HOW MUCH CAN NEWS SHOCKS ACCOUNT FOR AGGREGATE FLUCTUATIONS?

by

Ruomei zhang

A thesis submitted to the faculty of

University of Edinburgh

in partial fulfilment of the requirements for the degree of

MPhil of Economics

Department of Economics

University of Edinburgh

April 2010

ABSTRACT

Recent studies have highlighted the importance of news shocks in the literature on business cycles, that is, a-priori information that agents receive about future developments in the economy. To examine whether the news shocks can be a major source of aggregate fluctuations, in the first chapter I quantify the relative importance of the news shocks to total factor productivity (*TFP*) and surprised technology changes by employing two methods. The first method is the Beaudry and Portier's identification schemes (2006) and the second method is a two-step approach I develop in this study. Empirical results on the US quarterly data show that the news shocks play an important role in generating the business cycles, while the surprised technology changes is not a potential source of macro-economic fluctuations. In addition, the two-step approach seems to be able to solve the identification problem raised in the high dimensional systems in SVAR analysis. In the second chapter, I extend the empirical study of the news shocks to the European countries to test for the generality of the issues about the news shocks raised in the US literature. The empirical results are supportive for the hypothesis of news driven business cycles.

Contents

Part 1 the First Chapter

1. Introduction

What causes business cycles? This is one of the most difficult questions in macroeconomic theory. There are many candidates for this question, such as oil price shock, fiscal or monetary shocks. When the real business cycle model has been introduced in 1980s, the idea that shock to technology is the main driving force of business cycles initiated much controversy. Until now the researchers have still not reached a consensus on this issue. A large amount of literature by using new Keynesian models tries to propose that the non-technology and monetary shocks are the central element of business cycle fluctuations. In addition, there are some recent studies that tend to highlight the importance of information or expectations about fundamental developments in fluctuations. Cochrane (1994) proposes that "news shocks" may be important for business cycle fluctuations. Assume that agents receive new information today about development of new technology tomorrow; does this news cause an expansion today? Or if the impact of this new technology is smaller than expected before, does this lead a recession? This intuition about news shocks seems to be sensible to explain the ups and downs of economic activities. And Beaudry and Portier (2006) provide us with more formal evidence, which they propose a framework of bivariate vector autoregression that includes total factor productivity (*TFP*) and stock prices by imposing different identifications to find out the news shock about future technological developments are the important driving force in the macroeconomic fluctuations.

In this chapter, I aim to explore the relative importance of two shocks in the business cycle fluctuations, which are the news shock to *TFP* and surprised technology changes. As a starting point, I employ the simple stochastic neoclassical model with invisible labor to study some implications of unexpected and anticipated technological changes for the predictions of this model. The simulation results suggest that this model fail to recover the effect of anticipated technology innovation, it cannot cause comovement of consumption with output and capital stock. Then I turn to using the real data series (US postwar data) to investigate the role of these two shocks from the theoretical model, which are the news related to the technology in the economy and surprised technology shock. For this purpose, I follow the empirical strategy by Beaudry and Portier (2004a) to identify these two shocks and employ a structural vector autoregressive approach (SVAR) to do the analysis.

The BP's empirical work is replicated and the estimation results successfully reproduce the pattern as reported in BP's literature. The stock prices shock are orthogonal to the current TFP growth, but are highly correlated to the future changes of TFP. This analysis indicates that the news shocks about future development in the technology may be central to the business cycle fluctuations. In contrast, the estimation of surprised technology shock by using BP's approach causes the robustness problem between the bivariate system and higher dimensional VARs. This implies that the BP's identification scheme is not appropriate for identifying the temporary shock to technology. Then we employ a new two-step method to try to solve this problem and reexamine the transitory shock. The idea of this approach is: abstracting the residuals obtained from the bivariate VAR in the first step, these two innovations are treated as the exogenous regressors to another VAR including macro variables we are interested, and then examining this new VAR model to get the impulse response to the surprised technological changes in the second step. The results by using two methods both show that it plays a minor role in the business cycle fluctuations. In order to check the validity of this two-step approach, we also use it to investigate the role of permanent shock to *TFP* and the result is very plausible comparing with the impulse responses of permanent shocks in the BP's analysis.

The main findings in this study are: first, our empirical results are supportive for the news driven business cycles hypothesis. The news shock plays an important role in generating the macro fluctuations, while the surprised technology shock is not the significant potential resource of the fluctuations. Second, we introduce a two-step approach, and it can solve the identification problem in the higher dimensional system of SVAR analysis, and it can also provide an alternative to do the estimation of the permanent shocks to *TFP* by using the BP's approach.

The remainder of this chapter is organized as follows. Section 2 reviews the theoretical and empirical literature about the study of the news shocks. Section 3 investigates the performance of different kinds of technological shocks in the basic one-sector, neoclassical model. In the section 4 and 5, I analyze two types of shocks separately in each section by using real data series. And section 6 concludes.

2. Literature Review

Real business cycle theory single out the technology shocks as a central role in business cycle fluctuations. Prescott (1986) finds that they "account for more than half the fluctuations in the postwar period with a best point estimate near 75%". And King and Rebelo (1999) argue that the patterns displayed by simulated economy are similar to those exhibited by actual business cycles, when the persistent technology shocks are fed through a standard RBC model. But this idea is controversial and the debate on the role of technology shocks in fluctuations has existed for more than two decades. An influential paper by Gali (1999) sparked this debate, which he identifies the technology shocks as the only source of long-run changes for labor productivity and finds that labor input fall in response to the positive technology shock in the short run period. His result clearly contradicts the implications of basic RBC models. However, Beaudry and Portier (2004a) propose that the shocks to anticipated future changes in technology, namely the 'news shocks', can generate the business cycle fluctuations. This possibility is interesting as it brings to an alternative source of business cycles.

The news matter was recognized already by early economists. There is an old literature by Arthur Pigou (1926) that proposes the effect and quantitative significance of news about the future or changes in agents' expectations. But in the traditional business cycle theory, it didn't explicitly model expectations. They allow for expectations that were rational but still not are related to fundamental developments in the economy. There is a revival of interest in this idea motivated partly because of the investment boom of late 1990s and its subsequent economic slowdown.

Recently, there is a fast growing literature regarding the news-driven business cycle theory. Beaudry and Portier (2004b) propose the first model that produces an expansion with respect to the news of high future *TFP*. Their model requires strong complementarity between durables and non-durables consumption, and abstracts from capital as an input into the production of investment goods. Then Christiano, Motto and Rostango (2007) show that the habit persistence and investment adjustment costs generate comovement in consumption, employment and investment against the news about a future TFP shock. In their model, intertemporal substitution in the labor supply is sufficiently large to compensate the negative wealth effect on labor of the news shock. DenHann and Kaltenbrunner (2008) study the effects of news in a matching model. Jaimovich and Rebelo (2009) incorporate variable capital utilization, adjustment costs to investment, and preferences that exhibit a weak short-run wealth effect on the labor supply, so that their model can produce an economic boom with respect to the news about future total factor productivity or investment-specific technical change. Schmitt-Grohe and Uribe (2008) build a framework on the real-business-cycle model augmented with four real rigidities, which are investment adjustment costs, variable capacity utilization, habit formation in leisure and habit formation in consumption, and explore the role of both anticipated and unexpected component in the four structural shocks such as stationary or non-stationary neutral productivity shocks, non-stationary investment-specific (*IS*) productivity shocks and government spending shocks.

The idea of a prominent role for the news shock in macroeconomic fluctuations in the theoretical model has recently given rise to quite a few papers that we review above. It is therefore very interesting to investigate whether the empirical finding is in favor of news-driven business cycles theory. Is it a robust business cycle fact that can be documented for countries and samples? Beaudry and Portier (2004a, 2005) take the lead by using the structural vector autoregressive model (SVAR) approach to do their analysis with postwar US and Japanese data and came up with essentially the same finding between these two countries.

Since volatility of stock prices provides the important information for the future process of the economy, so they take an index of stock prices (*SP*) as signals about long-run trends in *TFP* and use a primary system that contains measured total factor productivity (*TFP*) and stock prices for estimation with the US data. In their studies, they develop a new empirical strategy that "performs two different orthogonalization schemes as a means of identifying properties of the data that can then be used to evaluate theories of business cycle". The two disturbances are identified in this system: one represents the stock prices innovations that are contemporaneously orthogonal to innovations in *TFP*; and the second drives long run movements in *TFP*. The empirical results show that the correlation between these two shocks is positive and almost equal to 1, that is, "the permanent changes in productivity growth are preceded by stock market booms". Then they extend their research by using aggregate Japanese data and US sectoral data. Their previous results are confirmed by the analysis of Japanese data. According to estimating the relationship between the innovations of US aggregate stock prices and sectoral manufacturing *TFP*, they find that the stock prices innovations do not have the contemporaneous effect on the US sectoral *TFP*, but such sectors as durable goods and equipment sectors drive US *TFP* growth in the long run. And Haertel and Lucke (2006) look at Germany as a third country and present a similar, but slightly weaker piece of evidence: there is a high correlation between a shock with permanent effects on *TFP* in the long run and a shock which has an immediate effect on stock prices (under a different identification scheme), but does not affect *TFP* on impact. More recently, Beaudry and Lucke (2008) employ the structural vector error correction model to identify five shocks that are popular candidate explanations for macro fluctuations (unanticipated *TFP*, news shocks to *TFP*, unanticipated *IS* (investment-specific), preference and monetary shocks). The results indicate that the news shocks to *TFP* is the most important contributes more to the macro volatility at business cycle horizons, and the surprised changes in technology account for very little of business cycle fluctuations.

Besides identification of news shocks by using the SVAR approach, Bayesian DSGE method has recently been employed by some researchers for investigating various empirical issues related to news shocks. Davis (2007) chooses the variable of interest rate to identify the news shocks in a structural term model, Fujiwara et al.(2008) introduce the anticipated and unanticipated shock components in *TFP* in the dynamic stochastic general equilibrium (DSGE) model and estimate their contribution to the business cycle fluctuations by Bayesian method for the US and Japanese economies. Schmitt-Grohe and Uribe (2008) formulate four structural shocks in their theoretical model, and assume that each of shocks features an anticipated component and an unanticipated component. According to their Bayesian estimates, the anticipated shock is the important source of aggregate fluctuations. Khan and Tsoukalas (2009) undertake a quantitative investigation on the role of news shock to *TFP* and *IS* (investment-specific) technology in generating business fluctuations. They build on the work of Beaudry and Lucke (2008) but using estimated DSGE models instead. And they find that the empirical results change sharply in different price-wage environments in order to make clear the reason why recent work on the news shocks obtains different conclusions about their quantitative importance by using estimated DSGE models.

3. The Simple Model

Real business cycle models investigate the role of technology shock in the economic growth and fluctuations. By using a simple neoclassical growth model of indivisible labor, we will explore some implications of unexpected and anticipated technological changes for the predictions of this basic model. The unanticipated technological innovations are assumed to affect contemporaneously on the production process. And the anticipation means that the technology shocks are expected some periods prior to their effect on the productivities.

This simple neoclassical growth model is expressed as follows:

$$\max_{C_t, I_t, L_t, K_{t+1}} \quad E_0 \sum_{t=0}^{\infty} \beta^t \left[\log C_t - \frac{L_t^{1+\chi}}{1+\chi} \right] \tag{3.1}$$

$$s.t. \begin{cases} Y_t \leq A_t K_t^{\gamma} L_t^{1-\gamma} \\ K_{t+1} \leq I_t + (1-\delta) K_t \\ C_t + I_t \leq Y_t \end{cases}$$

where C_t is consumption, $1-L_t$ is leisure time(i.e. L_t is labor supply) with total per-period time endowment normalized to 1, K_t is the predetermined capital stock (chosen at t-1), and A_t is a technology shock in period *t*. 0 <β< 1 is discount factor, χ ($\chi \geq 0$) is the inverse of the labor supply elasticity, 0< γ <1 ("capital share"), and δ (0< δ <1) is the rate of depreciation of capital. Naturally, there are the non-negativity constraints $C_t \geq 0$, $L_t \geq 0$ and $K_t \geq 0$.

To solve this model, we have the following first-order necessary conditions (FOCNs):

$$\frac{1}{C_t} = \beta E_t \left[\frac{1}{C_{t+1}} \left(1 - \delta + \gamma \frac{Y_{t+1}}{K_{t+1}}\right) \right] \tag{3.2}$$

$$L_t^{1+\chi} = (1-\gamma)\frac{Y_t}{C_t} \tag{3.3}$$

Equation (3.2) describes the intertemporal choice between consumption today and consumption tomorrow. Equation (3.3) describes the agent's intratemporal choice between the consumption and leisure. In addition, we define a variable R_{t+1}, the gross rate of return on a one-period investment in capital, which equals the marginal product of capital in production plus undepreciated capital:

$$R_{t+1} = 1-\delta+\gamma\frac{Y_{t+1}}{K_{t+1}} \tag{3.4}$$

3.1 The technology shock process

Consider how the anticipated shocks can be introduced into the economy. The anticipation of the technology process in our framework means that agents observe the outcome of a conventional technology process some periods prior to its impact on the output. The shocks here refer to the revelation of the information about future productivities rather than to the impact of the output change itself.

The following method will be used to describe the anticipation above for predictions of our RBC model, which is some periods of anticipation prior to the impact of the technological change leads the possible response of the economy to any given shocks. Assume that the technology shock a_t ($a_t = \log A_t$) has a following simple process, which is introduced by Fujiwara (2006):

$$\mathrm{a}_t = \rho \mathrm{a}_{t-1} + \eta_{1,t-p} + \eta_{2,t} \tag{3.5}$$

where $\eta_{2,t}$ is the temporary shock to the technology, $\eta_{1,t-p}$ is expressed as a news shock that it would be known to agents p periods before they actually affect *TFP*. For interpreting this technology process about news shocks clearly, we make a simple example. Suppose that today the agents receive a news that the productivity will increase at period 2, namely $p=2$. The equation (3.5) can be represented as:

$$\begin{pmatrix} a_t \\ \eta_{1,t} \\ \eta_{1,t-1} \end{pmatrix} = \begin{pmatrix} \rho & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} a_{t-1} \\ \eta_{1,t-1} \\ 0 \end{pmatrix} + \begin{pmatrix} \eta_{2,t} \\ \eta_{1,t} \\ 0 \end{pmatrix} \tag{3.6}$$

If agents receive a news shock $\eta_{1,0}$ at period zero, then the equation (3.6) turns to be:

$$\begin{pmatrix} a_0 \\ \eta_{1,0} \\ \eta_{1,-1} \end{pmatrix} = \begin{pmatrix} \rho & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} a_{-1} \\ \eta_{1,-1} \\ \eta_{1,-2} \end{pmatrix} + \begin{pmatrix} 0 \\ \eta_{1,0} \\ 0 \end{pmatrix} \tag{3.7}$$

The shock $\eta_{1,0}$ will not affect a_0 and the expectation of a_1 at period zero, but shock a_2 expected in period zero is now:

$$E_0 \begin{pmatrix} a_2 \\ \eta_{1,2} \\ \eta_{1,1} \end{pmatrix} = \begin{pmatrix} \rho^2 & 1 & \rho \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} a_0 \\ \eta_{1,0} \\ \eta_{1,-1} \end{pmatrix} \tag{3.8}$$

Since $a_0 = \eta_{1,-1} = 0$, then $E_0 a_2 = \eta_{1,0}$. Therefore, the shock on technology at period 2 expected in period zero indeed becomes $\eta_{1,0}$.

Then computing the steady state of the economy, and log-linearizing equations is fairly standard in this model setup. In the light of calibration technique used by Hansen (1985), the parameter values are provided as follows. Since the real rate of interest in the U.S. economy is observed by 4% per annum, the discount factor β is equal to 0.99. The capital share γ in the production is calculated by using the U.S. time series data and set to be approximately 0.36. The rate of depreciation of capital δ is found to be 0.025 because the rate of depreciation is 10% per annum. The assumption of $\chi = 0$ is in line with the explanation by Hansen (1985) that the representative agent's utility function is linear in leisure.[1] And the persistence parameter ρ=*0.95* and the standard deviation of ν_t is equal to 0.0072. Applying the linlagex toolbox[2] that designed by Meyer (2007), we calculate the impulse response functions for the temporary shock ν_t and the news shock $\zeta_{a,p}$ in this simple model.

3.2 The performance in the theoretical model

The figure 3.1 and 3.2 shows the dynamic effects of these two shocks $\eta_{2,t}$ and $\eta_{1,p}$. In the figure 3.1, we can see that with a positive temporary shock, the *TFP* is assumed to increase by one percent in this initial period. The increase in *TFP* leads an intertemporal substitution effect that the labor supply has to rise in response to this temporary productivity improvement. So output increases on the impact period due to the direct effect of the temporary shock to *TFP*, and some due to the increase in labor input. According to this additional output, the agents want to spread it over consumption both today and in the future, and they have to increase current saving in order to finance the additional consumption later on. Thus, only a small fraction of the output will be consumed at the current period and most of it will be invested. Hence the capital stock grows gradually through the accumulation of investment. By assumption, the effect of this temporary shock dies away slowly in the subsequent periods. So later in the impulse responses, the *TFP* converges slowly to its stationary level. The rate of return is high initially because of the positive temporary shock. As the output returns gradually to its usual level, the slower adjustment of capital stock eventually causes Y/K to drop below its initial value, and then causes the rate of return goes down below its normal level. This leads consumption to initially rise over time and then decline back toward the steady-state level. To sum up, the early phase of the impulse response function is dominated by the

[1] *"Since this utility function is linear in leisure it implies an infinite elasticity of substitution between leisure in different periods. This follows no matter how small this elasticity is for the individuals populating the economy. Therefore, the elasticity of substitution between leisure in different periods for the aggregate economy is infinite and independent of the willingness of individuals to substitute leisure across time". (Hansen (1985), pp.319.)*

[2] *Matlab codes and examples are available on the author's website: http://www.wm.tu-berlin.de/~makro/Meyer-Gohde/Working-Papers.htm.*

occurrence of temporary shock, which leads the rise of output, investment, consumption and work effort; the latter phase of the impulse responses is dominated by the transitional dynamics, which the economy reduce the capital stock and cause it back toward its stationary level.

The plot in figure 3.2 indicates the impulse responses at the situation that agents know the news at period zero that "productivity will become higher at period eight". This news makes the agents richer (wealth effect). Then agents want to consume more leisure and consumption, and so the consumption increases. This leads the labor supply decrease and hence causes the output drop. Therefore, we cannot generate positive comovement in consumption, output, labor supply, investment and capital stock against a news shock for higher productivity in the future. This is consistent with the finds of Beaudry and Portier (2004b). And after the materialized period, the performance of the impulse responses of economy is similar to the transitory shock in the model.

3.3 Summary

In this section we examine some implications of temporary and anticipated technology shocks for the predictions of a simple neoclassical model. Our simulation results show that the anticipated technological innovation effect cannot make a comprehensive model of the business cycle in the standard RBC structure. The comovement of consumption with the other economic variables such as capital and output contradicts the pattern of empirical work. And the results of transitory technological shocks indicate that it does have the transitory effect on the economic activity, which the impulse responses increase initially and eventually fade out when the temporary shock disappears.

4. Replication of News shock by BP approach

In this section, the BP approach (Beaudry and Portier (2005, 2006)) will be illustrated and replicated by using the real data for improving the study about the technology shock and macroeconomic fluctuations. Since stock prices have the forward-looking property, it will respond to the changes in expectations earlier than the realized changes in macroeconomic fundamentals affect the other economic variables. Especially, news about technology shocks can have impact effect on stock prices, but it may need some time to actually affect total factor productivity (*TFP*) because of an implementation lag. Thus, the variable of stock prices is very helpful for our understanding that expectation drives economic fluctuations. We will start from replicating the BP's empirical work reported in the literature. (A bivariate vector autoregression model of *TFP* and stock prices by employing two different orthogonalization schemes, and the higher dimensional systems, which contain consumption, investment and hours alternatively or jointly in addition to *TFP* and stock prices.)

4.1 Estimation and identification

4.1.1 Two orthogonalization schemes

In Beaudry and Portier's paper (2005, 2006), they introduced a new method of using orthogonalization techniques to learn about the nature of business cycle fluctuations. Assume that these two variables (*TFP* and stock prices) are integrated of order one and cointegrated with each other, i.e. $(\Delta TFP_t, \Delta SP_t)'$ is *I(0)*. And the reduced form moving average (Wold) representation for the bivariate system $(\Delta TFP_t, \Delta SP_t)$ is:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = C(L)\begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix}, \ \mathrm{E}(\mu_t, \mu_t') = \Omega \tag{4.1}$$

where $C(L) = I + \sum_{i=1}^{\infty} C_i L^i$. Actually most of our estimation is based on a moving average representation derived from the vector error correction model (VECM) between measured *TFP* and stock prices.

An impact restriction and a long run restriction can then be employed for this bivariate system with orthogonalized errors in structural form. The alternative representation can be given by:

(1) $$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \Gamma(L) \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}, \ \mathrm{E}(\varepsilon_t, \varepsilon_t') = I \qquad (4.2)$$

(2) $$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \tilde{\Gamma}(L) \begin{pmatrix} \tilde{\varepsilon}_{1,t} \\ \tilde{\varepsilon}_{2,t} \end{pmatrix}, \ \mathrm{E}(\tilde{\varepsilon}_t, \tilde{\varepsilon}_t') = I \qquad (4.3)$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$, $\tilde{\Gamma}(L) = \sum_{i=0}^{\infty} \tilde{\Gamma}_i L^i$ and the variance covariance matrices of ε and $\tilde{\varepsilon}$ are identity matrices. In order to recover the structural shocks, it is necessary to compute and find the distributed lag matrices Γ . However, there is one more variable than equations in the above system, so it needs to add a restriction to get the particular solution. In the following two cases, we will show the simple computation procedures that how to estimate the lag matrices Γ under the short-run and long-run restrictions, respectively.

Short run identification

In case (1), from (4.1) and (4.2), we have

$$\Gamma(L)\varepsilon_t = C(L)\mu_t \qquad (4.4)$$

Since $C_0 = I$, and (4.4) must hold for all *t*, we find

$$\Gamma_0 \varepsilon_t = \mu_t \qquad (4.5)$$

Square both sides and take expectations then it yields:

$$\Gamma_0 \Gamma_0' = \Omega \tag{4.6}$$

($\Gamma_0 \varepsilon_t \varepsilon_t' \Gamma_0' = \mu_t \mu_t' \Rightarrow \Gamma_0 \Gamma_0' E(\varepsilon_t \varepsilon_t') = E(\mu_t \mu_t') \Rightarrow \Gamma_0 \Gamma_0' * I = \Omega$)

For the short-run identification, this is done by estimating the Cholesky decomposition of Ω. We impose the 1, 2 element of Γ_0 be equal to zero, that means the second disturbance ε_2 has no contemporaneous impact on *TFP*. And equations (4.4) and (4.5) also implies that $\Gamma_i = C_i \Gamma_0$, for $i>0$ ($\Gamma(L)\varepsilon_t = C(L)\Gamma_0 \varepsilon_t$).

Long run identification

In case (2), the distributed lag $\widetilde{\Gamma}(L)$ is different from the one above. Since

$$\begin{matrix} \widetilde{\Gamma}(L)\widetilde{\Gamma}(L)' = C(L)\Gamma_0\Gamma_0' C(L) \\ \Gamma_0\Gamma_0' = \Omega \end{matrix} \Rightarrow \widetilde{\Gamma}(L)\widetilde{\Gamma}(L)' = C(L)\Omega C(L)' \tag{4.7}$$

we do not know Ω, so $\hat{\Omega}$ needs to be estimated and then we have the following estimation:

$$\tilde{\Gamma}(L)\tilde{\Gamma}(L)' = C(L)\hat{\Omega}C(L)' \tag{4.8}$$

Thus, for the long run multipliers we have,

$$\tilde{\Gamma}(1)\tilde{\Gamma}(1)' = C(1)\hat{\Omega}C(1)' \tag{4.9}$$

where $\widetilde{\Gamma}(1)$ is the lower triangular of Cholesky decomposition of $C(1)\hat{\Omega}C(1)'$. For the long run identification, we impose the 1, 2 element of the long run matrix ($\widetilde{\Gamma}_{12}^{1}$) to be equal zero, which makes that the disturbance $\widetilde{\varepsilon}_2$ has no long run effect on *TFP*. From here, we can obtain $\widetilde{\Gamma}(L) = C(L)C(1)^{-1}\widetilde{\Gamma}(1)$.

Therefore, ε_2 and $\tilde{\varepsilon}_1$ are referred to as the stock prices innovation and the permanent shock to *TFP*, respectively. These techniques we used above are not applied simultaneously, but sequentially to describe the joint behavior of measured *TFP* and stock prices. This idea by the use of two different ways to organize the real data means to "*help evaluate different classes of economic model and indicate directions for model reformulation*". If a particular theory suggests that the correlation between ε_2 and $\tilde{\varepsilon}_1$ would be close to zero, then their associated impulse responses will be very different. So in the following we adhere to this direction to measure the relevance of the theory by evaluating its validity of implications.

4.1.2 Simple structural interpretations

In order to study the implication of this strategy above, we will employ the basic model in section 3 to show the results with respect to the correlation between ε_2 and $\tilde{\varepsilon}_1$.

