ICT Innovations and Labor Hours: A Business Cycle Analysis*

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Abstract

This paper examines the impact of changes in information and communication technologies (ICT) on skilled and unskilled labor at the business cycle frequency. To achieve this, we construct aggregate hours series for both labor groups using the monthly outgoing rotation group of the Current Population Survey from 1994 to 2023. Our empirical analysis, conducted with a structural vector autoregressive model, shows that the working hours of both groups respond positively to ICT innovations with similar magnitudes. We demonstrate that our findings are consistent with a dynamic stochastic general equilibrium model in which ICT capital complements both skilled and unskilled labor, and suggest a plausible range of elasticity of substitution between capital and labor.

JEL classification: D24, E32, J23

Keywords: Information and communication technologies, Hours worked, Skill, Business cycle

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1 Introduction

This paper investigates the impact of changes in information and communication technologies (ICT) on 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, aggregate 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.[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 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).[2] This perspective suggests that advancements in ICT are typically perceived as more complementary to skilled workers. Additionally, the historical decline 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

[1] We follow Wolcott (2021) for classifying workers into two skill groups based on their educational attainments. Our main findings are preserved when we divide skilled/unskilled group in an alternative way, as shown in Appendix (Figures A15 to A17).

[2] In an economic context, particularly for empirical analysis, this technological progress is manifested as ICT capital, including IT hardware (e.g., computers), communications equipment, software and databases. In line with this, our empirical analysis employs the investment in information processing equipment and software series for the identification of ICT shocks, which will be detailed below.

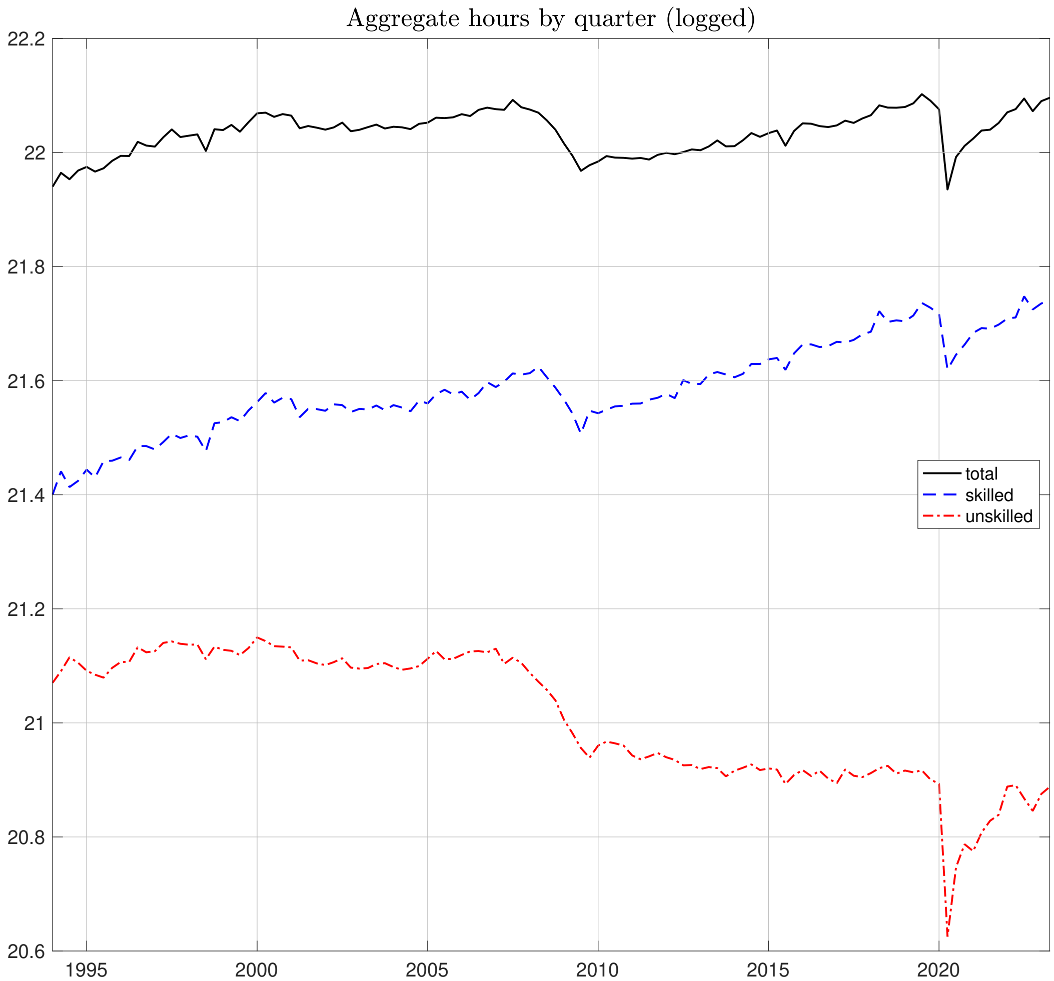

Figure 1: Aggregate working hours

Note: This figure reports quarterly aggregate working hours of skilled and unskilled workers, constructed using the monthly outgoing rotation group Current Population Survey (1994Q1 to 2023Q2). Workers are grouped based on individuals' educational attainment. We obtain monthly observations as the weighted sum of individual weekly hours and derive quarterly series by averaging the three monthly values in each quarter.

the labor market.

Building on such existing divergent views, our paper explores the interplay between ICT capital and labor market dynamics at the business-cycle frequency, an area that has been overlooked in the literature despite its significance. We begin by constructing series for hours worked by skilled and unskilled labor groups using the monthly outgoing rotation group of the Current Population Survey (MORG CPS) covering the period from 1994 to 2022. Employing these series in a vector autoregressive (VAR) model, we find that the working hours and employment levels of both labor groups do not exhibit statistically significant divergence in their responses; both groups experience an increase in working hours following a positive shock to ICT capital, with the magnitude of change being similar for both groups. This

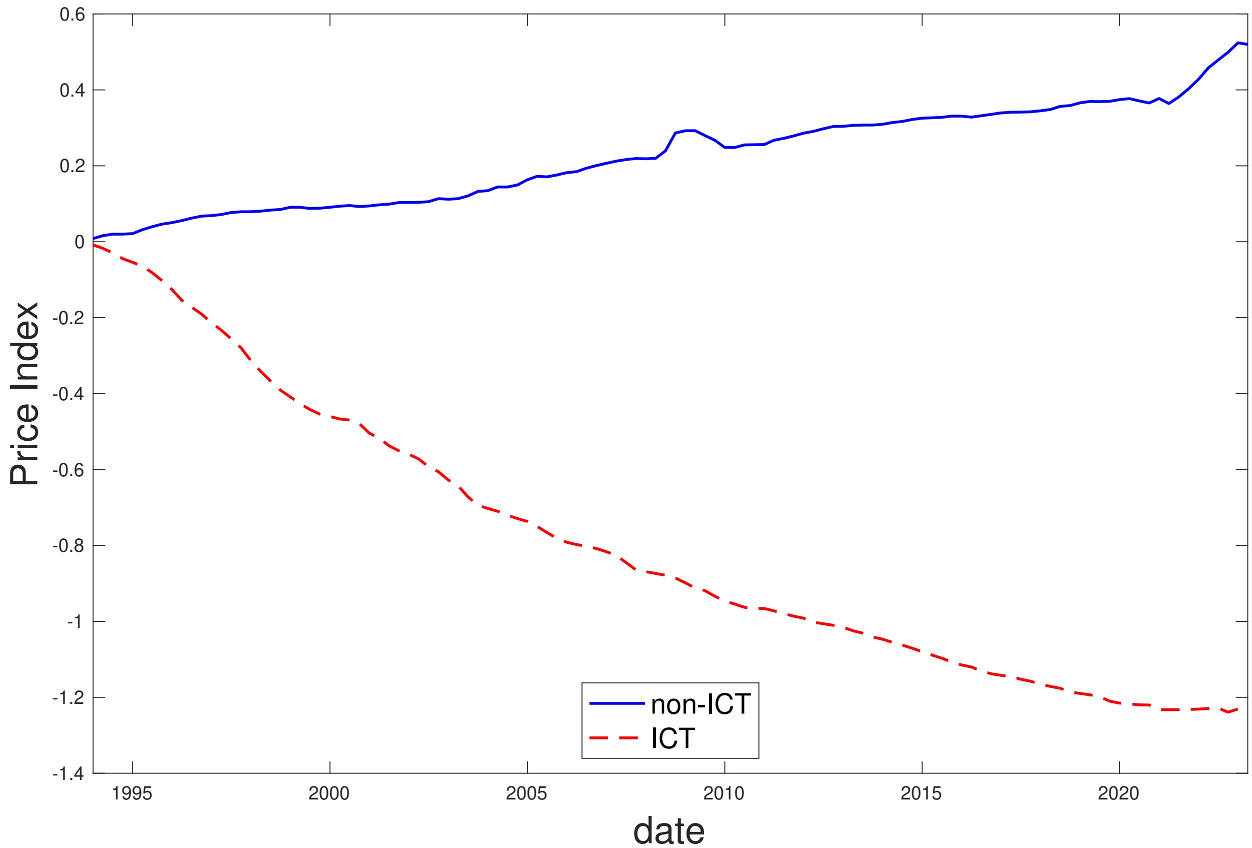

Figure 2: ICT and non-ICT capital prices

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

finding remains robust under various conditions: (i) different orderings, (ii) inclusion of a news shock component in the ICT shock, (iii) varying numbers of lags, (iv) exclusion of the Global Financial Crisis or COVID period from the sample, and (v) alternative shock identification methods.

Subsequently, we develop a dynamic stochastic general equilibrium (DSGE) model in which skilled labor is more complementary to ICT capital than unskilled labor, following the conventional approach (Taniguchi and Yamada, 2022).[3] Non-ICT capital, in contrast, enters the production function as factor-neutral. Our model suggests that working hours for skilled and unskilled labor move in opposite directions in response to a positive ICT shock, a prediction inconsistent with our empirical findings. Finally,

[3] While Brianti and Gáti (2023) consider a two-sector model where each sector separately produces consumption goods and ICT capital, we employ a one-sector model where ICT capital is not produced by an independent firm. This is to avoid a labor co-movement problem that often arises in a typical two-sector model (see Katayama and Kim (2018) for detailed discussions); as our main interest lies in the responses of aggregate hours to shocks to (ICT) capital, not in the heterogeneous responses of hours across different sectors, we believe that this approach is appropriate for the scope of our paper.

we demonstrate that a production function in which ICT capital is complementary to both worker groups, with specific ranges of elasticity of substitution between capital and labor, can generate hours responses that align with our empirical observations.

Our paper contributes to two key areas of literature. First, it advances the understanding of business-cycle dynamics for skilled and unskilled labor (e.g., Castro and Coen-Pirani (2008) and Balleer and van Rens (2013)). We find that a positive shock to ICT capital, which is often perceived as skill-biased technology, leads to similarly positive responses of both types of workers. This is different from earlier research that highlights the capital-skill complementarity and, thus, implicitly assumes unskilled labor would be substituted when ICT innovations occur, often based on analyses focusing on long-run dynamics. Second, we broaden the discussion on how different types of capital shocks influence economic fluctuations (see Fisher (2006), for example). A closely related study is Brianti and Gáti (2023), which demonstrates that shocks to ICT capital impact TFP and thus contribute to medium-run business cycle fluctuations in the U.S. In contrast, our focus is on the labor market dynamics rather than on general aggregate economic patterns.

It is worthwhile to highlight that our finding is not inconsistent with long-run evolution of the labor market: During the sample period (1994Q1–2023Q2) that we consider in the analysis, the skill premium (i.e., the wage ratio of skilled to unskilled workers) remained fairly stable, as shown in Figure 3. This observation implies that parameter values in the production function that conventionally used to explain the rising skill premium from the mid-1980s may be ill-suited for capturing short-run labor market dynamics at least from the mid-1990s onward. In other words, matching long-run changes in the skill premium during our sample period should not necessarily be the primary objective, particularly when such a parameterization compromises the model's ability to replicate short-run fluctuations. This further implies that production functions may exhibit different characteristics over time, opening a door for models that posit complementary relationships between ICT capital and both worker groups, particularly when examining 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 and 3.4, which yields impulse responses

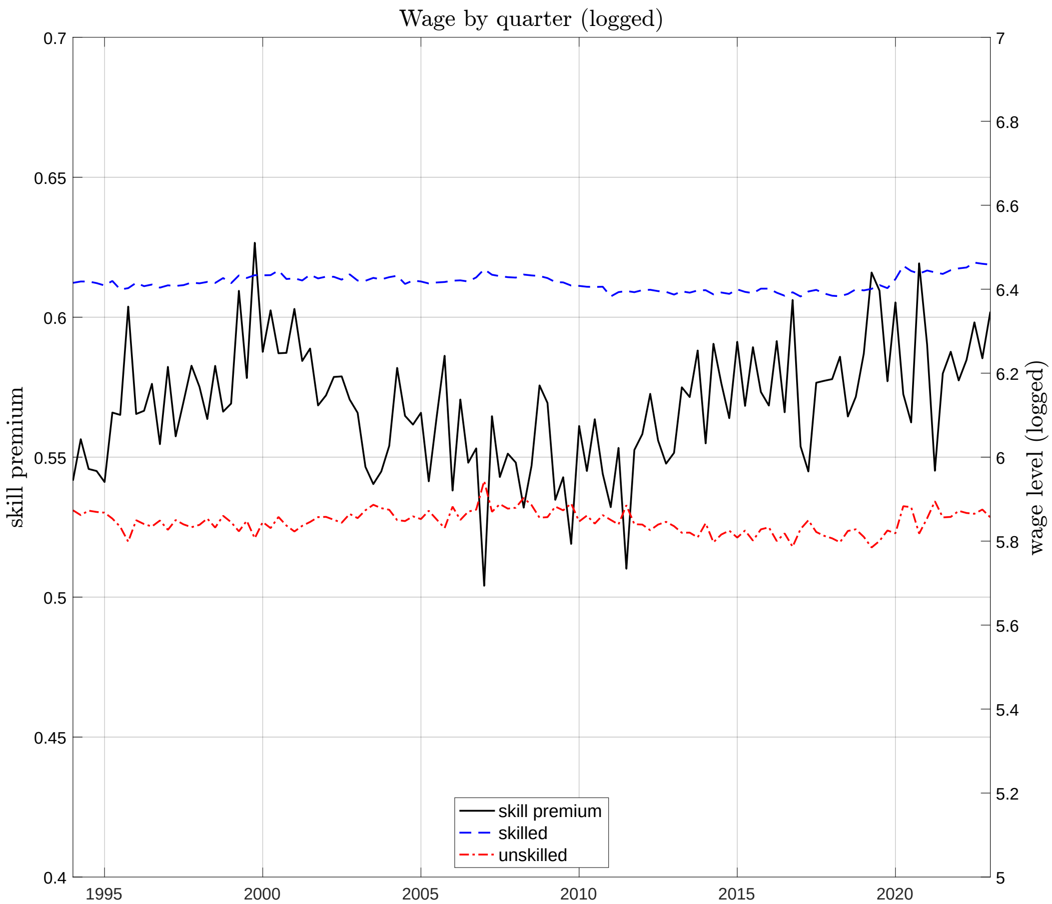

Figure 3: Wages and Skill Premium

Note: This figure reports wage of each skill group and skill premium (wage of skilled worker relative to unskilled one) between 1994Q1 and 2023Q2, constructed using the monthly outgoing rotation group Current Population Survey.

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 primary interest is in examining the impacts of ICT shocks on the labor market at the business cycle frequency. Specifically, we investigate if these shocks have heterogeneous effects on workers based on their educational level, a common proxy for skill level. As this requires working hours data for each skill level, we construct the quarterly working hours by categorizing workers according to their education level using data from the MORG CPS. In particular, we exploit weekly hours worked by skilled and unskilled workers.[4]

We classify a worker as "skilled" if the individual has completed at least one year of college, and "unskilled" if no college, following Wolcott (2021)[5]. After classifying the individuals according to their education levels, we aggregate the individual working hours using the weights provided by the IPUMS CPS and calculate the quarterly average of monthly total working hours for each group. Our measure excludes institutionalized and active military personnel and includes men and women between the ages of 25 to 54. Since the CPS metric for actual hours worked may exhibit random fluctuations (e.g., when a holiday occurs during the reference week), we eliminate outliers following Cociuba, Prescott, and Ueberfeldt (2018) and adjust for seasonality by employing the X-13 ARIMA-SEATS method.

We also construct the quarterly employment in a similar manner to the hours data. To explain in more detail, we classify an individual's status as employed if the variable EMPSTAT is "At work (code: 10)" or "Has job, not at work last week (code: 12)". We then aggregate the individual employment statuses using the weights provided by the IPUMS CPS. The rest of the procedure is the same as constructing the hours data, with the exception of the outlier adjustment process.[6] Similar to the case of working hours, the unconditional correlation between skilled and unskilled employment is 0.75 during our sample period.

Moreover, we construct a measure for ICT and non-ICT prices to convert investment variables in

[4] We use AHRSWORK1, which refers to hours worked last week at the main job.

[5] We also tried a different definition of skilled/unskilled labor: "skilled" if the individual has a college degree, and "unskilled" otherwise. The results from this alternative classification were still robust. Details for the robustness check are in section 2.4.

[6] The CPS survey went through a major change in the wording of the questionnaire and the methodology used to collect the data (Polivka 1996 and Polivka and Miller 1998). Since this redesign also affected the measurement of hours worked as well as employment status, we start our sample in 1994.

nominal terms to real terms. This involves chain-weighting gross private domestic investment price indexes based on investment types. Specifically, ICT investment covers intellectual property products and information processing equipment, whereas non-ICT investment includes industrial and non-residential equipment, such as transportation. More details of the data we use for the index construction are provided in Table A1. We convert nominal ICT and non-ICT investment data into real terms by deflating them with the ICT and non-ICT price indices derived above. We also convert other series expressed in nominal terms into real terms using the CPI.

Descriptions of the remaining data are provided in Table 1. We use TFP, real GDP, and ICT investments series to identify the ICT shock, following Brianti and Gáti (2023). In addition, Table 2 reports the cyclical properties of the HP-filtered series, highlighting the relative standard deviation of each variable and its correlation with the cyclical component of GDP.

