ICT Innovations and Labor Hours: A Business Cycle Analysis*

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Abstract

This paper investigates how changes in information and communication technologies (ICT) affect skilled and unskilled labor disproportionately at the business cycle frequency. We construct weekly hours series for the two labor groups using the monthly outgoing rotation group Current Population Survey from 1994 to 2022. Our analysis, based on a structural vector autoregressive model, reveals no statistically significant distinction in the hours' responses of skilled and unskilled labor to ICT innovation. This finding aligns with a dynamic stochastic general equilibrium model with a production function where ICT capital is complementary to both groups, different from the conventional modeling approach with skill-biased technology that is commonly employed in earlier literature.

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1 Introduction

This paper investigates how changes in information and communication technologies (ICT) affect skilled and unskilled labor at the business cycle frequency. The skilled and unskilled workers divided under education-based classifications have shown differential dynamics in various aspects including hours worked and wage (see Krusell, Ohanian, Ríos-Rull, and Violante (2000), Acemoglu (2002), and Castro and Coen-Pirani (2008) among many others). For instance, weekly hours worked by skilled workers have been on a constantly increasing trend since the mid-1990s, while those of unskilled workers are much lower in 2023 than in 1994, as shown in Figure 1. One factor that has been put forward as the main contributor to such divergence is changes in skill-biased technology (Katz and Murphy, 1992; Autor, Katz, and Krueger, 1998; Acemoglu, 1998, 1999), based on the observation that capital is more complementary to skilled workers than unskilled workers. In particular, since the seminal paper of Krusell, Ohanian, Ríos-Rull, and Violante (2000), production functions in a number of neoclassical models often feature such capital-skill complementarity (Castro and Coen-Pirani, 2008; He, 2012; Dolado, Motyovszki, and Pappa, 2021).

Changes in skill-biased technology are often associated with changes in ICT. While ICT capital represents a specific form of capital, a substantial body of literature argues that investments in ICT capital tend to exhibit skill-biased characteristics over the long term (Autor, Katz, and Krueger, 1998; Michaels, Natraj, and Van Reenen, 2014; Perez-Laborda and Perez-Sebastian, 2020). This perspective suggests that advancements in ICT are typically perceived as more complementary to skilled workers. Additionally, the historical decrease in capital prices, which has been identified as a key driver of the increasing skill premium (see He (2012), as an example), is largely attributed to the decline in the price of ICT capital, as depicted in Figure 2. This persistent decline in ICT capital prices provides support for the view that ICT capital would serve as a reasonable proxy for capital with skill-biased technology. Nonetheless, other papers, such as Brianti and Gáti (2023) and Moran and Queralto (2018) view ICT as possessing general-purpose technology attributes due to its effective spillovers and indirect impacts, albeit without a primary focus on its relationship to the labor market.

Our paper builds on these divergent views and delves into explicitly examining the joint dynamics of ICT capital and labor market dynamics at the business-cycle frequency. Despite its prevalence, few papers have explicitly examined the joint dynamics of ICT capital and labor market dynamics

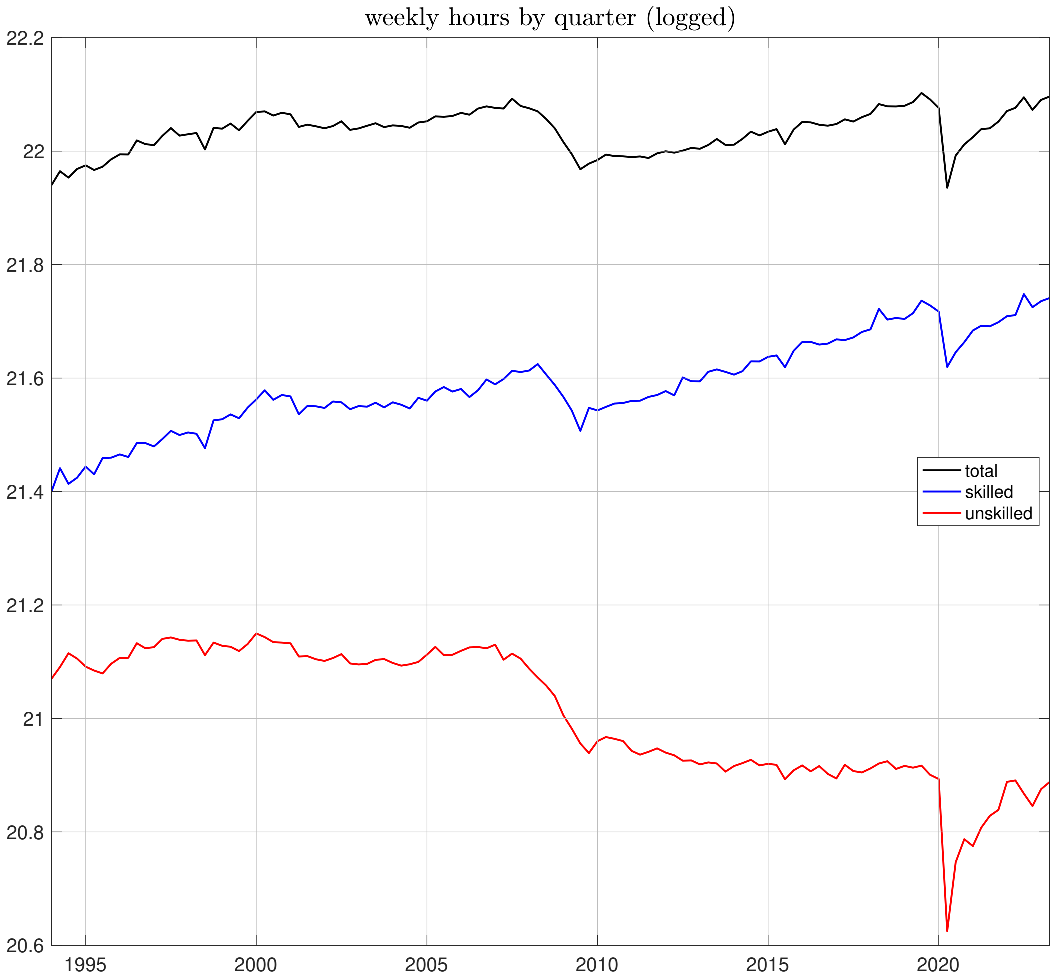

Figure 1: Weekly Working Hours

Note: This figure reports the weekly hours of skilled and unskilled workers based on individuals' educational attainment, constructed from the MORG CPS (1994Q1 to 2023Q2). We obtain monthly data as a weighted sum of each individual weekly hours and compute the quarterly data as an average of the monthly data series.

particularly at the business-cycle frequency. Therefore, we aim to shed light on understanding their relationship. In doing so, we first construct hours worked series for the skilled and unskilled groups using the monthly outgoing rotation group Current Population Survey (henceforth MORG CPS) spanning the period from 1994 to 2022. Employing this series in a vector autoregressive (VAR) model, we find that the working hours of the two labor groups do not show statistically significant divergence in their responses; the working hours of both groups exhibit a hike after a positive shock to ICT capital. We then build a dynamic stochastic general equilibrium (DSGE) model where skilled labor is more complementary to (ICT) capital than unskilled labor, following the conventional approach (Taniguchi and Yamada, 2022). This model shows that working hours by skilled and unskilled move in opposite

