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The Impact of ICT Shocks on Business Cycle Some Evidence from Iran

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Abstract

In this paper, we investigate empirically the effect of Information and Communication Technologies (ICT) and monetary shocks as sources of business cycle in the economy of Iran. We follow of Gali's (1999) who proposes identifying technology shocks by a bivariate structural vector auto regression (SVAR) model consisting of labor productivity growth and working hours. We expand bivariate model into the four-variable model by using annual data covering the period of 1974 - 2008. Therefore, the non-technology shocks decomposed into labor supply and monetary shocks. The technology shocks also decomposed into two sector-neutral technologies and the investment-ICT shocks. Additionally, we also employed simulating variance decompositions (VDC) and impulse response functions (IRF) for further inferences. We've reached to this point that productivity-enhancing ICT shocks reduce working hours and increase Total Factor Productivity (TFP). Although productivity-enhancing technology shocks are an important source of economic growth in Iran, they may have a negative impact on employment.

Keywords: ICT Shocks, Monetary Shocks SVAR, Impulse Response, Variance Decomposition.

1- Introduction

Traditional Keynesian theory emphasizes the central role of demand-side factors such as monetary, fiscal, and investment shocks in macroeconomic fluctuations. In contrast, Real Business Cycle (RBC) theory puts technology shocks as the main drivers of business cycles. A major prediction of RBC theory is a high positive correlation between productivity and employment.

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The underlying idea is that a positive technology shock increases both productivity and demand for labor, which, in turn, increases employment. Unfortunately for RBC theorists, a well-known stylized fact from US data—no correlation and indeed often negative correlation between productivity and employment—has led many economists to question the relevance of their theory. A substantial literature has recently emerged to empirically examine the relationship between productivity and employment more rigorously.

The pioneering paper by Gali (1999) finds that productivity enhancing technology shocks reduced working hours in the US as well as all other G7 economies except Japan. The substantial body of research that confirms and supports Gali's milestone findings include Basu, Fernald, and Kimball (2006), Francis and Ramey (2005), Francis, Owyang, and Theodorou (2003), Gali (2004), Gali and Rabanal (2004), Shea (1999) and Kiley (1998). A number of studies have challenged the robustness of such evidence, primarily on methodological grounds. These include Christiano, Eichenbaum, and Vigfusson (2003), Uhlig (2004), Dedola and Neri (2004), Peersman and Straub (2004), Chang and Hong(2006), and Chang, Hornstein, and Sarte (2006). In any case, a negative effect of productivity enhancing technology shocks on employment cannot be reconciled with standard versions of RBC models and is more consistent with the sticky prices of Keynesian models. The basic idea is that price rigidity prevents demand from changing in the face of lower marginal costs due to productivity gains; consequently firms can produce the same output with less labor. The central objective of our paper is to empirically investigate the effect of ICT and monetary shocks on productivity and employment in Iran. Therefore, one contribution of our paper re-examines the relationship between productivity and employment with ICT shocks by using Iranian data. The vast majority of the existing empirical literature on the relationship between productivity and employment looks at data from the US and other developed countries. The limited number of studies on RBC in developing countries includes Sangho, kim and Hyunjoon,lim(2009),Mendoza and Smith (2006), Carmichael, Keita, and Samson (1999), and Chyi (1998).

However, neither set of studies looks at the technology employment relationship or seeks to otherwise test for RBC theory. That is, those studies look at issues other than how technology shocks affect productivity and

employment or, more generally, how such shocks drive the business cycle in Iran and other developing countries. The relationship between technology shocks and productivity, employment, and the business cycle in developing countries is not less important than developed countries. To the contrary, technological shocks may play a bigger role in developing countries, due to their relative technological backwardness and hence greater scope for technological progress. While the role of technology in long-term economic growth has long been recognized and studied, there has been very little research on the role of technological shocks on the business cycles of developing countries. We hope that our paper will help to shed some light on the sources of business cycles in developing countries and thus contribute to the limited empirical literature on the topic. Therefore, we empirically investigate the Effect of productivity-enhancing technology shocks on Iranian employment.

The contribution of this paper is using ICT shocks as a technology shocks, because the diffusion of ICTs increase output growth in the medium to long term via capital deepening effects and total factor productivity gains and in the short term via lagged adjustment of wages to productivity gains.

The term "New Economy" is used to capture, among other things, the effects which produce and use of ICT has on the economy. So far, most interesting attention has been focused on the role of ICT for trend growth in which the evidence, in spite of the recent economic downturn, the use of ICT services, such as mobile phones and the Internet.

To the trend growth, ICT use is also likely to affect the shape of cyclical fluctuations over possibly two phases; First, the cycle may be well affected in the transition path to the higher trend growth associated with increasing ICT use. Second, once the transition path is complete, the greater share of ICT in the economy may be affected the cycle by itself.

