

Stock Prices, Total Factor Productivity and Economic Fluctuations Some Further Evidence from Japanese and U.S. Sectoral Data

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Abstract

Here we supplement some earlier work (Beaudry and Portier [2004]) with some new evidence obtained from Japanese and U.S. sectoral data. Our results show that (i) In the U.S. as well as for Japan, Stock Prices short run movements incorporate most (all) of the long run shocks to Total Factor Productivity and (ii) the Stock Price news is indeed a shock that does not affect sectoral *TFPs* on impact, but that increases *TFP* in the long run in the sectors that are driving *TFP* growth, namely durable goods, and among them equipment sectors.

Key Words : Stock Prices – Business Cycle – Productivity Shocks

JEL Classification : E3

1 Introduction

In a previous work (Beaudry and Portier [2004]), we have presented properties of the joint behavior of total factor productivity and stock prices on U.S. postwar data, properties which highlight new challenges for business cycle theory. In particular, we presented two orthogonalized moving average representation for these variables: one based on an impact restriction and one based on a long run restriction. We then examined the correlation between the innovations that drive the long run movements in TFP and the innovation which is contemporaneously orthogonal to TFP. We found this correlation to be positive and almost equal to 1, indicating that permanent changes in productivity growth are preceded by stock market booms. We showed why this observed positive correlation runs counter to that predicted by simple models where surprise changes in productivity drive fluctuations. We also discussed how the pattern could arise if agents have advanced information about future technological opportunities, or if productivity growth emerges as a delayed byproduct of a period high investment activity. In either case, the results suggests that changes in technological opportunities may be central to business cycle fluctuations even if surprise changes in productivity are not.

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In this paper, we extend this analysis to Japanese aggregate data and U.S. sectoral one. The analysis of aggregate Japanese data confirm our previous results: Stock Prices innovation do contain most (all) the information about the long run movements of aggregate TFP , and are responsible for short run business cycle fluctuations. The analysis of U.S. Manufacturing two-digit data shows that the Stock Price news is indeed a shock that does not affect sectoral $TFPs$ on impact, but that increases TFP in the long run in the sectors that are driving TFP growth, namely durable goods, and among them equipment sectors.

2 The Setup

The object of this section is to present a new means of using orthogonalization techniques –i.e. impact and long run restrictions – to learn about the nature of technological progress diffusion and business cycle fluctuations. We do not use these techniques simultaneously (as is now common in the literature), but is instead to use them sequentially. In particular, we will want to apply this sequencing to describe the joint behavior of stock prices (SP) and measured total factor productivity (TFP_t) in a manner that can be easily mapped into structural models. The main characteristic of stock prices that we want to exploit is that it be an unhindered jump variable, that is, a variable that can immediately react to changes in information without lag.

2.1 Two Orthogonalization Schemes

Let us begin our discussion from a situation where we already have an estimate of the reduced form moving average (Wold) representation for the bivariate system $\{TFP_t, SP_t\}$, as given below (for ease of presentation we neglect any drift terms).

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = C(L) \begin{pmatrix} \mu_{1,t} \\ \mu_{2,t} \end{pmatrix}$$

where L is the lag operator, $C(L) = I + \sum_{i=1}^{\infty} C_i L^i$, and where the variance co-variance matrix of μ is given by Ω . Furthermore, we will assume that the system has at least one stochastic trend and therefore $C(1)$ is not equal to zero. In effect, most of our analysis will be based on a moving average representation derived from estimation a vector error correction model (VECM) for TFP and stock prices.

