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

Job Market Paper

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Abstract

Measured productivity fluctuates far more over the business cycle than technology. This paper shows that these movements mainly reflect coordination failures in the goods market. I develop a New Keynesian DSGE model, inspired by Barro's (2025) critique of frictionless goods markets, in which households allocate time between work and search, firms supply unmatched capacity, and trades form through goods-market search and matching. Matching efficiency determines capacity utilization and thus measured TFP. Bayesian estimation on U.S. and Euro Area data – using survey-based capacity utilization – shows that incorporating goods-market frictions sharply improves model fit and reduces the need for cost-push shocks. The interaction of sticky posted prices and flexible search prices generates a state-dependent demand elasticity, while the coordination channel links search effort to effective output: excess demand raises TFP by increasing match rates, excess supply lowers it by leaving capacity idle. The model identifies Barro–Grossman (1971) regimes in the data: the missing deflation after 2008 reflects a low-efficiency, classical-unemployment regime, whereas the post-COVID inflation surge arises from a high-tightness, repressed-inflation regime. Thus, short-run productivity is coordination-driven, and policy operates in a state-dependent environment where stabilizing market efficiency is as important as managing 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 persistent puzzle: productive resources often sit idle in downturns even though underlying technology does not deteriorate. In booms, by contrast, buyers queue for scarce goods, delivery times lengthen, and firms struggle to meet demand. These fluctuations are clearly visible in measured total factor productivity (TFP), yet measured technology changes far less over the cycle. Standard TFP measures implicitly assume that matching buyers and sellers is instantaneous and costless, but in practice matching requires time, information, and organizational effort. Consumers search, firms advertise and hold inventories, and sales capacity expands and contracts with demand. When matching becomes less efficient, productive capacity goes unused; when matching improves, the same inputs generate more output. In short: measured productivity often reflects *market coordination*, not technology.

This perspective shifts part of "production" from the factory floor to the *interaction between buyers and sellers*. Matching is a productive activity: it converts potential output into actual sales. When households reduce search effort or firms cut back sales effort, output falls even if machines, labor, and ideas remain unchanged. A sizable empirical literature documents procyclical shopping time, inventory dynamics, and demand-driven capacity utilization – patterns inconsistent with the frictionless goods markets assumed in textbook New Keynesian (NK) models.[3] As Barro (2025) emphasizes, those models hardwire the assumption that firms supply any quantity demanded at posted prices, ruling out excess supply, excess demand, and rationing – features repeatedly observed in macroeconomic data.

Matching efficiency has a behavioral foundation: households must allocate time across work, search, and leisure. Reduced search effort slows transactions, depresses utilization, and lowers

[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). Additional to procyclical shopping effort – which is positively correlated with TFP and capacity utilization (Bai et al., 2025) – firms employ excess capacity to attract additional customers (Sun, 2024). 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.

measured productivity. Treating these *coordination failures* as "TFP shocks" overstates the role of technology and understates the role of market functioning. Traditional mechanisms – capital utilization, labor effort, or fixed production costs (Christiano et al., 2005) – operate inside the production process and cannot account for the systematic co-movement of TFP with sales, inventories, shopping time, and capacity utilization (Bai et al., 2025; Den Haan and Sun, 2024). A framework that allows output to be either *demand-determined or supply-determined*, depending on matching efficiency, offers a richer account of why measured productivity fluctuates.

To capture this mechanism, we develop a New Keynesian DSGE model (Cacciatore et al., 2020; Christiano et al., 2010) in which households allocate time between work and search, 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 – varies endogenously with goods-market tightness, defined as the ratio of buyer search effort to firms' unmatched capacity. Sticky posted prices interact with flexible search prices, generating a state-dependent price elasticity of demand, while utilization becomes an equilibrium outcome of matching rather than an exogenous choice. The model is estimated on U.S. and Euro Area data using Bayesian methods and survey-based capacity-utilization measures that are essential for identifying the matching channel. 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 delivers four main results. First, incorporating goods-market search-and-matching (SaM) markedly improves empirical fit – especially for capacity utilization and inflation – and largely eliminates the need for cost-push shocks because demand elasticity becomes endogenous. Second, short-run movements in measured TFP are driven primarily by matching efficiency and time allocation rather than technology or input utilization: excess demand increases search effort and match rates, raising TFP; excess supply leaves capacity idle, lowering TFP. Third, goods- and labor-market tightness jointly identify Barro and Grossman

(1971) regimes, revealing whether an economy is in classical or Keynesian unemployment, repressed inflation, or a Walrasian state. This framework helps to explain both the missing-deflation episode after 2008, which reflects low goods matching efficiency, and the post-COVID inflation surge, which arises from exceptionally tight goods markets and low demand elasticity. Fourth, the state dependence of demand elasticity weakens the standard NK link between inflation and the output gap and alters the transmission of monetary policy. These findings show that coordination failures and time-allocation inefficiencies explain 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. The first is the empirical literature on the measurement and determinants of short-run TFP fluctuations (Basu and Fernald, 2002; Basu et al., 2006; Comin et al., 2025; Fernald, 2014; Huo et al., 2023). This work shows that while technology drives long-run growth, capacity utilization accounts for most cyclical variation in measured productivity. Capacity utilization is typically inferred from neoclassical price equations derived from cost minimization and related to observable hours per worker. More recent studies exploit industry survey data on utilization (Comin et al., 2025), implicitly incorporating labor-supply variation – an especially important adjustment for European economies.

The second strand examines theoretical sources of endogenous TFP fluctuations within production. Classic mechanisms rely 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). Labor-effort models (Bils and Cho, 1994; Basu and Kimball, 1997) are frequently favored empirically (Lewis et al., 2019). Other frameworks emphasize composition and dispersion effects – heterogeneous industry shifts that generate aggregate TFP variation (Baqaee and Farhi, 2020; Lagos, 2006). A related channel arises in labor-market SaM models, where vacancy posting reallocates workers from production to hiring and thereby reduces effective productive capacity (Blanchard and Gali, 2010).

The third strand is the goods-market search-and-matching literature, which formalizes coordination frictions by modeling the costly matching of buyers and sellers. Goods-market SaM models formalize coordination frictions,[4] 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 evidenced by procyclical shopping and its link to productivity (Petrosky-Nadeau et al., 2016; Bai et al., 2025). Price setting in such environments becomes a three-dimensional problem, shaped by marginal costs and state-dependent excess demand or supply (Michaillat and Saez, 2024; Gantert, 2025). Complementary price-search models (Benabou, 1988, 1992; Burdett and Judd, 1983; Diamond, 1971; Kaplan and Menzio, 2016; Pytka, 2024) focus on the search for price dispersion rather than search as a productive input, and thus provide additional but distinct insights.

By embedding a goods-market SaM structure into a New Keynesian framework, this paper brings these strands together. It reconceptualizes short-run TFP as reflecting not only input utilization but also coordination efficiency – the effectiveness with which buyers and sellers match. The model derives goods-market tightness as an alternative indicator of cyclical gaps, quantifies coordination-driven TFP across major economies, and shows how matching frictions reshape the propagation and interpretation of business-cycle shocks. By endogenizing demand elasticity and capacity utilization, the framework incorporates a rationing logic into a modern DSGE structure (Barro and Grossman, 1971; Barro, 2025), reduces reliance on ad-hoc cost-push shocks, and reframes the monetary-policy trade-off when matching efficiency varies over the cycle.

The rest of the paper is organized as follows. Section 2 introduces the model and the TFP decomposition. Section 3 discusses the estimation and identification strategy. Section 4 discusses the estimation results. Section 5 analyzes the mechanisms of the model and efficiency wedge. Section 6 concludes.

[4]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); alternative frameworks (Qiu and Rios-Rull, 2022; Bai et al., 2025) are complementary.

2. Model Setup

The model builds on a state-of-the-art New-Keynesian business-cycle framework (Christiano et al., 2010) with capital utilization and a labor market that distinguishes employment, hours, and labor effort (Bils and Cho, 1994; Cacciatore et al., 2020). It features three agents – households, monopolistically competitive firms, and a government – trading on four markets: goods, labor, capital, and nominal bonds. Goods and labor markets are subject to search-and-matching (SaM) frictions, while capital and bond markets are Walrasian. The key innovation is the introduction of goods-market SaM (Michaillat and Saez, 2015, 2024) combined with price adjustment costs (Rotemberg, 1982) and directed search (Moen, 1997). Households supply costly yet productive search effort, and firms contribute unmatched production capacity to a matching function that generates trades. The interaction of household search and firm pricing creates an endogenous price elasticity of demand, while firms' trade-off between markups and capacity utilization under adjustment costs drives fluctuations in the utilization rate. A pen-and-paper version of the model is presented 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 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.[5] New matches are formed by beginning-of-period unemployed workers and firm i vacancies, $v_t(i)$ by a matching function

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

where $0 < \gamma_N \leq 1$ and $\psi_{N,t}$ varies with a labor mismatch shock. Labor-market tightness is defined by $x_{N,t} = \frac{v_t}{u_t}$ with $f_{N,t} = \frac{m_{N,t}}{u_t}$ and $q_{N,t}(i) = \frac{m_{N,t}}{v_t(i)}$.

[5]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.

The *goods market* is segmented by varieties of the differentiated good. Households allocate search effort, $D_t(i)$, to each variety i, while firm i supplies unmatched production capacity of its unique variety, $S_t(i)$. Household search is directed towards each variety individually (Moen, 1997).[6] Customer relationships 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 and each relationhip trades one unit of its variety. New matches are formed by

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

where $-\infty < \Gamma \leq 0$, $\gamma_T \in [0,1)$, and $\psi_{T,t}$ varies with a goods mismatch shock.[7] Goods-market i tightness is defined by $x_{T,t}(i) = \frac{D_t(i)}{S_t(i)}$ – the ratio of demand to unmatched supply – with $f_{T,t}(i) = \frac{m_{T,t}(i)}{D_t(i)}$ and $q_{T,t}(i) = \frac{m_{T,t}(i)}{S_t(i)}$.

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

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

where $\sigma \geq 0$, $0 \leq \beta < 1$, and $Z_t \geq 0$ is a discount factor shock. Households derive utility from consumption, C_t, as defined in

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

[6] From this assumption, 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.

[7] Goods-market matching efficiency varies with a goods mismatch shock, capturing exogenous shifts in matching technology as well as composition and dispersion effects from unmodelled heterogeneity (e.g., geography, product type, quality, or timing of supply).

where $\nu_D > 0$ determines search effort elasticity and $\mu_D > 0$.[8] Consumption and search habits are set by $0 \leq \theta_C, \theta_D < 1$ (Christiano et al., 2005; Qiu and Rios-Rull, 2022). Labor supply has three margins – employment, hours per worker, and labor effort. Labor disutility (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).[9] $H_t(i)$ is hours per worker at firm i where $\mu_{H,t} > 0$ varies with an hours supply shock, and $e_{H,t}(i)$ is labor effort at firm i with $\mu_e > 0$. Their supply elasticities are set by $\nu_H, \nu_e > 0$. Workers can adjust hours and effort instantaneously while employment is quasi-fixed.

Aggregate *search effort* is given by $D_t = \left(\int_0^1 D_t(i) di \right)^{1+\nu_D}$,[10] and the aggregate goods bundle (Dixit and Stiglitz, 1977) 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 of varieties which fluctuates with a price cost-push shock (Ireland, 2004). A household allocates his goods to consumption, C_t, and fixed-capital investment, $I_{K,t}$, where $T_t = C_t + P_{I,t}(1 + c_{I,t}) I_{K,t}$, with convex fixed-capital investment adjustment costs, $c_{I,t} = \frac{\kappa_I}{2} \left(\frac{I_{A,t}}{I_{A,t-1}} - 1 \right)^2$, and an investment (price) shock, $P_{I,t} > 0$. Investment adjustment costs do not apply to investment resulting from capital utilization, i.e. $I_{A,t} = I_{K,t} - \delta_K(e_{K,t}) K_{t-1}$, as they represent maintenance investment (Qiu and Rios-Rull, 2022). The capital stock is given by $K_t = (1 - \delta_{K,1} - \delta_K(e_{K,t})) K_{t-1} + I_{K,t}$, where $\delta_K(e_{K,t}) = \frac{\phi_{K,1}\phi_{K,2}}{2}(e_{K,t} - 1)^2 + \phi_{K,1}(e_{K,t} - 1)$ with $\delta_{K,1} > 0$ setting independent capital depreciation, and $\phi_{K,1}, \phi_{K,2} \geq 0$ setting capital depreciation (convexity) due to capital utilization. Each household follows its

[8]Search-effort disutility captures overall search costs – information gathering, shopping, travel, and other procurement expenses (Michaillat and Saez, 2015). Yet, information time accounts for only a small share of total shopping time (Petrosky-Nadeau et al., 2016).

[9]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.

[10]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.

intertemporal budget constraint given by

$$
\begin{aligned}
B_t &= (1 + r_{B,t-1}) B_{t-1} + \int_0^1 W_t(i) L_t(i) di + P_t ub \left(1 - \int_0^1 N_t(i) di\right) \\
&\quad + P_t r_{K,t} K_{e,t} - \int_0^1 P_t(i) T_t(i) di - Tax_t + \Pi_t
\end{aligned} \tag{7}
$$

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 set by nominal wages,[11] $W_t(i)$, unemployment benefits, ub, capital interest, $P_t r_{K,t}$, bond interest, $r_{B,t-1}$, and firm dividends, Π_t.[12] Expenses are set by consumption and investment expenditures, $\int_0^1 P_t(i) T_t(i) di$, and lump-sum taxes, Tax_t, charged 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 by employing labor and capital in a production function,[13] $F_t(i) = L_t(i)^{1-\alpha} K_{e,t}(i)^{\alpha}$, where $0 \leq \alpha \leq 1$. It maximizes its intertemporal profits 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.[14] Revenue is created by sales on private markets, $T_t(i)$, and by exogenous public spending, $G_t(i)$. Each firm i pays wages, $W_t(i)$, for effective labor, $L_t(i)$, and capital interest, $r_{K,t}$, for the effective capital stock, $K_{e,t}(i)$. The production capacity of a firm is given by

$$
\mathcal{Y}_t(i) = (1 - \mathcal{C}_t(i)) A_{H,t} F_t(i) - \vartheta, \tag{8}
$$

[11] Aggregate labor equals total employment across firms, $N_t = \int_0^1 N_t(i) di$. With infinitely many workers and random matching, all households share identical employment histories and perfect unemployment insurance.

[12] Each household owns an identical share of a mutual fund holding all firms, so dividend income Π_t is identical across households.

[13] Burnside et al. (1995); Basu et al. (2006) show that any evidence on non-constant-returns-to-scale vanishes as we include capacity utilization in the model.

[14] 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.

where $\mathcal{C}_t(i) = c_{P,t}(i) + c_{W,t}(i) + c_{N,t}(i) + c_{H,t}(i)$ summarizes firm adjustment costs. $c_{P,t}(i) = \frac{\kappa_P}{2}\left(\frac{P_t(i)}{P_{t-1}(i)}(1+\pi)^{\iota_P - 1}(1+\pi_{t-1})^{-\iota_P} - 1\right)^2$ 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 – spent on vacancies, $v_t(i)$, to search and match additional workers – with $\kappa_N \geq 0$ (Merz and Yashiv, 2007). $c_{H,t}(i) = \frac{\kappa_H}{2}\left(\frac{H_t(i) - \bar{H}(i)}{\bar{H}(i)}\right)^2$ are hours adjustment costs with $\kappa_H \geq 0$ (Cacciatore et al., 2020). The technology level, $A_{H,t} > 0$, varies with a shock, and firms have identical production fixed costs, $\vartheta \geq 0$. Matching on a goods market depends on the beginning-of-period unmatched production capacity, $S_t(i)$, given by

$$S_t(i) \; = \mathcal{Y}_t(i) - G_t(i) - (1-\delta_T)\, T_{t-1}(i) + (1-\delta_I)\, I_{S,t-1}(i), \tag{9}$$

where $I_{S,t-1}(i) = (1 - q_{T,t-1}(i))\, S_{t-1}(i)$ is the depreciated end-of-period inventory stock with $0 < \delta_I \leq 1$. Unmatched production capacity, $S_t(i)$, serves as a productive input to the goods-market matching function stimulating demand (Sun, 2024). Each firm maximizes its profits by setting its price in a trade-off between markups and utilization following from directed search (Moen, 1997) and sticky prices (Rotemberg, 1982). As a monopolist, it takes the demand function for its variety (18) into account while setting prices and deciding on unmatched capacity to maximize profits (8).

2.4. General Equilibrium

To close the model, we define the real gross domestic product of the economy by $Y_t = C_t + G_t + Inv_t$, where C_t is the numéraire good, and $Inv_t = P_{I,t} I_{K,t} + I_{S,t} - I_{S,t-1} - \delta_K(e_{K,t})\, K_{t-1}$ is private investment.[15] 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 survey data capacity utilization is defined as

$$\bar{cu}_t \; = \frac{Y_t}{\bar{\mathcal{Y}}_t}. \tag{10}$$

[15]Capital depreciation costs due to capital utilization are excluded from real GDP as this is maintenance investment and thus an intermediate input (Qiu and Rios-Rull, 2022).

where $\bar{\mathcal{Y}}_t$ is the long-run sustainable production capacity[16] given by

$$\bar{\mathcal{Y}}_t \;=\; \left(1-\bar{\mathcal{C}}\right) A_{H,t} \left(\bar{e}_H \bar{H} N_t\right)^{1-\alpha} \left(\bar{e}_K K_{t-1}\right)^{\alpha} - \vartheta. \tag{11}$$

The central bank follows a Taylor (1993)-type rule to determine the nominal interest rate by

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

where π is the steady-state inflation target, $\tilde{Y}_t$ is the output gap,[17] $i_r, i_{gap}, i_{\Delta gap} \geq 0$ and $i_\pi > 1$ are policy coefficients, and M_t is a monetary policy shock. The price and wage cost-push shocks follow an ARMA(1, 1) process and all other shocks follow an AR(1) process. The public spending shock is correlated with the technology shock while all other shocks are orthogonal (Smets and Wouters, 2007).

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.

[16] Long-run sustainable production capacity follows three assumptions (Comin et al., 2025): (1) the capital stock is measured at its predetermined level including non-utilized capital; (2) the level of employment is measured at its current level as it is a quasi-fixed long-term relationship; (3) labor matching costs, hours per worker, and labor effort are measured at their steady-state as deviations are not sustainable in the long-run. A discussion of the assumptions on the capacity utilization definition is given in Appendix C.2.

[17] The output gap is defined as the ratio of GDP over its flexible prices and wages counterpart absent price and wage cost-push shocks (Smets and Wouters, 2007)

Consumption Euler Equation. The *representative household* allocates consumption by

$$\begin{aligned}
\mathbb{U}_{\chi,t} &= \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{-\sigma} + \omega \frac{\chi_t}{\mathbb{U}_{C,t}}, && (13)\\
\chi_t &= (1-\omega)\,\beta \mathbb{E}_t \frac{Z_{t+1}}{Z_t}\chi_{t+1} - \frac{\mathbb{U}_{N,t}}{\left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}}, && (14)\\
\mathbb{W}_{C,t} &= \mathbb{U}_{\chi,t} - \beta\theta_C \mathbb{E}_t \frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1}, && (15)\\
\mathbb{W}_{D,t} &= \mathbb{U}_{\chi,t} - \beta\theta_D \mathbb{E}_t \frac{Z_{t+1}}{Z_t}\mathbb{U}_{\chi,t+1}, && (16)\\
muc_t &= \beta \mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}} \frac{Z_{t+1}}{Z_t} muc_{t+1}, && (17)
\end{aligned}$$

where $\mathbb{U}_{\chi,t}$ is the marginal utility of the consumption stock corrected for wealth effects by χ_t, and $\mathbb{W}_{C,t}, \mathbb{W}_{D,t}$ is intertemporal marginal (dis-)utility of consumption (search effort). Marginal (net) utility of consumption, muc_t, is given by $\mathbb{W}_{C,t}$ net of $\mathbb{W}_{D,t}$, which is forward-looking due to the potential long-term nature of customer relationships. Its value is determined by

$$P_{T,t} = 1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}, \tag{18}$$

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

$$\Xi_t = (-\epsilon_t)\left[1 + P_{D,t} - (1-\delta_T)\,\mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}\right]^{-1}, \tag{19}$$

which fluctuates with search prices and price cost-push shocks, and is inversely related to the total price, $\Xi_t = \frac{-\epsilon_t}{P_{T,t}}$. Substituting (18) in (17) leads to

$$\mathbb{W}_{C,t} = \beta \mathbb{E}_t \frac{1+r_{B,t}}{1+\pi_{t+1}} \frac{Z_{t+1}}{Z_t} \frac{P_{T,t}}{P_{T,t+1}} \mathbb{W}_{C,t+1}, \tag{20}$$

which highlights the inflation-like impact of search prices growth on household intertemporal consumption allocation (Gantert, 2025). 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 unmatched capacity to the goods market to form matches with buyers. The *asset value of production capacity* is given by

$$Q_{Y,t} = q_{T,t} Q_{T,t} + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left(1-\delta_I\right)\left(1-q_{T,t}\right) Q_{Y,t+1}, \tag{21}$$

which is forward-looking due to the option to hold unmatched goods in inventory. It increases in the expected asset value of matched goods, $q_{T,t}Q_{T,t}$. Marginal costs are defined by $mc_t = \frac{Q_{Y,t}}{e_{M,t}}$ where we correct for the matched capacity rate, $e_{M,t} = \frac{T_t + G_t}{\mathcal{Y}_t}$.[18] The *asset value of matched goods* is given by

$$\left(1+\varphi_t\right) Q_{T,t} = 1 + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \left[\Big[\left(1-\delta_I\right)\varphi_t - \left(1-\delta_T\right) \Big] Q_{Y,t+1} + \left(1-\delta_T\right) Q_{T,t+1} \right], \tag{22}$$

which increaeses in long-term contracts as they reduce search costs per good sold. However, long-term contracts also decrease unmatched production capacity tomorrow and thus increase goods-markets tightness, especially if $Q_{Y,t+1}$ is expected to be high. Inventories have the opposite effect on expected goods-market tightness. $Q_{T,t} < 1$ indicates a markup over the matching costs following from monopolistic competition and goods-market SaM. It is set by $\varphi_t = \frac{1}{\epsilon_t} \frac{\gamma_T x_{T,t}^{\Gamma}}{1-\gamma_T} \frac{m_{T,t}}{T_t} \frac{P_{T,t}}{P_{D,t}}$ and affected by goods-market SaM in three ways[19]: markups (1) increase in γ_T as search effort is more productive; (2) increase in the share of newly to overall matched goods, $\frac{m_{T,t}}{T_t}$; and (3) decrease in $P_{D,t}$ as firms lower prices to attract additional customers in tight goods markets.[20]

Each firm posts prices with a markup over marginal costs taking goods-market tightness and

[18] Marginal costs follow the standard NK definition and empirical implementation of De Loecker et al. (2020), ensuring comparability with markup studies. They are adjusted for the implicit cost of unsold capacity, preventing markups from reflecting unmatched production.

