

ICT and Future Productivity: Evidence and Theory of a GPT*

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Abstract

We employ Structural VARs to investigate the effects of ICT supply shocks on Total Factor Productivity (TFP) and other macroeconomic variables. In response to this sector-specific supply shock, relative prices of ICT goods and services immediately fall, ICT investment rises on impact, and TFP displays a significant delayed and persistent increase. Taking up the view of theories of ICT as a general-purpose technology, we analyze a two-sector general equilibrium model in order to rationalize previous results and estimate spillovers from the stock of ICT via impulse-response matching. We conclude that ICT accumulation is able to enhance productivity through a positive spillover effect which takes into account the overall level of diffusion of ICT capital in the economy.

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1 Introduction

Although there is large consensus on the importance of productivity as a driver of economic performance, there is less agreement on the underlying sources of productivity growth. For several years most of the business-cycle literature purposely decided to avoid such a question by proxying movements in productivity as exogenous shocks.¹ However, the robust empirical evidence of the slowdown in productivity right before the Great Recession has led recent literature to take a step back and devote more attention to the drivers of medium-term productivity growth.²

Along with Comin and Gertler (2006), theoretical contributions rationalize endogenous productivity dynamics by incorporating features of endogenous growth models in standard models of business cycles. Following Romer (1990), most of these papers augment final-good production functions with an expanding composite of intermediate goods invented by the Research & Development (R&D) sector in order to allow for an endogenous rate of adoption of new technologies.³ Guided by the prediction of such theoretical work that R&D developments matter for growth, other papers attempt to provide empirical evidence of a slowdown in the productivity of the R&D sector. Specifically, they show that although research effort keeps rising, the rate of new ideas and discoveries is slowing down.⁴

Motivated by this wave of research, this paper follows a different path and argues that Information and Communication Technology (hereafter ICT) plays an important role in driving medium-term productivity in sectors that are ICT users. Our contribution is twofold. First, we provide robust empirical evidence to show that current rises in ICT investment explain significant and persistent increases in future Total Factor Productivity (hereafter TFP). Second, we analyze a standard theoretical framework in order to both rationalize and draw conclusions from our empirical results.

In the empirical section, we identify technological shocks specific to the ICT sector in a Structural VAR context.⁵ Our multivariate system includes three key variables: TFP, ICT

¹Kydland and Prescott (1982) and Long Jr and Plosser (1983) are among the first papers which consider productivity shocks on general equilibrium models.

²See Cetto et al. (2016) and Byrne et al. (2016) among others.

³Bianchi et al. (2014), Anzoategui et al. (2016), and Moran and Queralto (2017) use similar techniques to endogenize growth. In particular, Bianchi et al. (2014) augment a DSGE model using a quality ladders model in the vein of Grossman and Helpman (1991). Moreover, Anzoategui et al. (2016) and Moran and Queralto (2017), similarly to Comin and Gertler (2006), use a model of expanding variety in the vein of Romer (1990).

⁴Jones (2009) and Bloom et al. (2017) are two important contributions that highlight these facts.

⁵An interesting paper related to our empirical work is Jafari Samimi and Roshan (2012). The

investment (hereafter ICTI), and relative prices (hereafter RP). ICTI is defined as the total expenditure in equipment and computer software meant to be used in production for more than an year. Thus, an increase in ICTI is ICT capital deepening. RP is the ratio between the price of the ICT good and the price level in the overall economy.

We use two identifying restrictions in order to back out an ICT technology shock. First, we expect it to be orthogonal to the current productivity of all the other sectors. Since the share of the ICT sector accounts for a negligible part in the whole economy, ICT shocks should have an approximately zero effect on TFP on impact. Thus, our first restriction will be a zero-impact restriction on TFP after an ICT shock. Moreover, following Greenwood et al. (1997) and Fisher (2006), we rely on RP and ICTI because we expect that a sectoral technology shock should decrease its relative prices and enhance expenditure in the underlying sector. For theoretical reasons discussed in more detail below, we do not impose any restriction on RP; instead, we let the ICT shock maximize the impact response of ICTI.⁶ In response to this shock, ICTI rises on impact and remains significant for several quarters. RP persistently and significantly declines for more than two years, suggesting that we are indeed identifying the correct sectoral shock. Our main result is that TFP, restricted not to respond on impact, rises after few quarters and remains significant and stable for at least 5 years, despite the tiny size of the ICT sector relative to the economy.

Although our results are robust over different specifications, an important critique to our empirical strategy is reverse causality coming from news on future TFP. As suggested by the news-shock literature, the positive reaction of ICTI on impact may be triggered by signals related future increases in TFP and not to contemporaneous ICT technological improvements. In other words, our identification strategy may confound our shock of interest with a news shock which contemporaneously enhances investment in ICT capital goods. We address this issue by providing a series of alternative identification strategies which we show deliver the same time series of ICT innovations as our initial specification. The heart of these robustness checks is sequential identification of news and ICT shocks: we firstly identify a news shock in the spirit of Barsky and Sims (2011), and subsequently we identify our sectoral ICT shock using the previous identification strategy. Encouragingly, controlling for signals regarding future movements in TFP does not affect our results. We view this as strengthening our

authors identify ICT shocks as a potential driver of the Iranian business cycle using a completely different identification strategy and obtaining qualitatively different results.

⁶However, as suggested by both Greenwood et al. (2000) and Basu et al. (2010), we are aware that conditioning our identifying restrictions only on the direction of RP does not properly measure for technological changes between sectors. This is the main reason why we never impose the direction of RP as an direct identifying condition.

statement relating movements in current ICT technology to future TFP.

In order to understand the economics behind our empirical results, we then analyze a two-sector DSGE model which allows ICT to be the general purpose technology (hereafter GPT) of the whole economy. There are two main justifications for interpreting ICT as a GPT. On the one hand, there is a vast literature that makes a case for the general-purpose nature of ICT capital.⁷ On the other hand, the small size of the share of the ICT sector both in overall investment and overall output makes our results of a strong and persistent TFP increase after an ICT shock hard to interpret in absence of an additional force such as an externality coming from the general-purpose property of ICT capital.

In our model, both sectoral production functions are fed with three inputs: (i) labor, supplied by households, (ii) hard capital, produced by the final sector, and (iii) ICT capital, produced by the ICT sector. As explained by both Basu et al. (2003) and Basu and Fernald (2007), a GPT should be able to enhance accelerations in productivity in sectors that are users of the underlying technology. We then interpret ICT as the GPT of the last 30 years of the U.S. economy assuming that exogenous technological changes in the ICT sector are able to affect economy-wide productivity above the direct effect coming from the technology increase itself.⁸ In particular, when an ICT technology shock arrives, both sectors accumulate ICT capital since it is easier to produce and cheaper to buy. This ICT capital deepening consequently enhances the productivity of both sectors by means of a spillover coming from the accumulated ICT capital stock.

Since the purpose of ICT capital is to improve information sharing, the quality and speed of communication mainly depends on the diffusion of these technologies among agents. As a simple example, owning a mobile phone enables one to contact another person instantaneously only if the other person is also endowed with the same technology. As a result, the effectiveness of ICT capital is intrinsically related to its own diffusion. This line of thought is what leads us to augment the production function of each sector with a spillover effect capturing the diffusion of ICT capital. Having a spillover arise from a state variable is also consistent with both the GPT literature above and with our empirical results, since it also leads to model dynamics in which the accumulation of ICT capital is a slow process and the benefits of an

⁷See for example Oliner and Sichel (2000) and Stiroh (2002) amongst others.

⁸A clarification is in place here. In a two-sector model, the overall residual productivity is a convolution of the two exogenous productivities. Thus sectoral productivity changes trivially show up in overall productivity. Our assumption of ICT capital being a GPT means that overall productivity responds more to an ICT-sector-specific technology shock than warranted by this shock directly. We address this question in detail in the main text in Section 2.

ICT technology shock show up in the production functions of ICT-users with lags.⁹

As a last step, we use both our empirical and theoretical results to estimate the key parameters of the model via impulse-response function matching to an ICT technology shock. The key parameters within this set are (i) the elasticity of productivity to ICT capital diffusion, namely the parameter which governs the spillover effect, and (ii) the standard deviation and (iii) persistence of ICT technology shocks. Results consistently point out a positive spillover effect of ICT capital deepening on TFP, confirming that within this class of theoretical models, data supports the existence of spillovers from ICT capital. Thus, our theoretical model suggests to interpret the responses obtained in the empirical section in light of ICT as a general-purpose technology which enhances productivity of ICT capital users through a spillover effect related to its own diffusion.