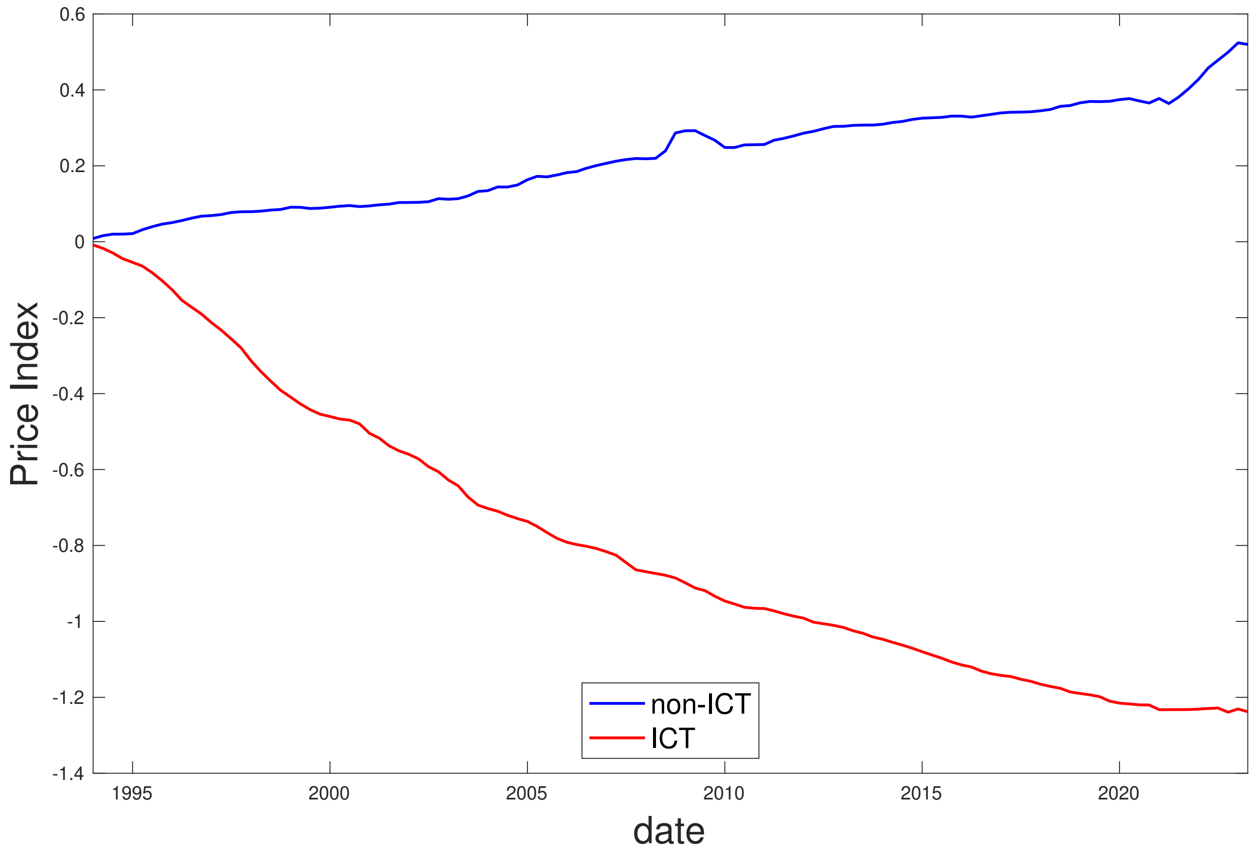

Figure 2: ICT and non-ICT Capital Prices

Note: This figure reports the historical ICT and non-ICT capital price indexes from 1994Q1 to 2023Q2. We constructed the indexes by chain-weighting the private fixed investment price indexes from FRED. The details of the construction are described in section 2.1. The unit of the measures is log level and the indexes are normalized to be at zero in 1994Q1.

directions when a positive ICT shock hits, a finding inconsistent with the empirical facts. We finally show that a production function where ICT capital is complementary to both labor can generate hours responses that are consistent with our empirical findings.

Our paper is related to two strands of literature. First, it contributes to the literature on the business-cycle dynamics of skilled and unskilled labor. In particular, we provide new evidence that a positive shock to ICT capital, often perceived as skill-biased technology, would not generate differential cyclical impacts on both types of workers, similar to the findings in Castro and Coen-Pirani (2008) and Balleer and van Rens (2013). Second, our paper is also related to a more broad line of literature examining the role of shocks to different types of capital in explaining economic fluctuations (Fisher (2006) as one example). One closely related to our work is Brianti and Gáti (2023): They show that shocks to ICT capital influence TFP and hence can contribute to medium-run business cycles in the U.S. We differ as we focus on the labor market dynamics, not on the general aggregate dynamics.

Our finding that skilled and unskilled workers may not differ critically when responding to a positive innovation in ICT at the business cycle frequency has important implications. First, changes in ICT, or more generally skill-biased technologies, may not be a primary factor for explaining divergence in the working hours of two worker groups at least *at the business cycle frequency*. It is worthwhile to highlight that our findings do not contradict existing papers that demonstrate the role of ICT capital that complements skilled labor and creates the skill premium in the long run. Instead, in line with the literature that shows possible divergence between short- and long-run production functions (Jones (2005) and Chirinko (2008)), our finding implies that a production function may feature different characteristics over time. Second, we provide support to production functions with certain ranges of elasticity of substitutions between capital and labor; in particular, to those modeling ICT capital as compliments to both worker groups especially when focusing on short-run dynamics.

The rest of the paper is organized as follows. In Section 2, we estimate impulse responses to ICT shocks using a structural VAR model. We then build a DSGE model where ICT capital is complementary to skilled labor in Section 3 and draw out predictions for working hours of labor with differential levels of education. Observing discrepancies in the response of working hours of skilled and unskilled labor, we demonstrate an alternative modeling approach in subsection 3.3, which yields impulse responses that are in line with those from the previous section. Section 4 concludes.

2 ICT Shocks on Labor Market Dynamics: Empirical Analysis

2.1 Data Our main interest is in examining the impacts of ICT shocks on the labor market at the business cycle frequency. Specifically, we explore if the shock has heterogeneous effects on workers depending on their educational level, which is a widely used proxy for skill level. As this requires hours data for each skill level, we construct the quarterly average working hours grouped by the workers' education level using the MORG CPS. In particular, we use weekly hours worked by skilled and unskilled workers.[1] In doing so, we classify a worker as "skilled" if the individual has completed at least one year of college and "unskilled" if no college. After classifying the individuals according to their education level, we sum up the individual working hours using the weights provided by the IPUMS CPS and take the quarterly average of the monthly data for each group. Our measure excludes institutionalized

[1] Specifically, we use AHRSWORK1, which is hours worked last week, main job.

and active military personnel and includes men and women between the ages of 25 to 54. CPS metric for actual hours worked may exhibit random fluctuations, such as when a holiday occurs during the reference week. Hence we eliminate outliers following Cociuba, Prescott, and Ueberfeldt (2018) and then adjust seasonality by employing the X-13 ARIMA-SEATS method.

We also construct the quarterly average employment level data in a similar way to constructing the hours data, but without eliminating outliers. To explain in more detail, we classified the individual's status as employed if the variable EMPSTAT is "At work (code: 10)" or "Has job, not at work last week (code: 12)". Then, we aggregated the data by summing up with their weights provided by the IPUMS CPS. The rest of the procedure is the same as constructing the hours data except for the outlier adjustment process.

Moreover, we construct the measure for ICT/non-ICT price to convert the investment variables denoted in nominal terms into real terms. This involves chain-weighting gross private domestic investment price indexes based on investment types. The data we use for constructing the series is provided in table A1. For the VAR analysis, we also convert the series expressed in nominal terms into real terms by dividing each series with CPI.

Descriptions of the rest of the data are provided in Table 1. We use TFP, real GDP, and ICT investments series to identify the ICT shock, similar in spirit to Brianti and Gáti (2023).

Table 1: Details on aggregate US data

Variable	Description	Source
TFP	Utilization-adjusted total factor productivity (dtfp_util)	Sanfrancisco FED
Real GDP	Real Gross Domestic Product, Billions of Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate (GDPC1)	FRED
ICT Investments	Private fixed investment in information processing equipment and software, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (A679RC1Q027SBEA)	FRED
ICT/non-ICT Prices	Constructed by chain-weighting the price indexes for private fixed investment	FRED
Investment	Private Nonresidential Fixed Investment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (PNFI)	FRED
CPI	Consumer Price Index: All Items for the United States, Index 2015=100, Quarterly, Not Seasonally Adjusted (USACPIALLMINMEI)	FRED
Hours	quarterly average of working hours of Men & Women, ages 25-54	IPUMS-CPS
Employment level	quarterly average of working hours of Men & Women, ages 25-54	IPUMS-CPS

2.2 Methodology To empirically examine the responses of skilled and unskilled labor to the ICT shocks, we follow Brianti and Gáti (2023). In particular, we assume that Y_t, an $n \times 1$ vector of endogenous variables, follows a structural VAR process as:

$$A_0 Y_t = \alpha + A_1(L) Y_{t-1} + \varepsilon_t, \tag{1}$$

where the number of lags is set to be L. Here, ε_t is a vector of n economic shocks, and A_0 is an $n \times n$ structural coefficient matrix. Variables are included in our baseline VAR model in the following order: ICT investment, TFP, real GDP, real ICT price index, skilled hours, and unskilled hours. This is an extended version of the benchmark trivariate VAR model from Brianti and Gáti (2023); we include the real ICT price index as well as hours worked by skilled and unskilled labor. The hours worked by each group is included separately in levels, which enables us to investigate their respective responses and further relative changes in a unified framework.[2]

We also follow the identification strategy of Brianti and Gáti (2023), and assume that A_0 is a lower triangular matrix. In other words, the structural shocks are identified through the Choleski decomposition. While it is feasible to identify multiple structural shocks, our main interest lies in the effects of an ICT shock alone. As such, we only identify the ICT shock from the model. For this, we assume that the ICT shock is the only shock to have a contemporaneous effect on ICT investment.

Since our sample period includes the post-COVID period, the extreme observations during the pandemic might distort the relationships between our variables of interest. Therefore, we adopt the method of Ng (2021) to "de-covid" the data. The COVID-19 episode can be incorporated into a time-series model through various approaches. Ng (2021) opts to treat it as the introduction of new shocks, rather than viewing it as the manifestation of outliers or a shift in the distribution of existing shocks. This methodology incorporates essential indicators associated with COVID-19 as controls, including the number of deaths, hospitalizations, or positive cases, along with dummy variables signifying the pandemic era.

[2]The point estimates of the IRF of the ratio are inferred by taking the difference between the response of skilled and unskilled hours. Similarly, the error bands are computed by taking the difference between the skilled and unskilled hours for each bootstrapped draw and sorting them. As Figure A1 shows, including the hours variables as their ratio or each of their levels derive similar results for the ratio's response.

$$Y_t = A_0^{-1}\alpha + \gamma D_t + \delta \mathbb{I}_{T_0 \le t < T_1} + A_0^{-1} A_1(L^{endo}) Y_{t-1} + \beta(L^{exo})\nu_t + A_0^{-1}\varepsilon_t \tag{2}$$

To utilize Ng (2021)'s method in our model, we incorporate the first differences of the number of positive cases during the pandemic (ν_t) to our VAR model as an exogenous variable. The lag of the exogenous variable is L^{exo}, and we use $L^{exo} = 2$ for the whole analysis. Additionally, we include two dummy variables: $\mathbb{I}_{T_0 \le t < T_1}$ and D_t. D_t is a one-time dummy that captures the jump at the beginning of the pandemic and $\mathbb{I}_{T_0 \le t < T_1}$ is a dummy that indicates one during the whole pandemic period, where $T_0 = 2020Q1$ and $T_0 = 2021Q2$.