[19] $\varphi_t \to 0$ as $\epsilon_t \to \infty$ (no monopol. competition); $\varphi_t = \frac{1}{\epsilon_t}$ as $\gamma_T \to 0 \Rightarrow P_{D,t} = 0$ (no goods-market SaM).

[20] Although demand elasticity (19) declines with $P_{D,t}$, firms cannot raise markups because households react to goods-market tightness and search prices by lowering search effort.

the household price elasticity into account. The *New-Keynesian Phillips curve* is given by

$$\begin{aligned}\frac{c'_{P,t}}{1-\mathcal{C}_t-\vartheta_{S,t}} &= \frac{\theta_{T,t}}{mc_t} - \frac{\gamma_T x^{\Gamma}_{T,t}}{1-\gamma_T}\frac{\theta_{S,t}}{P_{D,t}}\left(1-\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\left(1-\delta_I\right)\frac{e_{M,t+1}mc_{t+1}}{e_{M,t}mc_t}\right) \\ &\quad + \mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}\frac{mc_{t+1}}{mc_t}\frac{Y_{t+1}}{Y_t}\frac{c'_{P,t+1}}{1-\mathcal{C}_{t+1}-\vartheta_{S,t+1}},\end{aligned} \tag{23}$$

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, $\vartheta_{S,t}$ is the fixed costs share of overall costs, $\theta_{T,t}$ is the ratio of goods sold (excluding inventories) to GDP, and $\theta_{S,t}$ is the beginning-of-period share of unmatched production capacity.[21]

High markups ($mp_t = \frac{1}{mc_t}$) permit greater marginal price adjustment costs and thus higher inflation. Goods-market SaM frictions lower equilibrium adjustment costs – and hence inflation – for a given markup. As γ_T rises, search effort becomes more effective in matching goods, so smaller price changes suffice to meet demand. Higher search prices $P_{D,t}$ instead reduce demand elasticity (19) and raise inflation. Inventories act similarly: the ability to buy low and sell high increases firms' market power. When much capacity is locked in long-term contracts ($\theta_{S,t}$), goods-market SaM effects weaken because less output requires matching each period. With price adjustment costs, posted prices – and thus search prices and effort – adjust gradually and sub-optimally, generating fluctuations in matching efficiency. The interaction of sticky posted and flexible search prices drives cyclical variation in search prices and matching probabilities.

[21]The composite terms of the Phillips curve are defined as follows: (1) $\vartheta_{S,t} = \frac{\vartheta}{A_{H,t}F_t}$; (2) $\theta_{T,t} = \left(1+\frac{\Delta I_{S,t}}{T_t+G_t}\right)^{-1}$; and (3) $\theta_{S,t} = 1-\frac{G_t+(1-\delta_T)T_{t-1}-(1-\delta_I)I_{S,t-1}}{\mathcal{Y}_t}$.

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

$$
\begin{aligned}
Q_{K,t} &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \Big[r_{K,t+1} e_{K,t+1} + (1-\delta_{K,1}) Q_{K,t+1} \\
&\qquad - (1+c_{I,t+1}) P_{T,t+1} P_{I,t+1} \delta_K (e_{K,t+1}) \Big],
\end{aligned} \tag{24}
$$

$$
Q_{K,t} = P_{T,t} P_{I,t} \left[(1+c_{I,t}) + \frac{I_{K,t} \left\{ c'_{I,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{P_{T,t+1} P_{I,t+1}}{P_{T,t} P_{I,t}} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1} \right\}}{I_{K,t} - \delta_K (e_{K,t}) K_{t-1}} \right], \tag{25}
$$

$$
r_{K,t} = (1+c_{I,t}) P_{T,t} P_{I,t} (\phi_{K,1} \phi_{K,2} (e_{K,t} - 1) + \phi_{K,1}), \tag{26}
$$

where $Q_{K,t}$ is the *asset value of installed capital* (Tobin, 1969). It rises with investment adjustment costs and with search prices through $P_{T,t}$, since acquiring capital goods requires household search effort. The *representative firm* employs capital according to

$$
r_{K,t} = \alpha (1-\mathcal{C}_t) \frac{A_{H,t} F_t}{e_{K,t} K_{t-1}} e_{M,t} mc_t, \tag{27}
$$

where the capital interest rate increases in marginal productivity, marginal costs, and the matched capacity rate. Goods-market frictions, via $e_{M,t}$ and $P_{T,t}$, reduce both capital demand and utilization as firms and households anticipate imperfect matching of productive capacity.

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

$$
Q_{F,t} = \mathcal{C}'_{N,t} \frac{A_{H,t} F_t}{N_t} e_{M,t} mc_t - w_t e_{H,t} H_t + (1-\delta_N) \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} Q_{F,t+1}, \tag{28}
$$

$$
Q_{F,t} = 2 c_{N,t} \frac{A_{H,t} F_t}{q_{N,t} v_t} e_{M,t} mc_t, \tag{29}
$$

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. Firms post vacancies as long as the expected net return is greater or equal than its costs (free-entry condition). Each worker-firm match *bargains over the conditions of work* (Nash, 1950) maximizing the joint surplus by bargaining over the real wage, hours per worker, and labor effort jointly as described by

$$
\begin{aligned}
w_t H_t e_{H,t} &= ub + \frac{P_{T,t} \frac{\partial \mathbb{U}_{N,t}}{\partial N_t}}{\mathbb{W}_{C,t} \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}} + \eta_{H,t} Q_{F,t} \\
&\quad - \mathbb{E}_t \frac{1 + \pi_{t+1}}{1 + r_{B,t}} \left(1 - \delta_N\right) \left(1 - f_{N,t+1}\right) \eta_{H,t+1} Q_{F,t+1},
\end{aligned} \tag{30}
$$

$$
w_t e_{H,t} = \left(\mathcal{C}'_{H,t} - (1 - \alpha)\, c'_{H,t}\right) \frac{A_{H,t} F_t}{H_t N_t} \frac{Q_{Y,t}}{1 - \tau_{W,t}} - \frac{P_{T,t} \frac{\partial^2 \mathbb{U}_{N,t}}{\partial N_t \partial H_t}}{\mathbb{W}_{C,t} \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}} \frac{\tau_{W,t}}{1 - \tau_{W,t}}, \tag{31}
$$

$$
w_t H_t = \mathcal{C}'_{H,t} \frac{A_{H,t} F_t}{e_{H,t} N_t} \frac{Q_{Y,t}}{1 - \tau_{W,t}} - \frac{P_{T,t} \frac{\partial^2 \mathbb{U}_{N,t}}{\partial N_t \partial e_{H,t}}}{\mathbb{W}_{C,t} \left(\mathbb{U}_{C,t} - \mathbb{U}_{N,t}\right)^{\sigma}} \frac{\tau_{W,t}}{1 - \tau_{W,t}}, \tag{32}
$$

where $\mathcal{C}'_{H,t} = (1 - \alpha)^2 \left(1 - \mathcal{C}_t\right) - 4\alpha c_{N,t}$ and $\eta_{H,t} = \frac{\eta_t}{1 - \eta_t} \frac{1}{\tau_{W,t}}$. The household bargaining power, $0 \leq \eta_t \leq 1$, varies with an exogenous wage cost-push shock, and $\tau_{W,t}$ is a sticky wage wedge with $\tau_W = 1$ and increasing monotonically with wage inflation.[22] Real wages are set by a weighted average of opportunity costs and marginal productivity determined by the effective household bargaining weight, $\eta_{H,t}$. Hours per worker and labor effort are determined to maximize their marginal productivities over disutilities, taking wage and hours setting frictions into account.[23] Goods-market SaM influences labor demand via the matched capacity rate, $e_{M,t}$ (implicit in $Q_{F,t}$), and labor supply through search price effects on $P_{T,t}$. Higher $e_{M,t}$ raises the marginal value of labor, but if search prices rise with utilization, the resulting increase in $P_{T,t}$ and wages dampens labor expansion.

The equilibrium conditions imply that output depends not only on technology and inputs but also on their utilization across markets. Labor effort, capital utilization, fixed costs degression, and the matching probability jointly determine utilization.

2.6. Measuring Total Factor Productivity

Building on the equilibrium relationships of the model, we define measured TFP and decompose it into (utilization-adjusted) technology and utilization components. We linearize

---

[22]See Appendix A for details on wage bargaining and $\tau_{W,t}$.

[23]We use (32) and the production function to derive a steady-state 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). ϕ is set as a prior in the estimation to elicit the impact of labor effort on capacity utilization. Over the business cycle, it is also affected by variation in marginal hours adjustment costs, $c'_{H,t}$.

the relationships around their deterministic steady-states for ease of exposition, e.g. $\hat{gdp}_t = \frac{GDP_t - GDP}{GDP}$. Measured TFP in the model follows from the aggregate production identity and reflects both technology and utilization of inputs across capital, labor, and the goods market. Linearizing the production function and substituting for variable utilization rates yields

$$G\hat{D}P_t \;=\; \hat{A}_t + \alpha \hat{K}_{t-1} + (1-\alpha)\left(\hat{N}_t + \hat{H}_t\right) + \hat{u}_t^K + \hat{u}_t^L + \hat{u}_t^{\vartheta} + \hat{u}_t^G, \tag{33}$$

where $\hat{A}_t = A\left(A_{H,t},\, \psi_{T,t}\right)$ denotes utilization-adjusted TFP,[24] $\hat{u}_t^K$ capital utilization, $\hat{u}_t^L$ labor utilization, $\hat{u}_t^{\vartheta}$ fixed costs degression, and $\hat{u}_t^G$ goods-market utilization derived from the goods-market SaM block. Measured TFP (Solow (1957)-residual) is therefore

$$T\hat{F}P_t \;= \hat{A}_t + \hat{u}_t^K + \hat{u}_t^L + \hat{u}_t^{\vartheta} + \hat{u}_t^G \;=\; \hat{A}_t + \hat{\Phi}_t, \tag{34}$$

which consists of both utilization-adjusted TFP, $\hat{A}_t$, and utilization variation represented by the *efficiency wedge*, $\hat{\Phi}_t$ – variation in TFP explained by endogenous propagation of shocks in the model. Goods-market utilization, $\hat{u}_t^G$, 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 through ν_e, but also through working time provided to labor matching, $\hat{c}_{N,t}$; 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.

In the empirical analysis, we identify measured TFP and the *efficiency wedge* through observables and equilibrium relationships, use the decomposition (34) to identify the determinants of the *efficiency wedge*, and use the smoothed states from the Kalman filter to compute the efficiency wedge. Detailed derivations of the TFP decomposition are given in Appendix B.

[24]Whether the goods mismatch shock, $\hat{\psi}_{T,t}$, represents a true technology shock is ambiguous, as it may also reflect dispersion or composition effects. To account for this, section 3 defines upper and lower bounds of TFP decomposition, $\hat{\hat{A}}_{Up,t}$ and $\hat{\hat{A}}_{Low,t}$. The analysis uses the upper-bound case, while the lower bound – derived symmetrically – is presented in Appendix B. In general, we use the term "utilization-adjusted TFP" rather than "technology", as it further captures unmodeled dispersion or composition effects of technology, $A_{H,t}$ whose effect on TFP is similar to that of capacity utilization (Basu et al., 2006).

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 defining 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 and consumption, labor compensation, and capacity utilization, hours per worker, employment rate, GDP deflator, and the policy rate. Hours per worker and the employment rate are linearily detrended (Cacciatore et al., 2020). Growth rates are detrended by mean GDP growth, except capacity utilization growth which is de-meaned as the stationary rates (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 combine industrial and imputed service sector measures; construction and sources appear in Appendix C. Given sample size differences, the main analysis uses U.S. data, with Euro Area results provided as robustness checks.

General parameters of the model are calibrated while research question specific parameters are estimated. The calibrated parameters are in line with the literature (Blanchard and Gali, 2010; Christiano et al., 2010). The prior setup is shown in table 3. The calibration and estimation strategy is described in detail 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 steady-state zero profit assumption. The labor effort elasticity, ν_e, is inferred from steady-state 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, $\gamma_{T,ub} = 0.5$, 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 with a lower bound $\Gamma_{lb} = -5$ and estimated via $\Gamma^{prox} = \frac{\Gamma}{\Gamma_{lb}}$ with a Beta(0.1, 0.05) 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.

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 $1,000,000$ 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%. Posterior convergence is assessed using the Brooks and Gelman (1998) and Geweke (1999) diagnostics, which are available upon request. The observables–to–model mapping follows Pfeifer (2018), linking nine observables to the model's measurement equations as shown in Appendix C.3. Model comparison relies on the log data density, computed with the modified harmonic mean

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

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.

3.3. Identification of the Goods-Market SaM Mechanism

Identification relies on two complementary sources of information: (i) survey-based capacity utilization, which determines the *efficiency wedge* 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 *search productivity and price elasticity channels* of the goods-market SaM mechanism. Using (10) and (34), the *efficiency wedge* is given by

$$\hat{\boldsymbol{\Phi}}_{\boldsymbol{t}} = \frac{\hat{\boldsymbol{cu}}_{\boldsymbol{t}}}{1+\vartheta_{gdp}cu} + \frac{\vartheta_{gdp}cu\,\hat{\boldsymbol{gdp}}_{\boldsymbol{t}}}{1+\vartheta_{gdp}cu} - (1-\alpha)\,\hat{\boldsymbol{H}}_{\boldsymbol{t}} - \varphi_{\psi}\hat{\boldsymbol{\psi}}_{\boldsymbol{T,t}}, \tag{35}$$

where $\varphi_{\psi} = \frac{1-cu(1-(1-g_S)\delta_T\delta_I)}{\left(1+\vartheta_{gdp}cu\right)\delta_I}$. It depends on observables – capacity utilization, fixed-cost degression (proxied by real GDP), and hours per worker[26] – and on a latent goods mismatch shock.[27] This formulation extends the standard approach (Fernald, 2014; Comin et al., 2025) by including a market technology term that drives utilization exogenously. While this alters the behavior of the efficiency wedge in model and data, it does not affect the identification of goods-market SaM, only its accounting within the wedge.

Capacity utilization data further disciplines the goods-market SaM block through (10), which links capacity utilization to search productivity , $q_{T,t}$, and long-term contract and inventory dynamics. We rewrite (10) as

$$\hat{\boldsymbol{cu}}_{\boldsymbol{t}} = (1-g_S)\left[\delta_T\left(\hat{\boldsymbol{q}}_{\boldsymbol{T,t}} + \hat{\boldsymbol{S}}_{\boldsymbol{t}}\right) + (1-\delta_T)\,\hat{\boldsymbol{T}}_{\boldsymbol{t-1}}\right] + g_S\hat{\boldsymbol{G}}_{\boldsymbol{t}} + i_S\boldsymbol{\Delta}\hat{\boldsymbol{I}}_{\boldsymbol{S,t}} - \hat{\boldsymbol{\mathcal{Y}}}_{\boldsymbol{t}} \tag{36}$$

[26]Holding utilization fixed: (1) hours per worker affect both short-run capacity and output but are not part of long-run sustainable capacity; (2) fixed cost degression raises the marginal productivity of additional inputs.

[27]Goods mismatch shocks are treated as technology shocks (upper-bound) that exogenously move utilization. Under the lower-bound interpretation, they represent non-technological composition and dispersion effects.

where g_S is the government spending ratio, i_S is inventory-to-GDP ratio, and $\bar{\mathcal{Y}}_t$ is determined by input factors and utilization-adjusted TFP only – see (11). Conventional capacity utilization channels affect available production capacity, $S\left(\hat{e}_{H,t}, \hat{e}_{K,t}; \vartheta, \delta_T, \delta_I\right)$ – see (9). 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 in the goods-market SaM block. However, both capacity utilization and the *efficiency wedge* can also be described by 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 in the model.

Search prices as defined in (18) are a latent variable as shopping time data is not available on a quarterly basis. Cross-equation restrictions given by the consumption (20) and investment (25) Euler equations and the Phillips curve (23) discipline the search price component working through $P_{T,t}$, 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 (4) which separately helps to identify 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 (32), which is disciplined through employment decisions on the demand (28) and supply side (30). The capital utilization margin is identified by the capital interest rate as shown in (26), which is disciplined through capital investment decision on the demand (27) and supply side (25). Labor and capital supply are jointly determined with search prices working through $P_{T,t}$ and labor and capital demand are jointly determined with matched capacity, $e_{M,t}$.

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

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	Labor-effort elasticity ν_e Production fixed costs ϑ	Current state of the literature (Fernald, 2014; Lewis et al., 2019)
GM-Util	Goods-market SaM $(\psi_T, \gamma_T, \Gamma)$ Production fixed costs ϑ	Tests goods-market SaM mechanism (Michaillat and Saez, 2015)
Full-Util	All margins as in section 2	Full specification analysis

NOTE: Each model name in small caps indicates the active utilization margin. The Full-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.

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 TFP while keeping all other structures and priors identical. This approach isolates how the new goods-market SaM block improves model fit relative to existing utilization margins in the literature.

The benchmark combines Christiano et al. (2010); Lewis et al. (2019) and includes labor effort, capital utilization, and production fixed costs but excludes goods-market SaM. Alternative specifications sequentially introduce both mechanisms. The preferred specification combines the benchmark and goods-market SaM channels.[28] 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. Different combinations of the presented margins are evaluated in section 4 as e.g. the *preferred model* combining the KL&GM-Util margins. Posterior estimates, log data densities, and variance decompositions reported in section 4 quantify the relative explanatory

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

power of each specification.

Having established the estimation framework and identified the efficiency wedge and its decomposition, 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 TFP. We first discuss log data densities and posterior parameters. We then examine the implied dynamics of the efficiency wedge and recent U.S. business cycles. 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 model's log data density in all countries. The relative roles of price elasticity and search productivity vary by country, but priors and posteriors show well-identified parameters – especially for goods-market SaM. The model matches second moments of search effort and yields consistent TFP and efficiency wedge estimates. Applied to the U.S., it helps to explain both the "missing-deflation" and post-COVID inflation episodes using the Barro and Grossman (1971) framework. Variance decompositions show a shift away from price cost-push shocks due to the endogenous price elasticity, and results remain robust across checks.

4.1. Log Data Density – 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 the main variants and countries. Table D.6 gives a full overview of variants. Relative to the benchmark model, adding goods-market SaM shows a Bayes factor between 53 and 135 points, indicating a decisive improvement in fit for the preferred model. The data favors a contemporaneous SaM channel that complements the labor effort and fixed costs margins, while capital utilization and intertemporal SaM extensions add little explanatory power.

Table 2: Log Data Densities and Bayes Factors Across Different Model Variants

Model Setup		U.S.	Spain	Germany	France
*Models **including** survey-based capacity utilization data*					
KL-Util	**Benchmark**	5218.2	2757.7	2976.2	3255.2
G-Util		5224.6	2763.7	3028.7	3278.4
KLG-Util	Complements	5240.7	2764.8	2992.6	3273.8
KLG-Util	**Preferred**	5262.7	2785.3	3043.9	3281.7
Full-Util		5229.7	2751.5	3028.3	3279.7
Bayes Factors (compared to benchmark model)					
Complements		**45.0**	**14.2**	**32.8**	**37.2**
Preferred		**89.0**	**55.2**	**135.4**	**53.0**
*Models **excluding** survey-based capacity utilization data*					
KL-Util	**Benchmark**	4675.9	2456.7	2650.4	2876.2
KLG-Util	Complements (w/o CU)	4688.8	2466.1	2672.3	2893.2
KLG-Util	**Preferred** (w/o CU)	4713.1	2482.9	2719.4	2923.3
Bayes Factors (compared to benchmark model)					
Complements		**25.8**	**18.4**	**43.2**	**34.0**
Preferred		**74.4**	**52.4**	**138.0**	**94.2**

NOTE: The table shows log data densities and Bayes factors for different model variants estimated on U.S. data (1984q1-2019q4) and Euro Area data (1998q1-2019q4). Log data densities are calculated by the modified harmonic mean following Geweke (1999). Different variants are compared using the Bayes factor (Kass and Raftery, 1995): a value of 5 or higher indicates an improvement in data fit, a value of 10 or higher a decisive improvement in data fit.

Benchmark vs Preferred Model. Across economies, the hierarchy of models is consistent. Labor effort utilization outperforms capital utilization decisively, reproducing results in Lewis et al. (2019). However, the combination of the two improves the data fit further, thus informing our *benchmark model* choice. A simple G-Util model outperforms the benchmark with a Bayes factor between 12 and 105 – indicating a decisive improvement in data fit and highlighting the importance of goods-market SaM.

Combining the traditional utilization margins with goods-market SaM (KLG-Util) shows the highest performing model across countries – thus informing our *preferred model* choice. However, neglecting the capital utilization channel (LG-Util) does not lead to a decisive deterioration in data fit, confirming that the labor-effort and goods-market margins jointly capture most of the relevant dynamics.[29] Including intertemporal goods-market SaM margins (Full-Util) leads to a negative Bayes factor of roughly −31 to −67 points, except for France which shows an indecisive deterioration of −4 points. Hence, the data prefers short-lived, contemporaneous matching frictions to persistent contractual mechanisms.

Goods-Market SaM Channel Decomposition. We find that both the price-elasticity and search-productivity channels improve the fit of the KLG-Util model, though to different degrees across countries. To isolate their roles, we identify their separate contributions using the procedure in section 3.3. Two caveats apply: capacity utilization is observed but search effort is not; and the search-productivity channel affects the price-elasticity channel, creating interaction effects. The decomposition clarifies whether goods-market SaM primarily improves the measurement of capacity utilization (and thus the efficiency wedge) or improves the dynamics of other observables.

We isolate the effect of the price-elasticity channel by setting matching inputs in the preferred model to perfect complements ($\Gamma \approx -\infty$) and re-estimating the model. The resulting Bayes factors, ranging from 14 to 45, still show a decisive improvement over the benchmark model, though clearly weaker than the full preferred specification across all countries. This indicates that the price-elasticity channel and the search-productivity channel each make distinct and positive contributions to the performance gains from incorporating goods-market SaM.

Next, we drop capacity utilization data and re-estimate the model using the standard eight observables. The same pattern emerges[30]: the price-elasticity channel alone decisively improves fit, with Bayes factors of 18–43 across countries, while adding the search-productivity channel raises the improvement further to 52–138.

Lastly, we disentangle the impact of the price-elasticity and search-productivity channels in explaining capacity utilization data by computing its marginal data contribution via incremental Bayes factors. The price-elasticity channel affects utilization through its impact

[29] For the U.S., the G-Util vs. K-Util comparison replicates Qiu and Rios-Rull (2022) with a Bayes factor of 85. Adding both margins further improves the Bayes factor to 100.

