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From Servers to Rates: AI, ICT Capital, and the Natural Rate

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From Servers to Rates: AI, ICT Capital, and the Natural Rate
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ABSTRACT: This paper investigates the macroeconomic implications of the rising wave of investment in information and communication technology (ICT)—including AI-related hardware and software—in the U.S. economy. The analysis uses a structural macroeconomic model that treats ICT as a distinct type of capital and explores the degree to which ICT complements or substitutes for labor. The findings reveal three key insights. First, labor and ICT have historically been only moderately substitutable. Second, technological innovations that make it easier to turn ICT investment into productive capital act like demand shocks, boosting output and inflation. Third, given the uncertainty surrounding the interaction between AI-driven ICT capital and labor, the paper presents scenarios of possible trajectories for ICT investment under alternative assumptions. When ICT tends to complement labor, the economy experiences strong gains in output, but also inflationary pressure; the natural interest rate increases, requiring tighter monetary policy. Conversely, if ICT tends to replace labor, the same ICT investment path warrants a looser monetary policy stance.

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WORKING PAPERS

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Prepared by Giovanni Melina and Stefania Villa[1]

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1 Introduction

Digital investment has entered a new phase fueled by the rapid rise of generative artificial intelligence (AI). While earlier waves of innovation—such as cloud computing and widespread mobile broadband—laid the foundation, it is the widespread diffusion of AI applications that is now prompting firms to rethink their capital allocation strategies. In 2024, U.S. corporations already allocated over four percent of GDP to information- and communication-technology (ICT) assets, including high-performance servers, specialized software, and advanced network infrastructure. Recent sectoral analyses by Deloitte (Raskovich et al., 2024) and Gartner (2025) indicate that investment in "AI enablement" is accelerating at a pace unprecedented since the late-19990s technology boom, signaling a broad-based shift in corporate digital strategies.

Shifts in digital capital spending have important macroeconomic implications (Korinek, 2024; Korinek and Stiglitz, 2025), influencing labor demand, wages, prices and the natural rate of interest that plays a significant role in setting monetary policy (see, e.g., Obstfeld, 2025). In light of the limited empirical evidence and the substantial uncertainty surrounding the pace and nature of AI integration into production processes (see, e.g. Cazzaniga et al., 2024), this paper develops a dynamic stochastic general equilibrium (DSGE) model *à la* Smets and Wouters (2007) to investigate first how AI-driven ICT capital influences aggregate output, inflation, and the natural rate of interest. And second, how alterative future trajectories of AI-related ICT investment shape macroeconomic outcomes and affect the conduct of monetary policy. Key distinct features of the model are the separation of ICT from non-ICT capital, distinct adjustment costs for ICT investment, and a flexible degree of substitutability between ICT capital and labor. The model is estimated using Bayesian methods on U.S. quarterly data from 1980Q1 to 2024Q2.

The main result is that the macroeconomic consequences of AI adoption—and the resulting implications for monetary policy—depend critically on whether ICT capital complements or substitutes for labor.

Historically, estimates point to mild gross substitutability between ICT capital and labor. The model-implied natural rate shows a downward trend, and ICT investment specific technology (IST) shocks have historically played a modest but positive role in its fluctuations. Such shocks trigger a gradual rise in ICT investment, boosting output, raising labor in a hump-shaped pattern, pushing up inflation, and leading the central bank to gradually increase the policy rate. The natural rate of interest first falls, as households expect higher future income and initially increase savings, then rises above its steady state as productive capacity expands and expected returns increase.

Counterfactual simulations are conducted because the elasticity of substitution between ICT and labor is highly uncertain in light of the rapid AI adoption. Easier substitution leads to higher ICT investment but results in smaller employment and wage gains. Stronger complementarity dampens investment but strengthens employment, wage and consumption, thus pushing up the natural rate of interest.

Finally, scenarios assess two possible trajectories of AI-driven ICT investment over a five-year horizon. A conservative projection assumes a gradual rise in the ICT-to-GDP ratio, whereas an ambitious scenario foresees a significant increase surpassing the peak reached during the dot-com era. These cases are studied under various assumptions regarding factor substitutability. Across scenarios, annual GDP growth rises by 0.1 to 0.9 percentage point, inflation by 0.1 to 0.8 percentage point, and the natural rate of interest by up to 0.7 percentage point.

These findings carry important implications for monetary policy. As AI-related ICT investment accelerates, central banks will need to monitor not only the volume of investment but also how it interacts with labor markets. The degree of complementarity between labor and new technologies plays a central role in shaping wage dynamics, inflation pressure, and the trajectory of the natural rate. In settings where ICT adoption tends to boost labor demand, failing to recognize a structural rise in the natural rate may lead to an overly accommodative stance, fueling persistent inflation. Conversely, if ICT tends to displace labor, excessive monetary tightening may unnecessarily slow the economy.

This analysis should be interpreted with some caveats. First, while in the model the accumulation of ICT capital generates productivity gains in the other factors of production that help mitigate inflationary pressures, ICT—particularly with the growing adoption of AI—may also exert a direct impact on TFP (Cerutti et al., 2025), with ambiguous implications for inflation (Aldasoro et al., 2024). For simplicity, this channel is abstracted from, as the output effects already captured are quantitatively sizable. Second, although the effects of AI are likely to be heterogeneous across workers (Cazzaniga et al., 2024), the focus of the paper is on aggregate macroeconomic outcomes, which makes it possible to examine the transmission mechanisms of ICT IST shocks at the macro level within a simple framework.

The paper connects four strands of macroeconomic research. First, it builds on the DSGE tradition of Smets and Wouters (2007), by incorporating two types of capital (see Krusell et al., 2000; Bhattarai et al., 2022). Second, it contributes to the burgeoning literature on the labor market implications of AI, which often adopts a task-based approach to assess how occupations are exposed to automation or may benefit from productivity gains (Acemoglu and Restrepo, 2018, 2022; Webb, 2020; Felten et al., 2021, 2023; Pizzinelli et al., 2023; Cazzaniga et al., 2024; Eloundou et al., 2024; Korinek, 2024; Korinek and Stiglitz, 2025; Rockall et al., 2025).[1] Third, the paper relates to a growing literature on AI's macroeconomic and productivity impacts (e.g., Aldasoro et al., 2024). In this context, Acemoglu (2025) suggests modest gains and heightened inequality risks, while Aghion and Bunel (2024) emphasize productivity-enhancing channels through automation and innovation. Fourth, the paper contributes to the natural rate literature, building on empirical and model-based estimates and its structural drivers, including capital deepening, demographics, risk preferences, and productivity dynamics (Laubach and Williams, 2003; Edge et al., 2008; Justiniano and Primiceri, 2010; Barsky et al., 2014; Cúrdia et al., 2015; Del Negro et al., 2017; Holston et al., 2017; Neri and Gerali, 2019; Barrett et al., 2023; Berger et al., 2023; Holston et al., 2023; Nuño, 2025).

This paper contributes to the four strands in interrelated ways. It analyzes the transmission of ICT IST shocks within the broader role of structural shocks in explaining business cycle fluctuations, allowing for varying degrees of substitution between ICT capital and labor. It complements the literature on AI and labor markets by offering a macroeconomic framework in which the degree of factor complementarity can shape aggregate outcomes. In doing so, the paper also adds to the literature on AI's macroeconomic impacts. Finally, it contributes to the literature on the natural rate by highlighting how shifts in ICT investment—conditional on labor-technology interactions—can affect the equilibrium interest rate.

The remainder of the paper proceeds as follows. Section 2 lays out the model. Section 3 describes the data, calibration, and the main results of the Bayesian estimation. Section 4 analyses impulse-response functions, leveraging counterfactuals to disentangle important transmission channels. Section 5 constructs projections for AI-driven ICT investment. Finally, Section 6 concludes. Details on the data and additional results are appended to the paper.

2 Model

The framework builds on the Smets and Wouters (2007) dynamic stochastic general equilibrium (DSGE) model, which has been shown to replicate key features of business cycles. The model economy consists of households, labor unions, labor packers, retailers, final good firms, intermediate goods firms and a policymaker. This model is extended to explicitly include investment in ICT. ICT investment is subject to adjustment costs, modeled

[1] While most empirical evidence focuses on advanced economies, particularly the U.S., recent cross-country studies highlight significant heterogeneity in AI's labor market effects across regions and demographic groups (OECD, 2023; Albanesi et al., 2024; Briggs and Kodnani, 2023; Gmyrek et al., 2023; Korinek and Juelfs, 2023; Brollo et al., 2024; Berg et al., 2025; Cerutti et al., 2025).

analogously to those for standard capital, and accumulates into a separate ICT capital stock. This ICT capital is used in production alongside labor and non-ICT capital, the two standard inputs. A similar distinction between capital structures and capital equipment was originally introduced by Krusell et al. (2000) to explain the observed variations in the skill premium. For the sake of simplicity, variable capital utilization is not included, given the presence of two types of capital and two sources of investment adjustment costs. Subsection 2.1 details the novel features of the model related to ICT investment, while Subsection 2.2 presents the full set of linearized model equations.

2.1 Features Related to ICT Investment

The distinction between ICT and non-ICT capital affects the optimality conditions faced by households and firms. To identify the contribution of ICT investment to macroeconomic dynamics, both its depreciation rate and adjustment costs are allowed to differ from those associated with non-ICT capital.

Each household owns both types of capital—ICT and non-ICT—which it rents to intermediate goods producers. Households can increase the supply of capital services by investing in ICT capital, I^{ICT}, and in non-ICT capital, I_t. The law of motion for the ICT capital stock, K_t^{ICT}, is given by:

$$K_t^{ICT} = \left(1 - \delta^{ICT}\right) K_{t-1}^{ICT} + \exp\left(e_t^{x^{ICT}}\right) \left[1 - S^{ICT}\left(\frac{I_t^{ICT}}{I_{t-1}^{ICT}}\right)\right] I_t^{ICT}. \tag{1}$$

Here, δ^{ICT} denotes the depreciation rate of ICT capital, $e_t^{x^{ICT}}$ is a shock to the marginal efficiency of ICT investment and $S^{ICT}(\cdot)$ represents the adjustment cost function, which satisfies standard properties: $S^{ICT}(1) = S^{ICT\prime}(1) = 0$, and $S^{ICT\prime\prime} = \xi^{ICT} > 0$. Maximization of households' intertemporal utility yields the following first-order conditions with respect to K_t^{ICT} and I_t^{ICT} respectively:

$$Q_t^{ICT} = \beta E_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \left[R_{t+1}^{ICT} + Q_{t+1}^{ICT}\left(1 - \delta^{ICT}\right)\right] \right\}, \tag{2}$$

$$\begin{aligned} 1 &= Q_t^{ICT} \exp\left(e_t^{x^{ICT}}\right) \left[1 - S^{ICT}\left(\frac{I_t^{ICT}}{I_{t-1}^{ICT}}\right) - S^{ICT\prime}\left(\frac{I_t^{ICT}}{I_{t-1}^{ICT}}\right)\left(\frac{I_t^{ICT}}{I_{t-1}^{ICT}}\right)\right] \\ &+ E_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \left[Q_{t+1}^{ICT} \exp\left(e_{t+1}^{x^{ICT}}\right) S^{ICT\prime}\left(\frac{I_{t+1}^{ICT}}{I_t^{ICT}}\right)\left(\frac{I_{t+1}^{ICT}}{I_t^{ICT}}\right)^2 \right] \right\}, \end{aligned} \tag{3}$$

where Q_t^{ICT} denotes the Tobin's Q for ICT capital, and R_{t+1}^{ICT} is the real gross rental rate households receive for renting ICT capital to intermediate goods producers.

