating goods-market SaM decisively improves the model's fit — especially for capacity utilization — with tight posterior densities confirming the data's informativeness across countries. The variance decomposition reveals a shift from supply to demand shocks, while price cost-push shocks lose relevance as the price elasticity of demand becomes endogenous through the interaction of sticky posted prices and flexible search prices. Excess demand amplifies total factor productivity (TFP) variation through higher productive search effort, while excess supply dampens it, reflecting the time-allocation trade-off between work and search. The model explains key macroeconomic puzzles by reproduciong Barro and Grossman (1971) business cycle regimes: the "missing deflation" after 2008 corresponds to a classical-unemployment regime with weak goods market matching efficiency, whereas the post-COVID inflation surge reflects a repressed-inflation regime with excess tightness. These findings show that coordination failures and time-allocation inefficiencies explain major deviations of inflation and output from traditional New Keynesian predictions, weakening the inflation–output-gap link and emphasizing the role of market functioning for stabilization policy.

Literature Review. This paper contributes to three strands of literature. First, a large empirical literature estimates TFP and its determinants (Basu and Fernald, 2002; Basu et al., 2006; Comin et al., 2025; Fernald, 2014; Huo et al., 2023), showing that technology drives long-run growth while capacity utilization dominates short-run variation. Capacity utilization is typically inferred from price equations derived from cost minimization and related to observable hours per worker. More recent studies use industry survey data on capacity utilization (Comin et al., 2025), implicitly accounting for labor shocks — an especially relevant adjustment for European data.

Second, theoretical papers analyzing endogenous TFP fluctuations build on capital utilization of a quasi-fixed stock (Greenwood et al., 1988; Burnside et al., 1995), often combined with production fixed costs (Christiano et al., 2005; Smets and Wouters, 2007), and labor effort (Bils and Cho, 1994; Basu and Kimball, 1997) which tends to be favored by the data (Lewis et al., 2019). Other work emphasizes composition and dispersion effects, where shifts across heterogeneous industries create aggregation-driven TFP fluctuations (Baqaee and Farhi, 2020; Lagos, 2006). Similarly, labor-market SaM models generate TFP movements as vacancy costs reduce effective productive capacity when workers are reallocated from production to hiring (Blanchard and Gali, 2010).

Third, this paper builds on the goods-market SaM literature, which models coordination frictions through explicit search and matching costs. Goods market SaM models formalize coordination frictions[6], their amplification of unemployment (Michaillat and Saez, 2015; Lehmann and Van der Linden, 2010; Petrosky-Nadeau and Wasmer, 2015), productivity (Qiu and Rios-Rull, 2022), and inventory dynamics (Den Haan and Sun, 2024), and demand management for equilibrium selection (Diamond, 1982; Diamond and Fudenberg, 1989). Time-allocation and search effort are central, as search is procyclical and drives business-cycle variation (Petrosky-Nadeau et al., 2016; Bai et al., 2025). Price-setting becomes a three-dimensional decision, shaped by marginal costs and the state of excess demand or supply (Michaillat and Saez, 2024; Gantert, 2025). A related price-search literature (Benabou, 1988, 1992; Burdett and Judd, 1983; Diamond, 1971; Kaplan and Menzio, 2016; Pytka, 2024) models search for price dispersion rather than as a productive input, and is thus complementary but conceptually distinct from the mechanism studied here.

[6]Two approaches exist: quantity search, where supply enters the matching function, and variety search, where it does not. This paper adopts the quantity-search approach (Michaillat and Saez, 2015; Sun, 2024) and views the alternative frameworks (Qiu and Rios-Rull, 2022; Bai et al., 2025) as complementary.

Embedding a goods market SaM structure into a New Keynesian framework, the paper contributes to the literature by reconceptualizing short-run TFP as reflecting not only input utilization but also market coordination efficiency — the effectiveness with which buyers and sellers match in the goods market. It derives market tightnesses as alternative indicators for cyclical gaps and quantifies TFP dynamics across four major economies. Using survey-based measures of capacity utilization, the analysis shows how coordination frictions reshape the propagation and interpretation of business-cycle shocks. By introducing endogenous price elasticity of demand, the framework reduces reliance on ad-hoc cost-push shocks and redefines the monetary-policy trade-off in the presence of variable matching efficiency.

The rest of the paper is organized as follows. Section 2 introduces the model, its dynamics, and the TFP decomposition. Section 3 discusses the calibration, prior setting, estimation strategy, and identification strategy. Section 4 discusses the estimation results. Section 5 analyzes the drivers of the efficiency wedge across shocks before discussing the broader implications for the busniess cycle properties of the model. Section 6 concludes.

2. Model Setup

The model is based on a state-of-the-art New-Keynesian business cycle model (Christiano et al., 2005; Smets and Wouters, 2007) featuring capital utilization extended by a labor market differentiating between employment, hours per worker, and labor effort (Bils and Cho, 1994; Cacciatore et al., 2020). It has three types of agents - households, monopolistically competitive firms, and a central bank that trade on four markets - goods, labor, capital, and nominal bonds. Goods and labor markets are non-Walrasian and subject to search-and-matching (SaM) frictions. Capital and bond markets are Walrasian. The novel feature of the model is goods market SaM (Michaillat and Saez, 2015, 2024) paired with price adjustment costs (Rotemberg, 1982) and directed search (Moen, 1997). Households provide costly but productive search effort and firms provide unmatched capacity to a matching function creating trades. Households balance overall costs - search and price - which leads to an endogenous price elasticity of demand. And firms balances markups and capacity utilization when setting prices under adjustment costs creating fluctuations in the capacity utilization rate. A simplified pen-and-paper version of this model can be found in the companion paper (Gantert, 2025).

2.1. Labor and Goods Markets

Employment is a long-lasting relationship between workers and firms. Unemployed workers supply their labor inelastically. The employment rate[7] is determined by

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

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

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

where $0 < \gamma_N, \psi_N \leq 1$. 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 a unique variety and supplies its unmatched production capacity, $S_t(i)$. Household search is directed towards each variety individually[8] (Moen, 1997). Customer relationships with firm i form according to

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

where $0 < \delta_T \leq 1$ is an exogenous separation rate. Each formed relationship trades one unit of one variety of the differentiated good. New customer relationships are determined by

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

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

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

where $-\infty < \Gamma \leq 0$ and $0 \leq \gamma_T, \psi_{T,t} < 1$ with $\psi_{T,t}$ varying due to a goods mismatch shock[9]. 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 on market i is defined by $x_{T,t}(i) = \frac{D_t(i)}{S_t(i)}$, which offers a non-Walrasian view on the market equilibrium.

2.2. Households

There are infinitely many households on the unit interval. Each household has infinitely many workers. The representative household maximizes its intertemporal utility

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

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

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

where $\nu_D, \mu_{D,t} > 0$ determine search effort disuility[10], with $\mu_{D,t}$ varying due to a search effort shock. Consumption and search effort habits are determined by $0 \leq \theta_C, \theta_D < 1$ (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 labor effort. Each worker bargains over their hours and labor effort after the employment match is formed. Labor disutility

[9]The aggregate goods market matching efficiency varies due to a goods mismatch shock. 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.

[10]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, contrary to common belief, time allocated to gather information is not a substantial part of overall shopping time (Petrosky-Nadeau et al., 2016).

(Bils and Cho, 1994) is given by

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

where $X_t = \mathbb{U}_{C,t}^{\omega} X_{t-1}^{1-\omega}$ with $0 \leq \omega \leq 1$ is a flexible parameterization of short-run wealth effects on labor supply (Jaimovich and Rebelo, 2009)[11]. $H_t(i)$ is hours per worker at firm i where $\mu_{H,t} > 0$ varies due to an hours supply shock, and $e_{H,t}(i)$ is labor effort at firm i with $\mu_e > 0$. The supply elasticities are determined by $\nu_H, \nu_e > 0$, respectively. Workers adjust hours and labor effort instantaneously while employment is quasi-fixed as shown in (1). Aggregate shopping effort is given by $D_t = \left(\int_0^1 D_t(i) di \right)^{1+\nu_D}$[12]. The representative household likes to consume a large variety of goods (Dixit and Stiglitz, 1977). Its 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 which fluctuates due to a price cost-push shock (Ireland, 2004). Each household divides its 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 technology shock. We assume that investment adjustment costs do not apply to investment resulting from capital utilization, i.e. $I_{A,t} = I_{K,t} - \delta_K \left(e_{K,t}\right) K_{t-1}$, as they represent maintenance investment (Qiu and Rios-Rull, 2022). The capital stock is given by

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

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 $\delta_{K,1} > 0$ sets the independent capital depreciation, $\phi_{K,1} \geq 0$ sets the capital depreciation subject to capital utilization costs, and $\phi_{K,2}$ sets capital depreciation convexity due to capital utilization. Each household

[11] 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.

[12] We assume 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.

follows its intertemporal budget constraint given by

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

where B_t are one-period nominal 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 effective capital supply. Income is determined by nominal wages[13], $W_t(i)$, by unemployment benefits, ub, by capital interest, $P_t r_{K,t}$, by bond interest, $r_{B,t-1}$, and by firm dividends, Div_t[14]. Expenses are determined by consumption and investment expenditures, $\int_0^1 P_t(i) T_t(i) di$, and by lump-sum taxes, Tax_t, charged by the government to pay for unemployment benefits and public spending.

2.3. Firms

There are infinitely many firms on the unit interval. Each firm produces a unique variety i of the differentiated good by employing labor and capital in a Cobb-Douglas production function[15]

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

where $0 \leq \alpha \leq 1$. 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 the stochastic discount factor[16]. Firm revenue is determined by sales on private markets, $T_t(i)$, and by exogenous public spending, $G_t(i)$. Each firm i pays nominal

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

[14] We 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.

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

[16] The firm stochastic discount factor is equal to the household stochastic discount factor as all firms are owned by a mutual fund owned by the representative household.

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 production capacity of a firm is given by

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

where $\mathcal{C}_t(i) = c_{P,t}(i) + c_{W,t}(i) + c_{N,t}(i)$ summarizes firm adjustment costs[17]. $c_{P,t}(i) = \frac{\kappa_P}{2}\left(\frac{P_t(i)}{P_{t-1}(i)}(1+\pi)^{\iota_P-1}(1+\pi_{t-1})^{-\iota_P}-1\right)^2$ 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, where $\kappa_N \geq 0$ (Merz and Yashiv, 2007). Each firm searches for additional workers by posting vacancies, $v_t(i)$. The Hicks-neutral technology level, $A_{H,t} > 0$, varies due to a shock. Firms have identical production fixed costs, $\vartheta \geq 0$. Matching on each goods market depends on the beginning-of-period unmatched 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 production capacity, $\mathcal{Y}_t(i)$, less public consumption, $G_t(i)$, and long-term contracted consumption, and additional any depreciated end-of-period inventories from the previous period, $I_{S,t-1}(i) = (1-q_{T,t-1}(i))\,S_{t-1}(i)$ where $0 < \delta_I \leq 1$ are inventory depreciation costs. Unmatched production capacity, $S_t(i)$, serves as a productive input to the goods market matching function stimulating demand (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 (which depends on goods market tightness) of the representative household into account when setting prices.

[17] In previous versions of this paper, we included hours per worker adjustment costs following Cacciatore et al. (2020). As the results are robust to including hours per worker adjustment costs (see Appendix D), we intenionally leave out this mechanism to keep the model as parsimonious as possible.

2.4. General Equilibrium

To close the model, we 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. We subtract capital depreciation costs due to capital utilization from real GDP as it is maintenance investment and thus an intermediate input (Qiu and Rios-Rull, 2022). 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 survey data is defined as the share of utilized production capacity of its long-run sustainable capacity and 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

$$\bar{\mathcal{Y}}_t \; = \; \left(1 - \mathcal{C}_t\right) A_{H,t}\left(\bar{e}_H \bar{H} N_t\right)^{1-\alpha}\left(\bar{e}_K K_{t-1}\right)^{\alpha} - \vartheta + \left(A_{I,t} - 1\right) T_t, \tag{14}$$

which follows three assumptions (Morin and Stevens, 2004; Michaillat and Saez, 2015; Comin et al., 2025): (1) the capital stock is measured at the current available capital of a firm including non-utilized capital $e_{K,t}$; (2) the level of employment and vacancy costs are measured at their current level; (3) hours per worker and labor effort are measured at the steady-state as deviations are not sustainable in 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 matched capacity rate, $e_{M,t} = \frac{Y_t}{\mathcal{Y}_t}$, which is defined as production capacity sold on the market given short-run capital utilization and labor effort. The central bank follows a Taylor (1993)-type rule to determine the nominal interest rate

$$\frac{1 + r_{B,t}}{1 + r_B} \; = \left[\frac{1 + r_{B,t-1}}{1 + r_B}\right]^{i_r}\left[\left(\frac{1 + \pi_t}{1 + \pi}\right)^{i_\pi}\left(\tilde{Y}_t\right)^{i_{gap}}\left(\frac{\tilde{Y}_t}{\tilde{Y}_{t-1}}\right)^{i_{\Delta gap}}\right]^{1-i_r} \cdot M_t, \tag{15}$$

where 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. 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 (Smets and Wouters, 2007). All shock processes, except the price and wage cost-push shocks, follow an AR(1) process given by

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

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

$$\xi_t = \xi^{1-\rho_\xi} \xi_{t-1}^{\rho_\xi} \varepsilon_{\xi,t} \varepsilon_{\xi,t-1}^{\zeta_\xi}, \quad \varepsilon_{\xi,t} \sim \mathcal{N}(0, \sigma_\xi^2), \tag{17}$$

where ζ_ξ is the MA(1) coefficient. There are nine shocks sorted into three categories: *supply shocks:* a Hicks-neutral technology shock $A_{H,t}$, a price cost-push shock ϵ_t, and a goods mismatch shock $\psi_{T,t}$; *demand shocks:* an investment technology shock $P_{I,t}$, a discount factor shock Z_t, an exogenous spending shock G_t, and a monetary policy shock M_t; *labor shocks:* an hours supply shock $\mu_{H,t}$, and a wage cost-push shock η_t. The search effort shock, $\mu_{D,t}$, is used in robustness exercises as a demand-shock alternative to the goods mismatch shock.

2.5. Dynamic System of the Model Economy

The behavior of households and firms is governed by their first-order conditions. We assume that all firms use the same technology and are summarized by a representative firm.

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

$$\mathbb{U}_{\chi,t} = (\mathbb{U}_{C,t} - \mathbb{U}_{N,t})^{-\sigma} + \omega \frac{\chi_t}{\mathbb{U}_{C,t}}, \tag{18}$$

$$\chi_t = (1-\omega)\, \beta \mathbb{E}_t \frac{Z_{t+1}}{Z_t} \chi_{t+1} - \frac{\mathbb{U}_{N,t}}{(\mathbb{U}_{C,t} - \mathbb{U}_{N,t})^{\sigma}}, \tag{19}$$

$$\mathbb{W}_{C,t} = \mathbb{U}_{\chi,t} - \beta\theta_C \mathbb{E}_t \frac{Z_{t+1}}{Z_t} \mathbb{U}_{\chi,t+1} + \beta\,(1-\delta_S)\, \mathbb{E}_t \frac{Z_{t+1}}{Z_t} \mathbb{W}_{C,t+1}, \tag{20}$$

$$\mathbb{W}_{D,t} = \mathbb{U}_{\chi,t} - \beta\theta_D \mathbb{E}_t \frac{Z_{t+1}}{Z_t} \mathbb{U}_{\chi,t+1}, \tag{21}$$

$$muc_t = \beta \mathbb{E}_t \frac{1 + r_{B,t}}{1 + \pi_{t+1}} \frac{Z_{t+1}}{Z_t} muc_{t+1}, \tag{22}$$

where $\mathbb{U}_{\chi,t}$ is the intratemporal marginal utility of the consumption stock corrected for wealth effects by χ_t, and $\mathbb{W}_{C,t}, \mathbb{W}_{D,t}$[18] is intertemporal marginal (dis-)utility of the consumption stock (search effort). Marginal utility of consumption, 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 can use long-term contracts. Its value expressed in the numeraire good is determined by

$$P_{T,t} \ = 1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}, \tag{23}$$

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

$$\Xi_t \ = (-\epsilon_t) \left[1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1} \right]^{-1}, \tag{24}$$

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 total price, $\Xi_t = \frac{-\epsilon_t}{P_{T,t}}$. We rewrite (22) using (23) by

$$\mathbb{W}_{C,t} \ = \beta \mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}} \frac{Z_{t+1}}{Z_t} \frac{P_{T,t}}{P_{T,t+1}} \mathbb{W}_{C,t+1}, \tag{25}$$

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 $P_{D,t}$. We 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

$$Q_{Y,t} \ = q_{T,t} Q_{T,t} + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} (1-\delta_I)(1-q_{T,t})\, Q_{Y,t+1}, \tag{26}$$

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

[18]We 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.

production capacity, $q_{T,t}$. Marginal costs are defined by $mc_t = \frac{Q_{Y,t}}{e_{M,t}}$ where we correct for the matched capacity rate[19]. The *asset value of matched goods* is given by

$$(1+\varphi_t)\, Q_{T,t} \;= 1 + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left[\Big[(1-\delta_I)\,\varphi_t - (1-\delta_T) \Big] Q_{Y,t+1} + (1-\delta_T)\, Q_{T,t+1} \right], \quad (27)$$

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 matching costs. 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: (1) markups increase in γ_T as search effort is more productive in goods matching; (2) markups increase if the share of newly matched goods to overall sold goods is high, $\frac{m_{T,t}}{T_t}$; (3) markups decrease in $P_{D,t}$ as firms lower prices to attract additional customers in tight goods markets[20].

The *representative firm* posts 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

$$\begin{aligned} \frac{c'_{P,t}}{1-\mathcal{C}_t-\vartheta_{S,t}} \;&= \frac{\theta_{T,t}}{mc_t} - \frac{\gamma_T x_{T,t}^{\Gamma}}{1-\gamma_T} \frac{\theta_{S,t}}{P_{D,t}} \left(1 - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} (1-\delta_I) \frac{e_{M,t+1} mc_{t+1}}{e_{M,t} mc_t} \right) \\ &\quad + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{mc_{t+1}}{mc_t} \frac{Y_{t+1}}{Y_t} \frac{c'_{P,t+1}}{1-\mathcal{C}_{t+1}-\vartheta_{S,t+1}}, \end{aligned} \quad (28)$$

[19]The definition of marginal costs follows the assumption in NK models and the formula applied to the data (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).

[20]Even though the price elasticity of demand (24) decreases in $P_{D,t}$, firms cannot exploit this and raise markups as households are responsive to goods market tightness and their search prices.

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 both markets (excluding inventory changes), 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 production capacity available on any market 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 (24). Inventories have 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 in long-term contracts, 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 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 the goods market matching probability. The trade-off between sticky posted prices and flexible search prices is central to fluctuations in search prices and goods market matching probability.

Capital Allocation. The *representative household* invests into fixed-capital according to

$$\begin{aligned} Q_{K,t} &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \Big[r_{K,t+1} e_{K,t+1} + (1-\delta_{K,1}) Q_{K,t+1} \\ &\qquad - (1+c_{I,t+1}) P_{T,t+1} P_{I,t+1} \delta_K (e_{K,t+1}) \Big], \end{aligned} \tag{29}$$

$$Q_{K,t} = P_{T,t}P_{I,t} \left[(1+c_{I,t}) + \frac{I_{K,t} \left\{ c'_{I,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{P_{T,t+1}P_{I,t+1}}{P_{T,t}P_{I,t}} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1} \right\}}{I_{K,t} - \delta_K (e_{K,t}) K_{t-1}} \right], \tag{30}$$

$$r_{K,t} = (1+c_{I,t}) P_{T,t} P_{I,t} \left(\phi_{K,1}\phi_{K,2} (e_{K,t} - 1) + \phi_{K,1} \right), \tag{31}$$

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

$$r_{K,t} \; = \alpha \left(1 - \mathcal{C}_t\right) \frac{A_{H,t} F_t}{e_{K,t} K_{t-1}} e_{M,t} mc_t, \tag{32}$$

where the capital interest rate increases in the marginal capital productivity, marginal costs, and the matched capacity rate. Both capital supply and demand are affected 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 an imperfect matching rate of employed capacity. Goods market frictions have a direct impact on the capital utilization.

Labor Allocation. The *representative firm* employs labor according to

$$Q_{F,t} \; = \mathcal{C}'_{N,t} \frac{A_{H,t} F_t}{N_t} e_{M,t} mc_t - w_t e_{H,t} H_t + \left(1 - \delta_N\right) \mathbb{E}_t \frac{1 + \pi_{t+1}}{1 + r_{B,t}} Q_{F,t+1}, \tag{33}$$

$$Q_{F,t} \; = \frac{c'_{N,t}}{q_{N,t}} \frac{A_{H,t} F_t}{e_{H,t} H_t N_t} e_{M,t} mc_t, \tag{34}$$

where $\mathcal{C}'_{N,t} = (1 - \alpha)(1 - \mathcal{C}_t) + 2c_{N,t}$. The *firm asset value of marginal employment*, $Q_{F,t}$, increases in the marginal labor productivity and matched capacity rate 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 *labor effort* jointly. Labor effort is determined by

$$e_{H,t} \; = \left[\frac{\mu_{H,t}}{\mu_e} \frac{1 + \nu_e}{\nu_e} H_t^{\nu_H}\right]^{\frac{1}{1+\nu_e}}, \tag{35}$$

which increases in hours per worker. The elasticity of labor 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 derive an increasing returns to scale parameter in hours per worker following from latent labor effort by $\phi = 1 + \frac{\nu_H}{1+\nu_e}$ (Lewis et al., 2019). Real wage bargaining is determined by

$$\begin{aligned} w_t e_{H,t} H_t \; &= ub + P_{T,t} \frac{X_t \frac{\mu_{H,t}}{1+\nu_H} \left(1 + \frac{1+\nu_H}{\nu_e}\right) H_t^{1+\nu_H}}{\mathbb{W}_{C,t} \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}} + \frac{\eta_t}{1-\eta_t} \frac{Q_{F,t}}{\tau_{W,t}} \\ &- \left(1-\delta_N\right) \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1 - f_{N,t+1}\right) \frac{\eta_{t+1}}{1-\eta_{t+1}} \frac{Q_{F,t+1}}{\tau_{W,t+1}}, \end{aligned} \tag{36}$$

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 labor effort - are determined by opportunity costs equalizing marginal labor productivity. Goods market SaM affects labor demand through the matched capacity rate, $e_{M,t}$, implicitly given by $Q_{F,t}$, and labor supply through the impact of search prices on $P_{T,t}$. Marginal productivity of all three labor margins (thus the firm's value of labor) increase in the matched capacity rate, $e_{M,t}$. However, if search prices increase with capacity utilization, $P_{T,t}$ increases and counteracts labor expansion through higher wages.

The equilibrium conditions above imply that aggregate output depends not only on technology and factor inputs but also on how intensively these inputs are utilized in each market. Labor effort, capital utilization, and the probability that produced goods are successfully matched with demand jointly determine the economy's effective productive capacity. As a result, the Solow-residual measure of total factor productivity (TFP) in the data combines true technological progress with utilization-induced efficiency fluctuations. The following subsection formalizes this relationship by deriving TFP as a function of technology and the three utilization margins and by defining the resulting *efficiency wedge* that will later be identified in the estimation.