Moving to the effects on the business cycle of a greater role for ICT in the economy, several selected effects may be relevant. First, ICT uses entail a greater ability to control inventories which may further reduce the volatility arising from the stock cycle. Second, relating to aggregate investment flows, the higher depreciation rate and declining relative price of ICT goods *that it* tends to raise the gross investment rate, subsequently it increases the weight of ICT in GDP of a typically volatile component.

Finally, another characteristic of the ICT industry is the use of vertical supply linkages across national borders, emphasizing the increasing link between cycles in trade and domestic cycles. Although the development of vertical supply linkages is not limited to the ICT sector, the use of ICT often facilitates such developments in other industries.

The rest of our paper is organized as follows: the next section provides some background empirical information on effect shocks in the business cycles. Section 3 presents the *model, data, and estimation methodology*. Section 4 highlights the empirical findings and in the Section 5, we draw conclusions and policy implications from our main empirical findings.

2- Related to the Empirical Literature

A lot of studies have empirically examined the roles of technology shocks in the business cycles in order to evaluate the plausibility of the technology-driven real business cycle hypothesis. The main resrach work is done by Gali's (1999), who proposes identifying technology shocks by a bivariate SVAR model consisting of labor productivity growth and working hours. He developed the long-run restriction that only technology shocks permanently affect on the level of labor productivity. This idea is very attractive in the restriction seems theoretically robust and the method didn't use Solow's residuals, which may be affected by non technological factors such as unobservable factor utilization variations. By applying the SVAR to U.S. data, he shown that identified technology shocks can reduce working hours. This result has attracted much attention, since it is opposite to the prediction of the standard real business cycle model. In the subsequent work, Gal´ı (2005) shown that the result is basically common across the G-7 countries except for Japan.

Many researchers have investigated potential flows in his method. Broadly speaking, those are categorized into three classes: The first is a bias due to reducing the underlying economy to a finite ordered VAR model. This is emphasized by Chari, Kehoe, and Mc-Grattan (2004), although Erceg, Guerrieri, and Gust (2005) and Christiano, Eichenbaum, The SVAR with the long-run restriction is originally developed by Blanchard and Quah (1989) and Shapiro and Watson (1988) and Vigfusson (2006) show that the bias appears to be not so problematic or be methodologically reduced. The second is that results derived from the long-run restriction are extraordinarily

affected by the low frequency correlation between variables in the system, even if the correlation is not causal. This is examined by Fernald (2007) and Francis and Ramey (2008). The third is the possible misidentification of nontechnology shocks as technology shocks. Such misidentification can happen since certain types of nontechnology shocks permanently affect labor productivity via the level of capital-labor ratio. The shock examined often in the literature is a capital tax shock. This paper calls such shocks as the *nontechnology permanent shocks* and develops a method to identify those. The method is applied to the G-7 countries' data.

The literature finds that the nontechnology permanent shocks don't appear to be reflected in U.S. technology shocks identified by Gal´ı's method. Francis and Ramey (2005) included a series of capital tax rate as an exogenous variable in the system and confirm that Gal´ı's result is unchanged. Gal´ı and Rabanal (2004) find near-zero correlation between a capital tax rate series and an identified technology shocks series. They also find insignificant coefficients in an ordinary least squares regression of the tax series on current and lagged identified technology shocks. Fisher (2006) tests whether the series of Federal Funds rate, oil shock dates, log-changes in real military spending, and changes in capital tax rate. Granger-cause identified technology shocks and finds that no Granger-causality is not rejected except for oil shock dates.

Sangho,kim and Hyunjoon,lim(2009) has proposed Gali's method so as to deal with nontechnology permanent shocks, which affect labor productivity in the long-run together with technology shocks. Including real investment-output ratio in the SVAR system is a key to identify nontechnology permanent shocks. In addition, they've shown that studying nominal investment-output ratio is effective in diagnosing nontechnology permanent shocks. Applying their new SVAR system to G-7 countries' data shows that the role of nontechnology permanent shocks is important in Japan. Especially, their new system changes the response of working hours to technology improvement from positive to negative and makes clear that negative nontechnology shocks as well as negative technology shocks induce Japan's stagnation in the 1990s.

However these studies focus only on observable non technological factors. The factors that are unobservable or measured with difficulty, e.g., a depreciation rate, potentially affect labor productivity. Therefore this paper

proposes identifying the Information and Communication Technologies (ICT) and monetary Shocks with the following three long-run restrictions.

3- Data, Model, and Estimation Methodology:

In this section, we lay out our basic empirical framework. We explain why we choose total factor productivity (TFP) as our measure of productivity as well as how we construct our TFP data. We also describe how we plan to identify technology shocks by using bivariate structural vector auto regression (SVAR) model.