Now consider deriving from this Wold representation alternative representations with orthogonalized errors. As is well know, there are many ways of deriving such representations. We want to consider two of these possibilities, one that imposes an impact restriction on the representation and one that imposes a long run restriction. In order to see this most clearly, let us denote these two alternative representations by:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \Gamma(L) \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}, \quad (1)$$

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \tilde{\Gamma}(L) \begin{pmatrix} \tilde{\epsilon}_{1,t} \\ \tilde{\epsilon}_{2,t} \end{pmatrix}, \quad (2)$$

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 $\tilde{\epsilon}$ are identity matrices. In order to get such a representation, say in the case of (1), we need to find the Γ matrices that solve the following system of equations:

$$\begin{cases} \Gamma_0 \Gamma_0' = \Omega \\ \Gamma_i = C_i \Gamma_0 \text{ for } i > 0 \end{cases}$$

However, since the above system has one more variable than equations, it is necessary to add a restriction to pin down a particular solution. In case (1), we will pin down a solution by imposing that the 1,2 element of Γ_0 be equal to zero, that is, we choose an orthogonalization where the second disturbance ϵ_2 has no contemporaneous impact on *TFP*. In case (2), we impose that the 1,2 element of the long run matrix $\tilde{\Gamma}(1) = \sum_{i=0}^{\infty} \tilde{\Gamma}_i$ equals zero, that is, we choose an orthogonalization where the disturbance $\tilde{\epsilon}_2$ has no long run impact on *TFP* (the use of this type of orthogonalization was first proposed by Blanchard and Quah [1989]).

2.2 Some Simple Structural Interpretations

Here we illustrate the implications of sequentially using impact and long-run restrictions in a canonical optimal growth model in which technological improvements come either as surprises or diffuse slowly across the economy but where agents recognize the potential impact of an innovation well before it has improved productivity. We will show that these two models deliver different predictions with respect to the correlation between ϵ and $\tilde{\epsilon}$. As we want to derive simple and explicit results, the models we present here do not aim at realism as many assumptions are made in order to allow analytical solutions. The second example is taken from Beaudry and Portier [2004]

A Simple Optimal Growth Model with Technology and Preference Shocks: Let us now consider an economy in which preferences of the representative household are given by

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\log C_t - \Lambda_t \frac{L_t^\sigma}{\sigma} \right] \quad (1)$$

where C is consumption, L labor and Λ a stationary preference shock.

$$\Lambda_t = e^{\eta_{2,t}} \quad (2)$$

This preference shock acts here as a “demand” shock. A government spending shock would be a more natural candidate for a demand shock, but the present formulation has the advantage of analytical tractability, and for our purpose, is equivalent to a government spending shock. The household accumulates capital, and we assume full depreciation, so that

$$K_{t+1} = I_t \quad (3)$$

where K is capital and I investment. The budget constraint of the household, that rents capital and labor services to the representative firm, is given by

$$C_t + I_t = w_t L_t + \kappa_t I_{t-1} \quad (4)$$

where κ is the rental rate of capital services and w the wage rate.

The representative firm in this economy produces according to the CRS technology

$$Y_t = \theta_t K_t^\gamma L_t^{1-\gamma} \quad (5)$$

where θ is again a random walk technology shock.

$$\theta_t = \theta_{t-1} e^{\eta_{1,t}} \quad (6)$$

$\eta_{1,t}$ and $\eta_{2,t}$ are assumed to be *iid* processes with identity covariance matrix and zero mean.

We assume that agents behave competitively, maximize utility or profit at given prices and that markets clear. In such an economy, as shown in the appendix, the solution is log-linear. With this solution, one can perform the short-run and long-run orthogonalizations we presented above, and recover the shocks ϵ and $\tilde{\epsilon}$ as functions of the structural shocks $\eta_{1,t}$ and $\eta_{2,t}$. Since firms make zero profits every period, the stock market value of firms is uninteresting in this model, but there are still asset price fluctuations in the bond market. Hence, here we will focus on the joint behavior of TFP and the bond price as the system of interest, that is, the bond price will play the role of the variable X_t introduced in the preceding section.