The paper is structured as follows. We present empirical results and main robustness checks in Section 2. We then present and analyze the two-sector DSGE model in Section 3. We estimate via impulse-response matching key parameters of the model and run a series of related experiments in Section 5. Concluding remarks, caveats and prospective future research are discussed in Section 6.

2 Empirics

In this section we present our main empirical results. Our attempt is to properly identify technological shocks which are specific to the ICT sector in a Structural VAR context and analyze their impact on key macroeconomic variables.

2.1 Main Specification

We start by illustrating our main specification where we impose minimal discipline on the identification strategy. In subsequent sections, we try vastly different alternative empirical strategies. It turns out that the set of results presented here are consistent with the different robustness checks.

⁹Notice that differently to Basu et al. (2003) and Basu and Fernald (2007), we interpret the general-purpose nature of ICT in the spirit of an endogenous growth model.

2.1.1 Data

Our first-step specification is the following 5-variable VAR

$$\begin{pmatrix} TFP_t \\ ICTI_t \\ GDP_t \\ C_t \\ RP_t \end{pmatrix} = B(L) \begin{pmatrix} TFP_{t-1} \\ ICTI_{t-1} \\ GDP_{t-1} \\ C_{t-1} \\ RP_{t-1} \end{pmatrix} + i_t \quad (1)$$

where TFP_t is the log-level of Fernald total factor productivity at time t , $ICTI_t$ is the log-level of real information and communication technology investment at time t ,¹⁰ GDP_t is the log-level of real gross domestic product at time t , C_t is the log-level of real consumption at time t , and RP_t is the log-deviation of the ratio between prices of ICT goods and services and the consumer price index (CPI).¹¹ Our dataset is quarterly and covers the U.S. economy from 1989:Q1 to 2017:Q1.¹² $B(L)$ is a (5×5) matrix of lag-operator functions of the same order. Following the Bayesian Information Criterion (BIC), we choose one lag, which implies that we regress variables at time t with their own lagged values at $t - 1$.¹³ Finally, i_t is a (5×1) vector of correlated innovations where $\Sigma = i_t' i_t$.

2.1.2 Empirical Strategy

Our simplest identification strategy assumes that an ICT-investment technological shock (hereafter ICT shock) has no impact effect on TFP and maximal impact effect on ICTI. We justify these assumptions with both empirical and theoretical arguments. First of all, using data released in April, 2018 by the Bureau of Economic Analysis (BEA) the real value

¹⁰ $ICTI_t$ is defined as the total expenditure at time t in equipment and computer software meant to be used in production for more than an year.

¹¹Except for RP_t that is not cointegrated with the remaining variables, we opt for estimating the VAR in levels since it produces consistent estimates of the impulse responses and is robust to cointegration of unknown forms. In particular, as suggested by Hamilton (1994) when there is uncertainty regarding the nature of common trends, estimating the system in levels is considered the conservative approach. The alternative approach is to estimate the system as a vector error correction model (VECM); our results remain very similar also in this case.

¹²All data are from the BEA except for TFP, which is the series constructed by John Fernald, available on his website.

¹³The Hannan-Quinn Criterion (HQ) suggests to use two lags. Results remains consistent following this second criterion.

added of the information sector on real GDP is slightly below 5% for the underlying quarter.¹⁴ Thus, since the share of this sector accounts for a negligible part in the whole economy, we think it safe to assume that an ICT shock is orthogonal to current TFP. In addition, the theory of multi-sector models, firstly presented by Greenwood et al. (1997), predicts that a productivity increase in one sector should lead to sectoral output becoming cheaper. Thus, we expect that an ICT shock should enhance sector-specific investment since ICT goods are now easier to produce and cheaper to buy. As a result, we expect an ICT shock to have a maximal impact effect on ICTI.

Using a notation similar to Barsky and Sims (2011), we implement our identification strategy as follows. Let y_t be the (5×1) vector of observables of length T presented above. The reduced-form VAR takes the following form,

$$y_t = B(L)y_{t-1} + i_t$$

Assume now that there exists a linear combination that maps innovations i_t to structural shocks s_t ,

$$A_0 s_t = i_t$$

which implies the structural-form VAR

$$A_0^{-1} y_t = C(L)y_{t-1} + s_t$$

where $C(L) = A_0^{-1}B(L)$ and $s_t = A_0^{-1}i_t$. The impact matrix A_0 must be such that $\Sigma = A_0 A_0'$. Notice that A_0 is not unique since for any D such that $DD' = I$, $\tilde{A}_0 = A_0 D$ satisfies $\Sigma = \tilde{A}_0 \tilde{A}_0'$.

The matrix of impact responses to all shocks is:

$$\Pi(0) = \tilde{A}_0 D$$

and is specifically formed by the following elements, denoting the responses of variable i to shock j ,

$$\Pi_{i,j}(0) = e_i' \tilde{A}_0 D e_j$$

where e_k is a selector column vector of the same dimension as \tilde{A}_0 with 1 in the k th element and zero elsewhere. In particular, notice that e_j is selecting a specific column of D . Let this

¹⁴There are many ways to quantify the size of the ICT sector, both in terms of what share one considers and how one defines the ICT sector. The number presented in the text refers to the value added share of the ICT sector, defined as in Section 1. The statement that the ICT sector is tiny is however not sensitive to the definition of the sector or to the choice of share. Even with broader definitions, one obtains numbers in the range of 5%.

column be denoted by γ_j . Using this notation, $\tilde{A}_0\gamma_j$ is the vector of impact responses of all the variable to shock j .

Observe from System 1 that TFP_t is ordered first and $ICTI_t$ second. Our identification strategy is then the solution to the following problem:

$$\max_{\gamma_j} \Pi_{2,j}(0) = e'_2 \tilde{A}_0 \gamma_j \quad (2)$$

subject to

$$\Pi_{1,j}(0) = e'_1 \tilde{A}_0 \gamma_j = 0, \quad \text{and} \quad (3)$$

$$\gamma'_j \gamma_j = 1 \quad (4)$$

where j represents the arbitrary position of the ICT shock. Then, in order to ensure that this identification belongs to the space of possible orthogonalizations of Σ , the problem is formulated in terms of choosing γ_j conditional on any orthogonalization, \tilde{A}_0 . Objective function 2 imposes that an ICT shock has a maximal impact effect on ICT investment. Constraint 3 orthogonalizes current TFP to ICT shocks and Constraint 4 satisfies the condition that γ_j is derived from an orthogonal matrix D .

2.1.3 Main Set of Results

Appendix A shows the estimated impulse responses of System 1 to the identified ICT shock. The shaded gray areas are the 90% and 95% confidence bands from a bias-corrected bootstrap procedure of Kilian (1998) using 2000 simulations. Our main interest, Figure 1, shows the impulse response of TFP to an ICT shock. TFP takes around 4 quarters before displaying a positive and significant effect and reaches its peak of 1.2% after 24 quarters. In Figure 2, real ICT investment has a large and positive impact response of almost 2% that gets even larger after a quarter. Then, it slowly starts to decay remaining significant for more than 40 quarters. In Figures 3 and 4, we present responses of real GDP and real consumption, respectively. Real GDP has a significant impact response of 0.3% and reaches its peak of almost 0.5% approximately at the same time as TFP. Similarly, real consumption has an impact effect of 0.2% with a delayed peak of 0.5%. Finally, Figure 5 depicts that response of relative prices. Despite imposing no restriction here, the response of RP is broadly in line with multi-sector theory. Relative prices drop significantly on impact by 0.4% and remain persistently below their own steady state value for almost 9 years.

In addition, Table 1 in Appendix B presents forecast error variance decompositions for the ICT shock on each variable. The table shows decompositions on impact, and at a one-, two-, four-, six-, and ten-year horizon. These results are very interesting in their own right,

as they hint that the ICT sector may have a particular role for the overall productivity of the economy.

In line with the impulse responses, ICT shocks, which are orthogonal to current productivity, explain nothing of current TFP fluctuations. At a ten-year horizon, however, this fraction is over a third! This crucial result is a strong sign that the ICT sector matters for overall productivity over and beyond the direct contribution of its sectoral productivity (which, as we have seen, is marginal). At the same time, ICT shocks drive almost the whole variation in ICT investment on impact, with a slow decay over time to below 50% after 10 years. Interestingly, both output and consumption have a remarkable reaction on impact: 26% and 19%, respectively. Moreover, this effect tends to increase reaching 40% in both cases at the maximal horizon. Finally, ICT shocks only account for a small fraction of movements in relative prices. The fraction of fluctuations explained on impact is only 6% with a peak of 14% between four and six years. Overall, these variance decompositions all seem to suggest that the ICT shock leads to complex forms of reallocation and accumulation that take place over the medium run in the economy. Our structural model of Section 3 provides a theoretical framework to think about these dynamics and to give them an economic interpretation.