2.3 Main Finding from the Benchmark VAR Model

Figure 3 shows the impulse responses from our baseline VAR specification.[3]

The first row of Figure 3 illustrates impulse responses of ICT investment, TFP, and the real GDP, which are the same variables as the baseline of Brianti and Gáti (2023). The results are qualitatively identical while their magnitudes differ slightly: the increase of TFP and that of real GDP in response to the ICT shock is significant and persistent, which confirms that the ICT shocks are a source of medium-run fluctuations in TFP and economic activity. Moreover, the real ICT price decreases in response to the ICT shock which indicates that the shock is a supply-side shock in the ICT sector.

We now turn to labor market variables, which are of our main interest. As is conventionally assumed, if unskilled labor is a substitute for the ICT capital, the unskilled hours will decrease in response to the shocks. However, this is not the case in the short (or medium) run. The second row of Figure 3 illustrates the impulse responses of the ratio between skilled and unskilled hours, along with their respective levels. We can observe that the shock leads to an increase in both skilled (0.515% at the peak) and unskilled (0.380% at the peak) hours, which are all statistically significant. Moreover, our findings indicate that there is no significant difference between the working hours of the two skill groups when there is a shock to ICT capital.

Since the extensive margin of working hours plays a crucial role in labor market dynamics at the business cycle frequency (Heckman, 1984; Hansen, 1985; Chang and Kim, 2007, and many others), we

[3] We also report the impulse responses from a model where we do not apply any modification for the COVID period's observations in Figure A2. The result remains very similar to the baseline case.

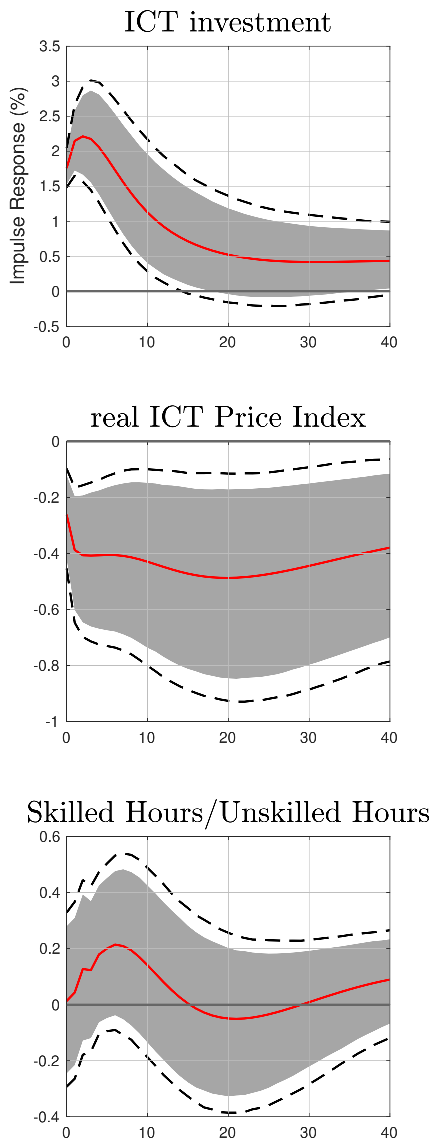

Figure 3: Baseline Impulse Responses

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

conduct the same baseline analysis by substituting the hours variables for the corresponding employment level variables. Figure 4 plots the impulse responses of the baseline variables with the employment levels to the ICT shock. It is easy to observe that results are similar to what can be observed from Figure 3. Despite the insignificant response of the unskilled employment level to the ICT shock, the ratio between the skilled- and the unskilled employment levels remains still insignificant. All in all, we find no evidence that the ICT shock induces heterogeneous responses to the skilled and the unskilled labor

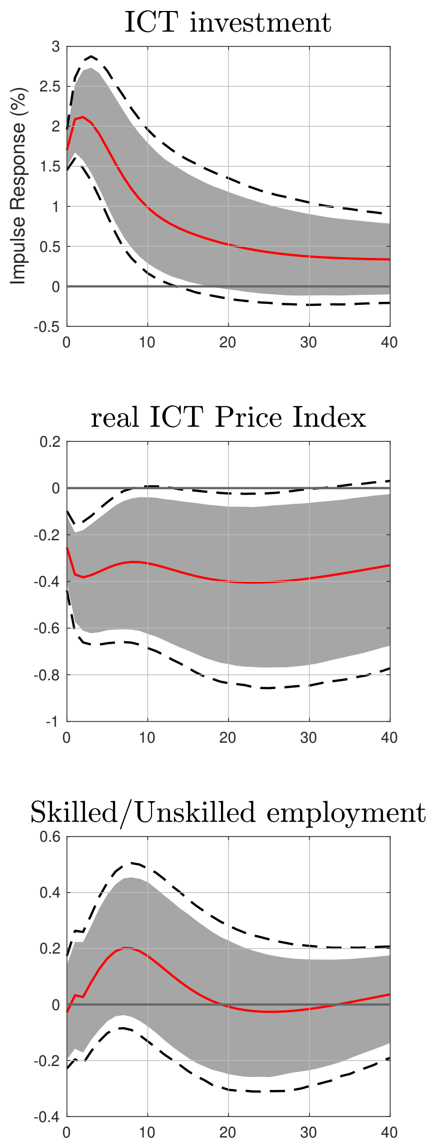

Figure 4: Responses of Employment Level

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

also at the extensive margin.

We further investigate how much the ICT shock accounts for the business cycle by conducting a forecast error variance decomposition analysis. Figure 5 highlights that the ICT shock is (i) a major driver of a business cycle and (ii) influential to the labor market: the ICT shock explains up to 45% of the variance of real GDP and it remains over 40% across the horizon. This result is consistent with Brianti and Gáti (2023)'s claim that productivity improvement in ICT is a source of medium-run

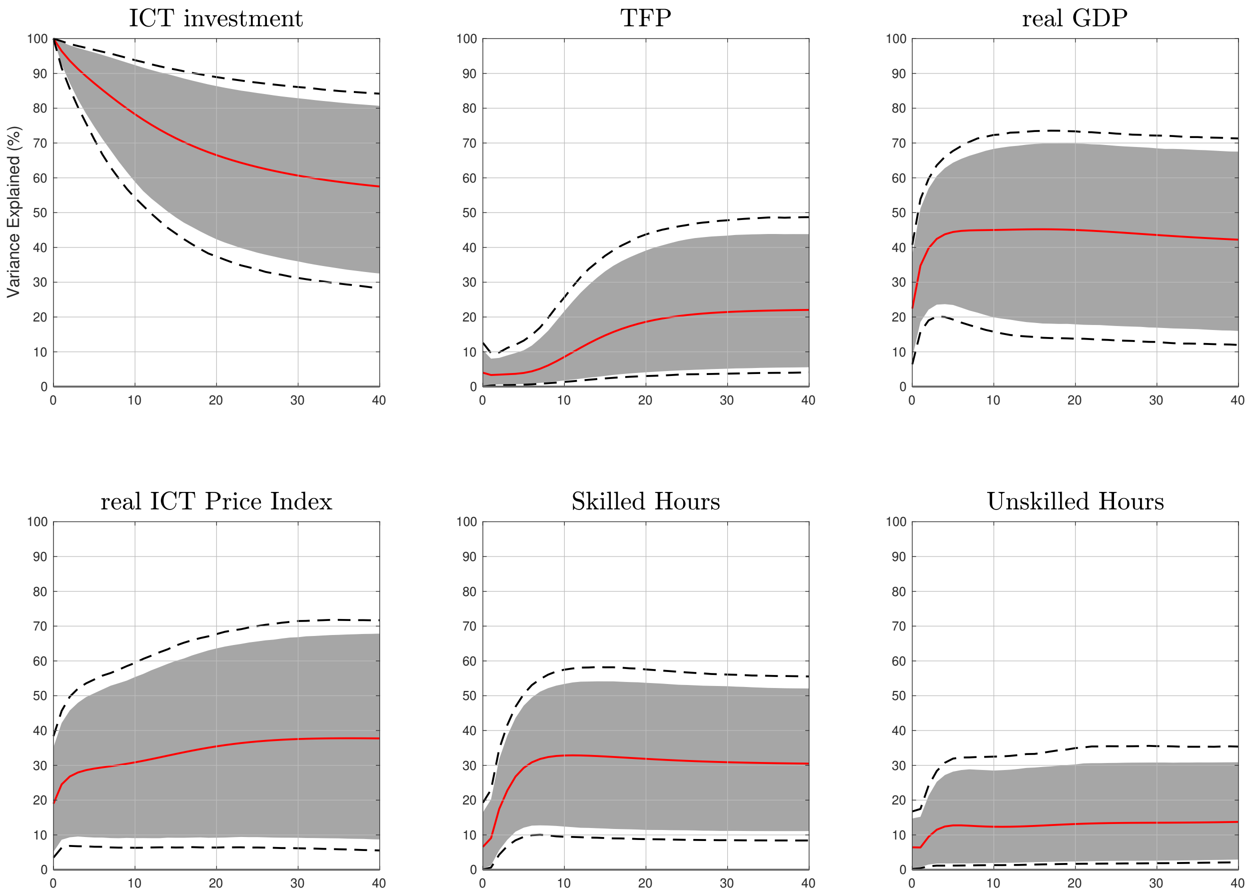

Figure 5: Baseline Forecast Error Variance Decomposition

Note: This figure reports the variance decomposition to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding variance explained in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

fluctuations in economic activity. While the magnitude is small, the shock can explain the labor market dynamics to some extent: about 13% (unskilled hours) to 33% (skilled hours) can be attributed to the ICT shock.