For the computation easily, we assume that the household accumulates capital with full depreciation, then $K_{t+1} = I_t$. Then the first order condition of equation (3.2) becomes:

$$\frac{1}{C_t} = \beta\gamma E_t \frac{1}{C_{t+1}} \frac{Y_{t+1}}{K_{t+1}} \tag{4.10}$$

Imposing this condition $K_{t+1} = I_t = Y_t - C_t$ into equation (4.10), then we got

$$\frac{1}{C_t} = \beta\gamma E_t \frac{C_{t+1} + I_{t+1}}{I_t} \cdot \frac{1}{C_{t+1}}$$

$$\Rightarrow \frac{I_t}{C_t} = \beta\gamma (1 + E_t \frac{I_{t+1}}{C_{t+1}}) \tag{4.11}$$

Solving forward and imposing the usual transversality condition leads to

$$C_t = (1-\beta\gamma)Y_t, \qquad I_t = \beta\gamma Y_t \tag{4.12}$$

Given consumption formula (4.12), the other first order condition of equation (3.3) implies

$$L_t = \left(\frac{1-\gamma}{1-\beta\gamma}\right)^{1/1+\chi} \tag{4.13}$$

Based on the production function, the equilibrium law of motion of consumption can be easily computed. Then we have in logs and omit the constant terms:

$$c_t = a_t + \gamma c_{t-1} \tag{4.14}$$

Given that the technology process (3.5) in section 3.1 (here assume that *p=1*), ΔTFP_t (here TFP_t is instead of the variable a_t we used above) is given by:

$$\Delta TFP_t = (1-L)(\rho a_{t-1} + \eta_{1,t-1} + \eta_{2,t}) = (1-L)(\rho L a_t + L\eta_{1,t} + \eta_{2,t}) \tag{4.15}$$

And also $a_t = \rho a_{t-1} + \eta_{1,t-1} + \eta_{2,t} \Rightarrow a_t = \dfrac{L}{1-\rho L}\eta_{1,t} + \dfrac{1}{1-\rho L}\eta_{2,t}$,

Thus, the structural moving for ΔTFP_t is provided by:

$$\Delta TFP_t = \frac{L-L^2}{1-\rho L}\eta_{1,t} + \frac{1-L}{1-\rho L}\eta_{2,t} \tag{4.16}$$

Since the stock prices SP satisfy the equation $SP_t\, E_t \dfrac{C_{t+1}}{\beta C_t} = 1$, we take this equation in logs, and it can be given by:

$$SP_t + \ln E_t C_{t+1} - \log\beta - c_t = 0 \tag{4.17}$$

For any variable x, $e^{\ln x} = x$, so we can write $E_t C_{t+1} = E_t e^{\ln C_{t+1}}$.

If x ~ N (μ, V) then $E(e^x) = e^{\mu} e^{V/2}$, and assume that the consumption is conditionally lognormally distributed and the variance of log consumption is σ^2 on time t, so we have

$$E_t C_{t+1} = E_t \left[e^{\ln C_{t+1}} e^{\sigma^2/2} \right] = e^{E_t \ln C_{t+1}} e^{\sigma^2/2}$$

$$\Rightarrow \ln E_t C_{t+1} = E_t \ln C_{t+1} + \sigma^2/2 = E_t c_{t+1} + \sigma^2/2$$

Based on the equation (4.17), the expression of ΔSP_t can be obtained by:

$$\begin{aligned}\Delta SP_t &= SP_t - SP_{t-1} \\ &= c_t + \log\beta - \ln E_t C_{t+1} - (c_{t-1} + \log\beta - \ln E_t \ln C_t) \\ &= c_t - c_{t-1} - (E_t c_{t+1} - c_t) \\ &= \frac{(1-L)(L-1)}{(1-\gamma L)(1-\rho L)} \eta_{1,t} + \frac{(1-L)(1-\rho(1-\gamma L)-\gamma)}{(1-\gamma L)(1-\rho L)} \eta_{2,t}\end{aligned} \tag{4.18}$$

Therefore, the structural moving average for *TFP* and the stock market prices in this model can be expressed as follows:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \begin{pmatrix} \dfrac{L-L^2}{1-\rho L} & \dfrac{1-L}{1-\rho L} \\ \dfrac{(1-L)(L-1)}{(1-\gamma L)(1-\rho L)} & \dfrac{(1-L)(1-\rho(1-\gamma L)-\gamma)}{(1-\gamma L)(1-\rho L)} \end{pmatrix} \begin{pmatrix} \eta_{1,t} \\ \eta_{2,t} \end{pmatrix} \tag{4.19}$$

Performing short-run and long-run identification on this system[3], we obtain

$$\varepsilon_1 = \eta_2,\ \varepsilon_2 = \eta_1,\ \tilde{\varepsilon}_1 = \eta_1,\ \tilde{\varepsilon}_2 = \eta_2$$

Then we have that ε_2 is co-linear to $\tilde{\varepsilon}_1$.

The shock in the second model, which the technology innovation is first anticipated in the stock price and only later reflected in changes of productivity, is referred to as a news shock because it brings news about future growth in productivity. To find whether this shock exists or not, we turn to an analysis of this issue for US postwar data.

3 The procedure of short-run and long-run identification is provided in the appendix B.

4.2 Data description and specification issues

Here we try to collect the data as possible as close to those employed by Beaudry and Portier (2006). In BP's paper, the data of total factor productivity (*TFP*) and stock prices are needed. The sample covers the period from 1948 to 2000, using the quarterly data.

The total factor productivity (*TFP*) is contrasted as follows:

$$TFP_t = \log\left(\frac{Y_t}{H_t^{\bar{s}_h} KS_t^{1-\bar{s}_h}}\right) \tag{4.20}$$

where Y and H denote the output and hours of nonfarm business measures. The labor share $\bar{s}_h$ sets to be 67.66%, which is the average value of the annual series reported by BLS. And KS is the capital share that measures the services derived from the stock of physical assets and software.

The second series refers to the stock prices. The quarterly Standards & Poors 500 Composite Stock Prices Index (S&P 500) is used here, deflated by the seasonally adjusted implicit prices deflator of GDP in the nonfarm private business sector and transformed in per-capita terms by dividing it by the population aged 15 to 64. Since the population series is annual, it has been interpolated assuming constant growth within the quarters of the same year. We denote the log of this index by *SP*.

The consumption (*C*) is the per-capita value of real personal consumption of nondurable goods and services, and the investment measure (*I*) is the per-capita terms of the sum of real personal consumption of durable goods and real fixed private domestic investment.

Then the idea is to check for stationary of the series in order to estimate the model in the appropriate way. A standard Augmented Dickey Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) are used to check for the unit roots. The calculated statistics in the table (Table 4.1 in the appendix) suggest that *TFP* and *SP* are *I(1)* processes, which can use the VECM framework to recover the Wold representation. However, we should be very careful to specify the matrix of cointegration relationships in the VECM framework in order to avoid the potential misspecification. Based on the emphasis explained in Hamilton (1994) [4], if the researcher worries about the misspecification in a VECM model, maybe it is best to analyze the VECM model with full rank matrix of cointegrating relationships, which means to estimate the system in levels. Then one can analyze this system allowing for the reduced rank matrix of cointegration, and examine whether the resulting representation is similar to that estimated by VECM in levels. Next, we follow this principal to estimate and report the results basing on a Wold representation derived from the VECM framework, which have been confirmed that the estimation results are robust to those estimated in levels. In order to avoid the problem of misspecification due to the omitted cointegration, we apply the Johansen trace test to examine a long-run equilibrium relationship of *TFP* and *SP* (Table 4.2 in the appendix). The null of no cointegration between *TFP* and *SP* can be rejected, so we adopt the specification of bivariate vector error correction models (VECM) in the following estimation. For the number of lags that include in this VECM, here we choose five lags according to the likelihood ratio test, which is same as the BP's choice. Hence, the following analyses proceed with one cointegrating relationship with five lags of data.

4.3 Empirical results

4.3.1 Preliminary results in a bivariate system

We start from a VECM of (TFP_t, SP_t) above to investigate the two orthogonalized shocks ε_2 and $\tilde{\varepsilon}_1$ described in section 4.1, which are recovered by imposing an impact

[4] *It is explained in the chapter 20, section 4 of Hamilton (1994) entitled "Overview of Unit Roots – To Difference or Not to Difference".*

and a long-run restriction respectively[5]. The level impulse responses of (TFP_t, SP_t) related to the shocks ε_2 and $\tilde{\varepsilon}_1$ are plotted in Figure 4.1. This figure shows that these responses associated with the shock ε_2 and the shock $\tilde{\varepsilon}_1$ appear very similar. The shock ε_2, which has no contemporaneous impact on *TFP*, seems to permanently affect *TFP*; and the shock $\tilde{\varepsilon}_1$, which has a permanent effect on *TFP*, has no impact effect on *TFP* but has a substantial effect on *SP*. They indicate that "permanent changes in *TFP* are reflected in stock prices before they actually increase productive capacity".

From the quasi-identity of the shock ε_2 and $\tilde{\varepsilon}_1$ shock that is shown in Figure 4.2, this plot implies the similarity between the effects of these two shock series. In effect, the correlation coefficient between the shocks ε_2 and $\tilde{\varepsilon}_1$ is 0.83, which means these two orthogonalization schemes recover essentially the same shock series. This similarity is also confirmed by the graph of forecast error variance decomposition (Figure 4.3). The ε_2 shock can explains most of the long variability of *TFP*, while the $\tilde{\varepsilon}_1$ shock also explains the variance of stock prices, but none of the short-run movements of *TFP*. These results are in line with the view that "*improvements in productivity are generally anticipated by market participants due to a lag between the recognition of a technological innovation and its eventual impact on productivity*", which we call the news view.

4.3.2 Controlling for variable rates of factor utilization

However, there are some potential problems in the measure of *TFP*; for example, it does not take account of the correlation for variable rates of capital utilization, labor hoarding or composition bias. Thus, they introduced an alternative measure of *TFP*, which is denoted by BLS measure. The BLS measure of capacity utilization (CU_t) is

[5] *The VECM models are estimated by using the software Jmulti, which is available on the website: http://www.jmulti.de.*

used to adjust the *TFP* measure for its capital services[6]. The results about using this measure show that the observation of the high correlation between ε_2 and $\tilde{\varepsilon}_1$ is very robust (Figure 4.4). The plots of unadjusted data are similar to the patterns of the quarterly version. However, the result based on the adjusted *TFP* data is different. It suggests that *TFP* starts growing only four years after the initial rise in the stock market. The long lag between stock prices rises and the increase in *TFP* is potentially in line with a delayed impact of technological innovation on productivity. And in the authors' opinion: "*the substantially delayed responses associated with the adjusted measures of productivity constitute the more believable response to the actual changes in technology*".

4.3.3 Empirical results in the higher dimension systems

All the estimations above are based on the bivariate system $\{TFP, SP\}$. For examining whether these observations exist in higher dimensional systems, Beaudry and Portier used the approach that presented above for studying the systems, which contain consumption, investment, output and hours alternatively or jointly in addition to *TFP* and *SP*. The comovement of different macroeconomic variables is an important feature for the business cycles. The comovement patterns may include the significant clues about the mechanisms and shocks that generate business fluctuations. Hence, investigating the comovement of these macro variables to news shocks is very important to study the business cycle fluctuations.

In the three-variable system $\{TFP, SP, C\}$, the shock is recuperated by imposing the 1,2 and 1, 3 element of the long run matrix $\sum_{i=0}^{\infty}\widetilde{\Gamma}_i(1)$ to be equal zero. For defining ε_2, it needs to do: (1) imposing no restrictions on the shock ε_1 to let it potentially represent an unanticipated technology shock; (2) imposing the impact restriction that 1, 2 element of

[6] *The adjusted TFP is computed in the following form:*

$$TFP_t^A = \log\left(\frac{Y_t}{H_t^{\bar{s}_h}(CU_t KS_t)^{1-\bar{s}_h}}\right).$$

Γ_0 be equal to zero, and recuperating the shock ε_2; (3) imposing ε_3 has on long run impact on *TFP* or consumption to make it be a temporary shock.

In the four-variable system {*TFP, SP, C, H*}, the shock $\tilde{\varepsilon}_1$ is isolated by imposing the long run matrix $\sum_{i=0}^{\infty}\tilde{\Gamma}_i(1)$ be lower triangular. For isolating the shock ε_2, it requires: (1) imposing no restriction on the shock ε_1 to let it capture a traditional surprise productivity shock; (2) imposing the impact restriction that 1,2 element of Γ_0 be equal to zero to make sure that ε_2 is not contemporaneously correlated with *TFP*; (3) imposing the first and third element of the third column of the long run matrix be equal zero, as to let ε_3 be a temporary shock to technology; (4) imposing ε_4 as an hours specific shock, and then there are zeros in the first three element of the last column of the impact matrix.

The empirical estimations of these two different systems both show the similar results with the bivariate system (Figure 4.5, 4.6 and 4.7). In Figure 4.5, the dynamics associated with shocks ε_2 and $\tilde{\varepsilon}_1$ seem to be similar; the responses of stock prices and consumption are rarely affected regardless of which the measure of *TFP* is used. But the timing of the response of *TFP* to both ε_2 and $\tilde{\varepsilon}_1$ depends on the measure of *TFP* used. With unadjusted measure, *TFP* starts growing quickly. Relatively, the short-run responses of *TFP* with the adjusted measure are negative, and after 12 quarters it increases from its initial level. And from Figure 4.6, the results indicate that the responses of stock prices, consumption and hours are very similar no matter what the measure is used. There is a substantial hump-shaped response of hours to either the shock ε_2 or $\tilde{\varepsilon}_1$. Moreover, the timing for the response of *TFP* depends heavily on the measure of *TFP* used as in the case of the three-variable system. To compute the variance decomposition for investment and output, these two variables replace the hours in the four-variable system. The impulse responses of these latter two systems are very similar to the patterns in Figure 4.6. According to Figure

4.7 the variance decompositions imply that the shocks ε_2 and $\tilde{\varepsilon}_1$ explain a significant fraction of business cycle fluctuations.

4.4 Summary

In this section, in order to improve my understanding about the study of news shock in the business cycles, I reproduce the BP's empirical work by using their two orthogonalized schemes for the real data series of US. The estimation I made seems plausible in replicating the patterns of the impulse responses functions and variance decompositions except a little difference in the magnitude of changes reported by Beaudry and Portier. And the empirical results imply that substantial fraction of business cycle fluctuations can be driven by the news shock, which anticipate future changes in the technology process.

5. The study of surprised technology shock in the system

From the estimations above, the empirical results show that the news shock regarding long run changes in *TFP* captured by the stock market can generate the business cycle fluctuations. Does the other shock in this system play the role of business cycle fluctuations? The RBC literature indicates that the technology shocks play the central role in generating the cyclical movements in macroeconomic data. But some researchers, like Gali (1999), use the new-Keynesian models of aggregate fluctuations to call into question that the transitory shocks to *TFP* can generate the aggregate cycle. What is the performance of related macroeconomic variables to the temporary shock in the BP's system? Can these surprised changes in total factor productivity cause the business cycle? Beaudry and Portier (2004a) propose that the surprise technological disturbances may be a potential important resource of the economic fluctuations. But they do not explore the role of this surprised technology shock, and hence we turn to this study of the role of temporary shock, which has no long-run impact on *TFP*. In this section, we first employ the BP approach to examine this transitory shock, and find that their identification scheme can cause the robustness problem when extending our analysis from bivariate VAR to the higher dimensional systems. Then another two-step approach is introduced to try to solve this problem and give a more accurate examination on the temporary shocks to *TFP*.

5.1 The BP approach

5.1.1 The bivariate system {TFP, SP}

The empirical analysis starts from the simple case of bivariate system $\{TFP, SP\}$. In this system, the shock $\tilde{\varepsilon}_2$ is imposed by the restriction that 1, 2 element of the long-run matrix equals zero.

The level impulse response on this system associated with the $\tilde{\varepsilon}_2$ shock is displayed on Figure 5.1. In this figure, the temporary shock $\tilde{\varepsilon}_2$ is identified to have no long run effect on *TFP* so that *TFP* increases dramatically in the short run. This effect is significant immediately after the shock occurs, and then it decreases gradually only after several quarters. The stock prices increase in response to this temporary shock. This temporary shock $\tilde{\varepsilon}_2$ to *TFP* acts like aggregate demand shocks that causing *TFP* and stock prices to move in the same directions. But $\tilde{\varepsilon}_2$ shock here has more persistent effect on *TFP* that the response of *TFP* to the temporary shock in this bivariate system is still positive in the long run. This temporary positive shock leads an increase in the total factor productivity, and makes the agents feel optimistic about the future of economy. Then it drives the stock prices up since the stock prices reflect the investors' expectations on the future prospects of the economy.

For different horizons *h* the forecast error variance decompositions of *TFP* and *SP* attributed to this temporary shock $\tilde{\varepsilon}_2$ are listed in the Table 5.1. Clearly, according to our estimates, the temporary shock $\tilde{\varepsilon}_2$ is not an important source for the determination of stock prices. After *h=24*, $\tilde{\varepsilon}_2$ explains none of the variance of stock prices. But shock $\tilde{\varepsilon}_2$ explains a large fraction of the variance of *TFP* in the short run.

5.1.2 The higher dimensional system

Then we extend our estimation to the higher dimensional systems. In the three-variable system {*TFP,SP,C*}, the identification is imposed by the restriction that the 1,2 and 1,3 elements of the long run matrix equal to zero and then recuperating the shock $\tilde{\varepsilon}_1$. From the impulse responses to the temporary shock $\tilde{\varepsilon}_2$ that plotted in the Figure 5.2, we can see that this temporary shock $\tilde{\varepsilon}_2$ has small effect on the *TFP* in the short-run period, and it dies out over time. But the response of stock prices to this shock is relatively large in the short term compare to its effect on *TFP*. The increase in the total factor productivity may lead the wealth effect that make the consumers feel wealthier and consume more in the current period. Thus for the consumption, $\tilde{\varepsilon}_2$ has the positive effect in the short run but gradually dies away in the long term.

Table 5.2 presents variance decompositions for the shock $\tilde{\varepsilon}_2$ in this three-variable system. $\tilde{\varepsilon}_2$ explains less than 35% of *TFP* variance in the whole period. Inversely, the temporary shock ε_2 explains a large fraction of stock prices variance at the short horizons (accounts for more than 50% of variance during 12 quarters), but the effect goes down gradually as *h* increases. After *h=36* periods, $\tilde{\varepsilon}_2$ shock explains a fraction of 18% of the variance in stock prices. And this temporary shock $\tilde{\varepsilon}_2$ accounts for less than 5% of the variance of consumption.

When the variables of investment (*I*), output (*C+I*) or hours worked (*H*) are introduced in the four-variable system, the restriction is imposed that the long run matrix is lower triangular. In these systems, the empirical results are similar to those of three-variable system. Figure 5.3 shows the impulse responses of the case $\{TFP, SP, C, I\}$. (Because the results of $\{TFP, SP, C, C+I\}$ is very similar to the patterns of $\{TFP, SP, C, I\}$, here we don't show the impulse responses of $\{TFP, SP, C, C+I\}$). The temporary shock $\tilde{\varepsilon}_2$ has a transitory effect on the investment and dies out after a few years (10 quarters). The *TFP* increases, firm's earnings increases. And then part of the increase will finance new investments, so the response of investment to $\tilde{\varepsilon}_2$ rises in the short-run period. With the effect of the shock ε_2 disappears, the investment returns to its stationary level over time. And in the four-variable system $\{TFP, SP, C, H\}$ (Figure 5.4), the pattern of response of hours worked is similar to the investment, that is, $\tilde{\varepsilon}_2$ has a small and transitory effect on it for nearly three years. Because of this positive shock $\tilde{\varepsilon}_2$, the rate of return is higher. This induces the representative household to work additional hours, so the hours worked increases in response to the shock $\tilde{\varepsilon}_2$. But here the response of consumption is more sluggish, and seems to increase in the long run. When extend this analysis to longer term, we can find that the effect of transitory shock $\tilde{\varepsilon}_2$ on the consumption will decrease after 50 quarters. From the Table 5.3, this temporary shock $\tilde{\varepsilon}_2$ again explains very little of fraction of the variances of the variables in all the four-variable systems.

5.1.3 Summary

Overall, using the BP approach to examine this surprised technology change $\tilde{\varepsilon}_2$, we can discover that it does not play an important role for generating the business cycle fluctuations. Its effect on the impulse responses of related macro variables is small and not permanent in the long run, and these results are in line with those of forecast error variance decompositions, which $\tilde{\varepsilon}_2$ can only account for very little faction of macroeconomic movements.

In addition, the impulse responses to the temporary shock seem not to be robust when one moves from the bivariate system to the higher dimensional VARs. Compare the performances for the variables *TFP* and stock prices in the two-variable VAR with those of three or four-variable systems, we can see that the pattern is obviously different, especially the shortrun effect of this temporary shock on *TFP* is smaller and it is much larger on stock prices in the higher dimensional system. The reason for this is related to the BP's identification scheme. In the bivariate system, the identification is imposed so that the permanent and transitory shocks can be isolated. But in the higher dimensional systems such as the three-variable system, the lower triangular long run restriction imposed by BP is identified for making the permanent shock set apart from the other two transitory shocks (there are two cointegrating relations in this three-variable VAR)[7]. This

[7] *The lower triangular long-run restriction in the trivariate system* $A_3(1) = \begin{bmatrix} A_{11} & 0 & 0 \\ A_{21} & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{bmatrix}$ *that we use is a direct generalization of that in the long-run identification scheme of bivariate VAR, which*

imposed identification is not easy to distinguish the role of these two transitory shocks, and not appropriate for identifying the shock that has no long run effect on *TFP*. Thus, it causes no robustness between the empirical results in the bivariate and higher dimensional systems. For solving this robustness problem, we will introduce another method to explore the role of shock $\tilde{\varepsilon}_2$ in the next subsection.

5.2 Two-step approach

The identification approach using by BP in the higher dimensional system is appropriate for investigating the effect of the permanent shock $\tilde{\varepsilon}_1$, but it will cause the problem of robustness when used for analyzing the temporary shock $\tilde{\varepsilon}_2$. Moreover, it becomes more difficult and complicated for imposition of identifications as the dimension of SVAR system increases. In a higher dimensional system, setting more identification means high possibility of unnecessary and false restrictions imposed. And statistical information is difficult to check the validity of the identifying restrictions. Therefore, given that imposing the credible restrictions in the higher dimensional systems is difficult and the identification scheme by BP's strategy are not appropriate to specify the transitory shock $\tilde{\varepsilon}_2$, here we try to introduce a new approach for getting its impulse responses to the macroeconomic variables such as consumption, investment, output and hours worked, which are we interested. This new approach aims to solve the identification problem in the higher dimensional system of SVAR analysis, and it can also provide an alternative to do the estimation of the permanent shocks to *TFP* by using the BP's approach.

---

is $A_2(1)=\begin{bmatrix} A_{11} & 0 \\ A_{21} & A_{22} \end{bmatrix}$. *But based on the condition that there are two cointegrating vectors in the trivariate case, the appropriate identification is* $A_3(1)=\begin{bmatrix} A_{11} & 0 & 0 \\ A_{21} & 0 & 0 \\ A_{31} & 0 & 0 \end{bmatrix}$.

5.2.1 Description

The general idea of new approach is taking advantage of the residuals obtained from the bivariate VAR ($\{\Delta TFP_t, \Delta SP_t\}$) as the exogenous regressors to exploit another VAR of different variables we are interested, and then we focus on the dynamic effect of the temporary shock. This method contains two steps as follows.

In the first step, the expression from the original bivariate VAR model (equation 4.1) is:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \begin{pmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{pmatrix} \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix}$$

where $\mu_{1,t}$, $\mu_{2,t}$ are the residuals both obtained from this two-variable system $\{\Delta TFP_t, \Delta SP_t\}$, and we assume the error term $\mu_{1,t}$ is the permanent shock and $\mu_{2,t}$ the temporary shock. Since the empirical results in the Section 4 indicate that there is one cointegration relation between ΔTFP_t and ΔSP_t, namely that they possess one common trend, so that this common trend must be in terms of the single innovation $\mu_{1,t}$. An alternative representation of this system can be expressed as:

$$\begin{cases} TFP_t = C_{11}(L)\tau_{\varepsilon,t} + C_{12}^{*}(L)\mu_{2,t} \\ SP_t = C_{21}(L)\tau_{\varepsilon,t} + C_{22}^{*}(L)\mu_{2,t} \end{cases} \tag{5.1}$$

where $\tau_{\varepsilon,t} = \sum_{i=0}^{t} \mu_{1,t-i}$, which it is sum of permanent shock $\mu_{1,t}$, an *I(1)* process. $C_{i2}^{*}(L) = C_{i2}^{*}(L)/(1-L)$, *i=1, 2*, is an invertible lag polynomial with stationary roots since $\mu_{2,t}$ is an *I(0)* process based on our assumption. Then we extract these two errors $\mu_{1,t}$, $\mu_{2,t}$ from the system and treat them as the exogenous variables of another VAR.