From the perspective of firms, ICT capital is an input to production. The model explicitly captures the degree of substitutability or complementarity between K_t^{ICT} and labor, L_t. This extension of the Smets-Wouters model is particularly pertinent in the highly-debated context of emerging technologies such as AI, where the interaction between human labor and technological enhancements could significantly reshape shock transmission mechanisms and policy responses. These two inputs enter the production function through a constant-elasticity-of-substitution (CES) aggregator, E_t, which is then used alongside traditional (non-ICT) capital, K_t, in a Cobb-Douglas production function:

$$Y_t = \exp\left(e_t^a\right) K_t^{\alpha} {E_t}^{1-\alpha}, \tag{4}$$

$$E_t = \left[\alpha_{ICT}\left(K_t^{ICT}\right)^{\frac{\eta-1}{\eta}} + \alpha_L\left(L_t\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{5}$$

where Y_t denotes output, e_t^a is a TFP shock, α is the non-ICT capital share of income, η is the elasticity of substitution between ICT capital and labor, and α_{ICT} and α_L are distribution parameters. Krusell et al. (2000) use a similar, though more elaborate, CES specification to account also for the distinction between skilled and unskilled labor. A simpler CES functional form for the production function has also been adopted by Cantore et al. (2014) and Di Pace and Villa (2016).

The CES aggregator nests several familiar functional forms: Cobb-Douglas when $\eta \to 1$; the Leontief (fixed proportions) when $\eta \to 0$; and linear (perfect substitutes) when $\eta \to \infty$. When $0 < \eta < 1$, ICT capital and labor are gross complements; when $\eta > 1$, they are gross substitutes.

Cost minimization by intermediate goods producers yields the following optimality conditions governing the demand for non-ICT capital, labor and ICT capital, respectively:

$$R_t^k = \Theta_t \alpha \frac{Y_t}{K_t}, \tag{6}$$

$$W_t = \Theta_t\left(1-\alpha\right)\alpha_L \frac{Y_t}{E_t^{\frac{\eta-1}{\eta}} L_t^{\frac{1}{\eta}}}, \tag{7}$$

$$R_t^{ICT} = \Theta_t\left(1-\alpha\right)\alpha_{ICT} \frac{Y_t}{E_t^{\frac{\eta-1}{\eta}} \left(K_t^{ICT}\right)^{\frac{1}{\eta}}}, \tag{8}$$

where Θ_t denotes the Lagrange multiplier associated with the production function and equals the marginal cost, R_t^k is the rental rate of non-ICT capital and W_t is the nominal wage. Equation (6) equates the marginal product of non-ICT capital to its rental rate, ensuring that firms hire capital up to the point where its contribution to output matches its cost.

Equation (7) determines labor demand, linking the marginal contribution of labor—adjusted for its role in the CES composite input, E_t—to the real wage. Similarly, equation (8) governs the demand for ICT capital, showing that its marginal product (also expressed via the CES aggregator) must equal the real return on ICT capital. Together, these conditions highlight how the degree of substitutability between ICT capital and labor (governed by η) affects the relative demand for each factor and, ultimately, the transmission of shocks in the economy.

To facilitate the calibration, the CES distribution parameters can be re-parametrized based on the steady-state income shares of ICT capital and labor, $S^{K^{ICT}}$ and S^L, and the elasticity of substitution, η, so that $\alpha_{ICT} = \frac{S^{k^{ICT}}}{(1-\alpha)} \left(\frac{E}{K^{ICT}}\right)^{\frac{\eta-1}{\eta}}$ and $\alpha_L = \frac{S^L}{(1-\alpha)} \left(\frac{E}{L}\right)^{\frac{\eta-1}{\eta}}$. The terms E, K^{ICT} and L represent steady-state values of the corresponding variables.

2.2 Linearized Model Equations

This subsection reports the full set of model equilibrium conditions in log-linear form organized by agents, that is, households, firms, and monetary authority and equilibrium. Variables with a 'hat' denote percentage deviations from their respective steady state, while a variable without a time subscript denotes its steady-state value.

2.2.1 Households

Households maximize expected lifetime utility by choosing consumption, labor supply, and investment in both ICT and non-ICT capital, subject to budget and capital accumulation constraints. Utility depends on consumption, C_t, which exhibits habit formation—captured by parameter h—and labor, and specializes as $U_t(\cdot) = \ln(C_t - hC_{t-1}) - \frac{L_t^{1+\phi}}{1+\phi}$, where ϕ is the inverse of the Frisch elasticity of labor supply. Their decisions give rise to the Euler equation, wage-setting behavior, and non-ICT and ICT investment and Tobin's Q dynamics:

$$\frac{1+h}{1-h}\hat{C}_t = \frac{1}{1-h}E_t\left[\hat{C}_{t+1}\right] + \frac{h}{1-h}\hat{C}_{t-1} - \left(\hat{R}_t - E_t\left[\hat{\pi}_{t+1}\right]\right) + e_t^b, \tag{9}$$

$$\begin{aligned} \hat{W}_t =& \frac{\beta}{1+\beta}E_t\left[\hat{W}_{t+1}\right] + \frac{1}{1+\beta}\hat{W}_{t-1} + \frac{\beta}{1+\beta}E_t\left[\hat{\Pi}_{t+1}\right] - \frac{1+\beta\sigma_{wi}}{1+\beta}\hat{\Pi}_t + \frac{\sigma_{wi}}{1+\beta}\hat{\Pi}_{t-1} \\ &+ \frac{1}{1+\beta}\cdot\frac{(1-\beta\sigma_w)(1-\sigma_w)}{(1+\varepsilon_w\phi)\sigma_w}\left[\phi\hat{L}_t - \frac{h}{1-h}\hat{C}_{t-1} + \frac{1}{1-h}\hat{C}_t - \hat{W}_t\right] + e_t^w, \end{aligned} \tag{10}$$

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t\left[\hat{I}_{t+1}\right] + \frac{1}{\xi(1+\beta)}\hat{Q}_t + e_t^x, \tag{11}$$

$$\hat{I}_t^{ICT} = \frac{1}{1+\beta}\hat{I}_{t-1}^{ICT} + \frac{\beta}{1+\beta}E_t\left[\hat{I}_{t+1}^{ICT}\right] + \frac{1}{\xi^{ICT}(1+\beta)}\hat{Q}_t^{ICT} + e_t^{x^{ICT}}, \tag{12}$$

$$\hat{K}_{t+1} = (1-\delta)\hat{K}_t + \delta\left(\hat{I}_t + \xi e_t^x\right), \tag{13}$$

$$\hat{K}_{t+1}^{ICT} = (1-\delta^{ICT})\hat{K}_t^{ICT} + \delta^{ICT}\left(\hat{I}_t^{ICT} + \xi^{ICT} e_t^{x^{ICT}}\right), \tag{14}$$

$$\hat{Q}_t = \frac{R^k}{R^k + (1-\delta)} E_t\left[\hat{R}_{t+1}^k\right] + \frac{(1-\delta)}{R^k + (1-\delta)} E_t\left[\hat{Q}_{t+1}\right] - \left(\hat{R}_t - E_t\left[\hat{\pi}_{t+1}\right]\right) + \frac{1+h}{1-h} e_t^b, \tag{15}$$

$$\begin{aligned}\hat{Q}_t^{ICT} =& \frac{R^{ICT}}{R^{ICT} + (1-\delta^{ICT})} E_t\left[\hat{R}_{t+1}^{ICT}\right] + \frac{(1-\delta^{ICT})}{R^{ICT} + (1-\delta^{ICT})} E_t\left[\hat{Q}_{t+1}^{ICT}\right] - \\ &\left(\hat{R}_t - E_t\left[\hat{\pi}_{t+1}\right]\right) + \frac{1+h}{1-h} e_t^b.\end{aligned} \tag{16}$$

Equation (9) is the consumption Euler equation, which captures intertemporal consumption choices under habit formation. Consumption today, $\hat{C}_t$, depends on past and expected future consumption, the real interest rate—given by the nominal interest rate, $\hat{R}_t$, minus expected inflation, $E_t[\hat{\Pi}_{t+1}]$— and a risk premium shock, e_t^b, that affects intertemporal consumption-saving decisions.

Equation (10) characterizes wage setting under Calvo-style nominal rigidity with indexation. Here $\hat{W}_t$ is the real wage and $\hat{L}_t$ is hours worked. The households' discount factor is denoted by β, while σ_w and σ_{wi} capture the degree of wage stickiness and indexation, respectively. The term e_t^w is a wage mark-up shock, reflecting shifts in wage-setting power. The wedge between the marginal rate of substitution between consumption and leisure and the real wage—referred to as the wage mark-up—is given by $\phi\hat{L}_t - \frac{h}{1-h}\hat{C}_{t-1} + \frac{1}{1-h}\hat{C}_t - \hat{W}_t$.

Non-ICT and ICT investment dynamics are described by equations (11) and (12), respectively. The parameters ξ and ξ^{ICT} represent the elasticities of the investment adjustment costs, while $\hat{Q}_t$ and $\hat{Q}_t^{ICT}$ are the Tobin's Q for each capital type. Investment responds gradually to its driving forces due to these adjustment costs. The shocks e_t^x and $e_t^{x^{ICT}}$ capture variations in the marginal efficiency of investment, interpreted as IST shocks.

The laws of motion for non-ICT and ICT capital are defined by equations (13) and (14), respectively. Capital accumulates according to standard dynamics, with δ and δ^{ICT} denoting the depreciation rates of each capital type.

Finally, the value of non-ICT and ICT capital today, equations (15) and (16), is positively influenced by its expected future value and the expected real rental rate, while it is negatively affected by the anticipated real interest rate. The risk premium disturbance is represented by variable e_t^b. This shock is meant to broadly capture frictions in the financial markets, by representing a wedge between the policy rate and the return on household assets. A positive shock raises the required asset return, curbing current consumption, while also increasing capital costs and lowering the value of capital and investment. Differently from the discount factor shock, Smets and Wouters (2007) emphasize that this shock generates the observed co-movement between consumption and investment.

2.2.2 Firms

This subsection presents the equilibrium conditions associated with firms' behavior, including production, factor demand, and price-setting decisions. These conditions are derived from firms' profit maximization under nominal and real rigidities:

$$\hat{Y}_t = e_t^a + \alpha \hat{K}_t + (1-\alpha)\hat{E}_t, \tag{17}$$

$$\hat{E}_t = \alpha_{ICT} \left(\frac{K^{ICT}}{E}\right)^{\frac{\eta-1}{\eta}} \hat{K}_t^{ICT} + \alpha_L \left(\frac{L}{E}\right)^{\frac{\eta-1}{\eta}} \hat{L}_t, \tag{18}$$

$$\hat{R}_t^{ICT} = -\frac{1}{\eta}\left(\hat{K}_t^{ICT} - \hat{L}_t\right) + \hat{W}_t, \tag{19}$$

$$\hat{R}_t^k = -\left(\hat{K}_t - \frac{\eta-1}{\eta}\hat{E}_t - \frac{1}{\eta}\hat{K}_t^{ICT}\right) + \hat{R}_t^{ICT}, \tag{20}$$

$$\begin{aligned} \hat{\Pi}_t =& \frac{\sigma_{pi}}{1+\sigma_{pi}\beta}\hat{\Pi}_{t-1} + \frac{\beta}{1+\sigma_{pi}\beta} E_t\left[\hat{\Pi}_{t+1}\right] \\ &- \frac{(1-\beta\sigma_p)(1-\sigma_p)}{(1+\sigma_{pi}\beta)\sigma_p}\left[\hat{Y}_t - \frac{\eta-1}{\eta}\hat{E}_t - \frac{1}{\eta}\hat{L}_t - \hat{W}_t\right] + e_t^p. \end{aligned} \tag{21}$$

Equations (17) and (18) are the log-linearized versions of the production function and the CES aggregator, originally defined by equations (4) and (5) in Subsection 2.1.

Equation (19) is derived by combining firms' optimality conditions with respect to labor and ICT capital, as given in equations (7) and (8). It expresses the rental rate of ICT capital as a function of the relative use of ICT capital to labor and the real wage.

Similarly, equation (20) results from combining the optimality conditions for non-ICT capital and ICT capital, equations (6) and (8), and reflects how the rental rate of non-ICT capital responds to changes in the ratio between traditional and ICT capital, relative to the composite input, and adjusts with the return on ICT capital.

Finally, equation (21) represents the New Keynesian Phillips curve, which describes inflation dynamics under Calvo pricing with indexation. Parameter σ_p governs the degree of price stickiness, while σ_{pi} captures the extent of price indexation to past inflation. Inflation responds to expected and lagged inflation, the marginal cost—expressed as a function of output, the CES input, labor, and the real wage—and a price mark-up shock, e_t^p.