Table 1: Summary of data descriptions and sources

Variable	Description	Source
TFP	Utilization-adjusted total factor productivity (dtfp_util)	San Francisco Fed
Real GDP	Real gross domestic product, billions of chained 2012 dollars, quarterly, Seasonally Adjusted Annual Rate (GDPC1)	FRED
ICT Investment	Private fixed investment in information processing equipment and software, billions of dollars, quarterly, seasonally adjusted annual rate (A679RC1Q027SBEA)	FRED
Investment	Private nonresidential fixed investment, billions of dollars, quarterly, seasonally adjusted annual rate (PNFI)	FRED
Non-ICT Investment	Differences between *Investment* and *ICT Investment*	FRED
ICT/non-ICT Prices	Constructed by chain-weighting the price indexes for private fixed investment	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	Quarterly average of working hours of men & women, ages 25-54	IPUMS-CPS

Note: This table provides a brief description of variables used in our empirical analysis and their sources. The details of the construction of ICT and non-ICT prices and the Hours and Employment are described in section 2.1.

2.2 METHODOLOGY To empirically examine responses of skilled and unskilled labor to ICT shocks, we closely follow the methodology outlined in Brianti and Gáti (2023). To start, we assume that Y_t, an

Table 2: Business Cycle Statistics of Key Variables

	Std. Dev.	Relative Std. Dev. (σ_x/σ_{GDP})	Correlation ($\rho(x, GDP)$)
Real GDP	0.014	1	1
Real ICT Investment	0.040	2.932	0.625
Skilled Hours	0.019	1.408	0.723
Unskilled Hours	0.032	2.363	0.815
Skilled Employment	0.012	0.872	0.717
Unskilled Employment	0.026	1.892	0.762
Correlation Coefficients			
Skilled and Unskilled Hours		0.78	
Skilled and Unskilled Employment		0.75	

Notes: All statistics are calculated for the sample period 1994Q1–2023Q2. All variables are log-transformed and then filtered using the Hodrick-Prescott (HP) filter. The first column denotes the standard deviation, σ_x/σ_{GDP} the relative volatility, and $\rho(x, GDP)$ the contemporaneous correlation with GDP.

$n \times 1$ vector of endogenous variables, follows a structural VAR process as:

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

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 model extends the benchmark trivariate VAR model introduced by Brianti and Gáti (2023) by including the real ICT price index along with 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 relative changes within a unified framework.

We adopt the identification strategy of Brianti and Gáti (2023), assuming that A_0^{-1} is a lower triangular matrix. In other words, the structural shocks are identified through the Choleski decomposition. To achieve this, we posit that the ICT shock is the only shock to exert a contemporaneous effect on ICT investment. It is worthwhile to note that we only identify the ICT shock from our VAR model; our main goal is not to explain overall business cycle dynamics nor to provide a full structural decomposition of specific recessionary episodes. Rather, we aim to isolate the component of unexpected ICT investment movements that is attributable to ICT-specific technological shifts. While other structural shocks could be identified, our analysis focuses specifically on the transmission of ICT shocks.[7] As will be detailed below, we further demonstrate the robustness of our results by applying several different identification methods.

2.3 Impacts of ICT Shocks on the Labor Market Figure 4 shows the impulse responses to an ICT shock from our baseline VAR specification, i.e., equation (1).The first row of Figure 4 illustrates impulse responses of ICT investment, TFP, and the real GDP, which are the variables consisting of the baseline VAR model in Brianti and Gáti (2023). The results are qualitatively very similar while their magnitudes differ slightly; in response to the ICT shock, both TFP and real GDP increase significantly and persistently, 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. All of these findings are in line with Brianti and Gáti (2023).

We now turn to the responses of labor market variables, which are of our primary interest. The panels in the second row of Figure 4 report the impulse responses of the skilled and unskilled hours. What is particularly notable is the impulse responses of the unskilled hours. According to the capital-skill complementarity hypothesis often assumed in previous literature, an ICT shock should theoretically lead to a decrease in unskilled hours if they are substitutes for ICT capital. However, our empirical findings do not support this displacement effect.

Instead, we find that the shock leads to a significant increase in both skilled (0.515% at the peak) and unskilled (0.380% at the peak) hours. While the response of unskilled hours is relatively short-lived and significant only within the 90% confidence interval, the crucial takeaway is the absence of a negative response. When we compute the impulse responses of the two groups' working hours in ratio as shown in the third row of Figure 4, we see that there is no significant difference between their working hours when there is a shock to ICT capital.[8] A forecast error variance decomposition indicates that unexpected fluctuations in ICT capitals can explain the working hours of both skilled and unskilled

[7] Thus, we do not disregard the possibility that other structural shocks coexist within the same sample period and may influence ICT investment dynamics over time. The reduced-form VAR is estimated via Ordinary Least Squares (OLS). Confidence bands for the structural impulse responses are computed using Kilian's (1998) bootstrap-after-bootstrap method.

[8] The point estimates of the IRF for the ratio are inferred by calculating the difference between the responses of skilled and unskilled hours in logs. Likewise, the error bands are generated by computing the difference between the skilled and unskilled hours for each bootstrapped draw and sorting them afterwards. As Figure A7 shows, including the hours variables in ratio already in Equation (2) yields similar impulse responses to the ones inferred in this way.

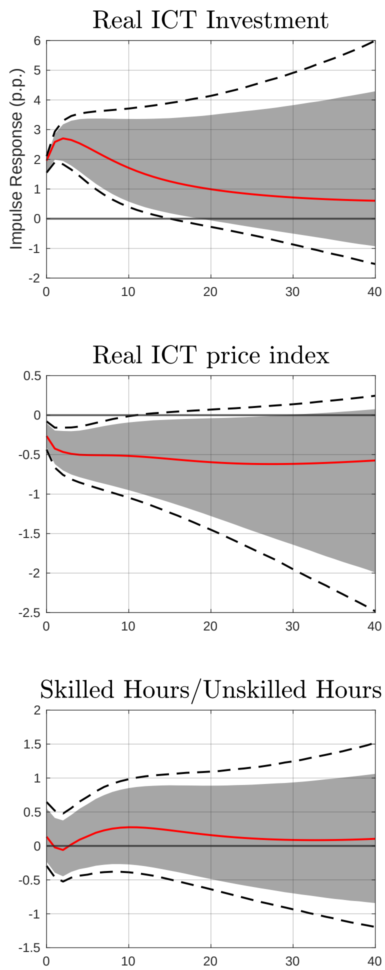

Figure 4: Impulse responses to an ICT shock

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 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The ratio between two hours is constructed by dividing skilled hours by unskilled hours for each draw and reordering them.

workers by about 30% and 15%.[9]

Next, we replace the two hours variables with employment by skill groups in our baseline model (equation (1)). This analysis, hence, aims to examine the responses of the labor market at the extensive margin, different from the adjustment of working hours, i.e., at the intensive margin. Of note, the former has been found to play a crucial role in explaining labor market dynamics at the business cycle frequency (Heckman, 1984; Hansen, 1985; Chang and Kim, 2007, and many others). Figure 5 plots the impulse responses of the employment by two skill groups to an ICT shock as well as their responses in

[9]Details of the forecast error variance decomposition is provided in Appendix B.

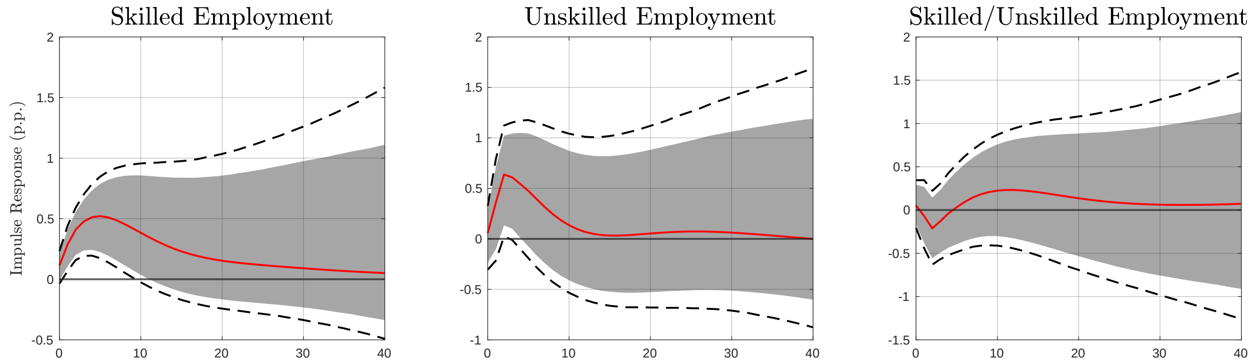

Figure 5: Impulse responses of skilled and unskilled employment to an ICT shock

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 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The ratio between two employments is constructed by dividing skilled employment by unskilled employment for each draw and reordering them.

ratio.[10] The results closely resemble those observed in Figure 4; similar to the results for working hours in Figure 4, unskilled employment exhibits a temporary increase rather than a decline. In addition, when we calculate the relative responses of the skilled and unskilled employment as before, the inferred responses are very similar to those from Figure 4 and indicate that there is no significant distinction between the two groups. Taking these results together, we do not find sufficient empirical support for the argument that the ICT shock would induce heterogeneous responses of the skilled and the unskilled groups, also in the extensive margin.

In contrast to ICT capital, non-ICT capital has traditionally been viewed as worker-neutral, meaning that innovations in non-ICT capital should produce similar effects on workers regardless of their skill levels (Krusell, Ohanian, Ríos-Rull, and Violante 2000). To investigate this, we substituted the investment and price index variables from our baseline case with those for non-ICT capital and re-estimated the impulse responses, which are shown in Figure 6. Consistent with previous studies, our findings reveal that non-ICT shocks result in qualitatively and quantitatively similar responses for both skilled and unskilled labor. As such, their relative responses are statistically indistinguishable, as presented in the last panel of Figure 6. More importantly, all of these three impulse responses are very much alike to those from our baseline model in Figure 6. Overall, these results suggest that both ICT and non-ICT shocks impact workers of varying skill levels in a similar manner.

[10] Responses of the other endogenous variables change little from Figure 4 and are available upon request.

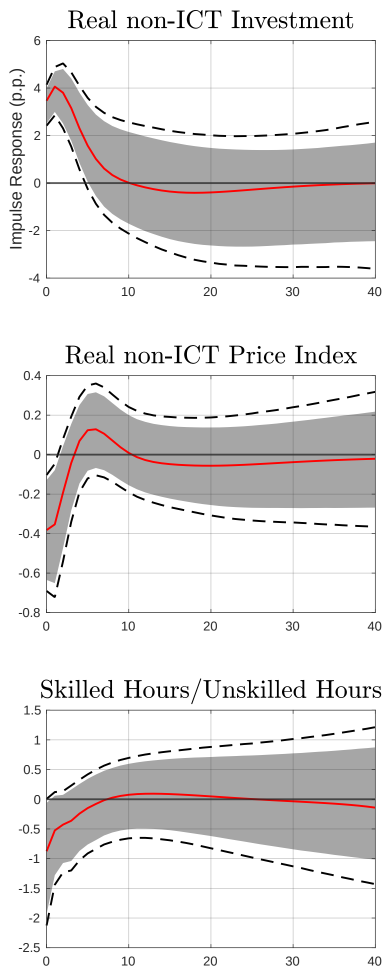

Figure 6: Impulse responses to non-ICT shocks

Note: This figure reports the impulse responses to a one-standard-deviation non-ICT investment shock, using data from 1994Q1 to 2023Q2. The black-dashed lines and the grey-shaded area represent 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The ratio between two hours is constructed by dividing skilled hours by unskilled hours for each draw and reordering them.

2.4 Identification Validity and Robustness Checks

We check the validity of our identification assumption in two ways. First, we estimate the correlation between the historical ICT shock estimates and 32 structural shocks identified by previous literature and report the correlation coefficients in Table A2, extending the analysis in Brianti and Gáti (2023).[11] These structural shocks range from commodity price shocks, technology shocks, monetary and fiscal policy shocks, to financial market shocks. Our ICT shock should be uncorrelated with these other structural shocks to maintain its own distinct structural interpretation. We also run the Granger causality tests with the above-mentioned structural shocks to

[11] Brianti and Gáti (2023) examined contemporaneous correlations with 10 previously-identified macro shocks.

examine if any of them have a predictive power for the ICT shock (Table A3). Therefore, the Granger test can provide support for the assumption that the ICT shock is not confounded with other shocks. In both analysis, most of the shocks are not related to the ICT shock at the 1% significance level and do not Granger cause the ICT shock identified in this paper.

One exception in Table A2 is the surprise investment-specific technology (IST) shock from Justiniano, Primiceri, and Tambalotti (2011), which is not unexpected given that the IST shock in their paper, which captures the change of the relative price of an investment, plays a similar role to our ICT shock.

The other series that appears correlated with our ICT shock is Gilchrist and Zakrajšek's (2012) Excess Bond Premium (EBP).[12] To address the concern that our identified ICT shock might be confounded by financial factors, we estimate a VAR where our baseline model is expanded by augmenting the EBP as the first variable in the system.

Following Junicke, Matěj, Mumtaz, and Theophilopoulou (2024), this recursive structure treats the EBP as an "internal instrument" for ICT shocks. As demonstrated by Plagborg-Møller and Wolf (2021), the impulse responses generated from this setup are asymptotically equivalent to those obtained through an external instrumental variable or proxy VAR approach. Under this Cholesky decomposition, the first shock captures the component of ICT fluctuations that is instrumented by, or explained by, surprises in the EBP. In other words, it represents ICT movements driven by financial market conditions. Consequently, the second shock, which is our primary interest, can be interpreted as a "pure" ICT innovation that is statistically orthogonalized and purged of financial influences. By comparing these two, we can ensure that our baseline results are not erroneously attributed to financial shocks.

Figures A2 and A3 report the impulse response functions to the first and second shocks, respectively. Interestingly, the impulse responses to the EBP-driven ICT component and the pure ICT shock exhibit a mirror-image pattern. Specifically, while a positive EBP surprise (financial tightening) leads to a contraction in ICT investment and a corresponding decline in hours worked mainly of skilled workers, a pure ICT technological shock induces an expansion in both. More importantly, both skilled and unskilled hours move in the same direction such that the ratio of skilled to unskilled hours show no significant divergence in responses to both shocks. This suggests that the labor market's response to ICT fluctuations is a fundamental feature of the data, regardless of whether the change is triggered by

[12] This series captures the residual corporate bond spread after netting out default compensation, and thus, the small but significant negative correlation between the two may suggests that technological advancements in ICT may have occurred in an environment with alleviated financial frictions.

financial conditions or technological shifts. Also, the overall responses to the pure ICT shock remain almost identical to our baseline results, which demonstrates that the balanced response of the two worker groups are indeed driven by the intrinsic technological characteristics of ICT capital, rather than being a byproduct of financial market fluctuations.

Furthermore, we apply alternative identification approaches in a VAR model where we switch the ordering of the variables such that the real ICT price (i.e., the relative price of ICT investment) is ordered first, followed by real ICT investment, TFP, real GDP, hours worked by skilled workers, and those by unskilled workers, and consider shocks that lowers the relative price of ICT. More specifically, we use three different identification schemes: i) short-run restrictions where the ICT shock is defined as the only one shock affecting the relative price of ICT investment contemporaneously (Justiniano, Primiceri, and Tambalotti (2011)), ii) long-run restrictions where the ICT shock permanently affects the relative price (Fisher (2006)), and iii) the max-share approach where the shock that contributes most to the variations of the relative ICT price in 40 quarters from the impact (Chen and Wemy (2015)).

The first approach yields results that are qualitatively consistent with our baseline Cholesky identification (Figure A4). However, the long-run and max-share restrictions produce much wider confidence intervals (Figures A5-A6). This is likely due to the limited time span of our data and also more generally to the lack of power associated with long-run restriction-based identification, which has been pointed out by a number of studies including Faust and Leeper (1997), Chari, Kehoe, and McGrattan (2008) and Kilian and Lütkepohl (2017).[13] Yet, the point estimates across all these alternative specifications are qualitatively consistent with our baseline results, which reinforces the validity of our main findings.

We then conduct a battery of checks to ensure the robustness of our baseline findings. One of those checks worthwhile to discuss here is the potential impact of news embedded in ICT shocks. To elaborate, the informational content integrated into these shocks might weaken the strength of our identification strategy, as outlined in Brianti and Gáti (2023). That is, agents may form expectations about the future based on a forthcoming ICT innovation, and it can potentially affect the responses of the variables of interest. Hence, we augment Kurmann and Sims (2021)'s news shock series to our VAR model, as done in Brianti and Gáti (2023), and compute impulse response. As shown in Figure 7, controlling for the

[13] We explored numerous variations in lag lengths and variable compositions for the long-run and max-share identification methods, and in no case did we find impulse responses that contradict our main results regarding the skilled and unskilled working hour dynamics.

news shock does not affect our main result much.[14]

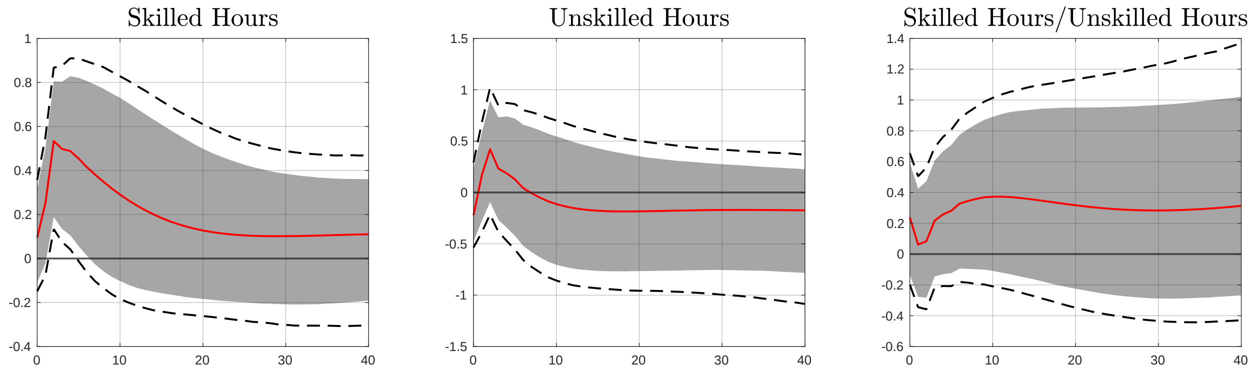

Figure 7: Robustness check: Controlling the news shocks (Kurmann and Sims, 2021)

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 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The ratio between two hours is constructed by dividing skilled hours by unskilled hours for each draw and reordering them.