2.6. Measuring Total Factor Productivity

Building on the equilibrium relationships derived above, this subsection defines TFP and decomposes it into (utilization-adjusted) technology and utilization components. We linearize the relationships around their deterministic steady-states for ease of exposition, e.g. $\hat{gdp}_t = \frac{GDP_t - GDP}{GDP}$. TFP in the model follows from the aggregate production identity and reflects both technological efficiency and utilization of inputs across capital, labor, and the goods market. Linearizing the production function and substituting for variable utilization rates yields

$$G\hat{D}P_t \;=\; \hat{A}_t + \alpha \hat{K}_{t-1} + (1-\alpha)\left(\hat{N}_t + \hat{H}_t\right) + \hat{u}_t^K + \hat{u}_t^L + \hat{u}_t^{\vartheta} + \hat{u}_t^{GM}, \tag{37}$$

where $\hat{A}_t = A\left(A_{H,t}, P_{I,t}, \psi_{T,t}\right)$ denotes technology[21] - or utilization-adjusted TFP[22], $\hat{u}_t^K$ capital utilization, $\hat{u}_t^L$ labor utilization, $\hat{u}_t^{\vartheta}$ increasing returns due to production fixed costs, and $\hat{u}_t^{GM}$ goods market utilization derived from the search-and-matching (SaM) block. Observed TFP (Solow (1957)-residual) is therefore

$$T\hat{F}P_t \;= \hat{A}_t + \hat{u}_t^K + \hat{u}_t^L + \hat{u}_t^{\vartheta} + \hat{u}_t^{GM} \;=\; \hat{A}_t + \hat{\Phi}_t, \tag{38}$$

so that variation in measured productivity reflects both genuine technology changes, $\hat{A}_t$, and fluctuations in utilization represented yb the *efficiency wedge*, $\hat{\Phi}_t$ - variation in TFP that is explained by endogenous propagation of shocks in the model.

Goods market utilization, $\hat{u}_t^{GM}$, captures efficiency losses due to incomplete matching between goods supplied and demanded, including long-term contracts and inventory changes. It depends on the matching probability, $q_{T,t}$, and the search price, $P_{D,t}$. Utilization in the labor margin enters analogously through ν_e, but also through working time provided to human resources, $\hat{c}_{N,t}$; utilization in the capital margin enters through $\phi_{K,2}$; and in the production fixed costs margin through ϑ. The *efficiency wedge* increases in all four channels.

[21] It is ambiguous whether the goods market efficiency shock, $\hat{\psi}_{T,t}$, is a true technology shock, as it might also contain market dispersion and composition effects. In section 3, we 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.

[22] The utilization-adjusted TFP 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 comparable to the impact of capacity utilization. Hence, we use the term "utilization-adjusted TFP" instead of "technology".

In the empirical analysis, we use the smoothed states from the Kalman filter to compute the utilization-adjusted TFP component which isolates the *efficiency wedge* emphasized by the different utilization margins. Detailed derivations of the TFP decomposition are given in Appendix B. The decomposition provides the basis for the results in section 4, where we compare how each utilization channel contributes to TFP dynamics in the data. Section 3 details how this structure is estimated and how the *efficiency wedge* and utilization margins are identified in the data.

3. Estimation and Identification

This section connects the theoretical model and the TFP decomposition to the data. It describes the datasets and prior choices, outlines the Bayesian estimation strategy, and explains how the key goods market SaM parameters are identified. The estimation includes survey-based capacity utilization that anchors the *efficiency wedge* in TFP. Identification relies on cross-equation restrictions linking utilization, consumption dynamics, and inflation to the goods market SaM block of the model. The section concludes by conceptually setting up the comparison of alternative model specifications — capital utilization, labor effort, and goods-market SaM - of the efficiency wedge.

3.1. Data and Prior Description

We estimate the model on quarterly U.S. (1984q1 - 2019q4) and Euro-Area data (1998q1 - 2019q4) using nine observables: real growth rates of GDP, private investment[23], private consumption, and labor compensation, survey data on capacity utilization, hours per worker, the employment rate, the GDP deflator, and the policy rate[24]. Hours per worker and the employment rate are linearily detrended following Cacciatore et al. (2020). All other variables are detrended following Smets and Wouters (2007). The policy rate is adjusted by the shadow rate for the zero-lower-bound period (Wu and Xia, 2016). Capacity-utilization data

[23] Euro Area data on investment contains public investment as well as no separate data is available. However, as public investment is mostly acyclica, this does not affect our observable significantly.

[24] U.S.: federal funds effective rate; Euro Area: EURIBOR 3-month average data.

combine industrial and imputed service-sector measures; construction and sources appear in section Appendix C. We consider the U.S. data for our main analysis while the Euro-Area data serves as a robustness exercise.

We use a combination of calibrated (general) and estimated (research question specific) parameters. The calibrated parameters follow the literature (Blanchard and Gali, 2010; Christiano et al., 2010). An overview is given in table C.6 in the appendix. The prior setup is shown in table 3. A detailed description of the calibration and estimation strategy is given in Appendix C.

We estimate several parameters through proxies to improve stability and constrain the permissible range. The steady-state markup determines ϵ with a Beta (0.2, 0.1) prior, which in turn determines the production fixed costs through a zero profit assumption. The labor-effort elasticity, ν_e, is inferred from increasing returns in hours per worker, $\phi = 1 + \frac{\nu_H}{1+\nu_e}$, with a Gamma prior with mean 1.75 and standard deviation 0.25 (Lewis et al., 2019). The capital-utilization elasticity, $\phi_{K,2}$, is estimated with a Gamma prior with mean 2 and standard deviation 1 (Christiano et al., 2010; Qiu and Rios-Rull, 2022). All three priors are deliberately wide to allow for potential trade-offs with the goods-market SaM block. For the goods market SaM parameters, γ_T, is normalized by an upper bound, $\gamma_{T,ub}$, reflecting the literature (Michaillat and Saez, 2015; Bai et al., 2025; Huo and Rios-Rull, 2020; Qiu and Rios-Rull, 2022) and estimated via $\gamma_T^{prox} = \gamma_T / \gamma_{T,ub}$ with a Beta(0.5, 0.2) prior. The same approach applies to Γ, bounded between $\Gamma_{lb} = -5$ and 0, using a Beta(0.1, 0.075) prior[25]. The search effort disutility parameter, ν_D, is modeled as a multiple of ν_H and estimated with a Gamma prior with mean 1 and standard deviation 0.5, which reflects the idea of equal disutility across time-uses (Huo and Rios-Rull, 2020). The inventory depreication rate, δ_I, uses a Beta (0.15, 0.05) prior for the industry share of the economy, accounting for $\delta_{S,I} = 1$ in services (Khan and Thomas, 2007). Finally, the contract separation rate, δ_T, uses a Beta (0.25, 0.15) prior (Mathä and Pierrard, 2011) where the wide prior adjusts for household–firm rather than inter-firm contracts.

[25] This interval allows mild complements around Cobb–Douglas elasticity while excluding extreme cases.

3.2. Estimation Strategy

We estimate the model using full-information Bayesian methods. The model is linearized around its deterministic steady state and solved using Dynare (Adjemian et al., 2024). The posterior distribution combines the likelihood obtained from the Kalman filter with the prior densities described above. We compute the posterior mode using the NewRat optimizer and draw four Markov chains of 3,000,000 iterations each from a random-walk Metropolis–Hastings algorithm, discarding the first half as burn-in. The proposal scale is tuned automatically to achieve an acceptance rate of approximately 30 percent. Posterior convergence is assessed using the Brooks and Gelman (1998) and Geweke (1999) diagnostics. Model comparison relies on the log data density, computed with the modified harmonic-mean estimator (Geweke, 1999). Differences in log data densities are evaluated using the Bayes factor (Kass and Raftery, 1995), where values above 10 indicate a decisive improvement in model fit. Marginal likelihoods and Bayes factors across model versions are computed using posterior draws of identical length and tuning parameters to ensure comparability across specifications. Convergence diagnostics available upon request.

The observables–to–state mapping follows Pfeifer (2018), linking nine time series observables to the model's measurement equations. The state vector includes the endogenous variables and nine exogenous shocks described in section 2.

3.3. Identification of the Goods Market SaM Mechanism

Identification relies on two complementary sources of information: (i) survey-based capacity utilization, which pins down the *efficiency wedge* of TFP and the goods market matching probability, $q_{T,t}$; and (ii) cross-equation restrictions linking the consumption and investment Euler equations and the New Keynesian Phillips curve to the latent search price, $P_{D,t}$. Together, these moments identify the capacity utilization and price elasticity channels of the goods market SaM mechanism.

Using TFPDEF and (13), we derive the relationship between the *efficiency wedge* and capacity utilization given by

$$\hat{\Phi}_t = \underbrace{\frac{\hat{\boldsymbol{cu}}_{\boldsymbol{t}} - \vartheta_{gdp} cu \hat{\boldsymbol{\vartheta}}_{\boldsymbol{S,t}}}{1 + \vartheta_{gdp} cu} - \frac{c_N \hat{\boldsymbol{c}}_{\boldsymbol{N,t}}}{1 - c_N} - (1-\alpha)\,\hat{\boldsymbol{H}}_{\boldsymbol{t}}}_{=\hat{\Phi}_{cu,t}} - \underbrace{\left[\varphi_{AI} \hat{\boldsymbol{A}}_{\boldsymbol{I,t}} + \varphi_{\psi} \hat{\boldsymbol{\psi}}_{\boldsymbol{T,t}}\right]}_{=\hat{\Phi}_{Bias,t}}, \tag{39}$$

where $\varphi_{AI} = \frac{1-cu}{\left(1+\vartheta_{gdp} cu\right)\delta_T \delta_I}$ and $\varphi_{\psi} = \frac{1-cu(1-(1-g_S)\delta_T\delta_I)}{\left(1+\vartheta_{gdp} cu\right)\delta_I}$. The *efficiency wedge* is determined by: (i) observables - capacity utilization, fixed cost degression (proxied by real GDP), hours per worker, and labor matching costs (proxied by employment data) - summarized by $\hat{\Phi}_{cu,t}$; and (ii) by two latent variables - investment technology and goods mismatch shocks - summarized by $\hat{\Phi}_{Bias,t}$[26]. If $\hat{\Phi}_{Bias,t}$ is small, the model and estimation setup in this paper is in line with Fernald (2014); Comin et al. (2025) using capacity utilization data to infer the *efficiency wedge* and thus "utilization-adjusted TFP" directly. If the TFP bias is large, we have to rely more on cross-equation restrictions to identify the *efficiency wedge* across models.

Capacity utilization data further disciplines the goods market SaM block through (13), which links capacity utilization to matching efficiency ψ_T, goods matching probability, $q_{T,t}$, and long-term contract and inventory dynamics. We rewrite (13) as

$$\bar{cu}_t = \bar{\mathcal{Y}}_t^{-1}\Big\{A_{I,t}\big[\boldsymbol{q}_{\boldsymbol{T,t}} S_t + (1-\delta_T)\,T_{t-1}\big] + \Delta I_{S,t} + G_t - \delta_K\left(e_{K,t}\right)K_{t-1}\Big\} \tag{40}$$

where $\bar{\mathcal{Y}}_t$ is given by (14). Conventional capacity utilization channels affect available production capacity, $S\left(e_{H,t}, e_{K,t}; \vartheta, \delta_T, \delta_I\right)$, as shown in (11). Hence, the goods matching probability, $q_{T,t}$, is a main determinant of capacity utilization as input factors are fixed through observables and long-term contracts and inventory investmenet are jointly determined through the goods market SaM block. However, both capacity utilization and the decomposition of the *efficiency wedge* can in principle be described by either the goods matching probability or the conventional utilization channels affecting available production capcaity. Hence, we rely on cross-equation restrictions laid out next to elicit the log data density of each channel as

[26] This definition of the TFP bias follows from the declaration of goods mismatch shocks as technology shocks. They drive capacity utilization exogenously but account as technology. Using the lower bound interpretation, goods mismatch shocks drop out of the TFP bias, however, investment technology shocks remain as they affect an implicit capital production function on the household side instead of the firm side.

described in section 3.4.

Search prices as defined in (23) are a latent variable as data is not available on a quarterly basis. Cross-equation restrictions given by the consumption (25) and investment Euler equations (30) and the Phillips curve (28) discipline the search price component, $P_{D,t}$, in conjunction with consumption, investment, and inflation data. Search prices are further disciplined by survey data on capacity utilization through their interaction with goods market tightness which also separately identifies the search effort disutility and goods market tightness components of search prices.

The labor effort margin is identified by hours per worker as shown in (35), which is disciplined through employment decisions on the demand (33) and supply side (36). The capital utilization margin is identified by the capital interest rate as shown in (31), which is disciplined through capital investment decision on the demand (32) and supply side (30). Labor and capital supply are jointly determined with search prices and labor and capital demand are jointly determined with short-run capacity utilization.

The joint estimation across these equations allows the data to distinguish whether fluctuations in TFP originate from underlying technology shocks or from utilization - and through which utilization channel. The key insight is that capacity utilization and inflation jointly anchor the SaM mechanism, while real activity variables discipline the propagation of utilization and search effort to output and prices.

3.4. Model Comparison Design

To evaluate the contribution of each utilization mechanism, we estimate and compare several nested versions of the model. Each variant activates a different channel linking input factors to measured total factor productivity (TFP) while keeping all other structures and priors identical. This approach isolates how the new goods-market search-and-matching (SaM) block improves model fit relative to existing utilization margins in the literature.

The benchmark follows Lewis et al. (2019) and includes labor effort and production fixed costs but excludes capital utilization and goods market SaM. Alternative specifications sequentially

Table 1: Model Variants by Active Utilization Channel

Model	**Active Utilization Channels**	**Purpose in Comparison**
K-Util	Capital-utilization costs $\phi_{K,2}$ Production fixed costs ϑ	Replicates standard DSGE (Christiano et al., 2010; Smets and Wouters, 2007).
L-Util *(Benchmark)*	Labor-effort elasticity ν_e Production fixed costs ϑ	Benchmark utilization mechanism (Comin et al., 2025; Fernald, 2014; Lewis et al., 2019).
GM-Util	Goods market SaM $(\psi_T, \gamma_T, \Gamma)$ (excl. intertemporal channels) Production fixed costs ϑ	Tests goods market utilization mechanism (Michaillat and Saez, 2015).
Full-Int-Util	All margins as in section 2 (Inventories imply durable consumption, which are otherwise excluded)	Full specification combining all utilization and dynamic margins.

NOTE: Each model name in small caps indicates the active utilization margin. The Full-Int-Util specification represents the complete version of the framework. Any combination of the presented models is possible. All variants share identical priors and data; differences in log data density therefore capture the marginal explanatory contribution of each utilization channel.

introduce both mechanisms. The preferred specification[27] combines the labor effort and goods market SaM channels, which together provide the best data fit and identification of the utilization margin. A further robustness model adds intertemporal SaM components (inventories and long-term contracts). All models are estimated with identical data, priors, and sampling settings, ensuring that Bayes-factor differences reflect economic — not numerical—variation. Table 1 summarizes the model hierarchy. The first block reproduces mechanisms common in the literature; the second introduces the new goods market SaM channel developed in this paper. Any combination of the presented margins is evaluated

[27]For expositional clarity, we label the models as the *benchmark* and *preferred* specifications to organize the comparison and terminology early on. The labels are a result from the estimation and are not presupposed in any way.

in section 4 as e.g. the *preferred model* combining the L&GM-Util margins. Posterior estimates, log data densities, and variance decompositions reported in section 4 quantify the relative explanatory power of each specification.Having established the estimation framework and identified the efficiency wedge and other utilization margins, we now turn to the empirical results. Section 4 presents the posterior estimates and model fit, compares the alternative utilization specifications introduced in section 3.4, and evaluates the contribution of each margin to fluctuations in total factor productivity (TFP). We first discuss log data densities and posterior parameters. We then examine the implied dynamics of the efficiency wedge and the decomposition of measured TFP into technology and utilization components. A variance decomposition of the business cycle shocks provides the empirical foundation for the interpretation of business cycle utilization behavior in section 5.

4. Estimation Results

Goods market SaM improves the log data density of the model across all countries considered. Whether the price elasticity, capacity utilization, or both channels drive the results depends on the country. The prior-posterior analysis shows clearly identified parameters across countries for all utilization channels, especially for the goods market SaM parameters which show a substantial productive impact for search effort but revoke intertemporal components. The variance decomposition shows a slight shift to demand shocks as the determinants of the business cycle with a clear shift away from price cost-push shocks within the class of supply shocks following from an endogeneized price elasticity of demand. The results are robust to a variety of exercises.

4.1. Does Goods Market SaM Explain the Data Better?

The goods market SaM mechanism decisively improves the model's ability to explain macroeconomic fluctuations. Table 2 summarizes log data densities for all model variants and countries. Relative to the benchmark with labor effort utilization, adding goods market SaM shows a Bayes factor between 77 and 150 points, indicating a decisive improvement in fit. The data therefore favors a contemporaneous SaM channel that complements the

Table 2: Log Data Densities Across Different Model Setups

Model Setup	U.S.	Spain	Germany	France
Models from the Literature				
K-Util	5096.2	2634.3	2905.1	3043.2
L-Util **Benchmark**	**5156.3**	**2675.4**	**2927.3**	**3092.5**
K&L-Util	5146.0	2680.1	2925.9	3085.9
Goods Market Search-and-Matching Models				
GM-Util	5163.5	2687.4	2975.2	3149.3
K&GM-Util	5156.6	2688.4	2978.1	3150.1
L&GM-Util **Preferred**	**5194.6**	**2710.0**	**3002.5**	**3160.8**
KL&GM-Util	5187.7	2709.1	3004.7	3160.8
Full-Int-Util	5155.8	2683.8	2986.8	3134.9
Bayes Factor: Preferred - Benchmark	**76.6**	**69.2**	**150.4**	**136.6**
Goods Market SaM Channel Decomposition				
L&GM-Util (Complements)	5177.8	2658.8	2940.6	3090.4
Bayes Factor: Complements - Preferred	**-33.6**	**-102.4**	**-123.8**	**-140.8**
No Capacity Utilization Data as an Observable				
L-Util (no CU)	4639.3	2462.4	2622.4	2823.7
L&GM-Util (complements & no CU)	4663.8	2471.6	2679.6	2898.0
L&GM-Util (no CU)	4662.9	2466.1	2693.1	2895.3
Bayes Factor: Preferred - Benchmark	**47.2**	**7.4**	**141.4**	**143.2**

NOTE: The table shows estimates for U.S. data (1984q1-2019q4) and Euro Area data (1998q1-2019q4). 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). Log data densities with an asteriks are obtained from a Laplace approximation given limited computing power.

labor effort margin, while capital utilization and intertemporal SaM extensions add little explanatory power.

Benchmark vs Preferred Model. Across economies, the hierarchy of models is consistent. Labor effort utilization outperforms capital utilization decisively (except for Spain), reproducing results in Lewis et al. (2019) and informing our *benchmark model* choice. A simple goods market SaM model (GM-Util) outperforms the benchmark with a Bayes factor between 15 and 114 - indicating a decisive improvement in data fit and highlighting the importance of goods market SaM.

Adding labor effort (L&GM-Util) complements good market SaM showing the highest performing model across countries - thus informing our *preferred model* choice. Combining all three utilization channels (KL&GM-Util) yields no additional gain, confirming that the labor effort and goods market margins jointly capture the relevant dynamics[28]. Including long-term contracts or inventories (Full-Int-Util) leads to a negative Bayes factor of roughly -35 to -60 points, suggesting that the data prefers short-lived, contemporaneous matching frictions to persistent contractual mechanisms.

This pattern implies that aggregate capacity utilization fluctuations arise mainly from behavioral effort on both sides of the goods market rather than from physical capital adjustment. The high posterior likelihood of the models with goods market SaM indicates that search effort and market tightness provide critical information about measured TFP variation.

Goods Market SaM Channel Decomposition. We find that both the *price elasticity of demand* and *capacity utilization* channels contribute to the decisive improvement in data fit of the L&GM-Util model. To assess their contributions, we separately identify their effects following section 3.3. This decomposition clarifies whether the inclusion of goods market SaM enhances the model primarily by improving the measurement of capacity utilization and TFP, or instead by refining the dynamics of other equations through the endogenous

[28]For the U.S., comparing GM-Util with K-Util replicates the findings of Qiu and Rios-Rull (2022) with a Bayes factor of 134.6. However, contrary to their findings, combining both margins leads to a decisively worse data fit. For the Euro Area countries, we find indecisive changes in the data fit when combining K&GM-Util.

price-elasticity channel.

Two caveats apply when identifying the separate contributions of the goods market SaM channels. First, we observe data on capacity utilization but not on search effort. Second, variation in price elasticity is partly driven by changes in capacity utilization, creating an interaction between the two channels.

First, we isolate the joint effect of the capacity utilization and interaction channels by setting the matching inputs to perfect complements ($\Gamma = -\infty$) and re-estimating the model. The resulting Bayes factors, ranging from -33.6 to -140.8, indicate a decisive deterioration in model fit once search effort loses its productive (substitutive) role. Hence, the joint contribution of the capacity utilization and interaction channels to goods market SaM performance is clearly positive. The residual Bayes factor captures the performance of the price elasticity channel alone. For the United States and Germany, the L&GM-Util (complements) specification still outperforms the benchmark, whereas the data fit deteriorates decisively for Spain and France. Overall, capacity utilization and its interaction with price elasticity jointly strengthen the model's data fit, while the price elasticity channel in isolation delivers mixed results.

Second, to decompose the joint effect of the capacity utilization and interaction channels, we drop the capacity utilization data and re-estimate the model. Even without targeting utilization directly, introducing goods market SaM raises the log data density, with Bayes factors between 7.4 and 143.2. This gain reflects the combined influence of the price elasticity and interaction channels. To further decompose them, we shut off the interaction term by imposing perfect matching complements. The data fit improves for Spain and France, remains unchanged for the U.S., and deteriorates decisively for Germany — indicating that Germany's model fit relies on interaction amplification, while the other countries do not. Hence, when explaining macroeconomic aggregates without capacity utilization data, the price elasticity channel dominates for the U.S., Spain, and France, whereas Germany depends on the interaction term for amplification.

Taken together, both goods market SaM channels contribute equally to the model fit for the U.S., whereas the interaction channel adds little. For Spain and France, the capacity utilization and interaction channels dominate,[29] while in Germany all three channels play a significant role.

Robustness Analysis. Overall, adding goods market SaM to the labor effort (benchmark) model creates the most effective framework in the literature for explaining business cycle and capacity utilization dynamics across countries. The decomposition of SaM channels shows that both the price elasticity and capacity utilization mechanisms enhance model likelihood, though their relative importance varies across countries. We therefore adopt the specification combining labor effort and goods market SaM — excluding intertemporal components — as the preferred model for the remainder of the analysis.