[30] This also provides a robustness check: since our constructed utilization measure may contain noise (section Appendix C), it is reassuring that coordination frictions matter even when using only the usual eight observables (Cacciatore et al., 2020).

on the dynamic equations of the traditional utilization channels. Its results are mixed: a decisive improvement for the U.S. (19.2), a weak one for France (3.2), but deteriorations for Spain (-4.2) and Germany (-10.4). The search-productivity channel shows a similar pattern: a decisive improvement for the U.S. (14.6) and a weak one for Spain (2.8), but a weak deterioration for Germany (-2.6) and a decisive one for France (-41.2).
Therefore, the direct contribution of SaM channels to explaining capacity utilization data is mixed[31]: a positive contribution for the U.S., a weak improvement for Spain, a weak deterioration for Germany, and a decisive deterioration for France. Nevertheless, goods-market SaM improves overall model fit through both the price-elasticity and search-productivity channels four all four countries. That all metrics favor goods-market SaM for the U.S. – our main case study – is particularly encouraging: coordination frictions are a salient feature of the data![32]

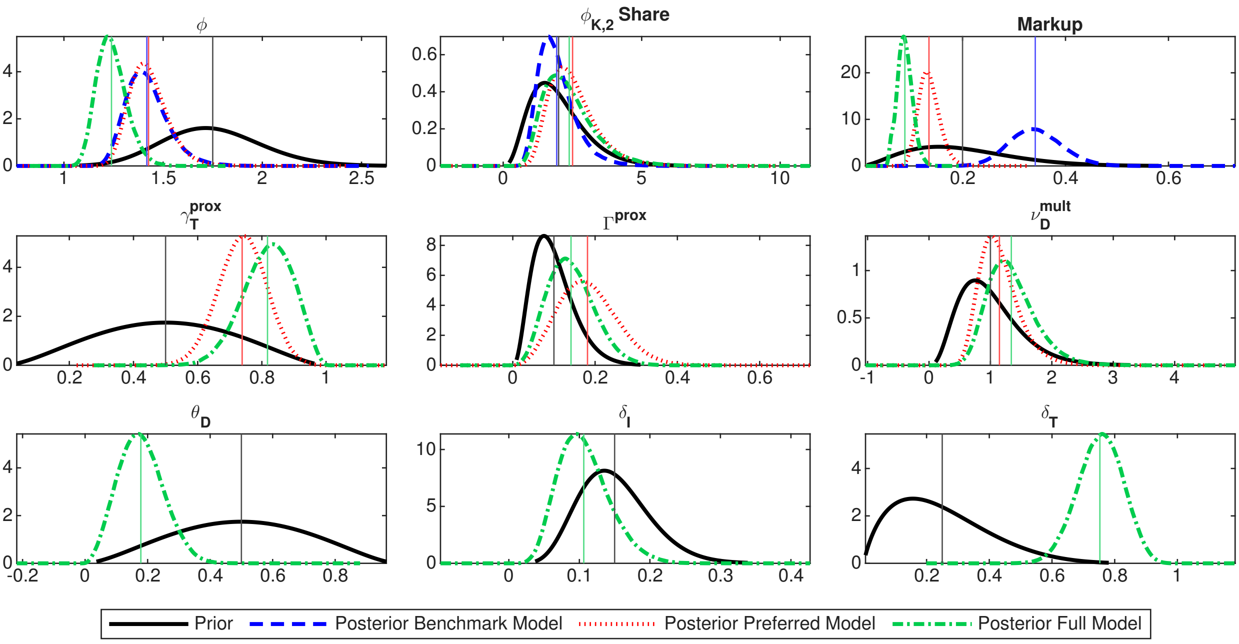
4.2. Prior-Posterior Analysis

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. Figure 1 highlights the posterior densities of the goods-market SaM parameters; a full overview is given in table 3. All posteriors are within their prior intervals, and posteriors of general parameters are mostly consistent across models.

Goods-market SaM. The estimated goods-market SaM parameters indicate search effort to be a salient feature of goods-market matching: the posterior of γ_T is high and precisely estimated. The search-productivity channel shows a strong impact of search effort on market efficiency: Γ centers around 0.16, close to a Cobb–Douglas form, though it remains largely prior-driven due to limited data informativeness. The curvature of the price-elasticity function is convex and the data is informative: $\frac{\nu_D}{\nu_H} \approx 1.15$ implies that time spent searching carries a similar

[31]Because our utilization measure is constructed, some of this variation may reflect measurement noise. That coordination frictions are still favored when excluding utilization data serves as a robustness check.
[32]Results are robust to alternative specifications altering the treatment of investment and output and sectoral weights in constructing utilization data (table D.7).

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



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

but slightly higher opportunity cost to working.[33]

Intertemporal goods-market SaM parameters are small. The posterior mean of the contract separation rate, δ_T, points to short-lived matches, while the posterior mean of θ_D indicates low habit persistence in search. The inventory depreciation rate is low and precisely estimated. However, as only approximately one-fourth of U.S. firms can hold inventories, the data clearly favor contemporaneous over intertemporal goods-market frictions – hence their exclusion from the preferred model. Overall, the posteriors highlight contemporaneous goods-market SaM as a key feature of the model with both the price-elasticity and search-productivity channels clearly identified.

Steady-state markups. Estimated steady-state markups decline once goods-market SaM is introduced, reflecting stronger effective competition as firms respond more flexibly to search conditions. A salient search-productivity channel (high γ_T and low Γ) makes search effort

[33] The estimated ν_D exceeds values in Michaillat and Saez (2015), is below those in Bai et al. (2025), and broadly aligns with Huo and Rios-Rull (2020).

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 captures a reduction in overhead costs as steady-state markups decrease roughly 21%-points compared to the benchmark model.

Capital utilization and labor effort. Turning to *traditional utilization margins*, the labor-effort elasticity ν_e remains significant and continues to dominate capital-utilization costs, which remain well identified.[34] The implied elasticity of capital utilization is well below literature estimates.[35] The evidence confirms the prominent role of labor effort in short-run utilization dynamics (Lewis et al., 2019).

Cross-Country Comparison and Robustness. Table 3 summarizes U.S. priors and posteriors, which remain largely consistent across models.[36] Cross-country evidence is similarly uniform (Appendix D.2)[37]: the U.S., Germany, France, and Spain exhibit tight posteriors with the same qualitative ordering – high γ_T, moderate Γ, convex ν_D, and low intertemporal margins. The data therefore consistently support a contemporaneous goods-market SaM mechanism that complements the benchmark model.

4.3. Validating Search-and-Matching through Moments of Latent Variables

Unmatched moments (Appendix D.4) show that hours per worker correlate with capacity utilization ($corr. = 0.67$) (Fernald, 2014) and search effort ($corr. = 0.57$) in U.S. data, though the imperfect link indicates that utilization surveys capture broader time-allocation behavior (Comin et al., 2025). The preferred model predicts procyclical search effort with

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[34]The posterior mean of the steady-state labor-effort elasticity, $\frac{1}{\nu_e} = \left(\frac{\nu_H}{\phi-1} - 1\right)^{-1}$, lies between 0.12 and 0.24, below the literature value of about 0.6 (Bils and Cho, 1994), implying lower labor-effort elasticity once goods-market SaM is introduced. In the short run, hours-adjustment costs κ_H raise this elasticity because hours per worker adjust slowly.

[35]The KLG-Util model yields a $\phi_{K,2}$ posterior mean of 3.06. The implied utilization elasticity $\sigma_{e_K} = \frac{\delta'_K}{\delta''_K e_{K,t}}$ ranges from 0.4 to 0.52, far below the benchmark 3.33 (Christiano et al., 2010).

[36]With goods-market SaM, the Frisch elasticity ν_H and hours-adjustment costs κ_H rise, while price-adjustment costs κ_P fall and investment-adjustment costs κ_I increase – reflecting time-allocation trade-offs and price-elasticity effects.

[37]Expected Euro Area differences include more rigid labor markets, country-specific investment patterns with consistent SaM effects, lower markups, and a stronger monetary focus on inflation.

Table 3: Prior-Posterior Estimates of the Model Parameters (U.S. Data)

Parameter	Distribution	Prior Mean	Prior Std.Dev.	Posterior Benchmark (90% HDP)	Posterior Preferred (90% HDP)	Posterior Full (90% HDP)
General Parameters						
ω	Beta	0.5	0.2	0.70 (0.33-0.96)	0.67 (0.41-0.94)	0.78 (0.60-0.97)
θ_H	Beta	0.7	0.1	0.75 (0.68-0.83)	0.70 (0.63-0.77)	0.73 (0.65-0.79)
ν_H	Gamma	2	0.5	1.67 (1.22-2.11)	2.21 (1.64-2.76)	2.17 (1.58-2.78)
$\frac{1}{mc}-1$	Beta	0.2	0.1	0.34 (0.26-0.42)	0.13 (0.10-0.17)	0.09 (0.06-0.11)
κ_H	Gamma	4	1.5	3.02 (2.28-3.77)	4.05 (3.14-4.91)	4.483 (3.51-5.45)
κ_I	Gamma	4	1.5	4.53 (3.11-5.90)	9.69 (7.11-12.21)	9.63 (6.80-12.42)
κ_W	Gamma	30	5	28.4 (20.9-35.9)	27.0 (19.5-34.4)	17.1 (10.4-23.5)
κ_P	Gamma	180	20	203.3 (169.1-234.5)	159.1 (131.9-185.9)	173.5 (144.5-202.5)
ι_W	Beta	0.5	0.15	0.38 (0.15-0.60)	0.44 (0.20-0.68)	0.44 (0.20-0.68)
ι_P	Beta	0.5	0.15	0.13 (0.04-0.20)	0.08 (0.03-0.13)	0.09 (0.03-0.14)
i_π	Gamma	1.8	0.1	1.76 (1.61-1.91)	1.81 (1.66-1.95)	1.87 (1.73-2.02)
i_{gap}	Gamma	0.12	0.05	0.15 (0.08-0.21)	0.10 (0.04-0.15)	0.09 (0.03-0.14)
$i_{\Delta gap}$	Gamma	0.12	0.05	0.12 (0.4-0.19)	0.14 (0.05-0.22)	0.10 (0.04-0.15)
Benchmark Utilization Parameters						
ϕ	Gamma	1.75	0.25	1.42 (1.25-1.58)	1.43 (1.27-1.58)	1.24 (1.12-1.36)
$\phi_{K,2}$	Gamma	2	1	1.93 (0.92-2.92)	2.51 (1.21-3.76)	2.38 (0.97-3.76)
Goods-Market SaM Utilization Parameters						
γ_T^{prox}	Beta	0.5	0.2	–	0.74 (0.62-0.86)	0.82 (0.70-0.95)
Γ^{prox}	Beta	0.1	0.05	–	0.18 (0.07-0.29)	0.14 (0.04-0.23)
ν_D^{mult}	Gamma	1	0.5	–	1.15 (0.64-1.64)	1.34 (0.73-1.96)
θ_D	Beta	0.5	0.2	–	–	0.18 (0.06-0.29)
δ_I	Beta	0.15	0.05	–	–	0.11 (0.05-0.16)
δ_T	Beta	0.25	0.15	–	–	0.75 (0.64-0.87)

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

a GDP elasticity of 0.53 and a relative standard deviation of 1.02, consistent with the behavioral regularities implied by goods-market SaM.[38] Goods mismatch shocks explain 30.0% of search-effort variation, with strong internal propagation through other business-cycle shocks.[39] Search effort is only weakly correlated with TFP (*corr.* $= -0.4$), capacity utilization (*corr.* $= 0.34$), and goods-market tightness (*corr.* $= 0.31$), reflecting time-allocation and matching-efficiency shifts beyond pure demand. Its GDP elasticity is about half that in Petrosky-Nadeau et al. (2016). Adding search shocks could address this, but current data do

[38] OLS of smoothed log search effort on log GDP; constant = 0.39. Without constant: elasticity = 1.04.

[39] Main drivers: investment (36.1%), monetary policy (7.9%), hours supply (7.1%), technology (5.7%), discount factor (5.4%), and price cost-push (5.0%).

not allow separate identification from goods mismatch shocks.

Model-implied U.S. TFP growth is tightly identified, with a correlation near one and standard deviations of 0.479% and 0.483% for the benchmark and preferred models.[40] The correlation with the data is 0.66, and the empirical standard deviation is 0.732% (Fernald, 2014). Deviations arise mainly from using (1) capital investment rather than estimated capital stock data and (2) aggregate data that ignore input composition and cross-industry productivity heterogeneity. Hence, model-generated TFP aligns closely with empirical estimates, and differences across models and decompositions reflect shifts in underlying drivers rather than divergent TFP behavior.

The growth rate of the efficiency wedge, as defined in (35), shows a consistently positive correlation between models and the data. Under the lower-bound definition – excluding goods mismatch shocks as technology shocks, consistent with Comin et al. (2025) – the benchmark and preferred models correlate at 0.96. The benchmark model fits the data more closely ($corr. = 0.54$) than the preferred ($corr. = 0.45$), and its standard deviation (0.32%) is close to the preferred model (0.31%) but distant to its empirical value (0.73%).

Including goods mismatch shocks as technology shocks (upper-bound definition) reduces the correlation between the two models to 0.36, revealing their differential response to goods-market frictions. The benchmark model then tracks the data poorly ($corr. = -0.16$), while the preferred model retains moderate fit ($corr. = 0.37$). Standard deviations improve: the preferred model rises to 0.67% and the benchmark to 0.43%.

Examining the correlation between TFP and efficiency wedge growth, the benchmark model aligns better with the data ($corr_{low} = 0.53$, $corr_{up} = 0.0$; data $corr. = 0.55$) than the preferred model ($corr_{low} = 0.37$, $corr_{up} = 0.04$). Both specifications thus capture the efficiency wedge reasonably well under empirical definitions (lower-bound) (Fernald, 2014; Comin et al., 2025), though their strengths differ. Yet, once goods mismatch shocks are treated as technology shocks, the implied business-cycle dynamics of the efficiency wedge diverge markedly – highlighting the sensitivity of its empirical identification to assumptions

[40] Growth rates are used instead of steady-state deviations, as external data are available only in this format.

about coordination frictions.

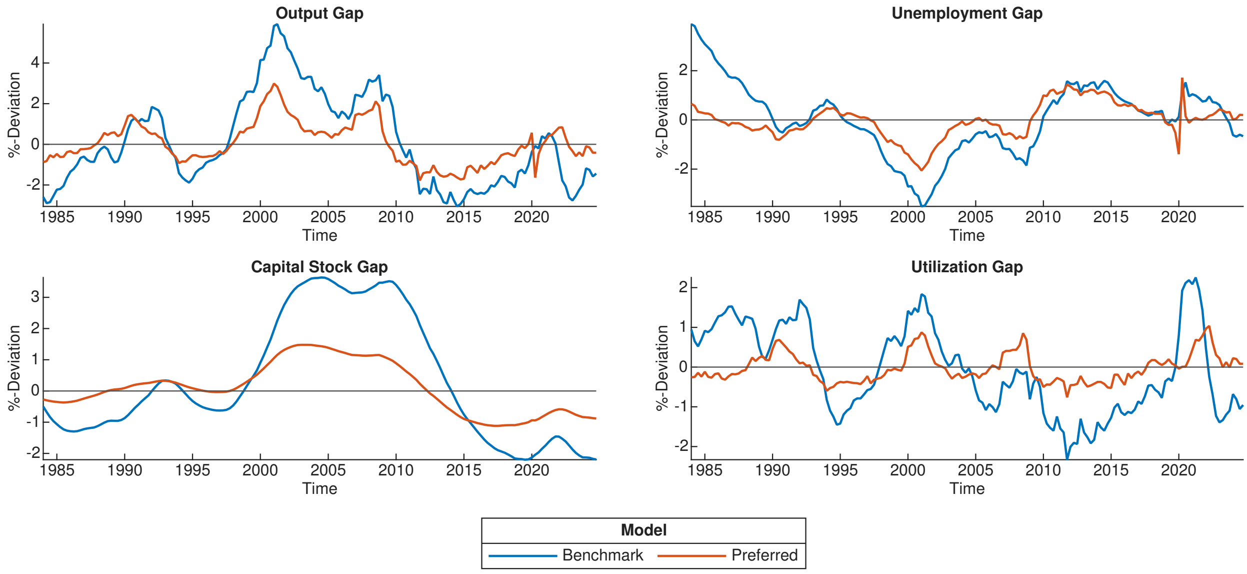
4.4. The U.S. Business-Cycle through the Lens of Goods-Market SaM

The model's output, unemployment, and market-tightness gaps reinterpret U.S. cycles through the lens of Barro and Grossman (1971)-regimes: the post-2008 "missing deflation" reflects coordination failures on the goods market, while post-COVID inflation spikes arise from surging goods-market tightness. To trace how these mechanisms shape 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. These gaps summarize the business-cycle state and the presence of excess demand or supply in specific markets. Output and unemployment gaps capture standard real and nominal fluctuations, while labor- and goods-market tightness gaps measure shifts in coordination efficiency. Together, they link the efficiency wedge to observable macro behavior, allowing U.S. business cycles to be reinterpreted as fluctuations in market coordination.

Figure 2 shows the smoothed latent gap variables implied by the benchmark and preferred models. The cyclical pattern is almost identical with correlations of each gap variable across models beyond 0.9. Standard deviations, however, are significantly lower in the preferred model: output gap (2.30% vs 3.77%), capacity utilization gap (2.02% vs 1.03%), capital stock gap (3.90% vs 2.60%); with the unemployment gap (2.06% vs 1.95%) being the exception. Consequently, differences in utilization gap coupled with differences in the capital stock gap account for the output gap discrepancy across models.

Recessions are represented by an interplay of the gap variables. Figure 3 (b) shows the 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 followed by a persistent slump, and

Figure 2: U.S. Business Cycles through the Lens of Gap Variables



NOTE: The figure shows U.S. time series on the output, unemployment, capital, and capacity utilization gaps derived from two model variants – benchmark and preferred models. The sample covers $1984q1 - 2024q4$ where the model is estimated on $1984q1 - 2019q4$ and $2020q1 - 2024q4$ is derived from a calibrated smoother applied to the model.

(3) the COVID recession followed by inflation spikes during reopening of the economy.[41] Therefore, the output and unemployment gaps derived from the model are largely in line with the general perception of these episodes.

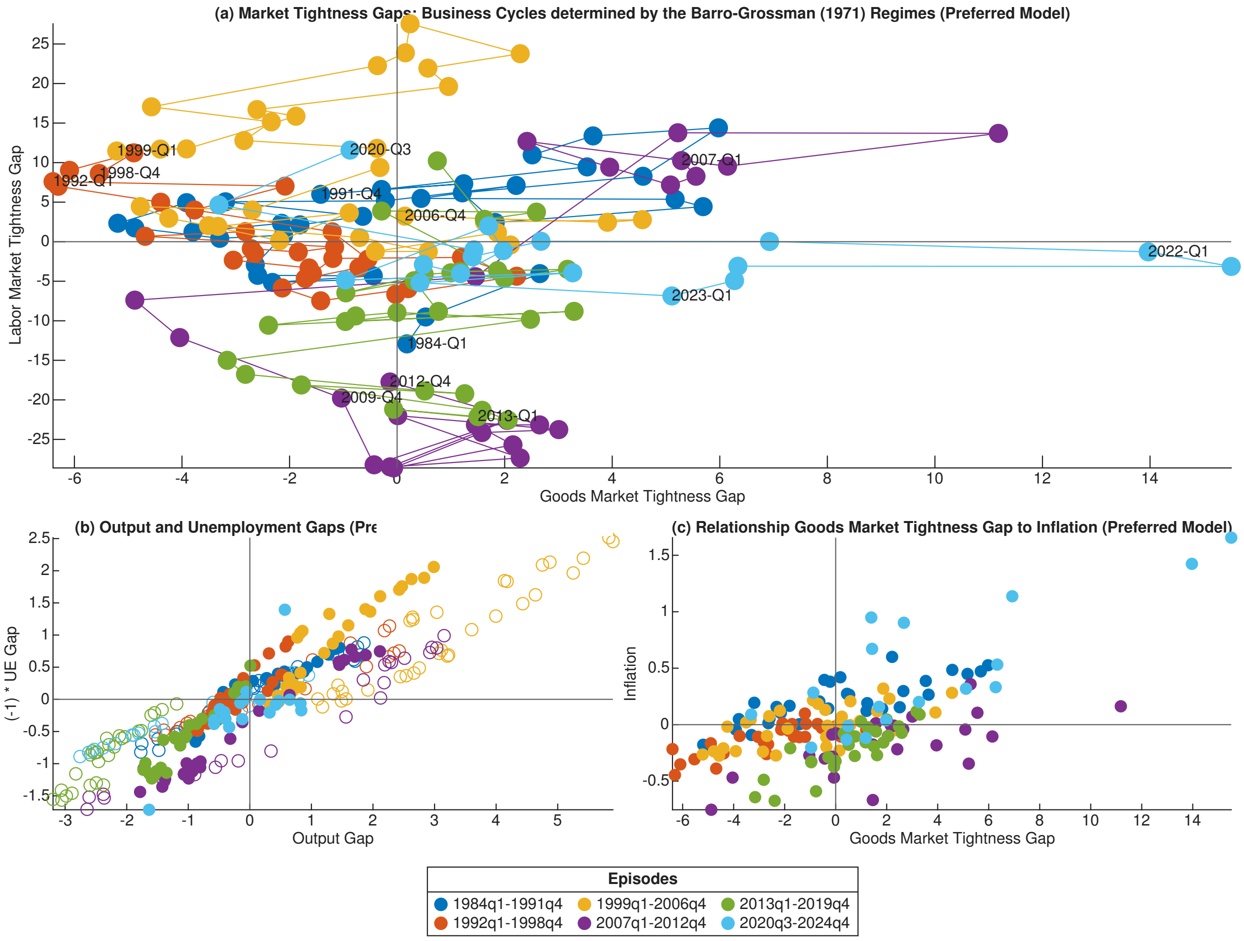
Barro and Grossman (1971)-Regimes. Using the search-and-matching framework on both goods and labor markets, we derive excess demand and supply regimes similar to Barro and Grossman (1971).[42] This allows us to determine whether either market is demand- or supply-determined at any point in time.[43] 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 the labor and goods-market tightness gaps for the U.S., identifying four regimes of the economy: (i) Walrasian equilibrium ($x_T < 0, x_N > 0$); (ii) Keynesian

[41] 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.

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

[43] Demand-determined indicates that demand relative to supply is above its steady-state value (or above its flexible price counterpart for the gap variable), vice-versa. The same definition applies to labor markets.