Other robustness check results are presented in the Appendix. In particular, we depart from the baseline VAR by changing the number of lags (Figures A8 and A9), altering the ordering of variables (Figure A10), excluding the COVID-19 pandemic period from the sample (Figure A11), controlling additionally for the Great Financial Crisis period (Figures A12, A13, and A14), and using an alternative definition of skilled/unskilled group: skilled as those with a college degree, otherwise unskilled (Figures A15, A16, and A17). Our main findings remain largely unchanged across these variations in specifications. In other words, ICT shocks continue to exert similar responses to macroeconomic indicators included in the VAR. More importantly, the shocks lead to a rise in both skilled and unskilled labor hours in the short run, and the magnitudes of these increases for both groups are significantly indistinguishable.

3 ICT shocks on Labor Market Dynamics: A Model

Our empirical analysis using a structural VAR model revealed that an ICT shock would increase the working hours of both skilled and unskilled labor. This section further investigates how such empirical findings can be explained theoretically.

[14]Responses of the other endogenous variables change little from Figure 4 and are available upon request.

3.1 Model We consider a social planner's problem to predict how a shock to ICT- and hard (non-ICT) capital affects the labor market. In particular, the planner maximizes the expected lifetime utility, discounted by the rate $\beta \in (0,1)$, by solving the following problem:

$$\max_{c_t,h_{s,t},h_{u,t},i_t,k_{t+1},i_{d,t},d_{t+1}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log c_t - \nu_s \frac{h_{s,t}^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} - \nu_u \frac{h_{u,t}^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} \right], \tag{2}$$

subject to

$$c_t + i_t + i_{d,t} = y_t, \tag{3}$$

$$k_{t+1} = p_t \left(1 - \Phi\left(\frac{i_t}{i_{t-1}}\right)\right) i_t + (1-\delta)k_t, \tag{4}$$

$$d_{t+1} = z_t \left(1 - \Phi\left(\frac{i_{d,t}}{i_{d,t-1}}\right)\right) i_{d,t} + (1-\delta_d)d_t, \tag{5}$$

where equation (3) is the resource constraint and equation (4), (5) describe the law of motions for ICT capital and hard (non-ICT) capital, respectively. c_t denotes consumption expenditure, i_t is an investment in ICT capital, $i_{d,t}$ is an investment in hard capital, $h_{j,t}$ with $j = s,u$ is skilled/unskilled working hours, $\delta, \delta_d \in (0,1)$ are depreciation rates of ICT and hard capital, respectively, and $\Phi\left(\frac{x_t}{x_{t-1}}\right) = \frac{\phi}{2}\left(\frac{x_t}{x_{t-1}} - 1\right)^2$ where $x_t = \{i_t, i_{d,t}\}$ with a constant $\phi > 0$ is the investment adjustment cost. We denote ICT and non-ICT shocks by p_t and z_t, respectively. Both shocks are assumed to follow AR (1) process in log-levels, following the convention. 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):

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

where the parameters $\mu > 0$, $\lambda > 0$, and α 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 smaller (resp. larger) 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 $0<\sigma<1$ and $\rho<0$ 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.[15] We finally note that the elasticity of substitution between hard capital and both types of labor is equal to one, which captures the idea that only ICT capital can have differential effects on workers (Taniguchi and Yamada (2022)).

The sufficient and necessary conditions for the optimal path, excluding feasibility conditions (equations (3), (4), and (5)) and the Transversality condition, are given as follows.

$$\nu_s h_{s,t}^{1/\chi} = (1-\lambda)(1-\alpha)(1-\mu)\frac{1}{c_t}(\lambda k_t^\rho + (1-\lambda)h_{s,t}^\rho)^{\frac{\sigma}{\rho}-1} h_{s,t}^{\rho-1} \frac{y_t}{\mu h_{u,t}^\sigma + (1-\mu)(\lambda k_t^\rho + (1-\lambda)h_{s,t}^\rho)^{\frac{\sigma}{\rho}}} \tag{7}$$

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

$$\begin{aligned}\frac{1}{c_t} &= \Gamma_{1,t}\left(p_t\left(1-\frac{\phi}{2}\left(\frac{i_t}{i_{t-1}}-1\right)^2\right) - p_t\phi\left(\frac{i_t}{i_{t-1}}-1\right)\frac{i_t}{i_{t-1}}\right) \\ &\quad + \beta\mathbb{E}_t\Gamma_{1,t+1}\left(p_{t+1}\phi\left(\frac{i_{t+1}}{i_t}-1\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right)\end{aligned} \tag{9}$$

$$\Gamma_{1,t} = \beta\mathbb{E}_t\frac{1}{c_{t+1}}\frac{\lambda(1-\alpha)(1-\mu)(\lambda k_{t+1}^\rho + (1-\lambda)h_{s,t+1}^\rho)^{\frac{\sigma}{\rho}-1} k_{t+1}^{\rho-1} y_{t+1}}{\mu h_{u,t+1}^\sigma + (1-\mu)(\lambda k_{t+1}^\rho + (1-\lambda)h_{s,t+1}^\rho)^{\frac{\sigma}{\rho}}} + \beta\Gamma_{1,t+1}(1-\delta) \tag{10}$$

$$\begin{aligned}\frac{1}{c_t} &= \Gamma_{2,t}\left(z_t\left(1-\frac{\phi}{2}\left(\frac{i_{d,t}}{i_{d,t-1}}-1\right)^2\right) - z_t\phi\left(\frac{i_{d,t}}{i_{d,t-1}}-1\right)\frac{i_{d,t}}{i_{d,t-1}}\right) \\ &\quad + \beta\mathbb{E}_t\Gamma_{2,t+1}\left(z_{t+1}\phi\left(\frac{i_{d,t+1}}{i_{d,t}}-1\right)\left(\frac{i_{d,t+1}}{i_{d,t}}\right)^2\right)\end{aligned} \tag{11}$$

$$\Gamma_{2,t} = \beta\mathbb{E}_t\frac{1}{c_{t+1}}\alpha\frac{y_{t+1}}{d_{t+1}} + \beta\Gamma_{2,t+1}(1-\delta_d) \tag{12}$$

Equations (7) and (8) denote labor market equilibrium conditions for unskilled and skilled labor, respectively. Equations (9), (10), (11), and (12) together describe joint dynamics of consumption and

[15] 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.

investment. $\Gamma_{1,t}$ and $\Gamma_{2,t}$ denote Lagrangian multipliers.

3.2 Model Predictions with Substitutable Low-Skilled Labor

In our model, labor market dynamics are exclusively influenced by ICT shocks (and non-ICT shocks), making the elasticities of substitution between ICT capital and labor crucial for determining how labor hours respond. Therefore, we start by examining the scenario where ICT capital and unskilled labor are substitutable. This approach aligns with the common assumption in the literature that ICT innovations are typically skilled-biased in the long run, implying that unskilled workers are more likely to be substituted as ICT innovations emerge.

Table 3: Calibrated 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	matching steady-state skilled hours ($\bar{h_s}$=0.15)
ν_u	-	scaling parameter of low-skilled Labor Disutility	matching steady-state unskilled hours ($\bar{h_u}$=0.15)
α	0.26	share of hard capital	Brianti and Gáti (2023)
μ	0.19	unskilled labor income share	jointly determined with λ to match the capital and labor income share
λ	0.2	ICT capital income share	jointly determined with μ to match the capital and labor income share
ρ	-0.495	the elasticity of substitution between skilled labor and ICT capital	Krusell, Ohanian, Ríos-Rull, and Violante (2000)
σ	0.401	the elasticity of substitution between unskilled labor and ICT capital	Krusell, Ohanian, Ríos-Rull, and Violante (2000)
ϕ	5.9	investment adjustment cost	Smets and Wouters (2007)
δ	0.124	ICT capital depreciation	Karabarbounis and Neiman (2014); Oliner (1992)
δ_d	0.056	hard capital depreciation	BEA, Karabarbounis and Neiman (2014)
ρ_p	0.9	persistence of AR(1) ICT Shock	-
σ_p	0.01	size of AR(1) ICT Shock	-
ρ_z	0.9	persistence of AR(1) non-ICT Shock	-
σ_z	0.01	size of AR(1) non-ICT Shock	-

Note: This table shows calibrated parameter values adopted for the analysis using the DSGE model from section 3. Unless otherwise noted, the above parameters are fixed at the values noted in this table for the rest of the paper.

Table 3 presents calibrated parameter values employed for our analysis.[16] Our parameter choices

[16]Later, when we examine the case of complementary ICT capital to unskilled labor, we will maintain the same values

draw heavily from Brianti and Gáti (2023), while some parameters are calibrated differently, as 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, ϕ, and δ are adopted from Woodford (2003); Chetty, Guren, Manoli, and Weber (2011); Smets and Wouters (2007); Karabarbounis and Neiman (2014); Oliner (1992), consistent with Brianti and Gáti (2023).[17] Additionally, the parameters governing income share, μ and λ, are calibrated to match the ICT capital income share to be 7% (Oulton, 2012), total caital income share to be approximately 1/3, and the total labor income share to be approximately 2/3.

We then solve the model with the perturbation method (Schmitt-Grohé and Uribe (2004)). Figure 8 presents the impulse responses of key macro variables from a one-time one-unit shock to ICT capital under 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 complement skilled hours but substitutable for unskilled hours, skilled hours increase while unskilled hours decline over time. As a result, the ratio between the two increases over time, peaking in 10 quarters after the impact.

Figure 8 demonstrates the impulse responses to an ICT shock implied by our baseline model calibration. One notable feature of the responses is the diverging responses of skilled and unskilled hours; while the former jumps immediately on impact and remains elevated, the latter shows a short-lived increase, only to remain strongly negative thereafter. As a result, the ratio of skilled to unskilled labor hours stays strictly positive throughout the response horizon, except for the impact, indicating a disproportionate shift in the labor market toward skilled workers. While this is consistent with our model setup where ICT capital and unskilled labor are substitutes, the responses of unskilled hours and the ratio of skilled and unskilled working hours differ greatly from their empirical equivalents in Figure 4. This implies that our baseline DSGE model structure should be modified to obtain (i) a positive impulse response of unskilled hours and (ii) no noticeable differences in the responses of both types of labor to the ICT shock.

Impulse responses to non-ICT shock are also presented in Figure 9. Responses are similar to those obtained from the empirical analysis (Figure 6), implying that the traditional production function

as in Table 3, except for σ.

[17] Brianti and Gáti (2023) calibrated δ by compromising the values from Karabarbounis and Neiman (2014) and Oliner (1992).

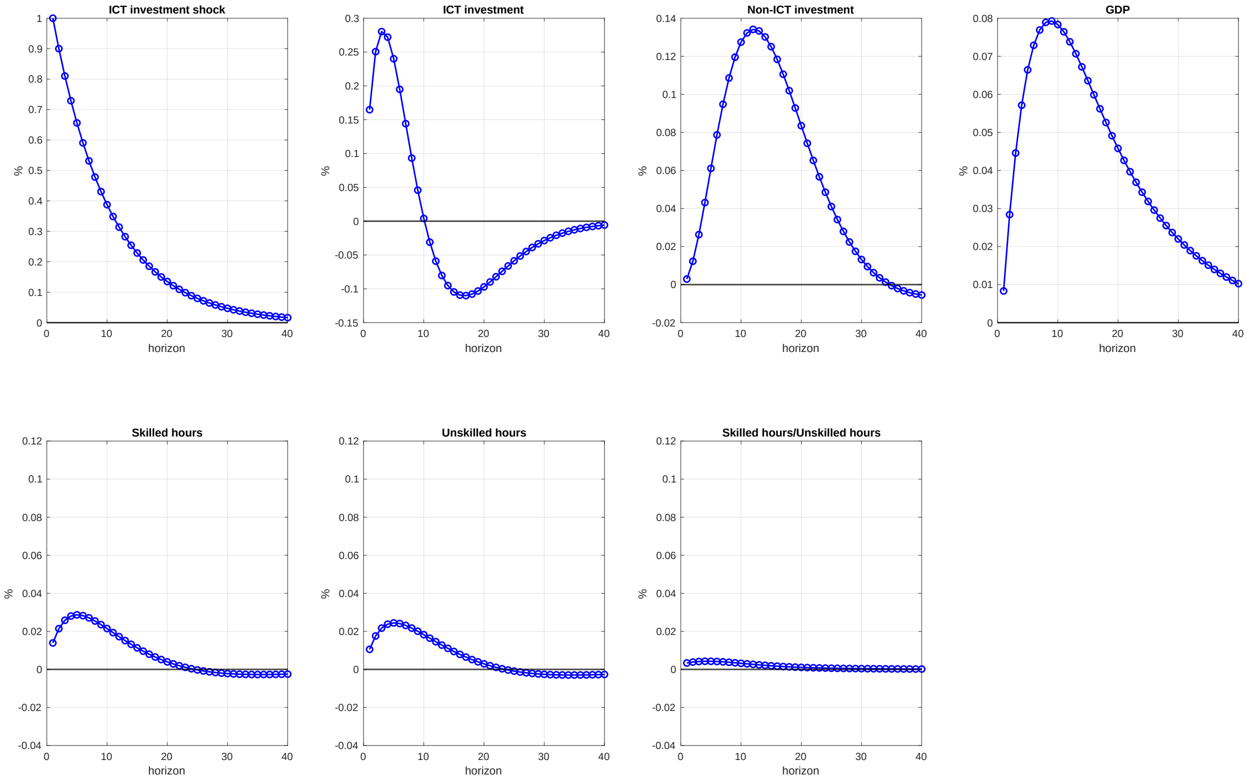

Figure 8: Impact of ICT shocks with ICT capital substituting for unskilled labor

Note: This figure reports the impulse responses from our theoretical model with substitutable unskilled labor, i.e., $\sigma = 0.401$, which is our baseline calibration.

successfully replicates the labor market dynamics with respect to the non-ICT shock. We further note that the positive impact on unskilled hours is slightly higher than that on skilled hours in the model. This is because the shock to non-ICT capital affects unskilled hours and a composite of skilled hours and ICT capital, implying that the response of skilled hours can be muted. If we lower the value of λ, the difference in the impulse response of skilled hours and that of unskilled hours becomes lower.

3.3 Bridging Gaps between Theoretical Predictions and Empirical Findings

How can a DSGE model explain the observed simultaneous increase in both skilled and unskilled labor hours, with no significant differences between them, in response to an ICT shock? The first candidate would be to introduce an asymmetric labor adjustment cost across different types of labor. This would not resolve the issue, however, because what we need is a higher response of unskilled hours to ICT shocks, which cannot be obtained with the labor adjustment cost, which mutes the response of labor rather than amplifies it. An alternative explanation would be to consider heterogeneous labor supply responses between skilled and unskilled workers by allowing different labor supply elasticities. According to Keane

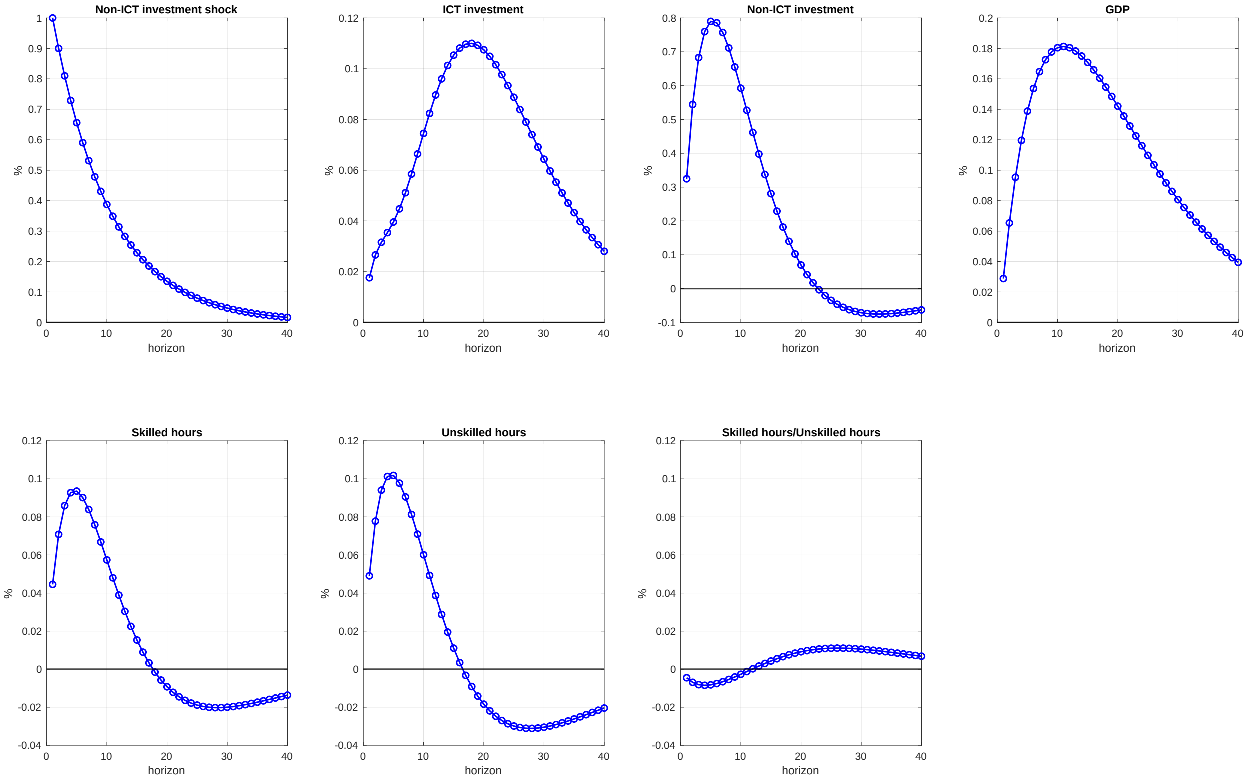

Figure 9: Impact of non-ICT shocks with ICT capital substituting for unskilled labor

Note: This figure reports the impulse responses from our theoretical model with substitutable unskilled labor, i.e., $\sigma = 0.401$, which is our baseline calibration.

and Wasi (2016), however, the difference in the elasticity of skilled- and unskilled workers is not sizable at the age of 25–54 except for workers who drop out from high school. In our sample, the share of high school dropouts in all of the unskilled workers is, on average, 8% only, implying that assuming the same elasticity for both types of workers as in Table 3 is not that problematic. Even when we allow for different elasticities between the two groups, our findings are preserved, indicating that this alternative strategy is again not the plausible answer to the above question.[18]

We propose that considering the possibility that ICT capital might complement unskilled labor rather than substituting it can resolve the discrepancy between the empirical fact and the prediction of the model. To explore this, we examine various values of σ, the parameter governing the elasticity of substitution between ICT capital and unskilled hours. Our analysis reveals that a range of negative σ values, indicating complementarity between ICT capital and unskilled labor, results in a slight positive change in the ratio of skilled to unskilled labor hours.