2.4 Robustness Checks

In section 2.3, we examine the responses of skilled and unskilled hours to ICT shocks and find that their responses are positive and similar in magnitude. However, there might be skepticism regarding whether these responses are specific to a particular setup or robust across multiple specifications because the finding is based on a simple VAR analysis. One factor that might threaten the robustness of our results is the news embedded in the ICT shocks. To elaborate, the news embedded in the ICT shock might compromise the strength of our identification strategy, following Brianti and Gáti (2023); agents might form their expectations about the future from an ICT innovation, and it can potentially affect the responses of the variables of interest. In Figure 6, we augment Kurmann and Sims (2021)'s news shock series to our VAR model. However, controlling the news shock does not seem to affect our main result much.

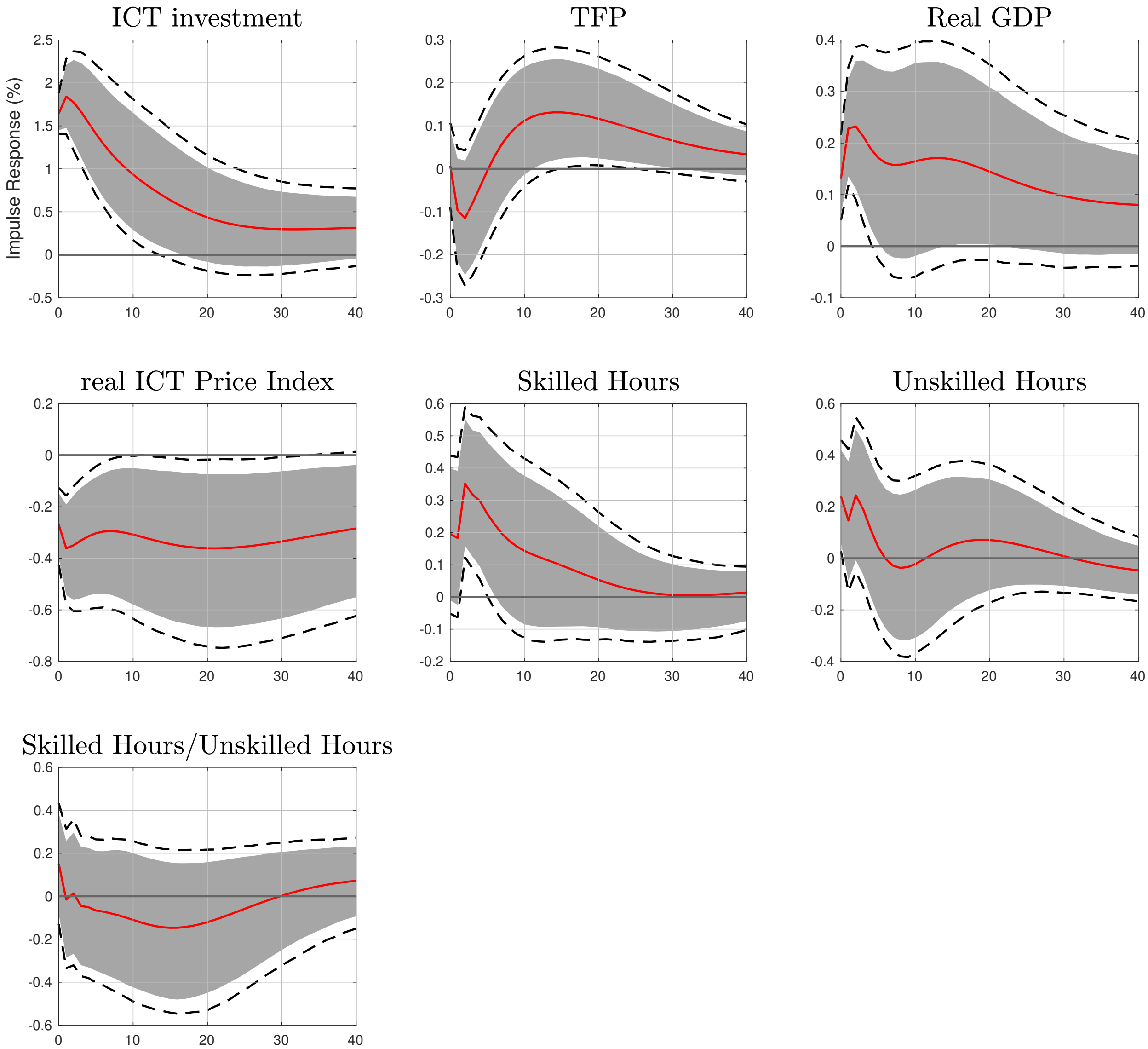

Figure 6: Robustness check 1: Controlling the news shocks (Kurmann and Sims, 2021)

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

Moreover, to check the robustness of our findings, we consider various specifications in the Appendix. We deviate from the baseline VAR by changing the number of lags (Figure A3 and A4), excluding the pandemic period from the sample (Figure A5), and subtracting the ICT price from the endogenous variables (Figure A6).

To sum up, our main findings stand resilient across diverse specifications: an ICT shock is still a source of business cycle fluctuation and leads to an increase in both skilled and unskilled labor hours in the short run. More importantly, the magnitudes of the increases in hours of both groups are not significantly different.

3 ICT shocks on Labor Market Dynamics: Model

In this section, we analyze if the empirical facts we find in the previous section can be reproduced by a the DSGE model that is in line with the previous literature.

3.1 Model We consider a social planners' problem to predict how the shock to ICT capital affects the labor market. In particular, the planner solves the following problem:

$$\max_{c_t, h_{s,t}, h_{u,t}, i_t, k_{t+1}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log c_t - \nu_s \frac{h_{s,t}^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} - \nu_u \frac{h_{u,t}^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} \right] \tag{3}$$

subject to

$$c_t + i_t = y_t \tag{4}$$

$$k_{t+1} = p_t \left(1 - \Phi(\frac{i_t}{i_{t-1}})\right) i_t + (1-\delta) k_t \tag{5}$$

where equation (4) is the resource constraint and equation (5) describes the law of motions for ICT capital. c_t denotes consumption expenditure, i_t is an investment in ICT capital, $h_{j,t}$ with $j = s, u$ is skilled/unskilled working hours, $\delta \in (0, 1)$ is a depreciation rate of ICT capital, p_t is an ICT shock, and $\Phi(\frac{i_t}{i_{t-1}}) = \frac{\phi}{2}(\frac{i_t}{i_{t-1}} - 1)^2$ with a constant $\phi > 0$ is the quadratic cost function of investment adjustment cost. Lastly, $\chi > 0$ is the Frisch labor supply elasticity, and $\nu_j > 0$ with $j = s, u$ measures disutility from working. We implicitly assume that both skilled and unskilled workers form a family and share their incomes, to focus on aggregate dynamics by making degenerate wealth distribution.

The final output, y_t, is produced according to a constant elasticity of substitution technology, following the previous literature (Krusell, Ohanian, Ríos-Rull, and Violante (2000), for example):

$$y_t = \left[\mu h_{u,t}^{\sigma} + (1-\mu)(\lambda k_t^{\rho} + (1-\lambda) h_{s,t}^{\rho})^{\frac{\sigma}{\rho}}\right]^{\frac{1}{\sigma}} \tag{6}$$

where the parameters $\mu > 0$ and $\lambda > 0$ govern the income share, σ and ρ determine the elasticity of substitution between skilled/unskilled labor and ICT capital. In particular, the elasticity of substitution between the composite of ICT capital and skilled labor and unskilled labor is $1/(1-\sigma)$ and the elasticity of substitution between ICT capital and skilled labor is $1/(1-\rho)$. If σ or ρ is larger (resp. smaller) than zero, the corresponding relation exhibits complementarity (resp. substitutability) with respect to ICT capital. The case with both σ and ρ equal to zero nests a Cobb-Douglas structure. As will be detailed below, we select the values to be $\sigma < 1$ and $\rho < 1$ for our first set of simulation exercises, so that the ICT capital is skill-biased, i.e., complementary to the skilled workers while substitutes for the unskilled.[4]

The social planner sets up the Lagrangian of the constrained maximization as follows:

$$\begin{aligned}\mathcal{L} = \max_{c_t, h_{j,t}, i_t, k_{t+1}, y_t} \sum_{t=0}^{\infty} \beta^t \Bigg[& u(c_t, h_{s,t}, h_{u,t}) + \Gamma_{1,t}(y_t - c_t - i_t) + \Gamma_{2,t}\left(p_t \left(1 - \Phi\left(\frac{i_t}{i_{t-1}}\right)\right) i_t + (1-\delta)k_t - k_{t+1}\right) \\ & + \Gamma_{3,t}\left(((\mu h_{u,t}^{\sigma} + (1-\mu)(\lambda k_t^{\rho} + (1-\lambda) h_{s,t}^{\rho})^{\frac{\sigma}{\rho}})^{\frac{1}{\sigma}}) - y_t\right)\Bigg]\end{aligned} \tag{7}$$

where $\Gamma_{j,t}$ $(j = 1, 2, 3)$ are the Lagrangian multipliers.