Figure 3: U.S. Business Cycles through the Lens of Market Tightness Gaps



NOTE: The figure shows scatter plots of market tightness gaps, output and unemployment gaps, and inflation representing U.S. business cycles 1984$q1-2024q4$ through the lens of the preferred model. (a) shows the relationship between goods- and labor-market tightness gaps; (b) shows the relationship between output and unemploymnet gaps for the benchmark (hollow dots) and preferred model (filled dots); and (c) shows the relationship between goods-market tightness gaps and inflation. Business-cycle episodes are identified by color as given in the legend.

unemployment ($x_T < 0, x_N < 0$); (iii) classical unemployment ($x_T > 0, x_N < 0$); and (iv) repressed inflation ($x_T > 0, x_N > 0$). Each regime informs us on optimal policy depending on the states of excess demand and supply.

For instance, the period following the Volcker disinflation is referred to as the "Great Moderation," characterized by subdued business-cycle fluctuations. During this time, the economy remained largely in a Walrasian equilibrium, with only mild episodes of Keynesian unemployment and periods of depressed inflation.[44] Goods-market tightness rose slightly toward the onset of the Great Recession. The framework implies mainly little need for policy intervention throughout most of this period, as goods markets exhibited mild excess supply while labor markets showed excess demand. This combination sustained a prolonged boom with limited inflationary pressure, though the positive output and negative unemployment gaps indicate emerging inflationary pressures around 1999.

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

Missing Deflation following the Great Recession. As shown in figure 3, the Great Recession and its aftermath were marked by persistent labor-market slack, while goods markets alternated between excess demand and supply. The output gap stayed negative until 2019, yet the preferred model shows a much smaller gap than the benchmark, reflecting an almost closed capacity utilization gap (figure 2). This indicates that the downturn stemmed not only from weak demand but from a fall in production capacity. Search effort and goods-market tightness both declined sharply; the former remained depressed through 2019, while the latter stayed slightly positive, signaling an even deeper contraction in production capacity (figure D.13).

The economy entered the crisis from a repressed-inflation regime with excess demand in both markets, then shifted into Keynesian unemployment around 2009, producing deflationary pressure (figure 3). Fiscal and monetary measures – e.g. the American Recovery and Reinvestment Act (2009), Payroll Tax Cuts and Unemployment Insurance Extensions (2010), and expansionary monetary policy – lifted demand, creating positive goods-market tightness gap but leaving labor slack. This mix of tight goods markets and weak labor demand *explains the absence of strong deflation.* As stimulus waned after the Budget Control Act (2011–2016), the

[44]Examining deviations of labor and goods-market tightness from their steady states (figure 4) provides an even clearer picture.

economy briefly re-entered Keynesian unemployment (2014–2015) – showing some renewed decrease in inflation – before converging towards equilibrium by 2016. By 2019, output and unemployment gaps had closed, with mild goods-market excess demand and low inflation. Overall, the Great Recession reflects a prolonged regime of labor-market slack. The *"missing deflation puzzle"* arises from moderately tight goods markets that muted deflationary pressures.[45] Excessive search effort paired with weak labor demand implies a *household time-allocation mismatch*, a key driver of the episode. Demand management was appropriate early on, but persistent slack in a classical-unemployment regime required supply-side measures. The model thus interprets the post-crisis stagnation as stemming from coordination failures in labor markets rooted in goods-market matching and time allocation, consistent with work on financial frictions, technology, and capital deepening (Christiano et al., 2015; Fernald, 2015).

Inflation Spikes following the COVID Recession. The pandemic generated a short but severe recession during the initial lockdown, placing the economy in a Keynesian-unemployment regime with low goods- and labor-market tightness gaps driven by abrupt shifts in consumption and labor allocation. It then transitioned into a classical-unemployment regime as potential output fell sharply – evident in the pronounced rightward shift of the labor-market Beveridge curve (figure D.14), signaling substantial matching inefficiency (Shimer, 2007; Şahin et al., 2014). Massive fiscal support and the rapid reopening of the economy subsequently triggered a surge in goods-market tightness: demand recovered faster than production capacity while labor markets stayed near equilibrium. Search effort rose sharply, shifting the goods-market Beveridge curve upward (figure D.14) and moving the economy toward a repressed-inflation regime. The resulting inflation spike reflected intense demand pressure.

Goods-market tightness gaps exhibit a clear positive relationship with the inflation spike, whereas the output gap would require strong nonlinearities to generate a similar pattern

[45] Persistent labor-market slack alongside steadier goods-market conditions is mirrored in the Beveridge curves: the labor-market curve shifted downward, indicating reduced matching efficiency, while the goods-market curve remained largely stable – showing only a brief drop at the onset of the recession before quickly recovering (figure D.14).

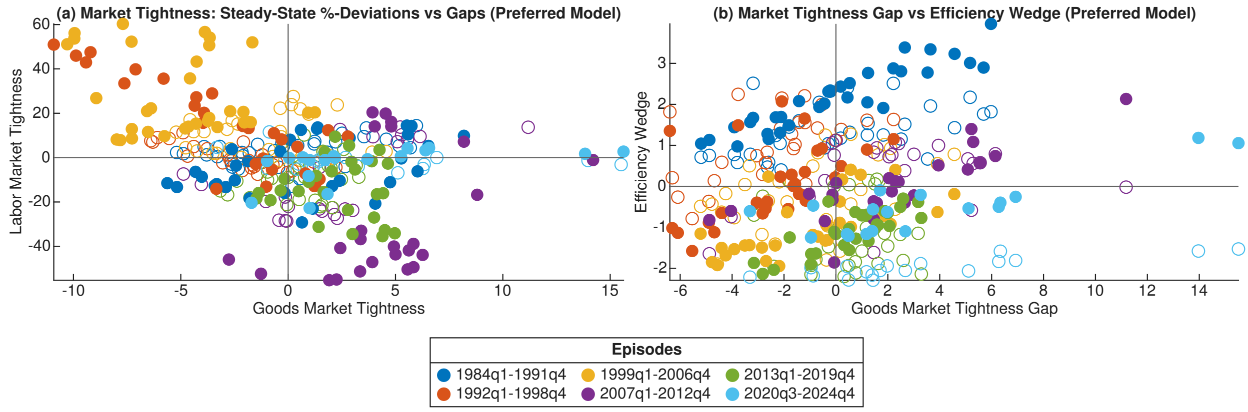
(Harding et al., 2022). Capacity-utilization gaps likewise show no clear correspondence with the sharp rise in inflation. The contrasting shifts in the Beveridge curves – an upward shift in the goods market and a rightward shift in the labor market – indicate that surging demand met constrained labor supply. Elevated unemployment alongside strong labor demand points to coordination frictions and limited productive expansion despite high search effort. Labor-market tightness remained near equilibrium, helping explain the absence of a wage–price spiral. Overall, the model attributes a substantial share of the post-pandemic inflation surge to heightened search effort and demand pressure, reflected in elevated goods-market tightness – a feature the textbook New Keynesian model struggles to capture.

The model shows that coordination efficiency in labor and goods markets drives regime shifts in the U.S. business cycle, helping explain both the post-2008 "missing deflation" and the 2022 inflation surge. The market-tightness-gap framework sharpens our understanding of business-cycle origins and policy design: demand management was appropriate after the Great Recession, but the ensuing classical-unemployment regime required supply-side measures. Whereas output and unemployment gaps identify recessions, market-tightness gaps guide policy and signal inflation risks. Together, they offer complementary perspectives on business-cycle dynamics.

4.5. Linking Back to the Efficiency Wedges

Business-cycle analysis in the Barro and Grossman (1971) framework relies on data for both labor- and goods-market tightness gaps. As figure 4 shows, both can be well approximated by steady-state deviations, with a correlation of 0.87 for goods-market tightness. Labor-market tightness is observable and also well proxied by real GDP (model: $corr(x_N, \text{gdp}) = 0.77$, $corr(x_{N,\text{gap}}, \text{gdp}) = 0.68$). By contrast, measuring the goods-market tightness gap is more difficult: its correlation with real GDP is essentially zero (-0.07) and only 0.22 with the output gap – hence the need for an additional framework. Natural candidates such as TFP and capacity utilization perform poorly: TFP correlates at -0.27 and capacity utilization at only 0.15. This pattern reflects technology- and supply-driven booms and busts, which move TFP and capacity utilization in the opposite direction of goods-market tightness.

Figure 4: Proxies for Market Tightness Gaps (U.S. Data)



NOTE: The figure shows scatter plots of proxies for the labor- and goods-market tightness gaps representing U.S. business cycles $1984q1-2024q4$ through the lens of the preferred model. (a) shows the relationship between labor and goods-market tightness deviations from steady-state (filled dots) and their gaps (hollow dots). (b) shows the relationship between the goods-market tightness gap and the efficiency wedge (lower-bound: hollow dots; upper-bound: filled dots). Business-cycle episodes are identified by color as given in the legend.

As figure 4 shows, the efficiency wedge is a better proxy for the goods-market tightness gap than standard slack measures, but its unconditional correlation remains low – 0.32 for the upper-bound definition and essentially zero for the lower-bound. Steady-state deviations of goods-market tightness perform only marginally better, with correlations of 0.05 (lower-bound) and 0.40 (upper-bound). These patterns underscore both the difficulty of proxying tightness gaps and the importance of properly incorporating goods mismatch shocks and their technology component into the efficiency wedge.

However, figure 4 also shows a strong linear relationship between the efficiency wedge and the goods-market tightness gap within individual business-cycle episodes. Once shifts in the natural efficiency rate (flexible-price benchmark) are accounted for, the efficiency wedge becomes a useful proxy. For 1999q1–2024q4, the upper-bound wedge correlates with the tightness gap at 0.68, whereas the lower-bound measure correlates at only 0.11, again underscoring the importance of including goods mismatch shocks when constructing the wedge. After adjusting for such shifts – analogous to the Beveridge-curve approach (Diamond and Şahin, 2015) – the regime analysis aligns closely with movements in the efficiency wedge, which summarizes fluctuations in goods-market coordination. Shopping time provides a similarly informative proxy ($corr. \approx 0.7$), consistent with Petrosky-Nadeau et al. (2016), and other sentiment-based indicators may serve a comparable role.

4.6. Variance Decomposition: The Determinants of the Efficiency Wedge

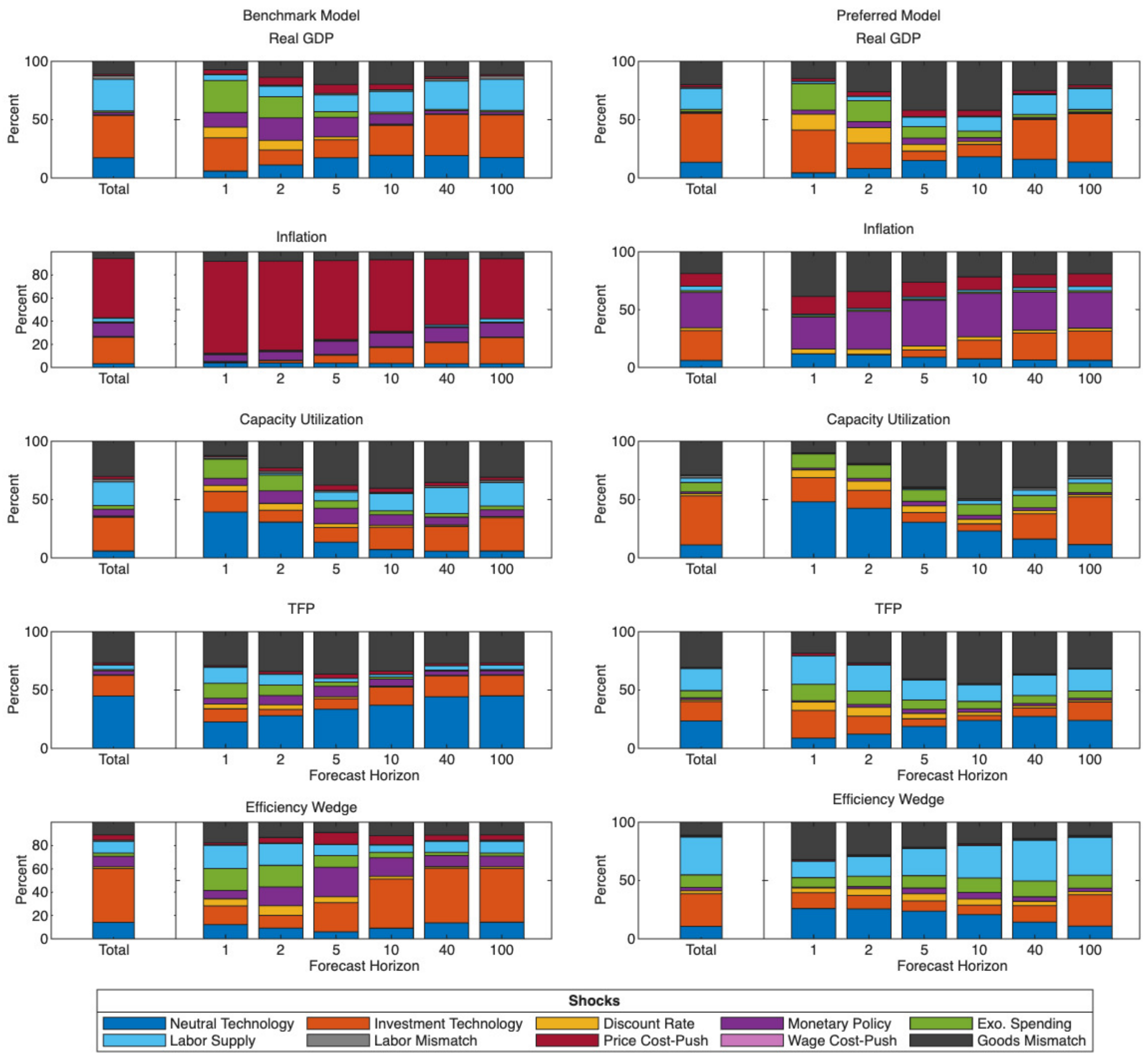
While the previous analysis identified business-cycle regimes through the lens of excess demand and supply, it did not examine the underlying drivers or how they change when introducing goods-market SaM. Figure 5 addresses this by presenting the variance decomposition of real GDP, inflation, capacity utilization, TFP, and the efficiency wedge (upper bound) for both the benchmark and preferred models. The figure reports unconditional decompositions as well as conditional decompositions at forecast horizons of 1, 2, 5, 10, 40, and 100 quarters ahead.

Real GDP. The main business-cycle drivers remain similar across the benchmark and preferred models: technology, investment, hours supply, and goods mismatch shocks dominate real GDP variation. Yet a modest shift occurs from labor and supply shocks toward demand and market-efficiency shocks as coordination frictions make demand a productive input.[46] At business-cycle frequencies, demand shocks dominate; in the medium-run, goods mismatch gains importance, and in the long-run, investment and hours supply shocks prevail. Monetary policy plays a smaller cyclical role as interest rate changes have weaker effects on consumption growth through search price dynamics (Gantert, 2025), consistent with (20). Apart from quantitative differences in the unconditional decomposition, patterns are similar across models.

Inflation. Inflation is primarily driven by demand and price cost-push shocks in both models. In the benchmark model – consistent with Smets and Wouters (2007); Justiniano et al. (2010) – price cost-push shocks dominate, explaining over 80% of inflation at business-cycle frequencies, while investment and monetary policy shocks account for up to one third of medium- and long-run variation. Introducing goods-market SaM alters this pattern substantially: price cost-push shocks explain no more than 16% (and only 10% on average) of inflation, while

[46] *Supply:* technology $A_{H,t}$, price cost-push ϵ_t, goods mismatch $\psi_{T,t}$; *Demand:* investment $P_{I,t}$, discount factor Z_t, spending G_t, monetary policy M_t; *Labor:* hours supply $\mu_{H,t}$, wage cost-push η_t, labor mismatch: $\psi_{N,t}$.

Figure 5: Conditional Variance Decomposition (U.S. Data)



NOTE: The figure shows the unconditional and conditional variance decomposition of 1, 2, 5, 10, 40, and 100 quarters ahead for the benchmark and preferred models. 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 each bar following the legend.

investment, monetary policy, and goods mismatch shocks together drive more than half of the variation, particularly at business-cycle frequencies.

Capacity Utilization. The three shocks directly affecting the resource constraint – technology, investment, and goods mismatch – account for most capacity utilization variation, as they exogenously shift available resources. In the benchmark model, hours supply shocks also matter (up to 20%), since they alter hours per worker and labor effort not captured in long-run sustainable capacity but relevant for GDP. These effects partly offset each other: labor effort responds quickly, while hours per worker adjust slowly. Investment and other demand shocks raise utilization by boosting demand.

Introducing goods-market SaM changes the composition: technology shocks gain importance at business-cycle frequencies, reflecting excess supply effects, while demand shocks play a larger role and hours supply shocks virtually disappear. This pattern highlights the model's time-allocation and coordination frictions – demand shocks increase search effort and thus utilization, whereas hours supply shocks trigger reallocation between work and search, neutralizing their aggregate impact. Consequently, capacity utilization becomes closely tied to time-allocation trade-offs central to the business cycle.

TFP and the Efficiency Wedge. Two shocks drive TFP exogenously – technology and goods mismatch – explaining most of its variation in both models, especially in the long run as utilization adjustments fade. The remaining variation reflects the efficiency wedge, which operates mainly in the short run. In the benchmark model, its decomposition resembles that of real GDP: demand shocks dominate initially, while resource-constraint shocks account for most long-run variation by expanding capacity. Hours-supply shocks raise labor effort and thus utilization throughout the forecast horizon.

Introducing goods-market SaM reduces the direct impact of technology shocks on TFP, as their propagation through the efficiency wedge offsets part of the exogenous effect. The efficiency wedge becomes more important overall, amplifying coordination frictions through internal propagation rather than only through exogenous components. It becomes less driven by demand shocks – especially monetary policy – and more influenced by hours-supply shocks, though primarily in the long run. In the short run, technology and goods-mismatch shocks explain a larger share of the wedge because exogenous capacity expansions generate substantial variation in coordination efficiency. A complementary perspective – TFP multipliers (TFP variation relative to GDP variation) – is shown in figure D.17.

Across both models, the determinants of the efficiency wedge closely mirror those of real GDP. The endogenous price elasticity of demand makes large price cost-push shocks unnecessary, illustrating how goods-market SaM better accounts for inflation episodes such as the post-COVID spike (section 4.4). Efficiency is shaped by time-allocation trade-offs and coordination frictions, developed further in the next section. The increasing role of hours-supply shocks in TFP variation shows how household time misallocation can depress productivity. Overall, capacity utilization and goods-market tightness capture the interaction of demand and supply mediated by household time allocation, demonstrating that goods-market SaM shifts cyclical variation from exogenous supply shocks to endogenous coordination frictions.

5. Inspecting the Mechanism: Coordination Frictions over the Business Cycle

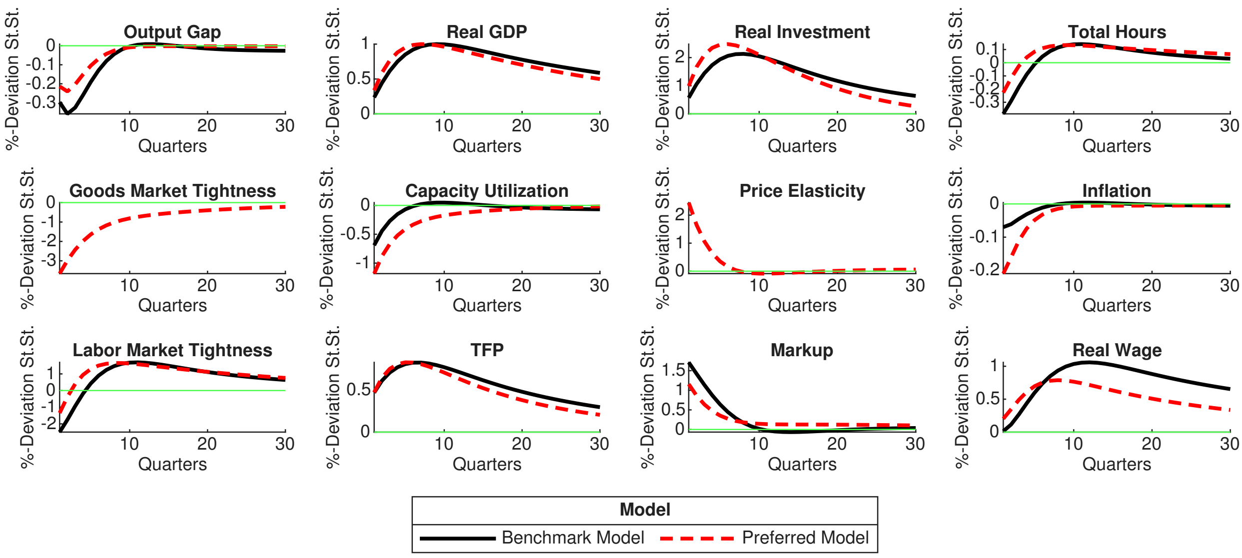
The posterior variance decomposition shows that demand shocks dominate short-run movements in output and inflation, while price cost-push shocks lose relevance because the price elasticity becomes endogenous. These results indicate that short-run productivity variation largely reflects coordination efficiency. To understand how these coordination regimes operate and why the data exhibit such state dependence, we turn to dynamic simulations of the estimated model and trace how goods-market SaM shapes impulse responses (IRFs) through its effects on price elasticity and capacity utilization.

5.1. Propagation of Demand and Supply Shocks

Goods-market tightness permits both demand- and supply-determined equilibria and drives the two key goods-market SaM channels identified in section 2: *endogenous price elasticity* and *productive search effort*, which determines capacity utilization. These channels shape firms' price-setting through the household demand equation and influence marginal costs via utilization, as shown in section 5.2. Building on Gantert (2025), we show how goods-market SaM alters model transmission and business-cycle dynamics. IRFs are normalized by scaling with each model's absolute maximum deviation of real GDP.

