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

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June 29, 2018

Abstract

Information and Communication technology (ICT) is able to explain accelerations in productivity in sectors that are ICT users. 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. In line with theories of ICT as a general-purpose technology, we analyze a two-sector general equilibrium model in order to rationalize previous results and estimate key parameters 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 performances, less agreement is on the underlying sources that enhance its growth. For several years most of the business-cycle literature purposely decided to avoid such a question by proxying movements in productivity as random shocks.[1] However, the robust empirical evidence of the slowdown in productivity right before the great recession is summoning the literature to take a step back and devote more attention on the drivers of medium-term productivity growth.[2]

Along with Comin and Gertler (2006), some theoretical contributions rationalize endogenous productivity dynamics by adapting features of endogenous growth models into DSGE models. Following Romer (1990), most of those papers augment final-good production functions with an expanding composite of intermediate goods produced by the R&D sector in order to allow for an endogenous rate of adoption of new technologies.[3] Consistent with those previous models, 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 is keeping 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 argue 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 a robust empirical evidence to show that current rises in ICT investment explains significant and persistent increases in future Total Factor Productivity (hereafter TFP). Second, we analyze a standard theoretical framework in order to both motivate and rationalize our empirical results.

Regarding the empirical section, the idea is to identify technological shocks which are only specific to the ICT sector in a Structural VAR context.[5] In order to have a reliable

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

[2] See Cette et al. (2016) and Byrne et al. (2016) among others.

[3] Bianchi 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).

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

[5] An interesting paper which is somehow related to our empirical part is Jafari Samimi and Roshan (2012). The authors identify ICT shocks as a potential driver of the Iranian business cycle using a

identification procedure our multivariate system needs to embody three key variables: TFP, ICT investment (hereafter ICTI), and relative prices (hereafter RP). Importantly, 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 has to be though as an ICT capital deepening. Moreover RP is the ratio between prices in the ICT sector over prices in the overall economy. To verify that we are correctly identifying an ICT technology shock, we firstly 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 we expect it should have an approximately zero effect on TFP on impact. Moreover, as pointed out by Greenwood et al. (1997) and Fisher (2006), embodying RP and ICTI is important because we expect that a sectoral technology shock should decrease its relative prices and enhance expenditure in the underlying sector.[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 and TFP, which does not react on impact, rises after few quarters and remains significant and stable for at least 5 years.

Although our results are robust over different specifications, there is an important critique that our empirical strategy had to carefully take into account, which is the reverse causality due to news on future TFP. A well-taken concern motivated my the news-shock literature is that the positive reaction of ICTI on impact may be triggered to signals related future increases in TFP and not to contemporaneous ICT technological improvements. In other words, our identification strategy may confound a news shock which contemporaneously enhances investment in ICT capital goods. In order to take into account this potential issue, we provide a series of robustness checks where sequentially 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 any conclusion drown so far. In particular, we can now state even more strongly the causality relation from movements in current ICT technological changes to future TFP.

Motivated by papers in line with Oliner and Sichel (2000) and Stiroh (2002), in order to formally explain which mechanism links current ICT to future TFP, we analyze a 2-sector DSGE model which allows ICT to be the general purpose technology (hereafter GPT) of

completely different identification strategy and obtaining qualitatively different results.

[6]However, 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.

the whole economy. 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 well-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. 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. Since the purpose of ICT capital is to improve information sharing, the quality and speed of communication must mainly depend on the diffusion of these technologies among agents. As a simple example, owning a mobile phone enables to contact someone instantaneously if the person you want to reach is endowed with the same technology. As a result, the effectiveness of ICT capital is intrinsically related to its own diffusion. We rationalize this line of thought augmenting the production function of each sector with a spillover effect driven by the diffusion of ICT capital. Consistently with this literature and our empirical results, the accumulation of ICT capital is a slow process and the benefits of an ICT technology shock show up in the production functions of ICT-users with lags.[7]

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 suggesting that the assumptions made in the theoretical model are supported by our empirical results. We confirm that ICT is a general-purpose technology which enhance 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 2-sector DSGE model in Section 3. We estimate via impulse-response matching key parameters of the model and run a series of related experiment in Section 4. Concluding remarks, caveats and prospective future research are discussed in Section 5.