3-1-Data Construction

Many empirical studies of the employment–productivity relationship use labor productivity as the measure of productivity, but this partial measure fails to take into account factor substitution between capital and labor. This subject is very important at the economy of Korea, which has continuously experienced capital deepening and adoption of new production technologies. Labor productivity generally depends on capital deepening as well as technological progress and structural efficiency changes. In addition, it is often argued that in order to reach the economic growth is productivity growth.

In light of these facts, we use total factor productivity (TFP), which incorporates the effects of both structural and technological changes, as well as labor productivity as our productivity measures.

The data for labor productivity, which is defined as the ratio of gross domestic product (GDP) to total labor force. We constructed our TFP data from various sources in the Central Bank of Iran database and used the data to estimate Solow residuals for the period 1974 - 2008. The capital stock is the real amount of tangible fixed assets, adjusted for the capital utilization rate.

The annual data for all variables except ICT the period 1974-2008 obtained from the Central Bank of Iran. Total annual investment in telecom of Iran (ICT data) obtained from The World Telecommunication/ICT Indicators Database (2009). The variables of GDP in 1997 prices used as the criterion of output and currency (M2) have been used as monetary measures. ICT shocks as a technology shocks. The ratio employed population to total population proxy working hours per capita (H) and data for labor

productivity (APL) which is defined as the ratio of gross domestic product (GDP) to total employment. All variables are expressed in their logarithmic transformation; Δ denotes the first difference operator. To evaluate the integration properties of the variables, we employ standard augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (Dickey and Fuller, 1981; Phillips and Perron, 1988). A variable is said to be integrated of order d, written *I*(d) if it requires differencing d times to achieve stationary For co integration, we employ the VAR based tests of Johansen (1988) and Johansen and Juselius (1990).

As a preliminary step, we first subject each variable to Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root tests. Table 1 shows the results of the unit root tests. The results generally suggest that most variables are integrated of order one as the null hypothesis that the series are not stationary which is accepted at level but rejected at first difference. In other words, the variables are stationary at first difference or I(1).

Table 1: Unit Root Tests

	ADF test statistic (with trend and intercept)		**P-P test statistic (with trend and intercept)**	
Variable	**Level**	**First Difference**	**Level**	**First Difference**
lnGDP	1.49	-3.86***	-o.97	-3.92***
lnM2	0.46	-3.66***	-0.47	-3.64***
lnTFP	-2.53	-7.66**	-2.48	-7.68**
lnALP	-1.22	-5.7***	-2.11	-4.11***
LnH	-1.46	-7.49***	-1.39*	-7.4***
lnICTindex	-1.56	-4.93***	-1.82	-4.97***

Notes: ***, ** and * denote significance at 1%, 5%, and 10% level, respectively

The first VAR model developed consists of six endogenous variables: *z* [lnGDP, lnTFP lnALP,lnm2,lnH,lnICT index,]. For this model, the maximum lag length, *k*, of two is chosen. Based on *Maximum Eigen value* and *Trace* tests of co integration, there are two co integration vectors existed among the variables. Table 2 provides detail results of these co- integration tests.

Table 2: Johansen Co integration Tests Results

Null Hypothesis about Rank (r)	*Max-Eigen* Statistic	5% Critical Value	*Trace* Statistic	5% Critical Value
r=0	55.88	40.07	142.1	95.75
r≤1	34.55	33.87	86.22	69.81
r≤2	29.8	27.58	51.67	47.85
r≤3	13.15	21.13	21.83	29.79
r≤4	6.78	14.26	8.7	15.49
r≤5	1.91	3.84	1.91	3.84

Note: Test regression includes a constant and a linear deterministic trend in the data. The test indicates zero co- integrating equation at the 5% significance level for each set of the variables

3-2- Bivariate Structural Vector Auto Regression (SVAR) Model

In view of the absence of a co integrating relationship among the variables, we specify a bivariate structural vector autoregression (SVAR) model of TFP and working hours to identify technology shocks in the economy of Iran. While Shea (1999) used the number of patents and R&D expenditures as proxies for technology shocks, Gali (1999) used the long-run restriction that only technology shocks can affect productivity permanently in a structural VAR model. Although Shea's method may be able to solve some measurement problems, such as those associated with procyclical movements of productivity, it cannot replace Gali's identification method due to the low explanatory power of the proxies.