2.2.3 Central Bank and Equilibrium

The central bank follows a Taylor rule:

$$\begin{aligned}\hat{R}_t^n = {}& \rho_i \hat{R}_{t-1}^n + (1-\rho_i)\left[\rho_\pi \hat{\Pi}_t + \rho_y\left(\hat{Y}_t - \hat{Y}_t^*\right)\right] \\ & + \rho_{\Delta y}\left[\hat{Y}_t - \hat{Y}_t^* - \left(\hat{Y}_{t-1} - \hat{Y}_{t-1}^*\right)\right] + e_t^r,\end{aligned} \tag{22}$$

where ρ_i, ρ_π, ρ_y and $\rho_{\Delta y}$ are policy parameters governing interest-rate smoothing, the responsiveness of the nominal interest rate to inflation deviations, to the output gap and to changes in the output gap, respectively. The term $\hat{Y}_t^*$ represents the level of potential output. This measure is obtained in a parallel model featuring flexible prices and wages without the two mark-up shocks. Such a model is also used to compute the natural rate of interest, R_t^*, as in Woodford (2003). Variable e_t^r is a monetary policy shock.

The resource constraint completes the model:

$$\hat{Y}_t = \frac{C}{Y}\hat{C}_t + \frac{I}{Y}\hat{I}_t + \frac{I^{ICT}}{Y}\hat{I}_t^{ICT} + \frac{G}{Y}e_t^g, \tag{23}$$

where G_t is government spending and e_t^g is a government spending shock.[2]

The eight exogenous variables, e_t^κ, with $\kappa = \{a, b, g, p, r, x, x^{ICT}, w\}$ follow AR(1) processes, with autoregressive parameters ρ_κ and i.i.d. exogenous shocks ε^κ with zero mean and standard deviations σ_κ, except for the price and wage mark up shocks, which follow ARMA(1,1) processes with MA coefficients μ_p and μ_w as standard in the literature.[3]

3 Estimation

This section reports the details and results of the Bayesian estimation. Subsection 3.1 presents the data and the measurement equations, Subsection 3.2 discusses the calibrated parameters and the posterior estimates, Subsection 3.3 describes the role of shocks in the variance of key macroeconomic variables, and Subsection 3.4 analyzes the evolution of the model-implied natural rate of interest.

[2] The model abstracts from explicit debt dynamics, thus shutting the debt-supply channel for interest rates (see, e.g., Mian et al., 2022; Campos et al., 2024). Although convenience yields are not explicitly modeled, they are partly captured by the risk-premium shock. In future research, fiscal tools (grants, R&D credits, digital infrastructure) could be incorporated to model their impact on ICT investment, with financing feeding through to debt issuance and the natural rate.

[3] In principle, ICT and non-ICT IST shocks could be correlated. Yet, when an alternative model allowing for such correlation is estimated, the resulting correlation is found to be negligible and does not improve the marginal log-likelihood.

3.1 Data and Measurement Equations

The model is estimated using quarterly data from 1980Q1 to 2024Q2. The starting date corresponds to a quarter when the ratio of ICT investment over GDP is above 2 percent so that the sample includes a period during which ICT investment constitutes a non-negligible share of economic activity. This allows for a meaningful analysis of its macroeconomic effects while avoiding potential distortions associated with the very early diffusion phase of ICT technologies. In addition, this sample ensures that this ratio evolves within a relatively narrow and gradually increasing range—reaching about 4 per cent by the end of the sample—which is beneficial for the Bayesian estimation of the parameters of interest. For the sake of comparison, estimates are also computed over a more recent sample, from 2005Q1 to 2024Q2, and over a sample that excludes the COVID years, from 1980Q1 to 2019Q4 (Appendix B).

The observable variables include: (i) real GDP, (ii) real non-ICT investment, (iii) real ICT investment, (iv) real private consumption, (v) hours worked, (vi) the GDP deflator, (vii) the real wage, and (viii) the shadow nominal interest rate. These variables align with the canonical Smets and Wouters (2007) observables, except for distinguishing between non-ICT and ICT investment and replacing the federal funds rate with the shadow nominal interest rate. This latter choice allows standard Bayesian estimation techniques to be applied even when the nominal interest rate is at the zero lower bound—as it was for part of this sample—and when unconventional monetary policies are in use, as in Melina and Villa (2023).

Except for the shadow nominal interest rate, which is borrowed from Wu and Xia (2016), the data are extracted from the ALFRED database.[4] All series are seasonally adjusted by their sources. GDP, consumption, non-ICT investment, ICT investment, the real wage and the GDP deflator are logged and expressed in first differences. Consistently, the shadow nominal interest rate is expressed in quarterly terms. Finally, hours worked are logged and demeaned. More granular details on data sources and transformations are reported in Appendix A.

The following set of measurement equations show the link between the observables in the dataset (denoted by ^{o}) and the endogenous variables of the DSGE model:

[4] The shadow nominal interest rate is complemented by the federal funds rate prior to 1990Q1 and after 2023Q2.

$$
\begin{bmatrix} \Delta Y_t^o \\ \Delta C_t^o \\ \Delta I_t^o \\ \Delta I_t^{ICT,o} \\ \Delta W_t^o \\ L_t^o \\ \pi_t^o \\ r_t^{n,o} \end{bmatrix} = \begin{bmatrix} \gamma \\ \gamma \\ \gamma \\ \gamma \\ \gamma \\ \bar{L} \\ \bar{\pi} \\ \bar{r}^n \end{bmatrix} + \begin{bmatrix} \hat{Y}_t - \hat{Y}_{t-1} \\ \hat{C}_t - \hat{C}_{t-1} \\ \hat{I}_t - \hat{I}_{t-1} \\ \hat{I}_t^{ICT} - \hat{I}_{t-1}^{ICT} \\ \hat{W}_t - \hat{W}_{t-1} \\ \hat{L}_t \\ \hat{\Pi}_t \\ \hat{R}_t^n \end{bmatrix} \tag{24}
$$

where γ is the common quarterly trend growth rate of GDP, consumption, non-ICT investment, ICT investment and wages; $\bar{L}$ is the average of hours worked; and $\bar{\pi}$ and $\bar{r}^n$ are the steady states of the quarterly inflation rate, and the interest rate, respectively.

3.2 Calibration, Priors and Posteriors

The parameters that cannot be identified in the data and are related to steady-state values of endogenous variables are calibrated, as shown in Table 1. The time period in the model corresponds to one quarter in the data.

Most parameters are assigned very standard values taken from the DSGE literature: the discount factor, β, is set to 0.99 to target an annual risk-free rate of 4 percent; the non-ICT capital depreciation rate, δ, is set to 0.025, corresponding to an annual depreciation rate of 10 percent; the labor share, S^L, is equal to two thirds of income; the elasticities of substitution in goods and labor markets, ε and ε_w, are equal to 6 in order to target a gross steady-state mark-up of 1.20. Finally, the government spending to GDP ratio, g_y, is set equal to 20 percent.

The remaining two parameters pertain to ICT investment. The ICT capital depreciation rate, δ^{ICT}, is calibrated at 0.057 in line with BEA tables on fixed assets,[5] computed as a weighted average of the depreciation rates of computers, communication equipment and software, using their shares in total ICT investment during the estimation period as weights. The ICT capital share, $S^{k^{ICT}}$, is set to 0.067, which corresponds to 20 percent of the total capital share (which is equal to 0.33), in line with the average share of ICT investment in total investment over the sample period.

The mean of the estimated parameters is computed with two chains of the Metropolis-Hastings algorithm, each with a sample of 500,000 draws. Table 2 reports information on the parameters' prior distribution and their posterior mean along with 95 percent probability intervals in parentheses.

[5] These tables are available at `https://www.bea.gov/itable/fixed-assets`.

Table 1: Calibrated Parameters

Parameters		Value	Steady-state target/reference
Discount factor	β	0.99	4% risk-free real rate p.a. (standard)
Non-ICT capital depr. rate	δ	0.025	10% non-ICT depreciation rate p.a. (standard)
Labor share	S^L	0.67	labour share 2/3 of income (standard)
Elasticity of substitution goods	ε	6	mark-up of 20%(Christiano et al., 2014)
Elasticity of substitution labor	ε_w	6	mark-up of 20%(Christiano et al., 2014)
Government spending to GDP	g_y	0.2	NIPA tables data
ICT capital depr. rate	δ^{ICT}	0.057	BEA tables on fixed assets
ICT capital share	$S^{k^{ICT}}$	0.067	BEA table on share of ICT inv. over total inv.

The locations of the prior means correspond to a large extent to those in previous studies on the U.S. economy, for example, Smets and Wouters (2007). The Inverse Gamma (IG) distribution is used for the standard deviation of the shocks and a loose prior with 2 degrees of freedom is adopted. The Beta distribution is used for all parameters bounded between 0 and 1. For the unbounded parameters the Normal distribution is adopted. In addition, the prior means of the constants in the measurement equations are set equal to average values in the dataset. As regards the parameters related to ICT investment, the prior mean of ICT investment adjustment costs is set to be equal to that of non-ICT investment. The prior distribution of the parameter measuring the elasticity of substitution between labor and ICT capital is on purpose loose. In fact, as shown in Figure 1, a prior mean of 1 and a standard deviation of 0.50 enable the prior distribution to encompass a range of values below or above unity, i.e. implying gross factor complementarity or substitutability, respectively.

Posterior estimates of standard parameters are broadly in line with previous studies. It is worth noting that the Calvo parameter for price stickiness is higher than that for wage stickiness. However, the difference is small, considering that both their values imply that firms adjust both prices and wages about every year and a half. The model exhibits low habit persistence, with a mean estimate of 0.21. The impulse responses of output and consumption (Figure 5 in Subsection 4.2), though, show a high degree of smoothness, implying that the model is able to generate endogenous persistence of these variables instead of relying entirely on additional features such as habit persistence. The estimated value of the Frisch elasticity of labor supply, $1/\phi$, implies a relatively low adjustment of labor supply to wage changes. As regards the Taylor rule parameters, in line with many other studies, estimates capture nominal interest rate inertia and that, during this period which includes the Great Moderation, monetary policy was aggressive on inflation, with an estimated coefficient of 1.92. Similarly to Smets and Wouters (2007), there is evidence of a weak response to the output gap, with an estimated coefficient of 0.04, and of a stronger response to changes in

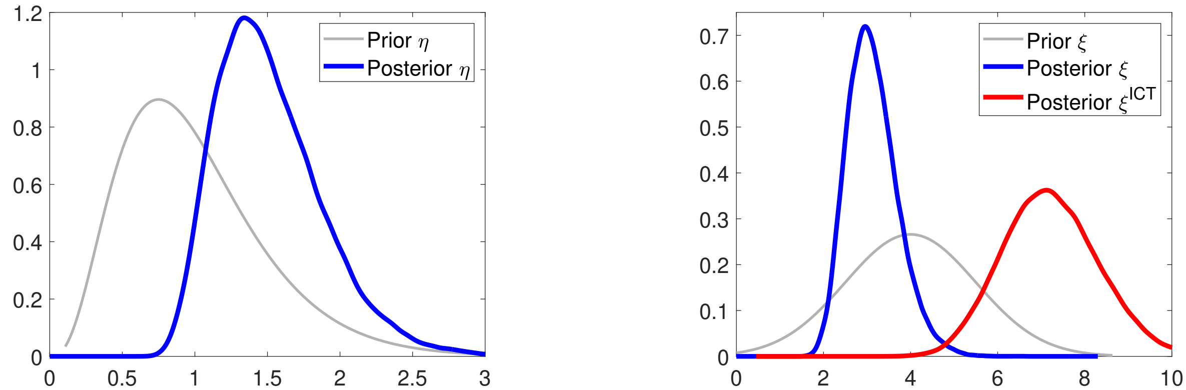
Table 2: Prior-Posterior Distributions and Posterior Means of Parameters (95 Percent Credible Intervals in Square Brackets)