Supply Shocks. Figure 6 shows the IRFs to an expansionary technology shock. In the benchmark model, real GDP and investment increase, while total hours fall amid declining but sticky prices and low capacity utilization. Real wages and markups increase with the

Figure 6: IRFs to an Expansionary Technology Shock

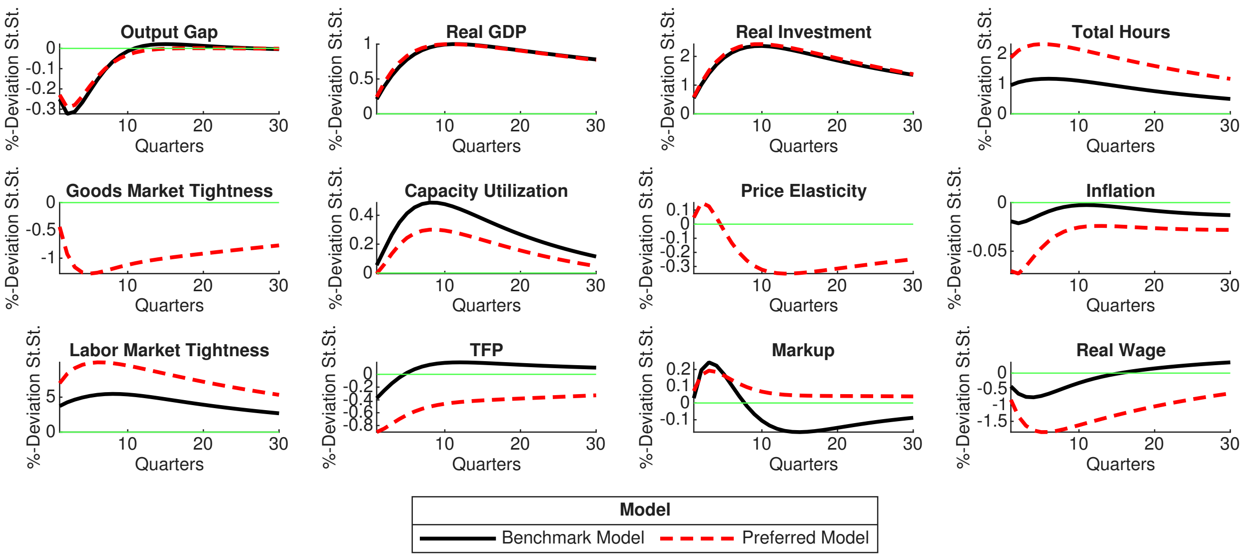


NOTE: The figure shows IRFs of different variables to an expansionary technology shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

exogenous TFP improvement. The economy enters a negative output-gap state (positive unemployment gap), and labor-market tightness mirrors total hours – initially slack due to higher capacity but recovering as demand strengthens.

Introducing goods-market SaM alters the IRFs quantitatively but not qualitatively. Higher technology expands capacity exogenously, but households must match it, generating *excess supply as low goods-market tightness reduces utilization*. Weak tightness lowers search prices, raises price elasticity, and compresses markups. Firms respond by cutting prices or expanding supply to reduce search prices further; both stimulate additional search effort. In equilibrium, firms mostly cut prices, since heightened elasticity makes demand highly responsive; they do so just enough to induce optimal search effort and balance markups and utilization. Total hours rise gradually, though real wages increase less because higher price elasticity boosts labor supply, reducing wage and markup volatility in line with the data. Output-gap variation falls as utilization declines – even under flexible prices – reflecting search-price convexity. An expansionary goods-mismatch shock produces similar dynamics, except that utilization rises exogenously (figure E.18). Both technology and goods-mismatch shocks

Figure 7: IRFs to an Expansionary Hours-Supply Shock



NOTE: The figure shows IRFs of different variables to an expansionary hours-supply shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

generate combinations of tight labor markets and slack goods markets, and vice versa, giving rise to Walrasian or classical-unemployment equilibria.

Time-Allocation Shocks. Figure 6 reports the IRFs to an expansionary hours-supply shock. In the benchmark model, real GDP and investment rise following the exogenous increase in hours per worker. Capacity utilization increases because higher hours raise output, though not long-run sustainable capacity, and input utilization rises with greater labor effort. A higher hours-supply elasticity lowers real wages, reduces inflation, and tightens labor markets. TFP initially declines as capital adjusts more slowly than labor, while markups rise. The economy enters a negative output-gap state due to sluggish price adjustment, accompanied by a negative unemployment gap driven by wage rigidity.

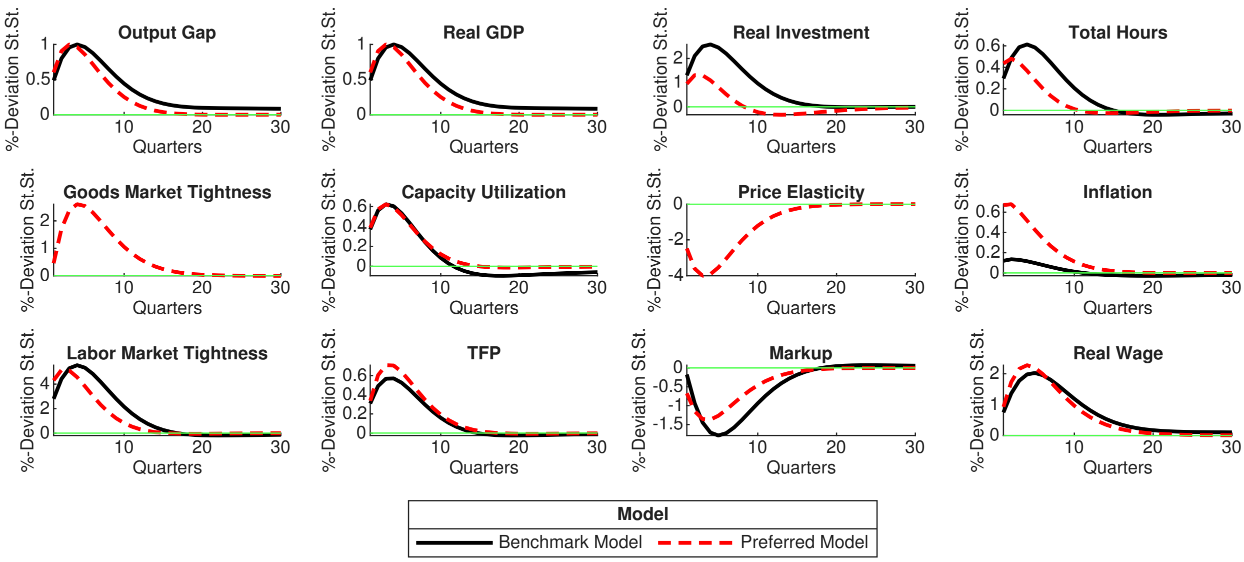
Introducing goods-market SaM alters households' time-allocation trade-offs. An hours-supply shock raises labor input, but the additional capacity must be matched, requiring more search effort. Firms respond by cutting prices or expanding capacity; both occur, though price cuts dominate, generating stronger disinflation and lower price elasticity. The reduced elasticity raises markups and depresses real wages relative to the benchmark. Total hours increase further because a stronger hours-supply response is needed to generate the same GDP rise under lower utilization. As hours per worker adjust slowly, firms hire more workers, reflected in higher labor-market tightness. Greater input use combined with weaker utilization makes the economy less efficient than in steady state. Thus, with time-allocation trade-offs, higher labor supply cannot raise output or productivity on its own and increases real GDP only through substantial *excess goods-market supply*. The resulting negative output gap and goods-market slack mirror the dynamics under labor-mismatch (figure E.19), wage cost-push (figure E.20), and price cost-push shocks (figure E.21).

Demand Shocks. Figure 8 reports the IRFs to an expansionary monetary policy shock. In the benchmark model, a cut in the nominal interest rate raises aggregate demand as sticky prices slow adjustment. Real wages and search effort increase, markups fall, and input allocation and utilization rise. The economy exhibits a positive output gap, a negative unemployment gap (high labor-market tightness), and positive TFP deviations, while the underlying flexible-price economy remains unchanged.

With goods-market SaM, a rate cut raises demand, increasing search effort and capacity utilization, which in turn boosts goods-market tightness and lowers price elasticity. Firms exploit the reduced elasticity to raise prices, so markups fall less than in the benchmark. Households reallocate time from work to search, as short-run demand is better met through higher utilization than through quasi-fixed inputs. Greater utilization makes the economy more efficient than in steady state. In a time-allocation framework, expansions therefore arise through utilization rather than input growth, while tighter goods and labor markets reduce price elasticity and dampen markup variation. Goods- and labor-market tightness rise jointly with output and employment gaps, confirming that demand shocks propagate through the standard output–unemployment gap channel, with tightness providing a complementary measure of cyclical pressure. Exogenous spending (figure E.22) and discount-factor (figure E.23) shocks display symmetric patterns.

Figure 9 shows the IRFs to an expansionary investment shock. In the benchmark model, the dynamics mirror those of monetary policy and other demand shocks: real GDP rises with

Figure 8: IRFs to an Expansionary Monetary Policy Shock across Models



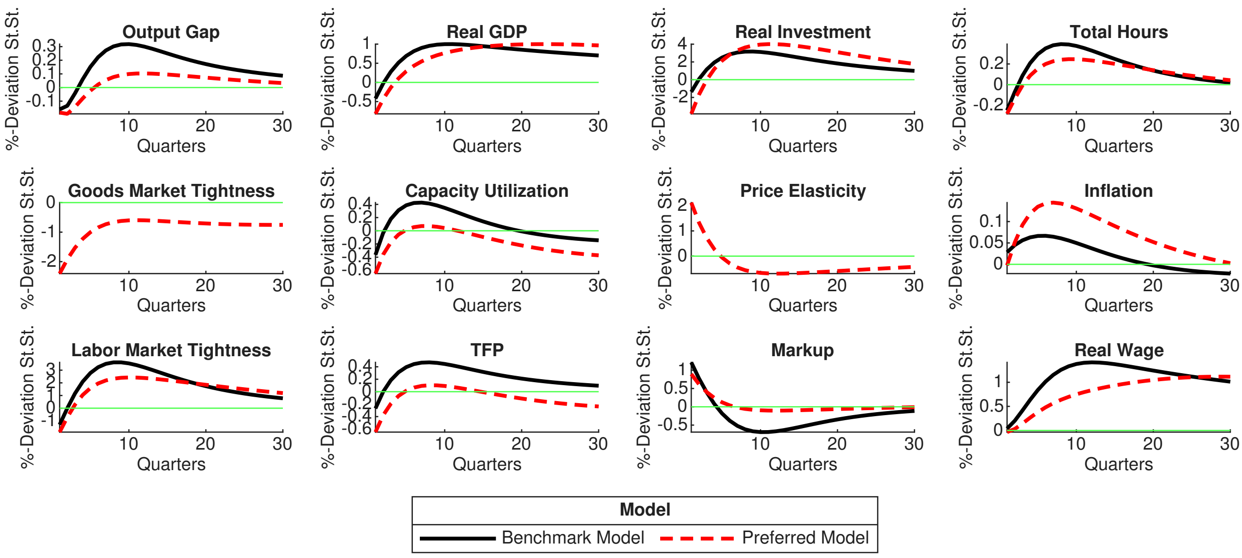
NOTE: The figure shows IRFs of different variables to an expansionary monetary policy shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

greater input use, higher inflation and real wages, lower markups, and increasing capacity utilization and TFP. Consistent with Justiniano et al. (2010); Smets and Wouters (2007), the investment shock thus represents a demand shock. Business-cycle slack appears as a positive output gap and tight labor markets, as the rise in aggregate demand dominates the rise in aggregate supply.

Introducing goods-market SaM produces a more nuanced pattern in which goods markets remain slack even when the output gap is positive. Real GDP, inputs, prices, and wages rise as in the benchmark, but capacity utilization and TFP fall, generating a negative response driven by short-run demand effects and long-run supply expansion.[47] As capital accumulation expands capacity, goods-market tightness drops and stays persistently below steady state – an *excess-supply* state. Search prices fall initially but increase beyond the steady-state due to strong output growth and search-price convexity, decreasing overall price elasticity in the medium-run. *The output gap remains positive but smaller, even alongside slack goods*

[47]Real GDP and inputs initially decline because investment adjustment costs delay capital accumulation and lower the valuation of current investment.

Figure 9: IRFs to an Expansionary Investment Shock across Models

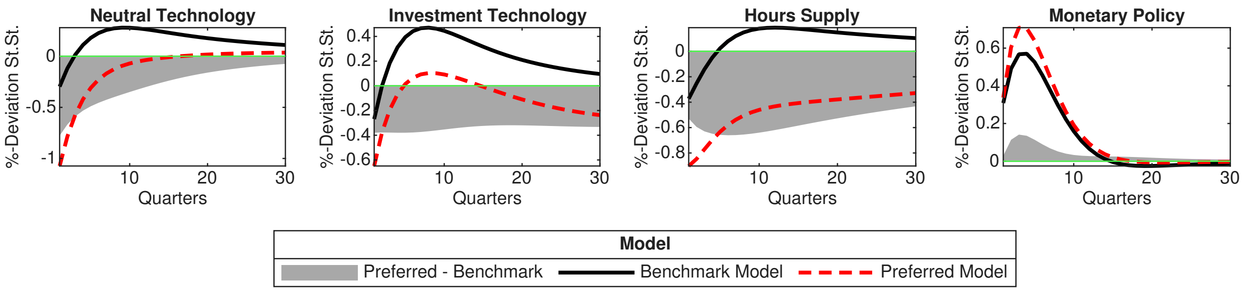


NOTE: The figure shows IRFs of different variables to an expansionary investment shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

markets, offering a distinct business-cycle pattern. Coordination frictions therefore reveal that investment shocks differ from demand shocks by embedding a technology-driven expansion: even when output exceeds potential, matching additional consumption is relatively easy. This helps explain why investment shocks can generate both prolonged booms (the Great Moderation) and persistent slumps (the post–Great Recession period). The Barro and Grossman (1971) regimes identify the resulting excess supply and motivate policy responses distinct from those to standard demand shocks.

Overall, goods-market SaM amplifies business-cycle dynamics through endogenous variation in price elasticity, with especially strong effects on utilization. This amplification arises from the costly but productive household search effort required to match available capacity. Goods-market tightness summarizes this process, identifies the short side of the market, and places time-allocation trade-offs at the center of the analysis. However, it remains an imperfect proxy for the optimal tightness implied by the flexible-price model (section 4.5). We therefore examine the dynamics of the efficiency wedge and its relation to the goods-market tightness gap to assess when this proxy is informative and how it helps characterize the state

Figure 10: The Cyclical Efficiency Wedge



NOTE: The figure shows IRFs of the efficiency wedge to different expansionary business cycle shocks according to (34). Variations are measured in percent deviations from the deterministic steady-state. The different curves represent the benchmark (black curves) and preferred (red dashed curves) model.

of the goods market.

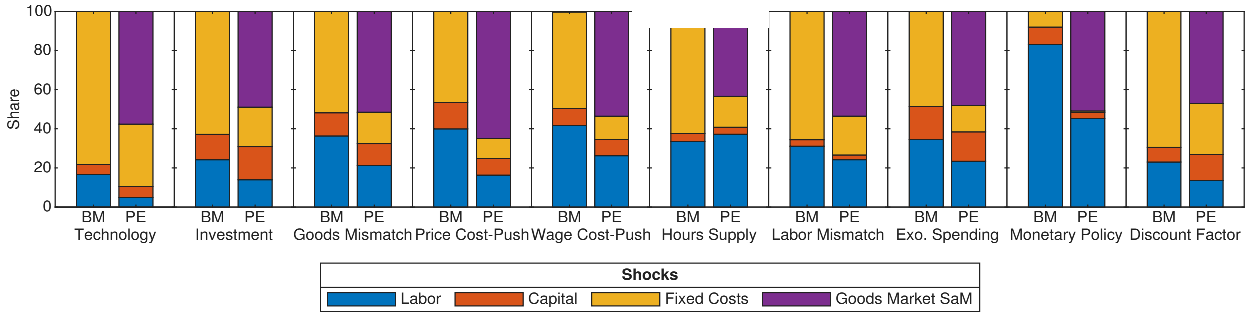
5.2. The Efficiency Wedge and the Barro and Grossman (1971)-Regimes

Figure 10 presents the efficiency-wedge dynamics for the benchmark and preferred models' IRFs.[48] Fluctuations in each model's wedge arise from the labor, capital, fixed-cost, and goods-market channels in (34). The dynamic decomposition of these channels appears in figure E.25, and their respective contributions to total variation are summarized in figure 11.

Efficiency Wedge IRFs. In the benchmark model, the efficiency-wedge IRF to an expansionary technology shock shows a brief initial decline followed by a persistently positive deviation, driven mainly by fixed-cost degression, with labor and capital utilization contributing up to 20%. Introducing goods-market SaM sharply changes this pattern: the wedge becomes persistently and substantially negative because fixed costs fall, shrinking the degression channel, while the additional capacity must first be matched, creating slack goods markets. Goods-market SaM accounts for nearly 60% of the variance share, implying smaller short-run TFP responses (figure 6) and a lower TFP variance share of technology shocks (figure 5). TFP therefore *underestimates* the technology shock due to *substantial excess supply.* Expansionary goods-mismatch and investment shocks exhibit the same mechanism: although investment shocks are typically classified as demand shocks, they generate substantial and persistent

[48] A complete overview is shown in figure E.24.

Figure 11: Decomposition of Efficiency-Wedge Fluctuations



NOTE: The efficiency-wedge variance shares are shown for the benchmark (BM) and preferred (PE) models. They are calculated as the share of absolute fluctuations in labor, capital, goods market, and fixed cost efficiency wedges.

excess supply as the capital stock expands.

Unlike technology shocks, hours-supply shocks do not exogenously expand capacity; the efficiency wedge therefore mirrors the TFP dynamics in figure 7. In the benchmark model, wedge movements are modest, whereas in the preferred model efficiency falls markedly—by up to 0.7% for a 1% increase in real GDP – consistent with figure 5. Benchmark variation is driven mainly by fixed costs, with labor effort contributing up to 35% (figure 11). In the preferred model, the determinants shift toward goods-market SaM (about 50%), reducing the role of fixed costs while preserving a sizeable labor-effort component. Hours-supply shocks thus generate expansions through input accumulation, lowering efficiency through *substantial excess supply*. The same mechanism applies to labor-mismatch and price- and wage–cost-push shocks, which display symmetric patterns.

Demand shocks generate expansions through lower markups, input expansion, and sticky prices. Because they are short run, firms rely on utilization rather than quasi-fixed inputs, raising the efficiency wedge in the benchmark model. Introducing goods-market SaM preserves but amplifies this pattern, as additional demand is met through extra search effort and the matching of otherwise idle capacity. In the benchmark model, the wedge is driven mainly by fixed costs and – under monetary policy – labor effort. In the preferred model, these determinants shift toward a more uniform distribution, with roughly 50% explained by goods-market SaM. All three demand shocks exogenously raise goods-market tightness, producing a more procyclical efficiency-wedge response due to *substantial excess demand.* *Excess demand and supply states* systematically amplify efficiency-wedge responses. Technology shocks generate muted TFP gains because the wedge turns negative; demand shocks are amplified through productive search under excess demand; and time-allocation shocks create expansions through excess supply rather than high utilization. In the benchmark model, the wedge is driven mainly by production fixed costs (up to 80%), with labor effort important and capital utilization largely irrelevant. In the preferred model, goods-market SaM accounts for over 50% of the wedge for most shocks, alongside a sharp decline in the role of fixed costs – consistent with the lower steady-state markup. Consistent with the log data density results in section 4, goods-market SaM becomes the dominant driver of the efficiency wedge across shocks. Allowing for *supply-determined equilibria* in a NK-DSGE model therefore fundamentally reshapes efficiency-wedge transmission.

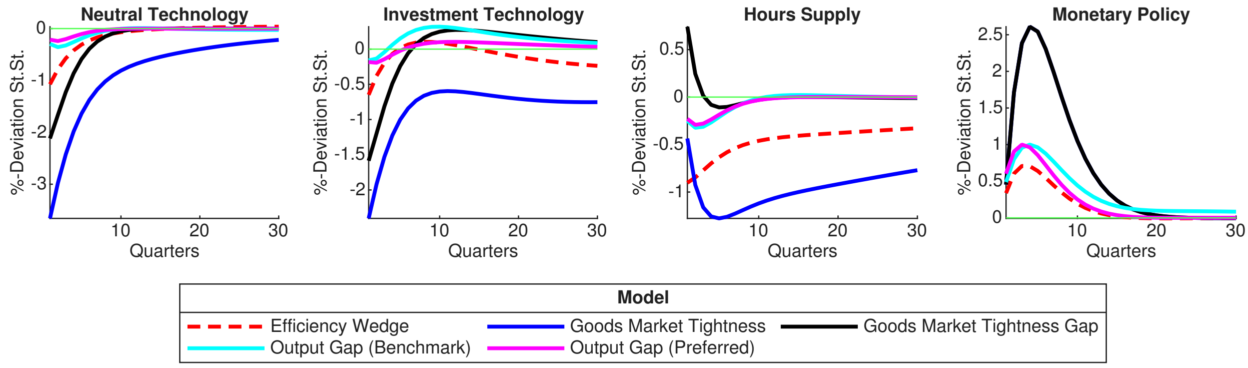
Connecting Shocks to Regimes and Policy Implications. We have shown that the efficiency wedge is a good proxy for the goods-market tightness gap after 1999q1, but this conditionality – and shifts in the "natural" efficiency wedge – depend on the shocks driving business-cycle fluctuations. To make the framework applicable and useful for policy, we must therefore understand under which conditions the proxies for the Barro and Grossman (1971) regimes are reliable and when they are not. Figure 12 reports the IRFs of the goods-market tightness gap and its proxies – goods-market tightness, the output gap, and the efficiency wedge.[49]

For an expansionary technology shock, the negative efficiency wedge closely tracks the goods-market tightness gap, matching both its persistence and variation. Goods-market tightness aligns with the gap only in the very short run but becomes overly persistent because flexible-price tightness falls steadily with higher technology. The output gaps of both models broadly co-move with the gap but exhibit little variation, making them susceptible to measurement error in practical use.

For an expansionary monetary policy shock, the goods-market tightness gap exhibits a persistent positive deviation. Because this nominal shock leaves the flexible-price economy

[49]We structure the analysis around the four main shocks. A complete overview for all shocks is given in figure E.26.

Figure 12: Cyclical Goods Market Tightness Gaps



NOTE: The figure shows IRFs of the efficiency wedge and its proxies to expansionary business-cycle shocks for the preferred model. Variations are measured in percent deviations from the deterministic steady-state.

unchanged, all four measures track the goods-market state closely. Thus, for standard supply and demand shocks, the framework offers little identification advantage beyond providing proxies with greater variation and therefore less vulnerability to measurement error.

This pattern changes for the investment shock. The initial goods-market tightness (gap) is strongly negative, indicating *excess supply*, whereas the output gap fails to capture this.[50] The efficiency wedge, by contrast, shows a clear initial negative deviation and tracks the tightness gap. In the medium run, however, the wedge falls below steady state because capital accumulation expands productive capacity; since this also occurs in the flexible-price economy, it reflects a *positive* goods-market tightness gap. In this region, the output gaps align better with the tightness gap than the efficiency wedge or goods-market tightness.