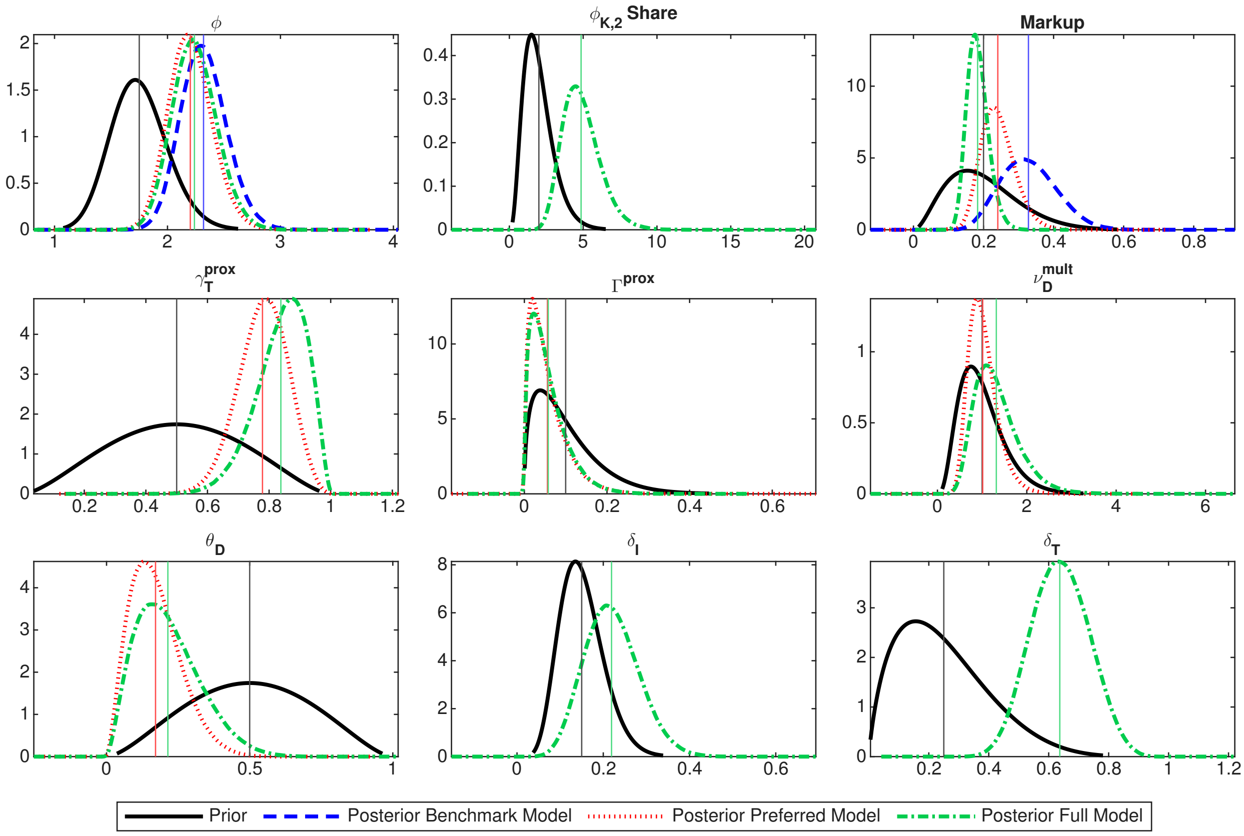
The results are robust to alternative specifications varying the treatment of investment and output, sectoral weights in the construction of capacity utilization data, the sample period, and hours-adjustment costs, as reported in table D.14. The preferred model also performs similarly when replacing the goods mismatch shock with a search effort shock, and estimation without capacity utilization data — potentially subject to measurement bias (section Appendix C) — yields consistent results. Bayes factors thus confirm that incorporating goods-market SaM mechanisms decisively improves model fit, motivating the following analysis of the posterior parameter estimates that underpin these findings.

4.2. Prior-Posterior Analysis

Posterior densities are sharply peaked and consistent across countries, indicating precise identification of the utilization mechanisms. The results confirm that the goods market SaM block is well supported by the data and that its parameters explain the improvement in model fit documented in section 4.1. Figure 1 highlights the posterior densities of the goods market SaM parameters and a full overview of the posteriors is given in table 3. The data is informative on the utilization parameters, all posteriors are well within their prior intervals, and posteriors of general parameters are mostly consistent across models.

[29] When capacity utilization data are not targeted, the price elasticity channel still weakly improves the data fit for Spain and France, providing some support for both channels.

Figure 1: U.S. Prior-Posteriors Densities of the Utilization Margins



NOTE: The figure shows the prior and posterior distribution for the benchmark (L-UTIL), preferred (L&GM-UTIL), and full (FULL-INT-UTIL) models. The estimation follows the description in Appendix C.

Goods market SaM. The goods market SaM parameters show a strong and productive search elasticity. The posterior mean of γ_T is high, implying that household and firm search efforts are salient features of the matching process. The curvature parameter Γ centers near zero, consistent with near-Cobb–Douglas substitutability rather than complementarity. Taken together, these findings confirm the importance of both price elasticity and capacity utilization channels. The disutility of search effort ν_D is comparable in magnitude to the labor effort elasticity ν_H, suggesting that time spent searching carries a similar opportunity cost to time spent working[30]. Together these results indicate that search effort is a quantitatively

[30]The search cost convexity parameter, ν_D, shows higher values than in Michaillat and Saez (2015), but lower values than in Bai et al. (2025), and is roughly in line with Huo and Rios-Rull (2020).

important margin of adjustment and a key driver of measured utilization dynamics in line with the literature (Bai et al., 2025; Michaillat and Saez, 2015; Qiu and Rios-Rull, 2022). The intertemporal goods market SaM parameters are small. Posterior means of the contract-separation rate δ_T and the inventory depreciation rate δ_I imply short-lived matches and limited persistence of inventories, confirming that the data favor contemporaneous rather than intertemporal goods market frictions. Consequently, the high fit of the preferred model arises mainly from current period search activity rather than from the accumulation of contracts or stocks of unsold goods in aggregate.

Steady-state markups. The posterior of the markup channel further clarifies the role of goods-market SaM in shaping utilization. Estimated steady-state markups decline once goods-market SaM is introduced, reflecting stronger effective competition as firms respond more flexibly to search conditions. A high search elasticity (γ_T) and low curvature (Γ) make search effort highly responsive to demand, which dampens steady-state markups, implying smaller effective fixed costs and higher capacity utilization, as firms operate closer to their efficient scale. The preferred model shows steady-state markups roughly 9%-points smaller than in the benchmark model. Hence, goods market SaM captures an endogenous reduction in overhead — another mechanism through which utilization affects measured TFP.

Capital utilization and labor effort. Turning to traditional utilization margins, the labor effort elasticity, ν_em remains significant[31] and continues to dominate over capital utilization costs[32], $\phi_{K,2}$, which increase without bound as we expand the prior standard deviation. This

[31]The posterior mean of the labor effort supply elasticity, $\frac{1}{\nu_e} = \left(\frac{\nu_H}{\phi-1} - 1\right)^{-1}$, increases to values between 0.68 and 0.86 given the respective ν_H posterior. This implies a labor effort supply elasticity at the upper bound proposed by the literature (e.g. Bils and Cho (1994)) with a less elastic margin as we add *goods market SaM*.

[32]The K&L-Util model shows a $\phi_{K,2}$ posterior of 5.29, the Full-Int-Util model of 4.85, both more than twice as high as their prior. The implied elasticity of the utilization rate to changes in the marginal utilization costs, $\sigma_{e_K} = \frac{\delta'_K}{\delta''_K e_{K,t}}$, of 0.21 is very low compared to the literature (Christiano et al., 2010) with an elasticity of 3.33

Table 3: Prior-Posterior Estimates of the Model Parameters for the U.S.

		Prior		Posterior		
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	Preferred (90% HDP)	Full (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.25 (0.06-0.49)	0.03 (0.00-0.07)	0.09 (0.00-0.15)
θ_H	Beta	0.7	0.1	0.79 (0.71-0.86)	0.85 (0.80-0.90)	0.85 (0.79-0.94)
ν_H	Gamma	2	0.5	2.87 (2.20-3.51)	2.91 (2.27-3.54)	3.08 (2.36-3.81)
$\frac{1}{mc}-1$	Beta	0.2	0.1	0.33 (0.20-0.46)	0.24 (0.16-0.32)	0.18 (0.13-0.23)
κ_I	Gamma	4	1.5	1.72 (1.22-2.21)	3.12 (2.36-3.86)	2.82 (1.99-3.64)
κ_W	Gamma	30	5	30.3 (22.0-38.3)	26.6 (18.9-34.2)	25.3 (17.4-33.3)
κ_P	Gamma	180	20	170.5 (138.9-201.0)	161.7 (132.8-190.2)	171.1 (141.7-201.1)
ι_W	Beta	0.5	0.15	0.44 (0.20-0.67)	0.48 (0.23-0.72)	0.39 (0.17-0.62)
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	1.77 (1.62-1.91)	1.72 (1.58-1.86)	1.76 (1.61-1.90)
i_{gap}	Gamma	0.12	0.05	0.03 (0.01-0.04)	0.02 (0.01-0.04)	0.03 (0.01-0.04)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.34 (0.20-0.47)	0.39 (0.20-0.57)	0.24 (0.14-0.34)
i_r	Beta	0.75	0.05	0.76 (0.72-0.80)	0.61 (0.54-0.68)	0.64 (0.57-0.71)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	2.32 (1.99-2.65)	2.2 (1.88-2.52)	2.25 (1.92-2.57)
$\phi_{K,2}$	Gamma	2	1	–	–	4.85 (2.83-6.84)
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.78 (0.65-0.91)	0.84 (0.71-0.97)
Γ^{prox}	Beta	0.1	0.075	–	0.06 (0.00-0.12)	0.06 (0.00-0.12)
ν_D^{mult}	Gamma	1	0.5	–	1.01 (0.50-1.49)	1.27 (0.53-2.01)
θ_D	Beta	0.5	0.2	–	0.17 (0.03-0.30)	0.22 (0.04-0.40)
δ_I	Beta	0.15	0.05	–	–	0.22 (0.12-0.32)
δ_T	Beta	0.25	0.15	–	–	0.64 (0.48-0.80)

NOTE: The table shows the prior (identical across models) and posterior distributions of the estimated parameters for the (1) benchmark model (L-UTIL), (2) preferred model (L&GM-UTIL), and (3) full model (FULL-INT-UTIL). The 90% HDP intervals are given in paranthesis.

pattern mirrors the literature's finding that variations in labor effort, rather than physical capital use, account for short-run productivity movements (Lewis et al., 2019).

Further posteriors across models. The complete prior-posterior overview can be found in table 3, which shows mostly consistent parameters across models. The Frisch elasticity, ν_H, is similar across models even though we introduce a time-allocation trade-off with goods market SaM. Nominal frictions are unaffected even though the relationship of markups changes markedly. Investment adjustment costs, κ_I, are larger after adding goods market SaM, indicating otherwise strong investment variation following from variation in the price elasticity.

Robustness. The cross-country evidence is largely uniform[33]: the U.S., Germany, France, and Spain exhibit tight posteriors with the same qualitative ordering — high γ_T, low δ_T, and negligible $\phi_{K,2}$. Hence, the data consistently support a contemporaneous goods-market mechanism that complements the labor-effort and fixed-cost margins, with the initially dominant margin differing across countries[34]. Prior-posterior tables for Spain, Germany, and France can be found in Appendix D.2.

The posterior evidence shows that the data favors a salient and contemporaneous goods-market SaM channel, characterized by high search elasticity and limited contract persistence. These parameter estimates provide the structural foundation for the dynamics discussed next. Section 4.3 translates these posterior results into observable business cycle behavior by examining the model-implied latent gaps for the United States.

4.3. The U.S. Business Cycle through the Lens of Goods Market SaM

Building on the estimated parameters, this section interprets the model's implications for the U.S. business cycle. We first examine implied second moments of non-targeted variables — search effort, utilization-adjusted TFP, and their correlation with capacity utilization — to assess how well the model captures behavioral regularities. These moments confirm that goods market search effort is procyclical and tightly linked to utilization, providing empirical support for the goods market SaM mechanism. We then analyze the model-implied output, unemployment, and market-tightness gaps to show how these endogenous utilization

[33] There are some expected deviations for the Euro Area: labor markets are more rigid; capital investment is country-specific but impact of goods market SaM is consistent; markups are generally lower; and monetary policy focuses more on inflation.

[34] Introducing goods-market SaM lowers steady-state markups in Germany while diminishing the contribution of labor effort in Spain and France, thereby improving the explanation of capacity utilization through distinct country-specific channels.

margins reshape the narrative of U.S. booms and recessions. The results reconcile the *missing deflation puzzle* after 2008 and the inflation spikes during 2021–22, consistent with shifting Barro and Grossman (1971)-type regimes of excess supply and demand.

Validation through Implied Second Moments. To evaluate the model's behavioral realism beyond the estimation targets, we examine several non-targeted second moments implied by the preferred specification. These include the volatility and persistence of search effort, the comparability of utilization-adjusted TFP with established estimates, and their joint correlation with capacity utilization. Matching these moments provides an external validation of the model's goods-market SaM mechanism and its ability to capture the interaction between time allocation, utilization, and measured productivity.

Table 4 shows correlations of key variables of the goods market SaM mechanism. Hours per worker is a reasonable proxy for capacity utilization and search effort in the U.S. (Fernald, 2014). However, the imperfect correlation shows that survey data on capacity utilization contains additional information (Comin et al., 2025), linked to shifts in household time-allocation. The model implies that search effort is strongly procyclical with a regression coefficient[35] in real GDP of 0.95 - a result close to Petrosky-Nadeau et al. (2016) analyzing the American Time-Use Survey. The unconditional variance decomposition shows that goods mismatch shocks explain 16.6% of search effort variation which implies strong internal propagation[36]. Surprisingly, however, search effort is not tightly linked to TFP, capacity utilization, or goods market tightness, showing the prevalence of shifts in optimal time-allocation and goods market efficiency besides demand shocks (procyclical search effort).

The model-implied U.S. TFP series are highly consistent across specifications, indicating tight identification by the observables. The estimated TFP time series correlate at approximately one, with standard deviations of 3.0% and 3.1% for the benchmark and preferred models (see

[35]We regress smoothed log search effort data on smoothed log real GDP data retrieved from the preferred model by OLS including a constant and an error term. The constant is estimated with 0.0756.

[36]For the preferred model, search effort variation is mostly driven by investment shocks (30.2%), monetary policy shocks (13.5%), and price cost-push shocks (32.9%). Neutral technology shocks play a minor role (3.3%).

Table 4: Correlations of Latent Variables Derived form the Preferred Model

	GDP	TFP	CU	x_T	$\tilde{x}_T$	H	D
GDP	1.00	0.53	0.45	−0.83	−0.56	0.45	0.62
TFP	0.53	1.00	0.19	−0.55	−0.61	−0.22	−0.06
CU	0.44	0.19	1.00	−0.14	−0.08	0.71	0.26
x_T	−0.83	−0.55	−0.14	1.00	0.88	−0.29	−0.26
$\tilde{x}_t$	−0.56	−0.61	−0.08	0.88	1.00	−0.08	0.13
H	0.45	−0.22	0.71	−0.29	−0.08	1.00	0.54
D	0.62	−0.06	0.26	−0.26	0.13	0.54	1.00

NOTE: Each model name in small caps indicates the active utilization margin. The FULL-INT-UTIL specification represents the complete version of the framework. Any combination of the presented models is possible. All variants share identical priors and data; differences in log data density therefore capture the marginal explanatory contribution of each utilization channel.

figure D.10). Hence, the capital stock is consistently inferred from investment data in both models. Differences in model comparison and in the TFP–efficiency-wedge decomposition (see section 2.6) therefore stem not from divergent TFP patterns but from shifts in their underlying determinants.

The efficiency wedge is likewise consistent across models but sensitive to how goods mismatch shocks are treated. When classified as technology shocks, the wedge correlates at 0.90 between the benchmark and preferred models, with standard deviations of 2.11% and 2.15%, respectively. Excluding them from technology raises the correlation to 0.95 and reduces the standard deviations to 1.29% and 1.42%. The TFP bias correlates at 0.93 and explains 56.8% and 50.9% of the efficiency wedge when goods mismatch shocks enter technology, compared with 0.0% and 16.6% otherwise (see figure D.11). Although the efficiency wedge is estimated consistently, the definition of technology shocks critically determines whether the composite capacity-utilization term in (39) serves as an accurate proxy, underscoring the importance of coordination frictions. Because goods mismatch shocks affect both utilization-adjusted TFP and capacity utilization, they bias the identification of the efficiency wedge — a cautionary note for approaches such as Comin et al. (2025).

Having established the consistency of TFP and the efficiency wedge identification, we next examine how these utilization mechanisms shape U.S. business cycle dynamics through the model-implied output, unemployment, and goods-market-tightness gaps.

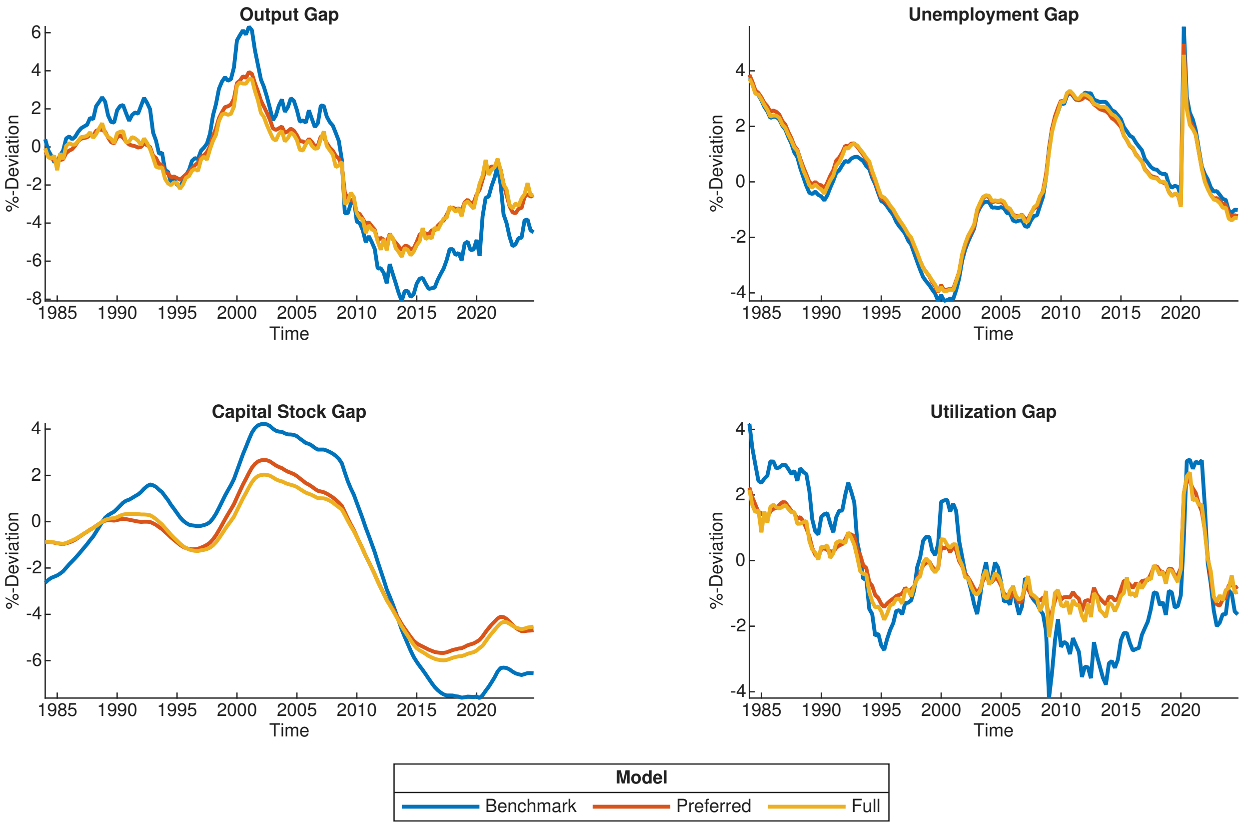
Business Cycle Dynamics. The consistent estimation of TFP and the efficiency wedge implies that the model captures well the utilization margins underlying business cycle fluctuations. To trace how these mechanisms manifest in macroeconomic dynamics, we use the smoothed latent states from the Kalman filter to construct cyclical gaps in output, unemployment, labor market tightness, and goods market tightness — defined as deviations from their flexible-price counterparts[37]. These gaps summarize the general state of the business cycle as well as excess demand and supply on specific markets. The output and unemployment gaps capture standard real and nominal activity fluctuations, while the labor- and goods-market tightness gaps measure shifts in coordination efficiency on either market. Together they link the efficiency wedge to observable macroeconomic behavior, allowing us to reinterpret U.S. business cycles as fluctuations in utilization and market coordination.

Figure 2 shows the smoothed latent gap variables implied by the benchmark and preferred models. The qualitative cyclical pattern is almost identical across models as the correlations for the gaps on output, capacity utilization, capital, and unemployment are 0.98, 0.93, 0.98, and 0.99. The quantitative pattern, however, shows lower standard deviations for the output gap (2.30% vs 3.77%), the capacity utilization gap (2.02% vs 1.03%), and capital stock gap (3.90% vs 2.60%), while the unemployment gap standard deviation (2.06% vs 1.95%) is close across models. Consequently, differences in utilization gap dynamics coupled with differences in the capital stock gap account for most of the output gap discrepancy across models.

Recessions are represented by an interplay of the gap variables. Figure 3 (b) shows the

[37]The flexible price economy of the model presented in section 2 is constrained efficient as labor is supplied inelastically and goods markets follow directed search (Moen, 1997). The flexible price economy thus also reprents the social planner assuming that market frictions are a basic part of the economy which can be optimized but not entirely cleared.

Figure 2: Identifying the U.S. Business Cycle with Gap Variables

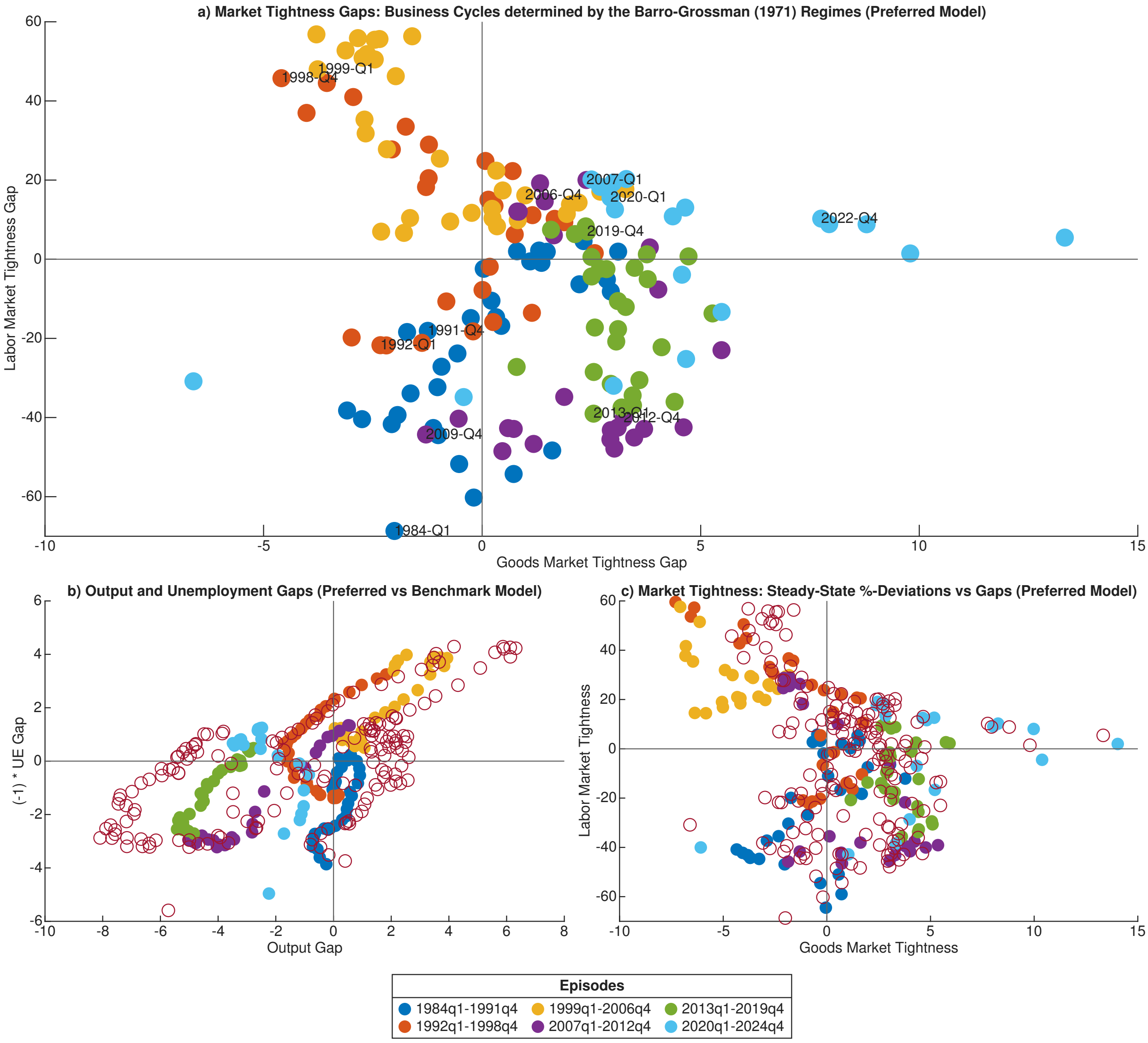


NOTE: The figure shows U.S. time series on the output, unemployment, capital, and capacity utilization gaps derived from three different model specifications: the benchmark, preferred, and full models. The sample covers 1984q1 - 2024q4 where the model is estimated on 1984q1 - 2019q4 and the period after is derived from a calibrated smoother applied to the model.

negative relationship between the output and unemployment gaps over the business cycle. Hence, a positive output gap appears most likely with unemployment below its natural rate. Combinations of a positive output gap and a unemployment above its natural rate are less likely, less pronounced, and often transitory. This pattern applies to figure 2 where it shows e.g. the (1) 1990s oil crunch, (2) the Great Recession and followed by a persistent slump, and (3) the COVID recession[38] followed by inflation spikes during reopening of the economy. Therefore, the output and unemployment gaps derived from the model are largely in line with the general perception of these episodes.