		Prior distribution			Posterior mean
Parameters		Distr	Mean	Std./df	
Structural parameters					
Calvo prices	σ_p	Beta	0.5	0.05	0.85 [0.83;0.88]
Calvo wages	σ_w	Beta	0.5	0.05	0.81 [0.76;0.86]
Price indexation	σ_{pi}	Beta	0.5	0.15	0.20 [0.08;0.32]
Wage indexation	σ_{wi}	Beta	0.5	0.15	0.68 [0.49;0.87]
Habit parameter	h	Beta	0.7	0.1	0.21 [0.16;0.26]
Inv. of Frisch elasticity	ϕ	Gamma	2.00	0.75	2.91 [2.33;3.50]
Non-ICT Inv. adj. costs	ξ	Normal	4	0.5	3.12 [2.18;4.02]
ICT Inv. adj. costs	ξ^{ICT}	Normal	4	0.5	7.20 [5.39;8.99]
Elasticity of substitution	η	Gamma	1.0	0.5	1.51 [0.94;2.07]
Inflation - Taylor rule	ρ_π	Normal	1.7	0.15	1.92 [1.73;2.11]
Output - Taylor rule	ρ_y	Gamma	0.125	0.05	0.04 [0.02;0.06]
Taylor rule changes in y	ρ_{Δ_y}	Normal	0.0625	0.05	0.16 [0.12;0.21]
Taylor rule smoothing	ρ_i	Beta	0.75	0.1	0.81 [0.78;0.85]
Constants					
Trend	$\bar{\gamma}$	Normal	0.4	0.2	0.34 [0.29;0.38]
Inflation	$\bar{\pi}$	Gamma	0.5	0.1	0.59 [0.47;0.72]
Interest rate	$\bar{R}$	Normal	0.8	0.2	0.94 [0.72;1.15]
Hours	$\bar{\ell}$	Normal	0.0	2.0	0.06 [-0.27;0.39]
Exogenous processes					
Technology	ρ_a	Beta	0.5	0.2	0.97 [0.96;0.99]
	σ_a	IG	0.1	2	0.58 [0.52;0.63]
Price mark-up	ρ_p	Beta	0.5	0.2	0.99 [0.97;1.00]
	σ_p	IG	0.1	2	0.13 [0.10;0.15]
	μ_p	Beta	0.5	0.2	0.79 [0.70;0.88]
Wage mark-up	ρ_w	Beta	0.5	0.2	0.48 [0.17;0.78]
	σ_w	IG	0.1	2	0.56 [0.49;0.62]
	μ_w	Beta	0.5	0.2	0.50 [0.21;0.78]
ICT Inv. specific	$\rho_{x^{ICT}}$	Beta	0.5	0.2	0.98 [0.97;1.00]
	$\sigma_{x^{ICT}}$	IG	0.1	2	0.45 [0.33;0.57]
Non-ICT Inv. specific	ρ_x	Beta	0.5	0.2	0.98 [0.97;1.00]
	σ_x	IG	0.1	2	0.43 [0.34;0.53]
Preference	ρ_b	Beta	0.5	0.2	0.88 [0.84;0.92]
	σ_b	IG	0.1	2	0.27 [0.21;0.32]
Monetary policy	ρ_m	Beta	0.5	0.2	0.17 [0.06;0.28]
	σ_m	IG	0.1	2	0.27 [0.23;0.30]
Government spending	ρ_g	Beta	0.5	0.2	0.92 [0.89;0.95]
	σ_g	IG	0.1	2	2.66 [2.42;2.90]

Figure 1: Prior and Posterior Distributions of Key Estimated Parameters

(a) Elasticity of Substitution between Labor and ICT Capital, η

(b) Adjustment Costs for Non-ICT Investment, ξ, and ICT Investment, ξ^{ICT}



the output gap, with a posterior estimate of 0.16. Turning to the exogenous shock processes, all shocks are very persistent except for the wage mark-up and the monetary policy shocks.

Figure 1 shows the prior and posterior densities of the elasticity of substitution between ICT capital and labor, η, and of the ICT and non-ICT investment adjustment cost parameters, ξ^{ICT} and ξ, respectively. All three parameters are well identified by the data, as evidenced by posterior distributions markedly departing from their priors. This is especially important for the elasticity of substitution. Although its 95 percent credible interval does not rule out the Cobb-Douglas case ($\eta = 1$), the posterior mean of $\eta = 1.51$ and a distribution concentrated around values above unity—despite a loose prior—favor moderate gross substitutability. This result contributes to the ongoing debate about the substitutability versus complementarity between labor and ICT capital, particularly in the context of AI diffusion (Pizzinelli et al., 2023; Cazzaniga et al., 2024). Importantly, the estimated elasticity reflects an economy-wide average over a period in which AI adoption was still not prominent. This motivates the counterfactual analysis presented later in the paper, which explores how different assumptions about η affect the transmission of ICT-specific shocks.

Turning to the adjustment cost parameters, the posterior distributions for ϕ_{ICT} and ϕ diverge significantly from their shared prior. The mass of the posterior for ϕ_{ICT} shifts toward much higher values, with an estimated mean of 7.20, whereas that for ϕ moves toward lower values, with a mean of 3.12. The higher adjustment costs for ICT investment likely reflect the substantial complementary inputs required to adopt new technologies—such as organizational restructuring, employee training, and process reengineering. These findings are in line with recent studies emphasizing the persistent frictions and firm-level heterogeneity associated with ICT adoption, reinforcing the view that ICT is a general-purpose technology with high implementation costs (e.g., DeStefano et al., 2025).

Estimates for a more recent period, 2000Q1-2024Q2, are reported in Table B.1 of Appendix B. Most of the deep parameters are very similar, with overlapping probability bands between the full sample and the recent sample. The standard deviations and persistence parameters of shocks vary to a larger extent.

Because the full sample includes the COVID years—which introduced unusual volatility into the macro time series—Appendix B also reports estimates for a pre-COVID subsample, 1980Q1-2019Q4. Most estimated parameters are comparable across the two samples, with the pre-COVID posterior means that lie within the full-sample credible intervals.[6] Notably, the ICT-specific parameters used in the simulations later in the paper are very similar across the two samples.

Impulse response functions (IRFs) to all shocks are reported in Figure B.1 of Appendix B. The dynamics of the IRFs of output, inflation and the monetary policy rate have the expected sign and shape, as well as relatively narrow confidence bands (at a 95-percent confidence level). While the shocks to ICT and non-ICT IST, risk premium, government spending and monetary policy behave as demand shocks, the responses to shocks to TFP, price and wage mark-up display dynamics in line with a supply shock.

3.3 Variance Decomposition

The estimated model can be used to assess the relative importance of shocks in explaining the fluctuations in output, inflation and the natural rate of interest. Table 3 reports the conditional variance decomposition. At a 1-year horizon demand shocks account for two thirds of output fluctuations, with risk premium shocks playing the largest role. The importance of ICT IST shocks increases over time, explaining 15.5 percent of output movements in the longer run. In contrast, the role of government and monetary policy shocks decay over time. Moreover, ICT IST shocks play a larger role for the variance of output than that of inflation. While, on impact, supply shocks—specifically the price mark-up shock—play a dominant role in affecting inflation dynamics, in the medium-to-long run demand disturbances are its main drivers.

Fluctuations in the natural rate of interest are driven primarily by the risk premium shocks both in the short and in the medium-to-long term, in line with the results by Gerali

[6] The main exceptions are the volatility and persistence of the monetary-policy shock; the volatility of the wage mark-up shock; habit formation; the non-ICT investment adjustment cost; price stickiness; and the parameters governing the monetary-policy response to the output gap. Including COVID quarters intuitively lowers the estimated habit persistence and the non-ICT investment adjustment cost while increasing the volatility of the monetary policy and wage mark-up shocks.

Table 3: Conditional Variance Decomposition for Selected Variables (Percent) at Various Time Horizons (Quarters)

	Structural shocks							
Horizon	TFP	Price mark-up	Wage mark-up	Risk premium	Non-ICT inv. specific	ICT inv. specific	Gov. spend.	Mon. policy
				Output				
4	19.1	10.0	4.3	37.0	1.4	1.4	3.9	23.1
20	22.9	21.8	5.6	17.7	14.8	10.0	0.7	6.4
40	19.5	21.5	3.6	10.8	25.2	15.5	0.4	3.6
				Inflation				
4	5.1	34.6	12.6	28.7	7.4	1.5	0.8	9.3
20	3.9	25.5	9.8	32.7	15.3	2.9	0.9	8.9
40	4.1	26.7	9.5	31.8	15.4	2.9	0.9	8.7
				Natural rate of interest				
4	19.1	*	*	51.0	11.9	1.3	16.7	*
20	11.1	*	*	61.6	14.7	2.5	10.1	*
40	10.8	*	*	59.8	16.8	2.9	9.8	*

Notes. * The price mark-up, wage mark-up and the monetary policy shocks have zero effects on the natural rate of interest by construction.

et al. (2018).[7] TFP shocks are more relevant in the short run and their importance decays over time, contrary to the ICT and non-ICT IST shocks, the importance of which increases over time. Price mark-up, wage mark-up and monetary policy shocks have zero contributions by construction.

The drivers of the natural rate are debated in the literature. Some papers argue that it depends exclusively on structural factors, such as productivity growth and demographics (see, e.g. Del Negro et al., 2017; Gagnon et al., 2021). More recently, Nuño (2025) has emphasized the relevance of precautionary savings motives for the dynamics of the natural rate. The results on the importance of the risk premium shock in both the variance decomposition (Table 3) and the historical decomposition (Figure 3, discussed in the following subsection) confirm that shifts in households' preferences on savings are indeed relevant for explaining movements in the natural rate of interest.

3.4 Model-Implied Natural Rate of Interest

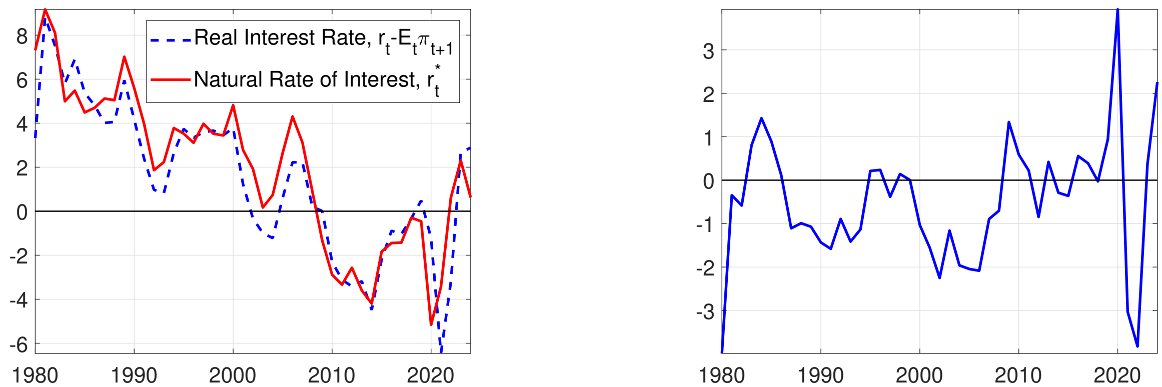
The model-implied natural rate of interest—defined as the mean of the marginal posterior distribution of the smoothed natural rate—broadly aligns with previous findings in the DSGE

[7]The risk premium shock may capture households' preference for safe assets, either due to increased riskiness in the economy or aging of the population.