For an expansionary hours-supply shock, the picture is more complex. A reduction in the disutility of labor lowers goods-market tightness but raises its gap in the short run. Households supply more hours and accept a lower real wage, yet they do so even more in the flexible-price economy, where wages and prices adjust freely. Goods markets therefore become slack – but would be even slacker in the flexible-price benchmark – capturing the time-allocation trade-off highlighted in figure 7. The tightness gap is short-lived, with a brief negative dip before returning to steady state. For business-cycle analysis, however, the early

[50]The small initial negative output-gap deviation is a calibration artifact that disappears under lower investment-adjustment costs, while the negative goods-market tightness gap persists.

quarters matter most, and in this region all proxies fail to identify the state of the goods market. Doing so would require knowledge of the natural goods-market tightness.

Overall, the goods-market tightness gap is a valuable benchmark for identifying goods-market conditions, but it is difficult to proxy. For demand shocks, it yields the same conclusions as the output-gap framework. For time-allocation shocks, it signals shifts in optimal time use that available proxies fail to capture. It is more informative for technology shocks, where proxies display greater variation, and especially for investment shocks, where it identifies slack goods markets even when the output gap indicates production above long-run capacity.

6. Concluding Remarks

This paper reinterprets short-run TFP fluctuations through goods-market search and matching. Extending the critique of frictionless product markets in Barro (2025), we show that measured productivity reflects not only technology and input utilization but also the efficiency with which buyers and sellers match. When households spend less time searching or firms operate with idle capacity, matching efficiency falls and measured TFP declines even without changes in production technology. Embedding this mechanism in a New Keynesian DSGE model introduces an endogenous coordination margin that reshapes shock propagation. Bayesian estimation on U.S. and Euro Area data provides strong empirical support. Goods-market frictions substantially improve fit – especially for capacity utilization and inflation – and sharply reduce the role of cost-push shocks. The estimation uncovers systematic asymmetries: excess demand raises TFP by increasing search effort and match rates, while excess supply lowers it by leaving capacity idle. These coordination forces help explain the post-2008 missing-deflation episode and the amplification of post-COVID inflation.

More broadly, goods-market coordination introduces state dependence into real and nominal dynamics. By endogenizing price elasticity and capacity utilization, matching efficiency weakens the standard link between inflation and the output gap and alters policy transmission. Understanding business cycles therefore requires understanding how effectively markets match buyers and sellers. Future research could incorporate heterogeneity, inventories, or optimal policy in environments where coordination failures interact with nominal rigidities.

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Appendix A. Model Setup and Derivations

Appendix A.1. Household Optimization Problem

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

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

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

First-order conditions.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$\begin{aligned}
muc_t &= \frac{P_t}{P_t(i)}\left[\mathbb{W}_{C,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} - \mathbb{W}_{D,t}c'_{D,t}(i) + \beta\left(1-\delta_T\right)\mathbb{E}_t\frac{Z_{t+1}}{Z_t}\mathbb{W}_{D,t+1}c'_{D,t+1}(i)\right],\\
\Leftrightarrow \frac{P_t(i)}{P_t} &= P_{T,t}\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} - P_{D,t}(i) + \left(1-\delta_T\right)\mathbb{E}_t\frac{1+\pi_{t+1}}{1+r_{B,t}}P_{D,t+1}(i)
\end{aligned} \tag{A.14}$$

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

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

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

$$
r_{K,t} \; = \left(1+c_{I,t}\right) P_{T,t} P_{I,t} \left(\phi_{K,1}\phi_{K,2}\left(e_{K,t}-1\right)+\phi_{K,1}\right), \tag{A.16}
$$

$$
Q_{K,t} \; = P_{T,t} P_{I,t} \left[\left(1+c_{I,t}\right) + \frac{I_{K,t}\left\{c'_{I,t} - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \frac{P_{T,t+1}P_{I,t+1}}{P_{T,t}P_{I,t}} \frac{I_{K,t+1}}{I_{K,t}} c'_{I,t+1}\right\}}{I_{K,t} - \delta_K\left(e_{K,t}\right) K_{t-1}}\right], \tag{A.17}
$$

$$
\begin{aligned}
Q_{K,t} \; &= \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} \Big[r_{K,t+1} e_{K,t+1} + \left(1-\delta_{K,1}\right) Q_{K,t+1} \\
&\qquad - \left(1+c_{I,t+1}\right) P_{T,t+1} P_{I,t+1} \delta_K\left(e_{K,t+1}\right) \Big],
\end{aligned} \tag{A.18}
$$

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

$$
Q_{K,t} \; = \frac{r_{K,t}}{\phi_{K,1}\phi_{K,2}\left(e_{K,t}-1\right)+\phi_{K,1}}, \tag{A.19}
$$

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

$$
Q_{K,t} \; = \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_t} \left[e_{K,t+1} r_{K,t+1} + \left(1-\delta_{K,1} - \delta_K\left(e_{K,t}\right)\right) Q_{K,t+1} \right]. \tag{A.21}
$$

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

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

$$= \frac{\left(\frac{T_t}{T_t(i)}\right)^{\frac{1}{\epsilon_t}} P_{T,t} - P_{D,t}(i) + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}(i)}{\left(\frac{T_t}{T_t(j)}\right)^{\frac{1}{\epsilon_t}} P_{T,t} - P_{D,t}(j) + \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}(j)},$$

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

$$\Xi_t(i) = (-\epsilon_t)\frac{muc_t}{\mathbb{W}_{C,t}} \left(\frac{T_t(i)}{T_t}\right)^{\frac{1}{\epsilon_t}} \frac{P_t(i)}{P_t} = (-\epsilon_t) P_{T,t}^{-1} \left(\frac{T_t(i)}{T_t}\right)^{\frac{1}{\epsilon_t}} \frac{P_t(i)}{P_t},$$

$$= \frac{(-\epsilon_t)\frac{P_t(i)}{P_t}}{\frac{P_t(i)}{P_t} + P_{D,t}(i) - \mathbb{E}_t \frac{1+\pi_{t+1}}{1+r_{B,t}} P_{D,t+1}(i)}$$

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

Appendix A.2. Firm Optimization Problem

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

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

where

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

First-order conditions.

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

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

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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix B. Utilization-adjusted TFP and TFP wedge

Calculating the utilization-adjusted TFP. Total factor productivity is defined as real GDP divided by the input factors in an appropriate production function (Solow, 1957). It is given by

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

Next, using $T_t = (1-\delta_T) T_{t-1} + q_{T,t} S_t$ to substitute for T_t, we get

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

and substitute for S_t with the firm resource constraint (9), we get

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

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

$$\begin{aligned} & q_{T,t} (1-\mathcal{C}_t) \frac{A_{H,t}}{TFP_t} e_{H,t}^{1-\alpha} e_{K,t}^{\alpha} \\ &= 1 - (1-q_{T,t}) (g_{S,t} + i_{S,t}) + i_{S,t-1} + q_{T,t} \vartheta_{GDP,t} \\ &\quad + \delta_K (e_{K,t}) k_{t-1} - (1-q_{T,t}) (1-\delta_T) t_{t-1} \end{aligned} \tag{B.2}$$

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 $t_{t-1} = \frac{T_{t-1}}{GDP_t}$. Note, $q_{T,t} = \psi_{T,t} \left[\gamma_T x_{T,t}^{\Gamma} + (1-\gamma_T)\right]^{\frac{1}{\Gamma}}$ contains endogenous reactions to goods-market tightness and to goods mismatch shocks.

Linearization. We linearize (B.2) around its deterministic steady-state and group all variables to their respective channel. However, there is an ambiguity in the goods mismatch shock, $\psi_{T,t}$, as it can be both a market technology shock or a composition and dispersion shock. We therefore derive a lower and upper bound of the TFP decomposition. Linearizing (B.2) leads to

$$T\hat{F}P_t = \hat{A}_t + \hat{u}_t^K + \hat{u}_t^L + \hat{u}_t^{\vartheta} + \hat{u}_t^{GM}, \tag{B.3}$$

where $\hat{u}_t^K$ summarizes the capital market impact on TFP, $\hat{u}_t^L$ summarizes the labor-market impact on TFP, $\hat{u}_t^\vartheta$ summarizes the impact of production fixed costs on creating short-run increasing returns-to-scale, $\hat{u}_t^{GM}$ summarizes the goods-market search-and-matching impact on TFP, and $\hat{A}_t$ summarizes technology shocks. The channels unaffected by the definition of goods mismatch shocks and technology are given by

$$\hat{\boldsymbol{u}}_{\boldsymbol{t}}^{\boldsymbol{K}} = \left[\alpha - \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\left(1-g_S\right)\delta_T\delta_I}k\phi_{K,1}\right]\hat{\boldsymbol{e}}_{\boldsymbol{K,t}}, \tag{B.4}$$

$$\hat{\boldsymbol{u}}_{\boldsymbol{t}}^{\boldsymbol{L}} = \left(1-\alpha\right)\hat{\boldsymbol{e}}_{\boldsymbol{H,t}} - \frac{c_N}{1-c_N}\hat{\boldsymbol{c}}_{\boldsymbol{N,t}}, \tag{B.5}$$

$$\hat{\boldsymbol{u}}_{\boldsymbol{t}}^{\boldsymbol{\vartheta}} = \frac{\vartheta_{GDP}cu}{1+\vartheta_{GDP}cu}\boldsymbol{g}\hat{\boldsymbol{d}}\boldsymbol{p}_{\boldsymbol{t}}. \tag{B.6}$$

The lower bound for $\hat{u}_t^{GM}$ and $\hat{A}_t$ is identified by no technology component for the goods mismatch shock and given by

$$\begin{aligned}
\hat{\boldsymbol{u}}_{\boldsymbol{t}}^{\boldsymbol{GM,Low}} &= \frac{\left(1-cu\right)g_S}{\left(1+\vartheta_{GDP}cu\right)\left(1-g_S\right)\delta_T\delta_I}\hat{\boldsymbol{g}}_{\boldsymbol{S,t}} - \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\left(1-g_S\right)\delta_T\delta_I}i_S\hat{\boldsymbol{i}}_{\boldsymbol{S,t-1}} \\
&+ \left(\frac{cu}{1+\vartheta_{GDP}cu} + \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\left(1-cu\right)\delta_T\delta_I}\right)i_S\hat{\boldsymbol{i}}_{\boldsymbol{S,t}} \qquad \text{(B.7)} \\
&+ \frac{\left(1-cu\right)\left(1-\delta_T\right)}{\left(1+\vartheta_{GDP}cu\right)\delta_T\delta_I}\hat{\boldsymbol{t}}_{\boldsymbol{t-1}} + \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\delta_I}\hat{\boldsymbol{q}}_{\boldsymbol{t}}, \\
\hat{\boldsymbol{A}}_{\boldsymbol{t}}^{\boldsymbol{Low}} &= \hat{\boldsymbol{A}}_{\boldsymbol{H,t}}. \qquad \text{(B.8)}
\end{aligned}$$

The upper bound for $\hat{u}_t^{GM}$ and $\hat{A}_t$ is identified by all technology component for the goods mismatch shock and given by

$$\begin{aligned}
\hat{\boldsymbol{u}}_{\boldsymbol{t}}^{\boldsymbol{GM,Up}} &= \frac{\left(1-cu\right)g_S}{\left(1+\vartheta_{GDP}cu\right)\left(1-g_S\right)\delta_T\delta_I}\hat{\boldsymbol{g}}_{\boldsymbol{S,t}} - \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\left(1-g_S\right)\delta_T\delta_I}i_S\hat{\boldsymbol{i}}_{\boldsymbol{S,t-1}} \\
&+ \left(\frac{cu}{1+\vartheta_{GDP}cu} + \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\left(1-cu\right)\delta_T\delta_I}\right)i_S\hat{\boldsymbol{i}}_{\boldsymbol{S,t}} \qquad \text{(B.9)} \\
&+ \frac{\left(1-cu\right)\left(1-\delta_T\right)}{\left(1+\vartheta_{GDP}cu\right)\delta_T\delta_I}\hat{\boldsymbol{t}}_{\boldsymbol{t-1}} + \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+\vartheta_{GDP}cu\right)\delta_I}\gamma_S\hat{\boldsymbol{x}}_{\boldsymbol{T,t}}, \\
\hat{\boldsymbol{A}}_{\boldsymbol{t}}^{\boldsymbol{Up}} &= \hat{\boldsymbol{A}}_{\boldsymbol{H,t}} + \frac{1-cu\left(1-\left(1-g_S\right)\delta_T\delta_I\right)}{\left(1+cu\vartheta_{GDP}\right)\delta_I}\hat{\boldsymbol{\psi}}_{\boldsymbol{T,t}}. \qquad \text{(B.10)}
\end{aligned}$$

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

$$cu_t = \frac{GDP_t}{\left(1-\bar{\mathcal{C}}\right) A_{H,t} \left(\bar{e}_H \bar{H} N_t\right)^{1-\alpha} \left(\bar{e}_K K_{t-1}\right)^{\alpha} - \vartheta}. \tag{B.11}$$

Substituting (B.11) in (B.1) and linearizing around its deterministic steady-state results in

$$\boldsymbol{T\hat{F}P_t} = \boldsymbol{\hat{A}_{H,t}} + \frac{\left[\boldsymbol{c\hat{u}_t} - \vartheta_{GDP} cu \boldsymbol{\hat{\vartheta}_{GDP,t}}\right]}{1+\vartheta_{GDP} cu} - (1-\alpha)\, \boldsymbol{\hat{H}_t}. \tag{B.12}$$

We use (B.3) and (B.11) to substitute for $(T\hat{F}P_t - \hat{A}_{H,t})$ and solve for the efficiency wedge

$$\boldsymbol{\hat{\Phi}}_t^{Low} = \frac{\left[\boldsymbol{c\hat{u}_t} - \vartheta_{GDP} cu \boldsymbol{\hat{\vartheta}_{GDP,t}}\right]}{1+\vartheta_{GDP} cu} - (1-\alpha)\, \boldsymbol{\hat{H}_t}, \tag{B.13}$$

$$\boldsymbol{\hat{\Phi}}_t^{Up} = \boldsymbol{\Phi}_t^{Low} - \frac{1 - cu\left(1-\left(1-g_S\right)\delta_T \delta_I\right)}{\left(1+\vartheta_{GDP} cu\right)\delta_I} \boldsymbol{\hat{\psi}_{T,t}}, \tag{B.14}$$

where the efficiency wedge is determined by observables – capacity utilization, production fixed costs (proxied by real GDP), and hours per worker – and a latent goods mismatch shock.

Appendix C. Connecting the Model with the Data

Appendix C.1. Calibration of the Model Parameters

Table C.4 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 U.S. data can lead to a biased α, where the impact of capital on production and TFP is overestimated. We follow the approach of Solow (1957); Fernald (2014); Comin et al. (2025) and solve for the steady-state of the employment

Table C.4: 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)
i_R	0.75	Policy Rate Inertia	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.

demand equation and its free-entry condition to to retrieve a steady-state equation for α as follows

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

where the labor demand FOCs determines real wages and thus in turn the labor share.[51] 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.

[51] 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.

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

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

which does not have a closed-form solution in ϵ as P_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, we 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

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

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 U.S. (BLS code: CNP16OV) and total population for the Euro Area countries (Eurostat code: namq_10_pe).

Real Consumption. Nominal consumption is calculated as nominal private consumption (BEA code: DPCERC; Eurostat code: namq_10_gdp). We subtract nominal durable private consumption (BEA code: DDURRC; Euro Area 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) investment (BEA code: A006RC, Eurostat code: namq_10_gdp).[52] We 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

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

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

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

[52] For the Euro Area 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.

For the Euro Area 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 U.S. and Euro Area total hours time series to retrieve business-cycle fluctuations in the total hours worked.

Employment Rate. The employment rate is based on the number of total non-farm employees for the U.S. (FRED code: PAYEMS) and total employees for the Euro Area 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 linearily 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

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

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. We connect the data with the model by applying the production capacity definition of the Federal Reserve Board. Capacity utilization is constructed by the output index divided by the capacity index where the long-run sustainable production index is defined as: *"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."*[53]

We follow the interpretation of Comin et al. (2025) and set three assumptions: (1) the capital stock is measured at the current available (predetermined) capital stock of a firm including non-utilized capital $e_{K,t}$; (2) the level of employment is measured at their current long-term rate; (3) labor matching costs, hours per worker, and labor effort are measured at the steady-state as any deviations are not sustainable in the long-run production capacity index. This interpretation is different to Morin and Stevens (2004); Michaillat and Saez (2015) as it assumes employment at the current quasi-fixed level instead of the long-run equilibrium (steady-state). As our framework allows us to separate extensive and intensive labor margins, we set only the flexible margins at steady-state levels as long-term employment changes much like the pre-determined capital stock the long-run production capacity of a firm. If we interpret an expansion of the capital stock as a new plant of a firm, additional employment is necessary to run this additional plant at normal operation. Setting employment to its steady-state rate would thus underestimate the employment rate at normal operation given the quasi-fixed predetermined capital stock.

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 U.S. definition of full capacity and apply it to the model when estimating Euro Area country data as well.

Capacity utilization data is for the entire observation period only available for the industry sector. For the service sector, which roughly is two-thirds of GDP, we lack data before 2011 for the Euro Area and for the U.S. completely.[54] Therefore, we backcast service sector capacity utilization rates. We follow Comin et al. (2025) and use a simple regression model to estimate the relationship

[53] 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/.

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

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

	U.S. (European Union)	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

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 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 U.S., as there is not service sector capacity utilization data available, we use European Union data from 2011q1 to 2019q4 to estimate (C.1) and calculate service sector capacity utilization data between 1984q1 to 2019q4 plugging in U.S. industry capacity utilization data. Table C.5 shows the R-squared of those exercises. Besides the regressions for the European Union and Spain, the R-squared are rather low. However, the sample 2011q1-2019q4 is rather short and not containing any major business cycle.[55] 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

[55]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.

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, thus taking into account the changing shares of industry and service sectors across time.[56] Finally, we calculate the growth rate of the economy-wide capacity utilization rate and demean each time series by

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

where the de-meaned growth rate is a direct observable of model capacity utilization growth rates, $\Delta \hat{CU}_t$.

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 U.S. 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 U.S. is given by the non-farm business sector labor compensation per hour (BLS code: COMPNFB). Real wage inflation is given

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

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 Euro Area 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 U.S. is given by the Federal Reserve Bank of New York, Effective Federal Funds Rate (FRED Code: EFFR) and for the Euro Area 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 U.S. and Euro Area 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

The growth rates of real GDP, real investment, real consumption, and real labor compensation are de-meaned by the mean growth rate (indicated by a bar) of real GDP (Smets and Wouters, 2007). The GDP deflator, the policy rate, and the capacity utilization growth rate are demeaned by their own mean. The log of total hours worked and the employment rate are linearily de-trended

Cacciatore et al. (2020). The data and structural model are connected as follows:

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

Appendix D. Additional Results to the Estimation Section

Appendix D.1. Additional Log Data Densities

Table D.6: Log Data Densities and Bayes Factors Across Different Model Variants

Model Setup		U.S.	Spain	Germany	France
Models ***including*** *survey-based capacity utilization data*					
K-Util		5182.0	2723.9	2939.9	3223.1
L-Util		5213.3	2748.4	2979.1	3244.9
KL-Util	**Benchmark**	5218.2	2757.7	2976.2	3255.2
G-Util		5224.6	2763.7	3028.7	3278.4
KG-Util		5232.3	2768.0	3029.4	3279.8
LG-Util		5261.4	2782.0	3042.2	3279.8
KLG-Util	Complements	5240.7	2764.8	2992.6	3273.8
KLG-Util	**Preferred**	5262.7	2785.3	3043.9	3281.7
Full-Util		5229.7	2751.5	3028.3	3279.7
Bayes Factors (compared to benchmark model)					
Complements		**45.0**	**14.2**	**32.8**	**37.2**
Preferred		**89.0**	**55.2**	**135.4**	**53.0**
Models ***excluding*** *survey-based capacity utilization data*					
KL-Util		4675.9	2456.7	2650.4	2876.2
KLG-Util	Complements (w/o CU)	4688.8	2466.1	2672.3	2893.2
KLG-Util	**Preferred** (w/o CU)	4713.1	2482.9	2719.4	2923.3
Bayes Factors (compared to benchmark model)					
Complements		**25.8**	**18.4**	**43.2**	**34.0**
Preferred		**74.4**	**52.4**	**138.0**	**94.2**

NOTE: The table shows log data densities and Bayes factors for different model variants estimated on U.S. data (1984q1-2019q4) and Euro Area data (1998q1-2019q4). Log data densities are calculated by the modified harmonic mean following Geweke (1999). Different variants are compared using the Bayes factor (Kass and Raftery, 1995): a value of 5 or higher indicates an improvement in data fit, a value of 10 or higher a decisive improvement in data fit.

Table D.7: 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				
KL-UTIL	5218.2	2757.7	2976.2	3255.2
KL-UTIL (ALT)	5223.2	2764.1	3002.1	3242.0
Bayes Factor: Baseline - Alternative	**-10.0**	**-12.8**	**-51.8**	**26.4**
KLG-UTIL	5262.7	2785.3	3043.9	3281.7
KLG-UTIL (ALT)	5258.7	2793.3	3058.5	3284.2
Bayes Factor: Baseline - Alternative	**8.0**	**-16.0**	**-29.2**	**-5.0**
Alternative Weights in Aggregate Capacity Utilization Construction				
Benchmark	5222.6	2757.7	2978.7	3253.7
Preferred	5267.0	2783.0	3044.4	3280.7
Bayes Factor: Preferred - Benchmark	**88.8**	**50.6**	**131.4**	**54.0**

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.2. Additional Results on the Prior-Posterior Analysis

Table D.8: Posteriors: International Comparison – Benchmark Model

Parameter	U.S. (90% HDP)	Spain (90% HDP)	Germany (90% HDP)	France (90% HDP)
General Parameters				
ω	0.65 (0.32-0.96)	0.60 (0.32-0.89)	0.06 (0.01-0.09)	0.44 (0.14-0.79)
θ_H	0.75 (0.68-0.83)	0.76 (0.69-0.84)	0.91 (0.88-0.94)	0.82 (0.77-0.88)
ν_H	1.66 (1.21-2.11)	2.34 (1.63-3.04)	2.40 (1.77-3.03)	2.07 (1.47-2.68)
$\frac{1}{mc} - 1$	0.34 (0.26-0.43)	0.10 (0.06-0.14)	0.33 (0.21-0.44)	0.13 (0.07-0.18)
κ_H	3.00 (2.27-3.74)	1.60 (0.87-2.30)	1.83 (1.09-2.54)	2.32 (1.50-3.14)
κ_I	4.55 (3.09-5.93)	6.93 (4.21-9.60)	11.48 (7.81-15.08)	11.6 (7.8-15.2)
κ_W	28.4 (20.8-35.8)	23.0 (16.7-29.3)	22.0 (16.1-27.7)	32.4 (24.4-40.0)
κ_P	202.5 (169.1-235.1)	174.7 (143.4-205.7)	165.6 (134.8-194.5)	166.3 (135.1-197.0)
ι_W	0.38 (0.16-0.60)	0.55 (0.33-0.77)	0.61 (0.39-0.82)	0.65 (0.46-0.85)
ι_P	0.13 (0.04-0.20)	0.06 (0.02-0.09)	0.08 (0.03-0.14)	0.08 (0.03-0.13)
i_π	1.76 (1.61-1.91)	1.65 (1.50-1.80)	1.80 (1.63-1.96)	1.88 (1.73-2.04)
i_{gap}	0.15 (0.08-0.21)	0.16 (0.10-0.23)	0.13 (0.05-0.21)	0.10 (0.04-0.15)
$i_{\Delta gap}$	0.11 (0.04-0.18)	0.12 (0.04-0.19)	0.13 (0.05-0.21)	0.15 (0.05-0.24)
Benchmark Utilization Parameters				
ϕ	1.42 (1.25-1.59)	1.62 (1.34-1.89)	1.79 (1.51-2.07)	1.71 (1.36-2.04)
$\phi_{K,2}$	1.94 (0.91-2.95)	0.61 (0.16-1.07)	2.74 (1.01-4.41)	1.32 (0.63-2.03)
Goods-Market SaM Utilization Parameters				
γ_T^{prox}	–	–	–	–
Γ^{prox}	–	–	–	–
ν_D^{mult}	–	–	–	–
θ_D	–	–	–	–
δ_I	–	–	–	–
δ_T	–	–	–	–

NOTE: The table shows the posterior densities of the estimated parameters of the benchmark model (KL-Util) for all four countries. The 90% HDP intervals are given in paranthesis.