[18] Results are available upon request.

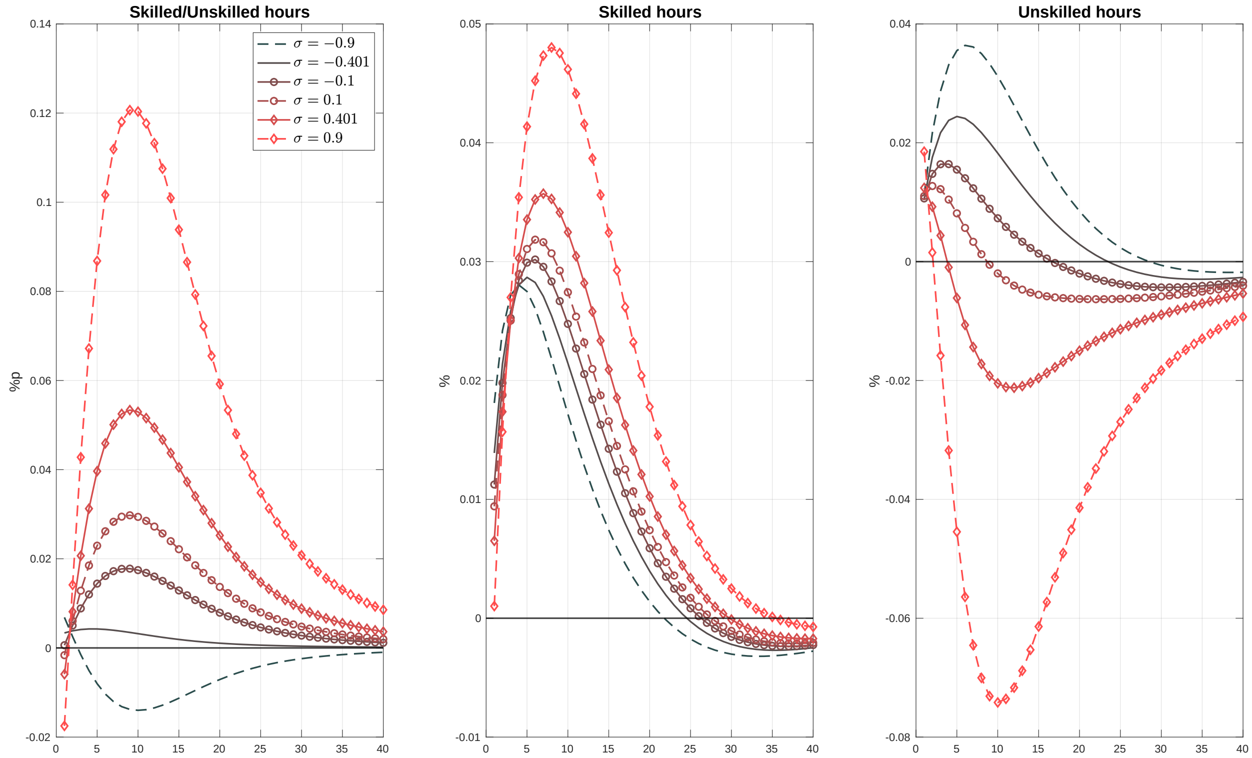

Figure 10: Impulse responses of hours with different σ values

Note: This figure reports the impulse responses of working hours from our theoretical model with different σ values. We fix $\rho = -0.495$ as in our baseline calibration.

Of note, three qualitative features of the impulse responses of hours are of our focus when matching the empirical finding reported in Figure 4: (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.

Figure 10 plots the impulse responses of labor hours for different values of σ. We first analyze the impulse responses assuming ICT capital is substitutable for unskilled labor. The circled-dashed line, diamond-solid line, and diamond-dashed line correspond to impulse responses with $\sigma = 0.1$, $\sigma = 0.401$, and $\sigma = 0.9$, respectively. While skilled hours increase, in line with Figure 8, none of the models with these σs accurately replicate the responses of unskilled hours, as with the case of our benchmark calibration shown in the previous section.

We then examine the impulse responses assuming ICT capital is complementary to unskilled labor; the circled-solid line, solid line, and dashed line in Figure 10, featuring $\sigma = -0.1$, $\sigma = -0.401$, and $\sigma = -0.9$, respectively, fall in this case. The ICT shock elicits positive responses to unskilled hours when $\sigma = -0.401$ or $\sigma = -0.9$, which is consistent with the empirical impulse responses. The ratio of skilled to unskilled hours increases for all cases except when $\sigma = -0.9$.[19] Thus, our analyses so far suggest that σ should be negative and small (in an absolute sense) to be in line with our empirical findings. In the next section, we estimate key model parameters to deepen our understanding of the relationship between the labor DSGE model and empirical findings.

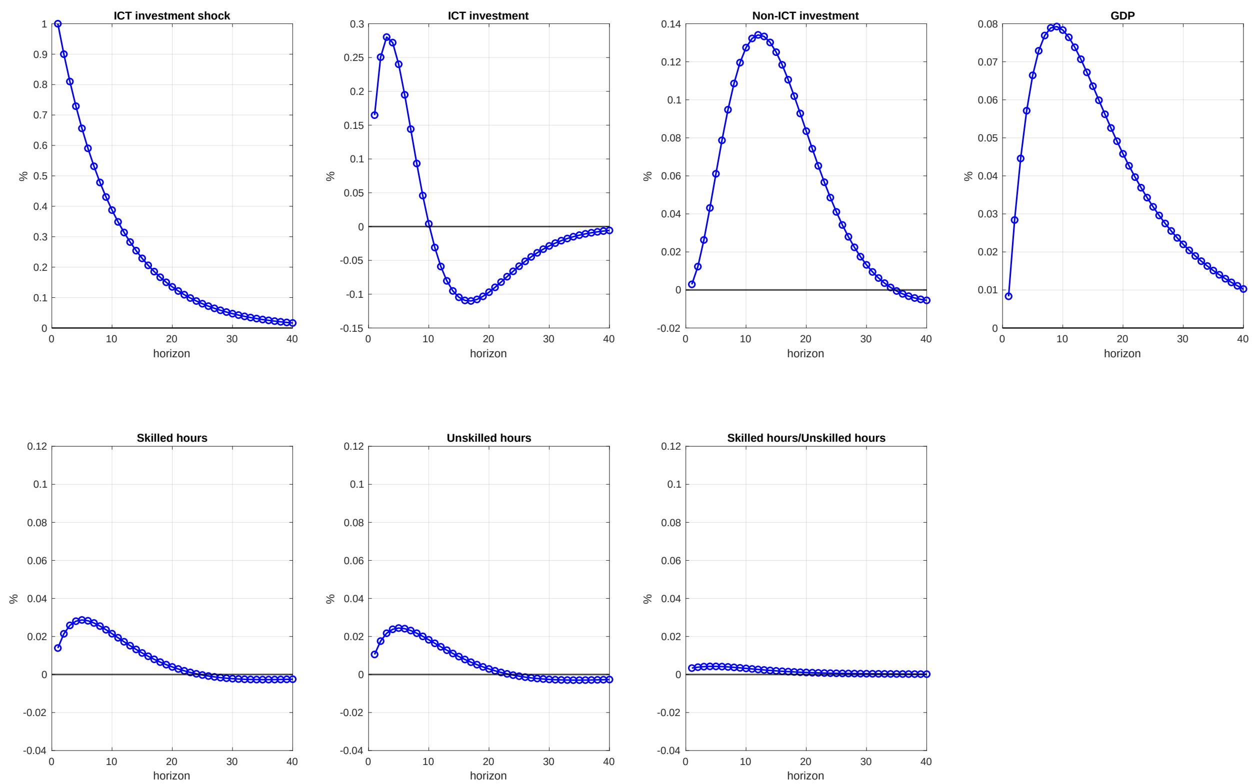

Figure 11: Impulse responses to an ICT shock (ICT capital complementary for low-skilled labor)

Note: This figure reports the impulse responses from our theoretical model with complementary low-skilled labor ($\sigma = -0.401$). The rest of the parameters still follow the baseline calibration. We fixed the limits of the y-axis same with Figure 8 for comparability.

Finally, Figure 11 presents the impulse responses derived from our DSGE model with a complementary relationship between ICT capital and unskilled labor by assuming $\sigma = -0.401$ for all six variables included in our VAR model. In contrast to those in Figure 8, unskilled hours rise in similar magnitude with skilled labor due to the complementarity with the ICT shock. We can observe that the ratio between both hours reacts at a small magnitude, which is also consistent with our empirical finding. In the Appendix Figure A18, we plot the impulse responses of key variables to non-ICT shocks. Results are both qualitatively and quantitatively similar to what is obtained from benchmark calibration (Figure

[19]This finding is related to the ratio of skilled to unskilled hours in our model, which would rise in response to the ICT shock if and only if $\rho < \sigma$.

9), indicating that different choice for σ does not influence the labor market dynamics when non-ICT shock drives the economic fluctuations, which is expected from our assumption on production function.

3.4 Estimation of the Elasticity Parameters

To understand how ICT capital interacts with labor at the business cycle frequency, we outlined a range of parameters that could produce positive responses of unskilled labor hours to ICT shocks in the previous section. This section delves further into estimating these key parameters to gain deeper insights into their dynamics within our theoretical model.

We estimate key parameters in our DSGE model from Section 3.1 by employing the approach outlined by Christiano, Eichenbaum, and Evans (2005) that aligns theoretical impulse responses with empirical ones. Specifically, we estimate the parameter set $\gamma \equiv (\rho, \sigma, \rho_p, \sigma_p)$, which are closely related to the elasticity of substitution between ICT capital and labor, as well as the shock process. This parameter set γ is determined as a solution to

$$\mathcal{J} = \min_{\gamma} [\hat{\Psi} - \Psi(\gamma)]' \mathbf{V}^{-1} [\hat{\Psi} - \Psi(\gamma)],$$

where $\Psi(\gamma)$ represents the mapping from γ to the theoretical impulse response functions, and $\hat{\Psi}$ is the corresponding empirical estimates depicted in Figure 4. $\mathbf{V}$ is a diagonal matrix containing the sample variances of the $\hat{\Psi}$ estimates along the diagonal. We focus on matching the impulse responses of skilled hours (h_s), unskilled hours (h_u), and ICT investment (i), as these responses are central to our primary findings.

Table 4: Parameter estimation results

Parameter	Estimates	S.E.	t-Statistics
ρ	-0.1468	0.0385	3.8118
σ	-0.0888	0.1575	0.5638
ρ_p	0.9797	0.0119	82.2158
σ_p	0.0936	0.0096	9.7881

Note: This table reports model parameter estimates obtained by matching the theoretical IRFs to the empirical IRFs in Figure 4 (ICT investment, skilled hours, and unskilled hours). The standard errors (S.E.) and the t-statistics of the estimates are reported in the third and fourth columns, respectively. Standard errors were computed using the asymptotic delta function method applied to the first-order condition following Christiano, Eichenbaum, and Evans (2005).

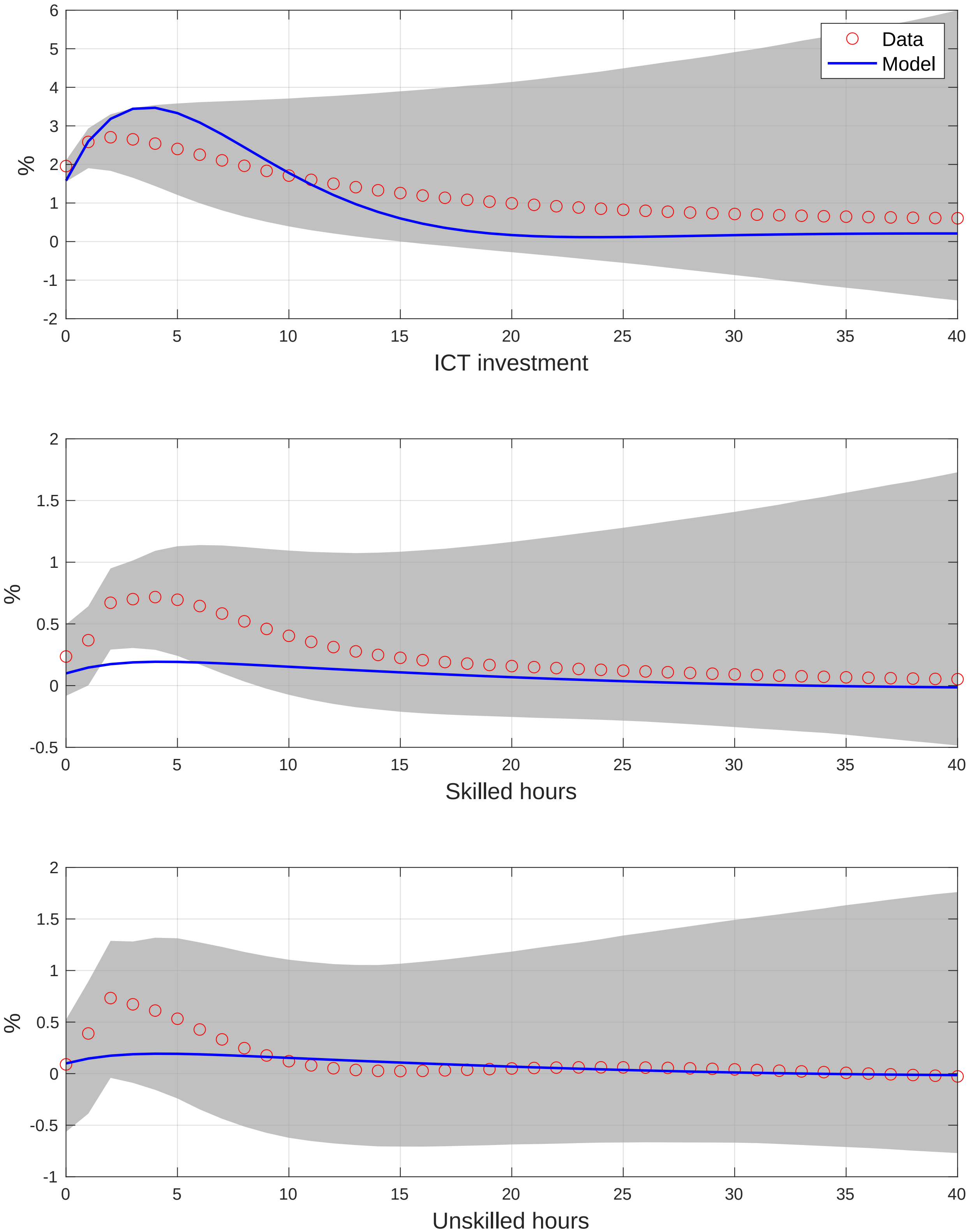

Figure 12: Impulse responses comparisons

Note: This figure compares the impulse responses from our structural VAR model (red circles) and estimated DSGE model (blue lines). Grey-shaded areas represent a 95% confidence interval of our empirical estimates. The empirical impulse responses based on the VAR model are identical to the ones shown in Figure 4.

Table 4 presents the resulting parameter estimates. Using these point estimates, we obtain the model-derived impulse responses of the three target variables and compare them to those from our baseline VAR model in Figure 12. The model-based impulse responses fall within the 95% confidence interval of the empirical IRFs for all variables, except for ICT investment during the initial impact and the following month. This suggests that the model with the estimated parameters effectively reproduces the labor market dynamics in response to the ICT shocks.

Delving into the parameter estimation results, two points are worth noting. First, the degree of complementarity between ICT capital and skilled labor, as suggested by our estimation, aligns closely with the findings of Krusell, Ohanian, Ríos-Rull, and Violante (2000). That is, our estimate for the parameter ρ is -0.3268, indicating an elasticity of substitution of approximately 0.75.[20] This is comparable to Krusell, Ohanian, Ríos-Rull, and Violante (2000)'s estimate of 0.67 and Taniguchi and Yamada (2022)'s estimate of 0.86. Second, σ is estimated to be at -0.32. Unlike our estimate of ρ, this value is in sharp contrast to what is typically estimated and used in the literature that matches the long-run trend; Krusell, Ohanian, Ríos-Rull, and Violante (2000) estimate σ to be about 0.40 while that in Taniguchi and Yamada (2022)' is about 0.89, which are all positive. As already alluded to in the previous section, our estimation result indicates that such positive values of σ would not reproduce the short-run response of unskilled hours found in Section 2. Instead, σ has to be negative and should be comparable to the value of ρ in magnitude (in the absolute sense).

We finally note that that our finding is not inconsistent with long-run changes in the labor market: During the sample period (1994Q1–2023Q2) that we consider in our main empirical analysis, skill premium hardly changes as reported in Figure 3. This implies that parameter values in the production function that can explain rising skill premium (i.e., the wage ratio of skilled to unskilled workers) from the mid-1980s may be ill-suited when studying short-run labor market dynamics at least from the mid-1990s. In other words, matching long-run changes in skill premium during our sample period should not necessarily be the primary objective, especially when such a parameterization fails to capture short-run fluctuations.

[20] We round our elasticity estimate to two decimal places.

4 Conclusion

We investigated whether changes in ICT affected skilled and unskilled labor differently at the business cycle frequency. We constructed hours worked series for the skilled and unskilled labor using the monthly outgoing rotation group CPS and estimated a structural VAR model. We found no significant differences between the responses of skilled and unskilled hours to ICT shocks both qualitatively and quantitatively. This result departed from a common view in the previous literature highlighting the capital-labor complementary focusing on the role of skill-baised technology. In the second part of the paper, we examined a set of DSGE models and demonstrated a production function where ICT capital was complementary to both worker groups, with specific ranges of elasticity of substitution between capital and labor, could match the hours responses that aligned with our empirical observations.

Our findings provided two important implications. First, it suggested that changes in ICT and further in skill-biased technologies might not explain divergences in the working hours of these two labor groups, at least at the business-cycle frequency. However, our findings did not contradict existing research demonstrating the role of ICT capital in complementing skilled labor and contributing to the skill premium in the long run. Rather, our results imply that production functions may exhibit different characteristics over time (Jones, 2005; Chirinko, 2008). Second, we provided supporting evidence to production functions with specific ranges of elasticity of substitution between capital and labor, especially the ones modeling complementary relationships between ICT capital and both skilled and unskilled workers, especially in the short run.