Figure 2: Model-Implied Natural Rate of Interest

(a) Natural Rate of Interest, r_t^*, and Real Interest Rate, $r_t - E_t[\pi_{t+1}^*]$

(b) Gap between Real Interest Rate and Natural Rate of Interest, $r_t - E_t[\pi_{t+1}^*] - r_t^*$

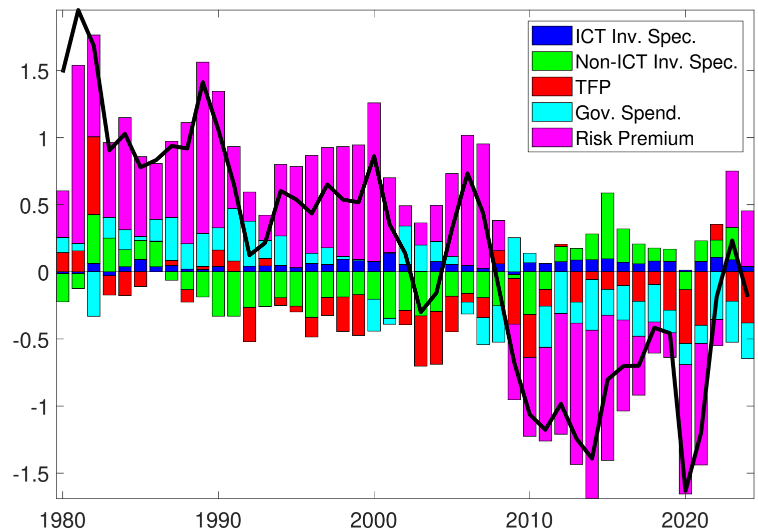


literature (Edge et al., 2008; Justiniano and Primiceri, 2010; Barsky et al., 2014; Cúrdia et al., 2015; Del Negro et al., 2017; Neri and Gerali, 2019; Martínez-García, 2021). Across the periods covered by these studies, the estimated levels and turning points are comparable. The main innovation of the present estimate lies in the use of more recent data within a framework that explicitly distinguishes between ICT and non-ICT investment.

As shown in Figure 2(a), the natural rate reached a peak of 8.4 percent in 1981, then followed a persistent downward trend interspersed with cyclical fluctuations of varying magnitudes. This trend continued into negative territory—hitting -5.2 percent in 2020—before moving back above zero and reaching an estimated 2.3 percent in 2023. Consistent with most DSGE-based approaches, the estimated natural rate represents a short-run equilibrium concept and is therefore more volatile than medium-term estimates derived from semi-structural or statistical models (Berger et al., 2023; Laubach and Williams, 2003; Holston et al., 2017, 2023; Barrett et al., 2023). However, these medium-term approaches are not immune to limitations. As emphasized by Wieland (2018), these estimates are often highly uncertain and have tended to hover near zero.

Figure 2(b) illustrates the resulting interest rate gap, defined as the difference between the model-based real interest rate (the nominal rate adjusted for expected inflation) and the model-implied natural rate. Periods in which the interest rate gap is negative indicate that the real rate falls below its equilibrium, suggesting an accommodative monetary policy stance; conversely, positive gaps signal a tighter policy posture. Historically, the gap turned positive during the early 1980s, aligning with a policy environment focused on containing high inflation. In more recent decades, episodes of negative gaps—including those preceding and following the global financial crisis and during the initial phases of the COVID-19 pandemic—

Figure 3: Historical Shock Decomposition of the Model-Implied Natural Rate of Interest



Notes: The bold line represents the annual average of quarterly deviations of the model-implied natural rate of interest from its steady-state value. Colored bars represent the contributions of structural shocks to these deviations as indicated in the legend. Price mark-up, wage mark-up and monetary policy shocks have zero contributions by construction.

have mirrored efforts to stimulate demand. The transition to a positive gap in the post-pandemic period reflects the shift toward tightening, prompted by a resurgence in inflationary pressures.

Figure 3 decomposes the estimated deviations of the natural rate of interest from its steady-state level across structural shocks.[8] Several insights emerge. First, risk premium shocks account for a sizable share of deviations, with negative contributions during periods associated with heightened uncertainty. This finding is consistent with the view that a growing preference for safe assets, whether driven by increased economic risk or an aging population, places downward pressure on the equilibrium rate (Del Negro et al., 2017; Jones, 2023).[9]

Second, TFP shocks display variability, partially offsetting or amplifying the effects of risk premium shocks. In the mid 1980s, TFP contributions were negative likely due to weaker productivity after the oil crises. By the early 1990s, contributions turned positive with the rise of information technology. The early 2000s dot-com collapse and the aftermath of the

[8]Price mark-up, wage mark-up and monetary policy shocks have a zero contribution by construction.

[9]The model allows for a significant contribution of the risk premium shock in the variance of the natural rate of interest, given that that the shock appears in the equations directly governing the dynamics of this rate, that is, the flexible-price/wage version of equations (9), (15) and (16).

global financial crisis saw consistently negative TFP contributions, reflecting technological slowdown.

Third, although ICT investment has steadily grown in importance, it remains a smaller fraction of total investment relative to its non-ICT counterpart, helping to explain why ICT IST shocks appear modest. Yet, their contribution is consistently positive throughout.

Fourth, the larger non-ICT component of investment leads to more sizable contributions from non-ICT IST shocks, which bolstered the natural rate in the early 1980s amid robust capital deepening, turned negative in the 1990s and early 2000s as manufacturing offshored and slowed, and returned to a positive contribution in the late 2010s alongside renewed capital spending, for example in sectors such as advanced manufacturing, automotive, and aerospace.

Finally, government spending shocks show more sporadic effects, likely reflecting their role as a residual category in a closed-economy DSGE framework, capturing disturbances not accounted for by other structural disturbances.[10]

4 The Effects of ICT Investment-Specific Technology Shocks

This section focuses on how AI-driven ICT capital influences aggregate output, inflation, and the natural rate of interest. Subsection 4.1 provides a comparison between ICT and non-ICT IST shocks, while Subsection 4.2 examines the role of complementarity between ICT capital and labor in the transmission mechanism of ICT IST shocks.

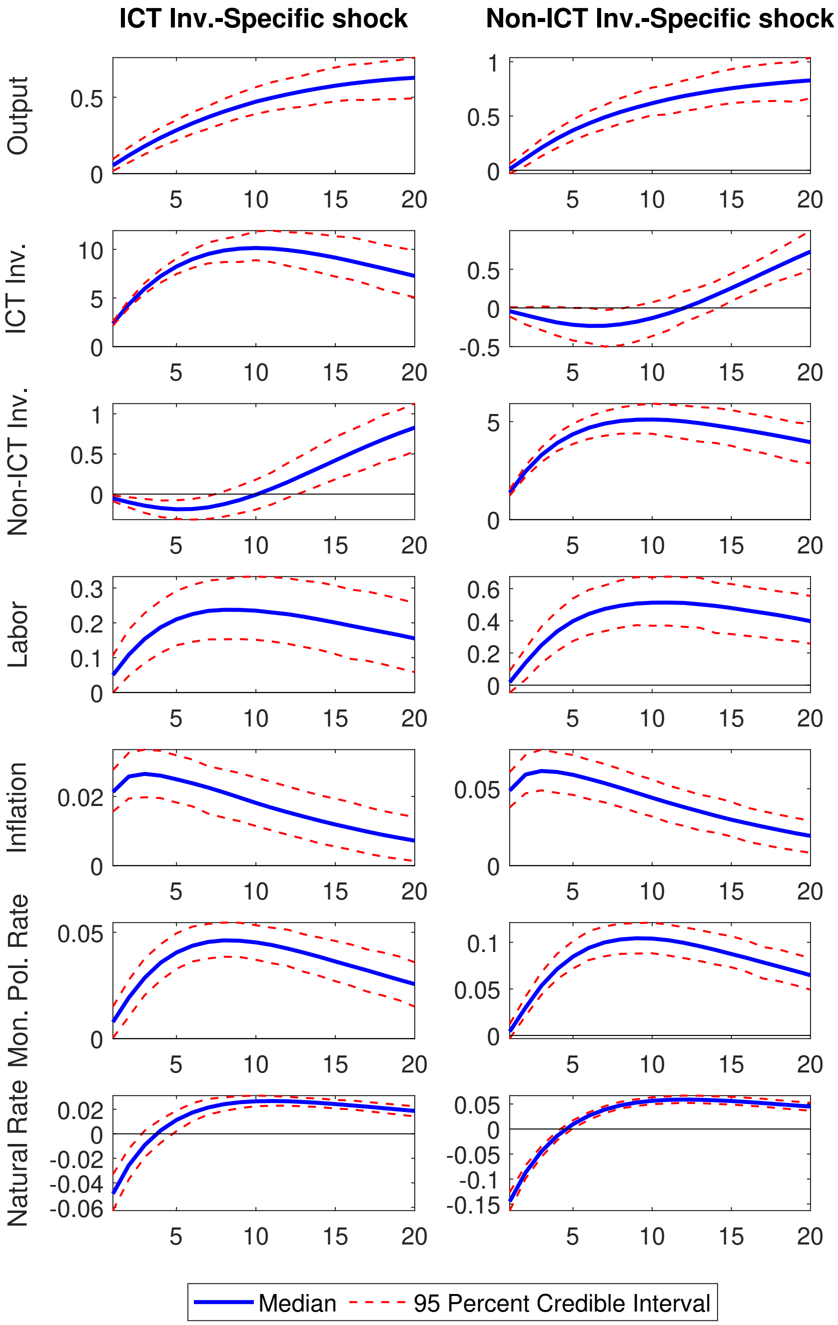
4.1 Comparing ICT and Non-ICT Shocks

A positive IST shock reduces the relative price of investment goods, inducing firms to expand investment to accumulate productive capacity for future periods. Figure 4 presents the Bayesian impulse responses of selected macroeconomic variables to positive ICT and non-ICT IST shocks, each of a size equal to their estimated standard deviations. All responses are reported over a five-year horizon (20 quarters) as percent deviations from the steady state, together with 95 percent credible intervals.

Under both ICT and non-ICT shocks, the responses of their respective investment exhibit a pronounced hump-shaped pattern due to the presence of investment adjustment costs.

[10]For the sake of completeness, Figure B.2 in Appendix B reports the historical shock decomposition of GDP growth, inflation rate, non-ICT and ICT investment growth. Just like in the historical decomposition of the natural rate, the ICT IST shock has a positive but small contribution to GDP growth and the inflation rate. As expected, the contribution is almost negligible in the fluctuations of non-ICT investment growth and very large in those of ICT investment growth.

Figure 4: Bayesian Impulse Responses of Selected Macroeconomic Variables to ICT and non-ICT Investment-Specific Technology Shocks



Notes: The shock size is equal to the estimated standard deviation. The responses of endogenous variables, reported on the Y-axes, are shown as percent deviations from their respective steady-state values. The time horizon on X-axes is measured in quarters. Dashed lines represent the 95 percent credible interval.

Following a positive ICT-specific shock, ICT investment rises, whereas non-ICT investment initially declines as resources are reallocated toward ICT. However, the initial decline of non-ICT investment is quantitatively small relative to the expansion in ICT investment. Over a five-year horizon, both types of investment lie above their respective steady states, reflecting that the new capital of a given type boosts the marginal product of the other type of capital. A parallel mechanism operates under a non-ICT IST shock, with non-ICT investment rising initially and ICT investment responding negatively in the short run but ultimately remaining above steady state after the first 3-4 years. Labor also rises in a hump-shaped fashion in the wake of both shocks, due to an increase in labor demand to meet higher production in an environment of gross substitutability. As the stock of each type of capital accumulates, the marginal product of labor increases.

IST shocks behave much like demand shocks by raising both real output and inflation. Given the high persistence estimated for these shocks—and the persistent responses of both types of investment and labor—output remains on an increasing trajectory above steady state for at least five years. Inflation also follows a hump-shaped path, peaking relatively quickly and subsequently declining over the medium term; nonetheless, its credible band remains above zero for the five-year horizon.

From a quantitative perspective, a typical ICT IST shock generates a peak increase in ICT investment of almost 10 percent, with output rising by around 0.6 percent over a five-year horizon. Inflation climbs by around 0.025 percentage points (10 basis points annually) in the first year before gradually easing. In contrast, a typical non-ICT IST shock triggers a 5 percent peak increase in non-ICT investment. Although smaller in its effect on investment, the larger weight of non-ICT capital in the overall economy leads to a larger medium-term output gain of about 0.8 percent and a higher inflation peak of around 0.06 percentage points (24 basis points annually). Despite the expansion of aggregate demand, the overall increase in inflation remains modest because of the monetary policy tightening and the increase in aggregate supply—determined by the accumulation of both ICT and non-ICT capital—that mitigates upward price pressures. More broadly, it is debated whether an AI-related shock should be viewed as a demand or a supply shock (Aldasoro et al., 2024): it can stimulate demand by boosting investment, while also raising supply through productivity gains. In this model, the demand-side channel dominates, yet second-round supply-side effects—stemming from the expansion of productive capacity—still dampen inflationary pressures.