[4] Related, Taniguchi and Yamada (2022) estimate $\sigma > 0$ and $\rho < 0$ based on the industry level data of 14 OECD countries. The estimate values are in line with Krusell, Ohanian, Ríos-Rull, and Violante (2000), indicating that ICT capital is relatively complementary to skilled labor while is relatively substitutable for unskilled labor.

The sufficient and necessary conditions for the optimal path are given as follows.[5]

$$\nu_s h_{s,t}^{1/\chi} = (1-\lambda)(1-\mu)\frac{1}{c_t} y_t^{1-\sigma}(\lambda k_t^\rho + (1-\lambda)h_{s,t}^\rho)^{\frac{\sigma}{\rho}-1} h_{s,t}^{\rho-1} \tag{8}$$

$$\nu_u h_{u,t}^{1/\chi} = \mu \frac{1}{c_t}\left(\frac{y_t}{h_{u,t}}\right)^{1-\sigma} \tag{9}$$

$$\begin{aligned}\frac{1}{c_t} &= \Gamma_{2,t}\left(p_t\left(1-\frac{\phi}{2}(\frac{i_t}{i_{t-1}}-1)^2\right) - p_t\phi\left(\frac{i_t}{i_{t-1}}-1\right)\frac{i_t}{i_{t-1}}\right) \\ &\quad + \beta\mathbb{E}_t\Gamma_{2,t+1}\left(p_{t+1}\phi\left(\frac{i_{t+1}}{i_t}-1\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right)\end{aligned} \tag{10}$$

$$\Gamma_{2,t} = \beta\mathbb{E}_t\frac{1}{c_{t+1}}\left[\lambda(1-\mu)y_{t+1}^{1-\sigma}(\lambda k_{t+1}^\rho + (1-\lambda)h_{s,t+1}^\rho)^{\frac{\sigma}{\rho}-1}k_{t+1}^{\rho-1} + \Gamma_{2,t+1}(1-\delta)\right] \tag{11}$$

Equation (8) and (9) denote labor market equilibrium conditions for unskilled and skilled labor, respectively. Equation (10) and (11) together describe joint dynamics of consumption and investment.

3.2 Predictions from substitutable low-skilled labor The dynamics of the labor market in our model are solely due to the ICT shock, making the elasticity of substitution with ICT capital a crucial factor in the responses of the hours variables. Consequently, we begin by investigating the scenario of substitutable ICT capital and unskilled labor, a condition commonly assumed in literature dealing with long-run frequency.

Table 2 presents the calibrated parameter values employed in our analysis. When examining the case of complementary ICT capital to unskilled labor later, we will maintain the same parameter values as those in Table 2, except for σ. Our parameter choices draw heavily from Brianti and Gáti (2023), while some parameters are calibrated differently because we consider a one-sector model while they consider a two-sector model. In particular, we borrow parameter values from Krusell, Ohanian, Ríos-Rull, and Violante (2000) when calibrating parameters governing the production function and β, χ, and ϕ are adopted from Woodford (2003); Chetty, Guren, Manoli, and Weber (2011); Smets and Wouters (2007), consistent with Brianti and Gáti (2023). Additionally, the parameters governing income share, μ and λ, are calibrated to match the value of $\frac{\text{mean}(h_u)}{\text{mean}(h)} = 0.36$ obtained from our data, and to establish the ICT capital income share as 1/3.

We then solve the model with the perturbation method (Schmitt-Grohé and Uribe (2004)). Figure 7 presents impulse responses of key macro variables from a one-time one-unit shock to ICT capital under

[5] We omit the transversality condition.

Table 2: Parameter Values

Parameter	Value	Description	Source
β	0.99	Discount rate	Woodford (2003)
χ	1	Frisch labor elasticity	Chetty, Guren, Manoli, and Weber (2011)
ν_s	-	Scaling Parameter of high-skilled Labor Disutility	match steady-state skilled hours ($\bar{h_s}$=0.15)
ν_u	-	Scaling Parameter of low-skilled Labor Disutility	match steady-state unskilled hours ($\bar{h_u}$=0.15)
μ	0.24	Unskilled labor income share	match $\frac{\text{mean}(h_u)}{\text{mean}(h)} = 0.36$ derived from the data
λ	0.44	ICT capital income share	match ICT capital income share to $\frac{1}{3}$
ρ	-0.495	the elasticity of substitution between high-skilled labor and ICT capital	Krusell, Ohanian, Ríos-Rull, and Violante (2000)
σ	0.401	the elasticity of substitution between low-skilled labor and ICT capital	Krusell, Ohanian, Ríos-Rull, and Violante (2000)
ϕ	5.9	Investment adjustment cost	Smets and Wouters (2007)
ρ_p	0.9	Persistence of AR(1) ICT Shock	-

the benchmark calibration. Since the shock lowers the price of ICT capital, investment in ICT capital increases and hence increases output level. Because ICT capital is assumed to be a complement to skilled hours but substitutable for unskilled hours, skilled hours increase while unskilled hours become lower over time. As a result, the ratio between the two increases over time (and fades away).

While predictions drawn from our baseline DSGE model as shown in Figure 7 align well with economic intuitions, this is inconsistent with the empirical finding reported in Figure 3: This implies that we need to modify the model structure to obtain (i) positive impulse response of unskilled hours and (ii) no significant differences in the responses of both types of labor to the ICT shock.

3.3 Resolving the Discrepancy Then, how can we explain the simultaneous increase of skilled and unskilled hours from the ICT shock and no significant differences between the two? Among possible resolutions, we suggest ICT capital being a complement to unskilled hours rather than being substitutable for unskilled workers as a plausible candidate. To demonstrate this, we first examine alternative values of σ, the parameter governing the elasticity of substitution between ICT capital and low-skilled hours. By doing this exercise, we show that there exist negative σ values (which make the unskilled labor complementary to the ICT capital) that make the response of the ratio between the hours of skilled and unskilled positive.

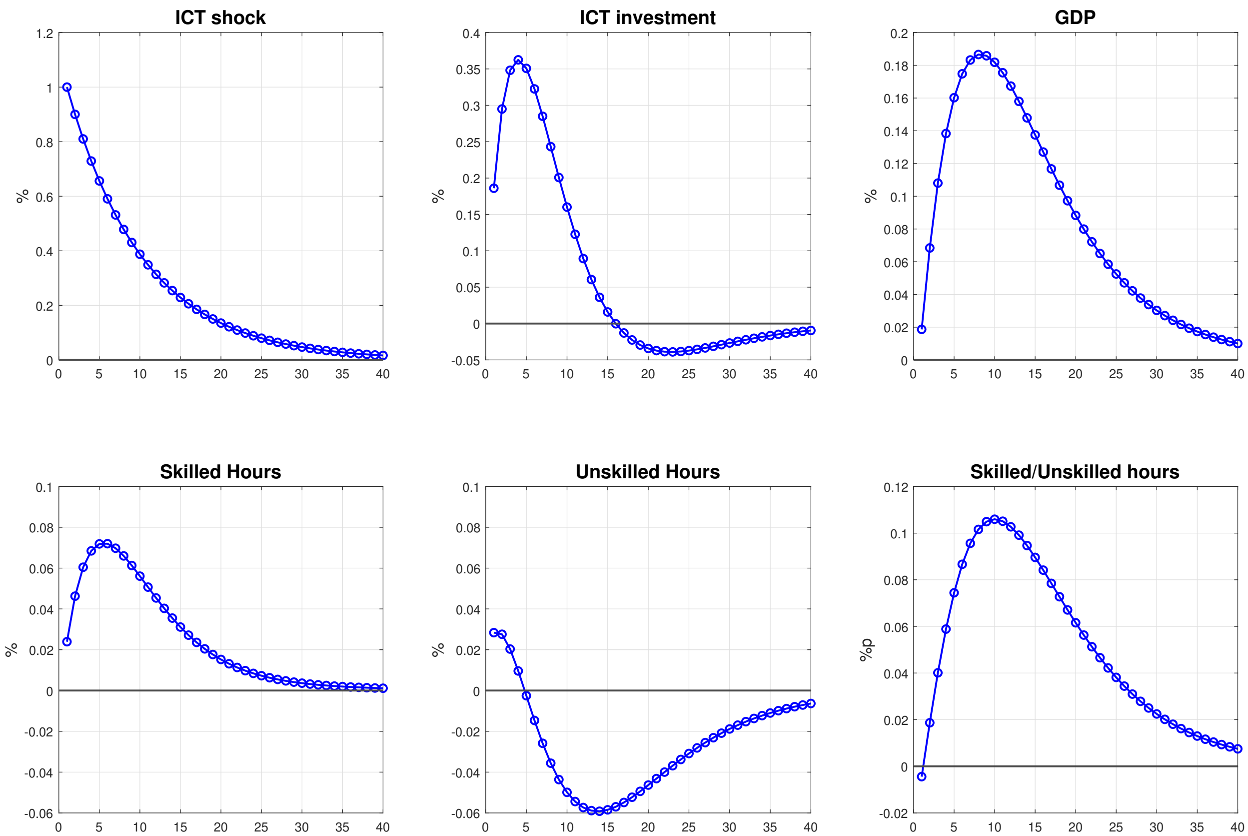

Figure 7: Impulse Responses to an ICT shock (ICT capital substitutable for low-skilled labor)

Note: This figure reports the impulse responses from our theoretical model with substitutable low-skilled labor.