In this model, the equilibrium joint behavior of TFP and the log bond price (denoted p^b) has a structural moving average given by:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta p_t^b \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \frac{(1-\gamma)}{1-\gamma L} - 1 & -\frac{(1-L)(1-\gamma)^2}{\sigma(1-\gamma L)} \end{pmatrix} \begin{pmatrix} \eta_{1,t} \\ \eta_{2,t} \end{pmatrix} \quad (7)$$

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

$$\epsilon_1 = \eta_1 \quad , \quad \epsilon_2 = \eta_2 \quad , \quad \tilde{\epsilon}_1 = \eta_1 \quad , \quad \tilde{\epsilon}_2 = \eta_2 \quad (8)$$

In particular, we have $\epsilon_2 \perp \tilde{\epsilon}_1$.

A Model with Delayed Response of Innovation on Productivity Let us now consider an alternative setting where stock prices continue to be a discounted sum of future profits but where technological innovations no longer immediately increases productivity but instead only increase productive capacity over time. The objective of this example is to emphasize what such an environment predicts regarding the correlation between ϵ_2 and $\tilde{\epsilon}_1$ derived using sequentially impact and long run restrictions. To this end, let us assume that measured TFP, denoted θ , is composed of two components: a non-stationary component D_t and a stationary component ν_t . The component ν_t can be thought of as either a measurement error or as a temporary technology shock. For the discussion, we will treat ν_t as a temporary shock to θ , although the measurement error interpretation has the same implications. In contrast, the component D_t is the permanent component of technology, and is assumed to follow the process given below:

$$\begin{cases} \theta_t &= D_t + \nu_t \\ D_t &= \sum_{i=0}^{\infty} d_i \eta_{1,t-i} \\ d_i &= 1 - \delta^i, \quad 0 \leq \delta < 1 \\ \nu_t &= \rho \nu_{t-1} + \eta_{2,t}, \quad 0 \leq \rho < 1 \end{cases} \quad (9)$$

We will call the process for D_t a diffusion process since an innovation η_1 is restricted to have no immediate impact on productive capacity ($d_0 = 0$), the effect of the technological innovation on productivity is assumed to grow over time ($d_i \leq d_{i+1}$) and the long run effect is normalized to 1. In contrast to the common random walk assumption for the permanent component of TFP, such a process allows for an S-shaped response of TFP to a technological innovation; which is consistent with many micro-based studies of the effects of technological innovation on productivity (Pakes [1985] mentions the “long and erratic lag structure between invention and the current benefits derived from it”) We now want to derive the implied structural moving average for ΔTFP and ΔSP . To that end, consider a simple Lucas’ tree type of model, where the ownership of the unique tree of the economy is tradable and where it pays dividend θ_t .

Households consume and trade firms shares. Preferences are represented by:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\sigma}}{1-\sigma} \quad (10)$$

with $\sigma \geq 0$. The household can buy or sell shares S_t at unit price P_t . As there is a unique tree in the economy, the stock market value is $SP_t = P_t$. The household budget constraint is given by

$$C_t + P_t S_{t+1} \leq (P_t + \theta_t) S_t \quad (11)$$

Optimal behavior of the household is given by budget constraint (11), Euler equation (12)

$$P_t = \beta E_t \left[\left(\frac{C_t}{C_{t+1}} \right)^\sigma (P_{t+1} + \theta_{t+1}) \right] \quad (12)$$

and the transversality condition $\lim_{j \rightarrow \infty} E_t \beta^j P_{t+j} S_{t+j+1} = 0$.