The monetary policy rate tightens in response to higher inflation and output but does so gradually–producing a hump-shaped pattern–because of the estimated inertia in the Taylor rule. In contrast, the natural rate of interest drops initially and then rises persistently above its steady-state level after both ICT and non-ICT shocks. The immediate decline reflects the economy's internal resource-reallocation dynamics: as the relative price of investment goods falls and firms redirect resources toward building capital, households' short-run savings increase (and consumption demand slows, as shown in Figure 5) motivated by future higher returns on investment, which puts downward pressure on the equilibrium real interest rate. Over time, however, the accumulating capital boosts income and aggregate demand sufficiently to drive the natural rate above its steady state.

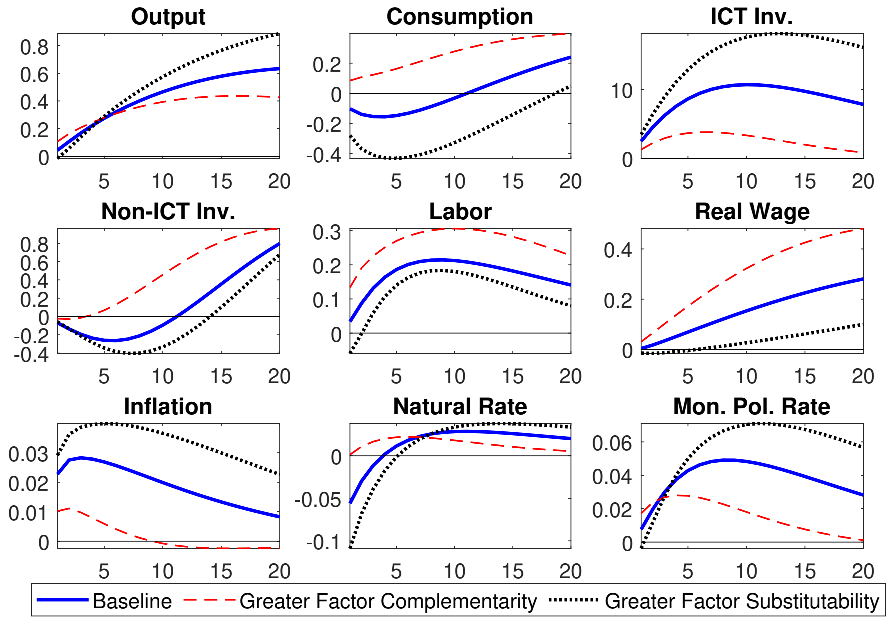
4.2 The Role of the Complementarity between ICT Capital and Labor

Figure 5 reports impulse responses to the ICT IST shock under three alternative elasticities of substitution between the two inputs. The solid blue line depicts the baseline calibration, with the elasticity (η) fixed at its estimated posterior mean of 1.51. The dashed red line is obtained with a lower η of 0.5, representing stronger factor complementarity, where boosting ICT capital requires a relatively stronger increase in labor. The dotted black is generated by raising η to 3, illustrating stronger factor substitutability, where ICT capital can more readily stand in for labor. These numbers are illustrative to gauge how sensitive the results are to the degree to which labor can be replaced with ICT capital.

With greater factor substitutability, ICT capital can more readily replace labor, so its marginal product surges to a larger extent after the shock. Firms therefore channel resources more aggressively into ICT investment, which peaks at 18.1 percent above steady state—more than two thirds higher than in the baseline—while non-ICT investment experiences a deeper short-run dip before entering positive territory after the first three years. The mirror image emerges when ICT and labor are more complementary: the same shock elicits a much more muted ICT-investment response (a peak of less than 4 percent) but spurs a rise in non-ICT investment that reaches almost 1 percent after five years.

Output inherits these patterns. When ICT capital can readily substitute for labor, the resulting capital deepening lifts output to more than 0.8 percent above steady state after five years, whereas stronger complementarity caps the medium-term gain at about 0.4 percent. Labor-market responses move in the opposite direction. Complementarity raises the marginal product of labor to a larger extent, drawing more hours into production and pushing real wages well above their baseline path; high substitutability, by contrast, dampens labor demand and wage growth as ICT capital takes over a larger share of production inputs. These divergent wage and employment effects shape household income and consumption: the complementarity scenario turns the baseline's initial consumption dip into a sustained rise, while the substitutability case delivers the strongest consumption dip and its weakest

Figure 5: Impulse Responses of Selected Macroeconomic Variables to an ICT Investment-Specific Technology Shock under Alternative Parametrizations of the Elasticity of Substitution between ICT Capital and Labor



Notes: The shock size is equal to the same estimated standard deviation in all three scenarios. Baseline simulations are obtained with the estimated posterior mean of η equal to 1.51. Greater factor complementarity is achieved with η equal to 0.50, while greater factor substitutability is obtained with η equal to 3.00. The responses of endogenous variables, reported on the Y-axes, are shown as percent deviations from their respective steady-state values. The time horizon on X-axes is measured in quarters.

recovery.

Price dynamics scale with the strength of the shift in aggregate demand due to the investment surge. Inflation peaks at roughly 0.04 percentage points when substitutability is high, at almost 0.03 points in the baseline, and at slightly above 0.01 points under more complementarity.

The natural rate of interest tracks the way the shock reshuffles consumption versus saving across scenarios. When ICT capital can readily substitute for labor, the high marginal product of ICT capital makes consumption contract initially because households channel the freed-up income into savings. The extra savings push the natural rate down by roughly 0.1 percentage point before a stronger rebound sets in once higher future earnings materialize. The baseline shows the same pattern on a smaller scale. Under strong factor complementarity, consumption rises from the outset; the natural rate therefore hovers at or slightly above steady state throughout, erasing the initial dip and curbing the subsequent overshoot. In short, the depth of the natural-rate trough and the height of its rebound scale directly with the temporary shift of income from consumption to saving induced by the shock.

5 Scenarios for ICT Investment

There is mounting evidence that AI is reshaping corporate technology priorities with a scale and intensity reminiscent of the late-1990s digital boom, raising the prospect of renewed ICT capital deepening with potentially significant macroeconomic implications. This section first computes two scenarios for U.S. ICT investment based on available data and projections. Then, it incorporates these scenarios in the model to assess how the ongoing surge in AI adoption could influence the medium-term trajectories of output, inflation, and the natural rate of interest. Two ICT investment paths are simulated under alternative parameterizations of the elasticity of substitution between ICT capital and labor, to reflect the uncertainty about whether future advances in AI will make ICT capital primarily complement or substitute for labor.

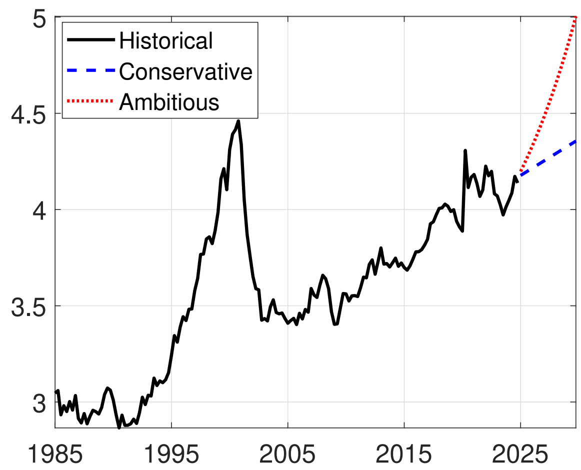
5.1 Evolution of ICT Investment and Scenarios

A striking signal of the AI transformation is the sharp upswing in corporate technology budgets. According to recent survey evidence by Deloitte (Raskovich et al., 2024), in 2024 U.S. firms allocated 7.5 percent of revenue to digital transformation, with 5.4 percent directed specifically through IT departments—nearly double the share from just four years earlier—largely in response to the rapid uptake of generative AI. Global forecasts reinforce this trend: Gartner (2025) projects worldwide IT spending to grow by 9.8 percent in 2025, reaching U.S. $5.6 trillion, with U.S. firms contributing disproportionately to this expansion. Much of the increase is attributed to investments aimed at enabling and operationalizing AI across business functions. These developments point to a renewed phase of ICT capital deepening, making it a timely and relevant focus for macroeconomic analysis.

Figure 6 displays ICT investment as a share of GDP from 1985 to 2024, along with two illustrative projections over a five-year horizon, from 2025 to 2029. The ratio rose steeply during the 1990s, fueled by the rapid diffusion of personal computing, enterprise software, and internet infrastructure. This surge culminated in a peak of approximately 4.5 percent of GDP in 2000, just before the dot-com crash. Afterwards, the share of ICT investment declined, reflecting the unwinding of the tech boom, but eventually settled into a slower but steady upward trend over the following two decades.

From the early 2000s through the mid-2010s, growth in ICT investment was sustained by the gradual expansion of cloud computing, mobile technologies, and digital services. While

Figure 6: ICT Investment Scenarios (Percent of GDP)



Notes: U.S. historical data is taken from the Bureau of Economic Analysis. Scenarios reflect authors' assumptions.

less pronounced than the boom of the 1990s, this steady progress reflected the ongoing integration of digital tools into business operations. More recently, a clear uptick has taken shape since 2023, driven by the rapid adoption of generative AI and a renewed corporate focus on digital transformation. This emerging momentum raises the prospect of a new phase of ICT capital deepening, one that, much like the surge of the 1990s, could significantly influence productivity growth, investment dynamics, and the broader macroeconomic environment.

A conservative scenario extends the linear trend observed since 2003, implying a gradual rise in the ICT-investment-to-GDP ratio to 4.3 percent by 2029. Based on the IMF's World Economic Outlook projections (April 2025) for nominal GDP, this trajectory corresponds to average nominal ICT investment growth of approximately 6.3 percent per year, consistent with gradual increases in AI-related spending, but still below the peak reached in 2000.

An ambitious scenario assumes that the momentum identified by industry analysts translates into a steeper trajectory, pushing the ICT-to-GDP ratio to 5.0 percent by 2029 and thereby surpassing its historical high. Reaching this level would require nominal ICT investment growth of about 9.4 percent annually, capturing the rapid expansion of AI-optimized servers, enterprise software, cloud infrastructure, and advanced data center capabilities.

5.2 Macroeconomic Implications

The two ICT investment paths are fed into the model by simulating sequences of ICT IST shocks that replicate the targeted trajectories for ICT investment in real per capita terms under each scenario. In other words, these simulations are conducted by holding the ICT investment path constant across calibrations and adjusting the ICT IST shocks accordingly.[11] This approach—rather than fixing the shock and allowing investment to vary (as done, e.g., in Figure 5)—ensures that differences in macroeconomic outcomes reflect the structural properties of the model, not variations in the investment response. It also aligns the exercise with the motivating scenarios, which are defined in terms of observable investment trajectories.[12]

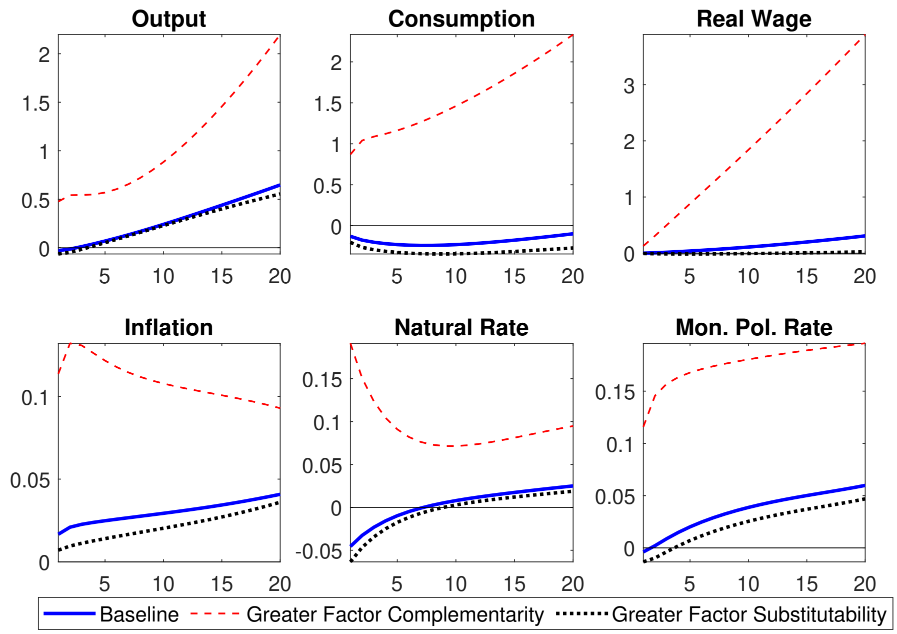
As previously in the paper, three alternative calibrations of the elasticity of substitution between ICT capital and labor are motivated by the uncertainty surrounding the extent to which AI will replace or complement human labor. The baseline scenario adopts a calibration consistent with the posterior mean of the estimated model parameters, including an elasticity of substitution, η, equal to 1.51—suggesting moderate gross substitutability between ICT capital and labor. Two alternative assumptions allow exploring how the labor-technology relationship influences macroeconomic outcomes. The first assumes greater complementarity, with $\eta = 0.50$, reflecting a scenario in which ICT capital tend to enhance, rather than substituting for, labor input. The second assumes greater substitutability, with $\eta = 3.00$, capturing a setting where AI and related technologies can more easily displace human labor.