[7]Notice 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 Empirics

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

2.1 Main Specification

In this section we present our main specification where we impose minimal discipline on the identification strategy. It turns out that the set of results presented here are consistent with different robustness checks. Our first-step specification is the following 5-variable VAR

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

where TFP_t is the log-level of Fernald total factor productivity at time t, ICT_t is the log-level of real information and communication technology investment at time t,[8] 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 ratio between prices of ICT goods and services and the consumer price index (CPI).[9] All the variables have a quarterly frequency from 1989:Q1 to 2017:Q1 and refer to the U.S. economy. $B(L)$ is a (5×5) matrix of lag-operator functions of the same order. Following the Bayesian Information Criterion (BIC), the lag operator functions is one which implies that we regress variables at time t with their own lagged values at $t-1$.[10] Finally, i_t is a (6×1) vector of correlated innovations where $\Sigma = i_t' i_t$.

[8]Notice that $ICTI_t$ 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.

[9]Except 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. In any case our results are very similar when estimating a vector error correction model (VECM).

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

2.2 Empirical Strategy

Our simplest identification strategy implies that an ICT-investment technological shock (hereafter ICT shock) has no impact effect on TFP and maximal impact effect on ICT investment. We justify these assumptions with both empirical and theoretical argument. First of all, using data released on April, 2018 by the Bureau of Economic Analysis (BEA) the real value added of the information sector on real GDP is slightly below 5% for the underlying quarter. Thus, since the share of this sector accounts for a negligible part in the whole economy, we assume that an ICT shock is orthogonal to current TFP. In addition, in line with theoretical results firstly presented by Greenwood et al. (1997), 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 ICT investment.

Following a similar notation of Barsky and Sims (2011), we implement our identification strategy as follows. Let y_t be the (5×1) vector of observables of length T. Once can form the reduced form moving average representation:

$$y_t = \bar{B}(L)y_t + i_t \quad \Rightarrow \quad y_t = A(L)i_t$$

where $A(L) = [I - \bar{B}(L)]^{-1}$ and $\bar{B}(L)$ has no constant terms. Assume now there exists a linear combination that maps innovations i_t to structural shocks s_t:

$$s_t = A_0 i_t$$

This entails the structural moving average representation:

$$y_t = C(L)i_t$$

where $C(L) = A(L)A_0$ and $i_t = A_0^{-1}s_t$. 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 a all shocks is:

$$\Omega = \tilde{A}_0 D$$

and

$$\Omega_{i,j} = e_i'\tilde{A}_0 D e_j$$

where e_k is a selection column vector of the same dimension of $\tilde{A}_0$ with 1 in the kth element and zero elsewhere. In particular, notice that e_j is selecting a specific column of D, which will be denoted by γ_j. As a result, $\tilde{A}_0\gamma_j$ denotes the vector of impact responses of all the variable to shock j.

Let observe from System 1 that TFP_t is ordered first and ICT_t second. In order to implement our identification strategy, we need to mathematically solve the following problem:

$$\max_{\gamma_j} \Omega_{2,j} = e_2' \tilde{A}_0 \gamma_j \tag{2}$$

subject to

$$\Omega_{1,j} = e_1' \tilde{A}_0 \gamma_j = 0, \quad \text{and} \tag{3}$$

$$\gamma_j' \gamma_j = 1 \tag{4}$$

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 denoted in terms of choosing γ_j conditional on any orthogonalization, $\tilde{A}_0$. Objective function 2 imposes that an ICT shock as 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.

2.3 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 2000 bias-corrected bootstrap procedure of Kilian (1998). In particular, Figure 1 shows 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%, starts to increase and finally reaches its peak of almost 0.5% approximately at the same time of TFP. Similarly, real consumption has an impact effect of 0.2% with a delayed peak of 0.5%. Finally, in Figure 5, relative prices has a significant and negative impact response of 0.4% and remain persistently below their own steady state value for almost 9 years.