[38]The model is only estimated until 2019q4. Data between 2020q1 and 2024q4 is inferred from the estimated model by using a calibrated smoother with available observables until 2024q4.

Figure 3: Identifying the U.S. Business Cycle with Market Tightnesses



NOTE: The figure contains three subfigures: a) shows a scatter plot in goods and labor market tightness gaps; b) shows a scatter plot in output and unemploymnet gaps; and c) shows the relationship between market tightness gaps and steady-state deviations. Different business cycle episodes are identified by different colors as given in the legend. The non-fileld dots in b) show data for the benchmark model while the filled dots show data for the preferred model. The non-filled dots in c) show gap data, while the filled dots show steady-state deviations.

Using the search-and-matching framework on both goods and labor markets, we can derive an excess demand and supply framework[39] similar to Barro and Grossman (1971). This allows

[39] As Michaillat and Saez (2015) show and Barro (2025) argues, this might be a suitable DSGE-representation of the original four-regime model of Barro and Grossman (1971) which allows for an alternative interpretation

us to determine whether either market is demand- or supply-determined at any point in time. Demand-determined indicates that demand relative to supply is above its steady-state value (or above its flexible price counterpart for the gap variable). The same definition applies to labor markets. This alternative view on the business cycle based on market tightness gaps offers additional information to identify the type of a recession or boom.

Figure 3 presents (a) the labor and goods market tightness gaps and (c) the labor and goods market tightness deviations from steady-state for the U.S. dataset. We follow Barro and Grossman (1971) and identify four regimes of the economy: (i) Walrasian equilibrium ($x_T < 0, x_N > 0$); (ii) Keynesian unemployment ($x_T < 0, x_N < 0$); (iii) classical unemployment ($x_T > 0, x_N < 0$); and (iv) repressed inflation ($x_T > 0, x_N > 0$). The respective regime informs us on optimal policy depending on the states of excess demand and supply. For instance, the period following the Volcker-disinflation is generally considered as the "Great Moderation", i.e. a period where business cycle fluctuations where small. We see an economy that is initially in Keynesian unemployment due to tight monetary policy, but with a tendency towards equilibrium. The 1990 oil-price shock again pushed the U.S. economy briefly into a Keynesian-unemployment regime. Unemployment remained elevated for several years before converging toward a Walrasian equilibrium, where the economy stayed until 2005. Hence, our framework suggests demand-management during the 1990 recession but otherwise does not suggest any policy intervention for most of this period as goods markets showed slight excess supply while labor markets showed excess demand. This combination produced a prolonged boom with limited inflationary pressure. The same analysis through the lens of the output gap suggests inflationary pressure around 1999.

Macroeconomic Puzzles through the Barro and Grossman (1971)-Lens. We apply our model and the Barro and Grossman (1971)-regimes to revisit two recent macroeconomic puzzles: The "missing deflation puzzle" (Ball and Mazumder, 2011; Coibion and Gorodnichenko, 2015) in the aftermath of the Great Recession; and the inflation spike following the reopening of the economy after COVID. The framework highlights coordination failures reducing the

of business cycles compared to the output gap paradigm proposed by the New-Keynesian literature.

potential of the economy and repressed inflation due to spikes in goods market tightness as explanations for this episodes.

Figure 3 shows that the Great Recession and its aftermath (2007–2015) represent a pronounced shift to a Keynesian unemployment regime initially driven by collapsing goods market tightness and weak effective demand. Low capacity utilization remained subdued despite accommodative monetary policy as the economy shifted into a classical unemployment regime. The labor market shows excess supply but the good market excess demand as its matching efficiency deteriorated sharply as both households and firms reduced search effort. Inflation remained subdued throughout, reflecting excess supply on the labor market. The economy was in a persistent slump throughout the 2010s where the labor markets gradually recovered and goods market matching efficiency improved. The model thus interprets the post-crisis stagnation and "missing deflation puzzle" as outcomes of a prolonged excess labor supply regime rooted in goods market and time-allocation coordination failures which is in line with the literature focusing on financial frictions, technology, and capital deepening (Christiano et al., 2015; Fernald, 2015).

As to why the natural rate declines: Goods mismatch shocks mostly cancel out as they affect both the actual and natural capacity utilization ratio exogenously and multiplicative. The variance decomposition of the goods market tightness gap shows that it is mostly shocks that affect the optimal time-allocation between search and work, i.e. price and wage cost-push and monetary policy shocks. This episode shows a significant and persistent decline in search effort and goods market tightness. Households reduces their search, but firms cut their supply even more (see figure D.10). The efficiency gradually recovered and the output gaps of the benchmark and preferred model are close only in 2017. Hence, mismatch in the *time-allocation trade-off* explains the *missing-deflation puzzle* following the Great Recession in our goods market SaM model.

The COVID-19 pandemic and subsequent recovery (2020–2022) mark a rapid transition from a Keynesian-unemployment regime to a repressed inflation regime with excess demand. The initial lockdown shock generated severe goods market slack and a collapse in utilization, as restrictions curtailed both supply and demand. It briefly shifted to a classical unemployment regime as the potential production of the economy decreased substantially. Massive fiscal support and the swift reopening of the economy then triggered a surge in market tightness: demand rebounded faster than production capacity, driving utilization and employment above equilibrium and pushing the economy into a repressed inflation regime. Search effort and goods market tightness spiked, but TFP declined (see figure D.10). Subsequently, inflation rose sharply, reflecting intense demand pressure. The model interprets this episode as a coordination-driven boom — tight goods and labor markets pushed the economy beyond the Walrasian boundary. Labor market tightness, however, remained close to equilibrium which might be a reason why we did not observe wage-price spirals.

These results show that labor and goods market coordination efficiency — not technology — governs regime shifts in the U.S. business cycle, providing a unified explanation for both the post-2008 "missing deflation" and the 2022 inflation surge, which is shown in figure 2 by the smaller output gap deviations following the Great Recession and the stronger capacity utilization gap increase during the 2022 inflation spike. The market tightness gap framework helps us to understand the origin of the business cycle better and thus propose better policies. For instance, it shows why demand-management policies during the aftermath of the Great Recession where not as successful as expected and tight monetary policy during the 2022 inflation spike was necessary. While the output-unemployment gap framework allows to identify recessions well, the market tightness gap framework allows to derive appropriate policies and to identify high inflation risks. Hence, the two are complementary views of the business cycle.

Linking Back to Efficiency (Wedges). The regime analysis aligns closely with the behavior of the model's efficiency wedge, which summarizes fluctuations in goods market coordination and utilization efficiency. Periods of weak tightness and low utilization - such as the aftermath of the Great Recession - correspond to large negative wedges, whereas the tight goods and labor markets of 2021–22 yield positive wedges as firms operate near full capacity. The efficiency wedge thus provides a structural interpretation of the regimes identified above, linking measured TFP and observed macro dynamics within a single mechanism. Yet neither goods market tightness nor the efficiency wedge itself is directly observable. As shown in table 4, capacity utilization and search effort are poor proxies for goods market tightness, while real GDP tracks it more closely but with an unexpected negative correlation (-0.56), indicating that available capacity rises more than search effort in booms and falls more in recessions, which highlights the importance of supply-determined equilibria for business cycle analysis. The two market tightness gaps can be approximated by steady-state deviations of their actual tightnesses (see figure 3), with correlations of 0.88 for goods and 0.99 for labor markets. Hence, model-based measures remain essential for capturing these coordination dynamics.

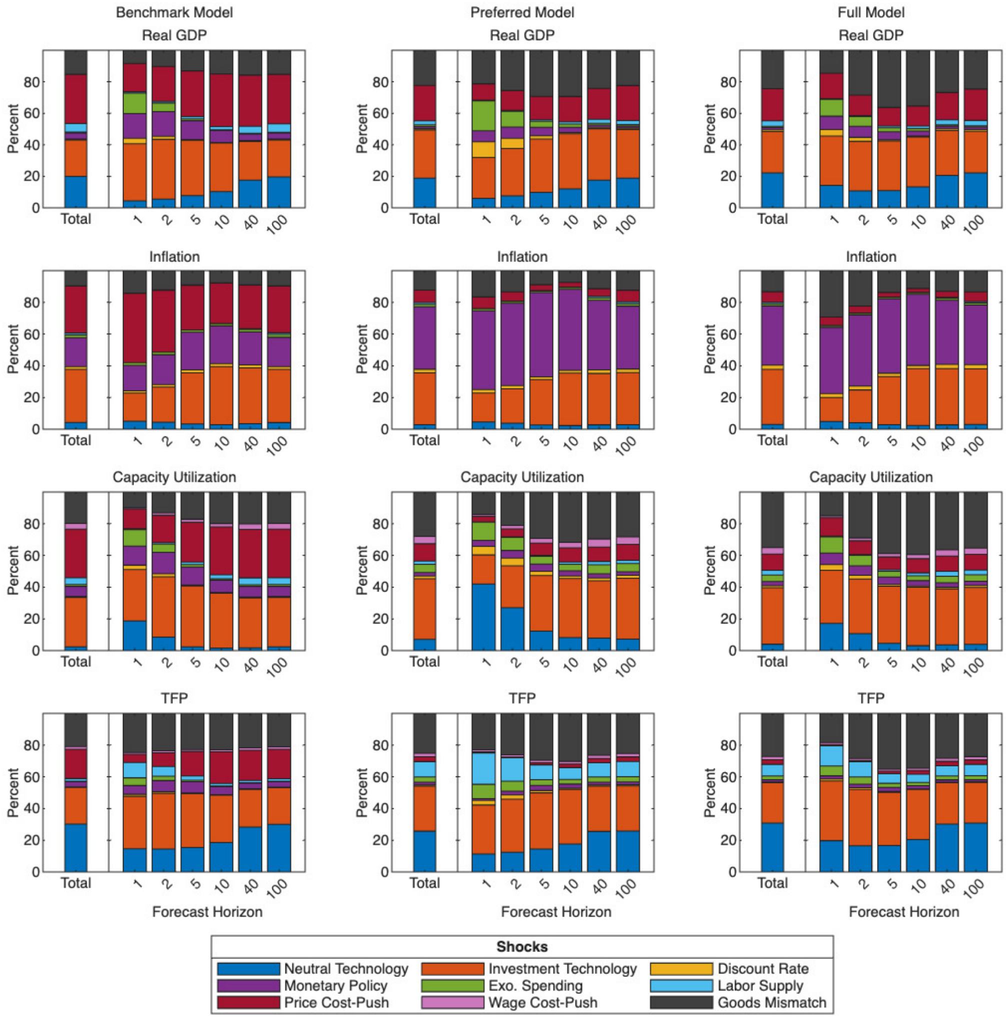
4.4. Variance Decomposition: The Determinants of the Efficiency Wedge

While identifying the business cycle through the lens of excess demand and supply framework in detail, we have excluded any analysis of the actual drivers and whether they change as we implement goods market SaM. Figure 4 shows the variance decomposition for real GDP, inflation, capacity utilization, and TFP for the benchmark and preferred models. It shows both the unconditional variance decomposition and the the conditional variance decomposition of 1, 2, 5, 10, 40, and 100 quarters ahead. The dominant driving forces of the business cycle (share of variation in GDP) are the Hicks-neutral technology ($18.4\% - 21.6\%$), the price cost-push ($21.5\% - 31.6\%$), the investment ($23.0\% - 30.5\%$), and goods mismatch shocks ($15.2\% - 24.0\%$). Demand shocks increase their share of variation in GDP as we introduce *goods market SaM*. Short-run fluctuations are mainly determined by demand shocks while the longer-run is determined mostly by supply and labor shocks[40].

Real GDP. As we add *goods market SaM*, the business cycle determinants shift to demand shocks. However, the shift is quantitatively moderate and depends on the classification of goods mismatch shock. The benchmark model explains real GDP variation mainly by neutral

[40] *Supply shocks:* Hicks-neutral technology shock $A_{H,t}$, price cost-push shock ϵ_t, and goods mismatch shock $\psi_{T,t}$; *demand shocks:* investment shock $P_{I,t}$, discount factor shock Z_t, exogenous spending shock G_t, and monetary policy shock M_t; *labor shocks:* hours supply shock $\mu_{H,t}$, and wage cost-push shock η_t.

Figure 4: Conditional Variance Decomposition of Benchmark and Full Model



NOTE: The figure shows the unconditional and conditional variance decomposition of 1, 2, 5, 10, 40 and 100 quarters ahead for the three main models: (1) benchmark model; (2) preferred model; and (3) full 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.

technology (18.4%), investment (23.0%), price cost-push (31.6%), and goods mismatch shocks (15.2%). Monetary policy (3.8%) and labor supply shocks (5.6%) play a smaller role while the remaining shocks are neglectable in explaining real GDP. Demand shocks explain predominantly the short-run while supply shocks explain the long-run. Adding *goods market SaM* increases variation in GDP explained by investment and goods mismatch shocks by about 7%-points each, while price cost-push shocks loose substantial explanatory power with 9%-points of GDP variation. Monetary policy and labor supply shocks explain less than 3% of GDP variation. In total, we find that the share of supply shocks in explaining variation in GDP decreases from 66.5% to 63.7% as a lower bound, and from 51.3% to 41.1% as an upper bound. The conditional variance decomposition shows a consistent picture across models when analyzing demand, supply, and labor shocks as groups but a shift within groups in line with the unconditional variance decomposition changes.

Inflation. Inflation is a phenomenon mainly driven by demand and cost-push shocks across models. In the benchmark model, its main determinants are investment (33.1%), monetary policy (18.1%), price cost-push (29.9%), and goods mismatch shocks (9.7%). Its conditional variance decomposition shows that price cost-push shocks explain a large part of short-run variation while it the long-run investment shocks increase their share. Adding *goods market SaM*, we find that price cost-push shocks (7.9%) decrease their share in explaining inflation variation significantly while monetary policy shocks (39.5%) largely pick up the difference. This pattern is also visible in the conditional variance decomposition where monetary policy shocks largely take over from price cost-push shocks across the entire forecast horizon.

Capacity Utilization. The variance decomposition of capacity utilization and its changes across models follows largely that of real GDP with two caveats: neutral technology shocks are negatively correlated with capacity utilization which implies a low degree of explanatory power; and wage cost-push shocks play a small but increasing role when adding *goods market SaM* as it shifts productive input from measured hours worked towards latent search effort. The conditional variance decomposition of the benchmark model shows a long-run picture consistent with the unconditional decomposition. In the short-run exogenous spending and neutral technology shocks play a significant role. Their impact decays however within two quarters. Adding *goods market SaM* increases the short-run impact of both shocks while also increasing the persistence of their impact.

Total Factor Productivity. The broader picture of the variance decomposition of TFP follows that of real GDP, however, again with some caveats: price cost-push shocks are less important in the benchmark model and almost neglectable in the preferred model; goods mismatch shocks show their "technology component" by being a signifcant and consistent determinant across models; and neutral technology is a significant and consistent determinant across models regradless of the impact of capacity utilization on TFP. The increasing role of exogenous spending shocks shows the impact on productivity shifting demand from a market with goods market frictions to a frictionless market[41]. And more importantly, the increasing role of labor supply shocks across the forecast horizon shows the importance of household time-allocation and how misallocation over the business cycle can affect productivity. This becomes visible when analyzing the variance decomposition of TFP relative to the variance decomposition of GDP (see figure D.12). While all three shocks with a technology component show about the same "multiplier" and price cost-push shocks show about 5 times lower variance share in TFP relative to their variance share in GDP, demand and labor shocks shows increases between 30% and 14-times more than in the benchmark model which implies multiplicators between 1 and 4 with an outlier of almost 90 for the wage cost-push shock. Some of the shocks do not drive real GDP much, but shift optimal time-allocation by affecting one side of the trade-off exogenously. This further emphasizes the importance of time-allocation for TFP in this model. Otherwise, the conditional variance decomposition for either model is rather stable across time favoring demand and labor shocks somewhat in the short-run and putting more weight on supply shocks in the long-run.

Discussion. The variance decomposition reveals a modest but broad shift from supply to demand shocks shocks across all variables. As search effort becomes a costly yet productive margin, the model endogenizes the price elasticity of demand, sharply reducing the explanatory power of price cost-push shocks. Demand and monetary policy shocks — interpreted as a wider class of demand disturbances, including financial shocks — now account for much of inflation variability, easing traditional policy trade-offs. For capacity utilization and TFP,

[41] Goods traded on the private markets underly goods market SaM frictions where matches are incomplete while the government buys directly from the firms. Hence, a shift towards public consumption shifts goods to a market with 100% capacity utilization.

demand shocks dominate because search effort acts as a productive demand component, while labor supply shocks capture the exogenous time-allocation trade-off between work and search. Neutral technology shocks raise utilization mainly through supply expansion, which boosts efficiency but not necessarily output when aggregate demand adjusts sluggishly. Overall, capacity utilization reflects the interaction of latent aggregate demand and supply, mediated by households' time allocation. These results confirm that goods-market SaM shifts cyclical variation from exogenous supply to endogenous coordination shocks. Section 5 analyzes how these shocks propagate through the efficiency-wedge and utilization channels to assess their macroeconomic implications.

5. Drivers of TFP over the Business Cycle

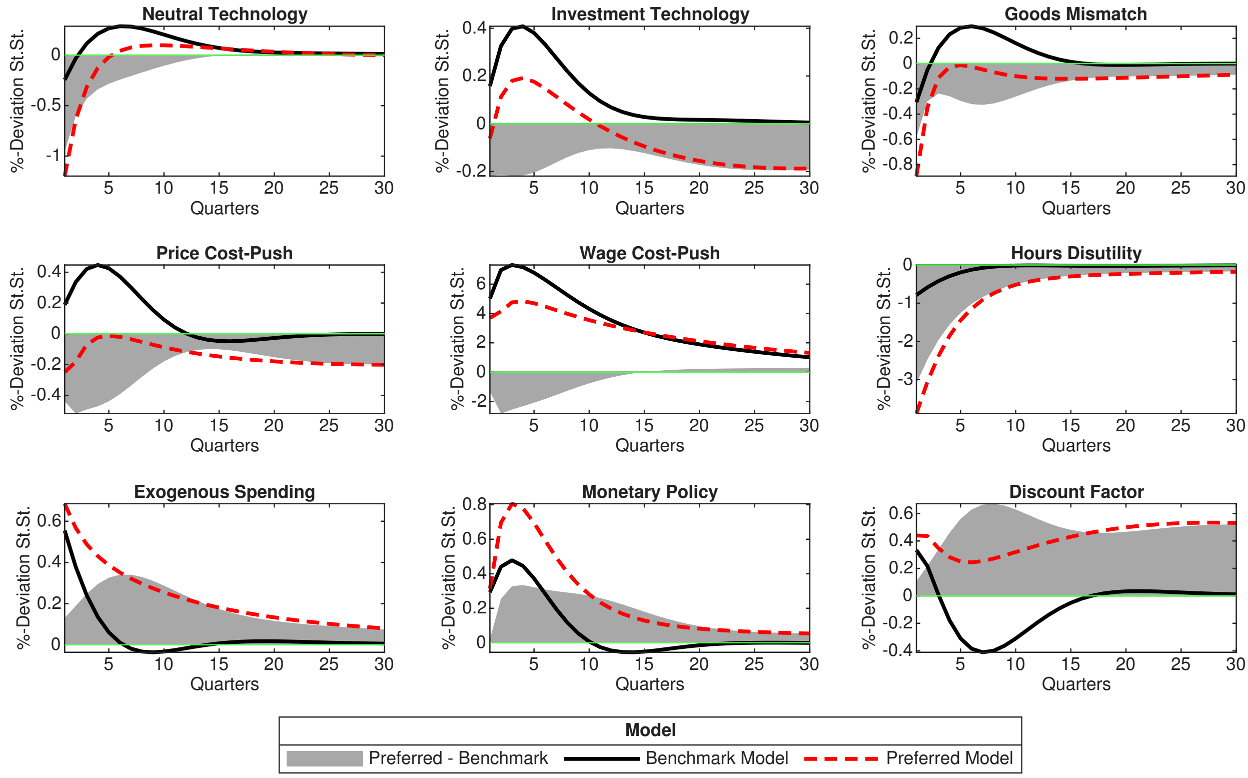
Goods market SaM decisively improves the explanation of the data and the efficiency wedge through its price elasticity of demand and especially capacity utilization channel. TFP and the efficiency wedge on aggregate are better explained by a latent and productive household search effort margin than mismeasurement of input factors and IRS due to production fixed costs. The variance decomposition of real GDP shifts from price cost-push shocks towards demand and mismatch shocks, but also hours disutility shocks, which highlights the importance of considering time-allocation trade-offs. As up to 70% of business cycle variance is drive by the efficiency wedge, it depends on the efficiency wedge transmission channels of each shock whether they are an important determinant of the business cycle. In this section, we elicit the impact of *goods market SaM* on the efficiency wedge transmission channels of each shock to feature its potential as a business cycle determinant. We use impulse response analysis (IRFs) of the efficiency wedge and decompose its determinants. When we have identified the dynamics of a model with potentially supply-determined business cycles, we analyze their impact on the general transmission channels and its implications for (monetary) policy.

5.1. The Efficiency Wedge and Total Factor Productivity

How large is the efficiency wedge between TFP and utilization-adjusted TFP for the different business cycle shocks? A positive efficiency wedge indicates that TFP overestimates the underlying utilization-adjusted TFP, vice-versa. Figure 5 shows the efficiency wedge dynamics for the benchmark and preferred models using impulse response functions (IRFs). We normalize all IRFs by using a scaling factor calculated by the maximum absolute GDP deviation of a shock. This approach is meant to make real GDP variation comparable across IRFs and allow to analyze the differences in all other variables. We analyze in particular the differences in IRFs between the two models as indicated by the gray areas. The fluctuations in the efficiency wedge of each model can be driven by the labor, capital, goods market, and fixed costs channel as shown in (38). The dynamic channel decomposition is shown in figure E.13 and an overview of the share of variation explanation of each model and channel is given in table 5.

Neutral Technology and Goods Mismatch Shocks. The efficiency wedge IRF to an expansionary neutral technology shock shows a significant initial decrease - technology innovations are underestimated by TFP deviations. Prices are sticky, aggregate demand adjusts gradually, thus capacity utilization is below its steady-state. Worker decrease their effort, (firms decrease their capital utilization), and the efficiency wedge is initially $\approx 13\%$ below steady-state in the benchmark model. As prices adjust, the efficiency wedge turns positive over the medium-run due to the f*ixed costs IRS* channel (see figure E.13). We observe an overshooting of TFP by up to 20% as capacity utilization increases above its steady-state.
Adding *goods market SaM* more than doubles the initial negative IRF of the efficiency wedge compared to the benchmark model. The trade-off between sticky prices and household search effort leads to a stronger decrease in capacity utilization as goods market tightness drops significantly and additional production capcacity is only picked up as prices decrease. The overshooting effect of TFP is smaller as the *production fixed costs* channel is smaller (see table 5). Neutral technology shocks show significantly lower short-run TFP fluctuations in the preferred model while converging to to the technology component in the medium-run.