In the second step, we will explore a new VAR model, which contains the exogenous variables and other macroeconomic variables we are interested. At this stage, the new model should be carefully treated because of the potential problem arising when these exogenous variables appear in the new VAR model. There are three main issues that may arise in any estimation by using the generated regressors, such as whether the estimators are (1) consistent, (2) efficient, and (3) whether the valid inferences would be made with standard errors that derived from the second step estimation. According to the discussion of these problems provided in Pagan (1984), most of two-step estimators are consistent and also many of them are efficient, but the associated problems with drawing valid inferences are rarely provided. Here in our analysis, the danger of using the generated regressors is that measurement errors in the estimated exogenous variables $\mu_{1,t}$ and $\mu_{2,t}$ obtained from the first step may interfere with valid inference. As advised in Oxley and McAleer (1993), the solution to this problem is by the use of Instrumental Variable (IV) or FIML method to yield the consistent standard error estimates. However, these computation procedures would not be ease of implementation, so that this issue will be left in the future study. In the following, all the standard tests will be used with considerable caution.

At first we should check the Granger causality between the macro variables (consumption, investment, output or hours) and benchmark variables (*TFP* and *SP*), namely testing whether the lagged value of this specific group of variables plays any role in the determination of *TFP* and *SP* in the VAR. It is one condition that holds to satisfy this new methodology and make this system to be appropriate. According to the test, we find that the variables Consumption investment and output do not Granger cause *TFP* and *SP* at the 5% and 10% confident level, and hours worked does not Granger cause them at the 1% level. In other words, this results show that the past value of the variables consumption, investment and hours worked do not help to predict the benchmark variables *TFP* and *SP*.

Next, a representation for the level of the endogenous variables that we are interested can be displayed like the form of equation (5.1):

$$\Pi(L)Y_t = \Psi(L)\tau_{\varepsilon,t} + \Phi(L)\mu_{2,t} + \eta_t \tag{5.2}$$

where Y_t is a vector of endogenous variables, one of the exogenous variables $\tau_{\varepsilon,t}$ is constructed in terms of partially summing the innovation $\mu_{1,t}$, which is the permanent shock obtained from the bivariate system in the first step, the other exogenous variable $\mu_{2,t}$ is a temporary shock that also comes out of the original bivariate VAR, and η_t represents a vector of stationary disturbances[8].

In this equation, $\Pi(L) = 1 - \Pi_1 L - \Pi_2 L^2 - \cdots - \Pi_p L^p$, Ψ(L) and Φ(L) are both the appropriate p^{th} order dimensional matrix lag polynomials. It's a clear expression to analyze the endogenous variables in levels including the current and lagged values of $\tau_{\varepsilon,t}$ and $\mu_{2,t}$. In addition, for the validity of doing the comparison with the results of BP's "old" style 4-variable VAR model, we set the vector Y_t contains two variables that choose from four macro variables consumption (C), investment (I), output (C+I), and hours worked (H), for example $Y_t = \{C_t, I_t\}$ (this bivariate VAR model contains two exogenous variables should be seen as an alternative to 4-variable system). In order to keep the numbers of lags in these two VAR model (the original and new one) same, we choose the lag length of variables in the equation (5.2) to be five.

In order to make this new model be appropriate, at first we do some specification tests for the equation (5.2). Because the term $\tau_{\varepsilon,t}$ is the sum of the permanent shocks $\mu_{1,t}$, it should be an *I(1)* process that contains a common trend. And the transitory shock $\mu_{2,t}$ should be an *I(0)* process since it is assumed to have no long-run effect on the level of the vector Y_t. According to the unit root tests, the results show that the exogenous regressor $\mu_{2,t}$ is stationary, the other one $\tau_{\varepsilon,t}$ and all endogenous variables (consumption, investment,

[8] *The only shocks in this system we are interested are the permanent and temporary TFP shocks, so the vector η_t is assumed to be the other shocks that be contained in this system. We are not interested in them, and for computation easily it can be considered as the measurement error, which are stationary and have no permanent effect.*

output and hours worked) are likely *I(1)* processes. By employing the cointegration test, we can find that there are two cointegrating relations in these 4-variable systems (for example includes C_t, I_t and two exogenous variables). All results are displayed in Table 5.4. Given that all conditions have been established, it then becomes reasonable to compare the temporary shock in this new and old style VAR system.

Since it is difficult to compute this augmented cointegrating regression that both the variables of Y_t are cointegrated with the exogenous variable $\tau_{\varepsilon,t}$, instead we try to estimate the endogenous variables in differences by multiplying (*1-L*) on both sides of equation (5.2), and then get an alternative VAR, which can be expressed as follows:

$$\Pi(L)\Delta Y_t = \Psi(L)\mu_{1,t} + \Phi(L)\Delta\mu_{2,t} + \Delta\eta_t \tag{5.3}$$

where $\mu_{1,t-i} = \Delta\tau_{\varepsilon,t-i} = \tau_{\varepsilon,t-i} - \tau_{\varepsilon,t-i-1}$. This VAR model can be estimated subject to the *MA(1)* error η_t, and the form of this measurement error should be checked at the same time. Consider the probability of the generated regressors' problem discussed above may arise in the system; there is another optional function to be presented.

Because there are two cointegrating relationships in the system that both variables in Y_t are cointegrated with $\tau_{\varepsilon,t}$, it is convenient and easy to reparametrize the equation (5.2) and express it as an error correction representation for the cointegrated variables:

$$\Delta Y_t = \Gamma Y_{t-1} + \Pi(L)\Delta Y_{t-1} + H\tau_{\varepsilon,t-1} + \Psi(L)\mu_{1,t} + \Phi(L)\mu_{2,t} + \eta_t \tag{5.4}$$

Then it is examined by using the method of OLS regression and get the estimated parameters we need to compute the impulse response functions with respect to the innovations $\mu_{1,t}$ and $\mu_{2,t}$. In order to make the equation be not the augmented regression, we should check the coefficient on the own lagged Y_t before calculating the IRFs. It suggests that all the coefficients are not unity by Wald tests.[9]

---

[9] *The coefficients of lagged* Y_t *are* $\Gamma_{C,H} = \begin{bmatrix} \underset{(0.0013)}{-0.0011} & \underset{(0.0091)}{-0.0136} \\ \underset{(0.0018)}{0.0081} & \underset{(0.0129)}{-0.0560} \end{bmatrix}$, $\Gamma_{C,I} = \begin{bmatrix} \underset{(0.0043)}{-0.0043} & \underset{(0.0037)}{0.0014} \\ \underset{(0.0296)}{0.1229} & \underset{(0.0251)}{-0.1062} \end{bmatrix}$ *and*

The results of impulse responses of endogenous variables[10] with respect to the transitory shock $\mu_{2,t}$ are displayed in the Figure 5.5. As can be seen in this figure, the temporary shock $\mu_{2,t}$ has a cyclical effect: consumption, hours worked, investment and output increase in the short run period, and return to the stationary level as the effect of transitory shock disappears. The impulse response patterns of these macro variables are very similar to those in the higher dimensional systems using the BP's approach, but the impact effects on the economic variables are larger since the temporary shock is singled out by employing this approach, not mixed up with other transitory shocks in the old 4-variable systems. Meanwhile, we also examine their impulse responses to the permanent shock $\mu_{1,t}$. The plots of Figure 5.6 seem to be plausible that the patterns are very similar to those obtained from the estimation of shock $\tilde{\varepsilon}_{1,t}$ by employing the BP's identification scheme, and it indicates that the two-step approach can validate BP's analysis of the permanent shocks to *TFP*.

5.2.2 Summary

According to this two-step method, we first estimate the original bivariate VAR system, and then abstract the residuals from this system and use these residuals as the exogenous regressors in a new two-variable VAR that contains two of macro variables consumption, hours worked, investment and output. This new model can be seen as an alternative four-variable VAR, and the estimated impulse responses by using this two-step methodology should be compared with those obtained from the old 4-variable case by BP approach.

$$\Gamma_{C,C+I} = \begin{bmatrix} \underset{(0.0080)}{-0.0056} & \underset{(0.0037)}{0.0014} \\ \underset{(0.0568)}{0.2235} & \underset{(0.0262)}{-0.1049} \end{bmatrix}$$ *where the corresponding standard error is in the round bracket.*

[10] *The impulse responses are estimated by using the software of Matlab, which is basing on the principle described in the Hamilton (1994).*

The impulse responses of consumption, investment, output and hours worked with respect to the shock $\mu_{2,t}$ are positive in the short run, and gradually die out over time. It suggests that this temporary shock has small effect on the macroeconomic variables, which is in line with the empirical results obtained from the old style four-variable systems using BP strategy. Thus, the temporary shock that is surprise changes in the total factor productivity plays a minor role in the business cycle fluctuations, and it is not a very important potential resource of the fluctuations. In addition, we also examine the role of permanent shock $\mu_{1,t}$ in the bivariate system, and obtain the similar result with those using BP's approach. In a word, the new two-step approach seems to be sensible to solve the robustness problem in the higher dimensional systems, and can be seen as the alternative method to investigate the permanent shocks in BP's analysis.

6. Conclusion

In this chapter, we try to examine the relative importance of two shocks in the business cycle fluctuations, which are the news shock to *TFP* and surprised technology changes. By applying the BP's empirical strategy and another two-step approach, we find that the substantial fraction of business cycle fluctuations can be explained by news shock; by contrast the temporary shock to *TFP* has very small effect on the economic activities, it's not an important for the business cycle fluctuations. The estimation results are supportive of hypothesis about the news-driven business cycle. In addition, we develop a two-step approach, which can solve the identification problem in the higher dimensional VARs, and also can be seen as an alternative method to BP's identification schemes to do the estimation of the permanent shocks to *TFP*.

Part 2 the Second Chapter

1. Introduction

Recently, it becomes popular to understand the role of expectation (news) shock in macroeconomic fluctuations. There are quite a few papers regarding the study of news shocks both on the theoretical and empirical aspects. For the empirical study, two main methods are applied to explore the quantitative importance of news shock in the business activities, which are the BP's identification schemes in the SVAR model and the Bayesian DSGE approach. Despite the empirical observations obtained by the researchers (such as Beaudry and Portier (2004a) or Schmitt-Grohe and Uribe (2008)) are supportive for the news-driven business cycles hypothesis, relatively little is known about the characteristics of such observations outside the United States and Japan. Haertel and Lucke (2006) followed the BP's study to investigate its effect in the Germany that can be seen as the third country and get the similar conclusion.

Since the institutional differences between the United States and European countries, mostly evident in the labor market, suggest that it may be inappropriate for the study of role of expectation in the business cycle fluctuations in the European countries. For this reason, we want to continue the study in this direction to look for the further evidence on the BP-hypothesis of delayed technology diffusion and news-driven business cycles by extending the studies to the European major countries.

We attempt to quantify the importance of news shocks in driving the economic fluctuations for the European countries such as France, UK, Italy, Spain and Netherlands by choosing the data starts from 1970. Following the BP's approach, we firstly identify two shocks in a bivariate system including the total factor productivity (*TFP*) and stock prices, which are the stock prices innovations and a permanent shock to *TFP*. According to our empirical results, we find that the correlation of these two shocks is relatively high in the most of five countries, and they can explain a sizable fraction of forecast error for main economic variables in the medium and long run when extending the study to the trivariate systems. All these findings support recent research that stresses the role of news and expectations on business cycles.

The remainder of this paper is organized as follows. In Section 2, we introduce the data description and summarize some stylized facts for these real data series. Then we discuss the empirical results in Section 3 and some concluding remarks are made in Section 4.

2. Data Description

Our sample includes five industrial European countries, namely, France, UK, Italy, Spain and Netherlands for which their historical data statistics are available. The analysis requires the quarterly data from 1970Q1 to 2006Q4. Following the methodology of Beaudry and Portier (2006), two different measures for *TFP* variable are computed: the standard Solow residual and the residual adjusted for variable capital utilization.

For the simple measure of *TFP*, it is calculated by the data series of GDP, hours worked, labor share, and capital stock that is interpolated by the constant growth rate within a year. The log of this measure is denoted as *TFP*.

The second measure of *TFP* is corrected by capacity utilization rate from industry survey, which is used to multiply with the capital stock data. Then take the log of this measure and it is denoted as *TFPa*.

The other variables such as stock prices (*SP*), consumption (*C*), investment(*I*) and Hours worked (*H*) are expressed as log-level of per capita by using the population aged 15 to 64.

For the stock price measure, we choose one stock price index from every country's stock market, and then deflated by the GDP deflator. All the detailed data descriptions are showed in the data appendix. The resulting five series of *TFP*, *SP*, *C*, *I* and *H* for these five countries are plotted in the Figure 1.

Compare with the similar data plots of US in Beaudry and Portier (2004a), we can find that the distinguishment between the US and European countries is the *SP* and *H* data series. The growth trend of stock prices in this figure is very volatile that there are large decreases and increases during the whole period, not like the stock prices of US increases steadily in the last 50 years. The large stock market is more liquid and less volatile than the small markets. "The countries with strong information disclosure laws, internationally accepted accounting standards, and unrestricted international capital flows tend to have larger and more liquid markets". Demirguc-Kunt and Levine (1996) propose that the "less volatility" sometimes is referred to reflecting the "greater stock market development" for simplicity although it may be not a necessary sign of stock market development.

According to the hours worked per capita, there is a large decrease in these European countries over the last 30 years comparing to the increasing trend in US. For example, by comparing the working hours per person per week, the U.S. has the highest value that is 25.1, Italy has 16.7, France 18.0, and the UK has the relatively higher value with 21.4. Alesina, Glaseser and Sacerdote (2005) find that labor regulation and union policies are the dominant causes in explaining the differences between the U.S. and European countries. For some political reasons, European Union density is much higher than union density within the U.S. The European labor market is more regulated than the US' one; in particular the European labor unions prevent firms to adjust the number of employees during recessions. The unions will artificially restrict labor supply in order to raise wages. Its structure is far from the highly competitive one of the US labor market.

3. Empirical results

3.1 Preliminary empirical results

For the specification of all data series, a standard Augmented Dickey Fuller (ADF) test is used for checking the unit roots. As the results showed in the Table1, all variables are treated as *I (1)* processes. And then we apply the Johansen trace test to test for a long-run equilibrium relationship between *TFP* and stock market prices. The results in the Table 2 indicate that null hypothesis of no cointegration relationship is rejected at 5% confident interval in all cases except Italy (it is rejected at 10% level), thus we use the specification of bivariate vector error correction models (VECM) for the empirical analysis. According to the lag order selection criteria, we choose four lags for UK and two lags for the other countries as the number of lags that included in the VECM.

According to the quasi-identity of the shocks ε_2 and $\tilde{\varepsilon}_1$ under the short-run and long-run restrictions, Figure 2, 3 show that there is a positive correlation between them for these two measures for all countries. The correlation coefficients are 0.74 (France), 0.44 (UK), 0.44 (Italy), 0.96 (Spain) and 0.86 (Netherlands) as calculated by the simple measure, respectively. And for the adjusted measure of *TFP*, the results are higher compare to the former, which are 0.84 (France), 0.46 (UK), 0.65 (Italy), 0.98 (Spain) and 0.87 (Netherlands). These results imply that there is a high co-linearity between two shock series in Spain, France and Netherlands.

Then we look at the impulse responses of { TFP_t , SP_t } to investigate the two orthogonalized shocks ε_2 and $\tilde{\varepsilon}_1$ further. As showed in the Figure 4, the upper panel result of each country represents the impulse responses of *TFP* and stock prices to ε_2, which does not have the short-run effect on *TFP*. And lower panels show the impulse responses to the other shock $\tilde{\varepsilon}_1$ that affects the *TFP* in the long run. In general, we can divide these five countries into three groups according to their performance.

(1) France and Netherlands are the first group. For the structural shock ε_2, it has a large short run effect on the stock prices, but then nearly a half of this effect will fade away in the next ten years. Unlike shock ε_2, there is an immediate effect of the other one $\tilde{\varepsilon}_1$ on the *TFP*, and its instantaneous effect on stock prices is smaller. These results are in line with the quasi-identity of the shocks ε_2 and $\tilde{\varepsilon}_1$, which is that these two shocks are not perfectly co-linear. The interpretation for the results is: when the agents know the new information about technology innovation, the stock market anticipates the future profits and then prices increase. Consider if the technology shock is gradually diffused, it slowly increases *TFP*, and meanwhile the economy competition will make the profits decrease and so that stock prices will be adjusted to the lower level for the remaining future profits. If the process of technology diffusion is faster, the competition will make the profits go back to the normal level quicker, and this can explain why the impulse response of stock prices to shock $\tilde{\varepsilon}_1$ is smaller on the short run.

(2) The second group contains UK and Italy. Their correlation coefficients are lower, and there is a big difference between their impulse responses to the shocks ε_2 and $\tilde{\varepsilon}_1$. The shock $\tilde{\varepsilon}_1$ affects instantaneously on the *TFP* and stock prices, and thereafter its effect is almost to be constant over the period. Nevertheless, the impulse responses also catch many movements in *TFP* and stock prices in a similar way. However, it is still not clear that how to keep a high level of stock prices (namely a high level of profits) during the long-run period if the economy is competitive.

(3) Spain belongs to the third group, which the shocks ε_2 and $\tilde{\varepsilon}_1$ are highly co-linear. The impulse responses to these two shocks are very similar. The stock prices innovation ε_2 has a permanent effect on *TFP*, and $\tilde{\varepsilon}_1$ that permanently affects *TFP* also has a substantial effect on stock prices.

The results for the adjusted measure of *TFP* are displayed in the Figure 5. The figure shows that the results of France, Netherlands and UK are very similar compare to the unadjusted measure of *TFP*, but the results from other two countries Italy and Spain are different. The result of Italy shows the responses to shock are both nearly constant over the whole period, and from Spain it indicates that the stock prices keeps increasing no matter in the short-run or long-run period.

Overall, the impulse responses for the bivariate system $\{TFP_t, SP_t\}$ in these five selected countries indicate that the stock market can receive the information about technology innovations which diffuse slowly to the economy and also affect the *TFP* in the long run period.

3.2 News shock and Comovement in trivariate systems

In this section we will investigate the trivariate system in which the variables such as output, consumption, investment or hours worked are alternatively introduced in addition to *TFP* and stock prices. The aim of this study is to check whether this type of shocks is relevant to the macroeconomic fluctuations. Here we will focus on the unadjusted measure of *TFP* to save space.

We first test the cointegration properties of these three-variable systems. Using the Johansen test we show the results with lags indicated by the selection criterion in Table 3. It can be found evidence of two cointegration relationships if consumption, investment, output or hours worked is added as the third variable in the most of trivariate systems in the 5% and 10% level. Therefore, we will treat all systems of France, UK, Netherlands and Spain having two cointegration vectors, and one cointegration relation in all three-variable systems of Italy.

For the identifications imposed in such systems, we will follow the agenda used by Beaudry and Portier (2004a): in the short run restriction the matrix *D(0)* is set to be lower triangular; in the long run restriction the (1,2) and (1,3) elements of long run matrix are equal to zero, and also set the (3,2) element of short run matrix to be zero. Then we will investigate whether the structural shocks and can generate the macroeconomic comovement and how important they are compare to the other shocks in term of the total variance of the macroeconomic variables. In order to do so, two standard approaches will be used, which are impulse response function and forecast error variance decomposition (FEVD).

3.2.1 Impulse response function

Figure 6 shows the impulse responses of the third variable (output (*C*+*I*), consumption (*C*), investment (*I*) or hours worked (*H*)) to the shocks ε_2 and $\tilde{\varepsilon}_1$ for these five countries. The responses of these four variables almost perform positively to both of identified shocks. Under the short-run identification, the responses of macroeconomic variables are very small on impact, but from the medium to long term the responses are increasing to be significant except the effect on hours worked. For long-run identification, the responses of output, consumption, investment and hours of Spain and Italy to shock $\tilde{\varepsilon}_1$ are significant from zero. And hours from other three countries France, UK and Netherlands has very similar response as it did under the short-run identification, which is positively significant in the medium term but decreases to be insignificant in the long run. Nevertheless, the impulse responses indeed show that both of the identified shocks can generate the comovement of the main macro aggregates. The hours worked behaves differently from the other main macro variables and also its responses are inconsistent in these five countries.

3.2.2 Forecast Error Variance Decomposition (FEVD)

In the Table 4, the results indicate how much the identified shocks ε_2 and $\tilde{\varepsilon}_1$ account for the total variance of the main macro variables in trivariate systems. The forecast error variance decomposition is always applied to checking how important the shock is comparing to other shocks in terms of the share of variance for the dependent variable explained by this shock. For the shock ε_2, its impact effect on the main macro variables is zero, but it is increasing gradually in the medium and long-run term. By contrast, the explanation power of shock $\tilde{\varepsilon}_1$ increases steadily as time goes by, and it contributes almost of the variance of output, consumption, investment in these five countries in the long run. Only different results are obtained when hours worked is added as the third variable. A large fraction of business fluctuations can be explained by the shock $\tilde{\varepsilon}_1$ for Italy and Spain in the long run period, but for the other three countries it account for small that less than one third in the whole period. This finding is consistent with the different plots of impulse responses in these five countries. Overall, this result suggests that these two shocks ε_2 and $\tilde{\varepsilon}_1$ can explain much of the variance of macro variables, they are important to the main aggregates especially in the medium and long-run period.

3.2.3 Summary

The empirical results by employing two standard approaches seem to be supportive for the hypothesis of news view, namely the news shocks can generate the comovement of output, consumption, investment and hours. Meanwhile, both these two shocks ε_2 and $\tilde{\varepsilon}_1$ can explain a sizable fraction forecast error variance for these macro variables in the medium and long run. In addition, the finding about effect of both two shocks on the variables hours worked in the five countries is interesting. Actually the response of hours worked to a technology shock is a controversial issue in the literature. The researchers provide different empirical evidence on the correlation between technology shocks and hours worked, such as Gail (1999) proposed that the technology shocks has negative effect on hours worked based on the SVAR estimation, but Christiano, Eichenbaum and Vigfusson (2003) showed the evidence of positive correlation between them. The effect of news shocks on hours worked is small or relatively large is unsettled and we should explain them based on the stylized facts of each country. Their relationship will be the focus in future studies.

4. Conclusion

We use several time series of quarterly data from 1970 to 2006 for five industrial European countries to test for the further evidence on the hypothesis of expectation driven business cycles. Our empirical approach employs the BP's two orthogonalization schemes to identify the news shocks in both the bivariate and three-variable systems. Although the performances of these two shocks on each country are slightly different, the estimation results shows that stock market can receive the information about technology innovations which diffuse slowly to the economy and also affect the *TFP* in the long run period. Moreover, they can account for substantial fraction of the business cycle fluctuations for all the countries. Therefore, our analysis can provide a useful perspective on the generality of the issues that the business cycle phenomena generated by the news shocks rose in the US literature.

Reference

Alesina, A., E. Glaseser, et al. (2005). "Work and Leisure in the United States and Europe: Why So Different?" National Bureau of Economic Research Working Paper No.11278.

Beaudry, P. and B., Lucke (2008). "Letting Different Views about Business Cycles Complete." Manuscript.

Beautry, P., and F. Portier (2004a, 2006). "News, Stock Prices and Economic Fluctuations." National Bureau of Economic Research Working Paper, American Economic Review 96: 1293-1307.

Beautry, P. and F. Portier (2004b). "When Can Changes in Expectations Cause Business Cycle Fluctuations in Neo-Classical Settings?" National Bureau of Economic Research Working Paper No.10776.

Beautry, P., and F. Portier (2005). "The 'News' View of Economic Fluctuations: Evidence from Aggregate Japanese Data and Sectoral U.S. Data " National Bureau of Economic Research Working Paper No.11496.

Blanchard, O. J. and S. Fischer. (1989). Lectures on Macroeconomics. London, the MIT Press.

Campbell, J. Y. (1994). "Inspecting the Mechanism: An Analytical Approach to the Stochastic Growth Model." Journal of Monetary Economics 33: 463-506.

Chauvet, M. (1999). "Stock Market Fluctuations and the Business Cycle." Journal of Economics and Social Measurement 25: 235-257.

Christiano, L. J., M. Eichenbaum, et al. (2003). "What Happens After A Technology Shock?" National Bureau of Economic Research Working Paper No.W9819.

Christiano, L., Motto, R. and Rostagno, M. (2007). "Monetary Policy and the Stock Market Boombust Cycle." Manuscript, Northwestern University.

Cochrane, J. (1994). "Shocks." Carnegie-Rochester Conference Series on Public Policy.

Costain, J., and Beatriz de-Blas-Perez (2006). "Productivity Shocks and the Business Cycle: Reconciling Recent VAR Evidence." mimeo.

Davis, J. (2007). "News and the Term Structure in General Equilibrium." Manuscript Northwestern University.

Demirgüç-Kunt, A. and R. Levine (1996). "Stock Market Development and Financial Intermediaries: Stylized Facts " World Bank Economic Review 10(2): 291-321.

Denhaan. W. and Kattenbrunner, G. (2008). "Anticipated Growth and Business Cycles in Matching Models." Manuscript. University of Amsterdam.

Diebold, F. X., and G.D. Rudebusch (1996). "Measuring Business Cycles: A Modern Perspective." the Review of Economics and Statistics 78: 67-77.

Doan, T., R.Litterman and C.Sims (1983). "Forecasting and Conditional Projection Using Realistic Prior Distribution." National Bureau of Economic Research Working Paper No.1202.

Fama, E. F. (1990). "Stock returns, Expected Returns and Real Activity." Journal of Finance 45: 1089-1108.

Fama, E. F. and K. R. French. (1989). "Business Conditions and Expected Returns on Stock and Bonds" Journal of Financial Economics 25: 23-49.