Figure 7 shows the responses of key macroeconomic variables to the sequence of shocks that reproduce the same conservative path of ICT investment under the three assumptions on η. This exercise is different from the impulse responses reported in Figure 5, where responses are computed in response to the same ICT IST shock. Here, under greater factor complementarity, the macroeconomic effects are markedly larger reflecting the fact that, when ICT capital and labor are strong complements, the same increase in ICT investment requires a proportionally larger increase in the labor input. This acts as a constraint on investment dynamics (as discussed in Section 4.2). Therefore, to deliver the same real per capita ICT investment path as in the baseline, the model requires larger ICT IST shocks in the complementarity case, resulting in a stronger macroeconomic impulse. The opposite occurs under greater factor substitutability. Here, ICT capital can more readily replace

[11] To convert the nominal growth rates into real per capita terms, the scenarios are adjusted using projections of the GDP deflator from the IMF World Economic Outlook and recent historical averages of U.S. population growth. After accounting for expected inflation and demographic trends, the conservative scenario implies real per capita ICT investment growth of approximately 3.3 percent per year, while the ambitious scenario corresponds to a faster pace of 6.4 percent annually.

[12] The literature remains divided on whether AI will deliver a significant boost to total factor productivity (TFP) (Acemoglu, 2025; Aghion and Bunel, 2024), potentially amplifying GDP effects beyond those generated by ICT IST shocks. Given the considerable uncertainty around the magnitude of the TFP impact (Cerutti et al., 2025), the simulations below deliberately exclude any TFP shock. Even without this channel, the resulting GDP effects are substantial. Including a positive TFP shock would shift the results upward but would not alter the qualitative conclusions.

Figure 7: Impulse Responses of Selected Macroeconomic Variables to a Sequence of ICT Investment-Specific Technology Shocks Consistent with a Conservative Path of the ICT-Investment-to-GDP Ratio



Notes: Baseline simulations are obtained with the estimated posterior mean of η equal to 1.51. Greater factor complementarity is achieved with η equal to 0.50, while greater factor substitutability is obtained with η equal to 3.00. The scenario implies a gradual rise in the ICT-investment-to-GDP ratio to 4.3 percent by 2029. Simulations are conducted by holding the ICT investment path constant across calibrations and adjusting the sequence of ICT IST shocks accordingly. The responses of endogenous variables, reported on the Y-axes, are shown as percent deviations from their respective steady-state values. The time horizon on X-axes is measured in quarters where quarter zero represents 2024Q4.

labor, so achieving the same investment path requires smaller IST shocks, leading to more muted aggregate effects.

Table 4 highlights the quantitative differences for GDP growth, inflation and the natural rate across the conservative and aggressive scenarios. Under the baseline calibration, the conservative scenario raises average annual GDP growth over a five-year horizon by 0.13 percentage point, with modest effects on inflation (0.12 percentage point) and a very small impact on the natural rate of interest (0.01 percentage point), in line with the historical shock decomposition (Figure 3). The ambitious scenario produces stronger effects, increasing GDP growth by 0.25 percentage point annually, inflation by 0.23 percentage point, and the natural rate by 0.02 percentage point.

Substantial differences emerge when alternative values of η are considered. Under greater factor complementarity, in the conservative case, GDP growth rises by 0.44 percentage point,

Table 4: Average Annual Impact over a Five-Year Horizon (Percentage Points)

	GDP Growth	Inflation	Nat. Rate
	Conservative Scenario		
Baseline calibration	0.13	0.12	0.01
Greater factor complementarity	0.44	0.44	0.37
Greater factor substitutability	0.11	0.09	-0.02
	Ambitious Scenario		
Baseline calibration	0.25	0.23	0.02
Greater factor complementarity	0.86	0.85	0.73
Greater factor substitutability	0.22	0.17	-0.03

Notes: Baseline simulations are obtained with the estimated posterior mean of η equal to 1.51. Greater factor complementarity is achieved with η equal to 0.50, while greater factor substitutability is obtained with η equal to 3.00. The conservative scenario implies a gradual rise in the ICT-investment-to-GDP ratio to 4.3 percent by 2029, while the ambitious scenario assumes a steeper trajectory for this ratio, reaching 5.0 per cent by 2029.

inflation by 0.44 percentage point, and the natural rate by 0.37 percentage point. Under the ambitious scenario, the corresponding impacts are 0.86, 0.85, and 0.73 percentage point, respectively. Greater factor substitutability leads to more muted effects.

5.3 Policy Implications

Taken together, these results highlight the critical role that the relationship between ICT capital and labor plays in shaping the macroeconomic consequences of an AI-driven investment surge, particularly for monetary policy. While increased ICT investment tends to support higher output across scenarios, its implications for inflation and the natural rate of interest differ substantially depending on whether technology complements or substitutes for labor.

Under greater factor complementarity, the economy requires a larger increase in labor input to fully utilize the additional ICT capital, resulting in stronger upward pressure on wages, inflation, and aggregate demand and pushing the natural rate of interest significantly higher. In the ambitious investment scenario, for example, the natural rate rises by almost three quarters of a percentage point annually, with important implications for monetary policy.

Conversely, in the case of greater factor substitutability, ICT capital can more easily displace labor, easing capacity constraints and dampening wage and price pressures. In this case, the natural rate rises only marginally or may even decline slightly, reflecting weaker demand-side dynamics. For monetary policymakers, this difference implies that the same observable increase in ICT investment could warrant very different policy responses, depending on the underlying labor-technology elasticity.

More broadly, the findings suggest that accurately assessing the trajectory of the natural rate in the AI era will require judgment on the nature of the technological change, not just real-time output and inflation data. A key question, beyond the scope of this paper, is whether the AI revolution will lead to a structurally higher natural rate of interest. Such a development would have significant implications for monetary policy, as a higher natural rate would imply that the central bank operates further away from the effective lower bound.

6 Conclusions

Expanding AI-ready ICT capital has direct implications for monetary policy. This paper demonstrates that the scale and integration of ICT investment into production—particularly when driven by generative-AI adoption—shape the macroeconomic environment in which monetary policy operates. By embedding a distinct ICT capital channel and its interaction with labor into an otherwise standard DSGE framework, the analysis maps improvements in ICT-investment efficiency into movements in output, inflation, and the natural rate of interest.

Several findings stand out. First, estimates point to moderate gross substitutability between ICT capital and labor historically. Second, counterfactual simulations show that the transmission mechanism of ICT IST shocks crucially depends on the elasticity of substitution between these two inputs, in particular concerning the dynamics of ICT investment, real wages and the natural rate of interest. These simulations are especially important given the wide uncertainty on how AI adoption will unfold.

Third, scenarios calibrated to conservative and ambitious AI adoption profiles underscore the macroeconomic stakes. Across assumptions about scale of the ICT investment surge and labor-technology substitution, annual GDP growth rises by 0.1-0.9 percentage point, inflation by 0.1-0.8 percentage point, and the natural rate by up to 0.7 percentage point. The same ICT investment leads to amplified inflation pressures, and a greater lift in the natural rate under strong complementarity; strong substitutability yields the opposite pattern.

From a monetary policy perspective, the interaction between new capital and labor market conditions critically shapes inflation dynamics and the level of the natural rate of interest. Misjudging that structural nexus risks either falling behind a rising natural rate or needlessly restraining the economy when AI dampens labor demand. Future research could extend the analysis by incorporating international spillovers, firm heterogeneity in adoption, and coordinated fiscal measures aimed at smoothing the transition to an AI-intensive production landscape.

Appendix

A Data

This section discusses the sources and transformation of the variables used in the estimation. Most of the data are extracted from the ALFRED database. ICT investment is defined as private fixed investment in information processing equipment and software (A679RC1Q027SBEA). Non-ICT investment is made of all the remaining components of private fixed investment (PNFI). The shadow nominal interest rate is borrowed from Wu and Xia (2016) and is complemented by the federal funds rate prior to 1990Q1 and after 2023Q2.

Following Smets and Wouters (2007), GDP, consumption, ICT and non-ICT investment are transformed in per-capita terms by dividing their real values by the labor force. Real wages are computed by dividing compensation per hour by the GDP deflator. As shown in the measurement equations in Subsection 3.1, the observable variables of GDP, consumption, ICT investment, non-ICT investment and wages are logged and expressed in first differences. The inflation rate is measured as a quarterly log-difference of GDP deflator. Hours worked are multiplied by a civilian employment index, expressed in per capita terms and demeaned. All series are seasonally adjusted by their sources.

B Additional Results

Table B.1 reports the posterior means of the estimated parameters over a more recent sample, from 2000Q1 to 2024Q2, while Table B.2 shows the posteriors of the parameters and shocks, based on a sample that excludes the COVID period, from 1980Q1 to 2019Q4. Figure B.1 shows Bayesian impulse response functions to all shocks in the full sample. Figure B.2 reports the historical shock decomposition of important macroeconomic variables beyond the natural rate of interest.

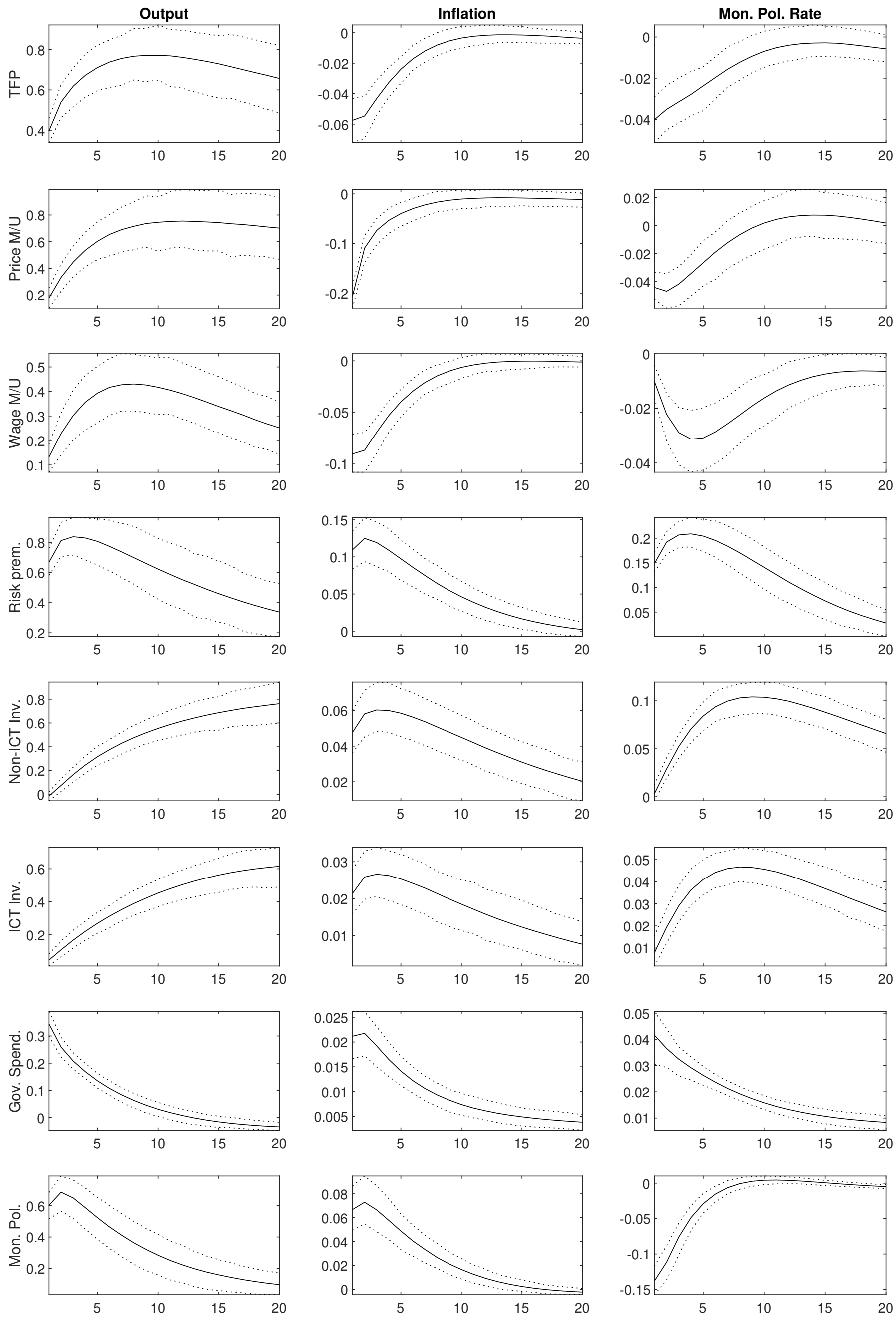
Table B.1: Prior-Posterior Distributions and Posterior Means of Parameters over a more Recent Sample–2000Q1-2024Q2 (95 Percent Credible Intervals in Square Brackets)