Figure 8 plots the impulse responses of the hours variables with different σ. To explain the empirical finding reported in Figure 3, we need three qualitative features of the impulse responses of hours variables: (i) the response of the ratio between skilled and unskilled should be positive but near zero, (ii) the response of the skilled hours should be positive, and (iii) the response of the unskilled hours should also be positive.

We first consider the impulse responses in the case of ICT capital being substitutable for unskilled labor. The circled-dashed line, the diamond-solid line, and the diamond-dashed line represent the impulse responses with $\sigma = 0.1$, $\sigma = 0.401$, and $\sigma = 1.5$, respectively. While skilled hours increase, consistent with figure 7, the model fails to replicate the responses of unskilled hours, which is in line with the benchmark calibration.

We then examine the impulse responses when ICT capital is complementary to unskilled labor with the circled-solid line, the solid line, and the dashed line, which represent the cases of $\sigma = -0.1$, $\sigma = -0.401$, and $\sigma = -1.5$, respectively. The ratio between skilled and unskilled hours rises unless

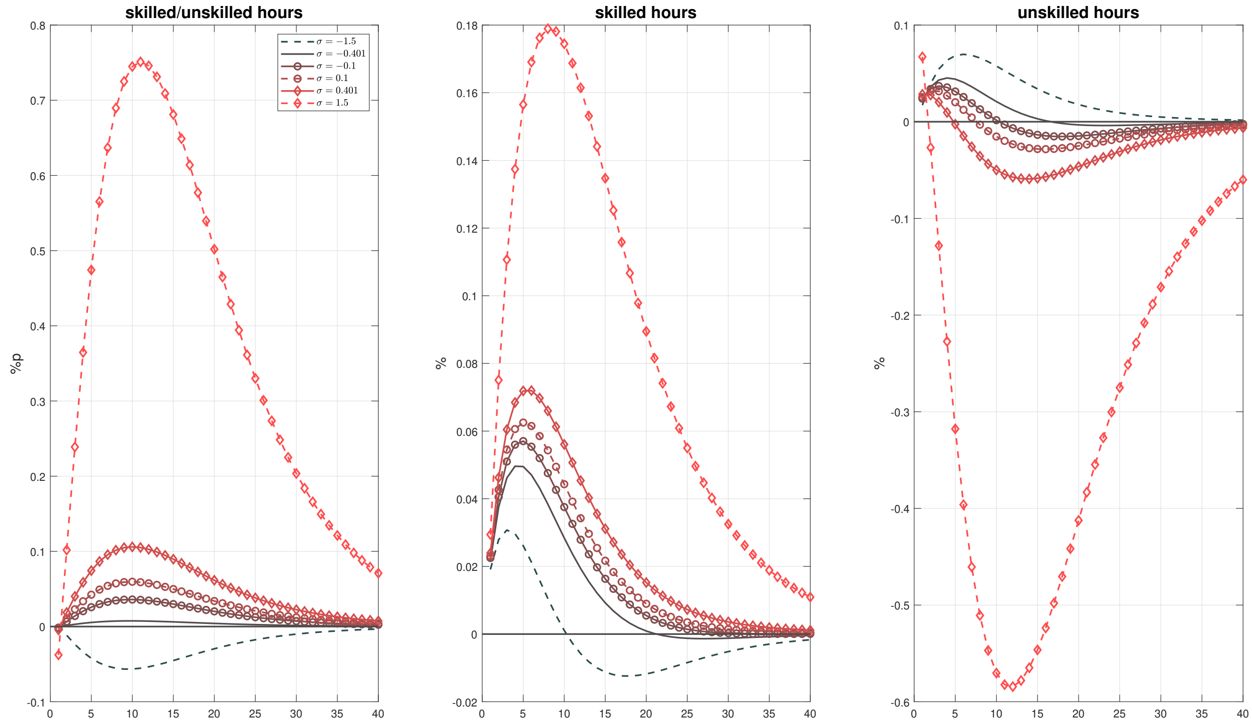

Figure 8: Impulse Responses of hours variables by different σ values

Note: This figure reports the impulse responses from our theoretical model with different σ values.

$\sigma = -1.5$.[6] Moreover, the ICT shock elicits positive responses to unskilled hours when $\sigma = -0.401$ or $\sigma = -1.5$, which is a consistent finding from the empirical analysis. Thus, we can conclude that σ should be sufficiently small and negative.

Figure 9 presents the impulse responses derived from our model with a complementary relationship between ICT capital and unskilled labor by assuming $\sigma = -0.401$. In contrast to Figure 7, unskilled hours rise in similar magnitude with skilled labor due to the complementarity of the ICT shock. We can observe that the ratio between both hours reacts in a small magnitude, consistent with our empirical finding. This finding, which seems to be somewhat contradictory to the usual assumption on the production function, is actually consistent with the previous papers that argue that (i) capital-skill complementarity has become lower since the mid-1980s (Castro and Coen-Pirani, 2008) and (ii) capital may not complement skilled workers (Balleer and van Rens, 2013). In addition, as Jones (2005) and Chirinko (2008) have pointed out, short- and long-run production can diverge from each other, implying that our suggestion on the production at the short-run may not be at odds with the conventionally accepted production function. In this sense, our finding complements the literature on production

[6]The ratio rises in response to the ICT shock when $\rho < \sigma$.

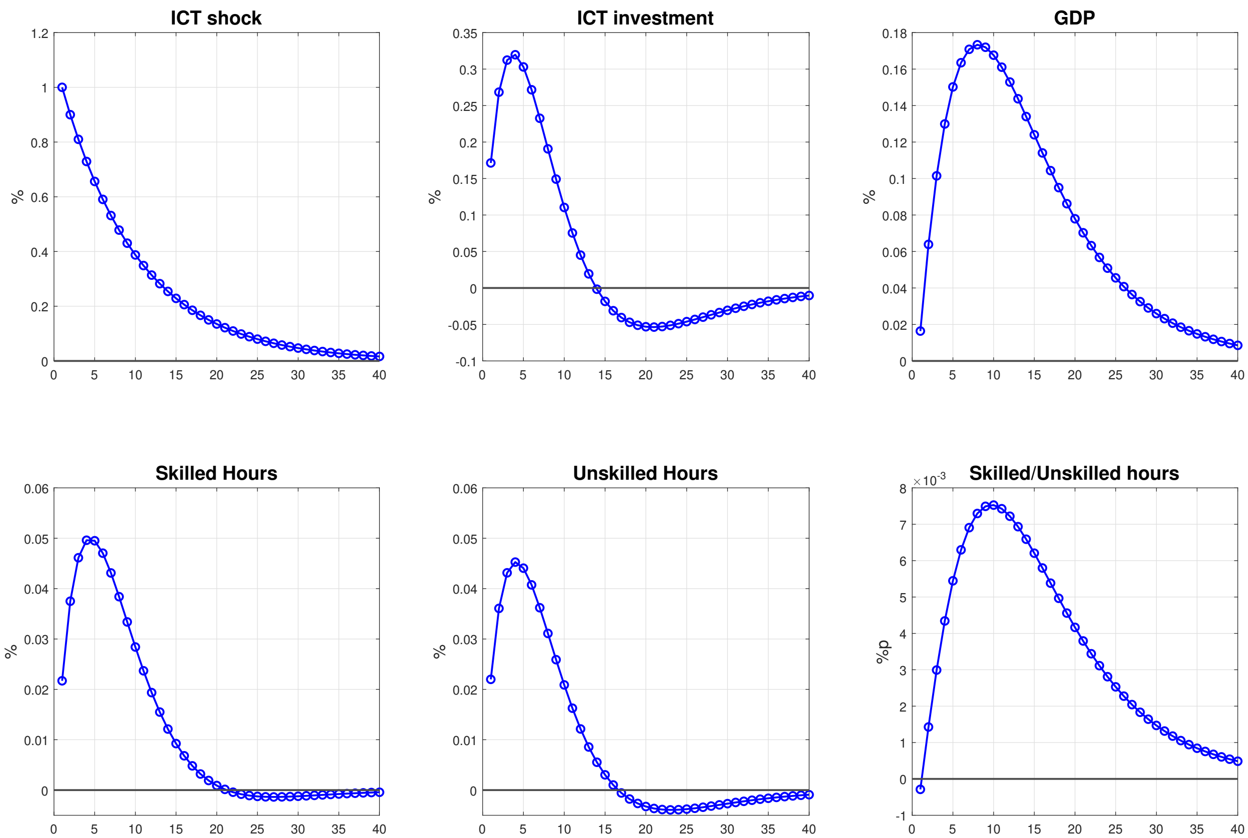

Figure 9: Impulse Responses to an ICT shock (ICT capital complementary to low-skilled labor ($\sigma = -0.401$))

Note: This figure reports the impulse responses from our theoretical model with complementary low-skilled labor.

function with two types of labors (skill and unskill).