At the competitive equilibrium, $S_t = 1$ and $C_t = \theta_t$ for all t . The stock market value SP_t is then given by

$$SP_t = \beta E_t \left[\left(\frac{\theta_t}{\theta_{t+1}} \right)^\sigma (SP_{t+1} + \theta_{t+1}) \right] \quad (13)$$

In order to obtain simple analytical results, we make the further assumption that households are risk neutral, so that $\sigma = 0$. In that case, equation (13) collapses to

$$SP_t = \beta E_t [(SP_{t+1} + (1 - \alpha)\theta_{t+1})] \quad (14)$$

Solving forward and using the transversality condition $\lim_{j \rightarrow \infty} \beta^j E_t [SP_{t+j}] = 0$, we obtain

$$SP_t = \beta E_t \left[\sum_{j=0}^{\infty} \beta^j \theta_{t+j+1} \right] \quad (15)$$

Using the process of θ_t given in (9), one can obtain the following structural moving average representation for TFP and stock prices first differences:

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \begin{pmatrix} (1 - \delta) \sum_{i=1}^{\infty} \delta^{i-1} L^i & \frac{(1-L)}{(1-\rho L)} \\ \frac{\beta(1-\delta)}{1-\beta\delta} \sum_{i=0}^{\infty} \delta^i L^i & \frac{\beta\rho}{1-\beta\rho} \frac{1-L}{1-\rho L} \end{pmatrix} \begin{pmatrix} \eta_{1,t} \\ \eta_{2,t} \end{pmatrix} \quad (16)$$

From the above representation, we see that the impact matrix on levels of TFP and SP is of the form:

$$\begin{pmatrix} 0 & 1 \\ \frac{\beta(1-\delta)}{1-\beta\delta} & \frac{\beta\rho}{1-\beta\rho} \end{pmatrix} \quad (17)$$

And the long run matrix for the levels of TFP and SP is of the form

$$\begin{pmatrix} 1 & 0 \\ \frac{\beta}{1-\beta\delta} & 0 \end{pmatrix} \quad (18)$$

Hence, performing our short-run and long-run identification on this system, the relationship between the identified errors ϵ_t , $\tilde{\epsilon}_t$ and the structural errors η_t are:

$$\epsilon_1 = \eta_2 \quad , \quad \epsilon_2 = \eta_1 \quad , \quad \tilde{\epsilon}_1 = \eta_1 \quad , \quad \tilde{\epsilon}_2 = \eta_2 \quad (19)$$

In particular, we have that ϵ_2 is co-linear to $\tilde{\epsilon}_1$ in this case. What we have found in our previous work is indeed that ϵ_2 is co-linear to $\tilde{\epsilon}_1$ on aggregate postwar U.S. data.

3 Data and Specification Issues

Our empirical investigation will use annual Japanese and US data.

3.1 U.S. Data

U.S. data cover the period 1948 to 2000. The two series that interest us for our bi-variate analysis are an index of stock market value (SP) and a measure of total factor productivity.

The stock market index we use is the quarterly Standards & Poors 500 Composite Stock Prices Index, deflated by the seasonally adjusted implicit prices deflator of GDP in the non farm private business sector and transformed in per-capita terms by dividing it by the population aged 15 to 64. We denote the log of this index by SP

The construction of our baseline TFP series is relatively standard. We restrict our attention to the non farm private business sector. From the U.S. Bureau of Labor Statistics, we retrieved two series: labor share (s_h) and capital services (KS) which measures the services derived from the stock of physical assets and software. The average value of the labor share is $\bar{s}_h = 67.66\%$. Output (Y) and hours (H) are non farm business measures, from 1947 to 2000 (also from U.S. Bureau of Labor Statistics). We then construct a measure of (log) TFP as

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

3.2 Japanese Data

Japanese data cover the period 1960 to 2000. Most are obtained from Hayashi and Prescott¹: TFP , GNP deflator, age 20-69 population in millions, Total Hours (Column V, sheet "Labor" of Hayashi-Prescott), Consumption (Private consumption, Column AB of the sheet "Product") and Investment (Private Fixed Capital Investment, Column AH of the sheet "Product"). The Hours series have been deflated by the 20-69 population one, investment and consumption series have been deflated by both GNP deflator and age 20-69 population. The Stock Price series is the end-of-year Nikkei 225², deflated by GNP deflator and age 20-69 population.