Fama, R. R. A. (1999). The Macroeconomics of Self-fulfilling Prophecies. London, the MIT press.

Fischer, S., and R.C.Merton (1984). "Macroeconomics and Finance: the Role of Stock Market." National Bureau of Economic Research Working Paper No.1921.

Fujiwara, I., Hirose, Y. and Shintani, M (2008). "Can News be a Major Source of Aggregate Fluctuations? A Bayesian DSGE Approach." IMES Discussion Paper 2008 -E-16 Bank of Japan.

Fujiwara, I. and H. Kang. (2006). "Expectation Shock Simulation with DYNARE." Quantitative Macroeconomics & Real Business Cycles QM&RBC Codes No.163.

Gali, J. (1999). "Technology, Employment and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?" American Economic Review 89: 249-271.

Haertel, T., and B. Lucke (2006). "New Evidence on News-Driven Business Cycle " mimeo.

Hamilton, J., and G.Lin (1996). "Stock Market Volatility and the Business Cycle." Journal of Applied Econometrics 11: 573-593.

Hamilton, J. D. (1994). Time Series Analysis, Princeton, N.J.; Chichester: Princeton University Press.

Hansen, G. D. (1985). "Invisible labor and the Business Cycle." Journal of Monetary Economics 16: 309-327.

Heijdra, B. J. and F. Van de Ploeg. (2002). The Foundations of Modern Macroeconomics. New York, Oxford University Press.

Jaimovich, N., and R.Sergio (2006). "Can News about the Future Drive the Business Cycle." mimeo.

Jaimovich, N., and Rebelo, S (2009). "Can News About the Future Drive the Business Cycle." American Economic Review (forthcoming).

King, R. G., C.I. Plosser and S.T. Rebelo (1988). "Production Growth and Business Cycles." Journal of Monetary Economics 21: 195-232.

King, R. G. and S. T. Rebelo. (2000). Resuscitating Real Business Cycles, National Bureau of Economic Research Working Paper No.W7534.

Kobayashi K., N. Tomoyuki and I. Masaru (2007). "Collateral Constraint and News-Driven Cycles." mimeo.

Love, D., and Jean-Francois Lamarche (2004). "Anticipated Technological Change and Real Business Cycles." mimeo.

Lütkepohl, H. (2004). "Recent Advances in Cointegration Analysis." mimeo.

Lütkepohl, H. and M. Krätzig (2004). Applied Time series Econometrics, Cambridge University Press.

Meyer-Gohde, A. (2007). "Solving Linear Rational Expectations Models with Lagged Expectations Quickly and Easily." SFB 649 Discussion Papers.

Moore, G. H. (1983). Business Cycle, Inflation and Forecasting Cambridge, Mass, Ballinger Publishing Co. for NBER.

Oxley, L. and M. McAleer (1993). "Econometric Issues in Macroeconomic Models with Generated Regressors." Journal of Economic Surveys 7(1): 1-40.

Pagan, A. (1984). "Econometric Issues in the Analysis of Regressions with Generated Regressors." International Economic Review 25(1): 221-247.

Pigou, A. (1926). Industrial Fluctuations. London, MacMillan.

Romer, D. (2006). Advanced Macroeconomics. New York, McGraw-Hill/Irwin.

Schmitt-Grohe, S. and M. Uribe (2008). "What's News in Business Cycle?" Manuscript, Columbia University.

Schwert, G. W. (1989). "Business Cycles, Financial Crises and Stock Volatility." National Bureau of Economic Research Working Paper No.2957.

Schwert, G. W. (1990). "Stock Returns and Real Activity: A Century of Evidence." Journal of Finance 45: 1237-1257.

Sims, C. A. (1980). "Macroeconomics and Reality." Econometrica 48: 1-48.

Uhlig, H. (1999). A Toolkit for Analyzing Nonlinear Dynamic Rational Expectations Models Easily. Oxford, Oxford University Press.

Weber, H. (2003). "Examining News Shocks." mimeo.

Whitelaw, R. (1994). "Time Variations and Covariations in the Expectation and Volatility of Stock Market Return." Journal of Finance 2: 515-541.

Appendix

Appendix A. Graphs in Part 1, Section 3

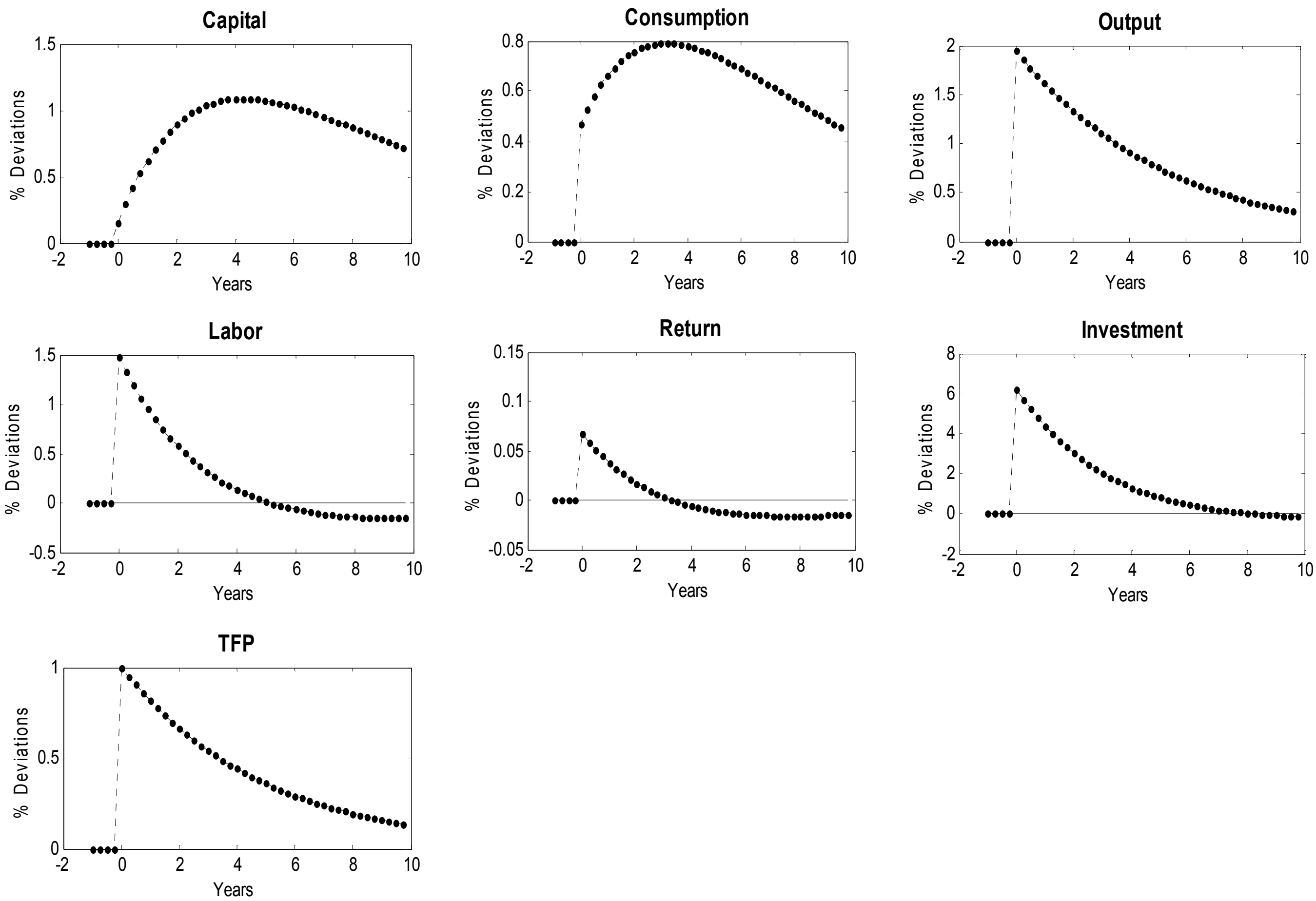


Figure 3.1 Impulse responses to the temporary shock in technology

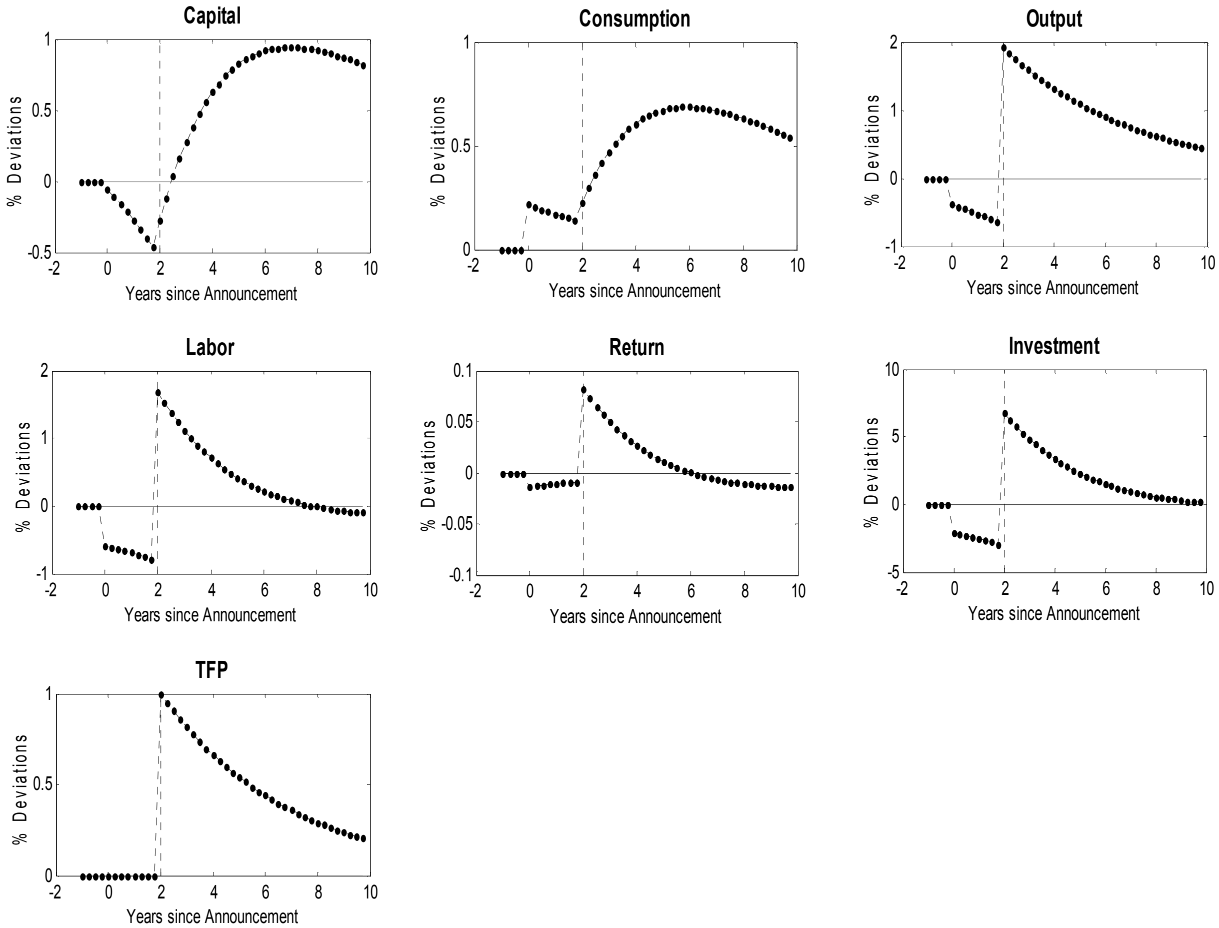


Figure 3.2 Impulse responses to a shock in technology anticipated/pre-announced 8 periods in advance

Appendix B. Short-run and long-run identifications

1. **According to the long-run restriction:**

The expression for ΔTFP_t in terms of the current and lagged values of $\{\tilde{\varepsilon}_{1,t}, \tilde{\varepsilon}_{2,t}\}$ is

$$\begin{aligned}\Delta TFP_t &= \frac{L-L^2}{1-\rho L}\eta_{1,t} + \frac{1-L}{1-\rho L}\eta_{2,t} \\ &= \frac{L-L^2}{1-\rho L}(\tilde{\tau}_{11}(0)\tilde{\varepsilon}_{1,t} + \tilde{\tau}_{12}(0)\tilde{\varepsilon}_{2,t}) + \frac{1-L}{1-\rho L}(\tilde{\tau}_{21}(0)\tilde{\varepsilon}_{1,t} + \tilde{\tau}_{22}(0)\tilde{\varepsilon}_{2,t}) \\ &= \left[\frac{L-L^2}{1-\rho L}\tilde{\tau}_{11}(0) + \frac{1-L}{1-\rho L}\tilde{\tau}_{21}(0)\right]\tilde{\varepsilon}_{1,t} + \left[\frac{L-L^2}{1-\rho L}\tilde{\tau}_{12}(0) + \frac{1-L}{1-\rho L}\tilde{\tau}_{22}(0)\right]\tilde{\varepsilon}_{2,t}\end{aligned} \tag{B.1}$$

The restriction that the $\{\tilde{\varepsilon}_{2,t}\}$ sequence has no long-run effect on TFP_t, so we have:

$$\tilde{\tau}_{12}(0) = 0 \tag{B.2}$$

And also the three other conditions:

$$\begin{cases} Var(\eta_{1,t}) = \tilde{\tau}_{11}(0)^2 + \tilde{\tau}_{12}(0)^2 = 1 \\ Var(\eta_{2,t}) = \tilde{\tau}_{21}(0)^2 + \tilde{\tau}_{22}(0)^2 = 1 \\ Cov(\eta_{1,t}, \eta_{2,t}) = \tilde{\tau}_{11}(0)\tilde{\tau}_{21}(0) + \tilde{\tau}_{12}(0)\tilde{\tau}_{22}(0) = 0 \end{cases} \tag{B.3}$$

Then the other three values of $\tilde{\tau}_{11}, \tilde{\tau}_{21}$ and $\tilde{\tau}_{22}$ can be obtained.

Thus, $\eta_{1,t}$ and $\eta_{2,t}$ can be expressed as:

$$\begin{pmatrix}\eta_{1,t} \\ \eta_{2,t}\end{pmatrix} = \begin{pmatrix}1 & 0 \\ 0 & 1\end{pmatrix}\begin{pmatrix}\tilde{\varepsilon}_{1,t} \\ \tilde{\varepsilon}_{2,t}\end{pmatrix} \tag{B.4}$$

2. **According to the impact restriction:**

The process of performing the contemporaneous restriction is identical to that of the simple optimal growth model.

Assume that the orthogonal innovations can be expressed by:

$$\boldsymbol{\eta}_t = P\boldsymbol{\varepsilon}_t \quad \text{or} \quad \boldsymbol{\varepsilon}_t = P^{-1}\boldsymbol{\eta}_t \tag{B.5}$$

where $P(=\begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix})$ is the Choleski factor of the covariance matrix $\sum_{\varepsilon}$ such that $P^{-1}(P^{-1})' = \sum_{\varepsilon}$.

Then, $$\Gamma(L) = \begin{pmatrix} \dfrac{L-L^2}{1-\rho L} & \dfrac{1-L}{1-\rho L} \\ \dfrac{(1-L)(L-1)}{(1-\gamma L)(1-\rho L)} & \dfrac{(1-L)(1-\rho(1-\gamma L)-\gamma)}{(1-\gamma L)(1-\rho L)} \end{pmatrix} P^{-1} \tag{B.6}$$

Given the restriction that the second disturbance ε_2 has no contemporaneous impact on *TFP*, namely that the 1, 2 element of Γ_0 be equal to zero, so we have:

$$p_{11} = 0 \tag{B.7}$$

Then the matrix P can be expressed as $\begin{pmatrix} 0 & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$, and $P^{-1} = \dfrac{-1}{p_{12}p_{21}}\begin{pmatrix} p_{22} & -p_{12} \\ -p_{21} & 0 \end{pmatrix}$.

Also by assumption that $P^{-1}(P^{-1})' = \sum_{\varepsilon}$, and $\sum_{\varepsilon}$ is identity matrix, so we can obtain the following equation and get the three other values.

$$\frac{1}{p_{12}^2 p_{21}^2}\begin{pmatrix} p_{22} & -p_{12} \\ -p_{21} & 0 \end{pmatrix}\begin{pmatrix} p_{22} & -p_{21} \\ -p_{12} & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \tag{B.8}$$

Thus, $\eta_{1,t}$ and $\eta_{2,t}$ can be expressed as:

$$\begin{pmatrix} \eta_{1,t} \\ \eta_{2,t} \end{pmatrix} = P^{-1}\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \tag{B.9}$$

Appendix C. Tables and Graphs in Part 1, Section 4

Table 4.1 Unit root test

	Levels		First difference	
	ADF	KPSS	ADF	KPSS
TFP	-0.606	1.871	-6.302	0.371
SP	-0.510	0.787	-10.022	0.241

Note: ADF is the augmented Dickey-Fuller statistic; KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test statistic. ADF critical value at 5% level is -2.875 and KPSS critical value at 5% level is 0.463.

Table 4.2 Johansen trace test

Hypothesis	Test statistics	Critical value (90%)	Critical value (95%)	Critical value (99%)	p-value
r=0	24.12	17.98	20.16	24.69	0.0124
r=1	0.94	7.6	9.14	12.53	0.9432

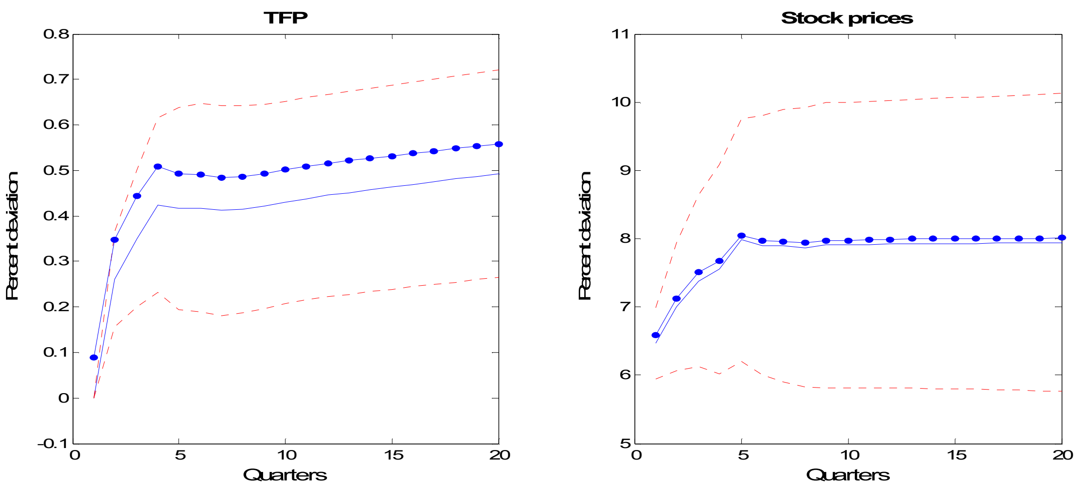


Figure 4.1 Impulse responses to shock ε_2 and $\tilde{\varepsilon}_1$ in the (*TFP*, *SP*) VECM.

Notes: The bold line represents the point estimate of the responses to a unit ε_2 shock (the shock that does not have instantaneous impact of TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification).The red dashed lines indicate the 90% confidence intervals.

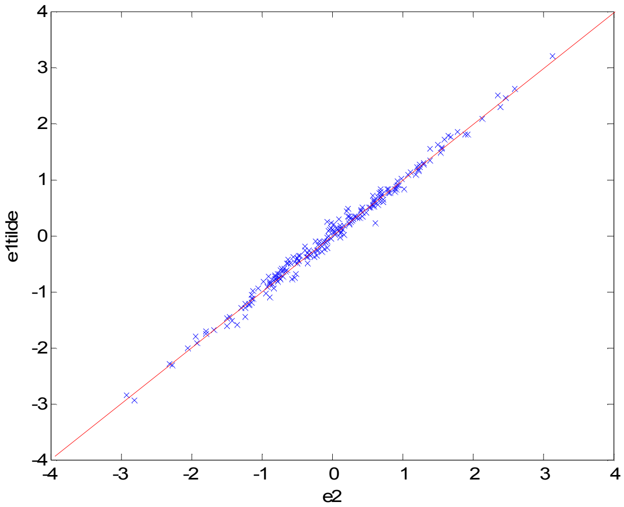


Figure 4.2 ε_2 **against** $\tilde{\varepsilon}_1$ **in the (*TFP*, *SP*) VECM**

Notes: The straight line is the 45°line.

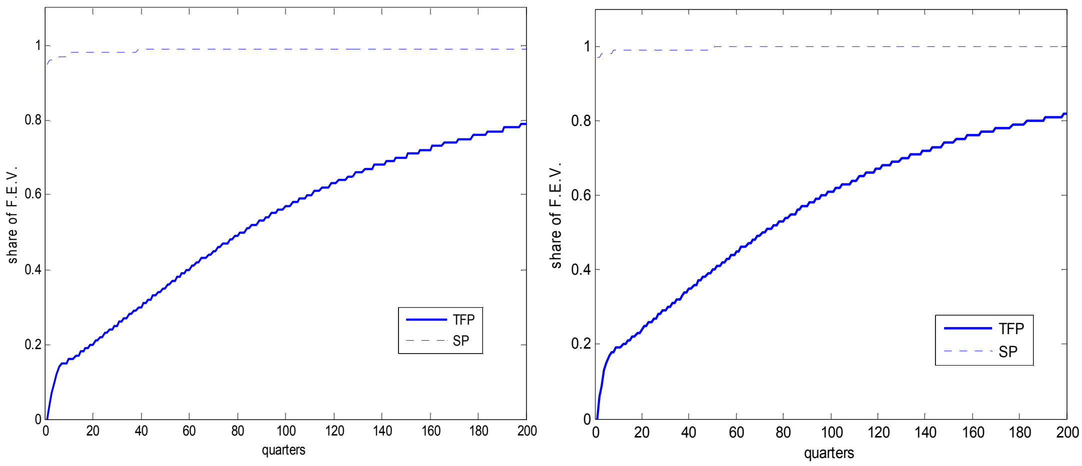


Figure 4.3 Share of the Forecast Error Variance Attributed to the shock ε_2 **and** $\tilde{\varepsilon}_1$ **in the (*TFP*, *SP*) VECM**

Notes: This figure shows the share of TFP and SP forecast error variance attributed to ε_2 *(left panel) and to* $\tilde{\varepsilon}_1$ *(right panel).*

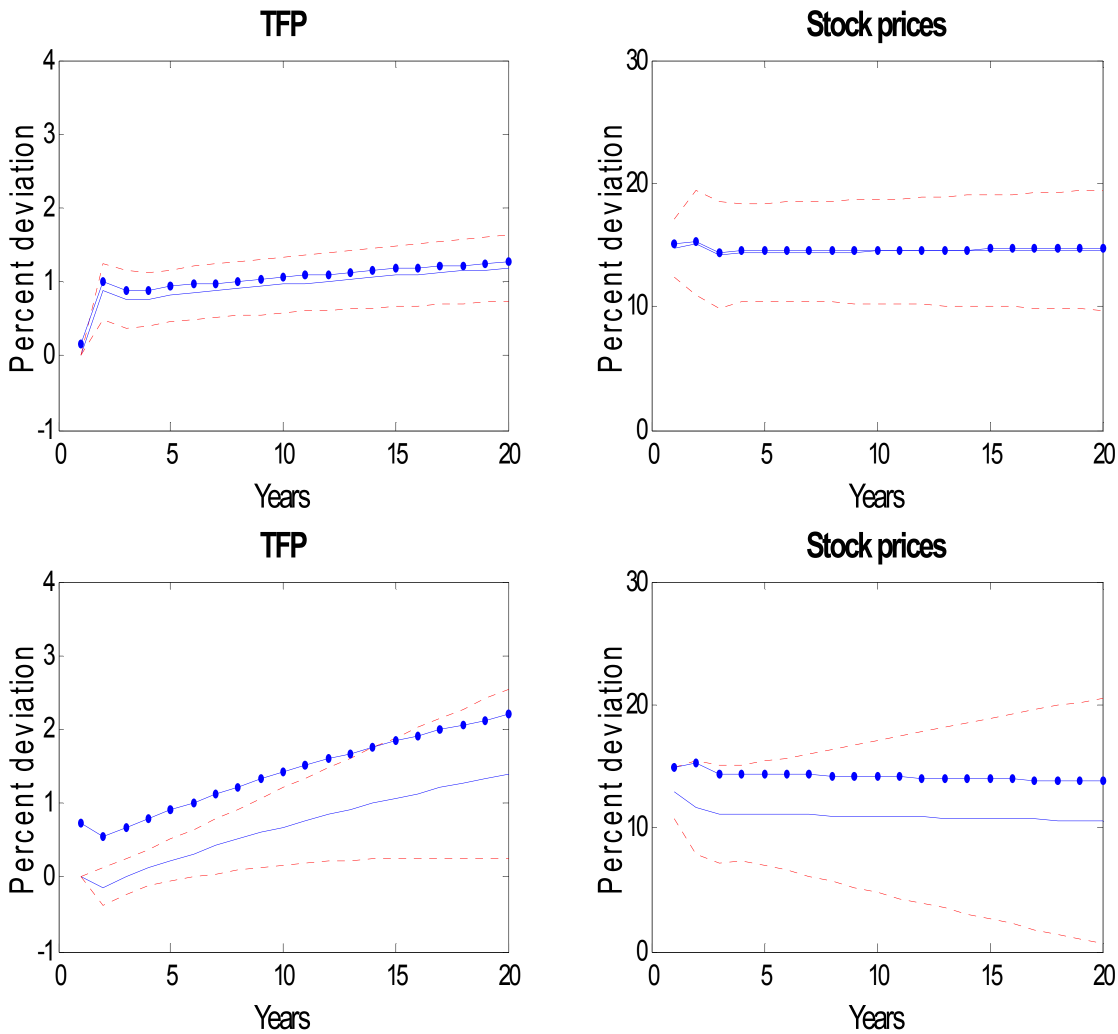


Figure 4.4 Impulse responses to shock ε_2 and $\tilde{\varepsilon}_1$ in the (TFP, SP) VECM: 1948-2000.