4 Conclusion

Are ICT complementary to both skilled and unskilled workers? Our answer is yes when it comes to the short run. To delve into the connection between ICT capital and skilled/unskilled labor, we constructed hours worked series for the skilled and unskilled labor using the monthly outgoing rotation group CPS and conducted a short-run zero restricted structural VAR model. As a result, we found no significant discrepancy between the responses of skilled and unskilled hours worked to ICT shocks, and the result was robust under various specifications. Interestingly, in our DSGE framework, the empirical finding cannot be supported if ICT capital is a substitute for unskilled labor despite the substitutable ICT capital and unskilled labor relationship being a common view in literature dealing with the long-run perspective. Hence, we suggested an alternative specification where ICT capital was complementary to both skilled and unskilled labor. This alternative modeling approach yielded the responses of working hours that are consistent with our empirical analysis results. Together, these findings demonstrated that ICT capital is complementary to both skilled and unskilled workers in the short run.

Our results had two main implications. First, changes in ICT, or skill-biased technologies more generally, might not be a primary factor for explaining divergence in the working hours of two worker groups at the business cycle frequency. It should be noted, however, that our findings did not contradict previous studies that showed the skill-biasedness characteristics of ICT capital that likely have driven skill premium in the long run. Second, our findings provide support to production functions with certain ranges of the elasticity of substitutions between capital and labor: in particular, to those modeling ICT capital as compliments to both worker groups especially when focusing on short-run dynamics.

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A Appendix

Table A1: Data used for constructing the ICT/non-ICT price indexes

	Variable	Description	Source
ICT	Expenditure	Private fixed investment: Nonresidential: Intellectual property products: Software, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (B985RC1Q027SBEA)	FRED
	Expenditure	Gross Private Domestic Investment: Fixed Investment: Nonresidential: Equipment: Information Processing Equipment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (Y034RC1Q027SBEA)	FRED
	Price	Private fixed investment, chained price index: Nonresidential: Intellectual property products: Software, Index 2017=100, Quarterly, Seasonally Adjusted (B985RG3Q086SBEA)	FRED
	Price	Gross Private Domestic Investment: Fixed Investment: Nonresidential: Equipment: Information Processing Equipment (chain-type price index), Index 2017=100, Quarterly, Seasonally Adjusted (Y034RG3Q086SBEA)	FRED
non-ICT	Expenditure	Private fixed investment: Nonresidential: Equipment: Industrial equipment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (A680RC1Q027SBEA)	FRED
	Expenditure	Private fixed investment: Nonresidential: Equipment: Transportation equipment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (A681RC1Q027SBEA)	FRED
	Expenditure	Private fixed investment: Nonresidential: Equipment: Other equipment, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate (A682RC1Q027SBEA)	FRED
	Price	Gross domestic product, chained price index: Gross private domestic investment: Fixed investment: Nonresidential: Equipment: Industrial equipment, Index 2017=100, Quarterly, Seasonally Adjusted (A680RG3Q086SBEA)	FRED
	Price	Gross domestic product, chained price index: Gross private domestic investment: Fixed investment: Nonresidential: Equipment: Transportation equipment, Index 2017=100, Quarterly, Seasonally Adjusted (A681RG3Q086SBEA)	FRED
	Price	Gross domestic product, chained price index: Gross private domestic investment: Fixed investment: Nonresidential: Equipment: Other equipment, Index 2017=100, Quarterly, Seasonally Adjusted (A682RG3Q086SBEA)	FRED

A.1 Additional Figures/Tables

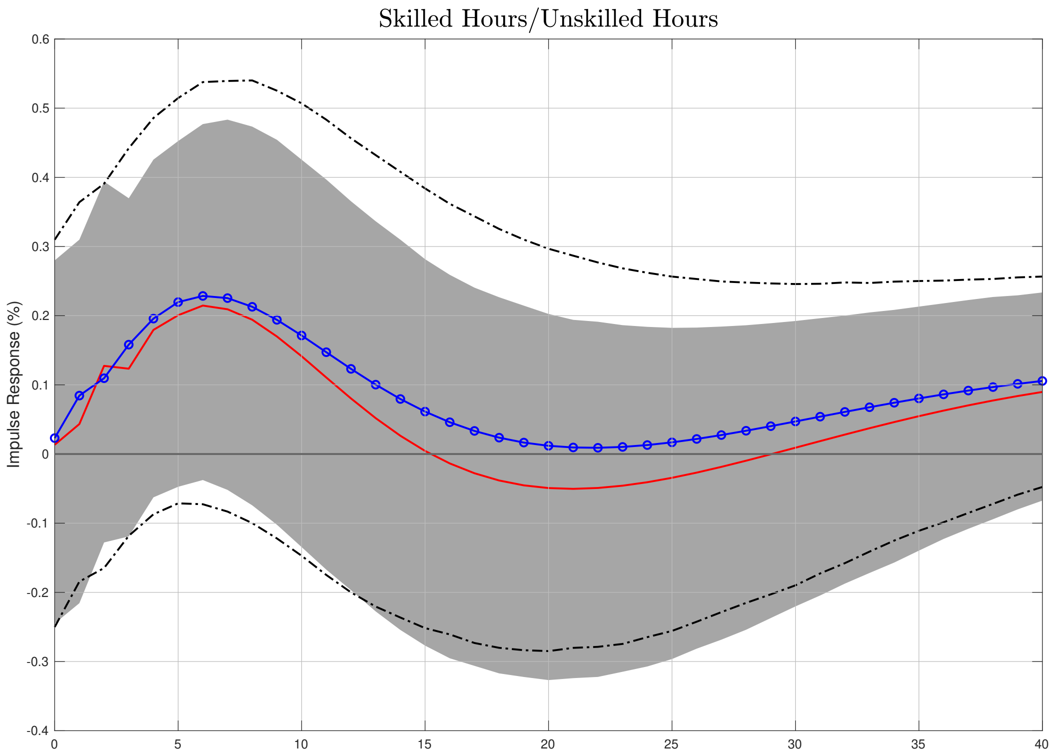

Figure A1: Effect on the hours' ratio

Note: This figure reports the impulse responses of the hours' ratio to the ICT investment shock, using data from 1994Q1 to 2023Q2. The red solid line represents the point estimates from our baseline specification and the blue circled line represents the point estimates from the result derived by adding the ratio directly to the VAR vector. The grey-shaded area and the black-dashed lines represent 90% error bands of the corresponding impulse responses. The error bands are derived by the standard bootstrap method with 10,000 draws.

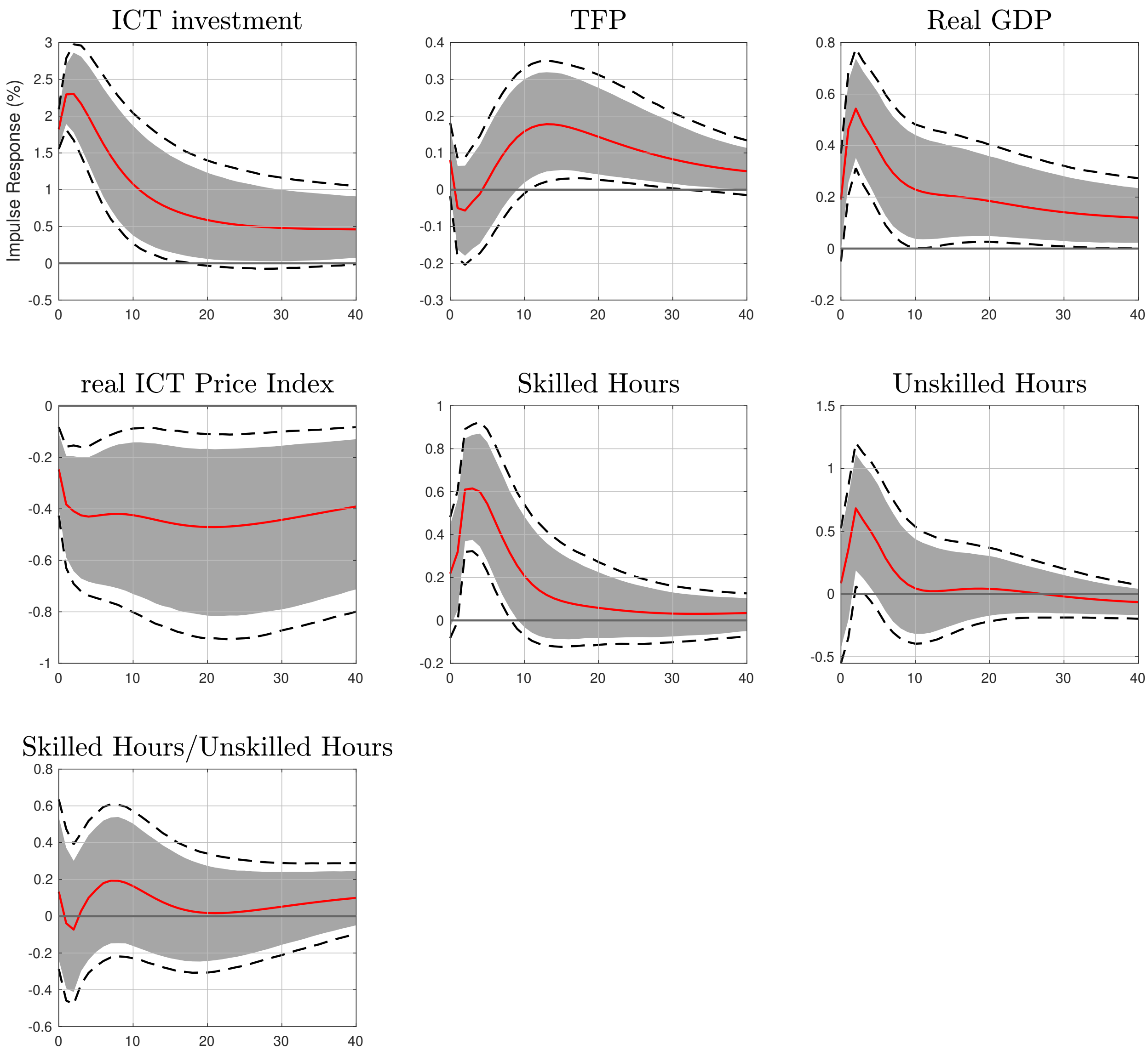

Figure A2: Impulse Responses without decovid

Note: This figure reports the impulse responses toa one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