3 Model

4 Experiments

5 Conclusion

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A Main Set of Results

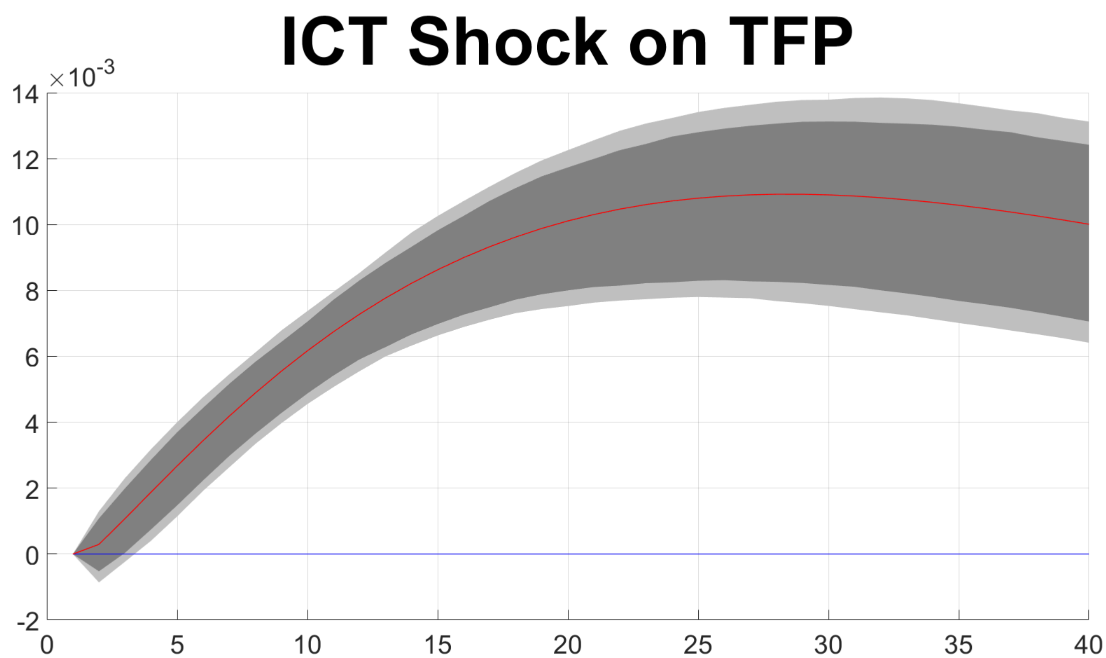

Figure 1: Empirical impulse response of TFP to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications of the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