2.2 Controlling for News Shocks

In this section, we present a set of robustness checks aimed to show that our previous results are not driven by future signals regarding exogenous productivity. The main concern against the specification of 2.1 is reverse causality coming from the presence of news about future TFP that is not accounted for. Indeed, the news-shock literature warns that the positive reaction of ICTI on impact may be triggered by signals related to future increases in productivity and not to a contemporaneous ICT shock. In other words, our identification strategy may confound our shock of interest with a news shock which contemporaneously enhances investment in ICT capital goods. We address this issue by providing two main alternative identification strategies which we show deliver the same time series of ICT shocks as our initial specification.

As a first-pass test, we check if our results are robust once we remove all the forward-looking variables whose fluctuations may be unrelated to sector-specific technological changes: consumption and output. Technically speaking, consumption and output may Granger-cause movements in future TFP for reasons which are orthogonal to ICT shocks. For example, the forward-looking nature of consumption may provide the VAR with information regarding future changes in TFP not related to an ICT shock, which our identification strategy is not able to filter out.

Our second test is running a VAR in which we identify both ICT shocks and news shocks.

In particular, we apply a sequential identification where we first identify a news shock in the spirit of Barsky and Sims (2011), and subsequently we identify our sectoral ICT shock using our original identification strategy. This second strategy has the specific purpose of filtering out all the current movements in forward-looking variables related to future fluctuations of TFP which are not related to current ICT shocks, as such fluctuations are all captured by the identified news shock.

As is illustrated in the rest of this section, both our robustness checks recover the same series for structural ICT shocks as our initial specification, and thus leave our results unaffected. We therefore conclude that controlling for signals regarding future movements in productivity does not affect our identified ICT shocks, and thus confirm the causal relation between current ICT investment and future TFP.

2.2.1 Removing Forward-Looking Variables

In this part of the paper, we employ a first-pass test of whether our ICT shock may be confounded with future signals of TFP unrelated to the ICT sector.

As discussed by Sims (2012), Forni and Gambetti (2014), and Barsky et al. (2015) the presence of forward-looking variables in the VAR is a necessary condition to correctly identify a news shock. In particular, since the univariate TFP process cannot predict its own future values,¹⁵ a news shock can only be identified if there are variables that Granger-cause TFP inside the VAR. For example, Beaudry and Portier (2006) use current movements in stock prices to predict future productivity, but also contemporary fluctuations in consumption, hours, investment, may implicitly reflect information regarding future technical change.

Thus, as a simple test we redo the exercise described in Section 2.1, omitting the two forward-looking macroeconomic variables not directly related with the ICT sector: consumption and output.¹⁶ If we are actually confounding news shocks with our ICT shock series then we would expect to see some differences in this second estimate, because absent the two forward-looking variables, our VAR is deprived of a source of information useful to recover a news shock and should thus no longer be able to capture it appropriately.

Without consumption and output, we thus estimate the following three-dimensional sys-

¹⁵It is well-accepted that TFP growth can be approximated as a white noise process, or, equivalently, that the TFP level process is a random walk.

¹⁶Notice that output implicitly reflects the behavior of hours and investment once we control for consumption.

tem

$$\begin{pmatrix} TFP_t \\ ICTI_t \\ RP_t \end{pmatrix} = B(L) \begin{pmatrix} TFP_{t-1} \\ ICTI_{t-1} \\ RP_{t-1} \end{pmatrix} + i_t \quad (5)$$

where TFP_t , $ICTI_t$, and RP_t are defined and treated as in System 1. As before, the dataset is quarterly and covers the U.S. economy from 1989:Q1 to 2017:Q1. Finally, analogously to before, we follow the Bayesian Information Criterion (BIC) to choose one lag. Using the same identification strategy presented in 2.1.2, we recover a series of ICT shocks. The newly recovered series is correlated at 95% with the one estimated in five-dimensional system, indicating that our main specification is not contaminated by news. Figure 6 in Appendix C shows the ICT shock series for both the three-dimensional system and the five-dimensional one. In line with the very high correlation coefficient, the two series overlap perfectly, suggesting that both procedures recover the same structural shock series. Thus, our first-pass test indicates that our initial result is not driven by the forward-looking power of consumption and output on TFP.

However, although this result is encouraging, the first-pass test has weak power because the jump of ICTI on impact may itself be triggered by exogenous signals on future TFP. In this case, ICTI would be itself the source to Granger-cause TFP and our ICT shock would be upward biased by news. To address this deeper concern, we proceed to employ a more complicated strategy aimed at directly capturing, and filtering out news.

2.2.2 Sequential Identification Strategy

In this part, we present an alternative procedure to rule out the presence of news from our recovered ICT shock. In this second test we run a VAR where we identify both ICT shocks and news shocks. In contrast to our first-pass test, this test aims to directly identify and filter out future signals unrelated to current ICT shocks.

We apply a sequential identification which involves first identifying a news shock in the spirit of Barsky and Sims (2011), and subsequently identifying the ICT shock using our original strategy. Specifically, in the first step the news shock is identified as the shock orthogonal to current TFP that best explains its future movements. Then, as a second step, the ICT shock is identified as the shock orthogonal to current TFP that maximizes the impact effect on ICT investment.

However, in order to correctly employ this procedure, we need to take care of a second issue. As Barsky and Sims (2011) warns,

A general objection to our empirical approach would be that a number of structural

shocks, which are not really news in the sense defined in the literature, might affect a measure of TFP in the future without impacting it immediately. Among these shocks might be research and development shocks, investment specific shocks, and reallocative shocks. Our identification (and any other existing VAR identifications) would obviously confound any true news shock with these shocks.

In other words, by naively employing the procedure presented above, any ICT shock would be interpreted as a news shock since it is orthogonal to current TFP and explains its future movements. Put plainly, to get the identification of the two shocks right, we need to add a restriction that is able to distinguish between them.

Thus, to avoid confounding ICT shocks with news shocks, we need to augment the first step with an extra restriction. The restriction we will use here is derived from a two-sector structural model in the tradition of Greenwood et al. (1997).¹⁷ Here, we refrain from presenting the model in its entirety; the reader is referred to Section 3. Instead, Proposition 1 presents the key property of the model that gives rise to our identification assumption.

Proposition 1. *In a two-sector economy, if both production functions are identical, then any economy-wide productivity shocks do not affect relative prices between the two sectors.*

Proof. See Appendix D. □

Proposition 1 implies that an anticipated future sector-neutral technological change (the so-called news shock) never affects relative prices between sectors. Obviously, this statement is correct under the extreme assumptions that (i) the shock is expected to have the same impact on the two sectors and (ii) production functions are identical. If those assumptions hold in the data, then the correct additional restriction would be to restrict the impulse response of relative prices to a news shock to hard zero at all horizons. However, this restriction would obviously penalize the identification of news shocks since it is unlikely that assumptions (i) and (ii) perfectly hold in the data. We therefore opt for a more moderate strategy where we impose that the response of relative prices to a news shock should be smaller than the response following an ICT shock. Practically speaking, we arbitrarily set the impulse response of relative prices to news to be zero on some specific horizons rather than at all horizons. While results are robust to different horizon restrictions, our favorite specification is the one which sets relative prices to have zero response in the first three periods.

¹⁷While our model belongs to the class of models along the lines of Greenwood et al. (1997), our exposition is closer to that of Oulton (2007). We discuss this choice in detail in Section 3.

Data

Motivated by Proposition 1, we augment our initial VAR system with stock prices, SP. As discussed above, SP is added in order to provide an additional forward-looking variable to the system.¹⁸ Thus, our current specification is the following six-variable VAR,

$$\begin{pmatrix} TFP_t \\ SP_t \\ ICTI_t \\ GDP_t \\ C_t \\ RP_t \end{pmatrix} = B(L) \begin{pmatrix} TFP_{t-1} \\ SP_{t-1} \\ ICTI_{t-1} \\ GDP_{t-1} \\ C_{t-1} \\ RP_{t-1} \end{pmatrix} + i_t \quad (6)$$

where TFP_t , $ICTI_t$, GDP_t , C_t , and RP_t are defined and treated identically to System 1. SP_t represents the log-transformation of Standard & Poor's 500 stock price index. As before, dataset is quarterly and covers the U.S. economy from 1989:Q1 to 2017:Q1 and following the BIC and HQ criteria we opt for one lag.