TFP growth (x_t) and total working hours growth (h_t) and ε_t^x technology shocks and ε_t^h non-technology shocks. Then, the k-lag VAR of TFP growth and working hours growth can be written as:

$$\phi(L) Z_t = \varepsilon_t$$

Where $\phi(L)$ is a kth-order matrix polynomial in the lag operator? The VAR can be rewritten in its moving average (MA) representation:

$$Z_t = C(L) \varepsilon_t$$

Where C (L) is an infinite polynomial matrix in the lag operator:

$$\phi(L) = C(L)^{-1}$$

We can rewrite:

$$\begin{bmatrix} \Delta x_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^h \end{bmatrix}$$

Each of the elements is a polynomial in the lag operator. Two disturbances of technology and non-technology shocks cause fluctuations in TFP and working hours, and are assumed to be orthogonal to each other. To identify the technology shock e_t^x , we impose the long-run restriction that the non-technology shock's long-run impact on productivity which is equal to zero. This implies that C12 (L) =0 and restricts the unit root in TFP to originate solely from technology shocks. C11 (L), C21 (L), and C22 (L) refer to the long-run impact of technology shock on productivity, long-run impact of technology shock on working hours and long-run impact of non-technology shock on working hours, respectively.

4. Empirical Results

We report and discuss the results of our estimation of the bivariate and four variable structural VAR model, and discuss the results.

4-1- Results of the Bivariate Structural VAR Model

In this sub-section, we report the results of our estimation of the bivariate model of productivity and working hours. We chose the lag length of four to minimize the Akaike Information Criterion (AIC), Schwarz Criterion (SC) or Bayesian Information Criterion (BIC).

However, changing the lag length does not affect on our results. We first define productivity as labor productivity, as in Gali (1999). Figure 1 shows the cumulative impulse response of labor productivity and working hours to technology and nontechnology shocks in the bivariate model. The responses are defined in terms of the natural logs of the levels rather than growth rates of the endogenous variables. The standard errors and confidence intervals are computed by bootstrapping 1,000 random draws. Labor productivity rose permanently to higher levels after initial adjustments in response to a one-standard deviation positive technology shock. The response of working hours to technology shock was negative but insignificant. Our finding of negative but insignificant effect of productivity-enhancing technology shocks on working hours is qualitatifely very similar to Gali (1999). As noted earlier, such evidence casts doubt on the validity of RBC theory and is more consistent with price rigidity which is a central assumption of

Keynesian models. Sticky prices prevent demand from adjusting in the face of lower marginal costs and thus encourage firms to produce the same amount of output with less labor.

Figure 2 shows the impulse response of the bivariate model after we replaced labor productivity with TFP as our measure of productivity. The confidence interval is computed by bootstrapping 1,000 random draws. The most striking feature of Figure 2 is that the response of working hours to technology shocks is negative. This evidence is more supportive of Keynesian-type sticky price model than RBC models. In fact, working hours did not show a positive and significant response to a positive technology shock until the second year. The effect of positive non-technology shock on TFP was statistically insignificant, even in the short run. This result is consistent with the assumption that TFP is statistically orthogonal with non-technology shocks such as demand shocks, even in the short run. All other results, including the permanent increase in TFP to higher levels, are qualitatively similar to the results which we obtained using labor productivity instead.

The estimated Solow residual may be an imperfect measure of total factor productivity in the presence of cyclical effects. To eliminate the cyclical effects, we adjusted the Solow residual by using a composite index of business cycles and demand-related instrumental variables. Figure 3 shows the impulse responses of the bivariate model when we used the adjusted TFP as our measure of productivity. They are generally similar to the responses we obtained earlier when we used the unadjusted TFP as our productivity measure. In particular, as it was the case for Figures 1 and 2, the initial response of working hours to technology shocks is negative rather than positive. We found that technology shocks have a negative impact on working hours is more supportive of sticky price models than RBC models. Working hours began to show a positive and significant response to positive technology shocks only in the second year (Table 2).

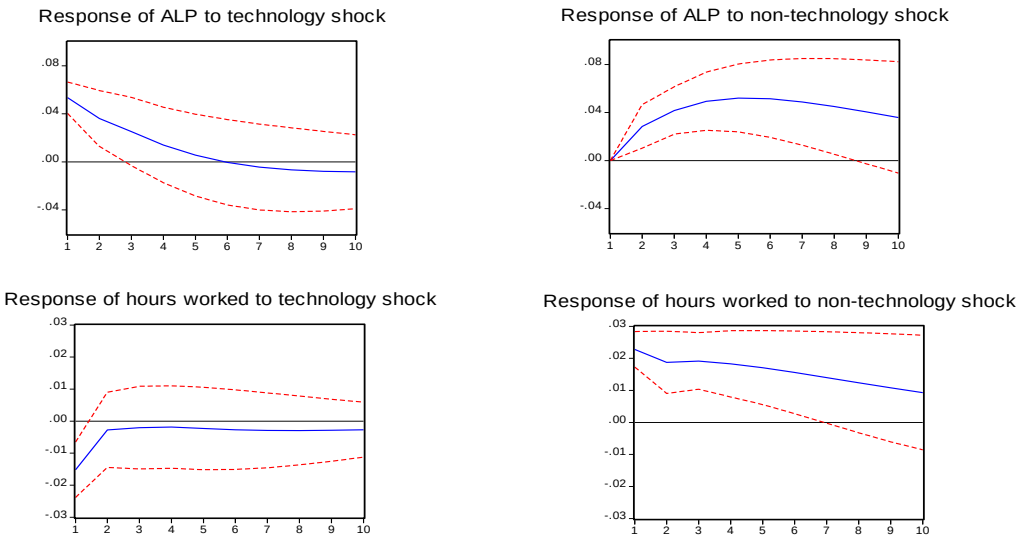

Figure 1: Impulse Response Functions: Bivariate Structural Vector Auto Regression (SVAR) Model