Notes: Using annual observations (1948-2000), without Adjusting TFP for Capacity Utilization (top panels) or with TFP Adjustment (bottom panels). The bold line represents the point estimate of the responses to a unit ε_2 shock (the shock that does not have instantaneous impact of TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification).

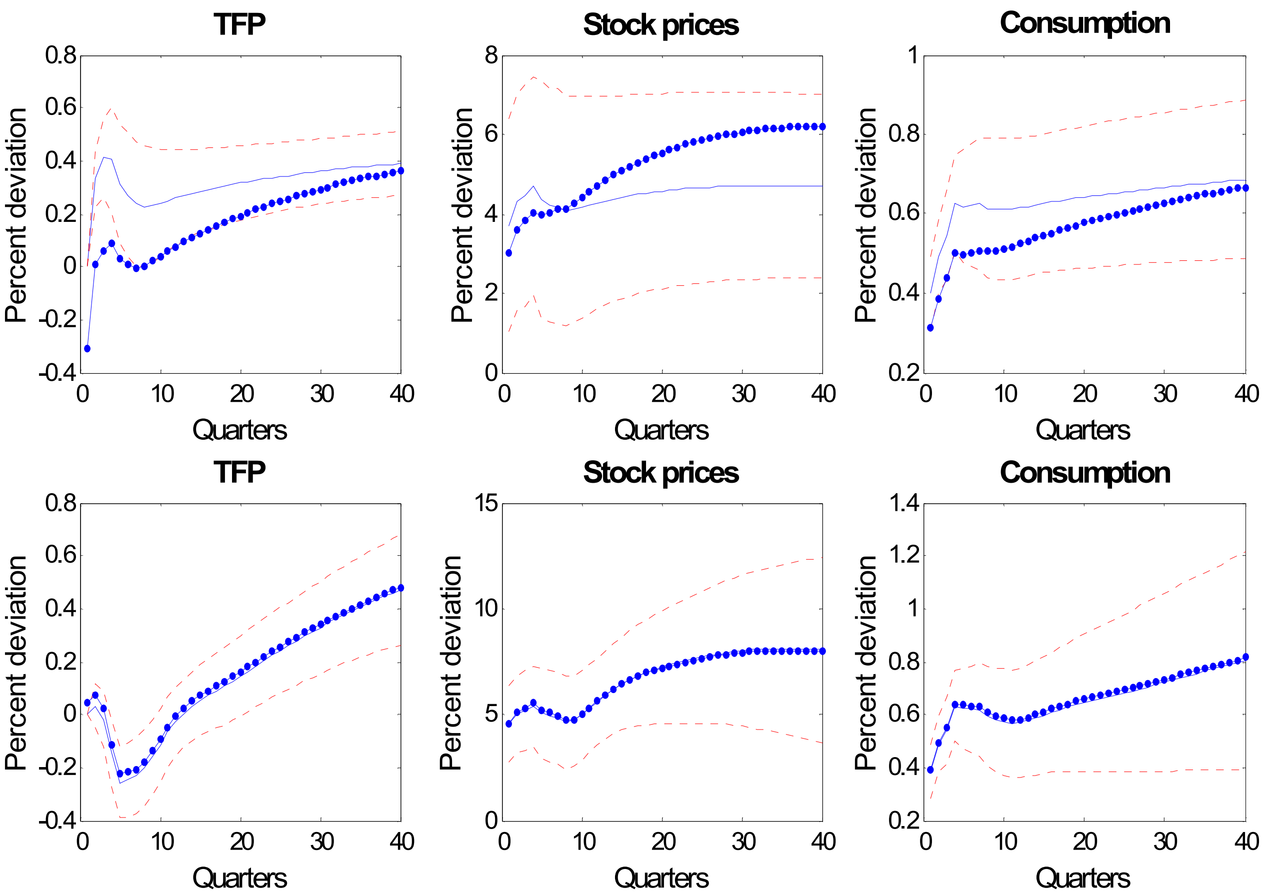


Figure 4.5 Impulse responses to shock ε_2 and $\tilde{\varepsilon}_1$ in the (TFP, SP, C) VECM

Notes: The bold line represents the point estimate of the responses to a unit ε_2 shock (the shock that does not have instantaneous impact of TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification).The red dashed lines indicate the 90% confidence intervals.

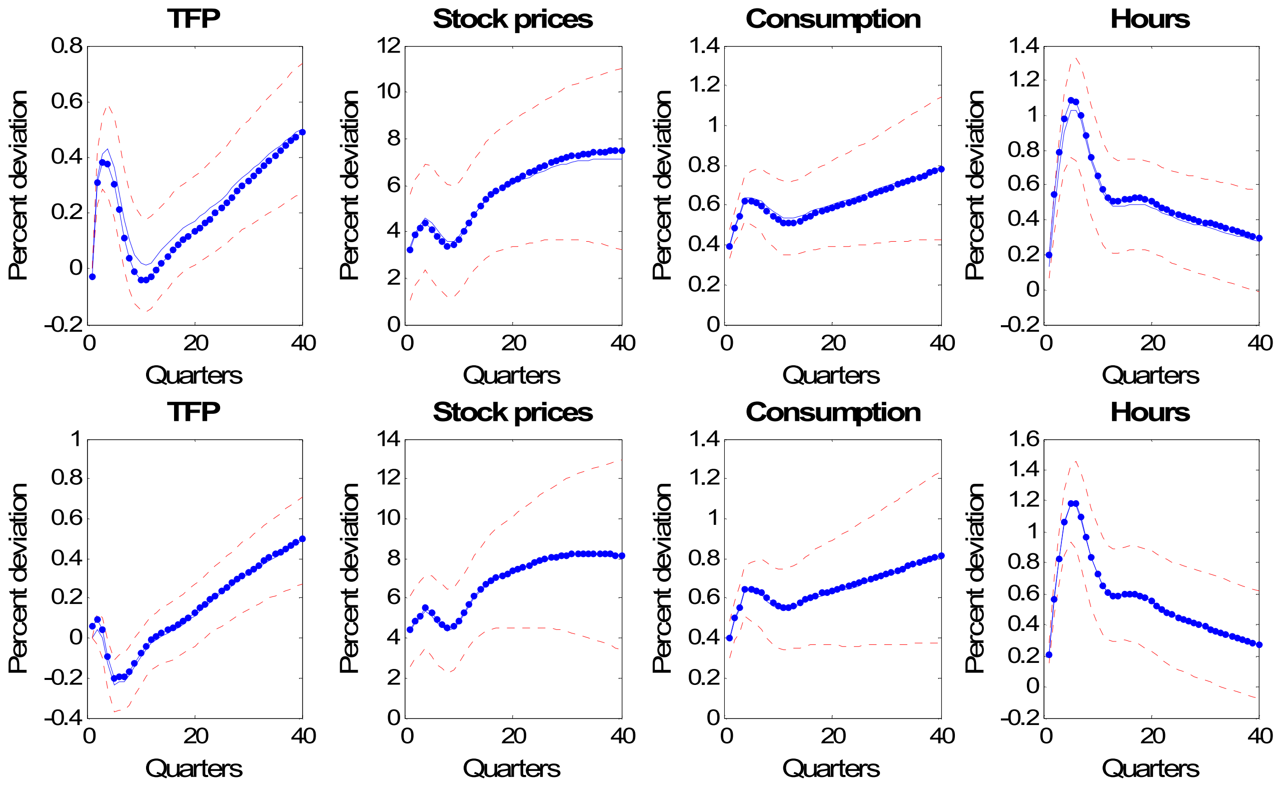


Figure 4.6 Impulse responses to shock ε_2 and $\tilde{\varepsilon}_1$ in the (TFP, SP, C, H) VECM

Notes: The responses without adjusting TFP for Capacity Utilization are in the upper panels; the responses with TFP Adjustment are in the lower panels. The bold line represents the point estimate of the responses to a unit ε_2 shock (the shock that does not have instantaneous impact of TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification).The red dashed lines indicate the 90% confidence intervals.

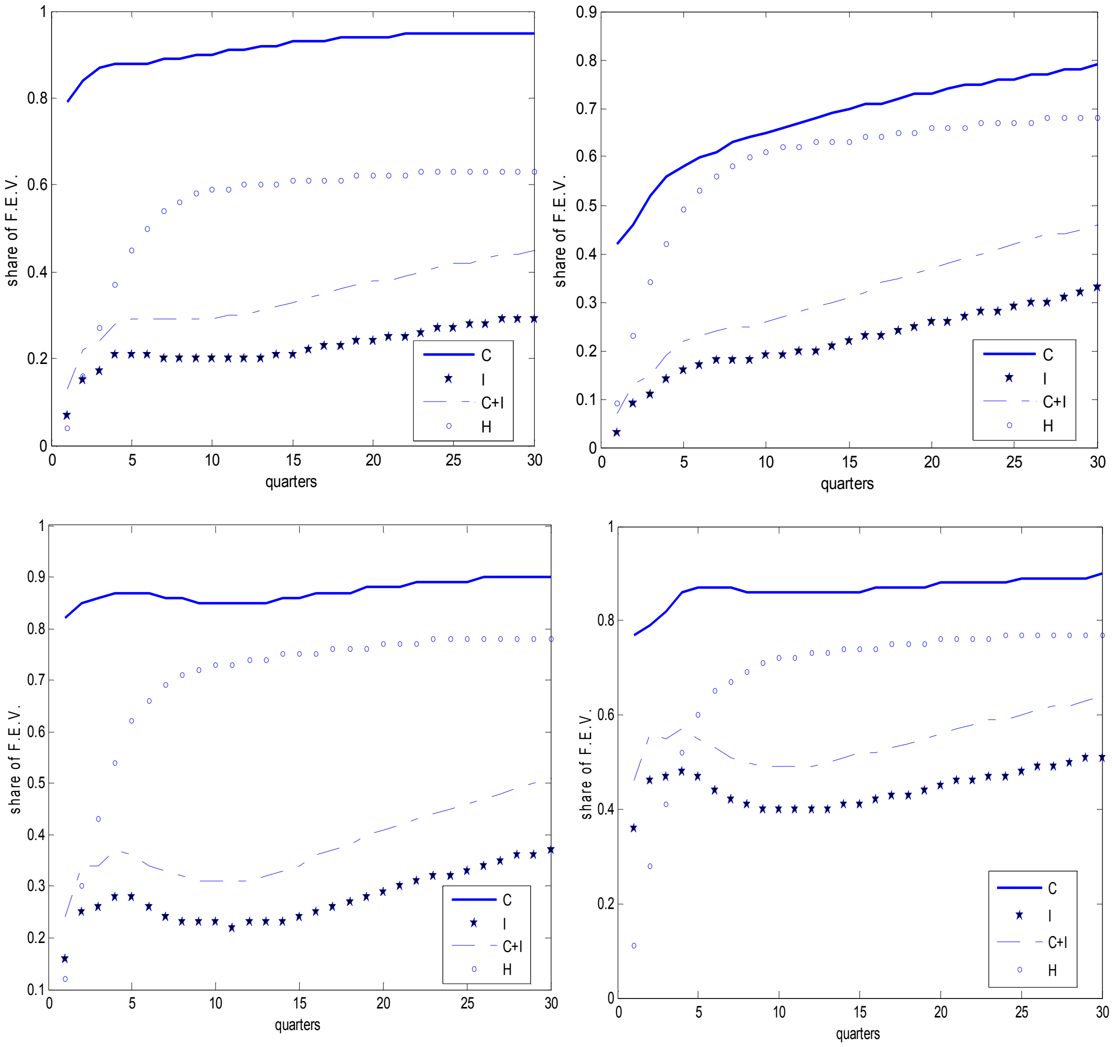


Figure 4.7 Share of the forecast error variance (F.E.V.) of consumption (C), investment (I), output (C+I) and hours (H) attributed to ε_2 (left panels) and $\widetilde{\varepsilon}_1$ (right panels) in VECMs, without Adjusting TFP for Capacity Utilization (upper panels) or with TFP Adjustment (lower panels)

Notes: The left panels show the share of the consumption and investment that is attributed to ε_2 *shock in the (TFP, SP, C, I) VECM, of output (C+I) in the (TFP, SP, C, C+ I) VECM, and of hours (H) in the (TFP, SP, C, H) VECM. The right panels show the same information in the case of shock* $\widetilde{\varepsilon}_1$.

Appendix D. Tables and Graphs in Part 1, Section 5

Table 5.1 Forecast error variance decomposition attributed to $\tilde{\varepsilon}_2$ in {TFP, SP}

h	1	4	8	12	24	36
TFP	0.99	0.84	0.77	0.74	0.67	0.61
SP	0.02	0.01	0.01	0.01	0	0

Table 5.2 Forecast error variance decomposition attributed to $\tilde{\varepsilon}_2$ in {TFP, SP, C}

h	1	4	8	12	24	36
TFP	0.17	0.26	0.31	0.33	0.34	0.28
SP	0.78	0.7	0.64	0.56	0.35	0.18
C	0	0.02	0.04	0.04	0.03	0.02

Table 5.3 Forecast error variance decomposition attributed to $\tilde{\varepsilon}_2$

h	1	4	8	12	24	36
TFP	0.16	0.24	0.27	0.29	0.31	0.29
SP	0.82	0.73	0.66	0.59	0.41	0.21
C	0	002	0.03	0.03	0.02	0.02
I	0.05	0.1	0.1	0.09	0.08	0.07
H	0	0.02	0.04	0.04	0.03	0.01
C+I	0.04	0.08	0.09	0.09	0.07	0.05

Notes: The table displays the share of the forecast error variance of TFP, stock prices, consumption and investment that is attributable to in the (TFP,SP,C,I) VECM, of output (C+I) in the (TFP,SP,C,C+I) VECM, and of hours (H) in the (TFP,SP,C,H) VECM.

Table 5.4 Results of Specification tests

Unit Root Tests				
	Levels		First difference	
	ADF	KPSS	ADF	KPSS
C	-1.455	5.3182	-6.1076	0.3537
I	-1.0374	4.9463	-7.565	0.0275
H	-1.8142	2.7958	-7.6441	0.078
$C+I$	-0.4973	1.837	-9.5215	0.0256
$\tau_{\varepsilon,t}$	-2.471	2.0788	-14.4411	0.0444
$\mu_{2,t}$	-14.27	0.2636	-	-

Johansen Cointegration test			
Hypothesis	Test Statistics	Critical value (95%)	p-value
$\{C, C+I\}$			
$r=0$	124.71	35.07	0.0000
$r=1$	21.76	20.16	0.0290
$r=2$	7.96	9.14	0.0855
$\{C, I\}$			
$r=0$	57.08	35.07	0.0000
$r=1$	22.98	20.16	0.0188
$r=2$	5.78	9.14	0.2157
$\{C, H\}$			
$r=0$	97.97	35.07	0.0000
$r=1$	23.18	20.16	0.0175
$r=2$	6.71	9.14	0.1466

Notes: ADF is the augmented Dickey-Fuller statistic; KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test statistic. ADF critical value at 5% level is -2.875 and KPSS critical value at 5% level is 0.463.

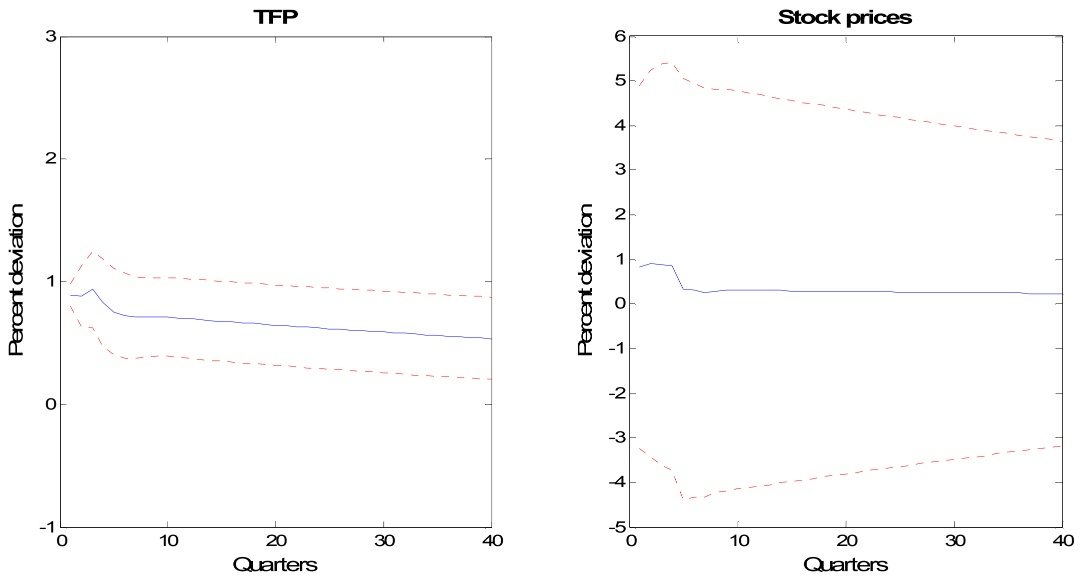


Figure 5.1 Impulse responses to the shock $\tilde{\varepsilon}_2$ in (TFP, SP)

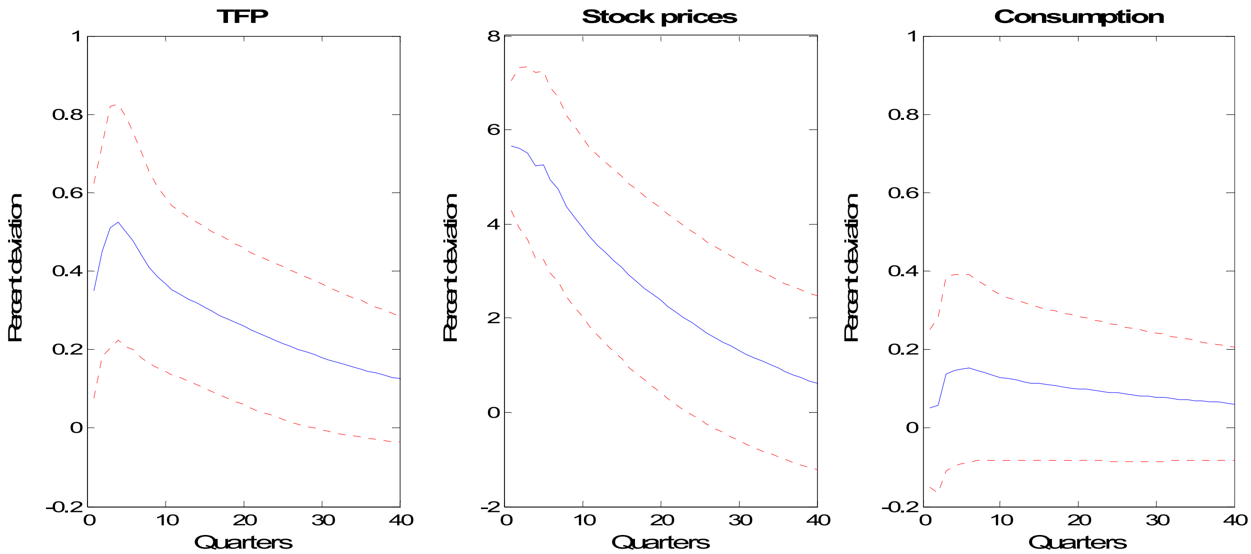


Figure 5.2 Impulse responses to the shock $\tilde{\varepsilon}_2$ in (TFP, SP, C)

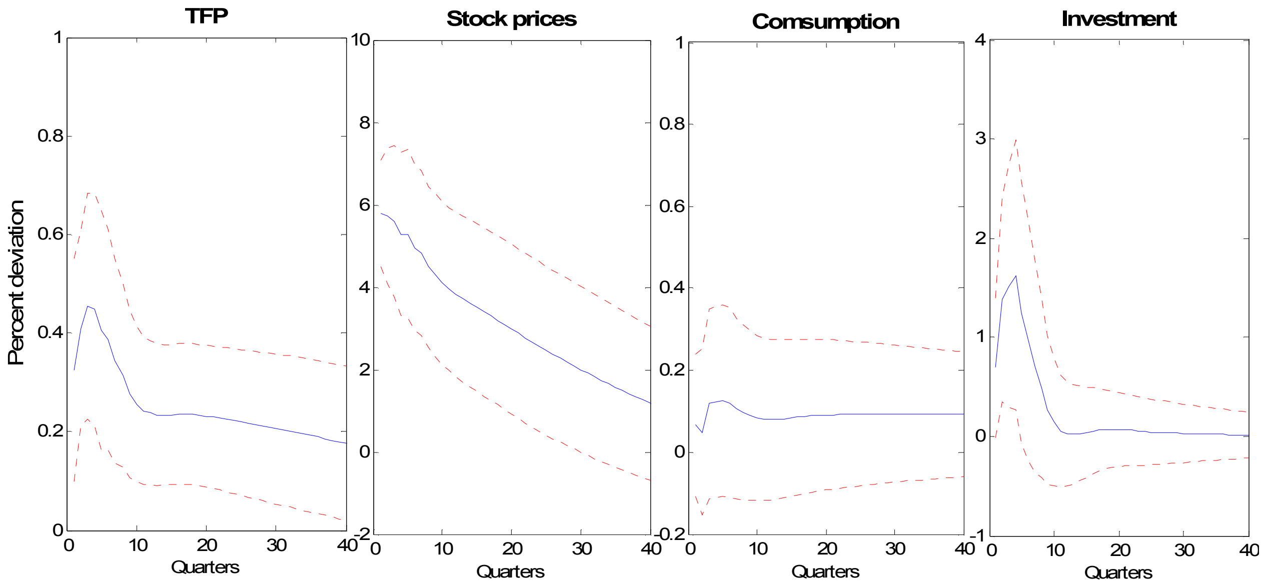


Figure 5.3 Impulse responses to the shock $\tilde{\varepsilon}_2$ in (TFP, SP, C, I)

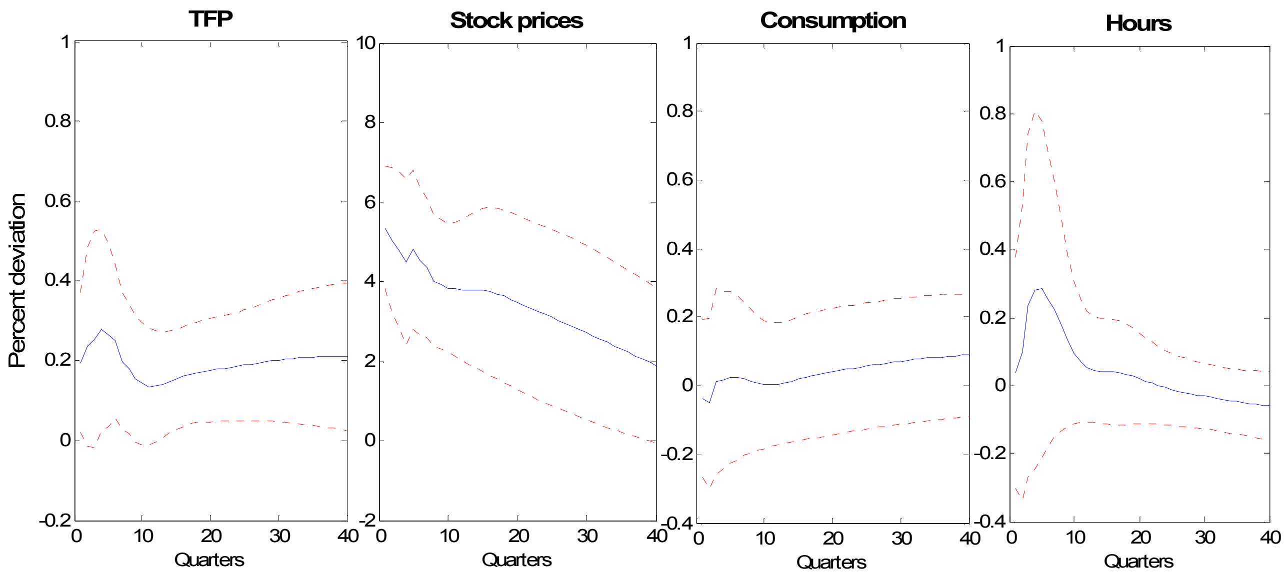


Figure 5.4 Impulse responses to the shock $\tilde{\varepsilon}_2$ in (TFP, SP, C, H)