Empirical Strategy

Using the notation of Section 2.1.2, assume for simplicity that $B(L) = B$ allows only for one lag. Define the impulse response of variable i to the identified shock j at time t as,¹⁹

$$\Pi_{i,j}(t) = e_i' B^t \tilde{A}_0 D e_j = e_i' B^t \tilde{A}_0 \gamma_j$$

and its variance decomposition up to time h as

$$\Omega_{i,j}(h) = \frac{\sum_{t=0}^h e_i' B^t \tilde{A}_0 D e_j e_j' D' \tilde{A}_0' B^t e_i}{e_i' (\sum_{\tau=0}^H B^t \Sigma B^t) e_i} = \frac{\sum_{t=0}^h e_i' B^t \tilde{A}_0 \gamma_j \gamma_j' \tilde{A}_0' B^t e_i}{e_i' (\sum_{\tau=0}^H B^t \Sigma B^t) e_i}$$

Given this and recalling that TFP is ordered first, ICTI second and RP sixth, the identification strategy can be summarized as follows,

Step 1 - Identification of γ_{news}

$$\max_{\gamma_{news}} \Omega_{1,news}(h) = \frac{\sum_{t=0}^h e_1' B^t \tilde{A}_0 \gamma_{news} \gamma_{news}' \tilde{A}_0' B^t e_1}{e_1' (\sum_{\tau=0}^H B^t \Sigma B^t) e_1}$$

¹⁸The presence of forward-looking variables in the VAR is a necessary condition to correctly identify a news shock. For more details on this discussion, see Sims (2012), Forni and Gambetti (2014), and Barsky et al. (2015).

¹⁹We also suppress the constant to simplify the notation. Of course, our identification strategy can be applied for $B(L)$ allowing for more than one lag and with the constant.

subject to

$$\begin{aligned}\Pi_{1,news}(0) &= 0, \\ \Pi_{6,news}(0) &= \Pi_{6,news}(1) = \Pi_{6,news}(2) = 0, \quad \text{and} \\ \gamma_{news}\gamma'_{news} &= 1.\end{aligned}$$

where the first constraint represents the zero-impact restriction of news on TFP. The second constraint is the restriction derived from Proposition 1 to have the response of relative prices to news relatively small.²⁰ Finally, the last constraint imposes that γ_{news} should be a column derived from the orthogonal matrix D .

Step 2 - Identification of γ_{ICT}

$$\max_{\gamma_{ICT}} \Pi_{2,ICT}(0) = e'_2 \tilde{A}_0 \gamma_{ICT}$$

subject to

$$\begin{aligned}\Pi_{1,ICT}(0) &= 0, \\ \gamma_{news}\gamma'_{ICT} &= 0, \quad \text{and} \quad \gamma_{ICT}\gamma'_{ICT} = 1.\end{aligned}$$

where the first constraint represents the zero-impact restriction of ICT on TFP and the last constraint imposes that both γ_{news} and γ_{ICT} should be two different columns derived from the orthogonal matrix D .

Results

Figures 7 and 8 in Appendix E.1 show estimated impulse responses to both news and ICT shocks. Figure 7 focuses on the responses of TFP, stock prices, and ICT investment, while Figure 8 shows the responses of GDP, consumption and relative prices. The shaded gray areas are the 90% and 95% confidence bands from the bias-corrected bootstrap procedure of Kilian (1998) using 2000 simulations.

A first comforting indication is that the responses to an ICT shock are almost identical to the ones from our main identification of Section 2.1. After few lags, TFP displays a positive and significant response and reaches its peak of 1.2% after 6 years. Interestingly, stock prices jump on impact and the effect remains significant over the medium run. Real ICT investment has a large and positive impact response and slowly starts to decay, remaining significant for a long period of time. Both real GDP and real consumption have a significant impact response

²⁰Our identification strategy is robust over different restrictions to relative prices. Results hold even if we set the zero restriction on other horizons.

and reach their peak approximately after 6 years. The response of relative prices is negative and persistent as we have previously discussed. Finally, the ICT shocks explains 27% of TFP fluctuations over a 10-year horizon. Also this result is completely in line with the previous results presented in Table 1 in Appendix B.

In addition, we show the impulse responses to a news shock to confirm that our identification strategy is picking up news shocks correctly. As the responses show, constraining the response of relative prices to news does not qualitatively affect the behavior of news shocks. Our identified news shock generates responses broadly in line with those found by the news shock literature. In particular, in line with Barsky and Sims (2011), it takes more than 2 years after the news shock for TFP to display a positive, significant and strongly persistent effect. Stock prices have a strong forecasting power and show a 4% impact effect which is persistent and significant in the long run. Real ICT investment does not show a positive impact response but it slowly starts to increase getting significant after almost 2 years. As found by Barsky and Sims (2011) in their main specification, real GDP has a non-significant impact effect, but it rises fast with all the variables of the system. Moreover, as was expected, considering the forward-looking nature of consumption, real consumption has a significant impact response and reaches its peak once the TFP response becomes significant. Finally, relative prices are initially constrained to have a zero response, and then show a small, negative and persistent deviation for at least five years which eventually dies out.

Thus, not only are the responses to the ICT shock in line with those of our main specification, but the identified news shock also seems to be capturing the right thing: anticipated future technology changes. Having thus correctly filtered out news components from our ICT shock, we now check how this newly recovered ICT shock series compares to the series backed out by our main specification of Section 2.1.2. It turns out that the correlation between the two shock series is 94%! Figure 9 in Appendix E.2 portrays the two ICT shock series. Again, the two recovered shocks are nearly identical, visually reinforcing the very high correlation between them. Thus we can confidently state that our initial result is not confounding any signal regarding future TFP with our estimated ICT shock.

3 Model

In the previous section, we have documented results regarding the relation of current ICT investment and future productivity. Clearly, to rationalize empirical dynamic responses of aggregate macroeconomic variables to ICT shocks, we need a two-sector approach that distinguishes ICT goods from other output. In this section, we present a simple two-sector model

that rationalizes our structural VAR estimates. The model presented has several common features with Greenwood et al. (1997) that design a two-sector economy where one sector displays a faster technology than the other. One different is that we focus specifically on ICT capital sector, rather than equipment, as the sector with faster technological improvements. This assumption will be necessary if we want to fit the fact that relative prices between the ICT investment and overall economy display a downward sloping trend.²¹

3.0.1 Household

Consider an economy inhabited by a representative agent which maximizes the expect values of his lifetime utility as given by

$$\mathbb{E} \left[\sum_{t=0}^{\infty} \beta^t U(c_t, l_t) \right] \quad (7)$$

with

$$U(c_t, l_t) = \log(c_t) - \frac{1}{1 + \frac{1}{\chi}} l_t^{1 + \frac{1}{\chi}}$$

where c_t and l_t represent consumption and labor at time t .

3.1 Final-Good Producers

Instead of working with the aggregate production function, assume that the production side of the final-good sector consist of a set $[0, 1]$ of firms. In each period, final-good firm $j \in [0, 1]$ produces $y_t^c(j)$ using the services of labor l_t , and two types of capital: hard capital, k_t^c and ICT capital, k_t^i . In addition, production function is augmented with (i) neutral productivity common across sectors, (ii) sector-specific productivity, and (iii) a positive spillover effect related to the diffusion of ICT capital in the whole economy. Production of final output of firm j is undertaken in accordance with

$$y_t^c(j) = A_t^c (k_t^c(j))^a (k_t^i(j))^b (l_t(j))^{1-a-b}, \quad 0 < a, b < 1 \quad (8)$$

where total factor productivity is equal to $A_t^c = \eta_t \theta_t^c (k_t^i)^\gamma$. η_t is the neutral technological component which moves along the following deterministic trend

$$\eta_t = (\Gamma^\eta)^t e^{\varepsilon_t}, \quad (9)$$

²¹In addition, we also rely on the results of Whelan (2003) and Oulton (2007) to correctly define productivity and output share in our setting.

$$\varepsilon_t = \rho_\nu \varepsilon_{t-1} + \nu_t \quad (10)$$

where $\rho_\nu \in (0, 1)$ and $\nu_t \sim N(0, \sigma_\nu)$ represents a neutral technology shock. θ_t^c is the sector-specific technological component, which moves along the following deterministic trend

$$\theta_t^c = (\Gamma^c)^t. \quad (11)$$

Then, γ represents the parameter that governs the size of the spillover effect of ICT capital in the production function. Moreover, $k_t^c(j)$ is the part of hard capital k_t^c used by firm j in order to produce final-good output. Similarly, $k_t^i(j)$ and $l_t(j)$ are the parts of ICT capital k_t^i and labor l_t used by firm j in order to produce final-good output, respectively.

Since all the final-good producers are identical ex ante and ex post, the following conditions hold,

$$\int_0^1 k_t^c(j) dj = k_{1,t}^c, \quad (12)$$

$$\int_0^1 k_t^i(j) dj = k_{1,t}^i, \quad (13)$$

$$\int_0^1 l_t(j) dj = l_{1,t}, \quad (14)$$

where $k_{1,t}^c$ is the aggregate part of hard capital k_t^c devoted to the final-sector, i.e. sector 1. Moreover, $k_{1,t}^i$ and $l_{1,t}$ are the aggregate parts of ICT capital k_t^i and labor l_t devoted to the final-good sector, respectively.