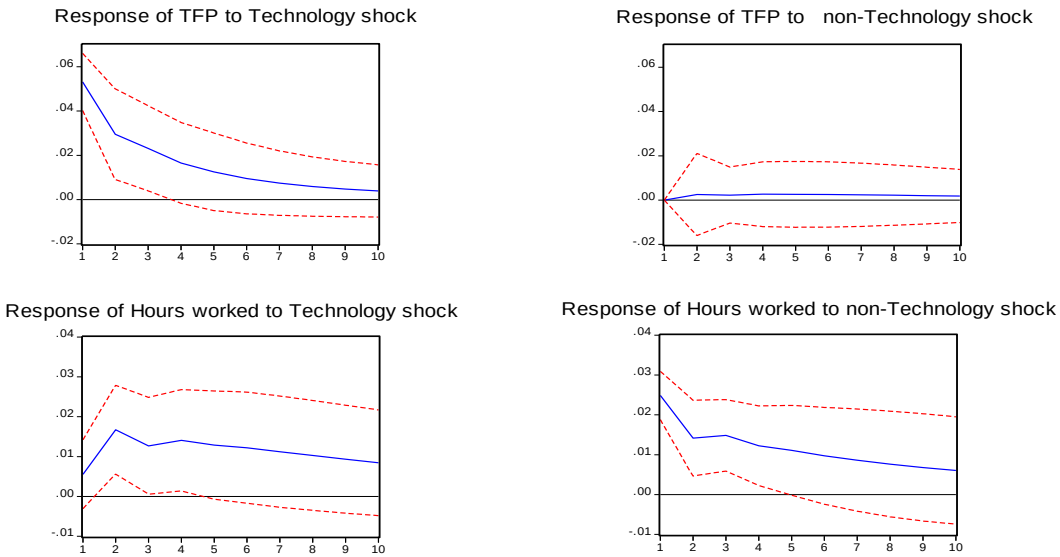

Figure 2: Impulse Response Functions

4-2- Four-Variable Structural VAR Model and its Results

So far we have used the bivariate structural VAR model of productivity and working hours to investigate the impact of technology shock on employment in Iran. Our estimation results indicate that positive technology shocks have a negative short run impact on employment and they are more consistent with sticky-price Keynesian models than RBC theory. The bivariate model lumped together all shocks other than technology shocks as non-technology shocks. These include demand shocks such as monetary policy, and labor supply shocks. Since it is unlikely that any of these diverse shocks affect productivity in the long run, the long-run restriction we used in our model remains appropriate.

Nevertheless, decomposing non-technology shocks may be helpful for a more in-depth analysis. For example, dividing non-technology shocks into labor supply shocks and monetary shocks allows us to analyze their effects on employment, output, and money. Monetary shocks generally reflect demand shocks. On the other hand, Gal´ı's system identifies technology shocks as a linear combination of shocks to the sector-neutral technology and the investment-ICT technology, since he doesn't explicitly deal with the latter technology. We now expand our bivariate model into the following four-variable model:

$$\begin{bmatrix} \Delta m_t \\ \Delta ICT_t \\ \Delta x_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^m \\ \varepsilon_t^{ICT} \\ \varepsilon_t^x \\ \varepsilon_t^h \end{bmatrix}$$

where Δm_t , ΔICT_t, Δx_t and Δh_t denote money growth, investment-ICT growth ,adjusted TFP growth and working hours growth, respectively two non-technology shocks: ε_t^h labor supply shock and ε_t^m monetary shocks and two technology shocks: ε_t^x sector-neutral technology shock alone and ε_t^{ICT} ratio total ICT investment to total investment respectively. Cij(L) represents the long-run multipliers of the shocks on the endogenous variables.

We follow Blanchard and Quah (1989) in assuming that there are two types of disturbances—demand disturbances which have no long-run effect on output and supply disturbances which may have a long-run effect on output. Due to nominal rigidities, demand disturbances have effects on output in the short run but those effects fade in the long run. Only supply disturbances affect on output in the long run. The Blanchard and Quah assumptions imply two long-run restrictions for our purposes. First, they allow us to retain our earlier restriction that only technology shock can affect productivity in the long run.