Finally, it is important to note that the ICT shocks identified in this study are primarily supply-driven in nature. A natural extension of this work would be to examine demand-side shocks that might exert differential influences on skilled versus unskilled labor. Investigating whether such shocks can generate the divergent impulse responses often discussed in the literature would provide deeper insights into labor market dynamics. We leave this for future research.

Data Availability Statement

The data that support the findings of this study are openly available in openICPSR at https://www.openicpsr.org/openicpsr/project/247079/version/V1/view, reference number 247079 (Ahn, Jo, and Shim (2026)).

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A Data Description: Constructing the ICT/non-ICT Price Index

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

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

Note: This table shows the details of the data used to construct ICT/non-ICT price indexes and the detail of the process is illustrated in section 2.1. The data shown in this table are from FRED database.

B Forecast Error Variance Decomposition of ICT Shocks

We analyze the contribution of ICT shocks to the business cycle through a forecast error variance decomposition analysis. It is important to note that this analysis is not without limitations; our baseline VAR model contains six variables, and as a result, the role of the ICT shocks can be overestimated compared to the case using a larger VAR model. We also note that the size of the confidence bands is large for this exercise. Despite some of these shortcomings, Figure A1 still demonstrates that the ICT shocks are (i) an important driver of a business cycle and (ii) influential in the labor market. Specifically, the ICT shock accounts for up to 44.5% of the variance of real GDP at its peak and above 42% in the longer run. This result is consistent with Brianti and Gáti (2023) in that productivity improvement in ICT is a source of medium-run fluctuations in economic activity. While the magnitude is somewhat smaller, the shock can explain the working hours of both skilled and unskilled workers by about 30% and 15%, respectively.

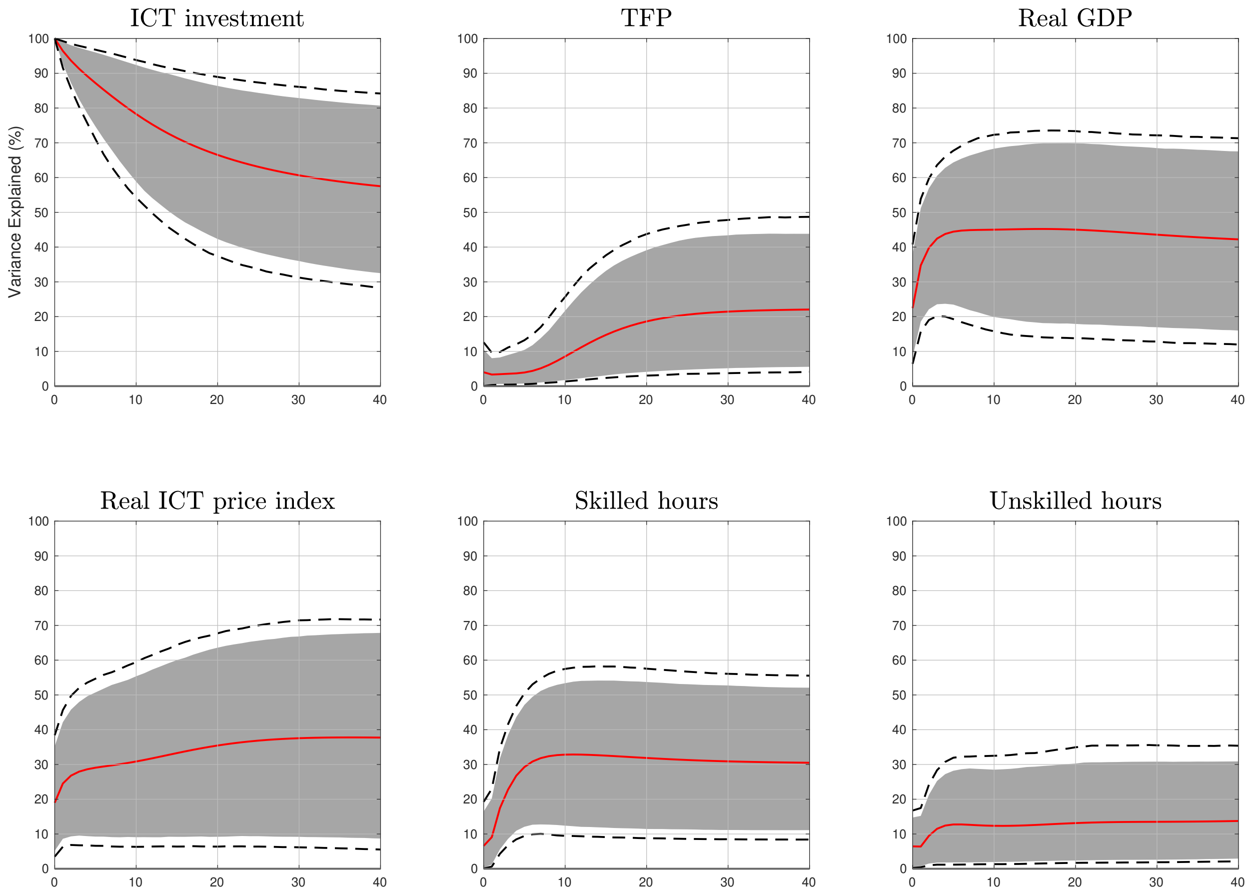

Figure A1: Baseline forecast error variance decomposition

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 95% and 90% error bands of the corresponding variance explained in red solid lines, respectively. The error bands are derived using residual bootstrap method.

C Identification Validity Checks

Table A2: Correlation test with other structural shocks

(a) Oil price shocks	Sample	Correlation	p-value
Kilian (2008)	1994:3-2004:3		
OPEC oil production		-0.0237	0.8830
Kilian (2009)	1994:3-2008:1		
Oil supply		0.1372	0.3226
Aggregate demand		-0.1444	0.2976
Oil-market specific demand		-0.1346	0.3319
Baumeister and Hamilton (2019)	1994:3-2019:4		
Oil supply		-0.0030	0.9749
Economic activity		0.2791	0.0024
Oil consumption demand		0.0513	0.5842
Oil inventory demand		0.0326	0.7284
(b) Surprise technology shocks	**Sample**	**Correlation**	**p-value**
Smets and Wouters (2007)	1994:3-2004:4	-0.1300	0.4119
Fernald (2014)	1994:3-2019:4	0.1485	0.1117
Justiniano, Primiceri, and Tambalotti (2011)	1994:3-2009:1		
Surprise TFP		-0.1055	0.4266
Surprise IST		0.4439	0.0004
Marginal efficiency of investment		0.3550	0.0058
(c) Technology news shocks	**Sample**	**Correlation**	**p-value**
Beaudry and Portier (2006)	1994:3-2015:3		
Short-run restrictions		-0.0125	0.9120
Long-run restrictions		-0.0286	0.8001
Barsky and Sims (2011)	1994:3-2007:3	0.0271	0.8470
Ben Zeev and Khan (2015)	1994:3-2012:1	-0.1111	0.3561
(d) Monetary policy shocks	**Sample**	**Correlation**	**p-value**
Romer and Romer (2004), extended by Wieland and Yang (2020)	1994:3-2007:4	0.0341	0.8067
Barakchian and Crowe (2013)	1994:3-2004:4	0.1386	0.3083
Gürkaynak, Sack, and Swanson (2005)	1994:3-2008:2	0.2972	0.0559
Gertler and Karadi (2015)			
FF4 shock from Fed Funds futures 3 months	1994:3-2007:2	0.2617	0.0560
FF1 shock with Ramey (2016)'s conversion	1994:3-2007:4	0.2707	0.0477

(e) Government spending shocks	Sample	Correlation	p-value
Fisher and Peters (2010)	1994:3-2008:4	-0.1756	0.1873
Ben Zeev and Pappa (2017)	1994:3-2007:4	0.0859	0.5367
(f) Tax shocks	**Sample**	**Correlation**	**p-value**
Mertens and Ravn (2011)	1994:3-2007:4		
Unanticipated tax changes		-0.3190	0.0187
Future tax change news		0.0980	0.4809
Leeper, Richter, and Walker (2012)	1994:3-2005:4	-0.0506	0.7383
(g) Financial market shocks	**Sample**	**Correlation**	**p-value**
Gilchrist and Zakrajšek (2012)	1994:3-2023:2		
Excess bond premium		-0.2508	0.0066
Change in excess bond premium		-0.1760	0.0588
Bassett, Chosak, Driscoll, and Zakrajšek (2014)	1994:3-2010:4		
Bank lending shocks		-0.1214	0.3317
Baker, Bloom, Davis, and Kost (2019)	1994:3-2019:4		
Economic policy uncertainty		-0.0969	0.3009
Change in economic policy uncertainty		-0.0268	0.7751

Note: This table reports the correlation and the corresponding p-values for the null hypothesis that the structural shocks are not correlated with the ICT shock.

Table A3: Granger test with other structural shocks

(a) Oil price shocks	Sample	F-test	p-value	$\bar{R}^2$
Kilian (2008)	1994:3-2004:3			
OPEC oil production		4.1465	0.0245	0.1630
Kilian (2009)	1994:3-2008:1			
Oil supply		0.2032	0.8168	0.0051
Aggregate demand		0.6305	0.5368	0.0227
Oil-market specific demand		0.9605	0.3901	0.0359
Baumeister and Hamilton (2019)	1994:3-2019:4			
Oil supply		0.5474	0.5801	0.0064
Economic activity		1.6274	0.2012	0.0256
Oil consumption demand		1.2175	0.3000	0.0184
Oil inventory demand		0.0508	0.9505	-0.0026

(b) Surprise technology shocks	Sample	F-test	p-value	$\bar{R}^2$
Smets and Wouters (2007)	1994:3-2004:4	0.1764	0.8390	-0.0298
Fernald (2014)	1994:3-2019:4	0.3969	0.6733	0.0037
Justiniano, Primiceri, and Tambalotti (2011)	1994:3-2009:1			
Surprise TFP		0.9011	0.4124	0.0163
Surprise IST		0.1349	0.8741	-0.0125
Marginal efficiency of investment		1.7765	0.1794	0.0473

(c) Technology news shocks	Sample	F-test	p-value	$\bar{R}^2$
Beaudry and Portier (2006)	1994:3-2015:3			
Short-run restrictions		0.1934	0.8246	-0.0155
Long-run restrictions		0.3665	0.6944	-0.0108
Barsky and Sims (2011)	1994:3-2007:3	1.557	0.2217	0.0640
Ben Zeev and Khan (2015)	1994:3-2012:1	2.1302	0.1272	0.0420

(d) Monetary policy shocks	Sample	F-test	p-value	$\bar{R}^2$
Romer and Romer (2004), extended by Wieland and Yang (2020)	1994:3-2007:4	0.2402	0.7874	0.0066
Barakchian and Crowe (2013)	1994:3-2004:4	1.5887	0.2145	0.0585
Gürkaynak, Sack, and Swanson (2005)	1994:3-2008:2	1.3258	0.2786	0.0330
Gertler and Karadi (2015)				
FF4 shock from Fed Funds futures 3 months	1994:3-2007:2	2.1220	0.1311	0.0796
FF1 shock with Ramey (2016)'s conversion	1994:3-2007:4	1.7481	0.1852	0.0659

(e) Government spending shocks	Sample	F-test	p-value	$\bar{R}^2$
Fisher and Peters (2010)	1994:3-2008:4	2.2065	0.1205	0.0617
Ben Zeev and Pappa (2017)	1994:3-2007:4	0.1759	0.8393	0.0039

(f) Tax shocks	Sample	F-test	p-value	$\bar{R}^2$
Mertens and Ravn (2011)	1994:3-2007:4			
Unanticipated tax changes		1.8752	0.1646	0.0706
Future tax change news		4.4784	0.0166	0.1571
Leeper, Richter, and Walker (2012)	1994:3-2005:4	0.3469	0.7090	-0.0144

(g) Financial market shocks	Sample	F-test	p-value	$\bar{R}^2$
Gilchrist and Zakrajšek (2012)	1994:3-2012:4			
Excess bond premium		4.5099	0.0131	0.0732
Change in excess bond premium		3.618	0.0301	0.0589
Bassett, Chosak, Driscoll, and Zakrajšek (2014)	1994:3-2010:4			
Bank lending shocks		2.3981	0.0997	0.0541
Baker, Bloom, Davis, and Kost (2019)	1994:3-2019:4			
Economic policy uncertainty		0.9982	0.3719	0.0145
Change in economic policy uncertainty		0.9342	0.3960	0.0134

Note: This table reports the F-statistics and the corresponding p-values for the null hypothesis that the two lags of economic indicators do not predict the ICT shock. The last column reports $\bar{R}^2$.

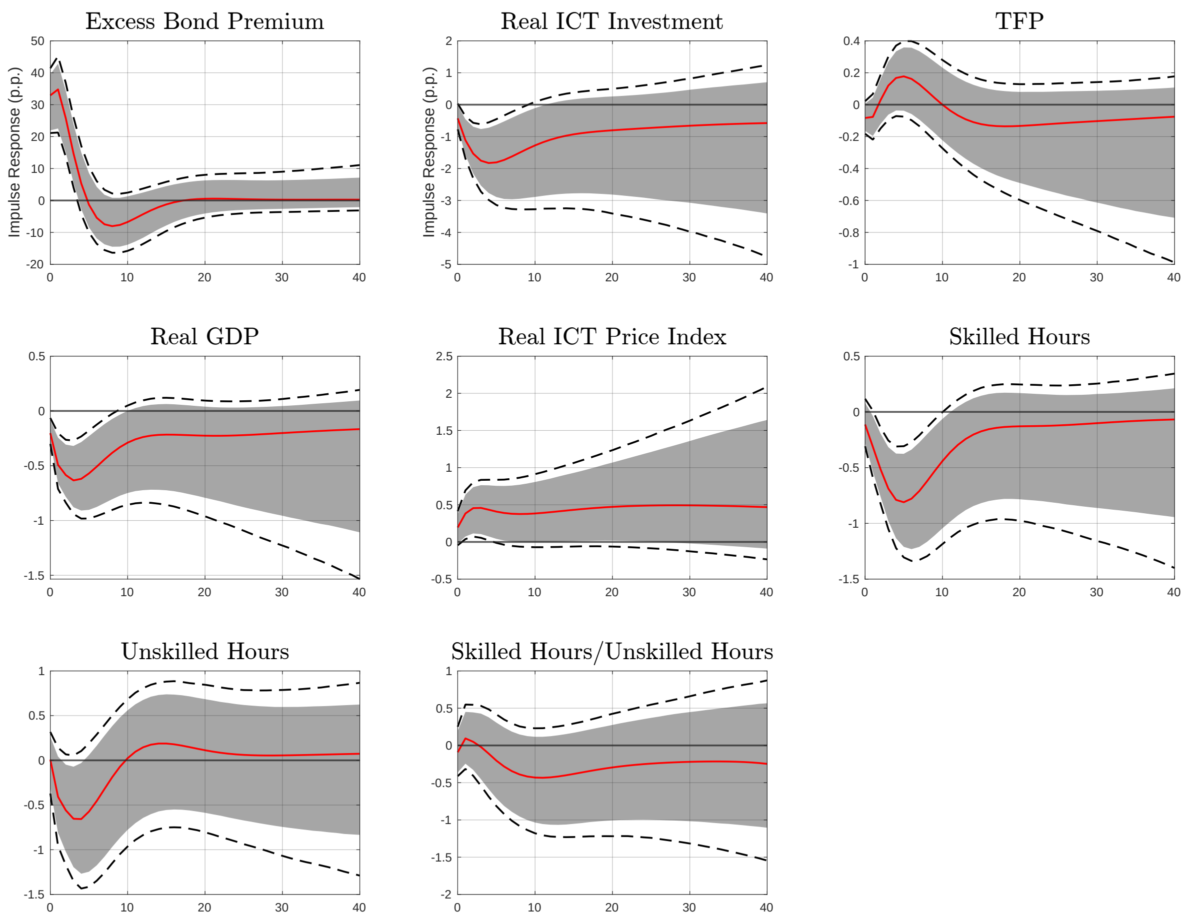

Figure A2: IRFs to the first shock from the VAR augmented with EBP

Note: This figure reports the impulse responses from a VAR model augmented with Gilchrist and Zakrajšek's 2012 excess bond premium (EBP) as the first variable in the system. The first shock captures ICT movements driven by financial market conditions. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The black-dashed lines and the grey-shaded area represent 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively.

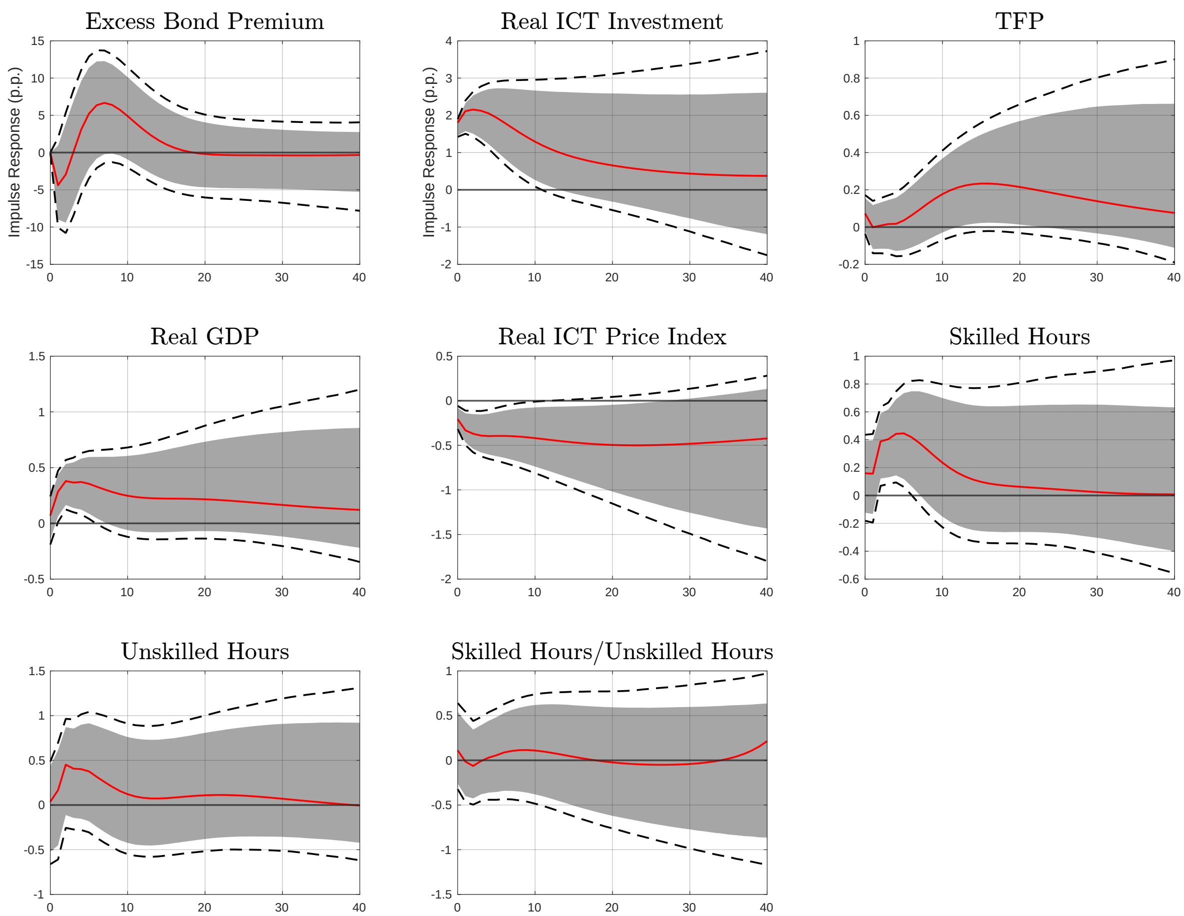

Figure A3: IRFs to the second shock from the VAR augmented with EBP

Note: This figure reports the impulse responses from a VAR model augmented with Gilchrist and Zakrajšek's 2012 excess bond premium (EBP) as the first variable in the system. The second shock captures a "pure" ICT innovation that is statistically orthogonalized and purged of financial influences. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The black-dashed lines and the grey-shaded area represent 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively.