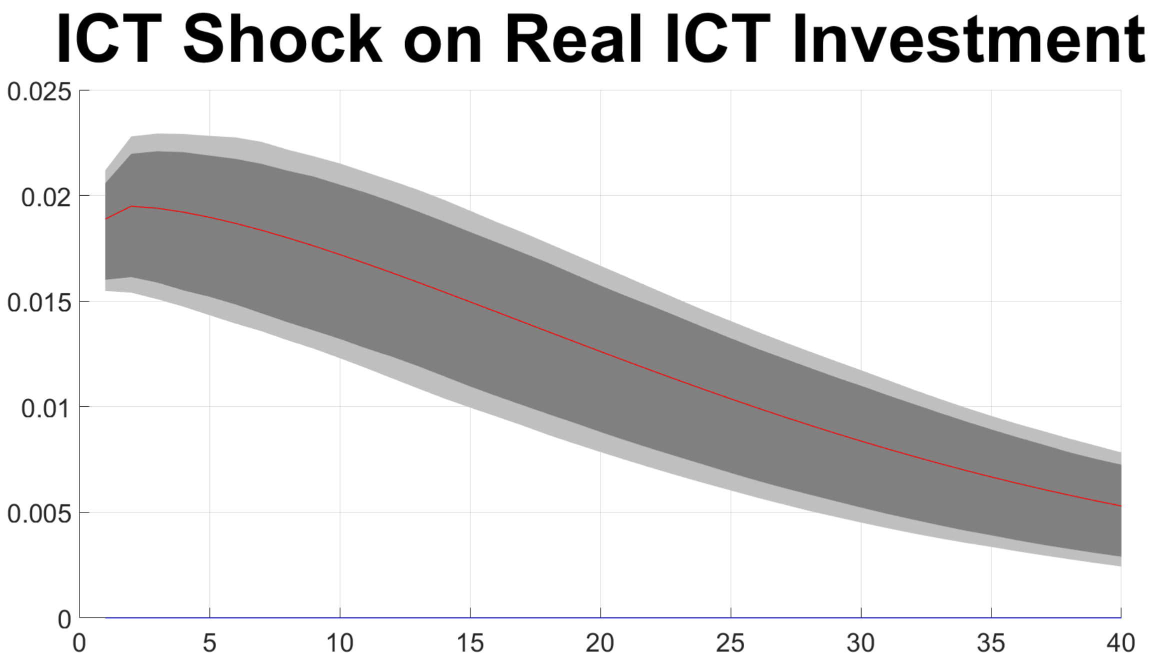

Figure 2: Empirical impulse response of real ICT investment to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications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

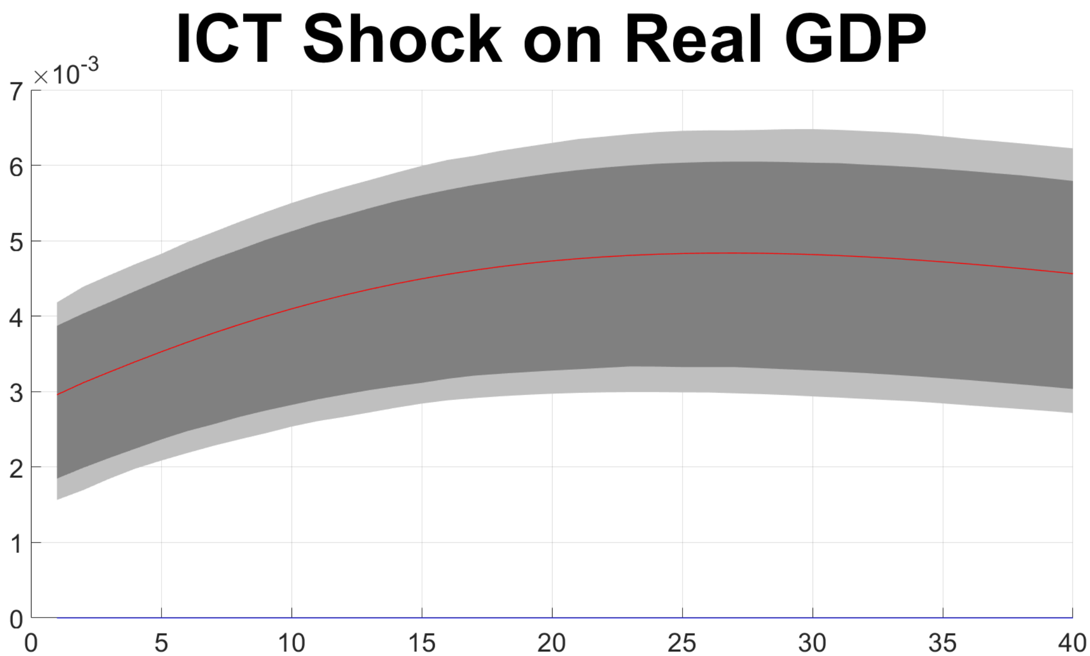

Figure 3: Empirical impulse response of real Gross Domestic Product to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap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