Note that the investment-ICT technology shock, which is another determinant of the steady state level of factor intensity, can still be identified with Fisher's method. Therefore we can identify the ICT investment technology shock, the nontechnology permanent shock, and the sector-neutral technology shock by imposing the following three restrictions:

Restriction1: The money m_t moves only with the monetary shock ε_t^m in the long-run.

Restriction2: The real ratio total ICT investment to total investment moves only with the ICT-investment technology shock ε_t^{ICT} and the nontechnology permanent shock ε_t^m in the long-run.

Restriction3: The labor productivity *h* moves only with the investment ICT shock ε_t^{ICT} the nontechnology permanent shock ε_t^m and the sector-neutral technology shock ε_t^x in the long-run.

The four-variable system, in which those restrictions can work, is represented as:

$$\begin{bmatrix} \Delta m_t \\ \Delta ICT_t \\ \Delta x_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} C_{11} & 0 & 0 & 0 \\ C_{21} & C_{22} & 0 & 0 \\ C_{31} & C_{32} & C_{33} & 0 \\ C_{41} & C_{42} & C_{43} & C_{44} \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^m \\ \varepsilon_t^{ICT} \\ \varepsilon_t^x \\ \varepsilon_t^h \end{bmatrix}$$

Figure 3 shows the impulse responses in the four-variable structural VAR model. In Figures 1, 2, and 3, working hours slightly fell at first in response to a positive technology shock. Such negative short-run response is more supportive of Keynesian-type sticky price models than RBC models. However, working hours then started to rise within a year. In response to a positive labor supply shock, working hours rose at first, and then it fell before reaching its new equilibrium after two year. In response to a positive demand or price shock, which was assumed to have no long-run effect on working hours and productivity, working hours rose slightly at first but returned to its initial level after two years. The GDP deflator increased rapidly for four year in response to a positive demand shock and kept increasing modestly thereafter.

Table 3: The Long Run Effect ICT and Monetary Shocks

	C_{11}	C_{21}	C_{22}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}	C_{44}
Values	0.09-	-0.22	-0.32	-3.65	5.41	1.09	-10.7	-16.37	2.34	3.37
p-value	0/0000	0/0005	0/0007	0/0003	0/0000	0/0000	0/000	0/0000	0/0000	0/0000

Table 3 shows that one s.d innovation monetary shocks in the long run0.09, 0.22, 3.65 and 10.7 percent decrease M2, ICT, TFP and Working hours. Also one s.d innovation ICT shocks in the long run 5.41 percent Increase TFP and 16.37 percent decrease working hours.