		Prior distribution			Posterior mean
Parameters		Distr	Mean	Std./df	
Structural parameters					
Calvo prices	σ_p	Beta	0.5	0.05	0.83 [0.78;0.87]
Calvo wages	σ_w	Beta	0.5	0.05	0.74 [0.67;0.81]
Price indexation	σ_{pi}	Beta	0.5	0.15	0.21 [0.07;0.35]
Wage indexation	σ_{wi}	Beta	0.5	0.15	0.48 [0.23;0.74]
Habit parameter	h	Beta	0.7	0.1	0.22 [0.15;0.28]
Inv. of Frisch elasticity	ϕ	Gamma	2.00	0.75	2.06 [1.05;3.13]
Non-ICT Inv. adj. costs	ξ	Normal	4	0.5	3.85 [2.66;5.00]
ICT Inv. adj. costs	ξ^{ICT}	Normal	4	0.5	8.23 [6.36;10.04]
Elasticity of substitution	η	Gamma	1.0	0.5	1.12 [0.48;1.77]
İnflation - Taylor rule	ρ_π	Normal	1.7	0.15	1.71 [1.46;1.97]
Output - Taylor rule	ρ_y	Gamma	0.125	0.05	0.13 [0.05;0.22]
Taylor rule changes in y	ρ_{Δ_y}	Normal	0.0625	0.05	0.03 [0.01;0.05]
Taylor rule smoothing	ρ_i	Beta	0.75	0.1	0.90 [0.87;0.93]
Constants					
Trend	$\bar{\gamma}$	Normal	0.4	0.2	0.30 [0.27;0.34]
Inflation	$\bar{\pi}$	Gamma	0.5	0.1	0.63 [0.50;0.78]
Interest rate	$\bar{R}$	Normal	0.8	0.2	0.50 [0.26;0.74]
Hours	$\bar{\ell}$	Normal	0.0	2.0	-0.10 [-0.42;0.23]
Exogenous processes					
Technology	ρ_a	Beta	0.5	0.2	0.78 [0.67;0.90]
	σ_a	IG	0.1	2	0.57 [0.49;0.65]
Price mark-up	ρ_p	Beta	0.5	0.2	0.88 [0.79;0.97]
	σ_p	IG	0.1	2	0.16 [0.12;0.20]
	μ_p	Beta	0.5	0.2	0.60 [0.35;0.84]
Wage mark-up	ρ_w	Beta	0.5	0.2	0.33 [0.06;0.57]
	σ_w	IG	0.1	2	0.83 [0.68;0.97]
	μ_w	Beta	0.5	0.2	0.46 [0.24;0.81]
ICT Inv. specific	$\rho_{x^{ICT}}$	Beta	0.5	0.2	0.86 [0.75;0.96]
	$\sigma_{x^{ICT}}$	IG	0.1	2	0.31 [0.24;0.37]
Non-ICT Inv. specific	ρ_x	Beta	0.5	0.2	0.74 [0.60;0.89]
	σ_x	IG	0.1	2	0.48 [0.34;0.62]
Preference	ρ_b	Beta	0.5	0.2	0.81 [0.74;0.89]
	σ_b	IG	0.1	2	0.56 [0.31;0.80]
Monetary policy	ρ_m	Beta	0.5	0.2	0.53 [0.40;0.67]
	σ_m	IG	0.1	2	0.13 [0.10;0.16]
Government spending	ρ_g	Beta	0.5	0.2	0.88 [0.81;0.94]
	σ_g	IG	0.1	2	2.38 [2.05;2.70]

Table B.2: Prior-Posterior Distributions and Posterior Means of Parameters in the pre-COVID Period–1980Q1-2019Q4 (95 Percent Credible Intervals in Square Brackets)

		Prior distribution			Posterior mean
Parameters		Distr	Mean	Std./df	
Structural parameters					
Calvo prices	σ_p	Beta	0.5	0.05	0.93 [0.86;0.96]
Calvo wages	σ_w	Beta	0.5	0.05	0.80 [0.75;0.86]
Price indexation	σ_{pi}	Beta	0.5	0.15	0.21 [0.08;0.33]
Wage indexation	σ_{wi}	Beta	0.5	0.15	0.51 [0.26;0.76]
Habit parameter	h	Beta	0.7	0.1	0.35 [0.29;0.41]
Inv. of Frisch elasticity	ϕ	Gamma	2.00	0.75	3.46 [2.65;4.50]
Non-ICT Inv. adj. costs	ξ	Normal	4	0.5	4.25 [2.83;5.63]
ICT Inv. adj. costs	ξ^{ICT}	Normal	4	0.5	6.46 [4.65;8.30]
Elasticity of substitution	η	Gamma	1.0	0.5	1.51 [0.94;2.09]
Inflation - Taylor rule	ρ_π	Normal	1.7	0.15	1.91 [1.69;2.14]
Output - Taylor rule	ρ_y	Gamma	0.125	0.05	0.08 [0.04;0.11]
Taylor rule changes in y	ρ_{Δ_y}	Normal	0.0625	0.05	0.34 [0.30;0.38]
Taylor rule smoothing	ρ_i	Beta	0.75	0.1	0.79 [0.74;0.83]
Constants					
Trend	$\bar{\gamma}$	Normal	0.4	0.2	0.34 [0.30;0.39]
Inflation	$\bar{\pi}$	Gamma	0.5	0.1	0.63 [0.54;0.73]
Interest rate	$\bar{R}$	Normal	0.8	0.2	0.09 [-0.23;0.41]
Hours	$\bar{\ell}$	Normal	0.0	2.0	0.94 [0.75;1.13]
Exogenous processes					
Technology	ρ_a	Beta	0.5	0.2	0.98 [0.97;1.00]
	σ_a	IG	0.1	2	0.53 [0.48;0.58]
Price mark-up	ρ_p	Beta	0.5	0.2	0.85 [0.75;0.99]
	σ_p	IG	0.1	2	0.10 [0.08;0.12]
	μ_p	Beta	0.5	0.2	0.71 [0.55;0.88]
Wage mark-up	ρ_w	Beta	0.5	0.2	0.68 [0.39;0.95]
	σ_w	IG	0.1	2	0.46 [0.40;0.53]
	μ_w	Beta	0.5	0.2	0.66 [0.36;0.97]
ICT Inv. specific	$\rho_{x^{ICT}}$	Beta	0.5	0.2	0.98 [0.97;1.00]
	$\sigma_{x^{ICT}}$	IG	0.1	2	0.35 [0.27;0.44]
Non-ICT Inv. specific	ρ_x	Beta	0.5	0.2	0.97 [0.96;1.00]
	σ_x	IG	0.1	2	0.46 [0.33;0.59]
Preference	ρ_b	Beta	0.5	0.2	0.87 [0.84;0.91]
	σ_b	IG	0.1	2	0.24 [0.19;0.28]
Monetary policy	ρ_m	Beta	0.5	0.2	0.05 [0.01;0.09]
	σ_m	IG	0.1	2	0.21 [0.19;0.23]
Government spending	ρ_g	Beta	0.5	0.2	0.93 [0.91;0.96]
	σ_g	IG	0.1	2	2.55 [2.31;2.79]

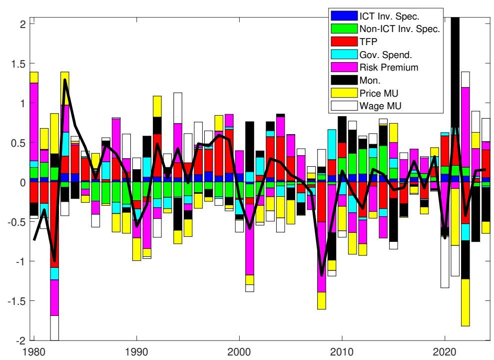
Figure B.1: Bayesian Impulse Responses of Selected Macroeconomic Variables to All Shocks



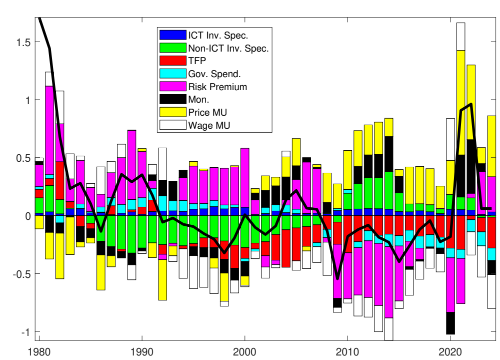
Notes: The shock size is equal to the estimated standard deviation. The responses of endogenous variables, reported on the Y-axes, are shown as percent deviations from their respective steady-state values. The time horizon on X-axes is measured in quarters. Dotted lines represent the 95 percent credible interval.

Figure B.2: Historical Shock Decomposition of Selected Variables

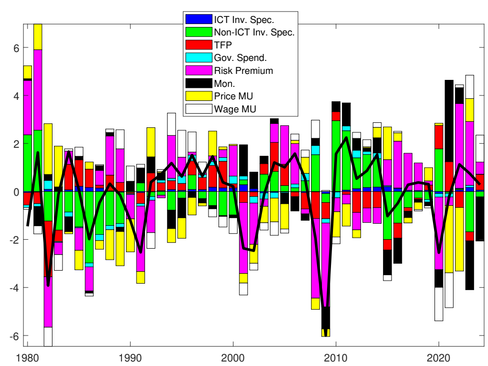
(a) GDP Growth



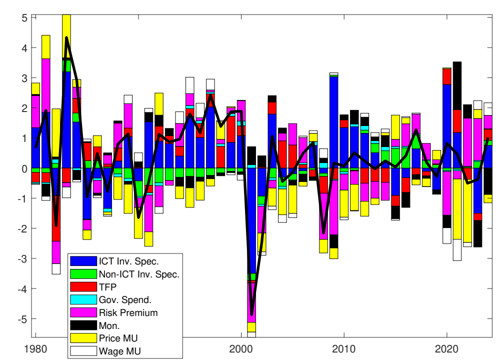
(b) Inflation rate



(c) Non-ICT Investment Growth



(d) ICT Investment Growth



Notes: The bold lines represent the annual average of demeaned quarter-on-quarters growth rates of the variables, except for inflation which represents the demeaned annualized rate. Colored bars represent the contributions of structural shocks to these deviations as indicated in the legend.

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