Table D.9: Posteriors: International Comparison – Preferred Model

Parameter	U.S. (90% HDP)	Spain (90% HDP)	Germany (90% HDP)	France (90% HDP)
General Parameters				
ω	0.66 (0.40-0.94)	0.71 (0.44-0.97)	0.40 (0.21-0.74)	0.51 (0.09-0.89)
θ_H	0.70 (0.63-0.77)	0.76 (0.70-0.82)	0.70 (0.66-0.75)	0.72 (0.65-0.78)
ν_H	2.22 (1.64-2.77)	3.64 (2.84-4.40)	3.26 (2.55-3.94)	2.91 (2.18-3.63)
$\frac{1}{mc} - 1$	0.13 (0.10-0.17)	0.15 (0.1-0.18)	0.11 (0.09-0.14)	0.11 (0.08-0.13)
κ_H	4.07 (3.17-4.95)	1.63 (0.87-2.37)	2.13 (1.19-3.07)	3.02 (1.96-4.05)
κ_I	9.8 (7.1-12.3)	7.8 (5.3-10.3)	7.1 (5.0-9.1)	11.5 (8.2-14.8)
κ_W	27.0 (19.4-34.4)	25.7 (18.5-3.1)	23.1 (16.5-29.5)	26.9 (19.6-34.2)
κ_P	158.9 (132.3-185.8)	152.5 (124.4-180.9)	188.4 (157.2-219.2)	150.8 (124.1-177.5)
ι_W	0.45 (0.20-0.68)	0.42 (0.20-0.65)	0.52 (0.28-0.77)	0.49 (0.26-0.71)
ι_P	0.08 (0.03-0.13)	0.06 (0.02-0.10)	0.08 (0.03-0.12)	0.11 (0.04-0.17)
i_π	1.81 (1.67-1.95)	1.81 (1.65-1.97)	1.66 (1.52-1.80)	1.85 (1.70-2.01)
i_{gap}	0.10 (0.04-0.15)	0.18 (0.11-0.24)	0.36 (0.25-0.46)	0.16 (0.09-0.24)
$i_{\Delta gap}$	0.14 (0.05-0.22)	0.14 (0.05-0.22)	0.13 (0.05-0.22)	0.13 (0.04-0.21)
Benchmark Utilization Parameters				
ϕ	1.43 (1.27-1.58)	1.53 (1.28-1.76)	1.67 (1.39-1.95)	1.44 (1.16-1.69)
$\phi_{K,2}$	2.55 (1.21-3.86)	1.13 (0.218-2.08)	2.10 (0.70-3.47)	2.12 (0.74-3.44)
Goods-Market SaM Utilization Parameters				
γ_T^{prox}	0.74 (0.62-0.86)	0.75 (0.60-0.90)	0.86 (0.76-0.97)	0.84 (0.73-0.97)
Γ^{prox}	0.18 (0.07-0.29)	0.07 (0.01-0.13)	0.06 (0.01-0.11)	0.10 (0.02-0.18)
ν_D^{mult}	1.14 (0.64-1.62)	2.52 (1.48-3.54)	3.81 (2.54-5.02)	3.61 (2.32-4.86)
θ_D	–	–	–	–
δ_I	–	–	–	–
δ_T	–	–	–	–

NOTE: The table shows the posterior densities of the estimated parameters of the preferred model (KL-Util) for all four countries. The 90% HDP intervals are given in paranthesis.

Table D.10: Posteriors: International Comparison – Full Model

Parameter	U.S. (90% HDP)	Spain (90% HDP)	Germany (90% HDP)	France (90% HDP)
General Parameters				
ω	0.78 (0.61-0.97)	0.72 (0.48-0.96)	0.54 (0.20-0.86)	0.50 (0.08-0.84)
θ_H	0.72 (0.65-0.79)	0.75 (0.69-0.82)	0.69 (0.64-0.74)	0.71 (0.64-0.79)
ν_H	2.17 (1.57-2.78)	3.53 (2.73-4.31)	3.46 (2.69-4.22)	2.86 (2.16-3.58)
$\frac{1}{mc} - 1$	0.09 (0.06-0.1)	0.10 (0.08-0.13)	0.10 (0.08-0.11)	0.09 (0.07-0.11)
κ_H	4.48 (3.51-5.45)	2.09 (1.18-2.99)	2.88 (1.76-3.96)	2.91 (1.90-3.88)
κ_I	9.63 (6.80-12.42)	7.19 (4.97-9.34)	5.31 (3.66-6.95)	10.59 (7.44-13.69)
κ_W	17.1 (10.4-23.5)	23.4 (16.6-30.3)	23.6 (16.7-30.4)	26.3 (19.0-33.4)
κ_P	173.5 (144.5-202.5)	167.8 (137.9-197.5)	190.7 (160.7-221.1)	160.0 (132.4-187.2)
ι_W	0.44 (0.20-0.68)	0.37 (0.16-0.57)	0.50 (0.26-0.74)	0.48 (0.25-0.71)
ι_P	0.09 (0.03-0.14)	0.07 (0.02-0.11)	0.07 (0.02-0.12)	0.11 (0.04-0.18)
i_π	1.87 (1.73-2.02)	1.78 (1.62-1.95)	1.69 (1.55-1.84)	1.89 (1.74-2.05)
i_{gap}	0.09 (0.03-0.14)	0.13 (0.06-0.19)	0.29 (0.22-0.36)	0.11 (0.05-0.17)
$i_{\Delta gap}$	0.10 (0.04-0.15)	0.07 (0.03-0.11)	0.10 (0.04-0.16)	0.11 (0.04-0.18)
Benchmark Utilization Parameters				
ϕ	1.24 (1.12-1.36)	1.40 (1.19-1.61)	1.59 (1.33-1.85)	1.44 (1.16-1.70)
$\phi_{K,2}$	2.38 (0.97-3.76)	1.91 (0.42-3.38)	3.68 (1.76-5.52)	2.47 (0.99-3.89)
Goods-Market SaM Utilization Parameters				
γ_T^{prox}	0.82 (0.70-0.95)	0.71 (0.56-0.86)	0.85 (0.74-0.96)	0.85 (0.75-0.96)
Γ^{prox}	0.14 (0.05-0.23)	0.13 (0.03-0.23)	0.07 (0.02-0.12)	0.15 (0.05-0.25)
ν_D^{mult}	1.34 (0.73-1.96)	2.04 (1.14-2.90)	3.92 (2.62-5.20)	3.48 (2.26-4.69)
θ_D	0.18 (0.06-0.29)	0.26 (0.07-0.44)	0.27 (0.09-0.44)	0.21 (0.05-0.36)
δ_I	0.11 (0.05-0.16)	0.13 (0.06-0.20)	0.13 (0.06-0.20)	0.15 (0.07-0.22)
δ_T	0.75 (0.64-0.87)	0.76 (0.63-0.90)	0.73 (0.61-0.85)	0.84 (0.75-0.93)

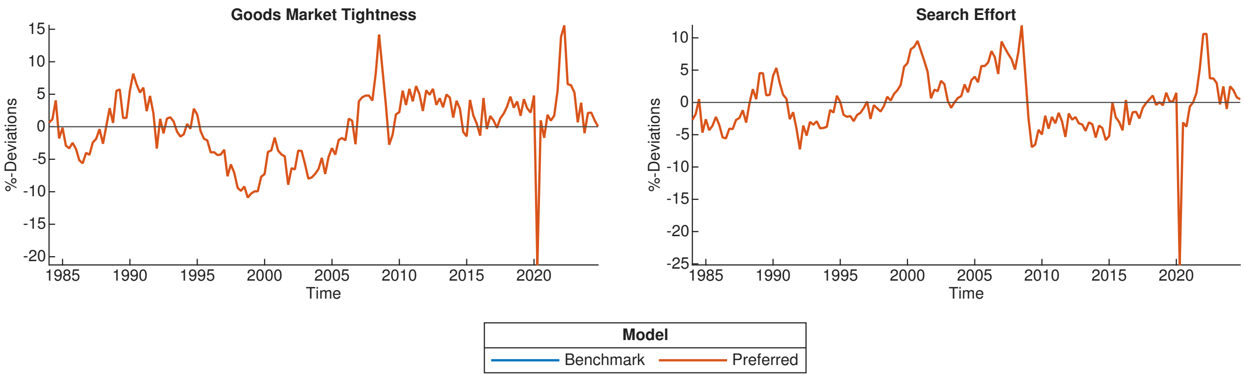
NOTE: The table shows the posterior densities of the estimated parameters of the full model (KL-UTIL) for all four countries. The 90% HDP intervals are given in paranthesis.

Table D.11: 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	31.9	1.34	−4.9	0.00	0.00
Preferred	7.8	0.19	0.00	18.2	1.13	−13.9	0.43	0.30
Full	8.8	0.22	0.06	24.0	1.08	−29.8	0.35	0.27
Spain								
Benchmark	11.4	0.29	0.00	49.0	1.10	−13.3	0.00	0.00
Preferred	7.9	0.20	0.00	18.1	1.15	−12.9	0.45	0.31
Full	9.4	0.23	0.08	25.7	1.09	−26.2	0.29	0.23
Germany								
Benchmark	10.6	0.27	0.00	27.1	1.33	−5.1	0.00	0.00
Preferred	6.8	0.17	0.00	14.2	1.11	−16.5	0.56	0.36
Full	8.4	0.21	0.05	20.4	1.09	−23.8	0.36	0.28
France								
Benchmark	10.9	0.27	0.00	38.2	1.13	−11.8	0.00	0.00
Preferred	7.1	0.18	0.00	16.2	1.11	−20.7	0.52	0.34
Full	8.2	0.20	0.05	20.9	1.08	−36.1	0.34	0.29

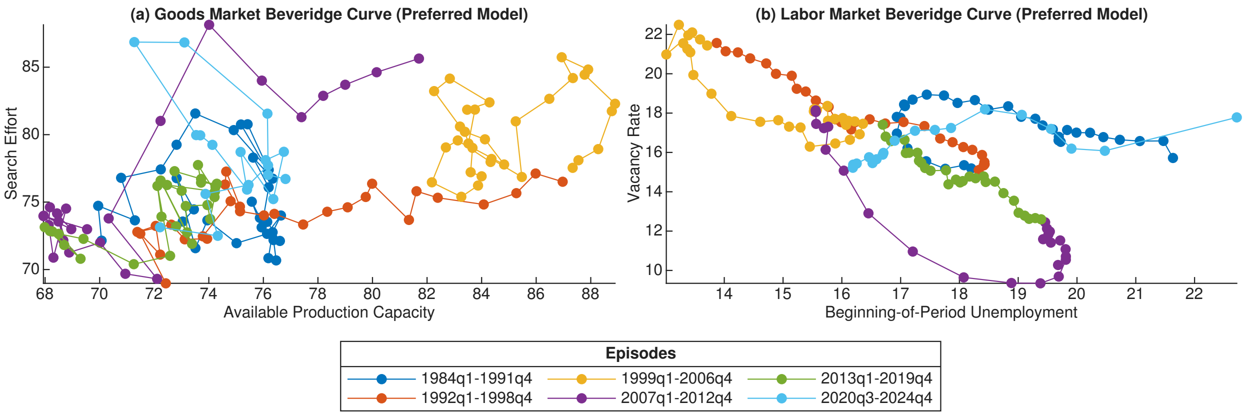
Appendix D.4. Additional Results on the U.S. Business Cycle

Figure D.13: Goods Market Tightness and Search Effort (U.S. Data)



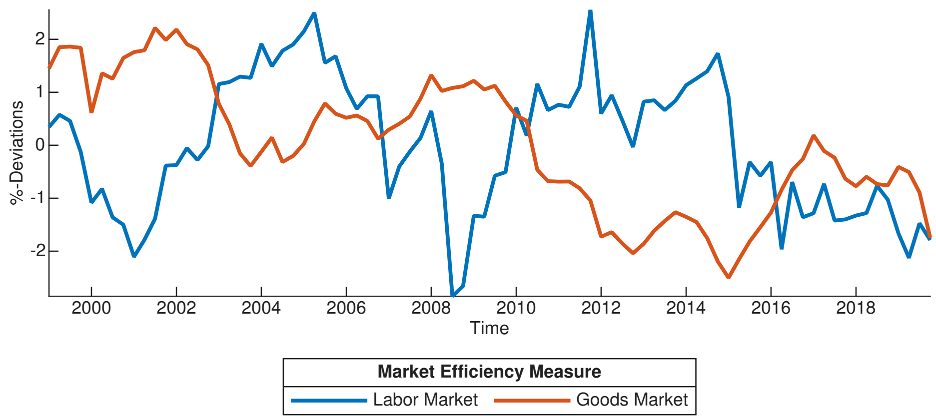
NOTE: The figure shows estimated goods market tightness and search effort for US data 1984q1-2024q4. Data is retrieved from a calibrated smoother using the preferred model.

Figure D.14: Beveridge Cycles (U.S. Data) - Goods and Labor Markets



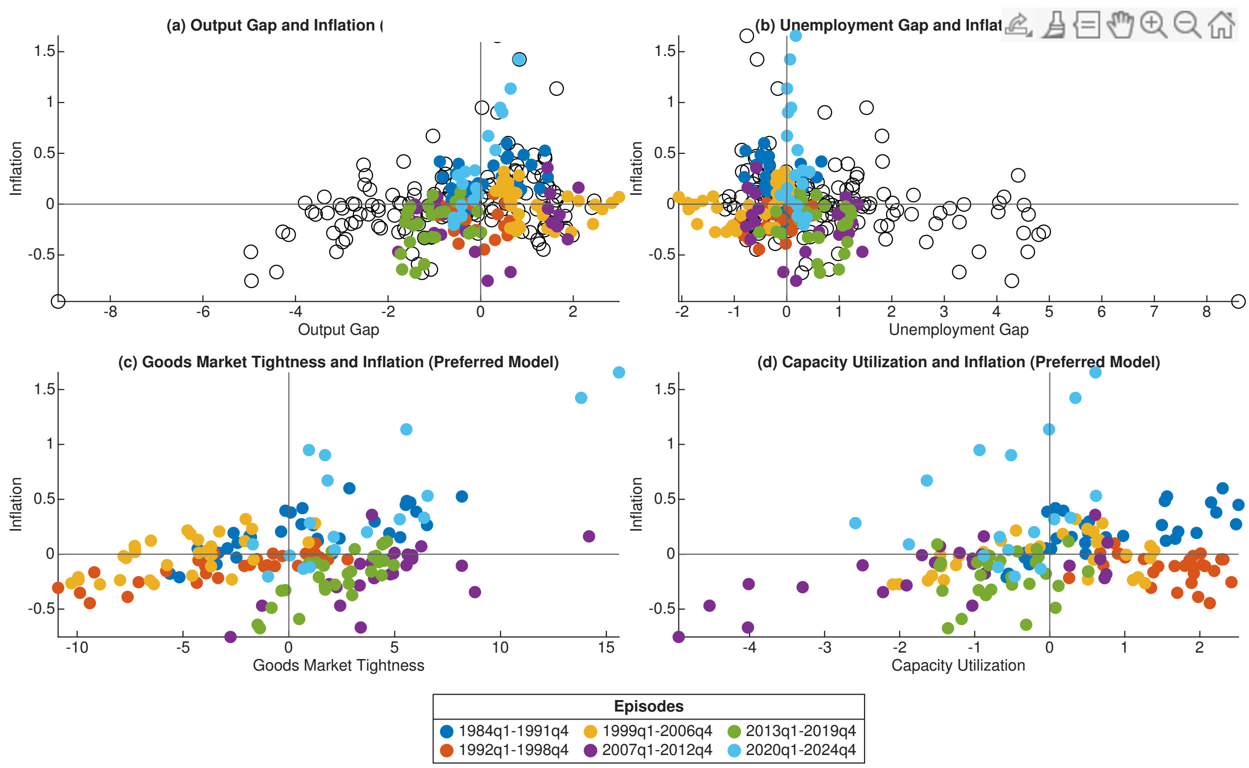
NOTE: The figure shows the matching processes of the model derived from U.S. data. It shows the Beveridge curves – demand and supply measures – of both the goods and labor markets.

Figure D.15: Matching Efficiency (U.S. Data) - Goods and Labor Markets



NOTE: The figure shows the efficiency of both markets, i.e. implied shifts in the Beveridge curves.

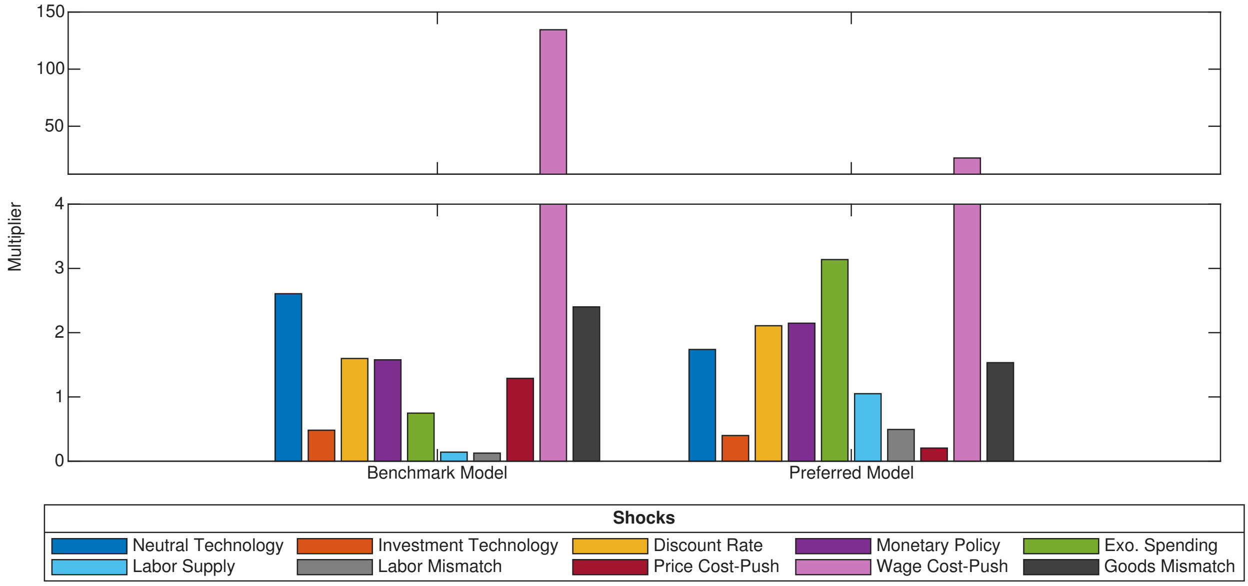
Figure D.16: Correlation of Inflation and Economic Slack Variables



NOTE: The figure shows the correlation of inflation and different economic slack variables for U.S. data (1984q1-2024q4). Subfigure (a) shows the correlation with the output gap and subfigure (b) shows the correlation with the unemployment gap. For both subfigures, we show the correlation with the gap variable derived from the model in colored dots and retrieved from the FED in hollow black dots. Subfigure (c) shows the correlation of inflation with goods market tightness percentage deviations from steady-state. And subfigure (d) shows the correlation between capacity utilization percentage deivations from steady-state and inflation.

Appendix D.5. Additional Results on the U.S. Variance Decomposition

Figure D.17: TFP Variance Multiplicators (relative to GDP Variance Shares)

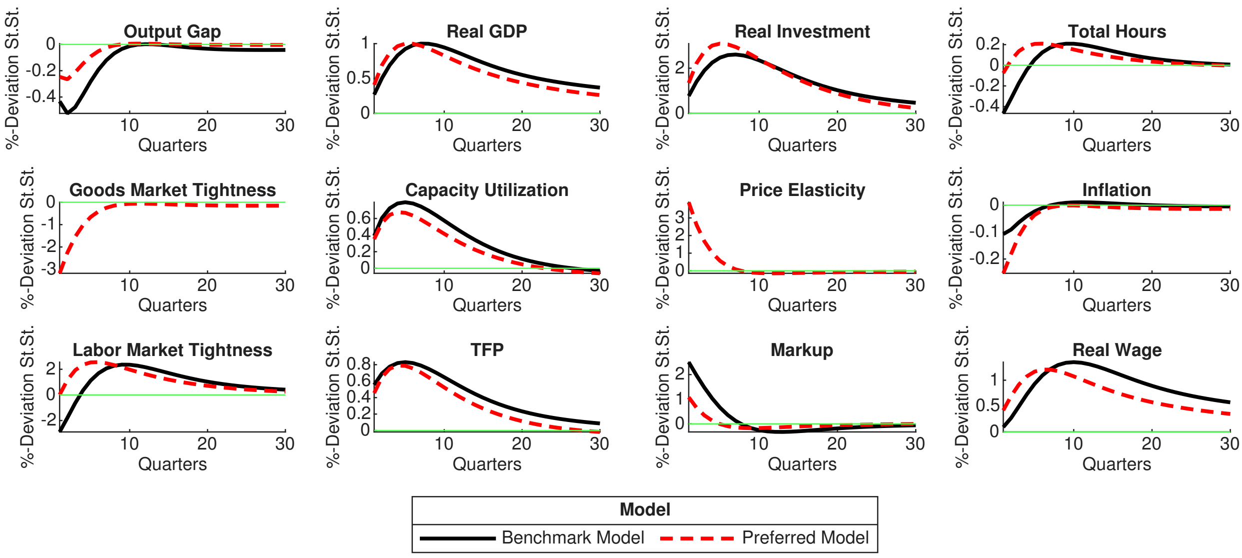


NOTE: The figure shows TFP variance multiplicators: This is the variance share of the variance decomposition of TFP for each shock divided by the variance share of the variance decomposition of real GDP for the respective shock. This statistic shows howfar each shock drives TFP more than real GDP.