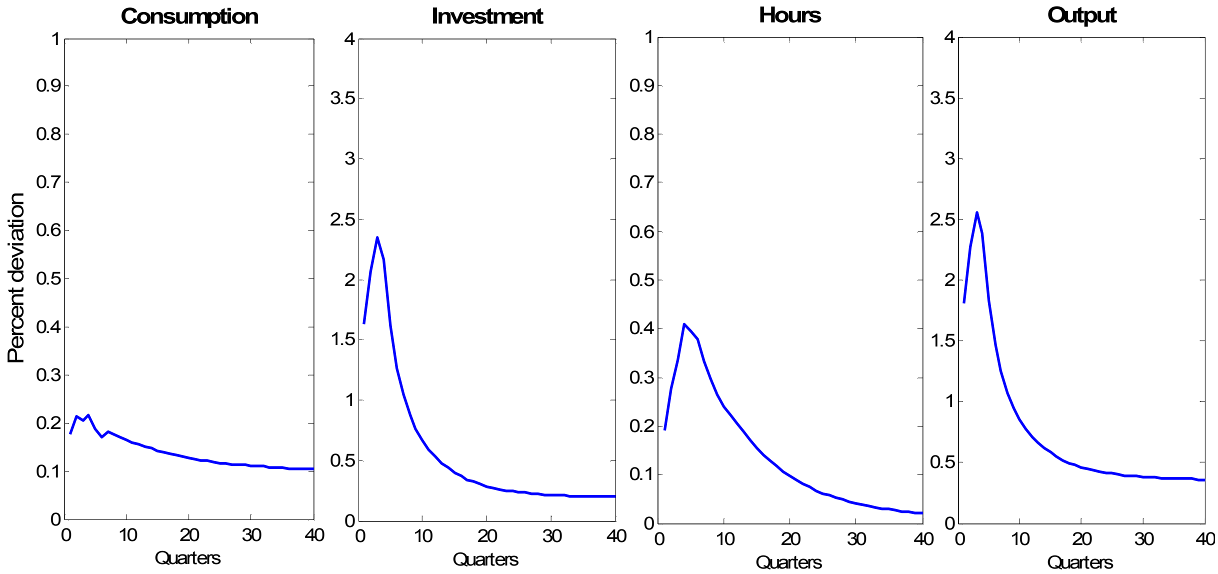


Figure 5.5 Impulse responses to the shock $\tilde{\varepsilon}_2$ in (ΔTFP, ΔSP)

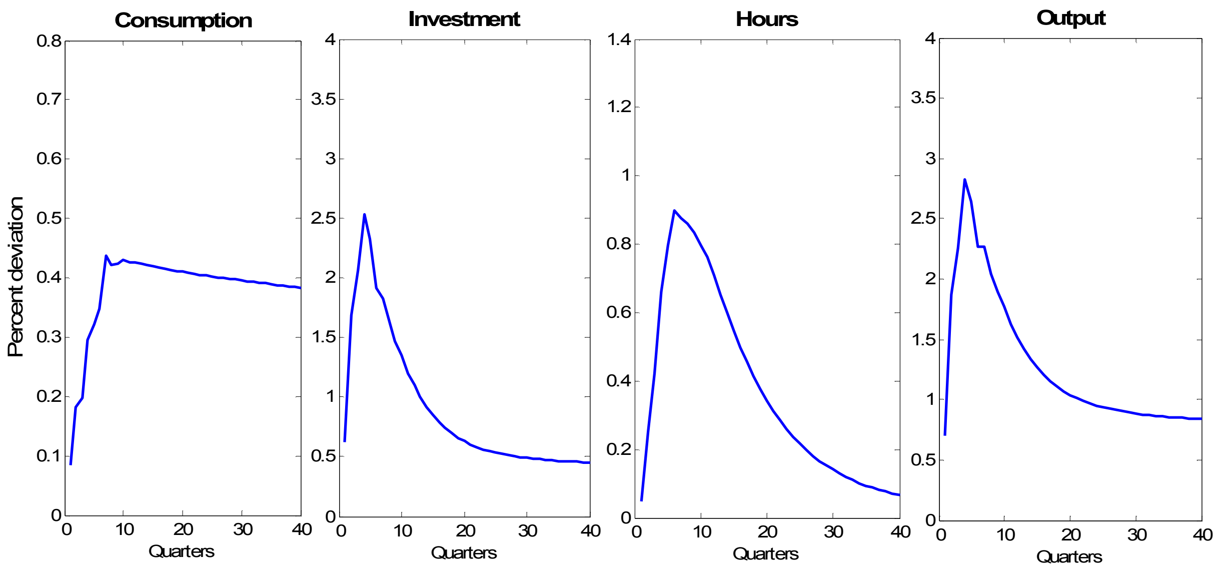


Figure 5.6 Impulse responses to the shock $\tilde{\varepsilon}_1$ in (ΔTFP, ΔSP)

Appendix E. Data appendix in Part 2

1. GDP (Gross domestic production), GDP deflator:

Description: index number (base 2000=100);

Sample period: 1970Q1-2006Q4;

Source: IFS.

2. Hours:

Description: index number (base 2000=100), average weekly hours worked of all employees;

Calculation: Hours worked per employee in total economy/52*Total Employment;

Sample period: 1970Q1-2006Q4;

Source: OECD Economic Outlook.

3. Labor's share:

Description: average number of labor's income share, France: 70%, UK: 69%, Italy: 65%, Spain: 69%, Netherlands: 63%.

Source: Groningen Growth and Development Centre, Industry growth accounting

Database for France, UK and Netherlands; Spain: obtained from Conesa and Kehoe (2004); Italy: obtained from Baghli, Cahn and Villetelle (2006).

4. Capital stock:

Description: index number (base 2000=100), capital stock in total economy;

Transition: interpolated with constant within-year quarterly growth rates;

Sample period: 1970-2007;

Source: OECD Economic Outlook.

5. Stock price index:

Description: SBF250 index for France, FTSE100 index for UK, Milan Comit General Share Price Index for Italy, Madrid General index for Spain, and Amsterdam all share index for Netherlands;

Sample period: 1970Q1-2006Q4 (end of the period);

Source: Datastream Advance.

6. Consumption, Investment:

Description: private consumption expenditure, gross fixed capital formation;

Sample period: 1970Q1-2006Q4;

Source: OECD Economic Outlook.

7. Population:

Description: thousands, population aged between 15 and 64;

Transition: interpolated with constant within-year quarterly growth rates;

Sample period: 1970-2007.

Source: AMECO.

8. Capacity Utilization:

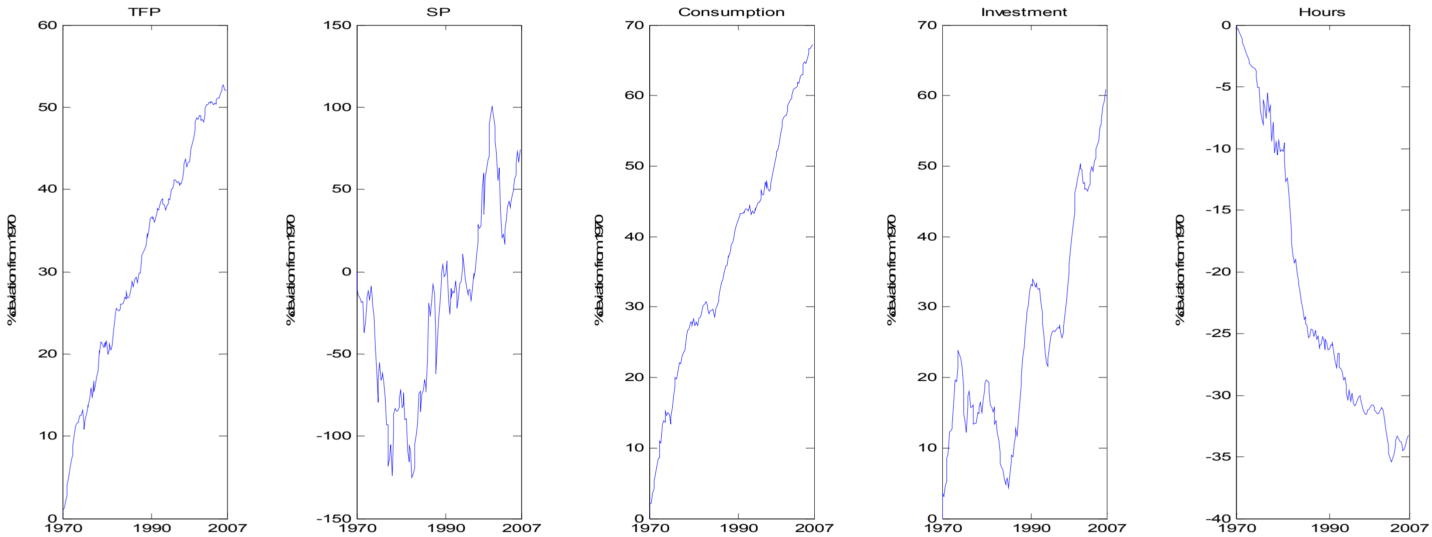
Description: percentage; France, UK, Italy and Netherlands: capacity utilization rate in total industry, Spain: utilization of productivity capacity.

Sample period: France, UK, Spain, and Italy: 1970Q1-2006Q4; Netherlands: 1971Q4-2006Q4.

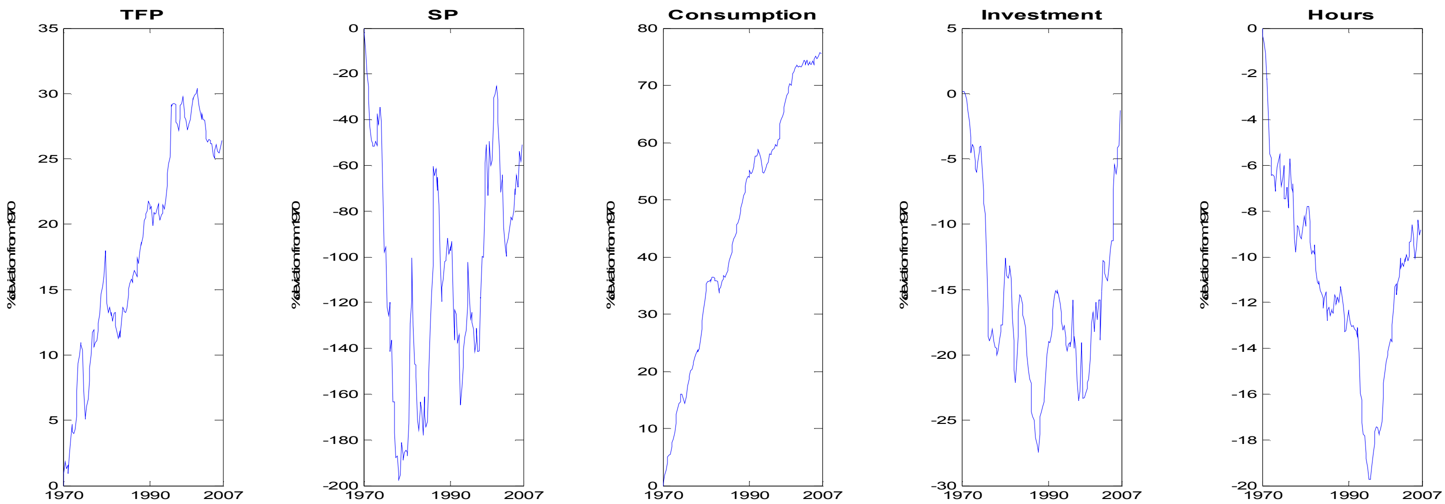
Source: European Commission for France, UK, Italy and Netherlands, Spain: from ministerio de economia Y Hacienda.

Appendix F. Graphs in Part 2, Section 2

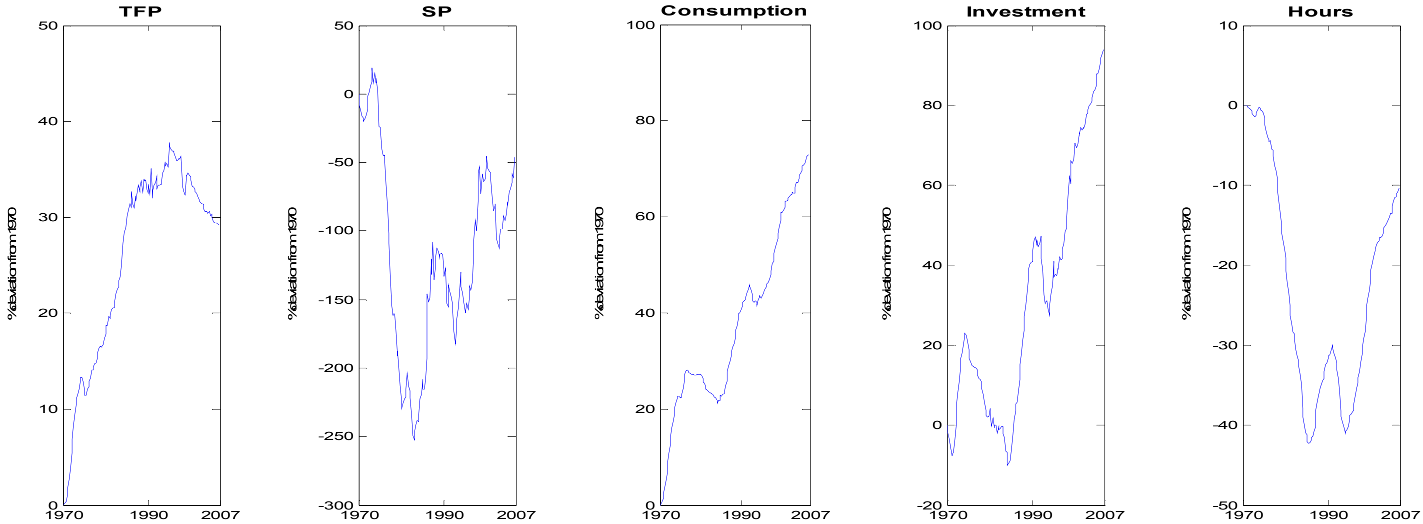
France



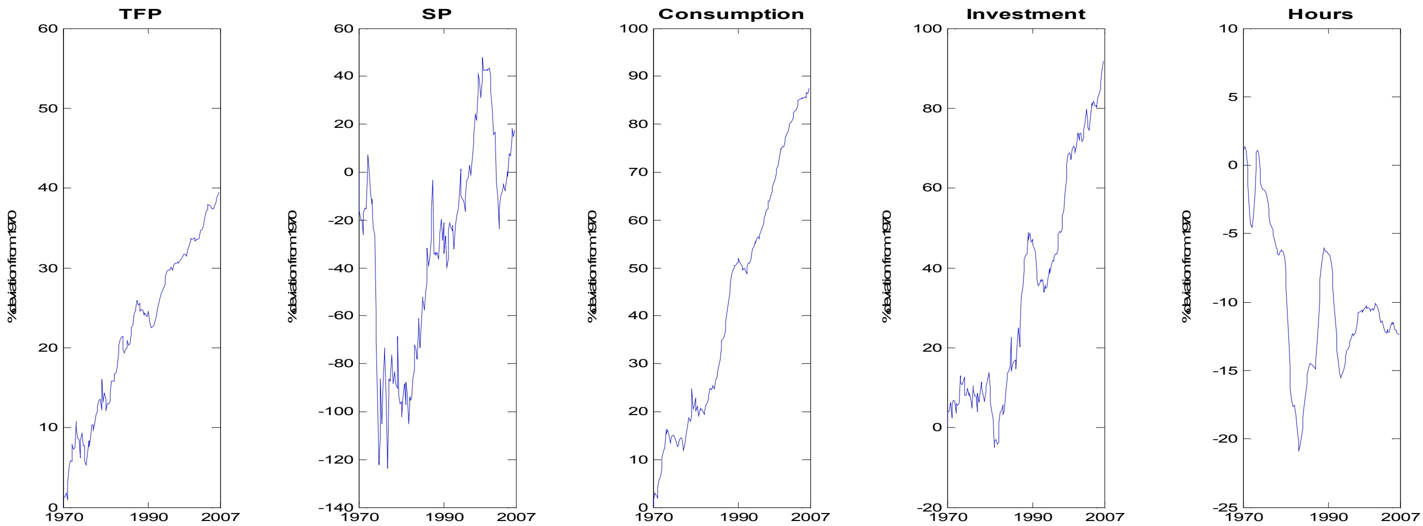
Italy



Spain


TFP
SP
Consumption
Investment
Hours
% deviation from 1970
1970
1990
2007

UK


TFP
SP
Consumption
Investment
Hours
% deviation from 1970
1970
1990
2007

Netherlands

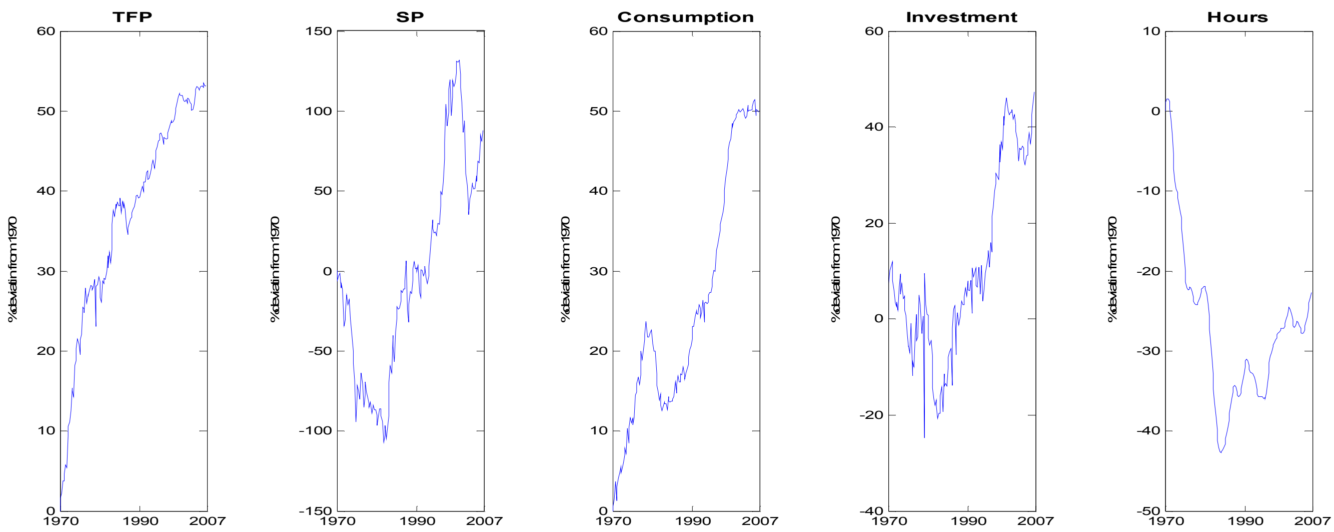


Figure 1. Data series of five countries

Notes:Those series are percentage deviations from 1970:Q1 level. All series have been divided by the 15 to 64 years old population of each countries, respectively.

Appendix G. Tables and Graphs in Part 2, Section 3

Table1. Unit root test

	TFP		*SP*	
	Levels	First difference	Levels	First difference
France	-1.993	-4.824	-0.819	-6.111
UK	-1.451	-5.580	-1.162	-5.064
Italy	-1.754	-6.253	-2.326	-5.565
Spain	-1.905	-4.314	-1.458	-4.742
Netherlands	-2.647	-6.806	-0.333	-5.711

Note: ADF critical value at 5% level is -2.875.

Table2. Johansen trace test

	Hypothesis r=0		Hypothesis r=1	
	Test statistics	p-value	Test statistics	p-value
France	46.23	0.0000	7.2	0.1192
UK	22.49	0.0224	5.96	0.2003
Italy	18.21*	0.0933	4.64	0.3363
Spain	34.9	0.0001	3.78	0.4575
Netherlands	42.29	0.0000	6.00	0.1973

*Note: 95% critical value for r=0 is 20.16, and for r=1 is 9.14. * denotes that it's rejected at the 10% level, 90% critical value is 17.98.*

Table3. Johansen trace test in trivariate systems

France:

Variables	Lag Length (1st Diff.)	Hypothesis *r*=0		Hypothesis *r*=1		Hypothesis *r*=2	
		Test statistics	p-value	Test statistics	p-value	Test statistics	p-value
TFP, SP, C	1	79.02	0.0000	14.93	0.2354	4.56	0.3465
TFP, SP, I	2	52.51	0.0002	21.98	0.0269	7.8	0.0916
TFP, SP, H	2	59.92	0.0000	23.15	0.0177	6.96	0.1321
TFP, SP, Output	0	34.9	0.0001	3.78	0.4575	8.22	0.0760

Notes: 95% critical value for r=0 is 35.07, for r=1is 20.16 and for r=2 is 9.14.

Netherlands:

Variables	Lag Length (1st Diff.)	Hypothesis *r*=0		Hypothesis *r*=1		Hypothesis *r*=2	
		Test statistics	p-value	Test statistics	p-value	Test statistics	p-value
TFP, SP, C	1	74.3	0.0000	26.36	0.0053	6.8	0.1414
TFP, SP, I	1	58.75	0.0000	22.57	0.0218	6.07	0.1920
TFP, SP, H	0	91.33	0.0000	28.06	0.0027	8.52	0.0663
TFP, SP, Output	1	58.62	0.0000	23.53	0.0154	6.34	0.1718

Notes: 95% critical value for r=0 is 35.07, for r=1is 20.16 and for r=2 is 9.14.

UK:

Variables	Lag Length (1st Diff.)	Hypothesis *r*=0		Hypothesis *r*=1		Hypothesis *r*=2	
		Test statistics	p-value	Test statistics	p-value	Test statistics	p-value
TFP, SP, C	0	48.04	0.0009	22.44	0.0228	5.6	0.2323
*TFP, SP, I**	0	47.43*	0.0012	18.85*	0.0766	4.66*	0.3355
TFP, SP, H	1	51.88	0.0002	23.45	0.0159	4.55	0.3482
TFP, SP, Output	0	39.99	0.0127	20.4	0.0463	5.52	0.2398

*Notes: 95% critical value for r=0 is 35.07, for r=1is 20.16 and for r=2 is 9.14. * denotes that it's rejected at the 10% level, 90% critical value is 17.98.*

Italy:

Variables	Lag Length (1st Diff.)	Hypothesis *r*=0		Hypothesis *r*=1		Hypothesis *r*=2	
		Test statistics	p-value	Test statistics	p-value	Test statistics	p-value
TFP, SP, C	1	56.77	0.0000	14.38	0.2703	6.14	0.1862
TFP, SP, I	0	38.24	0.0211	10.42	0.6053	4.41	0.3659
TFP, SP, H	0	44.36	0.0032	15.05	0.2285	5.54	0.2378
TFP, SP, Output	0	42.68*	0.0055	18.57*	0.0836	3.52*	0.5001

*Notes: 95% critical value for r=0 is 35.07, for r=1is 20.16 and for r=2 is 9.14. * denotes that it's rejected at the 10% level, 90% critical value is 17.98.*

Spain:

Variables	Lag Length (1st Diff.)	Hypothesis *r*=0		Hypothesis *r*=1		Hypothesis *r*=2	
		Test statistics	p-value	Test statistics	p-value	Test statistics	p-value
TFP, SP, C	3	73.15	0.0020	25.48	0.0023	5.96	0.2006
TFP, SP, I	3	41.75	0.0074	20.32	0.0475	8.29	0.0736
TFP, SP, H	3	87.35	0.0000	23.67	0.0146	6.2	0.1817
TFP, SP, Output	3	66.89	0.0000	21.95	0.0271	4.95	0.2988

Notes: 95% critical value for r=0 is 35.07, for r=1is 20.16 and for r=2 is 9.14.