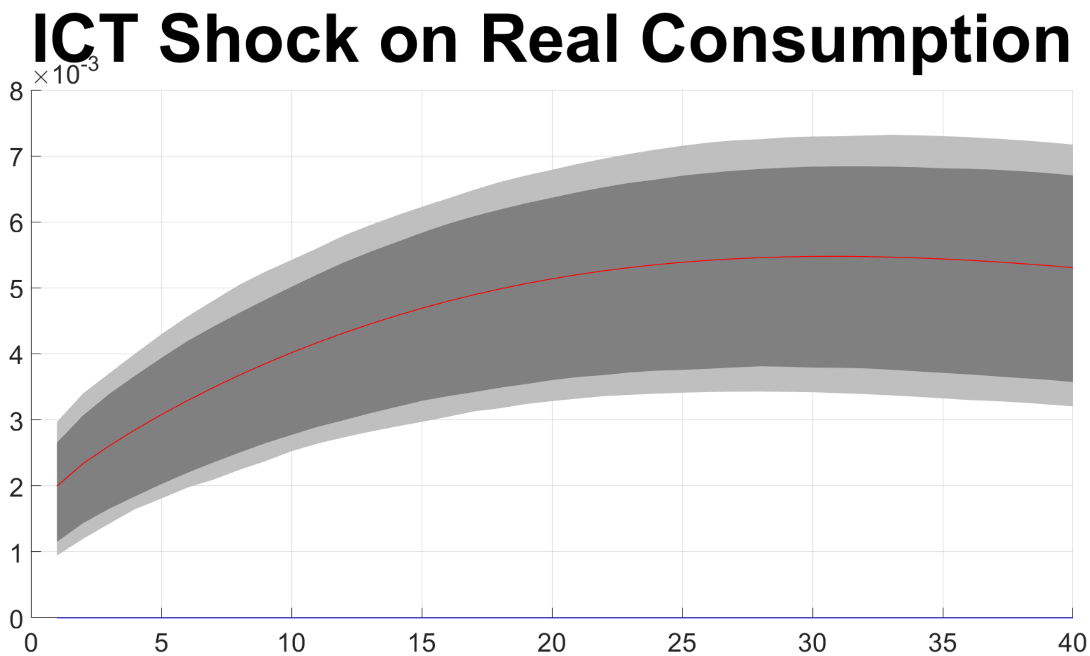

Figure 4: Empirical impulse response of real consumption to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications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

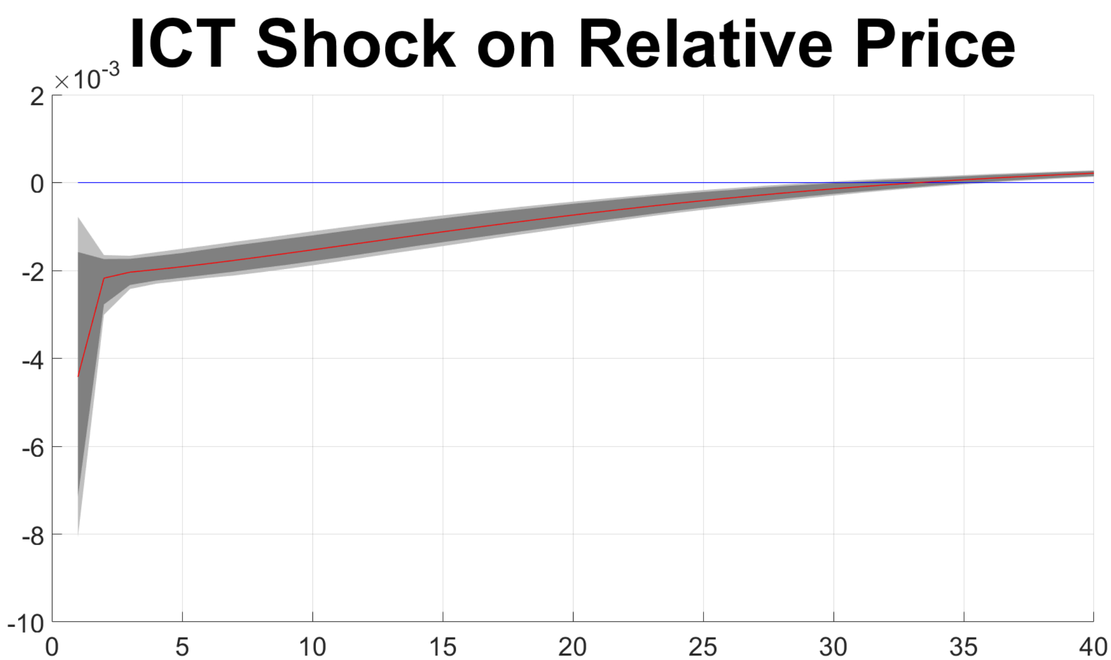

Figure 5: Empirical impulse response of relative price to an ICT shock. The red solid lines are the estimated impulse responses to our ICT shock. The shaded dark gray area and the shaded light gray area are the 90% and 95% confidence intervals, respectively, from 2000 bias-corrected bootstrap replications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