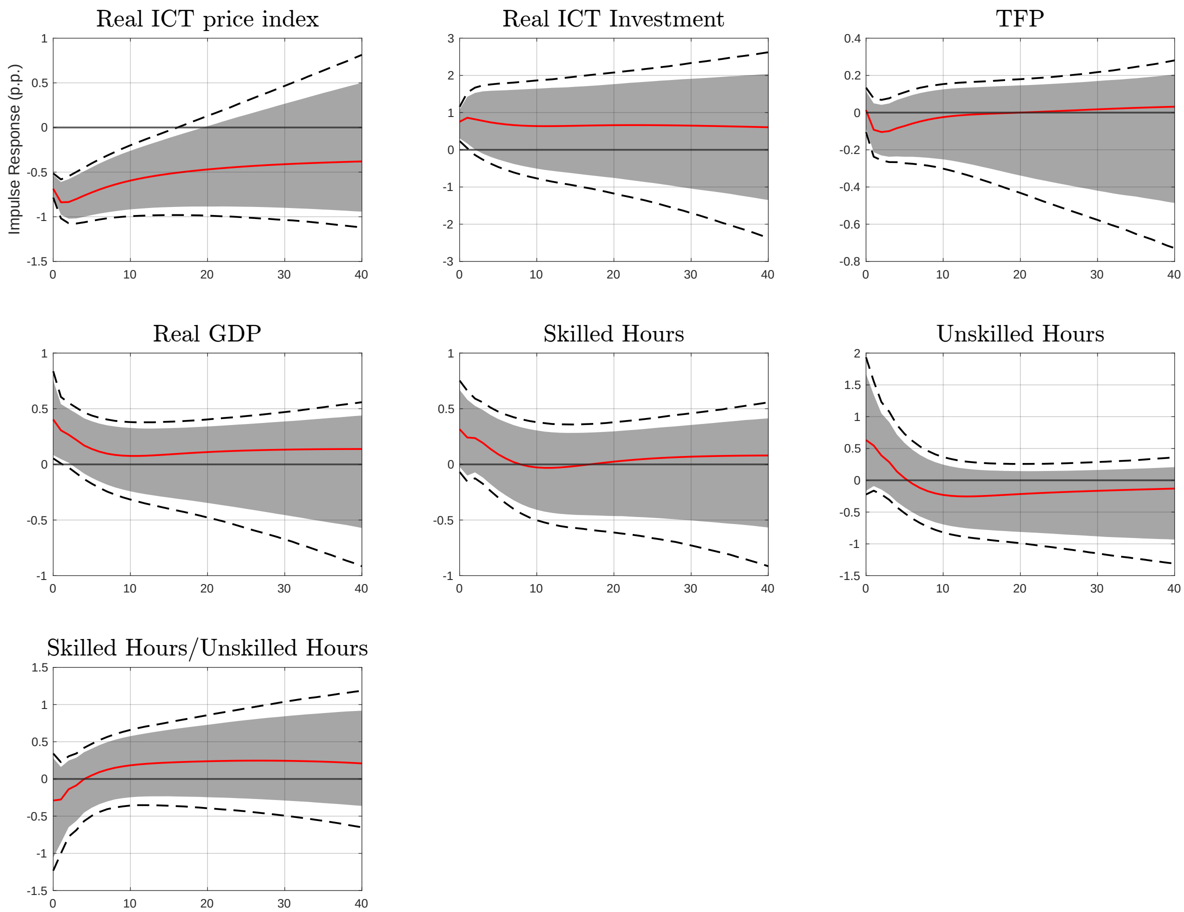

Figure A4: IRFs from alternative identification schemes: Short-run restriction on the relative ICT price

Note: This figure reports the impulse responses from a VAR model where the real ICT price (i.e., the relative price of ICT investment) is ordered first, followed by real ICT investment, TFP, real GDP, hours worked by skilled workers, and those by unskilled workers. An ICT shock is defined as the only one shock reducing the relative price of ICT investment contemporaneously. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The black-dashed lines and the grey-shaded area represent 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively.

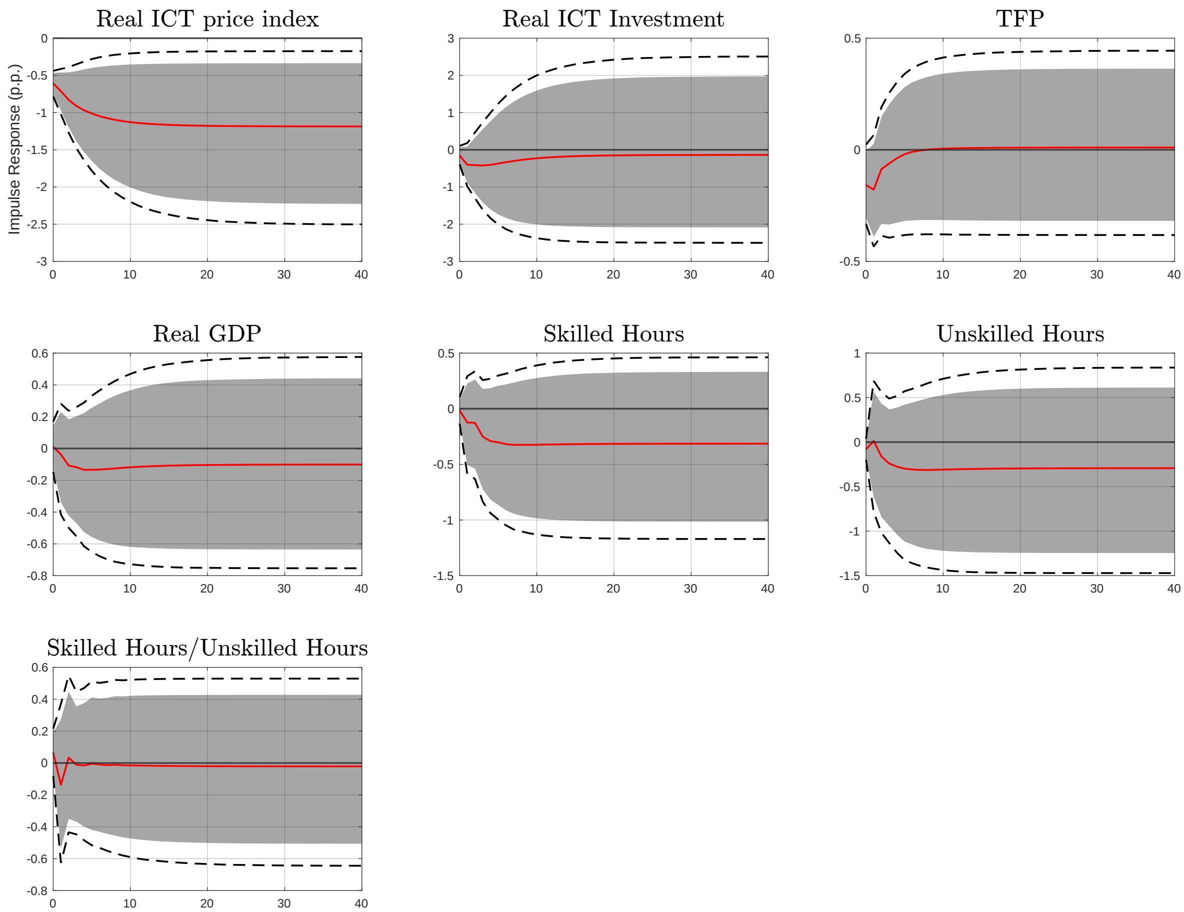

Figure A5: IRFs from alternative identification schemes: Long-run restrictions

Note: This figure reports the impulse responses from a VAR model where the real ICT price (i.e., the relative price of ICT investment) is ordered first, followed by real ICT investment, TFP, real GDP, hours worked by skilled workers, and those by unskilled workers. An ICT shock is defined as the shock that permanently reduces the relative price of ICT investment. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The black-dashed lines and the grey-shaded area represent 95% and 90% error bands of the corresponding impulse responses in red solid lines, respectively.

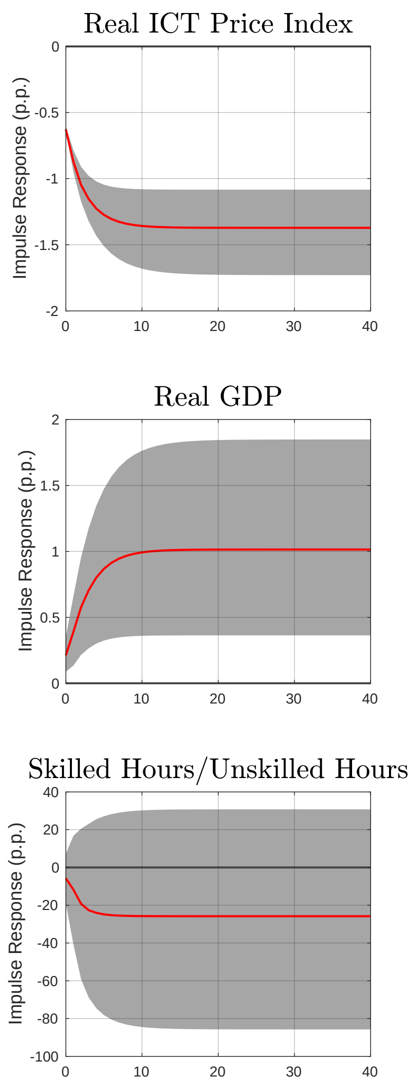

Figure A6: IRFs from alternative identification schemes: Max-share identifications

Note: This figure reports the impulse responses from a VAR model where the real ICT price (i.e., the relative price of ICT investment) is ordered first, followed by real ICT investment, TFP, real GDP, hours worked by skilled workers, and those by unskilled workers. An ICT shock is defined as the shock that contributes most to the variations of the relative ICT price in 40 quarters from the impact. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method. The grey-shaded area represents 68% error bands of the corresponding impulse responses in red solid lines.

D Robustness Checks

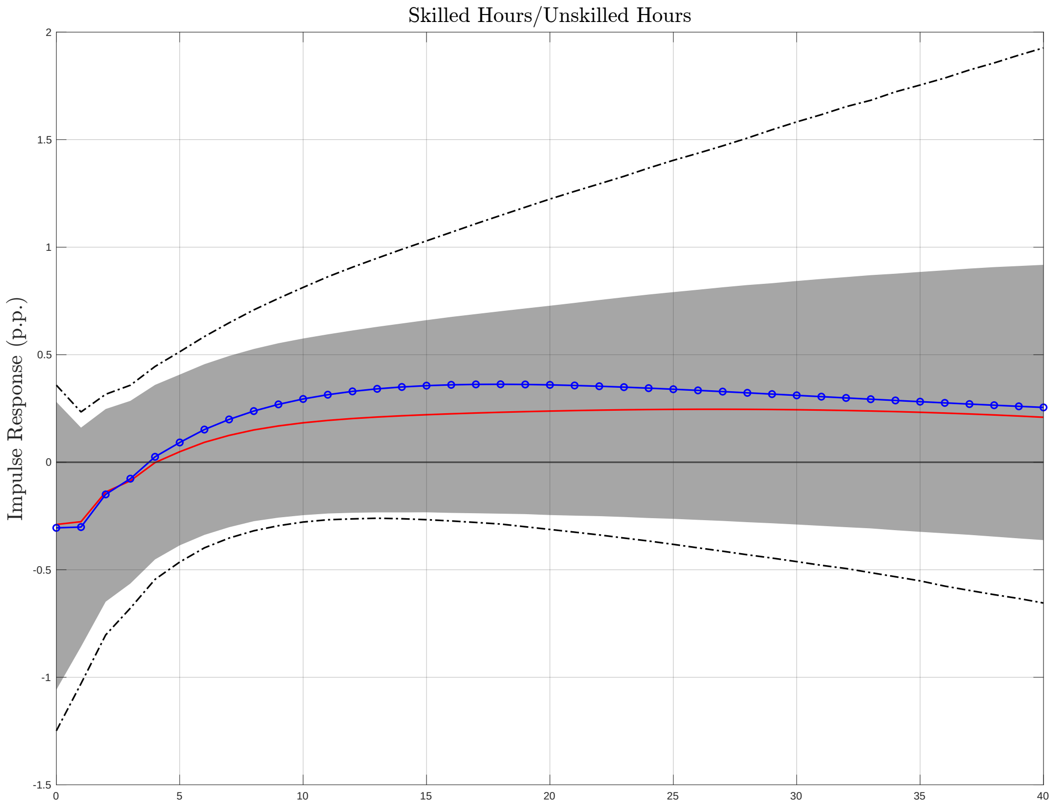

Figure A7: Impulse responses of the skilled/unskilled hours' ratio

Note: This figure reports the impulse responses of the hours' ratio to the ICT 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% and 95% error bands of the corresponding impulse responses, respectively. The error bands are derived using Kilian's (1998) bootstrap-after-bootstrap method.

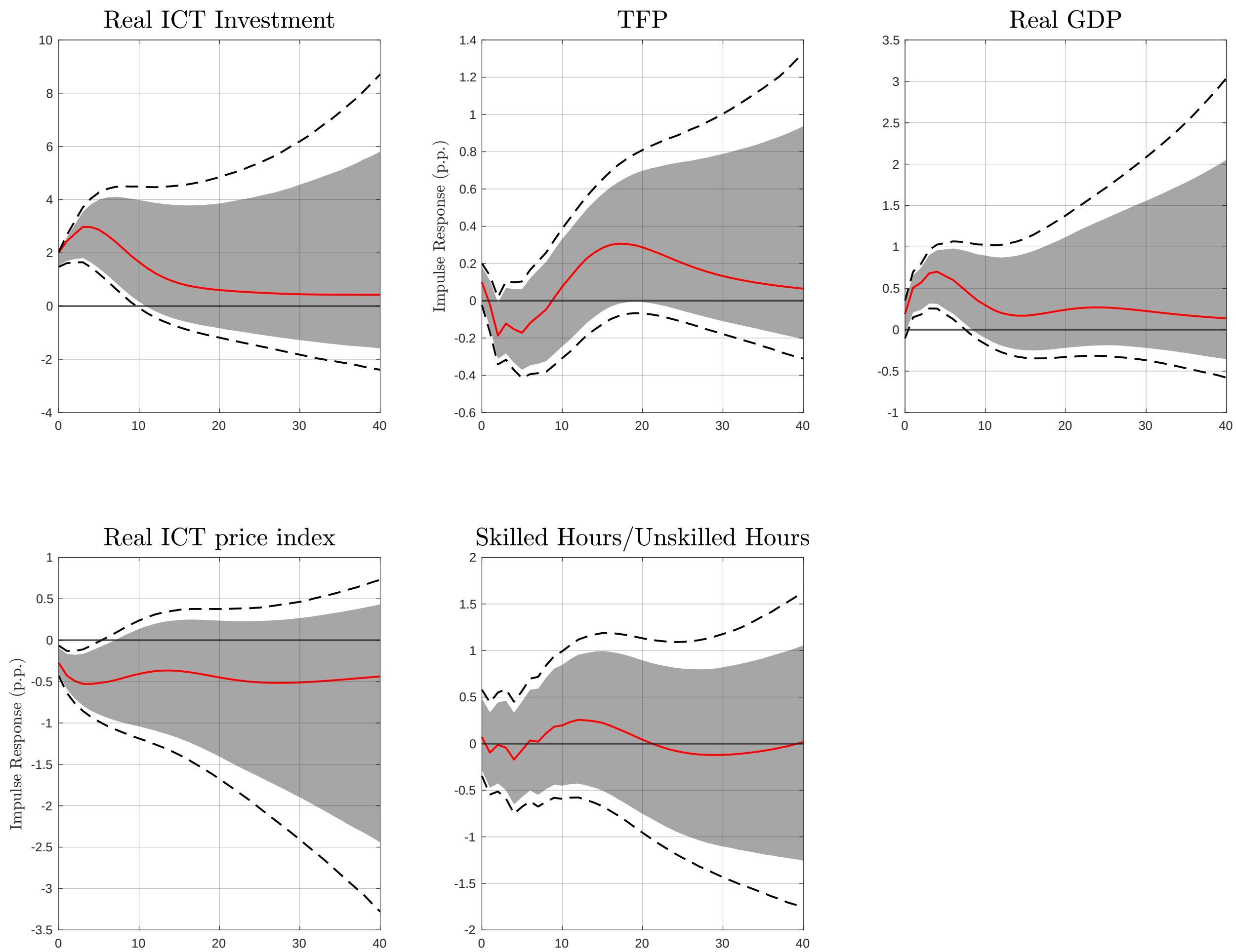

Figure A8: Robustness check 2: Different number of lags (four lags)

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 using Kilian's (1998) bootstrap-after-bootstrap method.