Specification: From our data on TFP and SP, we first want to recover the Wold moving average representation for ΔTFP and ΔSP . Since from unit root tests (not reported here) and cointegration tests, we found that SP and TFP are likely cointegrated I(1) processes, a natural means of recovering the Wold representation is by inverting a VECM. The second specification choice is related with the number of lags to include in the VECM. Again, our strategy is not to impose much to the data. According to likelihood ratio two lags are chosen for U.S. data and 6 for Japanese ones.

¹See Hayashi and Prescott [2002] and the web site http://www.e.u-tokyo.ac.jp/~hayashi/hp/hayashi_prescott.htm for the Excel Files)

²As obtained from <http://www.finfacts.com/Private/currency/nikkei225performance.htm>

4 Aggregate Results For The U.S. and Japan

4.1 Lessons for TFP movements

We estimate a VECM for (TFP, SP) with one cointegrating relation and recover two orthogonalized shock series corresponding to the ϵ and $\tilde{\epsilon}$ discussed in Section 2, that is, ϵ was recovered by imposing an impact restriction (a restriction on Γ_0) and $\tilde{\epsilon}$ was recovered by imposing a long run restriction. The level impulse responses on (TFP, SP) associated with the ϵ_2 shock and the $\tilde{\epsilon}_1$ shock are displayed on Figure 1 for the U.S. and 4 for Japan. The U.S. results are taken from Beaudry and Portier [2004].

A first striking observations is that for Japanese data too, those responses appear very similar when comparing one orthogonalization to another. More specifically, the dynamics associated with the ϵ_1 shock—which by construction is an innovation in stock prices which contemporaneously orthogonal to TFP —seems to permanently affect TFP, while the dynamics associated with the $\tilde{\epsilon}_1$ shock—which by construction has a permanent effect on TFP—has essentially no impact effect on TFP but has a substantial effect on SP . On the one hand, these results suggest that ϵ_2 contains information about future TFP growth which is instantaneously and positively reflected in stock prices. While on the other hand, they suggest that permanent changes in TFP are first reflected in stock prices before they actually increase productive capacity. From both U.S. and Japanese data, we observe that it takes at least 5 years for TFP to respond positively in a significant way. .

The similarity between the effects of these two shocks is further confirmed by the inspection of the forecast error variance decomposition plot (Figure 2 for the U.S.A. and 5 for Japan). Observe that the $\tilde{\epsilon}_1$ shock explains very little of the short run movements of TFP (less than 30% the first 4 years). On the other hand, the ϵ_2 shock also explains most of the long variance of TFP after 30 years (80% for Japan). This result derives from the quasi-identity between the ϵ_2 shock and the $\tilde{\epsilon}_1$ shock, as shown in Figure 3 for the U.S. and Figure 6 for Japan, which simply plots $\epsilon_{2,t}$ against $\tilde{\epsilon}_{1,t}$. In effect, the correlation coefficient between these two series is .98 (with a standard deviation of .03) for the U.S. and .91 (with a standard deviation of .07) for Japan, that is, these two orthogonalization techniques recover essentially the same shock series.

What kind of structural macroeconomic model is consistent with these two orthogonalization techniques generating the same shock series? For Japan as for the U.S., this pattern appears consistent with the view—which we call the news 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.

4.2 Lessons for Macroeconomic Fluctuations

The observation that our estimates of ϵ_2 and $\tilde{\epsilon}_1$ are highly correlated and induce similar impulse responses suggests that news about future technological developments may be a relevant driving force behind business cycle fluctuations. We have shown (Beaudry and Portier [2004] that output, consumption, investment and hours do respond positively in the short run to those technological disturbances on postwar U.S. data.