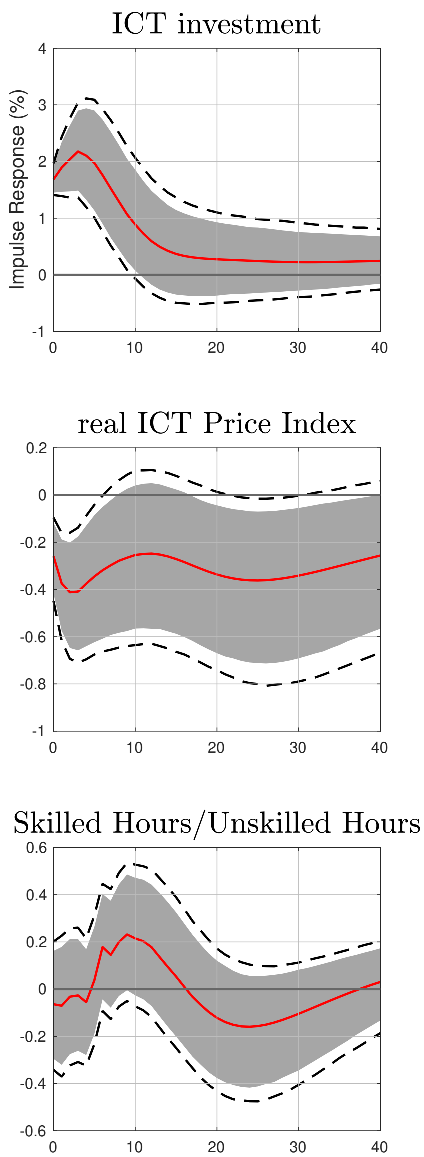

Figure A3: Robustness check 2: Different number of lags (lag 4)

Note: This figure reports the impulse responses to the one standard deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

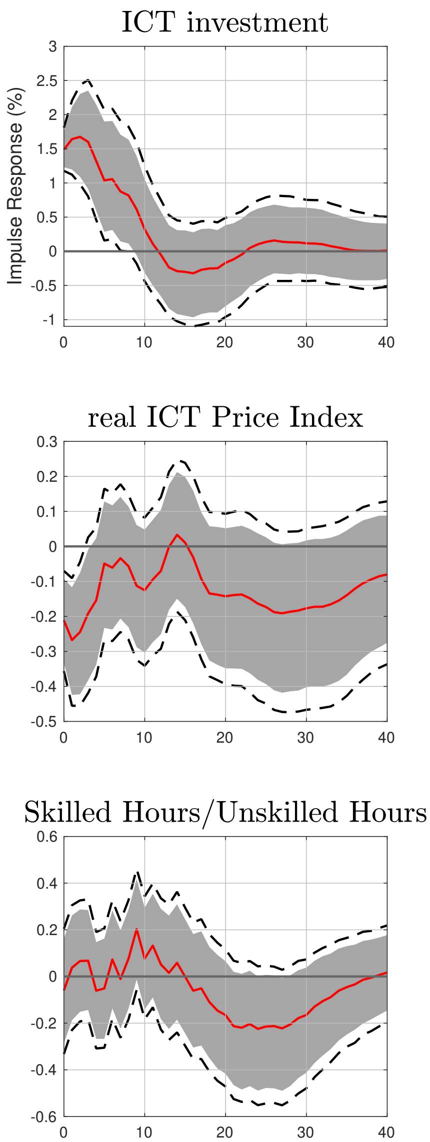

Figure A4: Robustness Check 3: Different number of lags (lag 8)

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

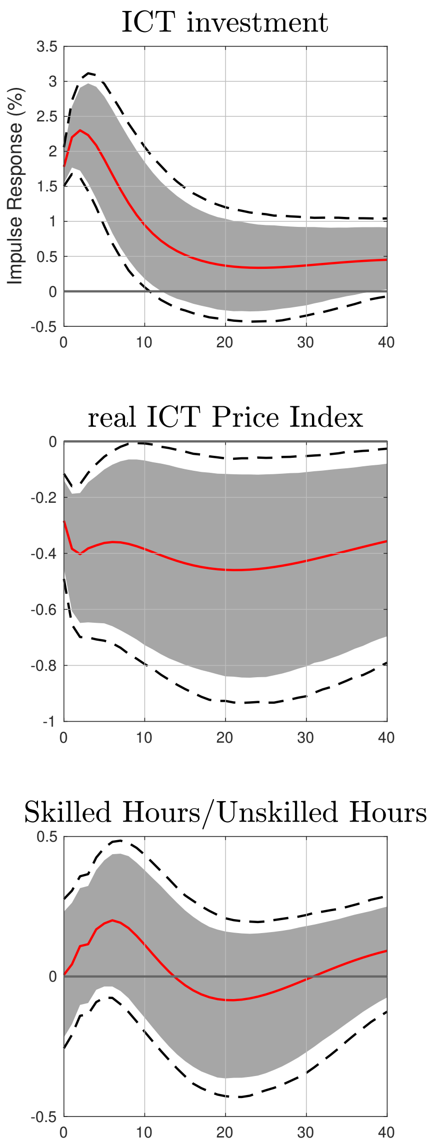

Figure A5: Robustness check 4: Excluding post-COVID period

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2019Q4. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.

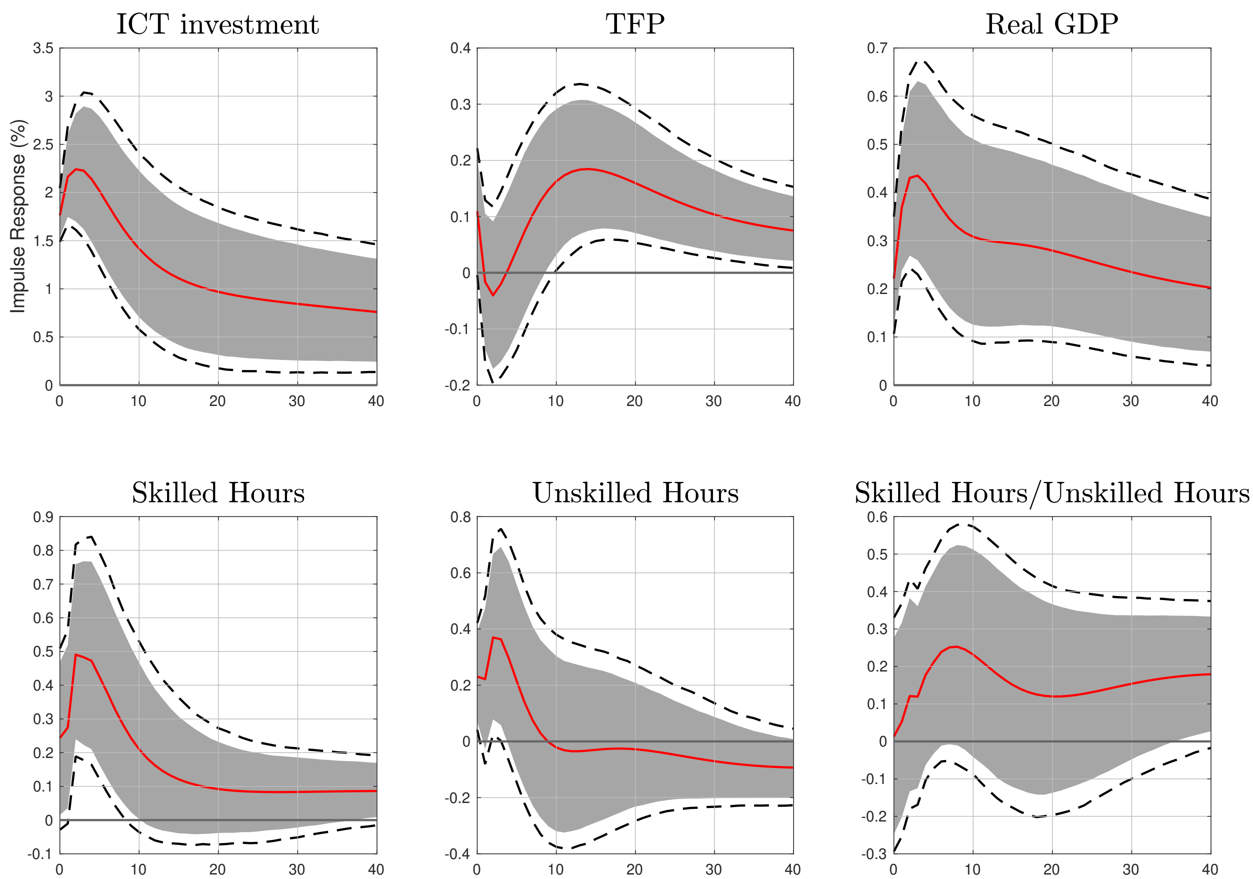

Figure A6: Robustness check 5: Excluding the ICT price

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 90% and 95% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived by the standard bootstrap method with 10,000 draws.