Table4. Forecast Error Variance decompositions

France:

Forecast Horizons	Output		Consumption		Investment		Hours	
	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$
1	0.01	0.23	0.02	0.39	0.01	0.21	0.00	0.09
4	0.11	0.38	0.09	0.51	0.12	0.40	0.05	0.04
8	0.26	0.53	0.20	0.60	0.23	0.52	0.12	0.05
16	0.48	0.70	0.36	0.71	0.37	0.62	0.22	0.08
24	0.58	0.77	0.46	0.77	0.45	0.67	0.27	0.09
40	0.62	0.84	0.56	0.85	0.52	0.74	0.31	0.08

Netherlands:

Forecast Horizons	Output		Consumption		Investment		Hours	
	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$
1	0.00	0.10	0.01	0.07	0.00	0.04	0.05	0.08
4	0.04	0.17	0.05	0.10	0.09	0.11	0.09	0.04
8	0.14	0.30	0.17	0.23	0.26	0.27	0.12	0.02
16	0.37	0.53	0.42	0.48	0.53	0.52	0.18	0.01
24	0.53	0.68	0.59	0.65	0.67	0.66	0.23	0.03
40	0.68	0.82	0.72	0.82	0.76	0.79	0.32	0.09

UK:

Forecast Horizons	Output		Consumption		Investment		Hours	
	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$
1	0.00	0.15	0.00	0.44	0.00	0.02	0.00	0.33
4	0.05	0.34	0.03	0.61	0.04	0.12	0.00	0.30
8	0.16	0.55	0.10	0.76	0.15	0.29	0.01	0.26
16	0.31	0.78	0.20	0.89	0.33	0.58	0.07	0.20
24	0.36	0.87	0.24	0.93	0.41	0.74	0.12	0.19
40	0.37	0.93	0.26	0.97	0.43	0.86	0.13	0.20

Italy:

Forecast Horizons	Output		Consumption		Investment		Hours	
	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$
1	0.00	0.52	0.00	0.14	0.00	0.50	0.00	0.05
4	0.16	0.84	0.04	0.34	0.13	0.79	0.10	0.23
8	0.34	0.95	0.07	0.45	0.31	0.93	0.36	0.54
16	0.45	0.99	0.11	0.57	0.44	0.98	0.66	0.83
24	0.47	0.99	0.13	0.64	0.47	0.99	0.76	0.91
40	0.48	1.00	0.15	0.69	0.48	0.99	0.82	0.96

Spain:

Forecast Horizons	Output		Consumption		Investment		Hours	
	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$	ε_2	$\tilde{\varepsilon}_1$
1	0.00	0.52	0.00	0.38	0.00	0.50	0.00	0.05
4	0.16	0.84	0.21	0.78	0.13	0.79	0.10	0.23
8	0.34	0.95	0.42	0.93	0.31	0.93	0.36	0.54
16	0.45	0.99	0.54	0.98	0.44	0.98	0.66	0.83
24	0.47	0.99	0.58	0.98	0.47	0.99	0.76	0.91
40	0.48	1.00	0.60	0.99	0.48	0.99	0.82	0.96

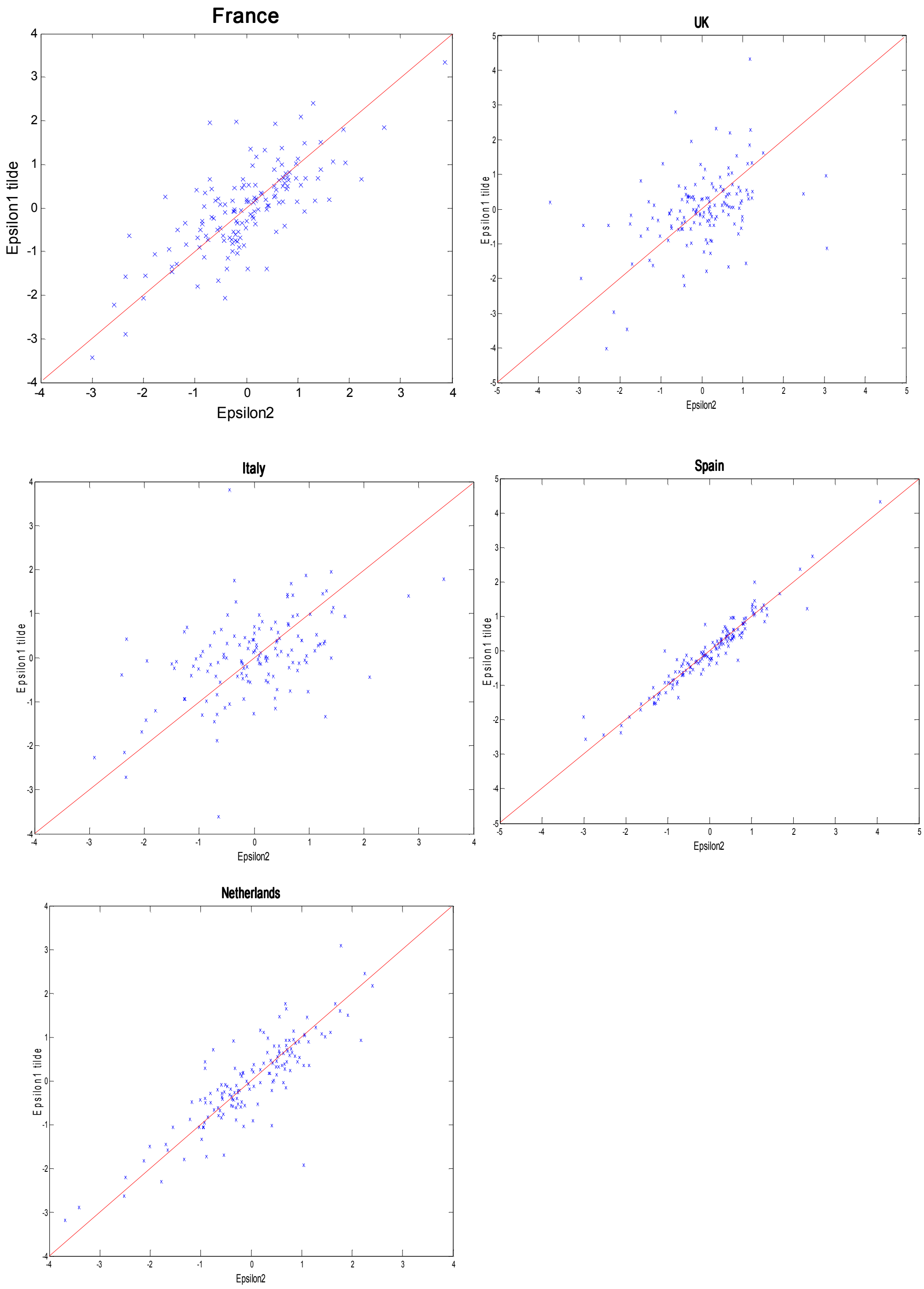


Figure2. Identified structural residuals (unadjusted measure of *TFP*)

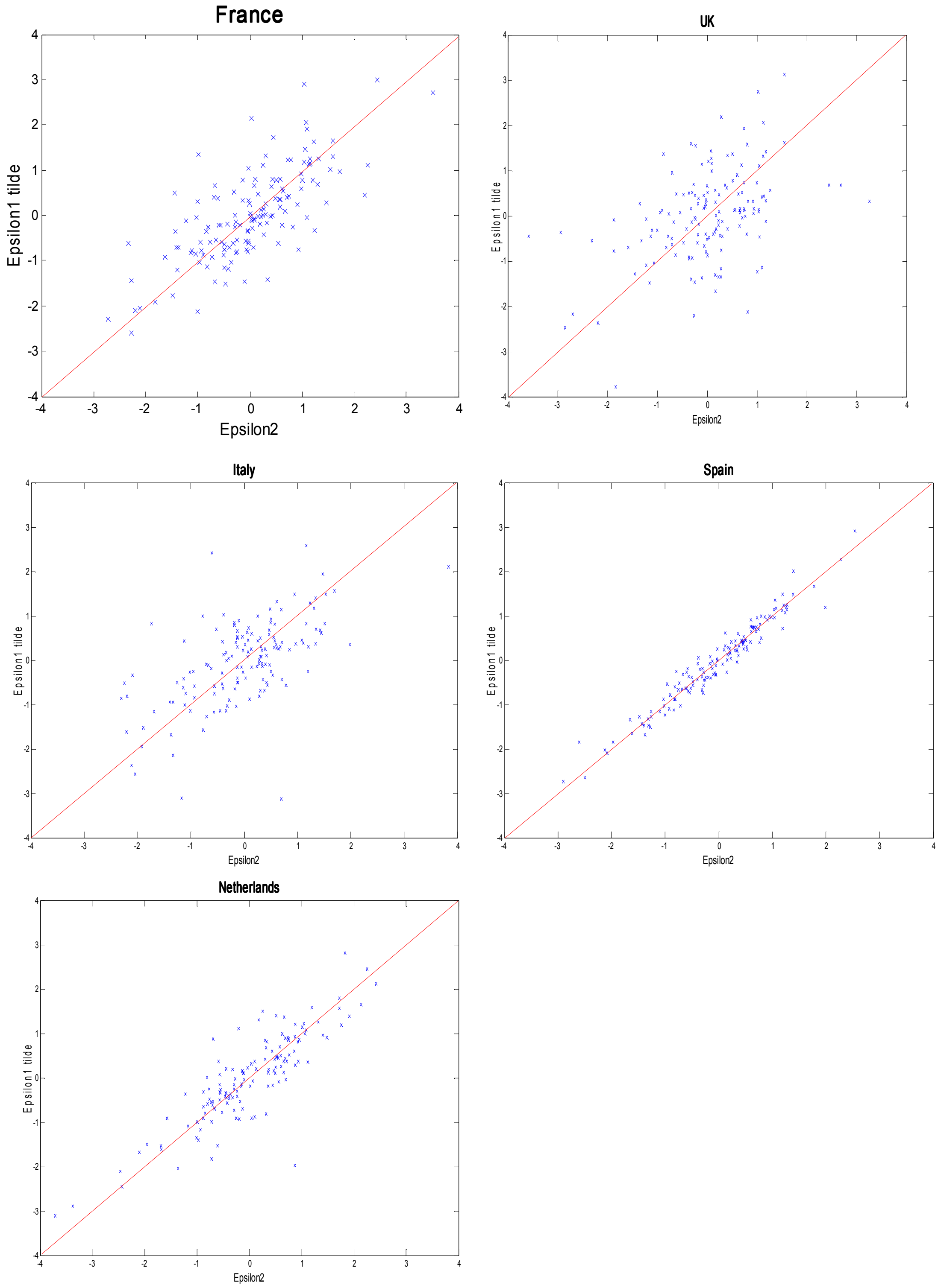
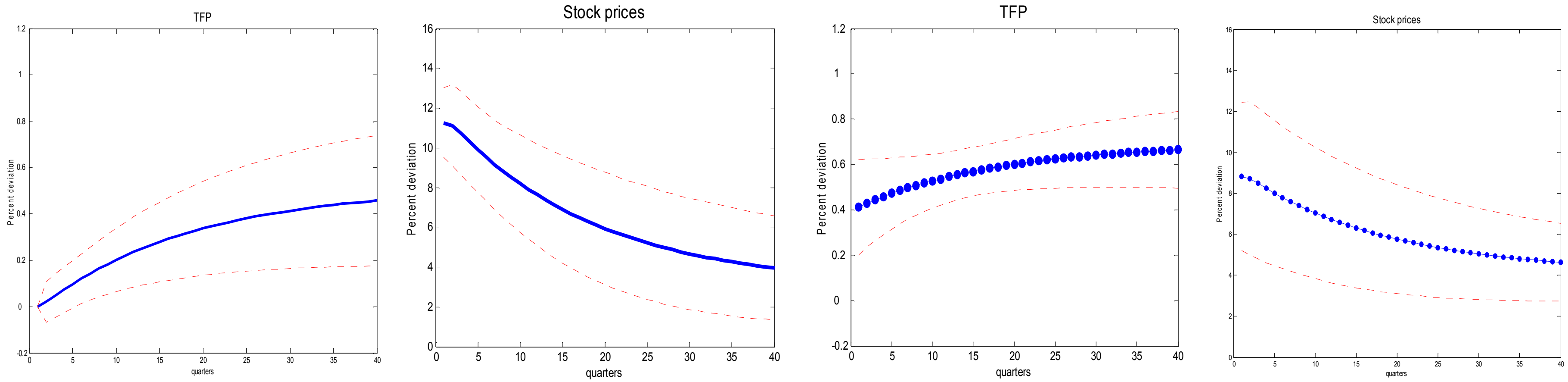
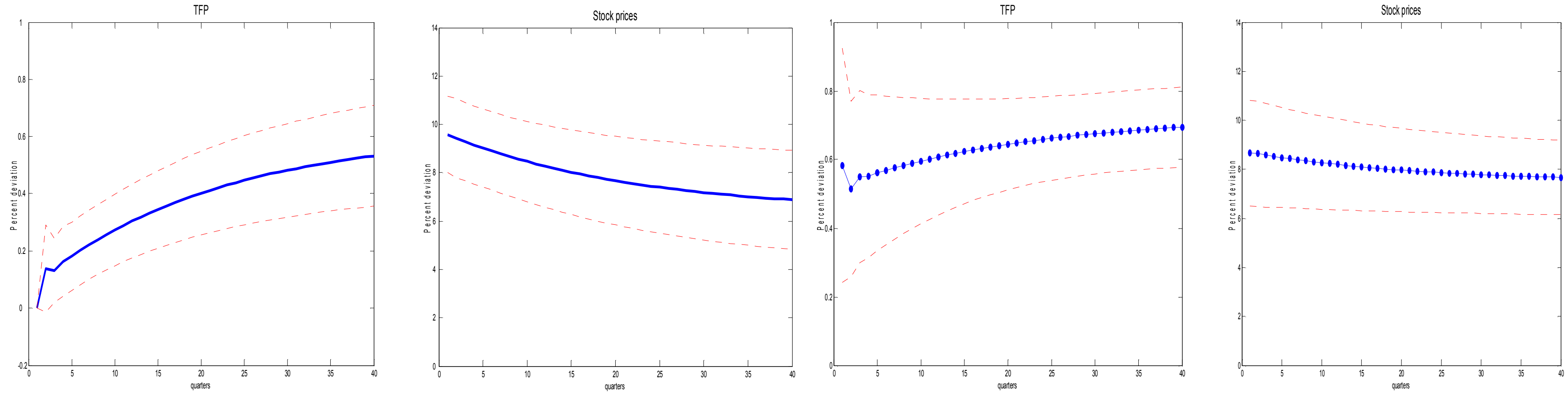


Figure3 Identified structural residuals (adjusted measure of *TFP*)

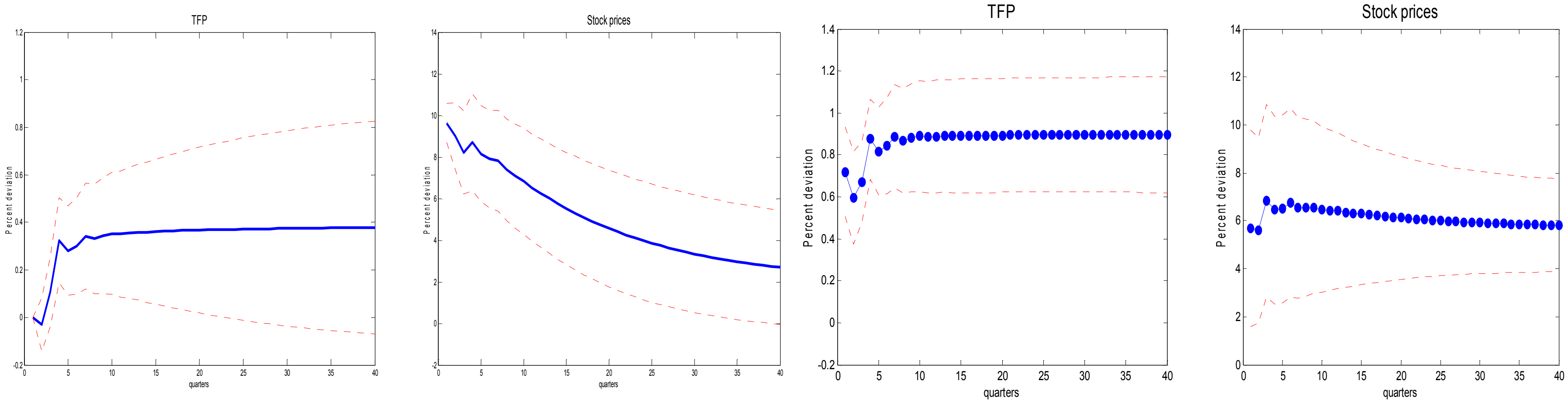
France:



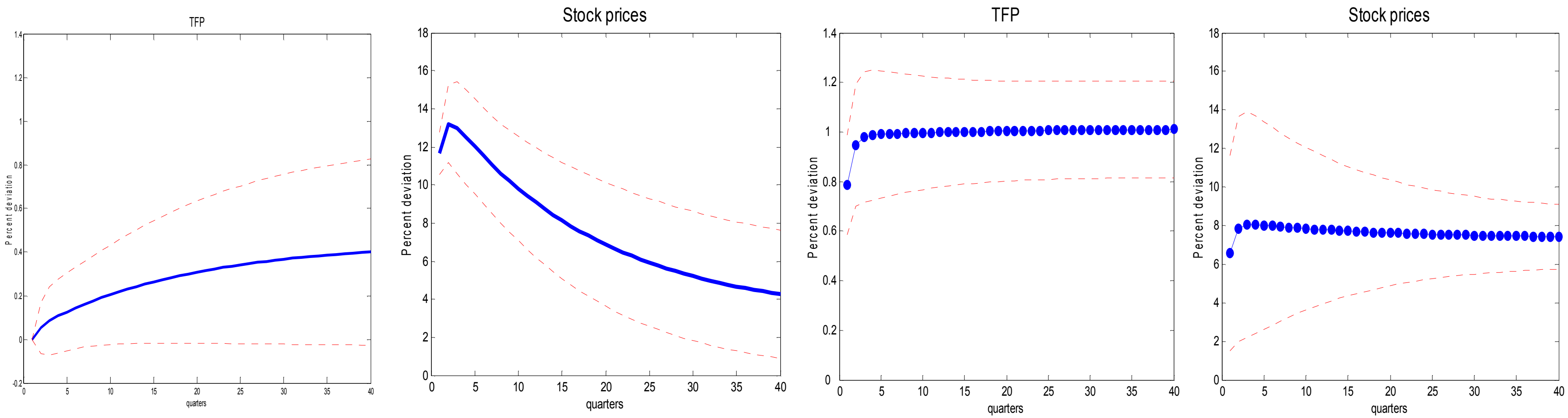
Netherlands:



UK:


TFP
Percent deviation
quarters
Stock prices
Percent deviation
quarters
TFP
Percent deviation
quarters
Stock prices
Percent deviation
quarters

Italy:


TFP
Percent deviation
quarters
Stock prices
Percent deviation
quarters
TFP
Percent deviation
quarters
Stock prices
Percent deviation
quarters

Spain:

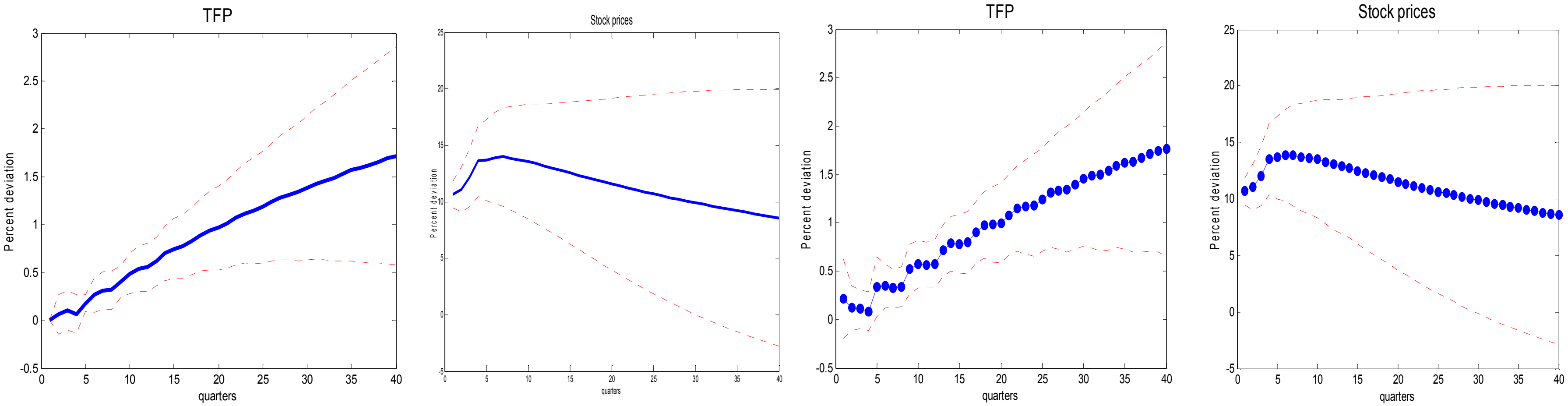
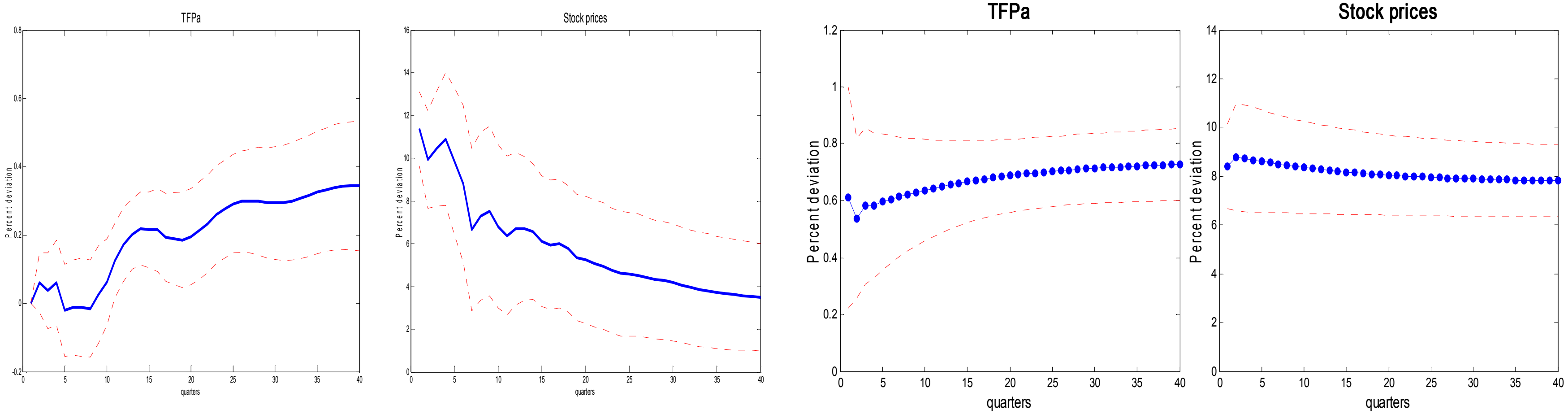


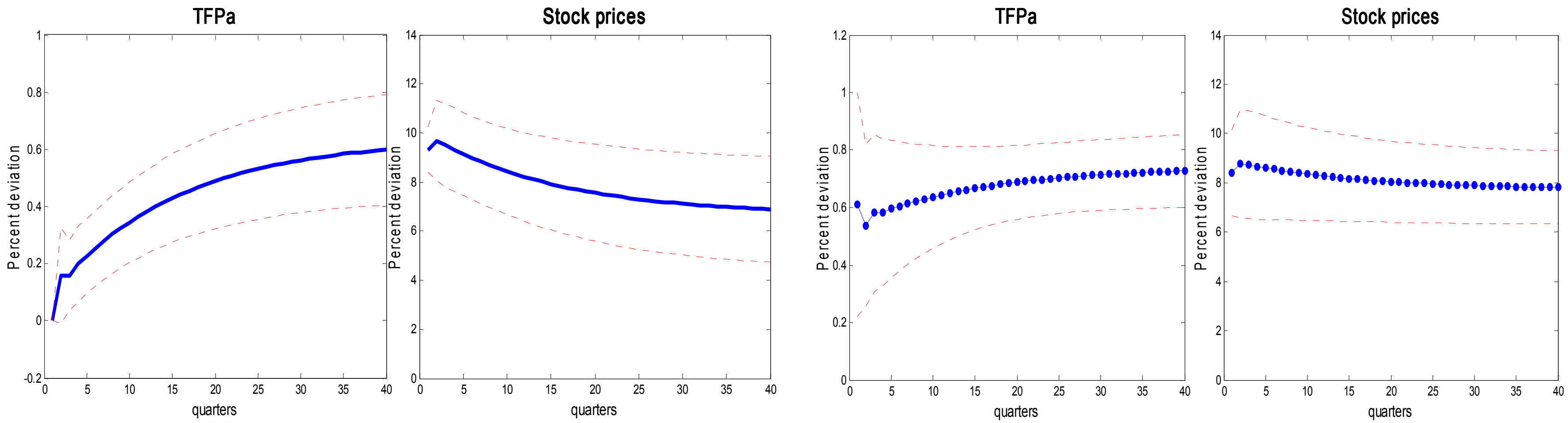
Figure4. Impulse response functions for *TFP* and *SP*

Notes: The bold line represents the point estimate of the responses to a unit ε_2 *shock (under the short-run identification). The line with circles represents the point estimate of the responses to a unit* $\tilde{\varepsilon}_1$ *shock (under the long-run identification). The red dashed lines indicate the 90% confidence intervals.*

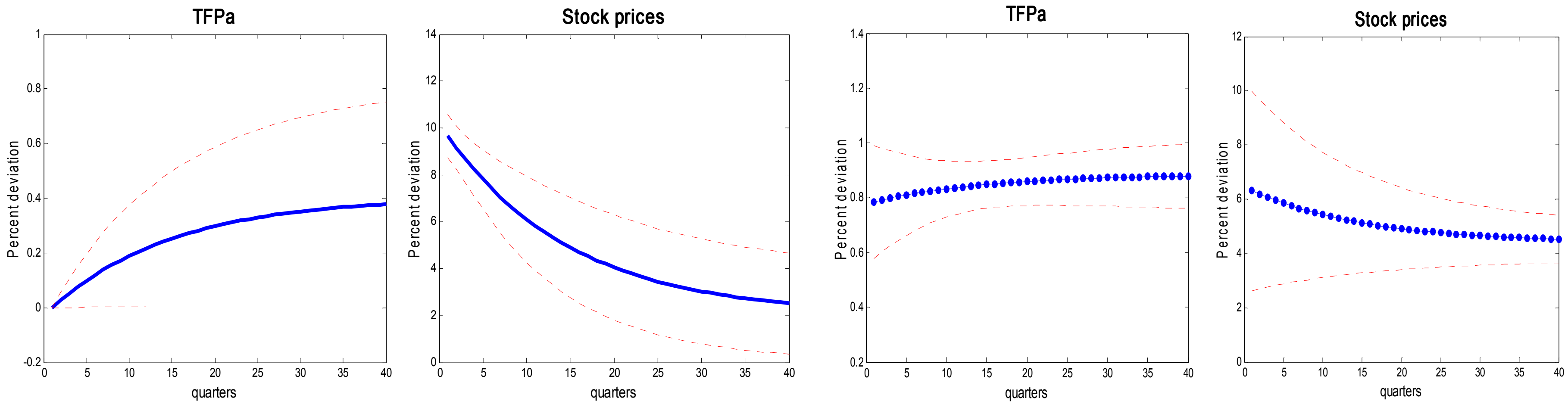
France:



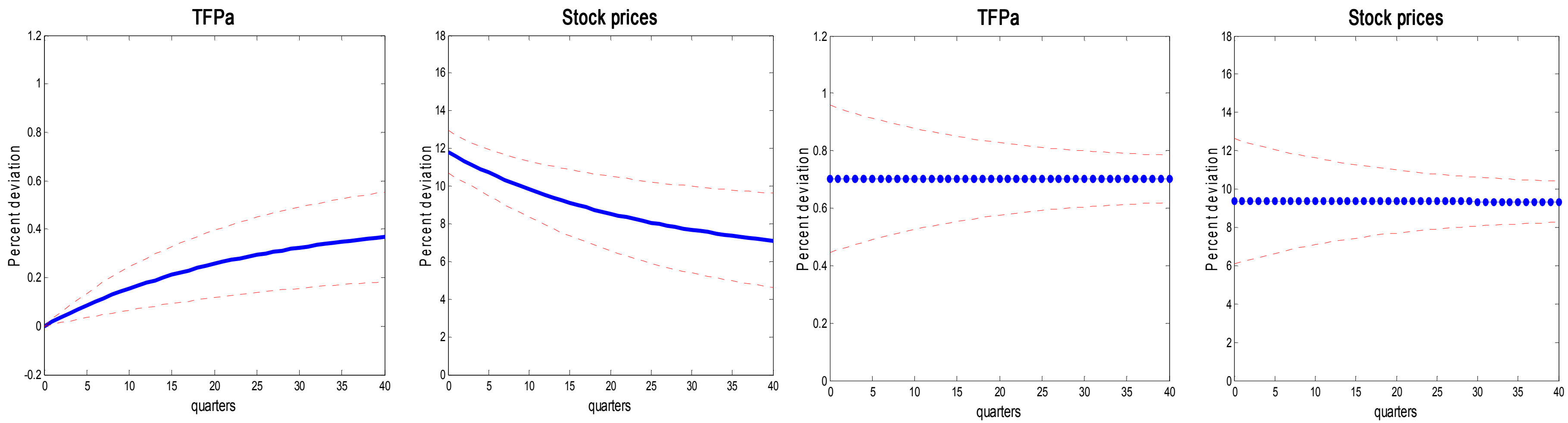
Netherlands:



UK:


TFPa
Stock prices
TFPa
Stock prices
Percent deviation
quarters

Italy:


TFPa
Stock prices
TFPa
Stock prices
Percent deviation
quarters

Spain:

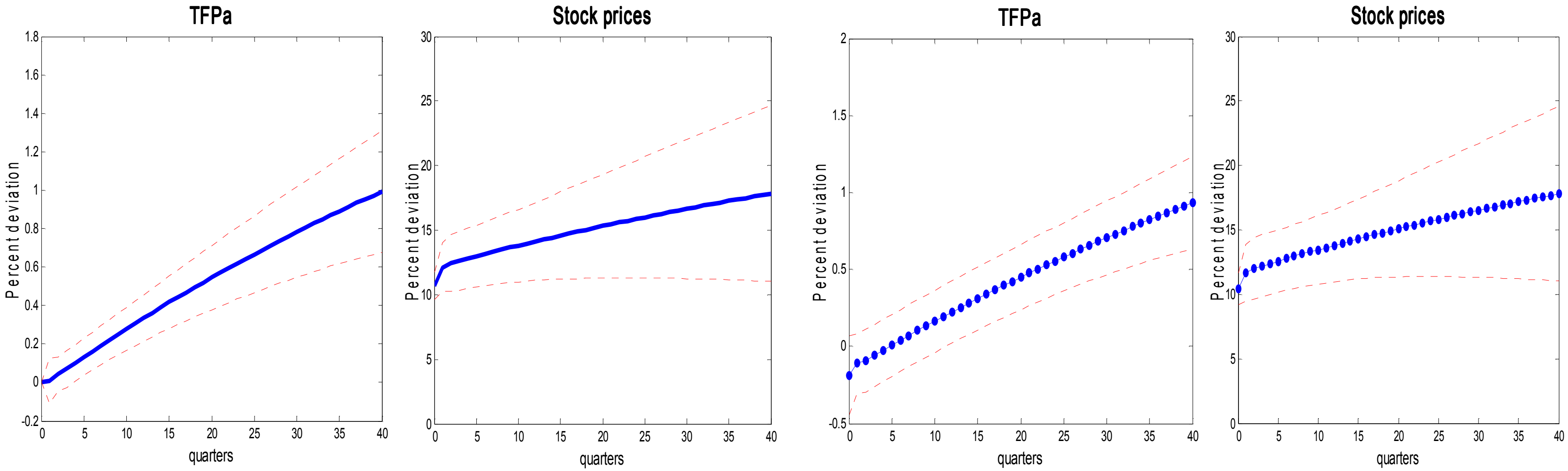
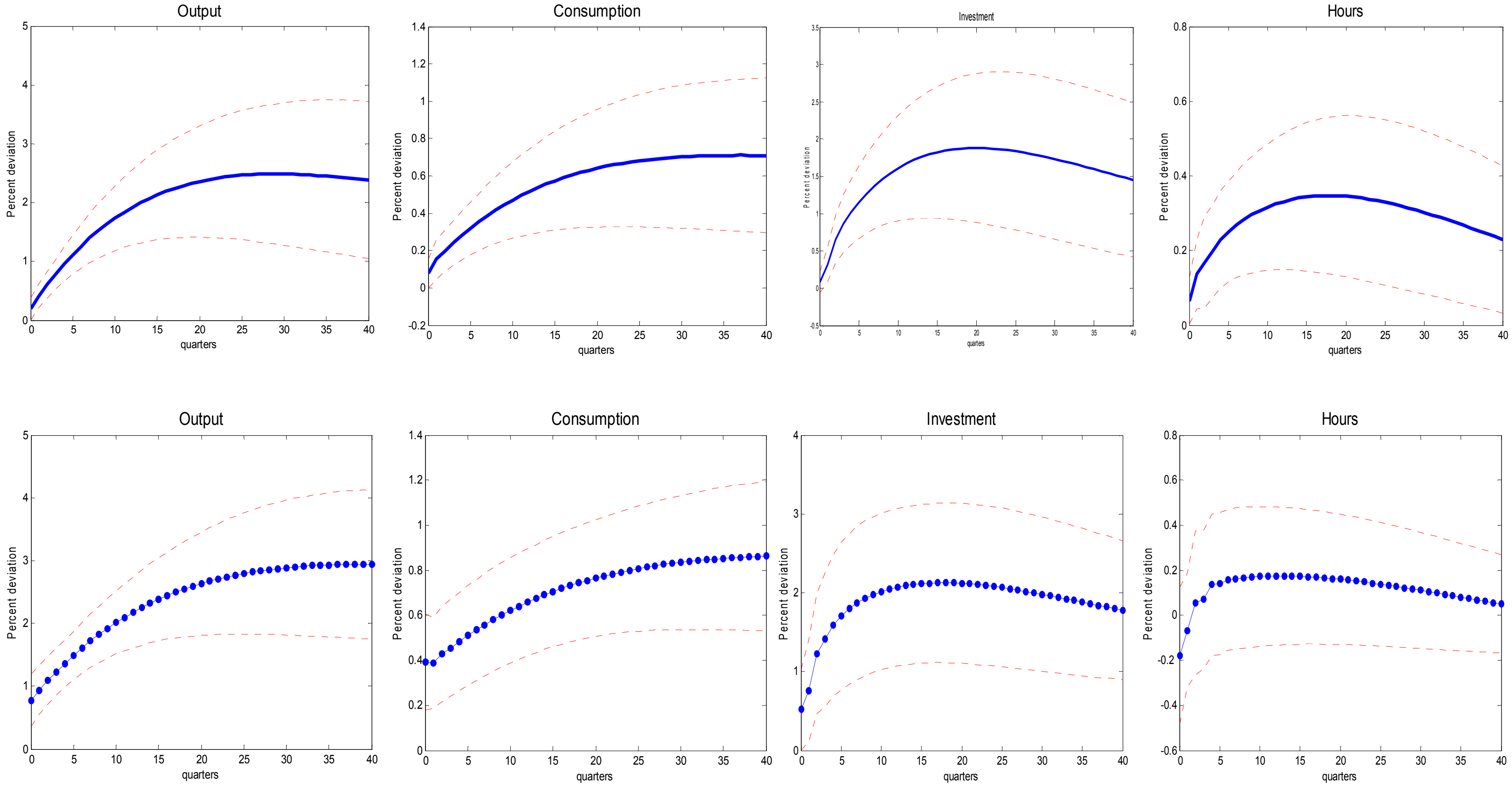


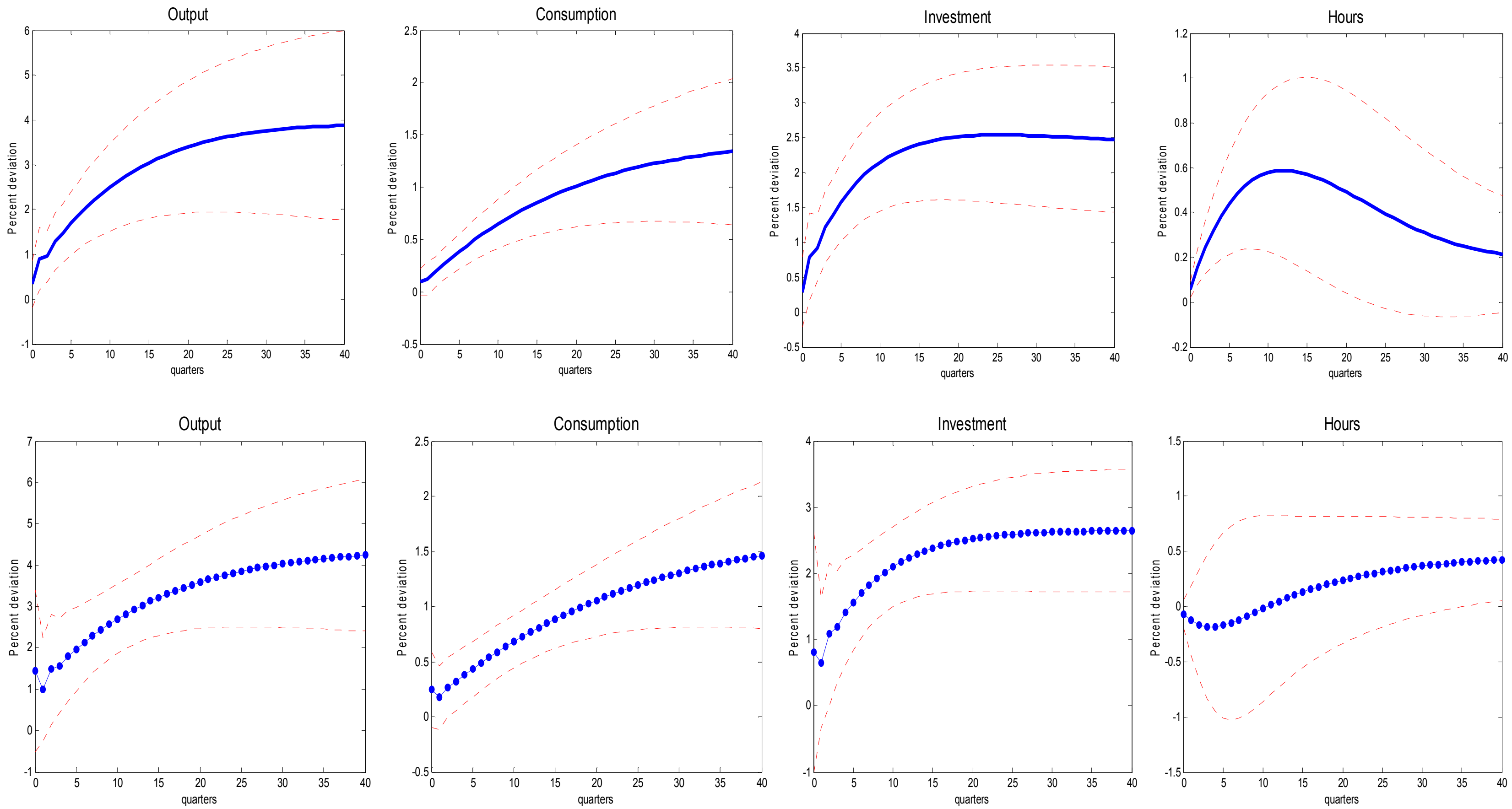
Figure5. Impulse response functions for *TFPa* and *SP*

Notes: The bold line represents the point estimate of the responses to a unit ε_2 *shock (under the short-run identification). The line with circles represents the point estimate of the responses to a unit* $\tilde{\varepsilon}_1$ *shock (under the long-run identification). The red dashed lines indicate the 90% confidence intervals.*

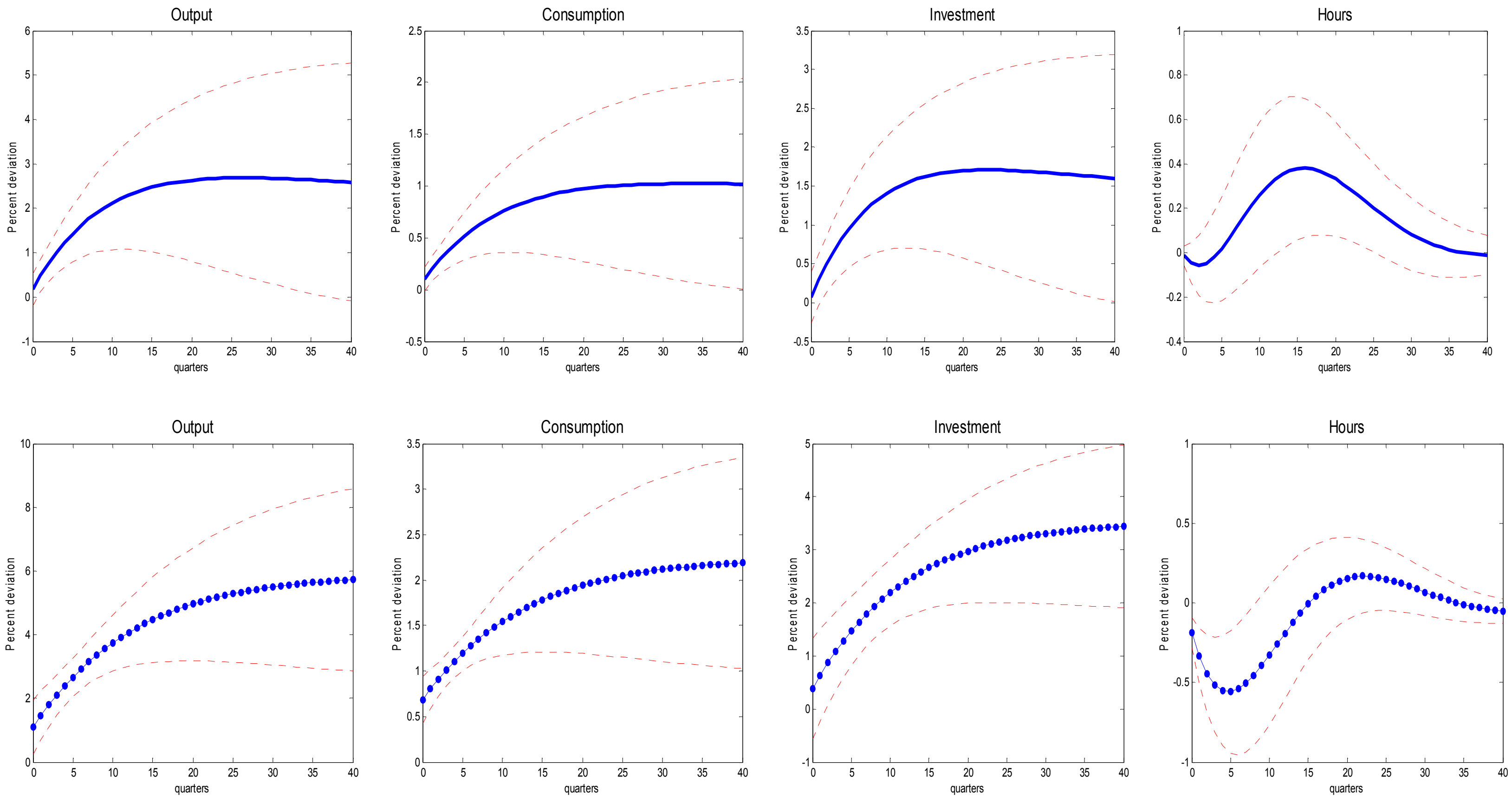
France:


Output
Percent deviation
quarters
Consumption
Percent deviation
quarters
Investment
Percent deviation
quarters
Hours
Percent deviation
quarters
Output
Percent deviation
quarters
Consumption
Percent deviation
quarters
Investment
Percent deviation
quarters
Hours
Percent deviation
quarters

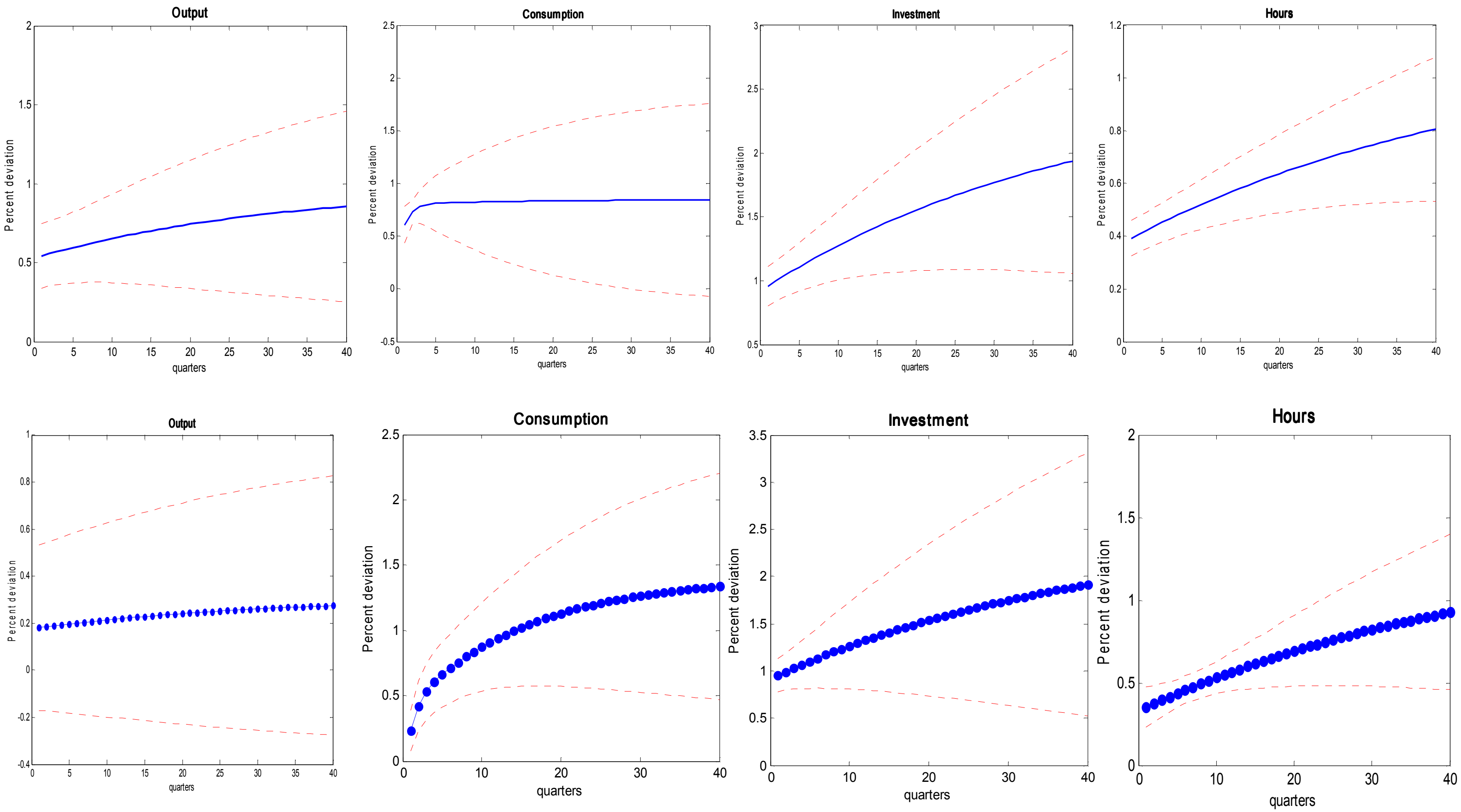
Netherlands:



UK:


Output
Consumption
Investment
Hours
Percent deviation
quarters
Output
Consumption
Investment
Hours
Percent deviation
quarters

Italy:



Output
Consumption
Investment
Hours
Percent deviation
quarters
Output
Consumption
Investment
Hours
Percent deviation
quarters

Spain:

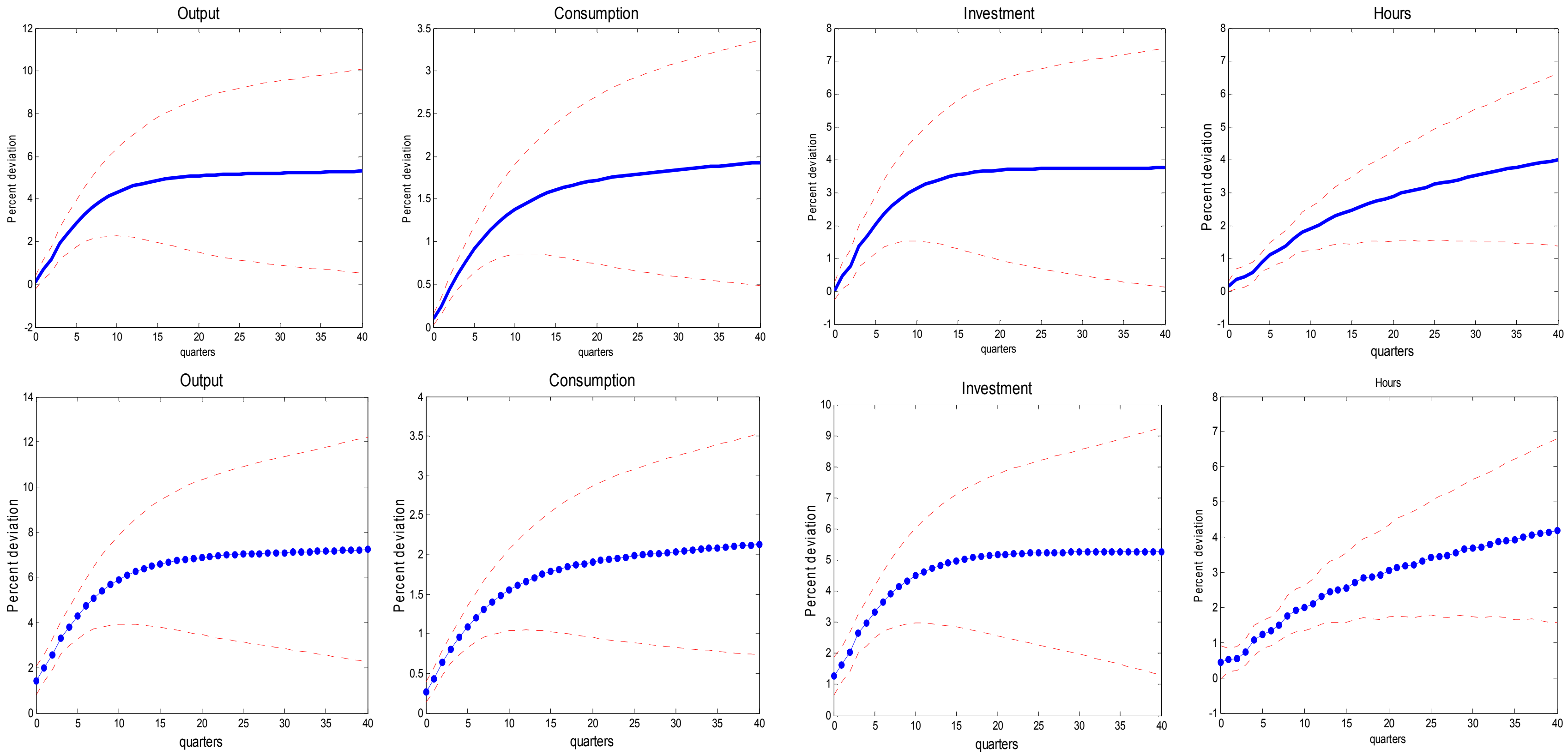


Figure6. Impulse responses of third variable in the trivariate systems

Notes: The bold line represents the point estimate of the responses to a unit ε_2 *shock (under the short-run identification). The line with circles represents the point estimate of the responses to a unit* $\tilde{\varepsilon}_1$ *shock (under the long-run identification). The red dashed lines indicate the 90% confidence intervals.*