Let us proceed to similar estimation for Japan. To that end, we estimate the following truncated moving average representation for different variables Z_t :

$$\Delta Z_t = \sum_{j=0}^J \phi_j^u u_{t-j} + \mu_t \quad (20)$$

where Z will either be consumption (C), investment (I), output ($C + I$) or hours (H), u is either ϵ_2 or $\tilde{\epsilon}_1$ and where μ a variable-specific disturbance that is orthogonal to u . The resulting sequence given by $\sum_{j=0}^n \phi_j$ provides an estimate of the impulse response function of X to a u shock, that is, the response to what we claim may be a news shocks. The truncation is done for $J = 5$.

Figure 8 displays the responses of consumption, investment, output (defined as $C + I$) and hours to ϵ_2 and $\tilde{\epsilon}_1$, that is, the responses to what we suggest may reflect news of a technological innovation which only diffuses slowly into productive system. As can be seen in the Figure, the responses to both shocks is virtually undistinguishable. Consumption and Hours increase by about .5% on impact, while the impact response of Investment and Output is more modest. After one year, all responses are above one percentage point.

As in the case of U.S. data, these results suggest that an ϵ_2 (1) creates business cycle like fluctuations, (2) does not affect TFP contemporaneously and (3) affect TFP in the long run. This pattern is consistent with the interpretation of ϵ_2 as being primarily a news shock. Such a structural interpretation is supported by the fact that the same responses for the economy are obtained from a short run identification in which we identify a news shock as ϵ_2 in our (TFP, SP) system as the innovation to stock prices that is orthogonal to current TFP, or if we examine the effects of $\tilde{\epsilon}_1$ which by definition affects long run TFP.

4.3 A Decomposition of Japanese Movements of TFP and Stock Prices

Here we use the estimated VARs to decompose historical movements into components explained by the various epsilons. Formally, and using the short run identification as an example, we use the estimated VAR decomposition (21) to decompose

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \hat{A}(L) \begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} + \Pi \begin{pmatrix} TFP_{t-1} \\ SP_{t-1} \end{pmatrix} + C + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \quad (21)$$

where C is a vector of constant term and Π is the cointegration coefficients vector. Starting from the observed initial conditions for TFP and SP , we can for example construct the series TFP^{ϵ_2} and SP^{ϵ_2} of the variations of TFP and Stock prices explained by ϵ_2 only (in other words what would have happened absent of ϵ_1 shocks as

$$\begin{pmatrix} \Delta TFP_t^{\epsilon_2} \\ \Delta SP_t^{\epsilon_2} \end{pmatrix} = \hat{A}(L) \begin{pmatrix} \Delta TFP_t^{\epsilon_2} \\ \Delta SP_t^{\epsilon_2} \end{pmatrix} + \Pi \begin{pmatrix} TFP_{t-1}^{\epsilon_2} \\ SP_{t-1}^{\epsilon_2} \end{pmatrix} + C + \begin{pmatrix} 0 \\ \epsilon_{2,t} \end{pmatrix} \quad (22)$$

Figure 9 display in its upper-left panel the predicted series of TFP absent of shocks over the whole period, which corresponds to the prediction that one can make with the VAR in 1968. Observe that the actual path for TFP is above the expected one after the mid 80's. The upper-right panel shows that the innovations to TFP of the short run identification, ϵ_1 (and also $\tilde{\epsilon}_2$ in the long run identification) are not responsible for this higher than expected TFP , as the predicted series absent of those shocks tracks almost perfectly the actual one. The lower-left panel shows that ϵ_2 or $\tilde{\epsilon}_1$ explain the evolution of the series after the mid 80's. Figure 10 shows the result of the same exercise for the Stock Price series, and shows how the non-permanent technological shock $\tilde{\epsilon}_2$ (and similarly ϵ_1) are responsible for the boom-bust dynamics of the 90's

Figures 11 and 12 perform similar exercises, but starting from the actual value of the series in 1989, and provide an accounting of the "lost decade". First, TFP has been way below its expected trend, as expected in 1989. Second, ϵ_2 or $\tilde{\epsilon}_1$ explain the evolution of the series. More specifically, the shocks ϵ_2 or $\tilde{\epsilon}_1$ in 1990 and 1992 (as shown on Figure 7 are responsible for most of TFP stagnation. Those two shocks are also responsible for most of the Stock Price bust of the 90's.