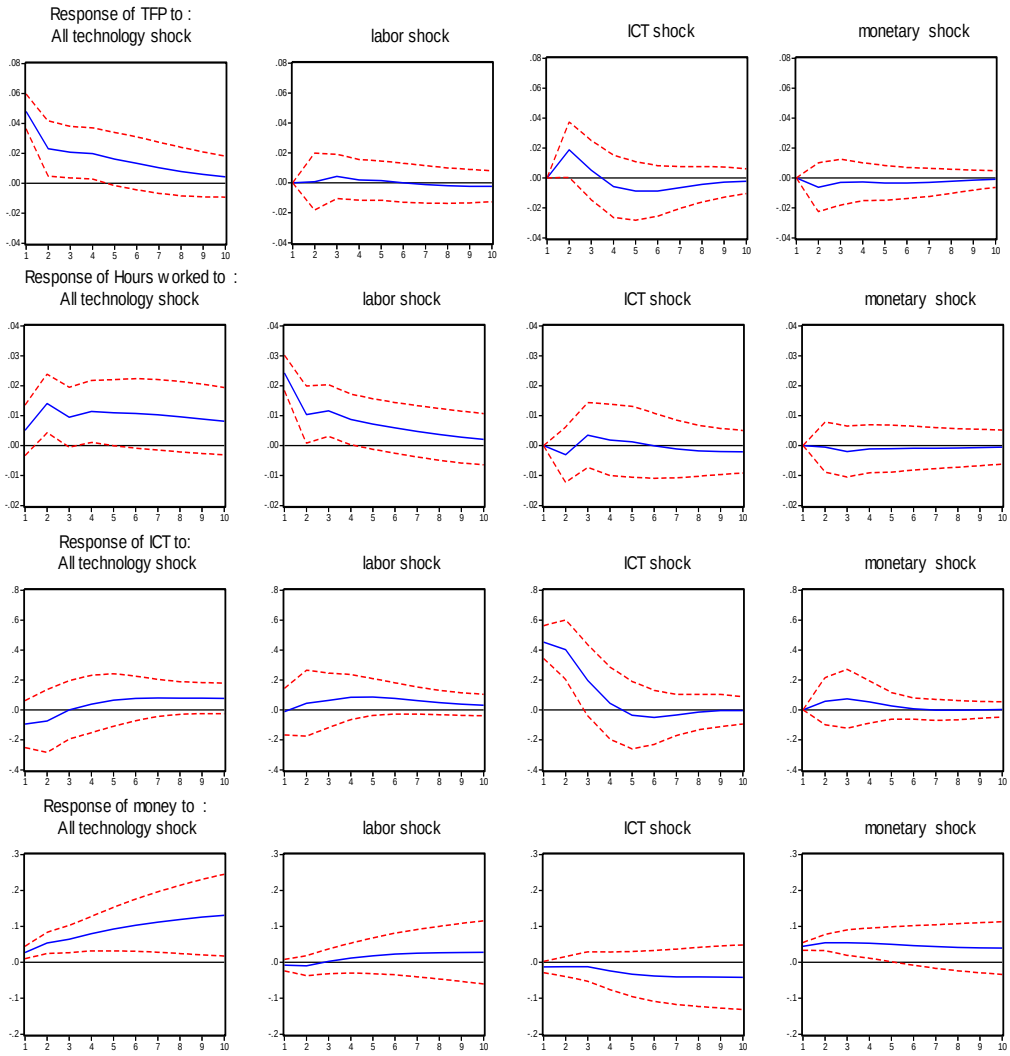

Figure 3: Impulse Response Functions (Four-variable structural VAR model)

The message of variance decompositions is similar. Table 4 and 5 show the contributions of technology shocks and nontechnology shocks to the variances of the forecast errors of TFP, hours, at different horizons. Those differ little across systems, regardless of variables and horizons. For example, at ten year horizon, the portions of variances for which ICT shocks account range 4 to 5 percent and 25 percent, for TFP, hours, respectively. The ranges are similar or narrower at other horizons. This finding means that

adding nontechnology permanent shocks doesn't change the roles of technology shocks and just reduces the role of nontechnology temporary shocks.

Table 4: Variance Decompositions of TFP

Period	S.E.	All technology Shock	ICT Shock	Labor Shock	Monetary Shock
1	0.047	3.498	0.006	84.616	11.878
2	0.056	4.627	1.253	71.317	22.801
3	0.060	4.067	1.124	69.966	24.841
4	0.064	4.288	1.898	71.094	22.718
5	0.067	4.531	3.196	71.299	20.973
6	0.069	4.594	4.135	71.435	19.835
7	0.070	4.534	4.541	71.693	19.230
8	0.070	4.468	4.642	71.968	18.920
9	0.071	4.424	4.639	72.170	18.764
10	0.071	4.398	4.620	72.288	18.693

Table 5: Variance Decompositions of Hours work

Period	S.E.	All technology Shock	ICT Shock	Labor Shock	Monetary Shock
1	0.024	22.56	2.109	24.306	51.024
2	0.030	22.191	11.990	21.951	43.866
3	0.034	18.920	11.185	19.699	50.193
4	0.037	17.426	13.390	17.914	51.268
5	0.039	16.453	15.558	16.755	51.232
6	0.041	15.935	17.908	16.066	50.089
7	0.042	15.637	20.218	15.657	48.486
8	0.044	15.437	22.308	15.386	46.867
9	0.045	15.285	24.134	15.163	45.416
10	0.046	15.167	25.688	14.954	44.189

4- Concluding Remarks

According to real business cycle (RBC) theory, the business cycle is driven largely by technology shocks rather than the traditional Keynesian demand shocks associated with macroeconomic policy or business confidence. A major empirically testable prediction of RBC theory is a positive relationship between productivity and employment. Empirical literature initiated by Gali (1999) finds that productivity-enhancing technology shocks reduced employment in the US and other developed countries. Although a number of studies challenge the robustness of this literature, the balance of evidence seems more supportive of a negative relationship than a positive relationship. This has cast serious doubt on the empirical validity of RBC theory among many economists.

In this paper, we re-examined the relationship between productivity-enhancing technology shocks and employment using annual Iranian data. More specifically, we used a bivariate structural VAR model of productivity and working hours with two types of shocks—technology and non-technology—along with the long-run restriction that non-technology shocks cannot permanently affect productivity. Our empirical results show a negative but an insignificant effect of positive technology shocks on working hours when we used labor productivity as the measure of productivity. Furthermore, when we even replaced labor productivity with total factor productivity (TFP) as our productivity measure, we found that technology shocks had a negative effect on working hours on impact in the short run. This finding lends more support to Keynesian- type sticky price model than to the presence of a real business cycle. We were able to replicate this finding- that is the absence of a positive effect on working hours in the very short run- when we adjusted our measure of total factor productivity, the Solow residual, to control for cyclical effects.