Figure 5: The Cyclical Efficiency Wedges across Models



NOTE: The figure shows IRFs of the efficiency wedge to different business cycle shocks according to (38). The deviations are measured in percentage deviations from the deterministic steady-state. The different curves represent the benchmark (black curves) and preferred (red dashed curves) model.

TFP underestimates the technology shock (see also figure E.14) due to *substantial excess supply!*

The efficiency wedge IRF to an expansionary goods mismatch shock shows a similar picture compared to the IRFs to neutral technology shocks. The initial negative deviation and positive medium-run overshoot are quantitatively larger as this shock exogenously increases capacity utilization. Adding *goods market SaM* reduces the positive impact of *production fixed costs* channel and households reduce search effort substantially (see table 5) following a wealth-type impact as supply is slow to respond due to its quasi-fixed nature. The efficiency wedge increases over the medium-run but never shows positive deviations. TFP underestimates the technology shock (see also figure E.14) due to *substantial excess supply!*

Investment Technology Shocks. The efficiency wedge IRF to an expansionary investment technology shock shows positive deviations over the short and medium-run for the benchmark model, but negative deviations over the medium-run for the preferred model. For the benchmark model, smaller initial deviations due to the pre-determined nature of the capital stock increase over the medium-run and show significant positive efficiency wedge deviations - technology innovations are overestimated by TFP deviations. The shock has two components: an increase in production capacity as the capital stock increases; and an increase in household wealth as they hold a larger capital stock. As sticky prices adjust gradually, the wealth (aggregate demand) channel is larger than the production capacity (aggregate supply) channel in the short-run. Both the *labor effort* and *production fixed costs* channels drive the efficiency wedge up (see table 5). As prices increase, the efficiency wedge decreases and converges back to its steady-state.

Adding *goods market SaM* amplifies the production capacity channel. In the short-run, excess demand is smaller in the preferred model as it requires additional household search effort. In the medium-run, the production capacity channel is larger than the wealth channel, leading to a negative efficiency wedge deviation due to *excess supply!* This effect is persistent as additional capital is build up and slowly depreciated over time. Compared to the other "technology shocks", the investment technology shock in the preferred model shows TFP IRFs that are closer to its underlying technology shock in the short-run but not in the medium-run (see also figure E.14).

Price Cost-Push Shocks. An expansionary shock increases substitutability of differentiated goods and thus reduces price markups. As prices fall relative to wages, aggregate demand and capacity utilization increase due to the *production fixed costs* channel and quasi-fixed input factors (see also figure E.13). The efficiency wedge is initially procyclical but turns slightly negative in the medium-run as additional capital is build up and aggregate demand converges back to its steady-state.

Adding *goods market SaM* flips the efficiency wedge response to being countercyclical as a significant decrease in search effort drags on it. Higher competition and lower price markups

Table 5: Decomposition of the Efficiency wedge Fluctuations

Channel	Model	eA	eI	eZ	eM	eG	eH	eP	eW	eT
	Benchmark	0.29	0.4	0.49	0.54	0.54	0.6	0.51	0.94	0.41
Labor	Preferred	0.16	0.25	0.26	0.34	0.3	0.5	0.18	0.86	0.26
	Full	0.04	0.06	0.1	0.12	0.07	0.25	0.06	0.66	0.08
	Benchmark	0	0	0	0	0	0	0	0	0
Capital	Preferred	0	0	0	0	0	0	0	0	0
	Full	0.16	0.3	0.3	0.29	0.13	0.12	0.19	0.04	0.38
	Benchmark	0	0	0	0	0	0	0	0	0
SaM	Preferred	0.61	0.56	0.65	0.63	0.6	0.44	0.66	0.13	0.62
	Full	0.68	0.56	0.55	0.56	0.76	0.58	0.68	0.27	0.47
	Benchmark	0.71	0.6	0.51	0.46	0.46	0.4	0.49	0.06	0.59
Fixed Cost	Preferred	0.22	0.19	0.08	0.03	0.1	0.06	0.15	0.02	0.12
	Full	0.12	0.08	0.05	0.03	0.03	0.06	0.07	0.02	0.07

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.

indicate higher real wages, thus higher labor supply. Households shift their time-allocation from search to market work, which balances out the procyclical *labor effort* and reduced *production fixed costs* channels (see also figure E.13). Price cost-push shocks are an important supply shock in the benchmark NK model. However, as they increase supply through a shift in time-allocation, they create an countercyclical efficiency wedge in the preferred model through *substantial excess supply!*

Labor Shocks. Contrary to the technology shocks, there is no exogenously added capacity following labor shocks. An expansionary wage cost-push shock increases real wages through higher household bargaining power. Higher income increases aggregate demand and in turn the efficiency wedge through *labor effort* and the *production fixed costs* channel. An expansionary hours disutility shock shifts time from search effort and *labor effort* to hours worked. Real GDP increases as households accept lower wages. Hence, a wage cost-push shock reallocates labor from an observable input to latent inputs while an hours disutility shock does the opposite (see also figure E.13). The *production fixed costs* channel cannot compensate for it following an hours disutility shock.

Adding *goods market SaM* leads to a smaller procyclical efficiency wedge for the wage cost-push shock and a larger countercyclical efficiency wedge for the hours disutility shock. In both instances, search effort is required to expand aggregate demand. However, the incentives to supply it are low as either real wages are high or hours disutility is low. Low search effort supply leads to *excess supply* lowering the efficiency wedge. Both shocks show the importance of the trade-off between productive time-use for the macroeconomy.

Demand Shocks. Expansionary exogenous spending, monetary policy, and discount factor shocks increase aggregate demand exogenously which implies a higher real GDP and thus an increase in the efficiency wedge through *labor effort* and the *production fixed costs* channel. As additional spending on consumption implies less spending on capital investment, there is a negative deviation of the efficiency wedge in the medium-run as real GDP decreases. This effect is strongest for the discount rate shock.

Adding *goods market SaM* implies procyclical and persistent search effort and thus a procyclical efficiency wedge as aggregate demand increases. The higher efficiency drives up real GDP which also increases the *labor effort* and *production fixed costs* channel for the exogenous spending and discount factor shocks. For the monetary policy shock, *labor effort* now decreases due to a countercyclical price elasticity of demand which affects labor supply. Additionally, we observe a shift of trading from the frictional to the frictionless (exogenous) goods market for the exogenous spending shock which implies an increase in aggregate capacity utilization. As real GDP is also persistently higher, the persistence of *labor effort* and the IRS effect of the *fixed costs of production* is amplified as well (see also figure E.13). All three demand shocks exogenously increase goods market tightness, which creates a more procyclical response of the efficiency wedge due to *substantial excess demand!*

General Pattern. For the benchmark model, we observe both the *labor effort* and *production fixed costs* channels to be roughly equally important determinats of the efficiency wedge[42]. For the preferred model, we observe a significant shift of the determinants of the efficiency wedge: about 44% to 66% of the variation in the efficiency wedge are now explained by goods market SaM while the other two channels loose significant explanatory power (see table 5), especially the *production fixed costs* channel following from a lower estimated steady-state price markup. In line with our log data density analysis in section 4, we find that *goods market SaM* is the single most important channel to explain the efficiency wedge across shocks[43]. Allowing for supply-determined equilibria in a NK-DSGE model alters alters the efficiency wedge transmission channels substantially, especially for supply shocks.

5.2. Impact on the Business Cycle and Monetary Policy

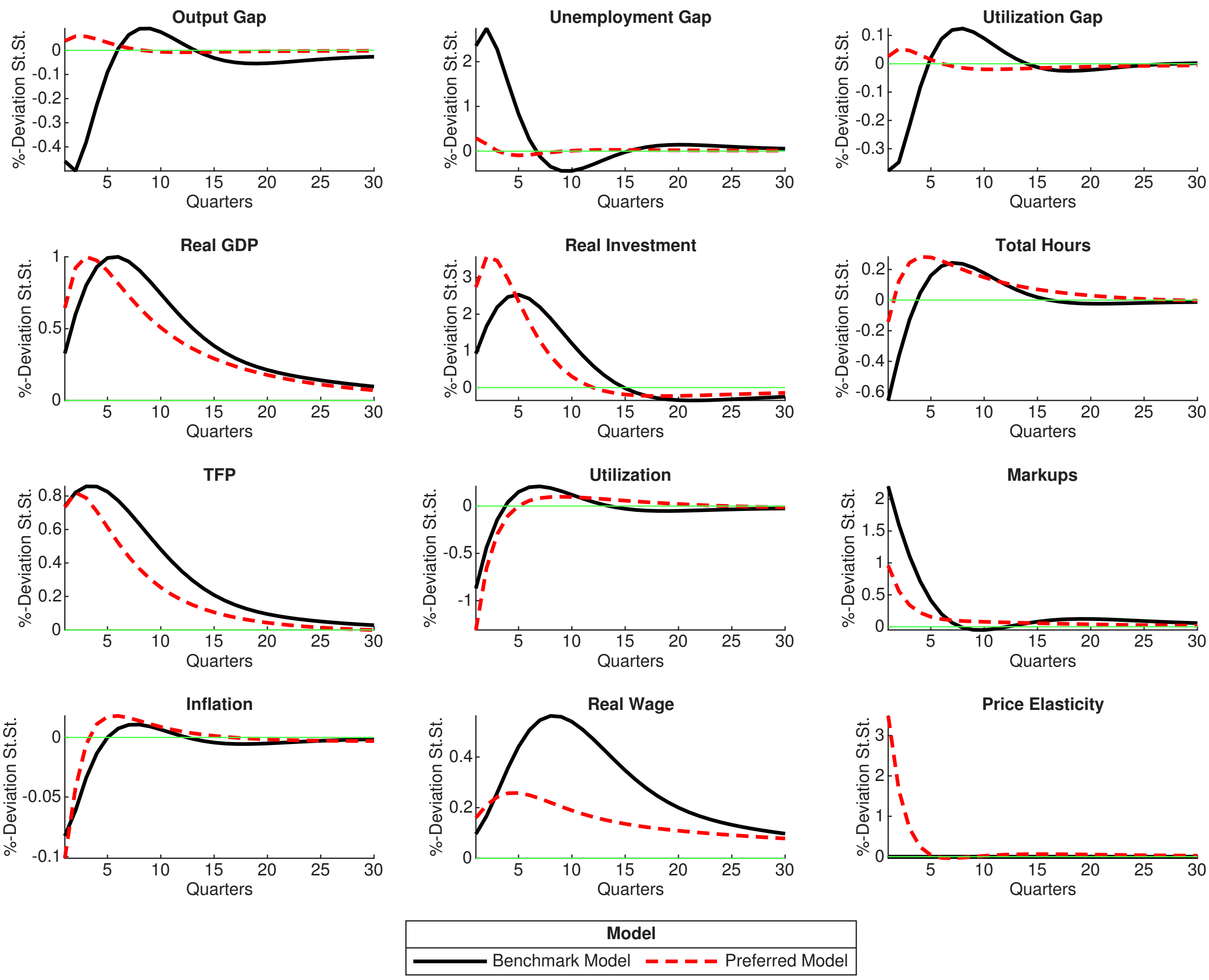
Goods market tightness allows for supply-determined equilibria and drives the two main *goods market SaM* channels identified in section 2: an endogenous price elasticity of demand and productive search effort that determines capacity utilization. Both channels affect the price-setting behavior of firms through the household demand equation and the firm's marginal cost, as shown in section 5.1. Based on the analysis of Gantert (2025), we show in this section how *goods market SaM* as a crucial determinant of model transmission affects the overall business-cycle properties. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Neutral Technology Shocks. The IRFs to an expansionary neutral technology shock for both benchmark and preferred models are given in figure 6. Responses are qualitatively symmetric but quantitatively distinct. In the benchmark model, real GDP increases in a hump-shaped pattern as the capital stock and hours worked adjust gradually. Consistent with standard NK dynamics, total hours initially fall due to sticky real wages and high markups that erode

[42]Even as we add a *capital utilization*, the other two channels often explain up to $\approx 80\%$ of variation in the efficiency wedge.

[43]The only exception is the wage cost-push shock which heavily depends on the *labor effort* channel across models. However, this shock does not explain much of the variation of real GDP.

Figure 6: IRFs to an Expansionary Neutral Technology Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

purchasing power. Capacity utilization decreases because supply expands faster than demand. Frictions in prices and wages prevent the model from reaching the flexible-price outcome, generating a short-run negative output gap with a positive unemployment gap and negative capacity utilization gap.

In the preferred model, real GDP peaks faster and with lower persistence. Both input factors increase more strongly on impact as households and firms expand search effort to absorb excess capacity. The initial excess supply increases the price elasticity of demand, stimulates household demand, compresses markups, and supports input supply despite smaller real wage responses. Hours worked become mildly procyclical, and output, unemployment, and capacity utilization gaps remain nearly acyclical. The preferred model thus replicates flexible price dynamics more closely: price stickiness still induces inflation variation, but the endogenous price elasticity channel stabilizes real quantities. The IRFs to an expansionary goods mismatch shock (figure E.15) are symmetric, with capacity utilization rising on impact due to the exogenous increase in matching efficiency.

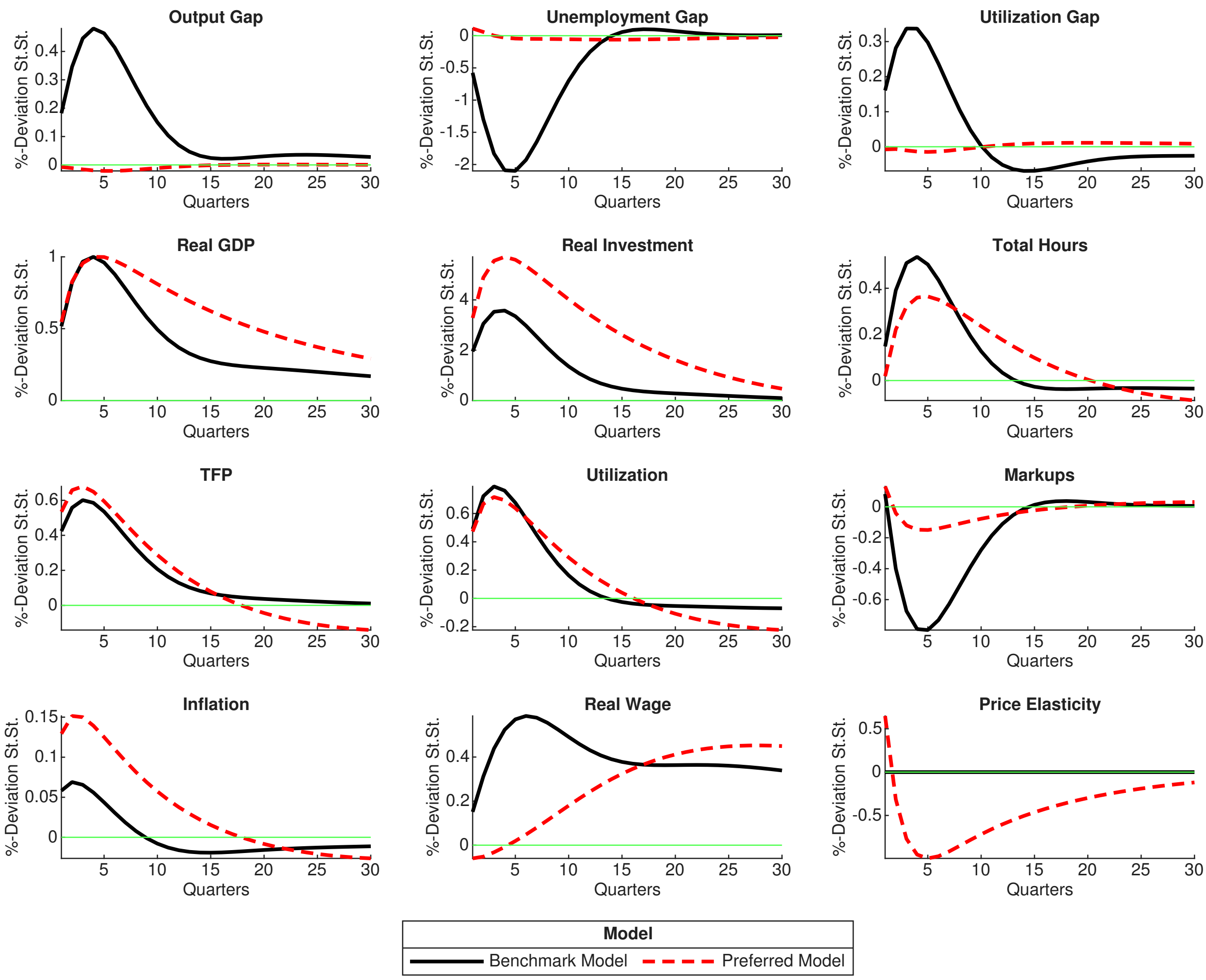
Investment Technology Shocks. The IRFs to an expansionary investment technology shock are reported in figure 7. In the benchmark model, real GDP follows a hump-shaped pattern, with strong short-run increases in investment and total hours worked. Higher capital valuation raises household wealth, fueling aggregate demand and prices. Lower markups and higher real wages expand input supply, creating a positive output gap, smaller unemployment gap, and higher capacity utilization.

In the preferred model, investment responds more strongly as the shock directly raises the productivity of goods already purchased, while total hours react less. Capacity utilization and TFP behave similarly to the benchmark in the short run but become countercyclical at medium horizons, reflecting abundant capacity after the investment surge. The low price elasticity of demand during tight goods markets allows firms to raise prices more aggressively than in the benchmark model. Consequently, the gap variables are mostly acyclical — the countercyclical elasticity of demand tempers aggregate demand overshooting and aligns the dynamics with those of the flexible-price model.

Price Cost-Push Shocks. The IRFs to an expansionary price cost-push shock are shown in figure 8. In the benchmark model, the exogenous increase in the price elasticity of demand lowers prices and markups, raising real wages and aggregate demand. Firms respond by increasing factor utilization, which temporarily boosts TFP. The resulting inflation-output trade-off resembles that of standard NK models: a positive output gap accompanies a negative unemployment gap and higher capacity utilization.

In the preferred model, a price cost-push shock lowers both markups and the price elasticity

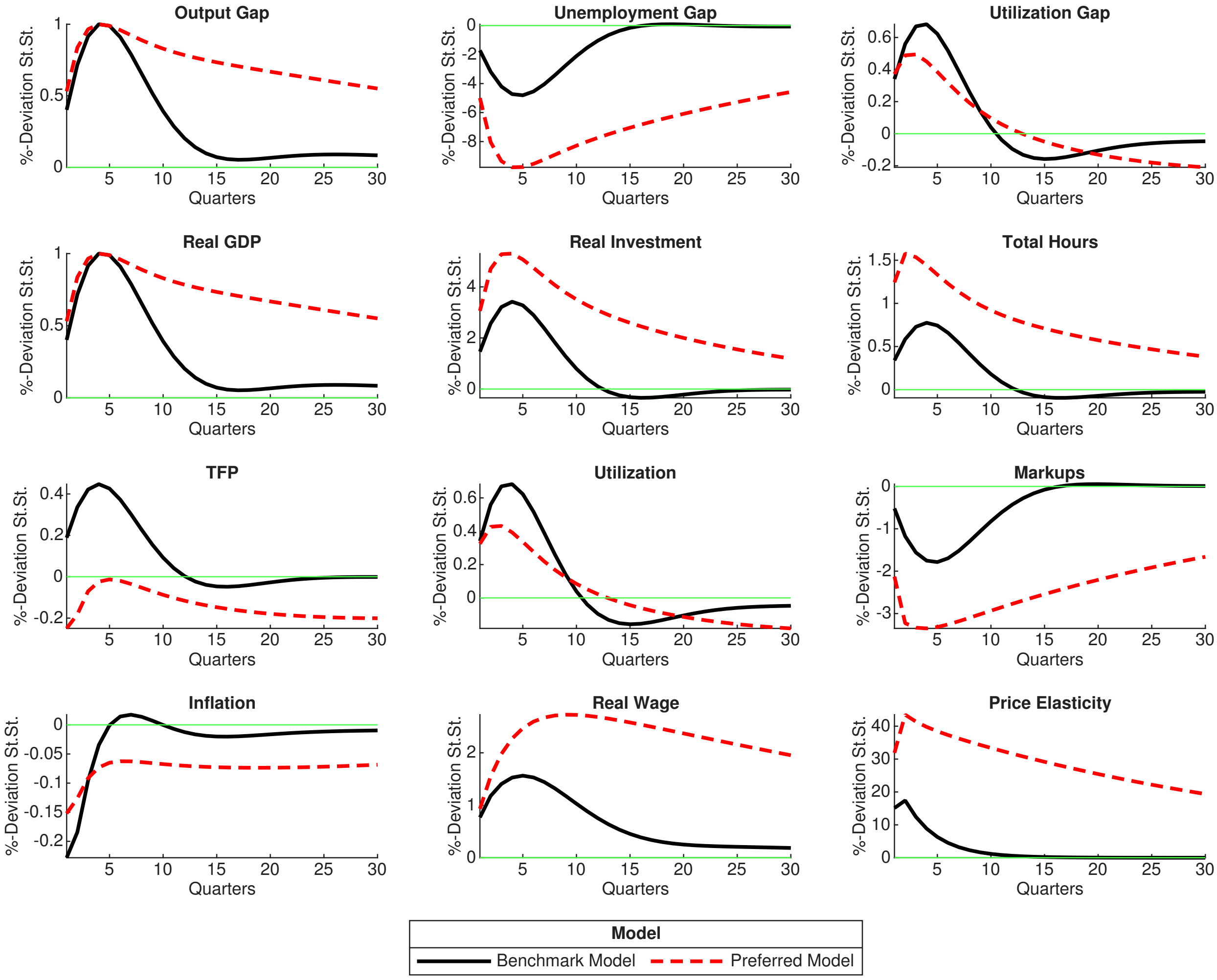
Figure 7: IRFs to an Expansionary Investment Technology Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

of demand, shifting time allocation from search to work as real wages rise. The sharp decline in price elasticity makes goods markets more competitive: prices fall, demand increases, and real GDP expands. Input demand — both investment and employment — rises strongly, while capacity utilization increases in the short run through fixed production costs and worker effort, as capital and labor adjustment remain gradual. The output gap turns markedly positive since the flexible price economy is unaffected by the shock. Employment gains make the unemployment gap more negative than in the benchmark, while the capacity utilization

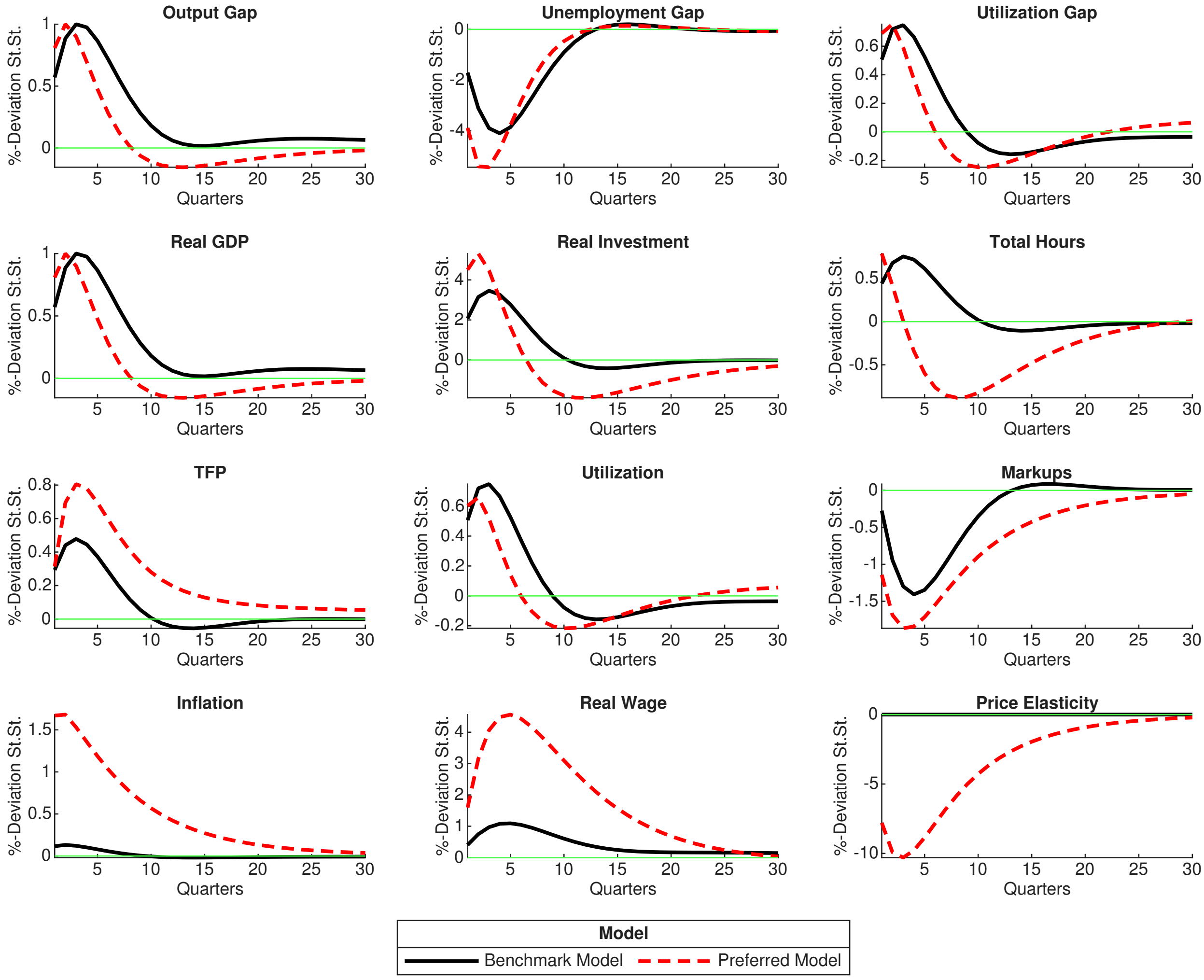
Figure 8: IRFs to an Expansionary Price Cost-Push Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

gap is positive but smaller, reflecting the reallocation of time from search to work. Despite the expansion, TFP declines after a brief rise in capacity utilization because the surge in input demand and reduced search effort generate an inefficient combination of goods supply and matching efficiency: productive capacity expands faster than the economy's ability to coordinate transactions, lowering overall measured efficiency even amid stronger competition.