Aggregate final-good output is defined as

$$y_t^c = A_t^c (k_{1,t}^c)^a (k_{1,t}^i)^b (l_{1,t})^{1-a-b}, \quad 0 < a, b < 1 \quad (15)$$

and it can be used for two purposes: consumption, c_t and investment in hard capital, i_t^c ,

$$y_t^c = c_t + i_t^c \quad (16)$$

Notice that elements in the equation above are normalized such that both output and investment are measured in units of consumption. Moreover, hard structures can be produced from final output on a one-to-one basis. The stock of hard capital evolves according to

$$k_{t+1}^c = (1 - \delta^c) k_t^c + i_t^c \quad (17)$$

where $0 < \delta^c < 1$ represents the period depreciation of hard capital.

3.2 ICT-Good Sector

Instead of working with the aggregate production function, assume that the production side of the ICT-good sector consist of a set $[0, 1]$ of firms. Similar to final-output production function, ICT-good firm $q \in [0, 1]$ produces $y_t^c(q)$ using the services of labor l_t , and two types of capital: hard capital, k_t^c and ICT capital, k_t^i . In addition, production function is augmented with (i) neutral productivity common across sectors, (ii) sector-specific productivity, and (iii) a positive spillover effect related to the diffusion of ICT capital in the whole economy. Production of ICT output of firm q is undertaken in accordance with

$$y_t^c(q) = A_t^c (k_t^c(q))^a (k_t^i(q))^b (l_t(q))^{1-a-b}, \quad 0 < a, b < 1 \quad (18)$$

where total factor productivity is equal to $A_t^c = \eta_t \theta_t^i (k_t^i)^\gamma$. η_t is the same neutral technological component which follows 9 and 10, θ_t^i is the sector-specific technological component which moves along the following deterministic trend

$$\theta_t^i = (\Gamma^i)^t e^{\zeta_t}, \quad (19)$$

$$\zeta_t = \rho_\iota \zeta_{t-1} + \iota_t \quad (20)$$

where $\rho_\iota \in (0, 1)$ and $\iota_t \sim N(0, \sigma_\iota)$ represents an ICT technology shock. Then, γ represents the same parameter that governs the size of the spillover effect of ICT capital in the production function. Moreover, $k_t^c(q)$ is the part of hard capital k_t^c used by firm q in order to produce ICT goods. Similarly, $k_t^i(q)$ and $l_t(q)$ are the parts of ICT capital k_t^i and labor l_t used by firm q in order to produce ICT goods, respectively.

Similarly, since all the final-good producers are identical ex ante and ex post, the following conditions hold,

$$\int_0^1 k_t^c(q) dq = k_{2,t}^c, \quad (21)$$

$$\int_0^1 k_t^i(q) dq = k_{2,t}^i, \quad (22)$$

$$\int_0^1 l_t(q) dq = l_{2,t}, \quad (23)$$

where $k_{2,t}^c$ is the aggregate part of hard capital k_t^c devoted to the ICT-sector, i.e. sector 2. Moreover, $k_{2,t}^i$ and $l_{2,t}$ are the aggregate parts of ICT capital k_t^i and labor l_t devoted to the ICT-good sector, respectively.

Aggregate ICT-good output is defined as

$$y_t^i = A_t^c (k_{2,t}^c)^a (k_{2,t}^i)^b (l_{2,t})^{1-a-b}, \quad 0 < a, b < 1 \quad (24)$$

and it can be only investment in ICT capital, i_t^i ,

$$y_t^i = i_t^i \quad (25)$$

Notice that elements in the equation above are normalized such that both output and investment are measured in the same units. Moreover, ICT goods can be produced from ICT output on a one-to-one basis. The stock of ICT capital evolves according to

$$k_{t+1}^i = (1 - \delta^i)k_t^i + i_t^i \quad (26)$$

where $0 < \delta^i < 1$ represents the period depreciation of ICT capital.

3.3 Market Clearing across Sectors

Since we are assuming our economy to be closed, input demands must equal supplies,

$$k_t^c = k_{1,t}^c + k_{2,t}^c, \quad (27)$$

$$k_t^i = k_{1,t}^i + k_{2,t}^i, \quad (28)$$

$$l_t = l_{1,t} + l_{2,t}. \quad (29)$$

Taking as given Equations 8-29 and assuming that factor markets are perfective competitive, representative household maximizes intertemporal utility function under the following constraint,

$$c_t + k_{t+1}^c + p_t k_{t+1}^i = \left(1 - \delta^c + r_t^c\right) k_t^c + \left(1 - \delta^i + \frac{r_t^i}{p_t}\right) p_t k_t^i + w_t l_t \quad (30)$$

where p_t represents the price of ICT capital expressed in consumption units. Since price of consumption is normalized to be one then p_t also represents the relative price between final output and ICT output.

3.4 Competitive Equilibrium and Solution Method

Competitive equilibrium is represented by (i) Equations 7-29, (ii) household's first order conditions with respect to consumption c_t , labor l_t , hard capital k_t^c , ICT capital k_t^i , (iii) final-good

producers' first order conditions with respect to $k_t^c(j)$, $k_t^i(j)$, and $l_t(j)$, and (iv) ICT-good producers' first order conditions with respect to $k_t^c(q)$, $k_t^i(q)$, and $l_t(q)$.

In order to simulate responses to (i) neutral technology shocks, ν_t and (ii) ICT shocks, ι_t we employ a standard first-order approximation of the log-transformation of the system around the detrended (stationarized) steady state. In order to stationarize the system we use results firstly presented by Greenwood et al. (1997) where they formally show the balance-growth path of the two sectors under the assumption that one sector is moving faster than the other. In our case, results are going to be slightly different since we need to take into account the additional effect provided by the spillover.²² Results are derived mostly using the code provide by Stephanie Schmitt-Grohe and Martin Uribe available on their websites.²³

4 Model Assessment

In this section we describes the parameter values and test the empirical performance of the model. Following Christiano et al. (2005), we partition those values into two groups. We calibrate parameters of the first group using steady-state relations or results from previous works. We estimate the second group of parameters by minimizing the distance between the model-implied impulse responses and the empirical results presented in 2.1. In particular, the second group focuses on parameters specifically related to the effect of ICT investment on future TFP: (i) the size of the spillover effect of ICT capital on productivity γ , (ii) the standard deviation σ_ι and (iii) persistence ρ_ι of ICT shocks.

4.1 Parameterization

We calibrate the model at a quarterly frequency. We set the discount factor β to $0.97^{\frac{1}{4}}$ to match the average yield of 3% of the 3-month Treasury bill using data from 1989:Q1 to 2017:Q1. Moreover, we set ICT share b equal to 0.0310 following Oulton (2012) and hard capital share a equal to 0.3. Moreover, adapting Oulton (2012) accordingly to our additional assumptions, we derive steady state growth rates of final-sector technology Γ^c and ICT-sector technology Γ^i solving the system,

$$\begin{cases} \mathbb{E} \left(\frac{p_t}{p_{t-1}} \right) = \frac{\Gamma^c}{\Gamma^i} \\ \mathbb{E} \left(\frac{c_t}{c_{t-1}} \right) = (\Gamma^c)^{\frac{1-b-\gamma}{1-a-b-\gamma}} (\Gamma^i)^{\frac{b+\gamma}{1-a-b-\gamma}} \end{cases} \quad (31)$$

²²The stationarized version of the steady state is available on request.

²³Code to replicate our results is available on request.

where $\mathbb{E}[p_t/p_{t-1}]$ and $\mathbb{E}[c_t/c_{t-1}]$ are derived from the simple mean of their empirical related values using quarterly data from 1989:Q1 to 2017:Q1. Estimation implies $\Gamma^c = 1.0034$ and $\Gamma^i = 1.0160$.²⁴ Finally, to avoid an over-identification problem we set the growth rate of sector-neutral technology Γ^η equal to one.

In addition, we set the frisch elasticity of labor supply χ to be equal to 1. Moreover, following Bureau of Economic Analysis (BEA) depreciation estimates, we set the quarterly depreciation rates for hard capital δ^c to be equal to 0.0206 in order to match an annual depreciation rate of 0.08. Similarly, according to BEA depreciation estimates (i) communication equipments and (ii) computer and electronic products depreciate at an annual rate of 0.15 and 0.14 respectively. Thus, we set the quarterly depreciation rates for ICT capital δ^i to be equal to 0.0398 in order to match the highest of the two values.