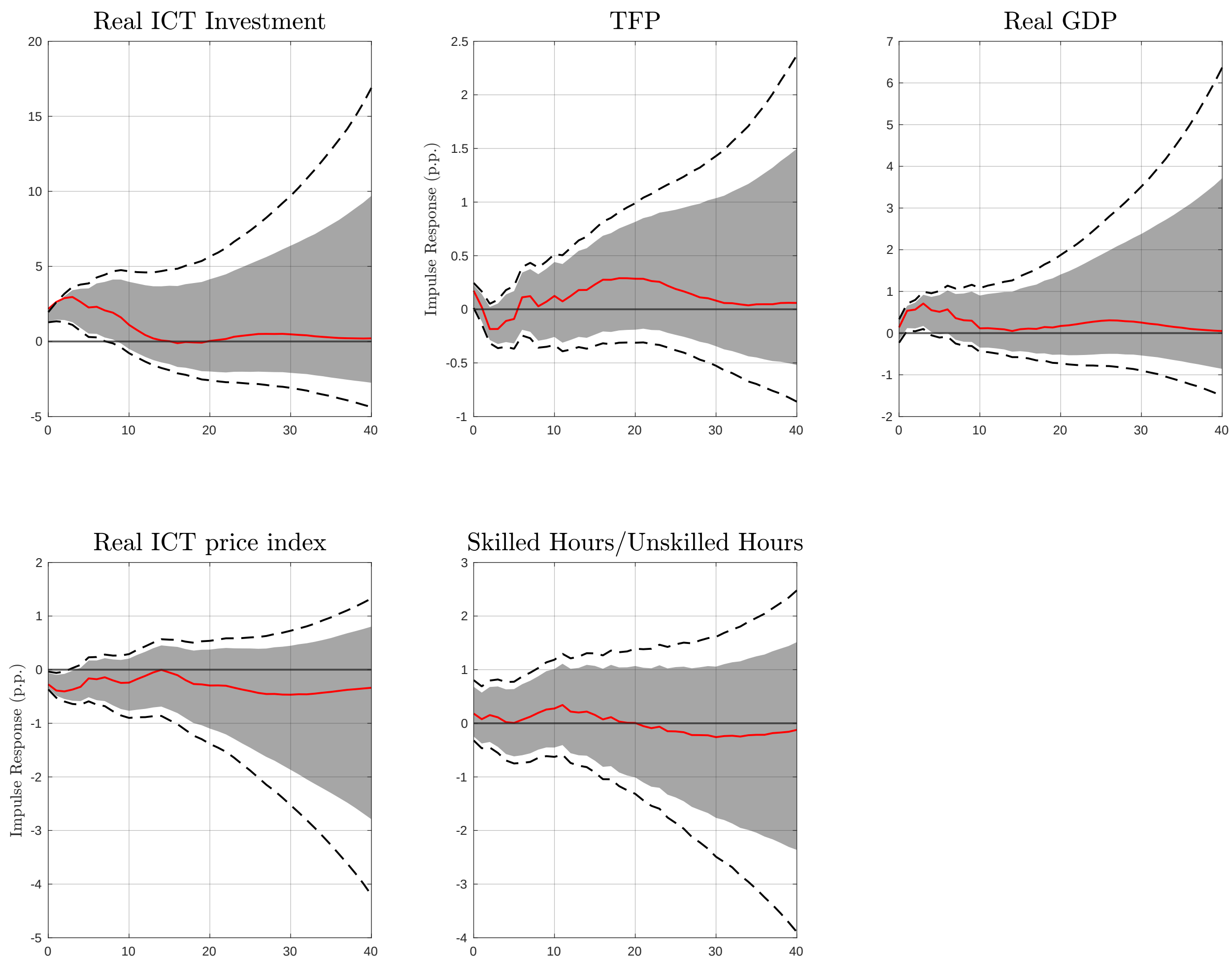

Figure A9: Robustness check 3: Different number of lags (eight lags)

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 using Kilian's (1998) bootstrap-after-bootstrap method.

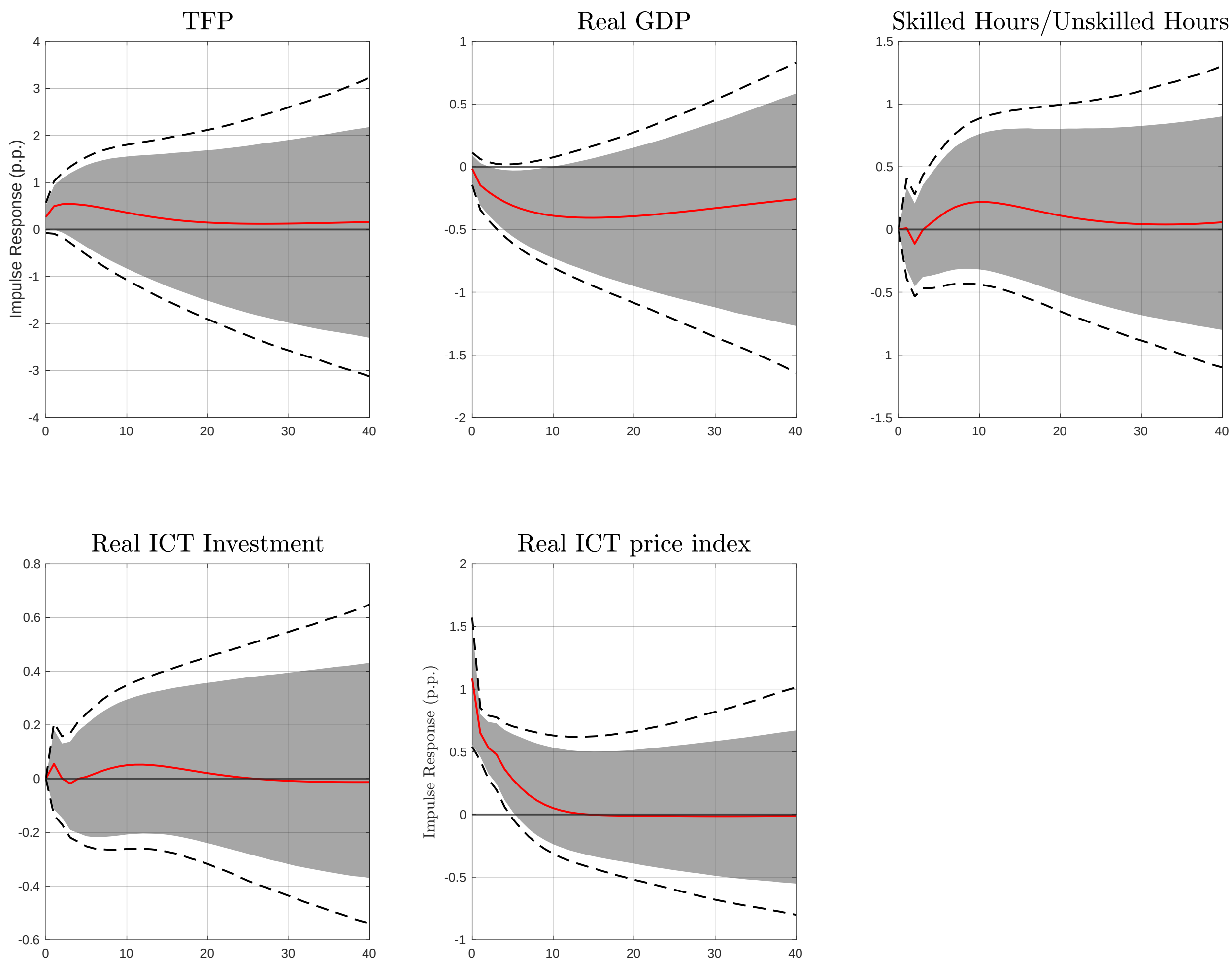

Figure A10: Robustness check 4: Different ordering of the endogenous variables

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 using Kilian's (1998) bootstrap-after-bootstrap method.

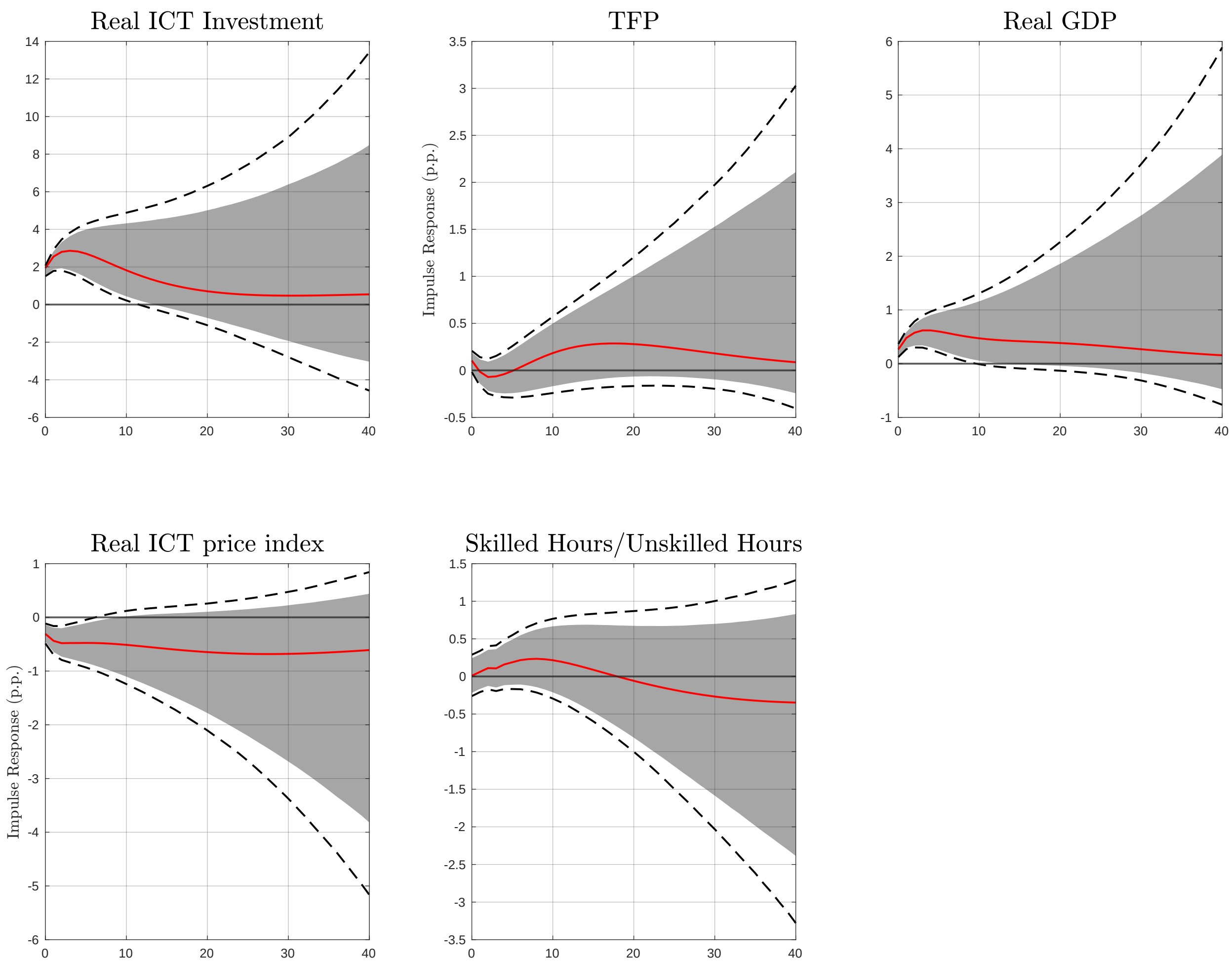

Figure A11: Robustness check 5: Excluding post-COVID period

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 using Kilian's (1998) bootstrap-after-bootstrap method.

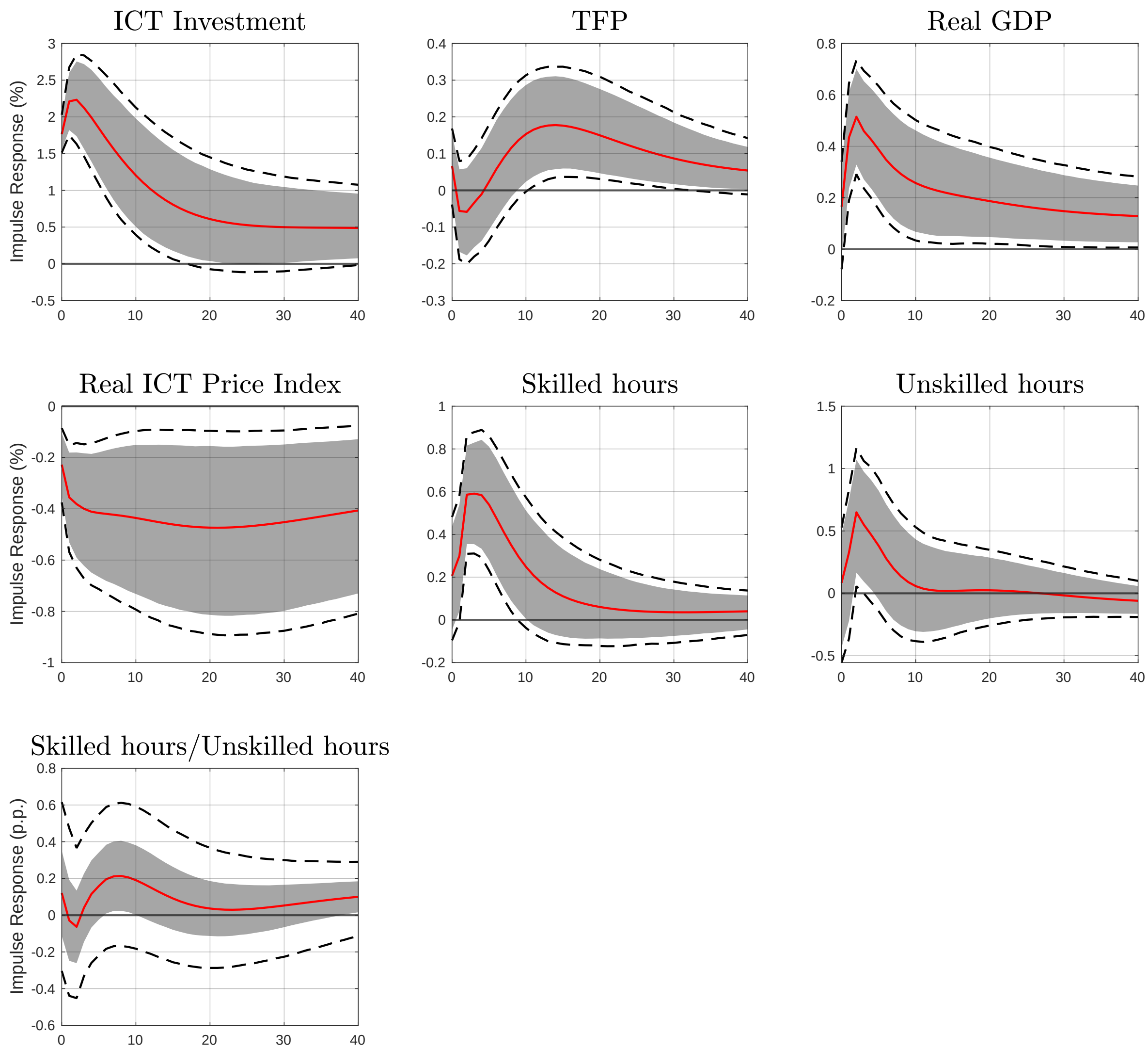

Figure A12: IRF from a VAR with a Great Financial Recession Indicator

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2019Q4, from a VAR with a Great Financial Recession Indicator. 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 residual bootstrap method with 100,000 draws.

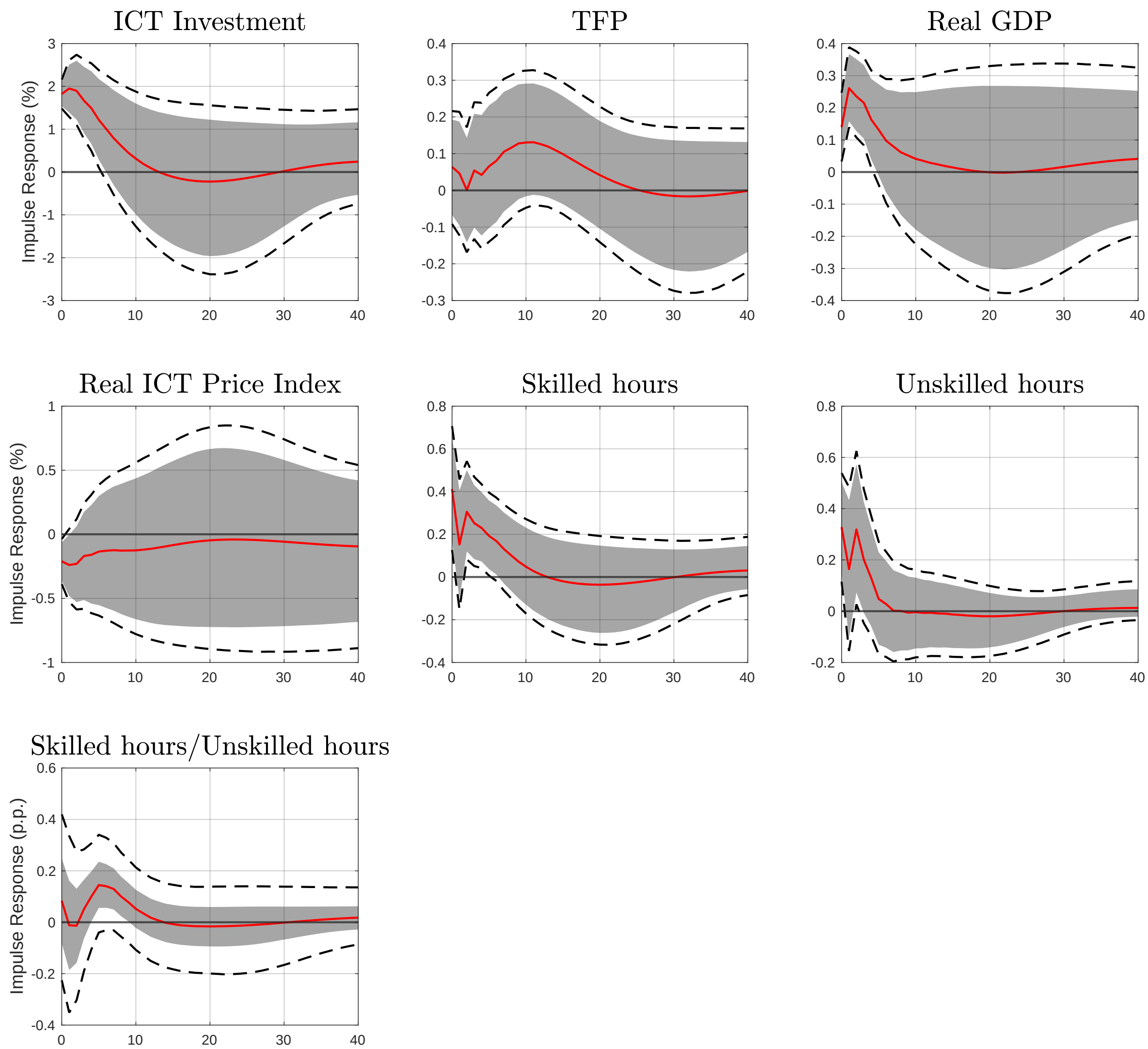

Figure A13: IRF from a VAR with pre-GFC sample (1994Q1 - 2007Q4)

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2007Q4. 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 using Kilian's (1998) bootstrap-after-bootstrap method.