5 Sectoral Results For The U.S.

The shock ϵ_2 , that is identified as the Stock Price innovation in a (TFP, SP) VAR (that is the shock that is orthogonal to current TFP , where TFP is measures in the Nonfarm Private Business sector), has been shown to be explaining most (all) of the long run variance of TFP . It is of interest to go deeper in the inspection of the TFP impact and long run response to this shock, as to give some food for a further more structural interpretation. It is of particular interest to inspect the response of different sectors to that shock.

In this section, we make use of the BLS *Multifactor Productivity Trends in Manufacturing*-published data for 20 SIC 2-digit Manufacturing³. We estimate the sectoral TFP response to an aggregate Stock Price innovation following a two-step procedure. We first estimate an aggregate ϵ_2 shock, as explained in section 2. We then project each sectoral productivity TFP^s , where s indexes the sector, on present and past values of ϵ_2

³As obtained from <http://www.bls.gov/mfp/home.htm>

$$\Delta TFP_t^s = \sum_{j=0}^J \phi_j \epsilon_{2,t-j} + \mu_t \quad (23)$$

where μ a variable-specific disturbance that is orthogonal to ϵ_2 . The resulting sequence given by $\sum_{j=0}^n \phi_j$ provides an estimate of the impulse response function of TFP^s to a ϵ_2 shock. We truncate at $J = 10$, and our sample runs from 1951 to 2000.

Table 1 displays the impact and long run response of sectoral TFP to a one-standard-deviation shock, while 2 displays the p-values associated to the tests $\phi_0 = 0$ (Impact) and $\sum_{j=0}^1 \phi_j = 0$ (“long run”). The whole IRF are displayed in Figures 13, 14 and 15. According to the “news” interpretation we have proposed, the impact response should be zero, while the long run one positive, at least for the sectors that have been driving aggregate TFP growth for the postwar period. What do we obtain? Neither Manufacturing TFP as a whole, nor Nondurable or Durable ones do significantly increase on impact. When one goes to the two-digit series, it is only in one out of 18 sectors, *Transportation Equipment* that the impact response is significantly different from zero (at 5%) , and is indeed negative. Therefore, one cannot interpret the zero response of aggregate as the result of some complex aggregation effect. As far as the long run is concerned, Manufacturing as well as Nondurable and Durable goods TFP do respond positively in the long run, although Nondurable TFP response is not significantly positively (at 5%)(see Figure 13). The fact that the response of Durable goods TFP is large and significant in the long run favors the importance of an embodied technological progress type of explanation for aggregate TFP , and is confirmed by the two-digit results. Most of the sectors (14 out of 18, the exceptions being *Food & Kindred Products*, *Textile Mills Products*, *Lumber & Wood Products* and *Furniture & Fixtures*) respond positively to the shock. The news ϵ_2 is associated with a significantly (at 5%) long run (10 years) response in those sectors that have been driving U.S. TFP growth over the last 40 years: *Industrial Machinery & Computer Equipment*, *Electric & Electronic Equipment*, *Transportation Equipment*, *Instruments* (at 6.6%) for durable goods, *Petroleum Refining* and *Rubber & Plastic Products* (at 16%) for nondurable goods.