4.2 Impulse-Response Matching

4.3 Interpretation of the Results

5 Experiments

6 Conclusion

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²⁴Notice that the value of γ is unknown at this step since it is going to be evaluated using impulse-response matching. This implies that the solution for Γ^c , Γ^i , and γ should be a fixed point where given γ^* we obtain $(\Gamma^i)^*$ and $(\Gamma^c)^*$ solving 31. Given $(\Gamma^i)^*$ and $(\Gamma^c)^*$ we obtain γ^* by minimizing the impulse-response matching. At this step we are simply solving the system for γ equal to zero but a more refine solution will be provided in future.

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A Main Set of Results

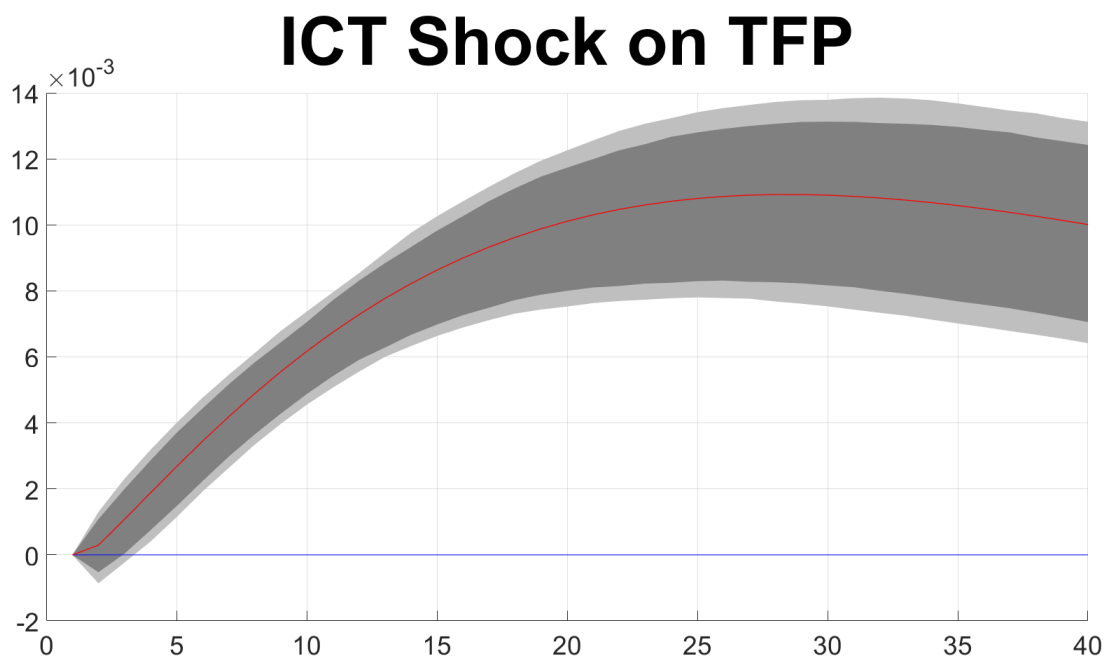


Figure 1: Empirical impulse response of TFP to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

ICT Shock on Real ICT Investment

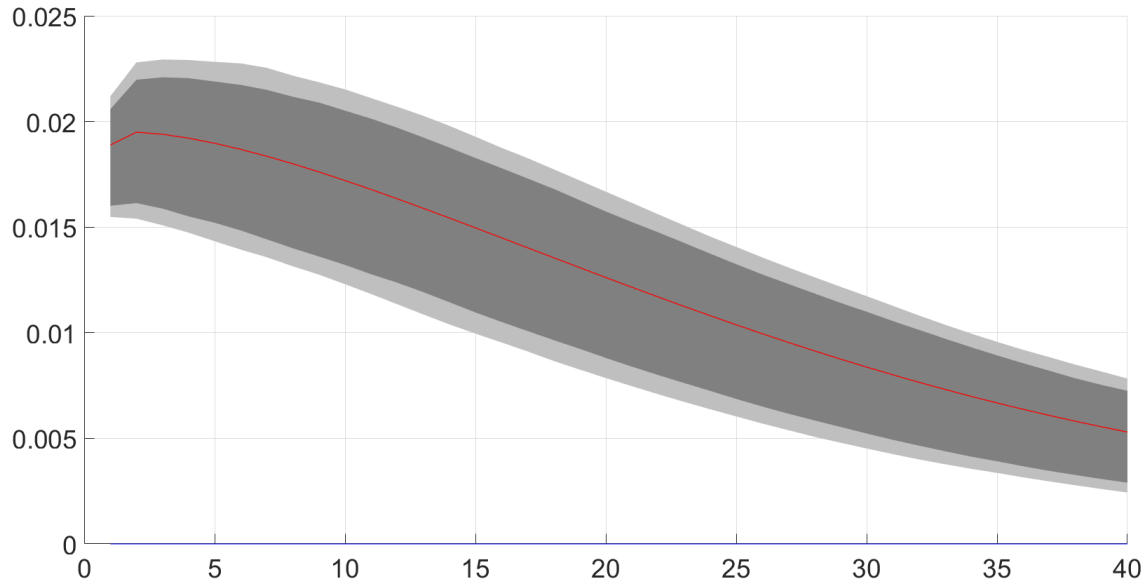


Figure 2: Empirical impulse response of real ICT investment to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

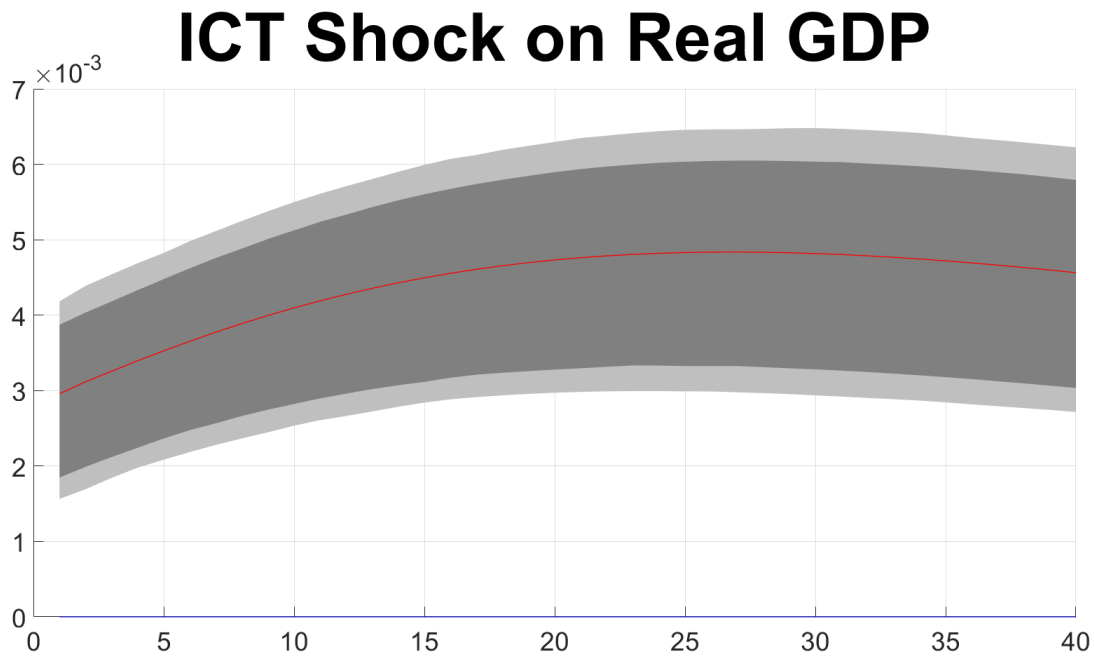


Figure 3: Empirical impulse response of real Gross Domestic Product to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