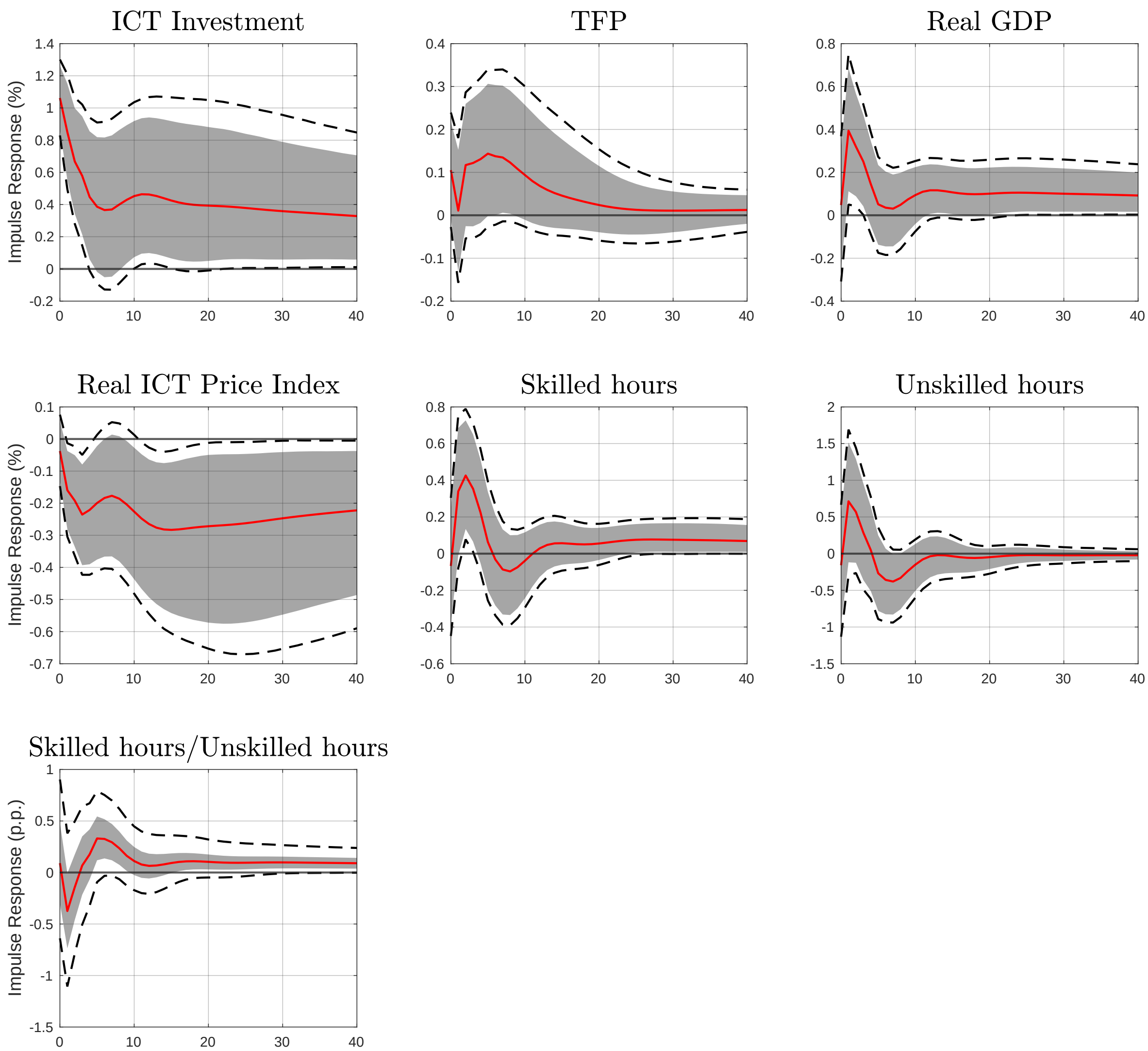

Figure A14: IRF from a VAR with post-GFC sample (2009Q3 - 2023Q2)

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 2009Q3 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 using Kilian's (1998) bootstrap-after-bootstrap method.

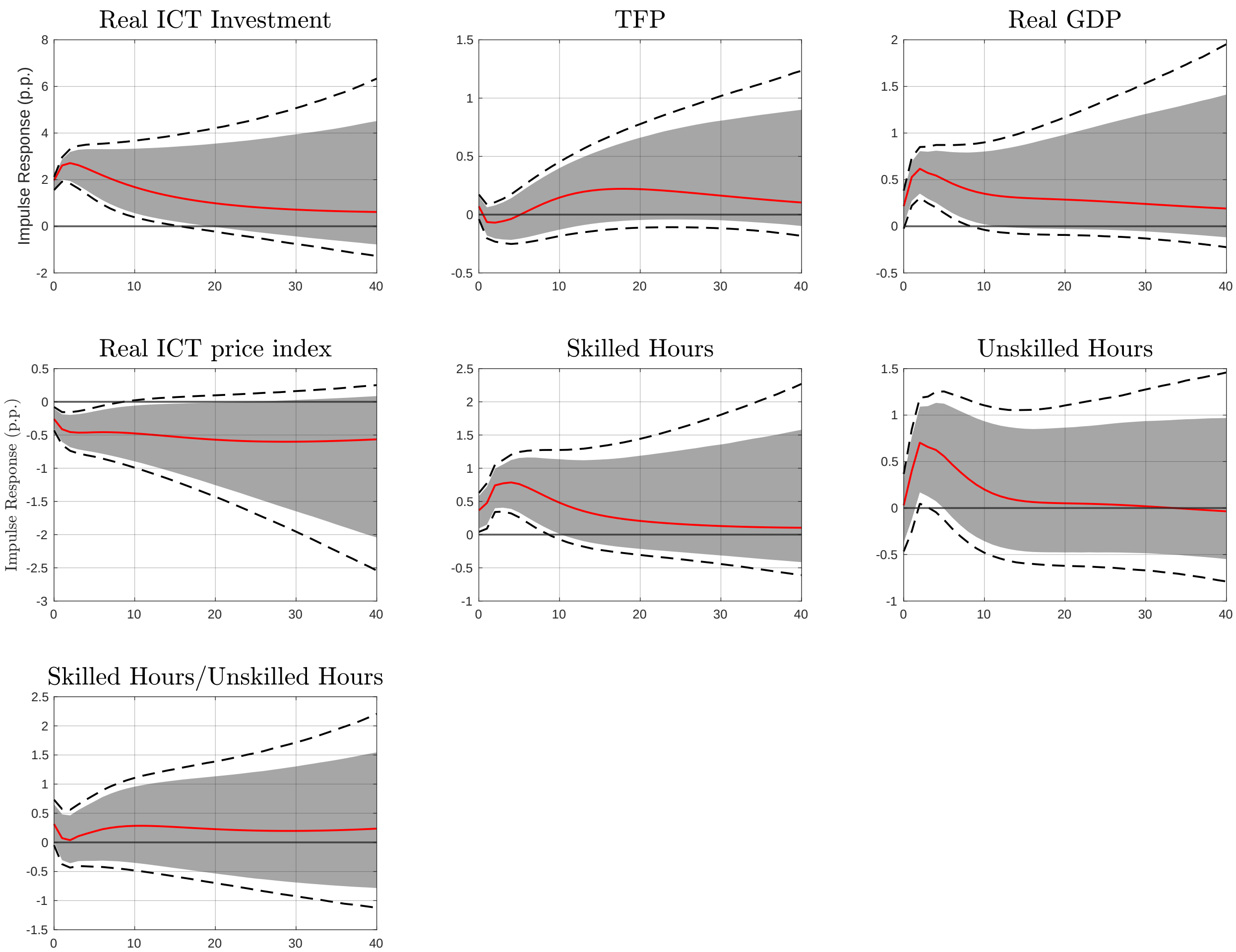

Figure A15: Robustness check 6: Responses of hours to an ICT shock with an alternative skilled/unskilled worker classification

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. For this exercise, we defined the skilled worker group as those with a college degree or higher, and those with some college education are included in the unskilled worker group. 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 using Kilian's (1998) bootstrap-after-bootstrap method.

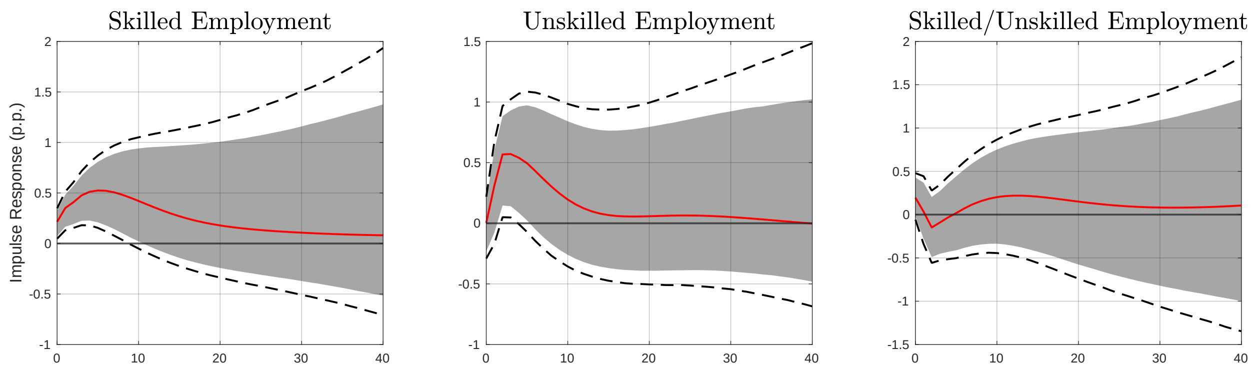

Figure A16: Robustness check 7: Responses of employment to an ICT shock with an alternative skilled/unskilled worker classification

Note: This figure reports the impulse responses to a one-standard-deviation ICT investment shock, using data from 1994Q1 to 2023Q2. For this exercise, we defined the skilled worker group as those with a college degree or higher, and those with some college education are included in the unskilled worker group. 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 using Kilian's (1998) bootstrap-after-bootstrap method.

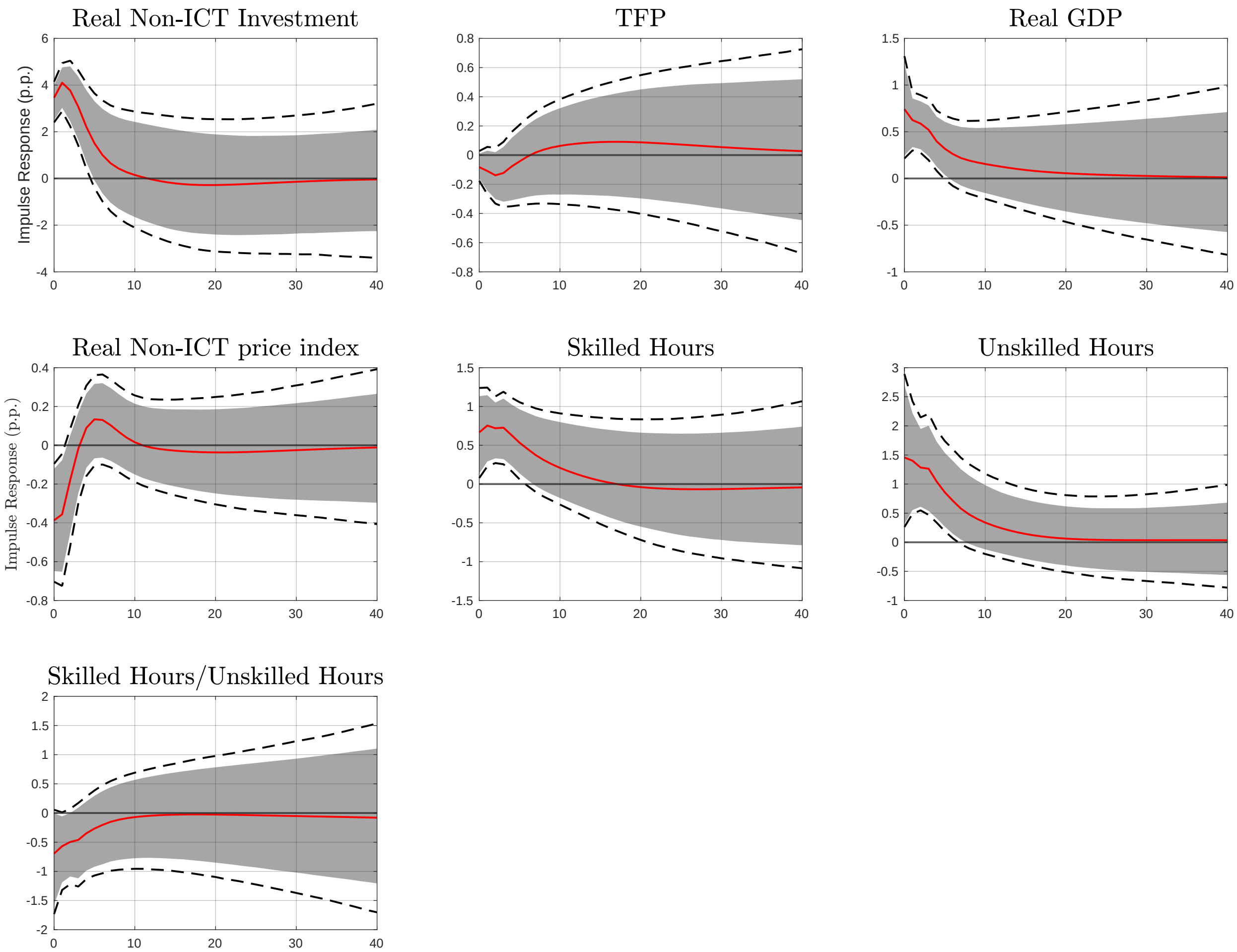

Figure A17: Robustness check 8: Responses of hours to a non-ICT shock with an alternative skilled/unskilled worker classification

Note: This figure reports the impulse responses to a one-standard-deviation non-ICT investment shock, using data from 1994Q1 to 2023Q2. For this exercise, we defined the skilled worker group as those with a college degree or higher, and those with some college education are included in the unskilled worker group. 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 using Kilian's (1998) bootstrap-after-bootstrap method.

E Theoretical Model: Non-ICT shocks

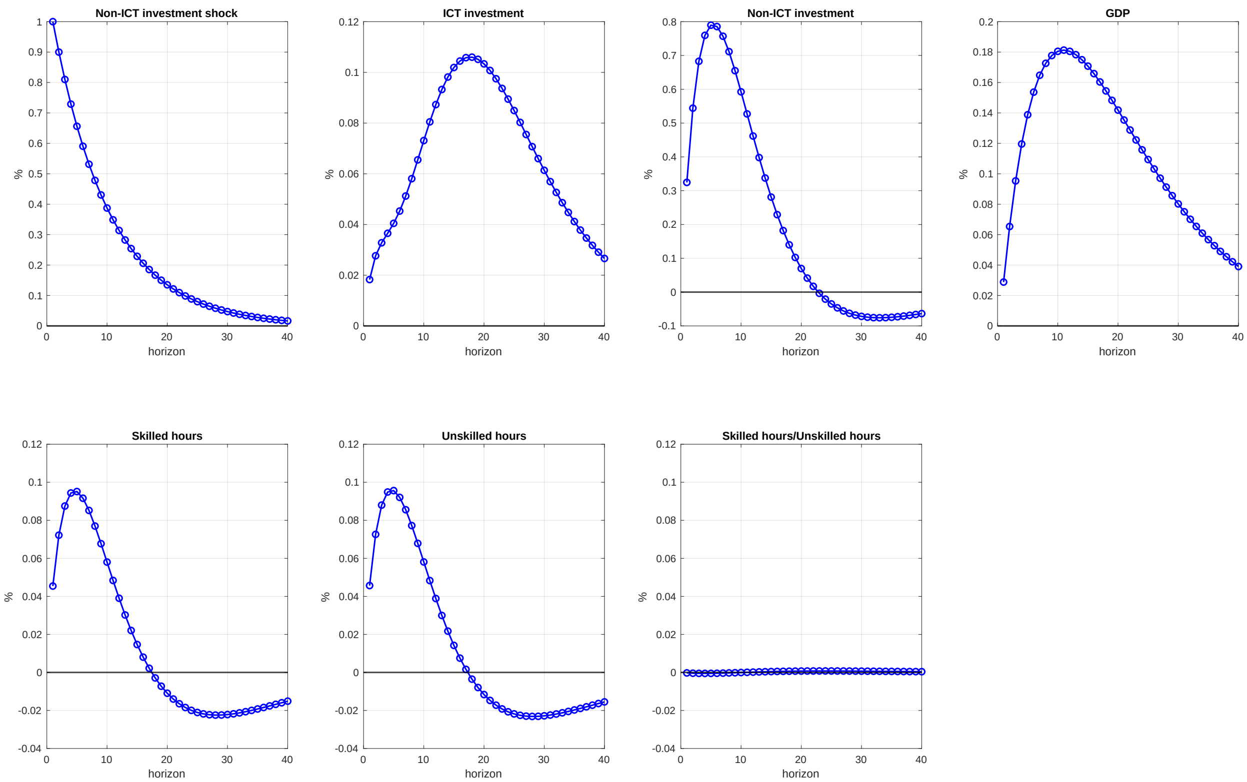

Figure A18: Impulse responses to an non-ICT shock (ICT capital complementary for low-skilled labor)

Note: This figure reports the impulse responses from our theoretical model with complementary low-skilled labor ($\sigma = -0.401$). The rest of the parameters still follow the baseline calibration. We fixed the limits of the y-axis same with Figure 9 for comparability.