Figure 9: IRFs to an Expansionary Monetary Policy Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Monetary Policy Shocks. The IRFs to an expansionary monetary policy shock are shown in figure 9. In the benchmark model, a lower nominal interest rate raises real GDP as sticky prices delay the adjustment of prices and inflation expectations. Real wages and capacity utilization rise, generating a positive output gap with a negative unemployment gap and positive capacity utilization gap — the standard demand-driven expansion.

In the preferred model, a rate cut stimulates demand but also raises search effort and capacity utilization, tightening goods markets and lowering the price elasticity of demand. Firms exploit the reduced elasticity to raise prices, yet markups fall more than in the benchmark model as real wages rise sharply to induce additional input supply. Over time, households reallocate time from work to search, generating a positive short-run TFP response but a negative capacity utilization deviation relative to long-run capacity. Medium-run output falls as investment and labor inputs decline while prices remain high due to the reallocation of time from production to search and persistent nominal rigidities. Hence, expansionary monetary policy shifts time allocation from production to search: output rises briefly but declines once the time reallocation becomes inefficient. This mechanism explains the weaker and less persistent output effects in the preferred model compared with the benchmark.Across shocks, the introduction of goods market SaM fundamentally alters the cyclical comovement of real activity and inflation. By endogenizing the price elasticity of demand, the model weakens the inflation–output trade-off and aligns real dynamics more closely with the flexible-price benchmark. Demand shocks transmit more efficiently through capacity utilization, while supply shocks become less contractionary. Monetary-policy shocks produce smaller and shorter-lived real effects because households' time allocation absorbs part of the stimulus through search rather than production. In this sense, frictional goods markets reduce the potency of conventional demand management and call for a broader interpretation of "slack" that includes the efficiency of market coordination alongside input utilization.

6. Concluding Remarks

This paper demonstrates that short-run productivity fluctuations are largely coordination phenomena rather than technological ones. Embedding goods market search-and-matching and household time allocation into a New Keynesian DSGE model reveals that matching efficiency drives cyclical total factor productivity (TFP) and regime shifts in the business cycle. The model reproduces key empirical features of the data — procyclical capacity utilization, countercyclical price elasticity, and subdued markup variation. Bayesian estimation across the U.S. and Euro Area shows that the model not only fits capacity utilization data better but also explains several macroeconomic puzzles. The "missing-deflation" puzzle after 2008 arises as a prolonged classical-unemployment regime with low goods-market matching efficiency, while the post-COVID inflation surge reflects a repressed-inflation regime driven by excess market tightness. These episodes show that coordination failures and time-allocation inefficiencies — not sticky prices or technology shocks — account for major deviations of inflation and output from traditional New Keynesian predictions. They challenge the demand-determined benchmark of the New Keynesian model by showing that market coordination and time allocation are key drivers of productivity and policy trade-offs. Consequently, monetary policy faces a weaker and state-dependent link between inflation and the output gap, underscoring the importance of market functioning for effective stabilization.

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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

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

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

First-order conditions.

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

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

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

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

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

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

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

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

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

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 $muc_t = \lambda_{1,t}P_t$, $\mathbb{W}_{C,t} = \lambda_{3,t}$, $\mathbb{W}_{D,t} = \lambda_{4,t}$, $\mathbb{U}_{\chi,t} = \frac{1}{(\mathbb{U}_{C,t}-\mathbb{U}_{N,t})^\sigma} + \frac{\omega X_t \lambda_{2,t}}{\mathbb{U}_{C,t}}$, 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

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

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

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

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

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

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

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

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

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

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 Labor 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 labor 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 labor 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

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

where $g_{S,t} = \frac{G_t}{GDP_t}$, $i_{S,t} = \frac{I_{S,t}}{GDP_t}$, $i_{S,t-1} = \frac{I_{S,t-1}}{GDP_t}$, $\vartheta_{GDP,t} = \frac{\vartheta}{GDP_t}$, $k_{t-1} = \frac{K_{t-1}}{GDP_t}$, 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 production fixed costs 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

$$\begin{aligned}
\boldsymbol{\Phi_{\vartheta,t}} \;&=\; (-1)\,\frac{\vartheta_{GDP}cu}{1+\vartheta_{GDP}cu}\boldsymbol{\hat{\vartheta}_{GDP,t}}, && \text{(B.5)}\\
\boldsymbol{\Phi_{Labor,t}} \;&=\; (1-\alpha)\,\boldsymbol{\hat{e}_{H,t}} - \frac{c_N}{1-c_N}\boldsymbol{\hat{c}_{N,t}}, && \text{(B.6)}\\
\boldsymbol{\Phi_{Capital,t}} \;&=\; \left[\alpha - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_{GDP}cu)\,(1-g_S)\,\delta_T\delta_I}k\phi_{K,1}\right]\boldsymbol{\hat{e}_{K,t}}. && \text{(B.7)}
\end{aligned}$$

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

$$\begin{aligned}
\boldsymbol{\Phi^{Low}_{SaM,t}} \;&=\; \frac{(1-cu)\,g_S}{(1+\vartheta_{GDP}cu)\,(1-g_S)\,\delta_T\delta_I}\boldsymbol{\hat{g}_{S,t}} - \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_{GDP}cu)\,(1-g_S)\,\delta_T\delta_I}i_S\boldsymbol{\hat{i}_{S,t-1}}\\
&\quad + \left(\frac{cu}{1+\vartheta_{GDP}cu} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_{GDP}cu)\,(1-cu)\,\delta_T\delta_I}\right)i_S\boldsymbol{\hat{i}_{S,t}} && \text{(B.8)}\\
&\quad + \frac{(1-cu)\,(1-\delta_T)}{(1+\vartheta_{GDP}cu)\,\delta_T\delta_I}\boldsymbol{\hat{t}_{t-1}} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+\vartheta_{GDP}cu)\,\delta_I}\boldsymbol{\hat{q}_t},\\
\boldsymbol{\tilde{A}_{Low,t}} \;&=\; \boldsymbol{\hat{A}_{H,t}} + \frac{1-cu\,(1-(1-g_S)\,\delta_T\delta_I)}{(1+cu\vartheta_{GDP})\,\delta_T\delta_I}\boldsymbol{\hat{A}_{I,t}}. && \text{(B.9)}
\end{aligned}$$

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

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

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

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

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

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

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

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

where the efficiency wedge is determined by the observables capacity utilization, production fixed costs share of GDP, labor matching cost, and hours per worker. However, they overestimate the efficiency wedge for investment-specific technology shocks ($\Phi^{Low}_{Bias,t} = \frac{1-cu}{(1+\vartheta_{GDP}cu)\delta_T\delta_I}\boldsymbol{\hat{A}_{I,t}}$) and additionally for goods market mismatch shocks if we identify them as technology shocks ($\Phi^{Up}_{Bias,t} = \Phi^{Low}_{Bias,t} + \frac{1-cu(1-(1-g_S)\delta_T\delta_I)}{(1+\vartheta_{GDP}cu)\delta_I}\boldsymbol{\hat{\psi}_{T,t}}$). 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 C.6 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 costs as a share of GDP is commonly set to 1% in the literature. As vacancy posting costs 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 costs share of production capacity can be derived from the vacancy posting costs share of GDP by correcting for capacity utilization and production fixed costs.

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 US 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[44] and its free-entry condition to to retrieve

[44] 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.

Table C.6: Calibrated Parameters of the Model

Parameter	Value	Description	Reference
ub	$\bar{N}_{Data}$	Unemployment benefits	Data
μ_H	$(H = 1)$	Hours supply disutility	Normalization
μ_e	$(e_H = 1)$	Labor 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	$\bar{cu}_{Data}$	Goods matching efficiency	Data
Ω	$\bar{C}_{I,Data}$	Industry share of GDP	Data
μ_D	$(x_T = 1)$	Search effort disutility	Normalization
ϑ	$(\Pi = 0)$	Production fixed costs	Christiano et al. (2010)
G	$\bar{g}_{S,Data}$	Government spending share of GDP	Data
β	0.99	Discount factor	Christiano et al. (2010)
α	$\bar{ls}_{Data}$	Capital elasticity of production	Data
σ	1.5	Elasticity of intertemporal substitution	Smets and Wouters (2007)
$\delta_{K,1}$	0.025	Capital depreciation rate	Christiano et al. (2010)
$\phi_{K,1}$	$(e_K = 1)$	Capital utilization cost exponent	Normalization

NOTE: The economy-wide capacity utilization is calculated by industry capacity utilization and estimated service capacity utilization weighted by their consumption shares. Details are shown in Appendix B.

a steady-state equation for α as follows

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

where the labor demand FOCs determines real wages and thus in turn the labor share. The output elasticity α depends on vacancy posting costs, the employment separation rate, and the targeted labor share corrected for capacity utilization and production fixed costs. If we set production fixed costs such that firm profits are zero in steady-state, $1 - \alpha$ is equal to the labor share.

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

$$\bar{\mu} \;=\; \frac{e_M}{Q_Y} \;=\; \frac{1}{mc},$$

where the gross markup is the inverse of the marginal costs, mc, or asset value of production capacity, Q_Y, corrected for short-run capacity utilization, $e_M = \frac{T+G}{\mathcal{Y}} = cu$, which is equal to long-run capacity utilization in steady-state. We use the firm FOCs to substitute for Q_Y and the goods market matching conditions to substitute for cu. It follows

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

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 while keeping $\bar{\mu}$ fixed. Hence, 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 production fixed costs from the firm profit condition given by

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

where we target the profit share of GDP, $\bar{\Pi}_{GDP}$. The production fixed costs increases in vacancy posting costs 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 production fixed costs but no additional profit is made by the firm (Christiano et al., 2010). 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 code: A191RC; Eurostat code: namq_10_gdp), $Defl_t$ is the GDP deflator calculated below, and Pop_t is non-institutional population over 16 years for the US (BLS code: CNP16OV) and total population for the EA countries (Eurostat code: namq_10_pe).

Real Consumption. Nominal consumption is calculated as nominal private consumption (BEA code: DPCERC; Eurostat code: namq_10_gdp). I subtract nominal durable private consumption (BEA code: DDURRC; EA data - Eurostat code: namq_10_fcs) following

Justiniano et al. (2010) for all model versions without inventories and durable consumption. 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[45]) investment (BEA code: A006RC, Eurostat code: namq_10_gdp). I add nominal durable private consumption following Justiniano et al. (2010) for all model versions without inventories and durable consumption. Real investment is

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

Real Government Spending. The steady-state target of exogenous government spending is calibrated according to the data mean of real government spending across the observation period for each country as given by

$$gs = \frac{1}{T}\sum_{t=1}^{T}\frac{Gov_t}{GDP_t},$$

where the GDP deflator and adjustment for population growth cancel out as both nominal government spending (BEA code: A822RC;Eurostat code: namq_10_gdp) and nominal GDP are adjusted.

Total Hours Worked. For the US, 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 US Bureau of Labor Statistics. Total Hours Worked is calculated by

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

For the EA countries, total hours worked are calculated from real labor productivity per hour worked (Eurostat code: namq_10_lp_ulc) given by

$$TH_{EA,data,t} = ln\left(\frac{GDP_t}{Defl_t \cdot Pop_t} \cdot lpr_t^{-1}\right).$$

We follow Cacciatore et al. (2020) and linearily detrend both US and EA total hours time series to retrieve business cycle fluctuations in the total hours worked.

[45] For the EA countries private investment data is not available. We use gross capital formation instead. This alternative should not be critical, as government investment is mostly acyclical.

Employment Rate. The employment rate is based on the number of total non-farm employees for the US (FRED code: PAYEMS) and total employees for the EA countries (Eurostat code: namq_10_pe). It is calculated by

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

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

Unemployment. The steady-state target for employment for each country is calculated by the data mean unemployment rate across the observation period as given by

$$\bar{N} = \frac{1}{T}\sum_{t=1}^{T}(1 - ue_t),$$

where ue_t is the current unemployment rate (FRED code: UNRATE; Eurostat code: ei_lmhr_m).

Labor Income Share. The steady-state target of the labor income share for each country is calculated by the data mean of annual labor income share across the observation period as given by

$$\bar{ls} = \frac{1}{T}\sum_{t=1}^{T} ls_t,$$

where we retrieve the labor income share data for all countries from Penn World Table (https://doi.org/10.34894/QT5BCC).

Capacity Utilization. The US 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[46]. The Federal Reserve Board defines production

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

capacity 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."*
Following Morin and Stevens (2004); Michaillat and Saez (2015); Comin et al. (2025), we derive from the above statement the following assumptions: (1) the capital stock is measured at the current available capital of a firm (as it is pre-determined) including non-utilized capital $e_{K,t}$; (2) the level of employment and vacancy costs are measured at their current level; (3) hours per worker and labor effort are measured at the steady-state as deviations are not sustainable in the long-run. The European Commission does not provide a clear-cut definition of full capacity. The EC survey asks for more subjective rates of capacity utilization from survey participants instead of calculating a measure of production capacity. Hence, we use the US definition of full capacity and apply it to the model when estimating Euro Area country data as well.

Capacity utilization data is for our entire observation period is only available for the industry sector. For the service sector, which roughly is two-thirds of GDP[47], we lack data before 2011 for the EA and for the US completely. Therefore, we backcast service sector capacity utilization rates. We follow Comin et al. (2025) and use a simple regression model to estimate the relationship between service and industry capacity utilization for the observation period where both time series are available. The estimated model is then used to backcast service sector capacity utilization based on the available industry sector capacity utilization data. The regession model is given by

$$cu_{S,t} = K + \beta_{cu} cu_{I,t} + \varepsilon_t \tag{C.1}$$

where $cu_{S,t}$ is service sector capacity utilization, $cu_{I,t}$ is industry sector capacity utilization, K is a constant, β_{cu} a coefficient to be estimated, and $\varepsilon \sim \mathcal{N}(0, \sigma_\vartheta)$ is an error term. We

[47] 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 US economy we neglect it in the analysis of economy-wide capacity utilization.

Table C.7: Correlation of industry and service sector capacity utilization in the European Union

	US (EU)	Spain	Germany	France	Italy
σ_{cu_I}	2.66%	3.64%	3.40%	2.86%	3.08%
K	0.47	0.33	0.69	0.54	0.54
β_{cu}	0.52	0.67	0.24	0.44	0.46
R^2	0.77	0.70	0.39	0.46	0.52

estimate this relationship for each Euro Area country considered separately with data from 2011q1 to 2019q4 and use the estimated model to calculate service sector capacity utilization between 1998q1 and 2010q4. For the US, as there is not service sector capacity utilization data available, we use EU data from 2011q1 to 2019q4 to estimate (C.1) and use it to calculate service sector capacity utilization data between 1984q1 to 2019q4 plugging in US industry capacity utilization data. Table C.7 shows the R-squared of those exercises. Besides the regressions for the EU and Spain, the R-squared are rather low. However, the sample 2011q1-2019q4 is rather short and not containing any major business cycle[48]. We rely on findings by Wohlrabe and Wollmershäuser (2017) who use additionaly business sentiment data for the different sectors to show that for Germany both service and industry capacity utilization rates are highly correlated. Hence, we are confident that the regression model backcasts service sector capacity utilization better than the R-squared would let us to belief. We construt an economy-wide capcacity utilization rate taking into account both industry and services capacity utilization time series by

$$cu_t \;=\; (1-\Sigma_{S,t})\, cu_{I,t} + \Sigma_{S,t} cu_{S,t}$$

where $\Sigma_{S,t} = \frac{C_{Service,t}}{C_t}$ is a consumption-based services weight[49], thus taking into account the changing shares of industry and service sectors across time. Finally, to detrend the

[48]We exclude 2020q1-2024q4 as the COVID business cycle has not concluded and represents an extraordinary business cycle not necessarily representing the average business cycle.

[49]Alternatively, we could have used services value-added weights. As the model focusess on household impact of goods market trade, we decided to take consumption based weights.

economy-wide capacity utilization rate, I demean each time series by

$$cu_{data,t} \;=\; cu_t - \frac{1}{T}\sum_{t=1}^{T} cu_t \;=\; \hat{CU}_t$$

where the de-meaned time series is a direct observable of model capacity utilization deviations from steady-state, $\hat{CU}_t$.

Inventory-Sales Ratio. The inventory-sales ratio gives a measure of production over sales and thus a proxy for goods market tightness. There is only data available for the US. We use real private inventories (BEA code: A371RX) and calculate the ratio given by

$$isr_{data,t} \;=\; \frac{Inv_{S,t}}{\frac{GDP_t}{Defl_t \cdot Pop_t}} \cdot C_{S,Weight,t},$$

where we weight with $C_{S,Weight,t} = 1 + \frac{C_{Service,t}}{C_t} - \frac{1}{T}\sum_{t=1}^{T} \frac{C_{Service,t}}{C_t}$ to account for the long-run trend in industy/service shares in the data but fixed shares in the model.

GDP Deflator. The GDP deflator is the log difference of nominal GDP and real GDP (BEA codes: A191RC and A191RX; Eurostat code: namq_10_gdp). Price Inflation is given by

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

Real Labor Compensation. Nominal labor compensation for the US is given by the non-farm business sector labor compensation per hour (BLS code: COMPNFB). Real wage inflation is given by

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

For the EA countries, we construct nominal labor compensation by nominal unit labor costs per hour worked and real labor productivity per hour worked as given by

$$\pi_{EA,W,data,t} \;=\; ln\left(\frac{ulc_t}{lpr_t}\right) - ln\left(\frac{ulc_{t-1}}{lpr_{t-1}}\right).$$

The seasonally adjusted nominal labor compenstaion time series are retrieved from the ECB: DE Code: MNA.Q.S.DE.W2.S1.S1._Z.ULC_HW._Z._T._Z.IX.D.N; ES code: MNA.Q.Y.ES.W2.S1.S1._Z.ULC_HW._Z._T._Z.IX.D.N; FR code: MNA.Q.S.FR.W2.S1.S1._Z.ULC_HW._Z._T._Z.IX.D.N; IT code: MNA.Q.Y.IT.W2.S1.S1._Z.ULC_HW._Z._T._Z.IX.D.N.

Policy Rate. The policy rate for the US is given by the Federal Reserve Bank of New York, Effective Federal Funds Rate (FRED Code: EFFR) and for the EA countries by the 3-month EURIBOR rate (ECB code: FM.M.U2.EUR.RT.MM.EURIBOR3MD_.HSTA). For the period of binding zero lower bound, we use the shadow rate of Wu and Xia (2016) for both the US and EA countries as the model does not incorporate a lower bound on its nominal interest rate. We 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. We calculate the quarterly interest rate by

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

Appendix C.3. Connecting the Data to the Model

As the model is stationary, we have to de-trend the data accordingly. We 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. We de-mean the GDP deflator, the FED funds rate, the unemployment rate, and capacity utilization by their respective mean rates. For hours per worker, we 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 we swap the capacity utilization observation equation for $isr_{data,t} = isr_t - \bar{isr}$ in the inventory-sales ratio robustness exercise. 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, we apply logs before taking the differences. For variables already in percentage units, we simply subtract their mean. For the real wage inflation rate, we adjust for labor 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. Steady-States Ratios of the Estimated Models

Table D.8: Steady-State Ratios of the Estimated Models

Model	$\frac{K}{Y}$	$\frac{I_K}{Y}$	$\frac{I_S}{Y}$	$\frac{K}{N}$	mp	Ξ	P_D	$\frac{P_D}{P_T}$
United States								
Benchmark	11.2	0.28	0.00	32.5	1.33	−5.0	0.00	0.00
Preferred	7.8	0.20	0.00	15.8	1.24	−7.4	0.43	0.30
Full	9.3	0.23	0.06	22.9	1.17	−11.2	0.31	0.26
Spain								
Benchmark	11.4	0.29	0.00	54.5	1.03	−37.7	0.00	0.00
Preferred	6.7	0.17	0.00	15.3	1.07	−38.5	0.71	0.41
Full	10.1	0.25	0.08	28.1	1.11	−22.4	0.22	0.19
Germany								
Benchmark	10.6	0.27	0.00	28.5	1.29	−5.6	0.00	0.00
Preferred	6.7	0.17	0.00	14.0	1.11	−16.9	0.58	0.37
Full	8.1	0.20	0.05	18.6	1.11	−17.2	0.39	0.30
France								
Benchmark	10.9	0.27	0.00	40.4	1.09	−16.0	0.00	0.00
Preferred	6.6	0.17	0.00	14.7	1.09	−27.1	0.65	0.39
Full	8.2	0.20	0.05	19.6	1.12	−18.9	0.41	0.31

Appendix D.2. Prior-Posterior Tables on EA Countries

Table D.9: Prior-Posterior Table for Spain

		Estimation				
		Prior		Posterior		
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	Preferred (90% HDP)	Full (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.85 (0.72-0.98)	0.02 (0.00-0.04)	0.85 (0.72-0.98)
θ_H	Beta	0.7	0.1	0.69 (0.58-0.81)	0.90 (0.85-0.98)	0.70 (0.63-0.78)
ν_H	Gamma	2	0.5	3.25 (2.48-3.99)	2.76 (2.15-3.34)	3.75 (2.85-4.64)
$\frac{1}{mc}-1$	Beta	0.2	0.1	0.03 (0.02-0.05)	0.07 (0.05-0.09)	0.12 (0.10-0.15)
κ_I	Gamma	4	1.5	1.6 (1.03-2.16)	5.89 (4.41-7.32)	6.75 (4.67-8.78)
κ_W	Gamma	30	5	29.9 (21.8-37.8)	22.7 (16.2-29.1)	28.4 (20.0-36.6)
κ_P	Gamma	180	20	167.8 (136.0-199.5)	176.6 (144.4-209.3)	176.2 (144.6-207.2)
ι_W	Beta	0.5	0.15	0.59 (0.39-0.80)	0.51 (0.28-0.74)	0.37 (0.16-0.57)
ι_P	Beta	0.5	0.15	0.08 (0.02-0.13)	0.05 (0.02-0.08)	0.10 (0.03-0.17)
i_π	Gamma	1.8	0.1	1.77 (1.62-1.93)	1.71 (1.55-1.88)	1.73 (1.57-1.88)
i_{gap}	Gamma	0.12	0.05	0.06 (0.04-0.09)	0.04 (0.01-0.06)	0.06 (0.04-0.09)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.11 (0.04-0.18)	0.15 (0.05-0.25)	0.14 (0.05-0.22)
i_r	Beta	0.75	0.05	0.89 (0.87-0.92)	0.66 (0.60-0.72)	0.89 (0.86-0.91)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	1.96 (1.67-2.24)	1.61 (1.37-1.85)	1.91 (1.64-2.17)
$\phi_{K,2}$	Gamma	2	1	–	–	2.16 (1.22-3.07)
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.94 (0.89-0.99)	0.65 (0.50-0.81)
Γ^{prox}	Beta	0.1	0.075	–	0.04 (0.00-0.08)	0.04 (0.00-0.09)
ν_D^{mult}	Gamma	1	0.5	–	1.12 (0.63-1.60)	1.65 (0.88-2.39)
θ_D	Beta	0.5	0.2	–	0.23 (0.04-0.41)	0.20 (0.05-0.33)
δ_I	Beta	0.15	0.05	–	–	0.21 (0.11-0.30)
δ_T	Beta	0.25	0.15	–	–	0.60 (0.46-0.73)

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) baseline full model, and (3) intertemporal 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 3,000,000 draws.