On the other hand, we find a positive effect of technology shocks on working hours in the medium and long runs, and it is possible to interpret this is as evidence of RBC models. However, in the medium and long horizons, the response of working hours to technology shocks cannot meaningfully distinguish between the RBC and sticky price models. The underlying reason is that prices are more flexible and thus adjust beyond the short run. In particular, if prices are set one period in advance, prices may fall after the second period in response to a positive shock. As a result,

working hours may increase rather than decrease because of an increase in real balances. Therefore, a positive impact of technology shocks on working hours in the medium and long run is consistent with sticky price model. Then we added two variables; the overall money level and ICT investment, to expand our bivariate model to a four-variable model. We divide non-technology shocks into labor supply shocks and demand or monetary shocks, and divided technology shocks into sector-neutral technology shock alone and ratio total ICT investment to total investment respectively. Our empirical results re-confirm a negative effect of productivity-enhancing technology shocks on working hours on impact. However, the effect turned positive and significant beyond the short run. The response of money to technology shocks was insignificant in the short run. All in all, in the case of Iran, our findings fail to provide convincing support for RBC models and are, if anything, more consistent with sticky price models in light of the negative response of working hours in the very short run.

Our results for Iran are thus qualitatively similar to those from the results of earlier studies for developed countries, in particular Gali (1999). According to our evidence, although technological progress has been an important source of long run growth in Iran, its impact on working hours has been negative in the short run. Given that much of advanced foreign technology came into Iran in the form of imported capital goods, there may have been substitution between capital and labor over time. Such interpretation is consistent with the fact that the Iranian economy has evolved from a labor intensive production structure to a capital- and technology intensive production structure. The implication for other developing countries is that while technological progress promotes economic growth it is unlikely to contribute to employment growth in the short run. But differently, our evidence indicates that the risk of jobless growth driven by technology shocks is relevant not only for developed countries but developing countries as well. While the procedure of job creation is a pressing socioeconomic concern in developing countries, our finding implies that policymakers should take measures to minimize potential short-run job losses arising from technology shocks.

A significant contribution of our study in literature is to use data from a developing country to look at the relationship between productivity-enhancing technology shocks and employment. Majority of the literature on

these issues is based on data from the US and other developed countries and the empirical literature that uses data from the developing countries is very limited. However, the impact of technology shocks on employment is just as relevant for developing countries, if not more so, in light of the fact that technological progress is widely viewed as a key ingredient of long run economic growth. The evidence from Iran suggests that while technology shocks contribute to higher productivity in the short run, they may reduce employment in the long run. Such evidence is consistent with the majority of empirical studies on the technology-employment relationship in developed countries.

We hope that our analysis will also contribute meaningfully to the very limited literature on the broader issue of the empirical validity of RBC theory in developing countries and inspire researchers to pursue the same topic with data from other developing countries in the future. At a broader level, such studies will help developing-country policymakers better understand the forces behind the business cycles of their respective countries and thus provide useful policy guidance.

In wake of the current global financial and economic crisis, understanding the sources of macroeconomic fluctuations has become more significant for developing countries. For example, in the case of Iran, our evidence implies that policymakers should pay greater attention to the role of price rigidity as a source of business cycles. In any case, future studies on the impact of productivity-enhancing technology shocks on employment in other developing countries will shed more light on the role of technology shocks on macroeconomic volatility. While technological progress is recognized as an important source of long-run growth in those countries, its impact on short run fluctuations has largely been neglected up to now.

The important future research can be study on what is behind the nontechnology permanent shocks. Our consideration points to the importance of a kind of the news shock, specifically on revising the expectation of future productivity. It’s desirable to identify such shock directly.

Notes

1. Examples of standard RBC models include those in Arias, Hansen, and Onanian (2007) and Guvenen (2006). However, Campbell (1994) shows that the effect of technology shocks on working hours depends on the specific nature of the technological process, and may even have a negative effect.
2. Chang and Hong (2006) and Chang, Hornstein and Sarte (2004) used TFP to investigate the dynamic relationship between technology shocks and employment in US manufacturing sector.
3. See, for example, La Croix (2007), Jorgenson (1995) and Dollar (1991).
4. To minimize the misspecification error, Peersman and Straub (2004) used sign restrictions, first suggested by Faust (1998), to identify structural shocks in VAR.
5. Some studies, including McGrattan (2004) and Holzl and Reinstaller (2004) interpreted the two shocks in the structural VAR as technology shocks and demand shocks. However, many supply shocks other than technology shocks, such as shocks arising from fluctuations in production costs or labor supply, have no long-run impact on productivity. Therefore, it seems more appropriate to classify shocks as technology shocks and nontechnology shocks rather than technology shocks and demand shocks.
6. Technology shocks can have a permanent effect on productivity because the level of the TFP is an unstable time series with a unit root.
7. To check for the robustness of our structural VAR results, we also used impulse responses from the standard VAR with Cholesky factorization to construct the innovations. The estimation results are very similar to those from our structural VAR models.
8. To check for the robustness of our structural VAR results, we also used impulse responses from the standard VAR with Cholesky factorization to construct the innovations. The estimation results are very similar to those from our structural VAR models.

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