ICT Shock on Real Consumption

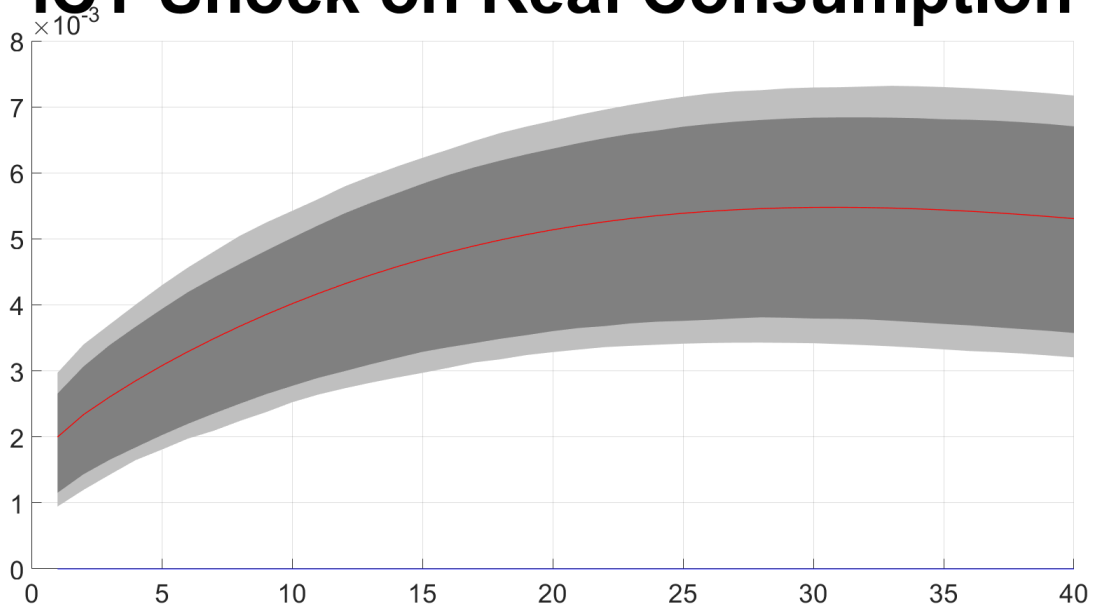


Figure 4: Empirical impulse response of real consumption to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

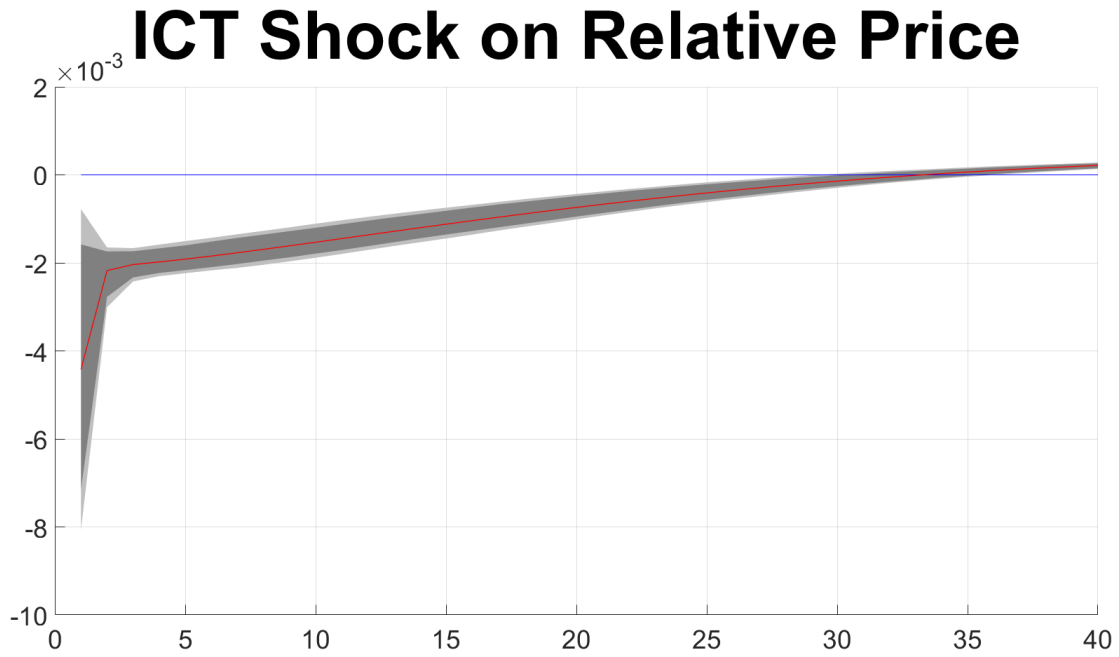


Figure 5: Empirical impulse response of relative price to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

B Variance Decomposition

	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$	$h = 40$
TFP	0	0.0023	0.0194	0.1088	0.2273	0.3382
ICT Investment	0.9997	0.9038	0.7964	0.6320	0.5310	0.4371
Real GDP	0.2620	0.3061	0.3486	0.3936	0.4046	0.3881
Real Consumption	0.1952	0.2638	0.3219	0.3931	0.4188	0.4064
Relative Prices	0.0618	0.0967	0.1276	0.1511	0.1516	0.1467

Table 1: The letter h denotes the forecast horizon. The numbers refer to the fraction of the forecast error variance of each variable at various forecast horizons to the identified ICT shock

C Removing Forward-Looking Variables

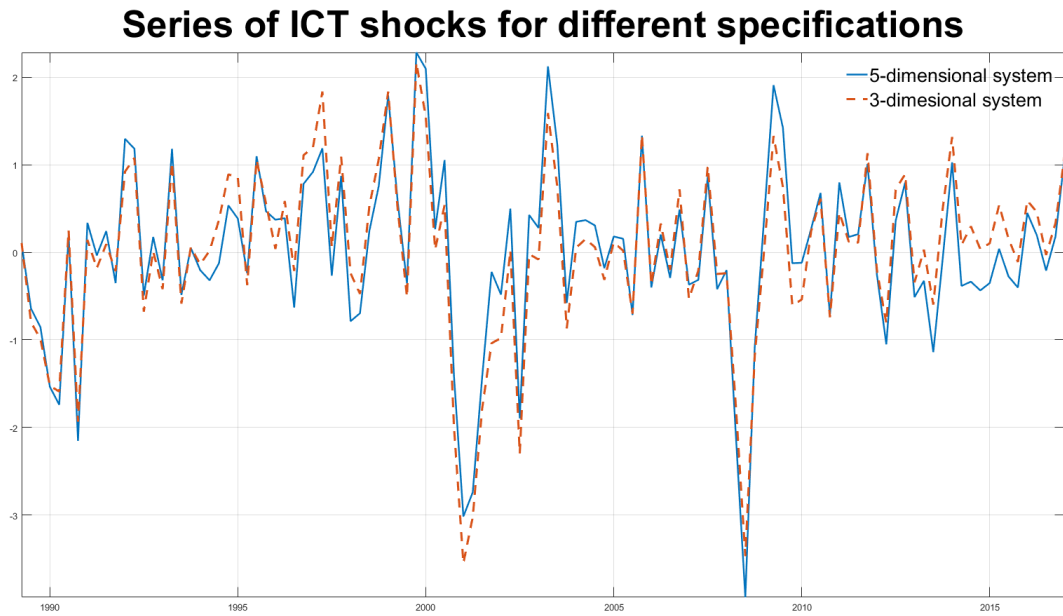


Figure 6: ICT shock series using the empirical strategy presented in 2.1.2. Blue solid line represents shock series for the 5-dimension system 1 presented in 2.1. Red dotted line represents shock series for the 3-dimensional system presented in C.