Table D.10: Prior-Posterior Table for Germany

		Estimation				
		Prior		Posterior		
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	Preferred (90% HDP)	Full (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.32 (0.01-0.85)	0.02 (0.01-0.04)	0.46 (0.01-0.86)
θ_H	Beta	0.7	0.1	0.90 (0.83-0.96)	0.96 (0.93-0.98)	0.72 (0.61-0.96)
ν_H	Gamma	2	0.5	2.76 (1.97-3.53)	3.13 (2.50-3.76)	3.46 (2.67-4.22)
$\frac{1}{mc} - 1$	Beta	0.2	0.1	0.29 (0.02-0.66)	0.11 (0.09-0.14)	0.12 (0.10-0.15)
κ_I	Gamma	4	1.5	1.11 (0.50-1.73)	1.88 (1.36-2.38)	2.57 (1.70-3.42)
κ_W	Gamma	30	5	27.0 (17.4-36.7)	23.7 (17.5-29.8)	21.7 (15.3-28.0)
κ_P	Gamma	180	20	172.5 (136.5-208.9)	158.4 (129.2-187.3)	162.4 (133.9-190.2)
ι_W	Beta	0.5	0.15	0.61 (0.36-0.86)	0.49 (0.26-0.72)	0.49 (0.26-0.72)
ι_P	Beta	0.5	0.15	0.15 (0.04-0.25)	0.07 (0.03-0.12)	0.07 (0.02-0.11)
i_π	Gamma	1.8	0.1	1.87 (1.69-2.05)	1.84 (1.69-1.99)	1.75 (1.58-1.92)
i_{gap}	Gamma	0.12	0.05	0.06 (0.01-0.12)	0.07 (0.03-0.11)	0.10 (0.03-0.16)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.12 (0.03-0.21)	0.16 (0.06-0.26)	0.16 (0.06-0.26)
i_r	Beta	0.75	0.05	0.86 (0.83-0.90)	0.65 (0.58-0.71)	0.72 (0.64-0.80)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	1.98 (1.49-2.45)	1.88 (1.61-2.15)	1.90 (1.61-2.19)
$\phi_{K,2}$	Gamma	2	1	–	–	3.16 (1.31-4.96)
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.87 (0.77-0.98)	0.87 (0.76-0.98)
Γ^{prox}	Beta	0.1	0.075	–	0.10 (0.00-0.20)	0.07 (0.00-0.14)
ν_D^{mult}	Gamma	1	0.5	–	1.50 (0.78-2.20)	2.84 (1.31-4.17)
θ_D	Beta	0.5	0.2	–	0.23 (0.04-0.41)	0.18 (0.03-0.33)
δ_I	Beta	0.15	0.05	–	–	0.16 (0.07-0.24)
δ_T	Beta	0.25	0.15	–	–	0.79 (0.68-0.91)

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) baseline full model, and (3) intertemporal 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 3,000,000 draws.

Table D.11: Prior-Posterior Table for France

		Estimation				
		Prior			Posterior	
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	Preferred (90% HDP)	Final (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.04 (0.02-0.05)	0.08 (0.02-0.13)	0.17 (0.02-0.45)
θ_H	Beta	0.7	0.1	0.71 (0.65-0.76)	0.88 (0.82-0.94)	0.79 (0.68-0.92)
ν_H	Gamma	2	0.5	1.55 (1.19-1.88)	2.86 (2.20-3.52)	3.08 (2.35-3.80)
$\frac{1}{mc} - 1$	Beta	0.2	0.1	0.09 (0.05-0.13)	0.09 (0.06-0.12)	0.13 (0.10-0.15)
κ_I	Gamma	4	1.5	1.62 (1.10-2.13)	1.73 (1.24-2.22)	2.39 (1.53-3.22)
κ_W	Gamma	30	5	28.0 (19.5-36.2)	26.4 (19.6-32.9)	25.4 (18.3-32.3)
κ_P	Gamma	180	20	165.0 (134.4-196.6)	168.8 (139.4-197.6)	163.8 (135.4-191.3)
ι_W	Beta	0.5	0.15	0.55 (0.34-0.78)	0.51 (0.29-0.73)	0.46 (0.24-0.69)
ι_P	Beta	0.5	0.15	0.09 (0.03-0.14)	0.07 (0.03-0.11)	0.08 (0.03-0.12)
i_π	Gamma	1.8	0.1	1.73 (1.57-1.89)	1.76 (1.60-1.91)	1.78 (1.62-1.94)
i_{gap}	Gamma	0.12	0.05	0.01 (0.00-0.01)	0.06 (0.02-0.10)	0.05 (0.02-0.09)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.15 (0.06-0.24)	0.18 (0.07-0.30)	0.13 (0.06-0.20)
i_r	Beta	0.75	0.05	0.78 (0.73-0.83)	0.56 (0.50-0.63)	0.70 (0.62-0.79)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	2.77 (2.40-3.16)	1.72 (1.44-2.01)	1.82 (1.50-2.13)
$\phi_{K,2}$	Gamma	2	1	–	–	1.97 (0.79-3.12)
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.94 (0.89-0.99)	0.92 (0.85-0.99)
Γ^{prox}	Beta	0.1	0.075	–	0.03 (0.00-0.06)	0.04 (0.00-0.08)
ν_D^{mult}	Gamma	1	0.5	–	1.57 (0.84-2.28)	2.25 (1.31-3.17)
θ_D	Beta	0.5	0.2	–	0.17 (0.03-0.31)	0.18 (0.03-0.32)
δ_I	Beta	0.15	0.05	–	–	0.15 (0.07-0.22)
δ_T	Beta	0.25	0.15	–	–	0.80 (0.70-0.91)

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) baseline full model, and (3) intertemporal 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 3,000,000 draws.

Appendix D.3. Prior-Posterior Tables on Goods Market SaM Decomposition

Table D.12: Prior-Posterior for Goods SaM Channel Decomposition (without Capacity Utilization Data)

		Estimation				
		Prior			Posterior	
Parameter	Distribution	Mean	Std.Dev.	Benchmark (90% HDP)	Preferred (90% HDP)	Perf. Compl. (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.16 (0.09-0.23)	0.03 (0.01-0.05)	0.07 (0.01-0.12)
$heta_H$	Beta	0.7	0.1	0.84 (0.79-0.90)	0.92 (0.88-0.96)	0.89 (0.85-0.93)
ν_H	Gamma	2	0.5	2.43 (1.90-2.94)	2.70 (2.13-3.26)	2.60 (2.04-3.15)
$\frac{1}{mc} - 1$	Beta	0.2	0.1	0.37 (0.21-0.52)	0.16 (0.08-0.22)	0.19 (0.12-0.25)
κ_I	Gamma	4	1.5	2.21 (1.65-2.76)	3.07 (2.16-3.98)	2.49 (1.82-3.15)
κ_W	Gamma	30	5	30.0 (22.1-37.7)	26.1 (18.5-33.5)	28.2 (20.5-35.8)
κ_P	Gamma	180	20	169.9 (138.1-201.6)	152.0 (123.6-180.3)	174.9 (143.0-206.4)
ι_W	Beta	0.5	0.15	0.50 (0.26-0.74)	0.51 (0.26-0.75)	0.57 (0.34-0.80)
ι_P	Beta	0.5	0.15	0.08 (0.03-0.13)	0.07 (0.02-0.11)	0.08 (0.03-0.13)
i_π	Gamma	1.8	0.1	1.75 (1.60-1.89)	1.77 (1.63-1.92)	1.83 (1.68-1.98)
i_{gap}	Gamma	0.12	0.05	0.03 (0.01-0.05)	0.03 (0.01-0.05)	0.03 (0.01-0.05)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.48 (0.33-0.64)	0.35 (0.13-0.55)	0.28 (0.11-0.45)
i_r	Beta	0.75	0.05	0.73 (0.68-0.78)	0.66 (0.58-0.74)	0.74 (0.69-0.79)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	2.63 (2.29-2.97)	2.51 (2.18-2.82)	2.48 (2.17-2.8)
$\phi_{K,2}$	Gamma	2	1	–	–	–
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.62 (0.46-0.78)	0.78 (0.65-0.92)
Γ^{prox}	Beta	0.1	0.075	–	0.13 (0.00-0.28)	–
ν_D^{mult}	Gamma	1	0.5	–	1.14 (0.28-1.93)	0.31 (0.10-0.51)
θ_D	Beta	0.5	0.2	–	0.24 (0.05-0.43)	0.33 (0.09-0.56)
δ_I	Beta	0.15	0.05	–	–	–
δ_T	Beta	0.25	0.15	–	–	–

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) baseline full model, and (3) intertemporal 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 3,000,000 draws.

Table D.13: Prior-Posteriors for Good Market SaM Channel Decomposition - Perfect Complements

		Estimation				
		Prior		Posterior		
Parameter	Distribution	Mean	Std.Dev.	Preferred (90% HDP)	Perf. Compl. (90% HDP)	Perf. Compl. (90% HDP) *(wo util. data)*
General Parameters						
ω	Beta	0.5	0.2	0.03 (0.00-0.07)	0.02 (0.01-0.02)	0.07 (0.01-0.12)
θ_H	Beta	0.7	0.1	0.85 (0.80-0.90)	0.90 (0.87-0.93)	0.89 (0.85-0.93)
ν_H	Gamma	2	0.5	2.91 (2.27-3.54)	2.28 (1.79-2.77)	2.60 (2.04-3.15)
$\frac{1}{mc}-1$	Beta	0.2	0.1	0.24 (0.16-0.32)	0.26 (0.18-0.34)	0.19 (0.12-0.25)
κ_I	Gamma	4	1.5	3.12 (2.36-3.86)	2.91 (2.09-3.72)	2.49 (1.82-3.15)
κ_W	Gamma	30	5	26.6 (18.9-34.2)	23.6 (16.7-30.3)	28.2 (20.5-35.8)
κ_P	Gamma	180	20	161.7 (132.8-190.2)	179.5 (145.9-211.7)	174.9 (143.0-206.4)
ι_W	Beta	0.5	0.15	0.48 (0.23-0.72)	0.52 (0.28-0.76)	0.57 (0.34-0.80)
ι_P	Beta	0.5	0.15	0.05 (0.02-0.08)	0.07 (0.02-0.11)	0.08 (0.03-0.13)
i_π	Gamma	1.8	0.1	1.72 (1.58-1.86)	1.81 (1.66-1.95)	1.83 (1.68-1.98)
i_{gap}	Gamma	0.12	0.05	0.02 (0.01-0.04)	0.02 (0.01-0.02)	0.03 (0.01-0.05)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.39 (0.20-0.57)	0.32 (0.15-0.47)	0.28 (0.11-0.45)
i_r	Beta	0.75	0.05	0.61 (0.54-0.68)	0.74 (0.68-0.79)	0.74 (0.69-0.79)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	2.20 (1.88-2.52)	2.40 (2.08-2.71)	2.48 (2.17-2.80)
$\phi_{K,2}$	Gamma	2	1	–	–	–
Goods Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	0.78 (0.65-0.91)	0.80 (0.67-0.93)	0.78 (0.65-0.92)
Γ^{prox}	Beta	0.1	0.075	0.06 (0.00-0.12)	–	–
ν_D^{mult}	Gamma	1	0.5	1.01 (0.50-1.49)	0.26 (0.07-0.44)	0.31 (0.10-0.51)
θ_D	Beta	0.5	0.2	0.17 (0.03-0.30)	0.39 (0.13-0.65)	0.33 (0.09-0.56)
δ_I	Beta	0.15	0.05	–	–	–
δ_T	Beta	0.25	0.15	–	–	–

NOTE: The table shows the prior and posterior distributions of the estimated parameters of the (1) benchmark model, (2) baseline full model, and (3) intertemporal 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 3,000,000 draws.

Appendix D.4. Log Data Densities

Table D.14: Log data density of different model setups in explaining U.S. data (1984q1-2019q4) and core Euro area data (1998q1-2019q4)

Model Setup	U.S.	Spain	Germany	France
Alternative Capital Utilization Assumption				
Capital Utilization (CW)	5096.2	2634.3	2905.1	3043.2
CW (ALT)	5099.2	2649.1	2926.2	3064.0
Bayes Factor: Baseline - Alternative	**6.0**	**29.6**	**42.2**	**41.6**
CW + WE + SaM	5187.7	2709.1	3004.7	3160.8
CW + WE + SaM (ALT)	5186.4	2712.2	3004.2	3156.6
Bayes Factor: Baseline - Alternative	**-2.6**	**6.2**	**-1.0**	**-8.4**
Alternative Weights in Aggregate Capacity Utilization Construction				
Benchmark	5159.9	2652.7	2884.2	3047.6
Preferred	5198.7	2685.8	2953.2	3124.1
Bayes Factor: Preferred - Benchmark	**77.6**	**66.2**	**138.0**	**153.0**
Alternative Time Period: 1967q1 - 2019q4				
Benchmark	7287.2	–	–	–
Preferred	7336.8	–	–	–
Bayes Factor: Complements - Preferred	**99.2**	**-**	**-**	**-**
Adding Hours Adjustment Costs				
Benchmark	5194.9	2678.4	2933.6	3096.4
Preferred	5235.9	2707.0	3007.0	3171.9
Bayes Factor: Complements - Preferred	**82.0**	**57.2**	**146.8**	**151.0**

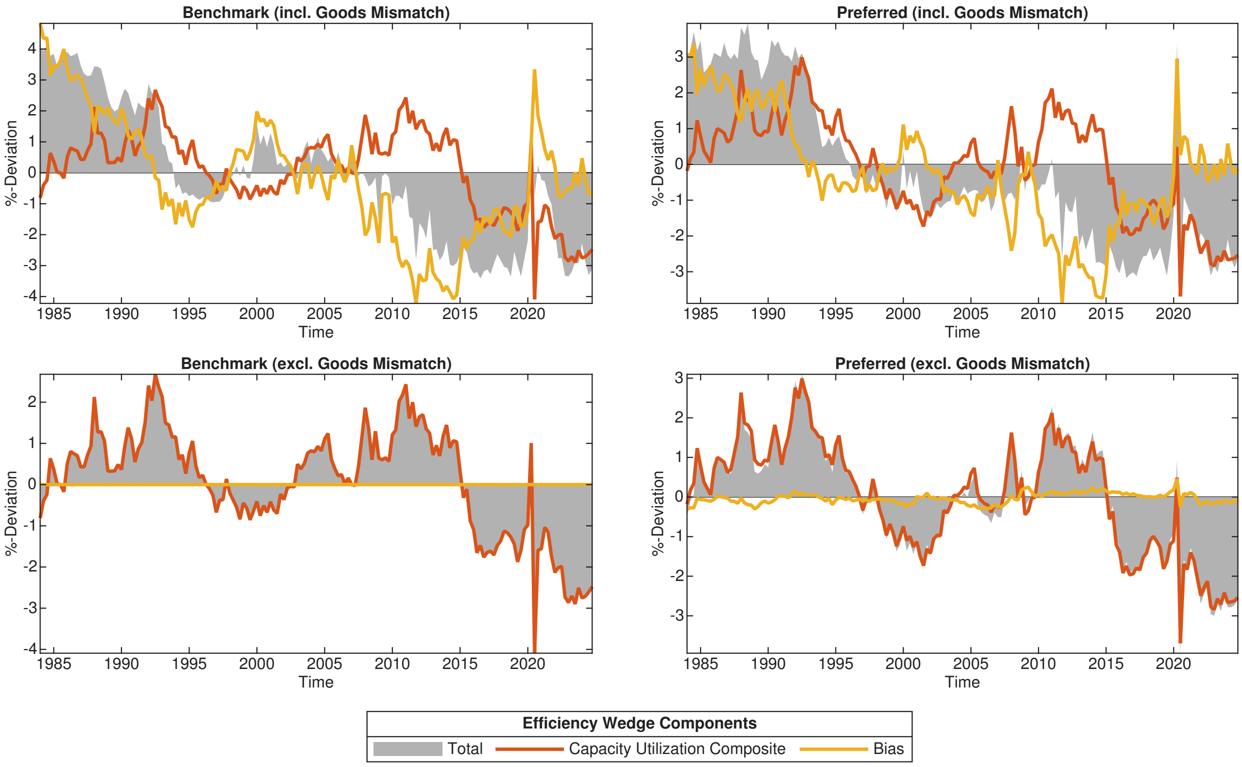
NOTE: Log data densities are calculated by the modified harmonic mean following Geweke (1999). To compare different versions of the model, I use the $2ln$ Bayer factor as described by Kass and Raftery (1995). Log data densities with an asteriks are obtained from a Laplace approximation given limited computing power.

Appendix D.5. TFP and Efficiency Wedge Decomposition

Figure D.10

TFP Growth Rate
Percent
Time
Efficiency Wedge Growth Rate
Percent
Time
Goods Market Tightness
%-Deviations
Time
Search Effort
%-Deviations
Time
Model
Benchmark
Preferred

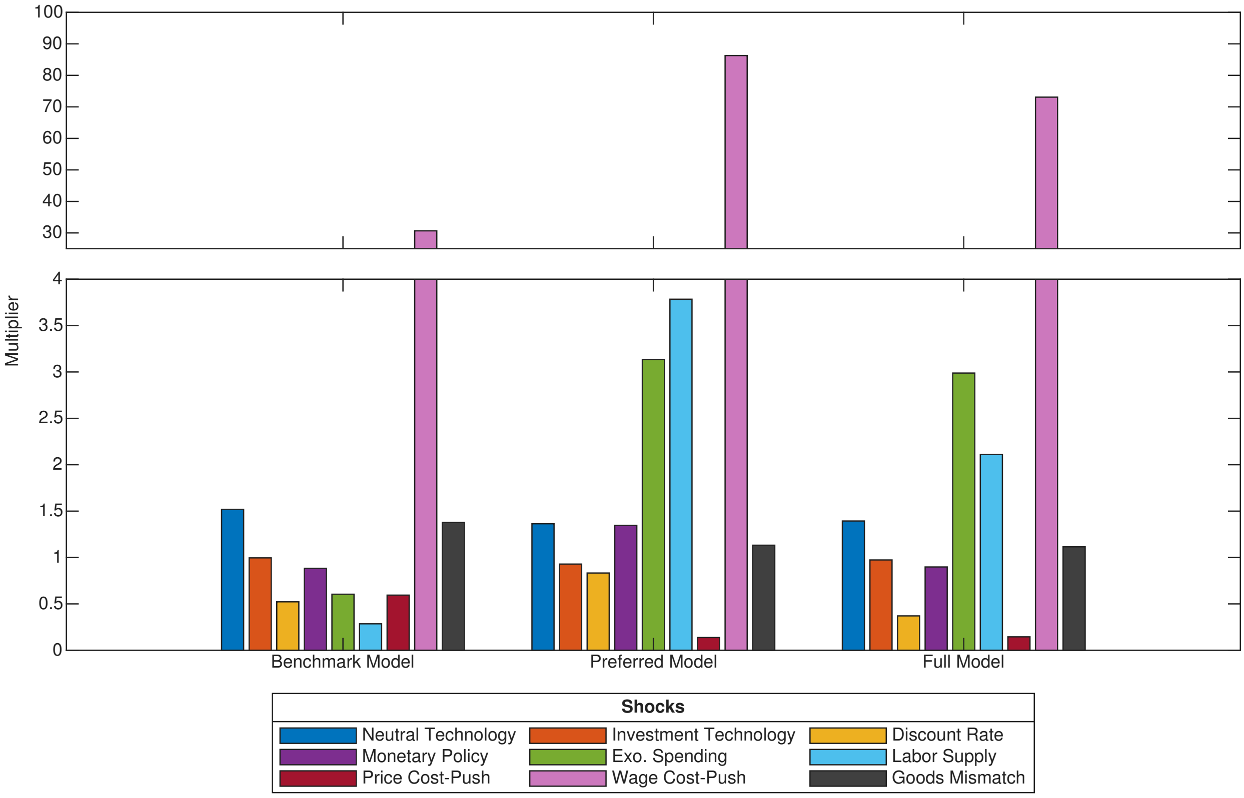
Figure D.11: Estimated Efficiency Wedges (both definitions)



NOTE: The figure shows estimated efficiency wedges for US data 1984q1-2024q4 decomposing them into the term explained by capacity utilization and other observables and the TFP bias. The upper graphs show the efficiency wedge and TFP bias including goods mismatch shocks as technology shocks. The lower graphs exclude the shock. Both the benchmark and the preferred model results are shown.