Appendix E. Additional Results for the Simulation Section

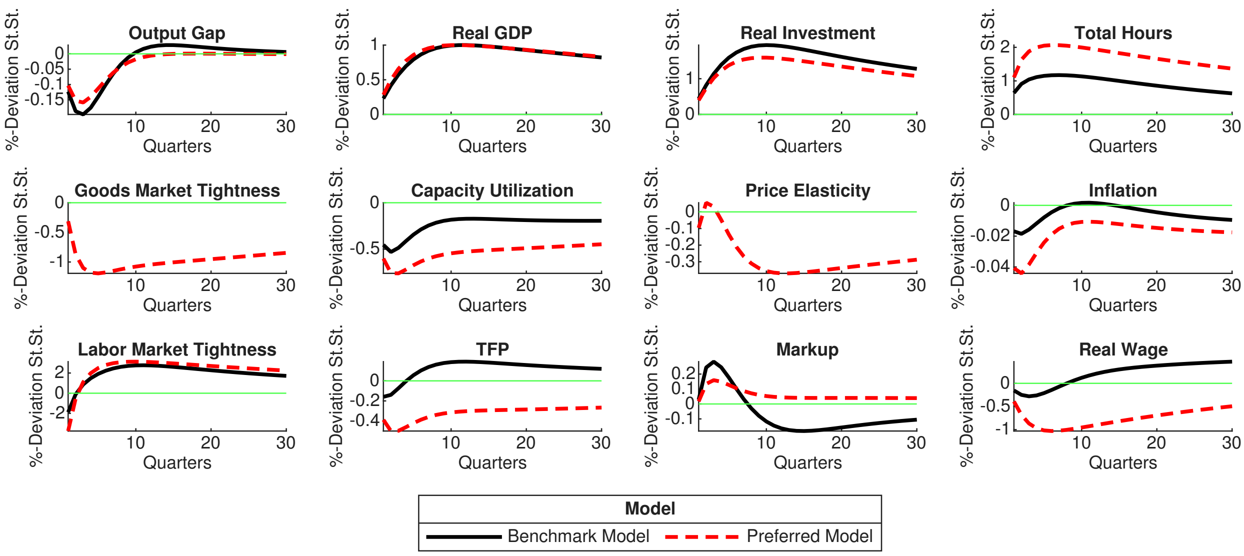
Appendix E.1. Additional IRFs to Business Cycle Shocks

Figure E.18: IRFs to an Expansionary Goods Mismatch Shock



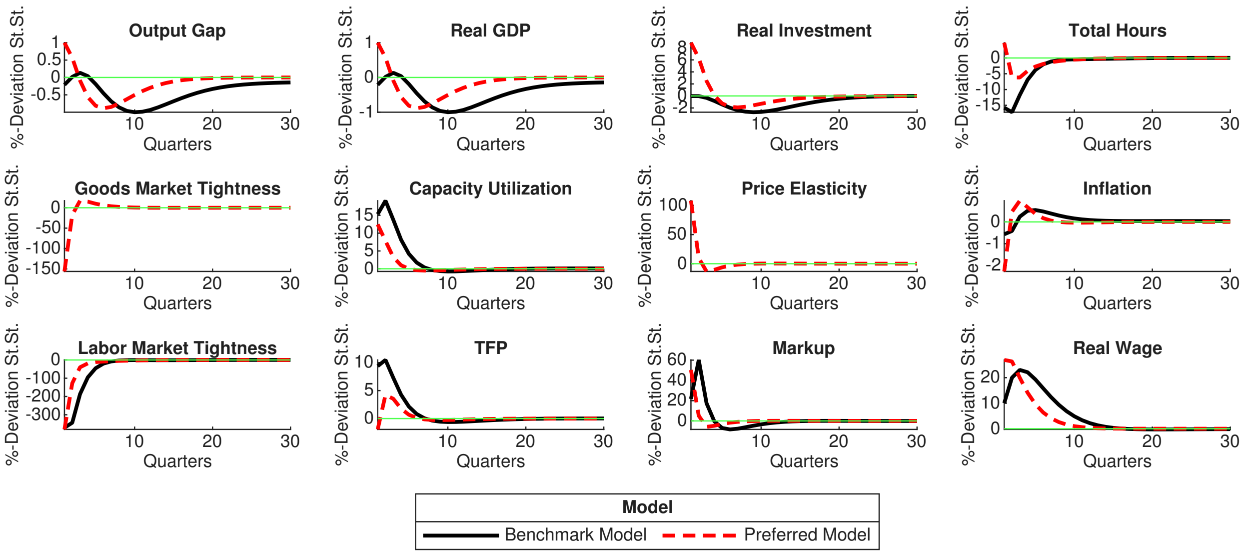
NOTE: The figure shows IRFs of different variables to an expansionary goods mismatch shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.19: IRFs to an Expansionary Labor Mismatch Shock



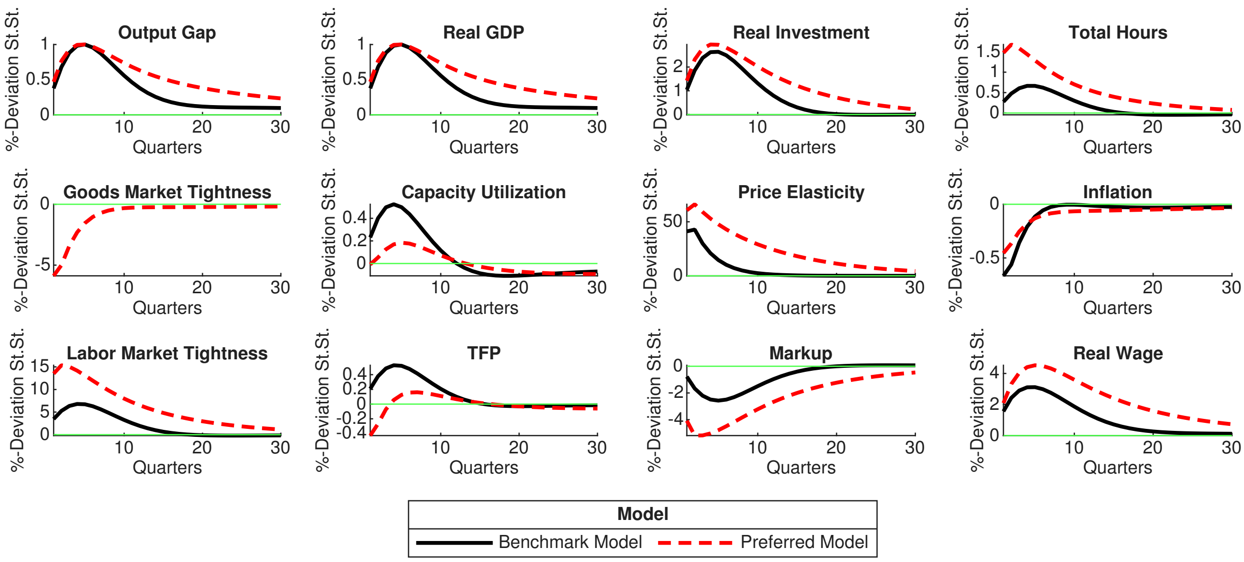
NOTE: The figure shows IRFs of different variables to an expansionary labor mismatch shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.20: IRFs to an Expansionary Wage Cost-Push Shock



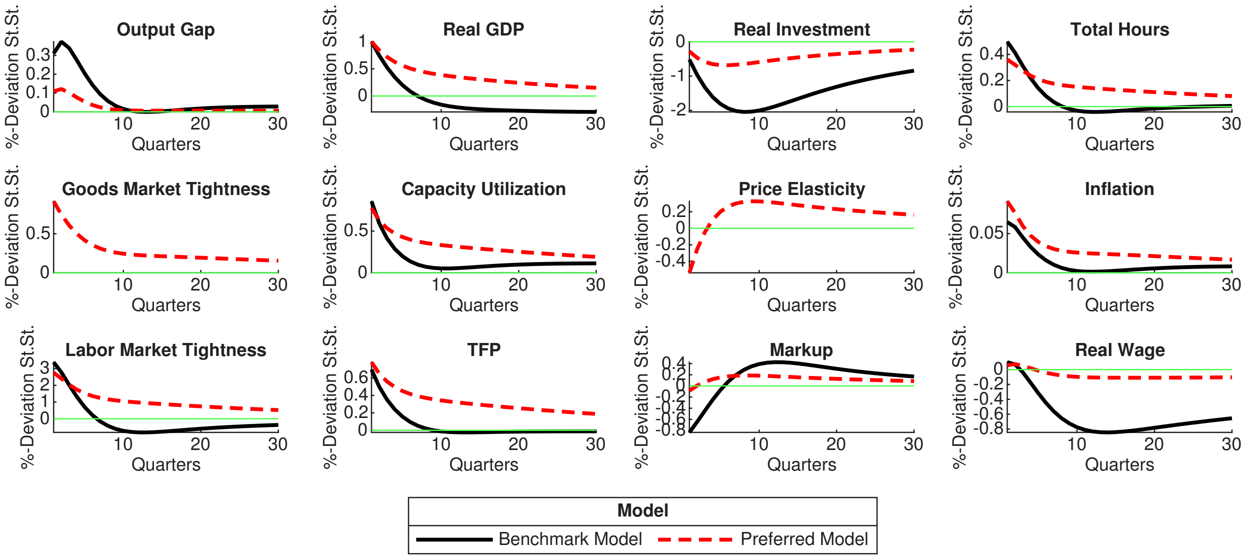
NOTE: The figure shows IRFs of different variables to an expansionary wage cost-push for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.21: IRFs to an Expansionary Price Cost-Push Shock



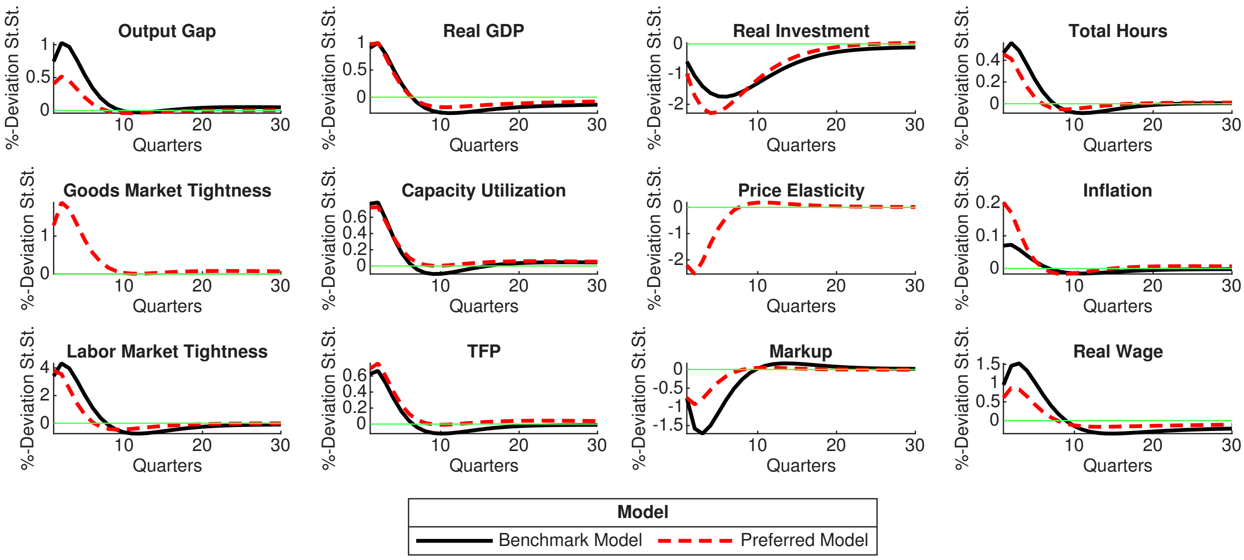
NOTE: The figure shows IRFs of different variables to an expansionary price cost-push for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

Figure E.22: IRFs to an Expansionary Exogenous Spending Shock



NOTE: The figure shows IRFs of different variables to an expansionary exogenous spending shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

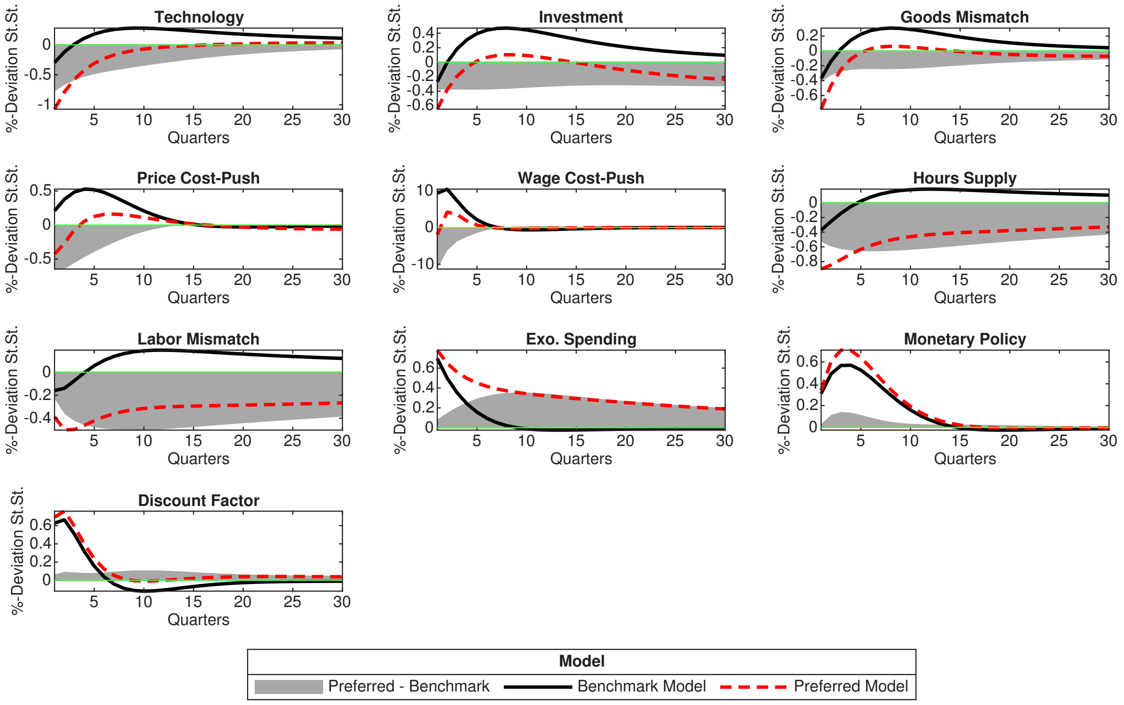
Figure E.23: IRFs to an Expansionary Discount Factor Shock



NOTE: The figure shows IRFs of different variables to an expansionary discount factor shock for both the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state. IRFs are normalized across models by scaling with the absolute maximum deviation of real GDP in each model.

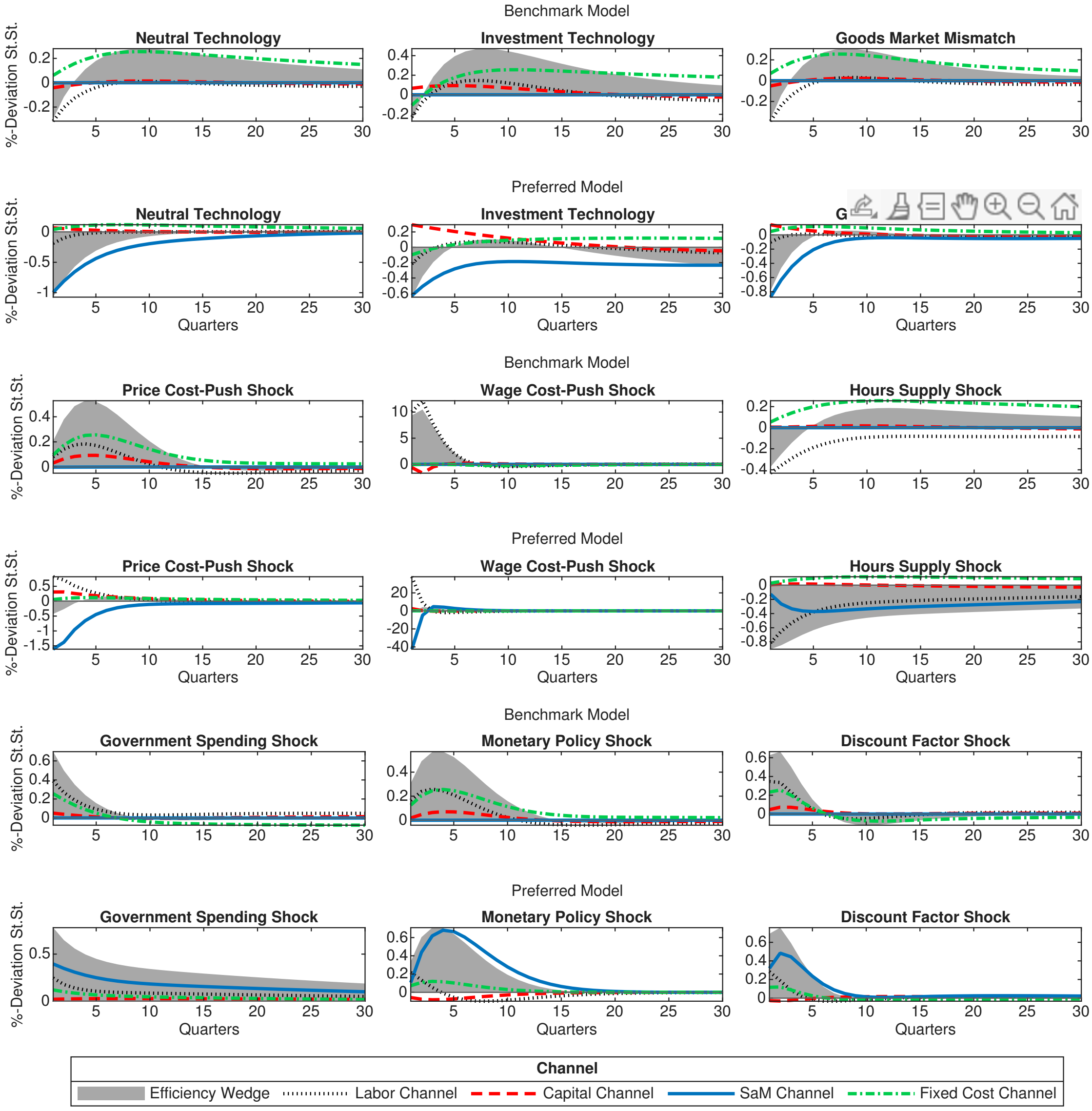
Appendix E.2. Additional Results on the Efficiency Wedge

Figure E.24: Efficiency Wedge Dynamics: Complete Overview



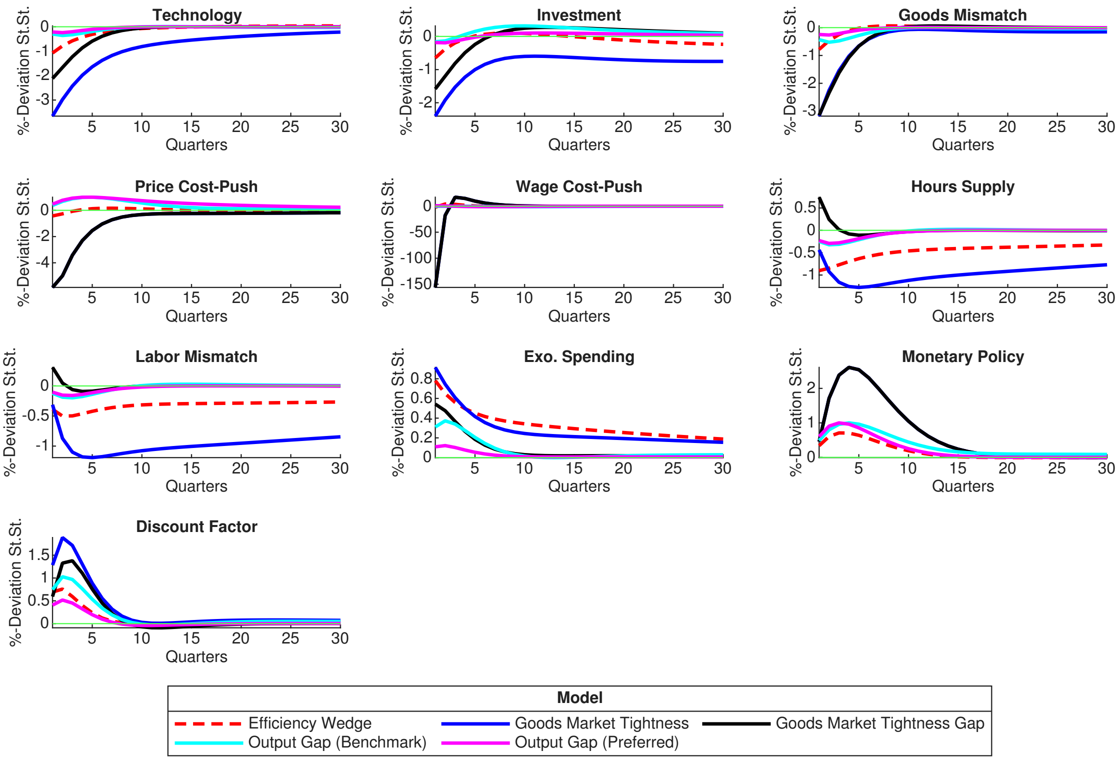
NOTE: The figure shows IRFs of the efficiency wedge (upper-bound) to expansionary shocks for the benchmark and preferred models. Variations are measured in percent deviations from the deterministic steady-state.

Figure E.25: Dynamics of the Determinants of the Efficiency Wedge



NOTE: The figure shows IRFs of the efficiency wedge (upper-bound) and its decomposition into four channels: (1) Labor, (2) capital, (3) goods market SaM, and (4) fixed costs. The upper graph for each shock shows the benchmark model, the lower bar the preferred model.

Figure E.26: IRFs for Goods-Market Tightness Gap Proxies: Complete Overview



NOTE: The figure shows IRFs of the efficiency wedge and its proxies to expansionary business-cycle shocks for the preferred model. Variations are measured in percent deviations from the deterministic steady-state.