D Proof of Proposition 1

Prova

E Controlling for News Shocks - Two-Step Identification Strategy

E.1 Impulse Responses

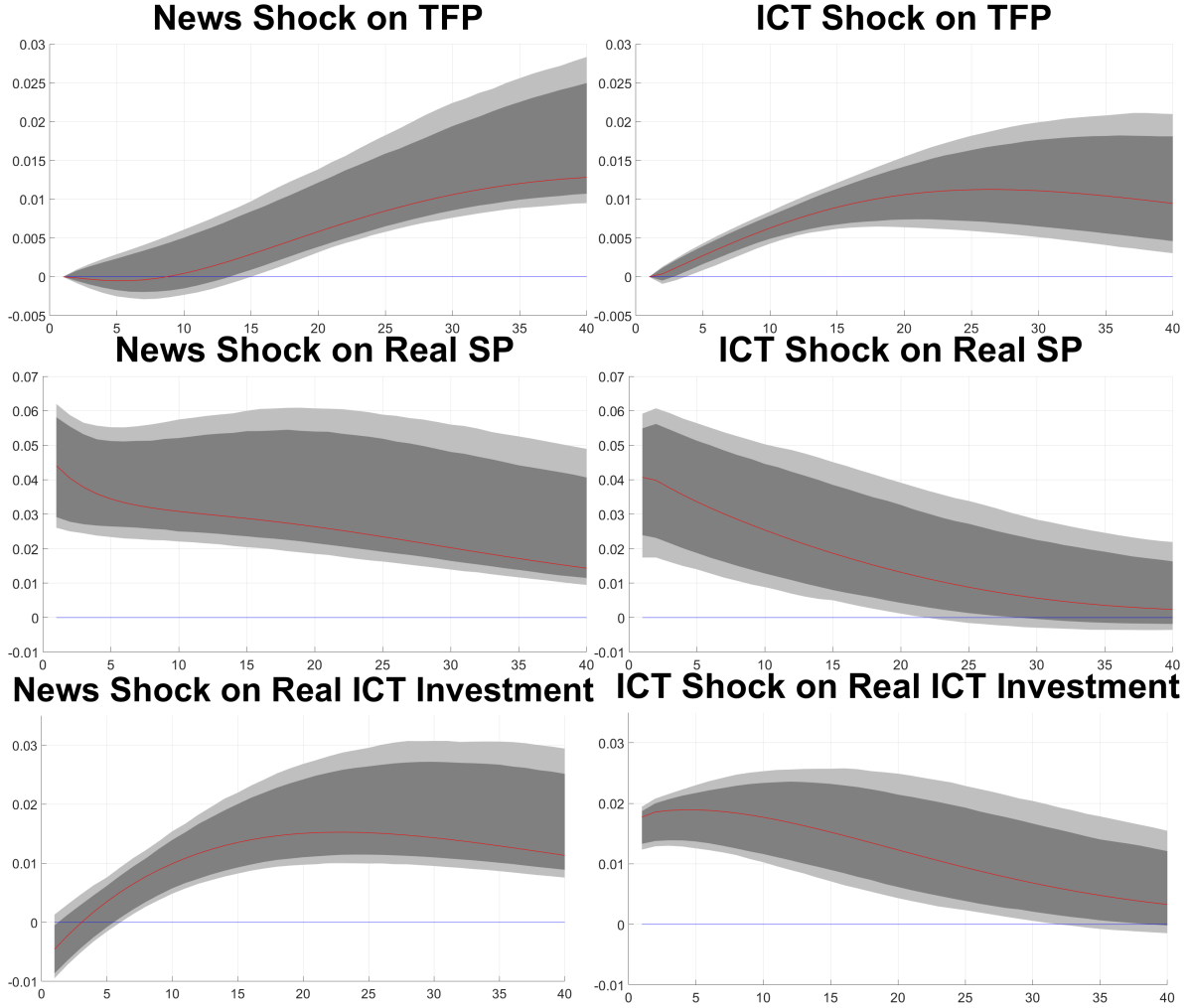


Figure 7: Empirical impulse responses of TFP, Real Stock Prices, and Real ICT Investment to a news shock and an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

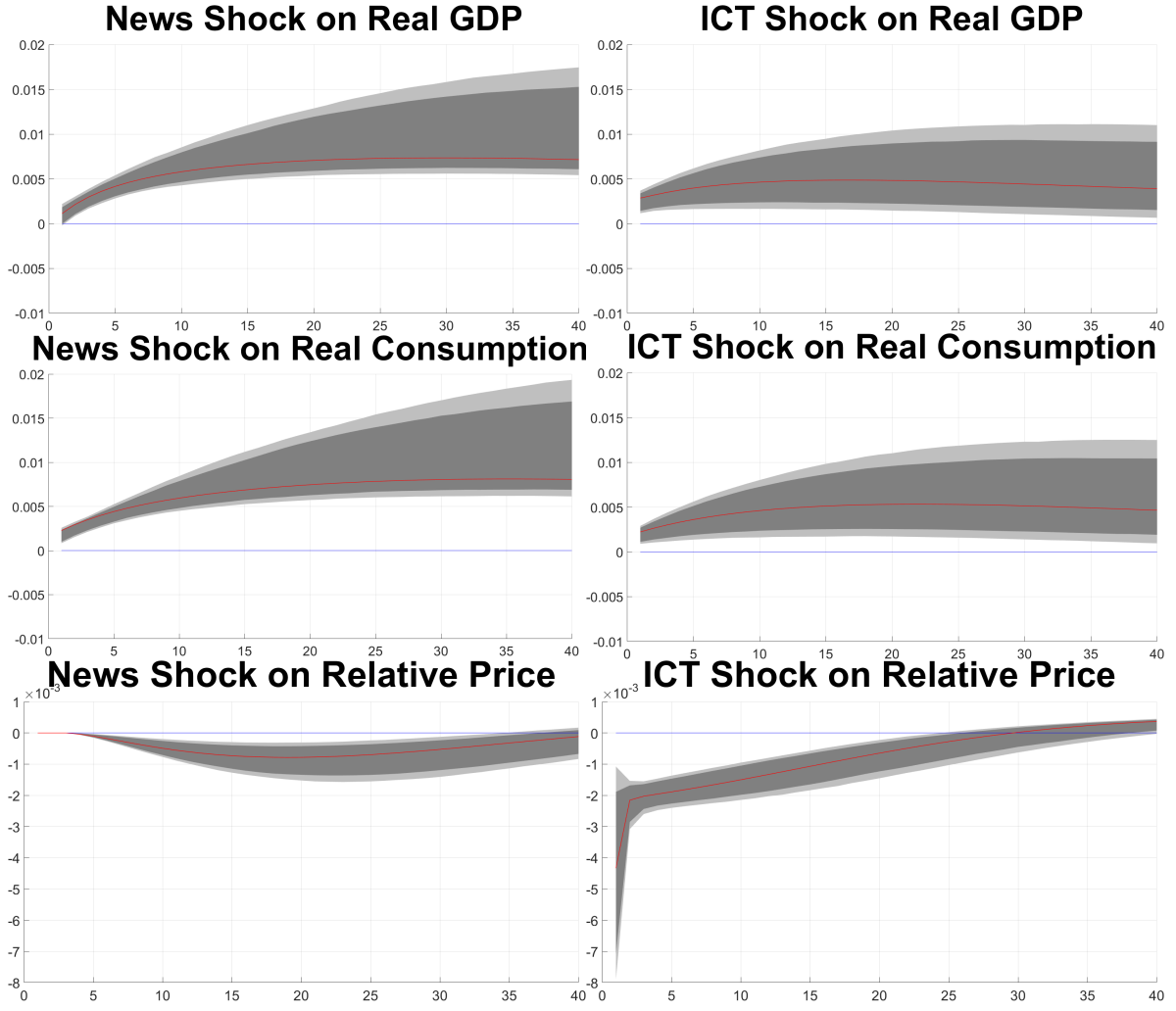


Figure 8: Empirical impulse responses of Real GDP, Real Consumption, and Relative Prices to a news shock and an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the reduced-form VAR. The horizontal axes refer to forecast horizon and the units of the vertical axes are percentage deviations.

E.2 ICT Shock Series

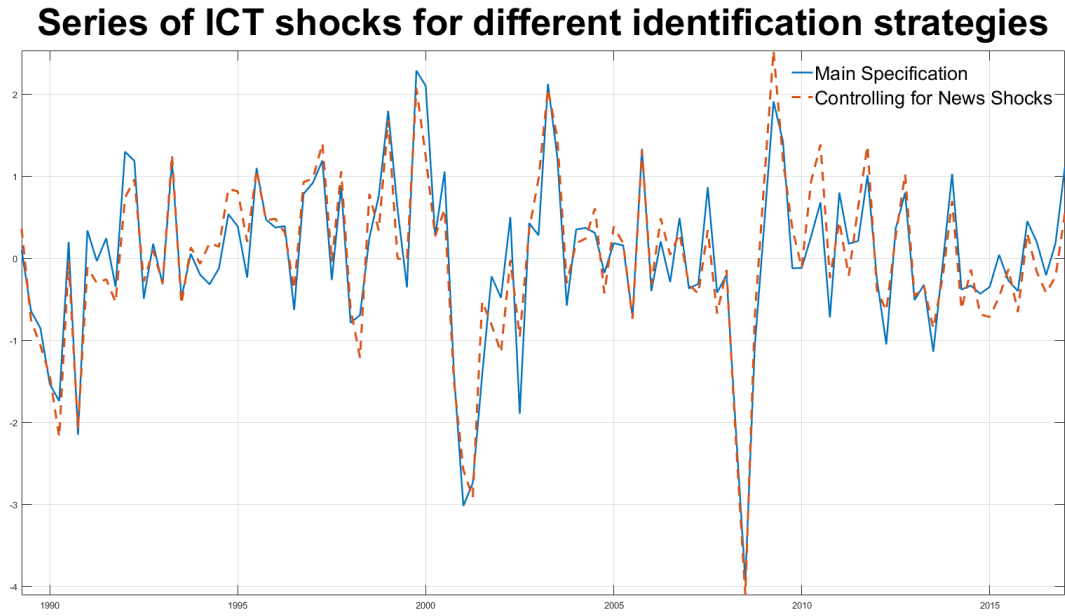


Figure 9: ICT shock series using two different empirical strategy. Blue solid line represents shock series for the 5-dimension system 1 presented in 2.1. Red dotted line represents shock series for the 6-dimensional system 6 presented in 2.2.2 where we employ a 2-step identification strategy in order to control for news shocks.