Appendix D.6. TFP Multiplicators

Figure D.12: TFP Variance Multiplicators (relative to GDP Variance Shares)



Appendix E. TFP Bias and Multiplicators Sensitivity Analysis

Appendix E.1. Determinants of the Efficiency Wedge

Figure E.13: Dynamics of the Determinants of the Efficiency Wedge

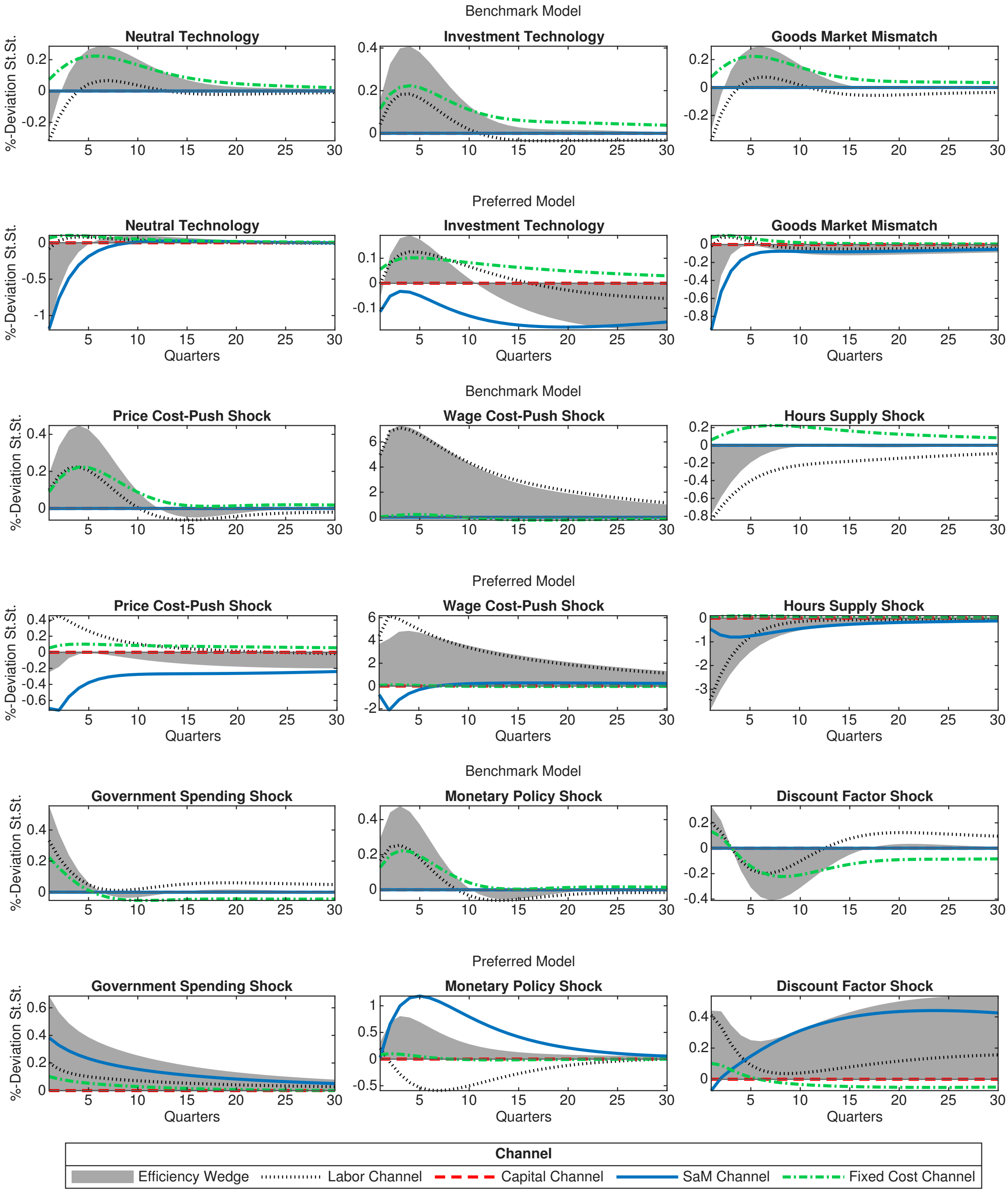
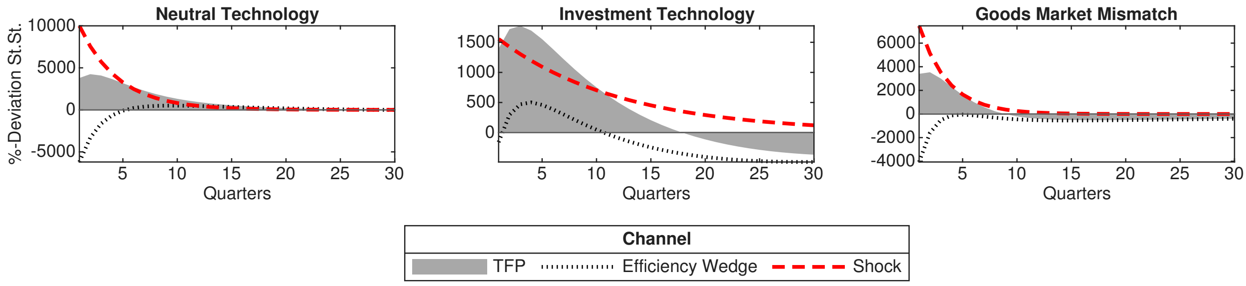


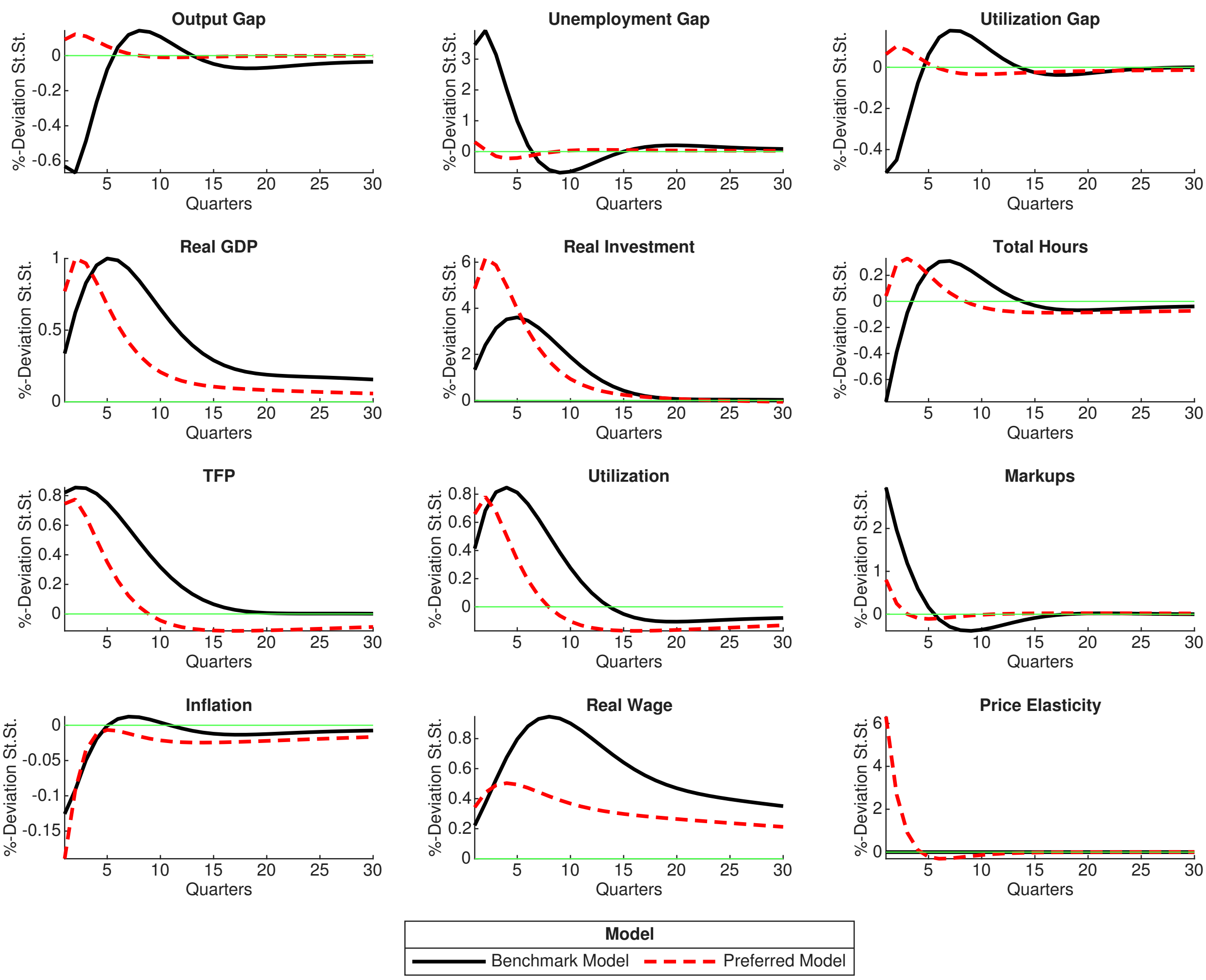
Figure E.14: Decomposing TFP into Wedge and Shock for the Technology Shocks



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).

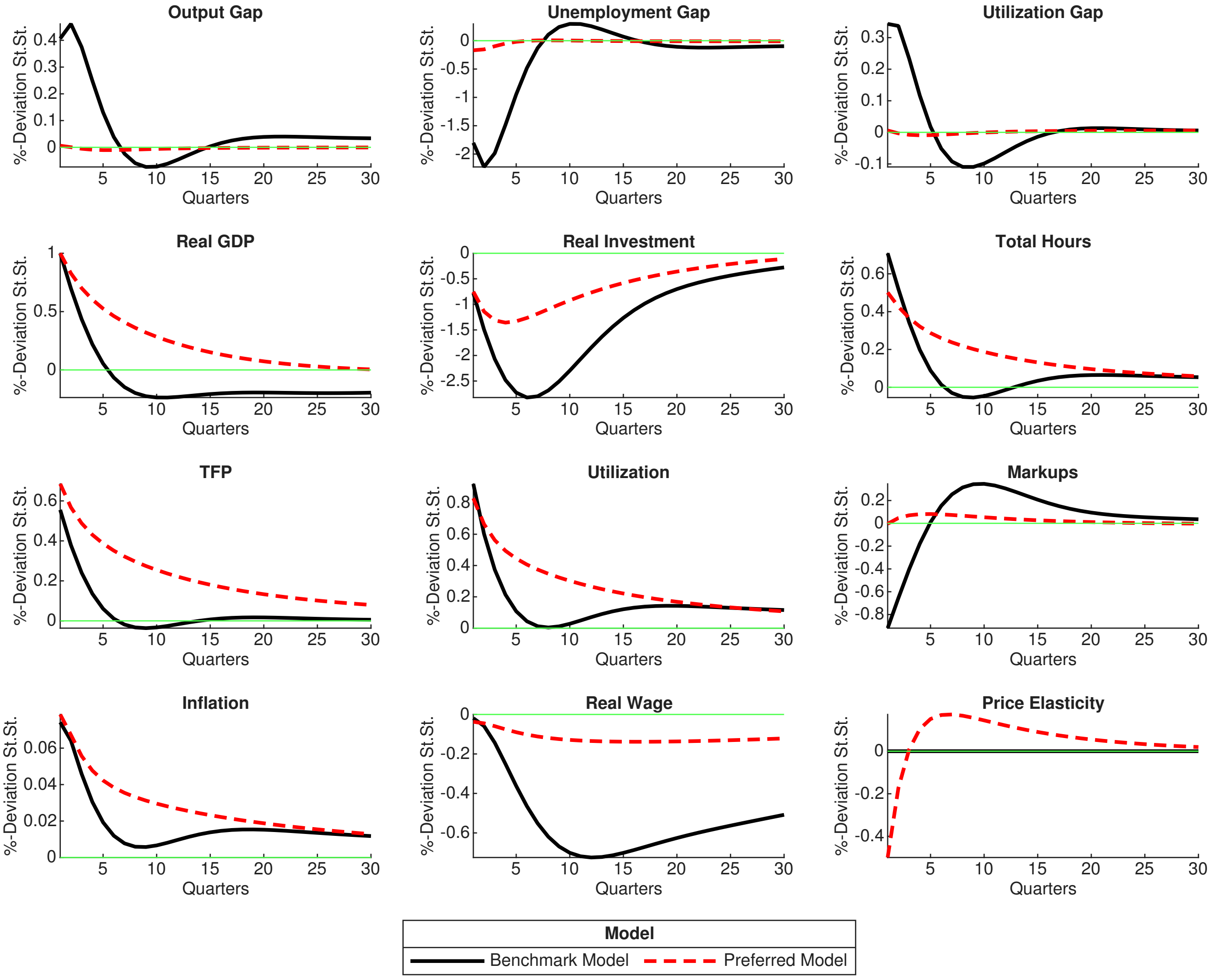
Appendix E.2. IRFs to Additional Business Cycle Shocks

Figure E.15: IRFs to an Expansionary Goods Mismatch Shock across Models



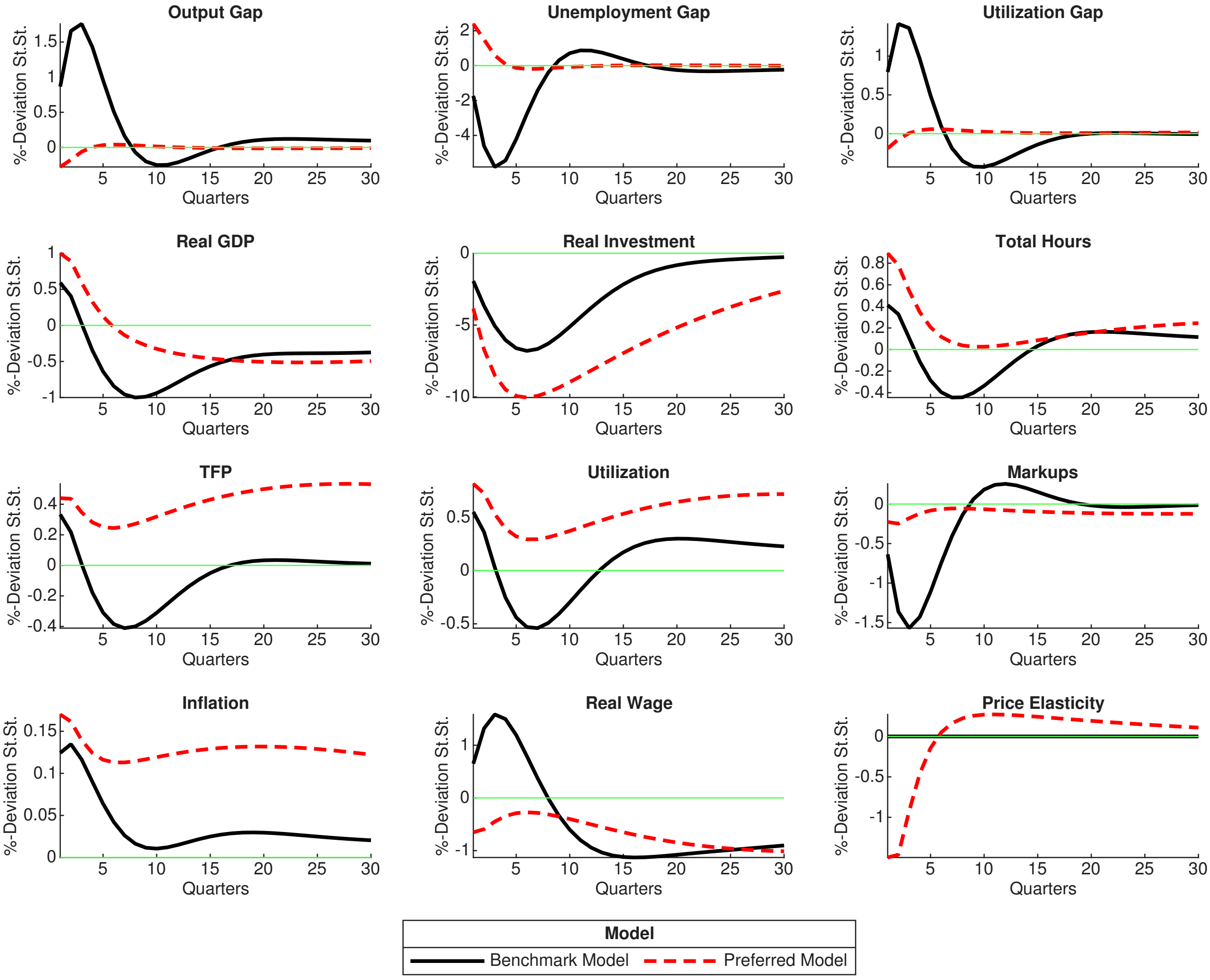
NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.16: IRFs to an Expansionary Exogenous Spending Shock across Models



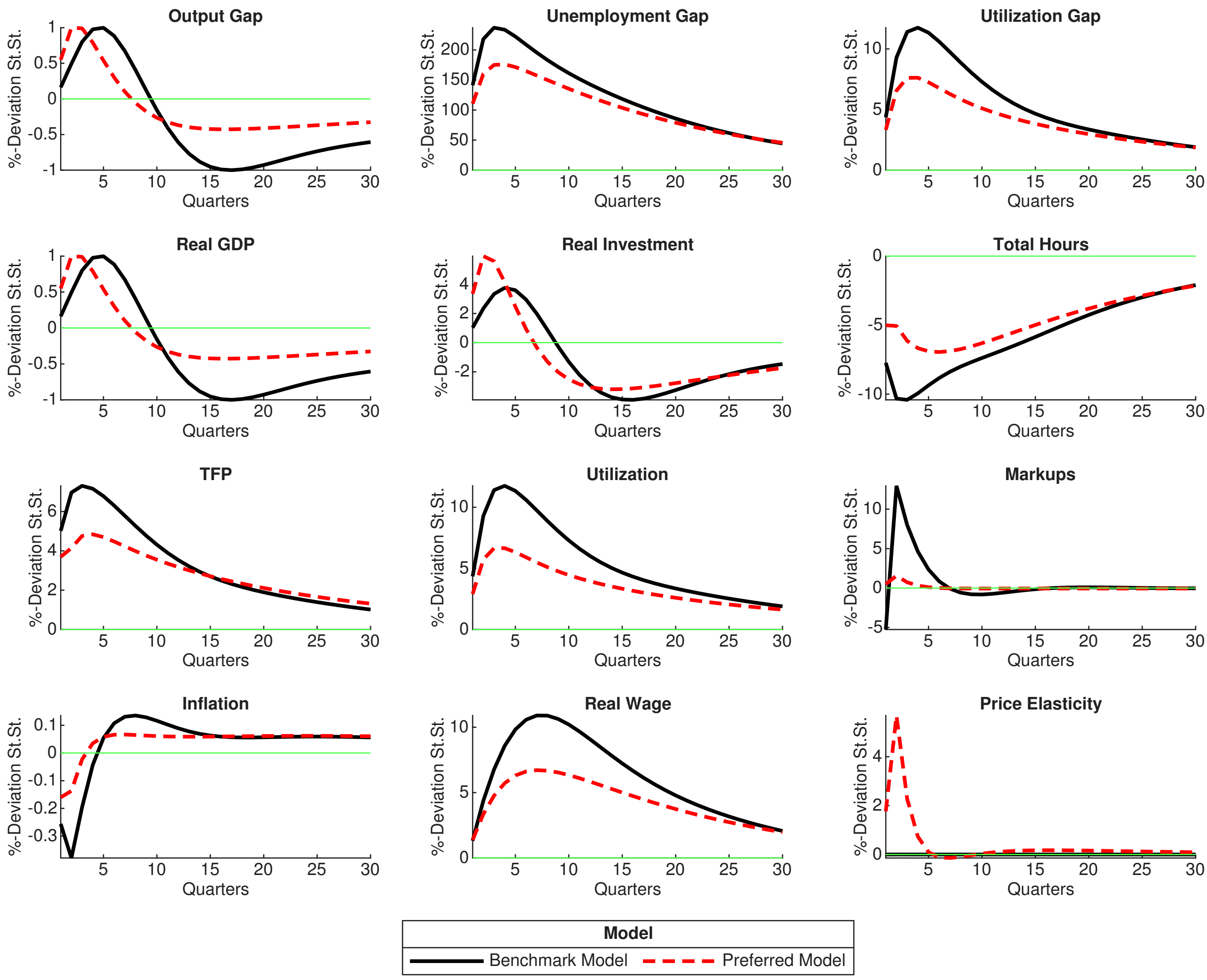
NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.17: IRFs to an Expansionary Discount Factor Shock across Models



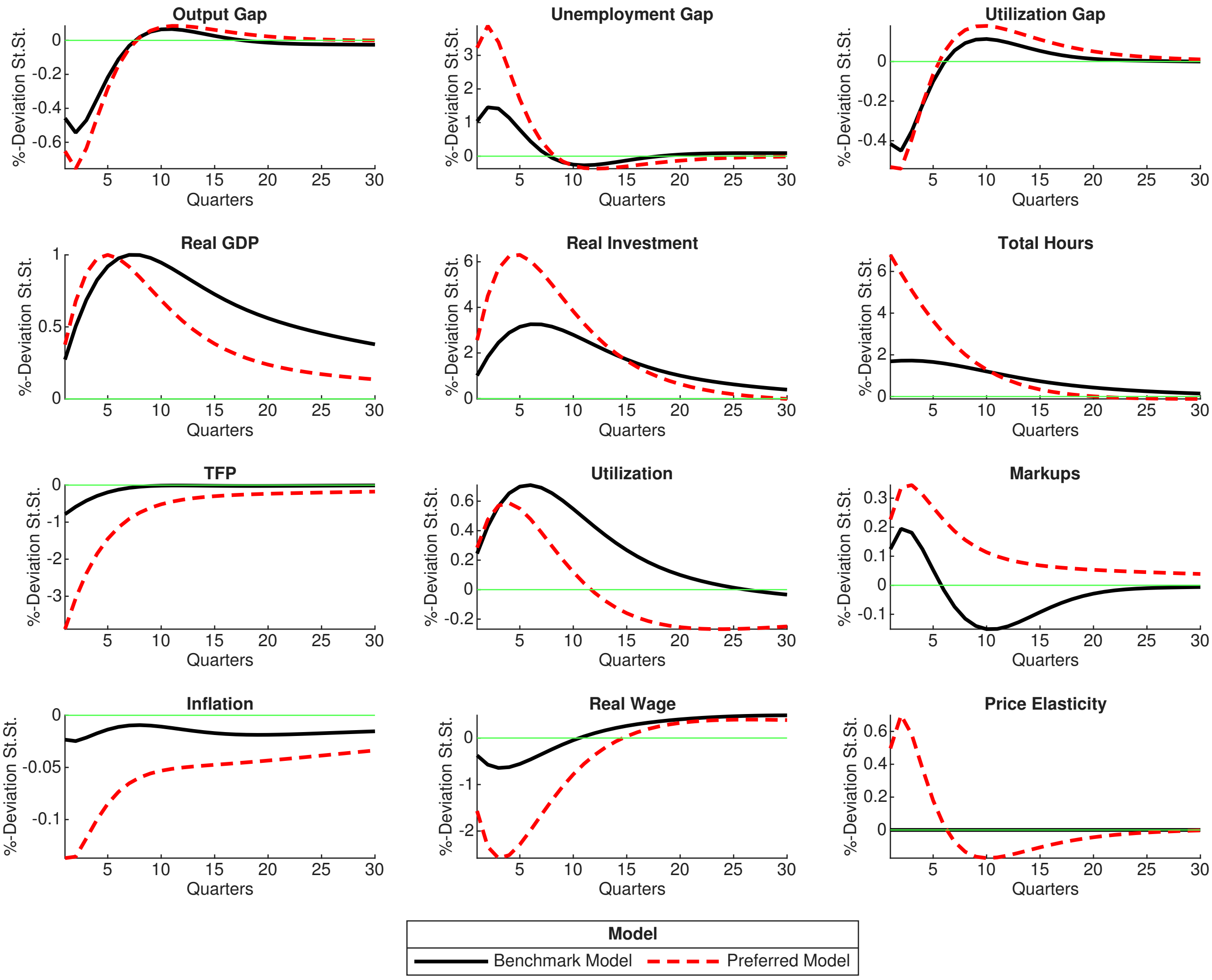
NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.18: IRFs to an Expansionary Wage Cost-Push Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.19: IRFs to an Expansionary Hours Disutility Shock across Models



NOTE: The figure shows IRFs of different variables to different business cycle shocks for both the benchmark and preferred models. The deviations are measured in percentage deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.