Those results give some extra support to our interpretation of this Stock Price innovation as an aggregate TFP news, that is widely spread across the sectors that are important for growth: not only this ϵ_2 explains the long run of aggregate TFP without affecting it in the long run

6 Conclusion

TO BE WRITTEN

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Appendix

A Tables

Table 1: Impact and Long Term Responses of TFP to a one-standard-deviation Stock price Innovation

ϵ_2

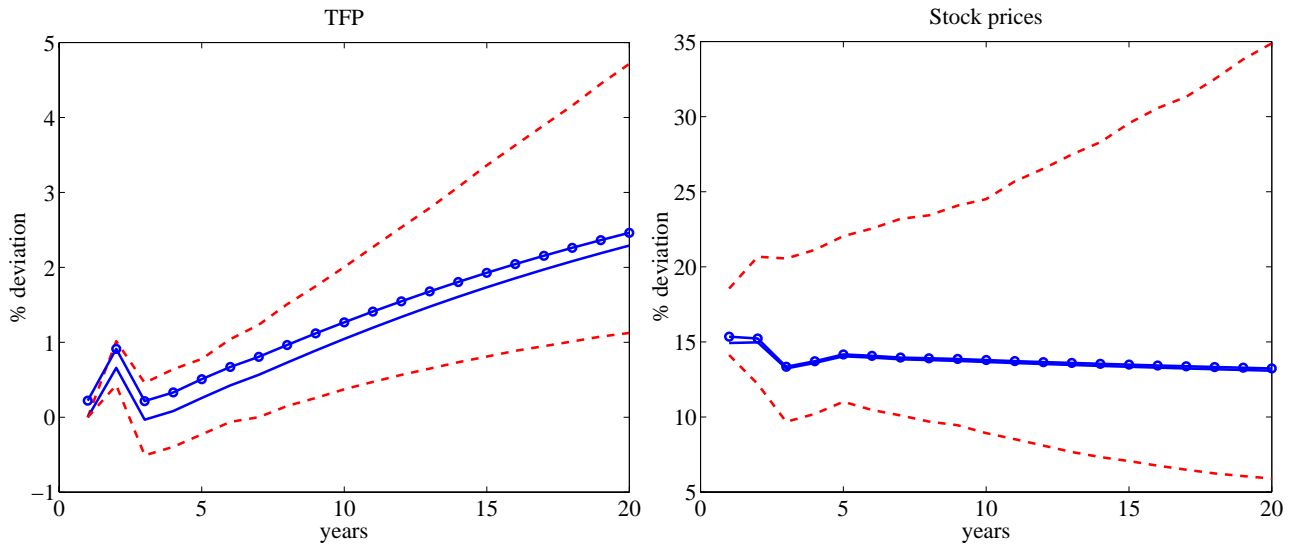
	Impact	10 years
Manufacturing	-0.1	2.9
Nondur. Goods	0.1	0.6
Durable Goods	-0.3	4.6
Non Durable		
Food & Kindred Prod.	0.4	-1.0
Textile Mills Prod.	0.2	-1.2
Apparel & Related Prod.	0.3	0.1
Paper & Allied Prod.	-0.3	1.5
Printing & Publishing	-0.2	0.8
Chem. & Allied Prod.	-0.4	2.5
Petroleum Refining	-0.0	1.7
Rubber & Plastic Prod.	0.3	2.1
Durable		
Lumber & Wood Prod.	-0.3	-0.3
Furniture & Fixtures	0.1	-0.7
Stone, Clay & Glass	-0.1	1.9
Primary Metal Ind.	-0.5	2.1
Fabricated Metal Prod.	0.1	0.4
Ind. Machinery,Comp.Eq.	0.3	5.4
Electric & Electr. Eq.	0.7	6.3
Transportation Equip.	-1.2	3.6
Instruments	-0.4	2.5
Misc. Manufacturing	-1.1	3.2

Table 2: P-value for the test that the impact or 10 years response of TFP to a Stock price Innovation ϵ_2 is zero

	Impact	10 years
Manufacturing	68.6 %	1.8 %
Nondur. Goods	86.8 %	61.6 %
Durable Goods	39.0 %	0.1 %
Non Durable		
Food & Kindred Prod.	33.3 %	53.3 %
Textile Mills Prod.	65.5 %	38.3 %
Apparel & Related Prod.	27.6 %	91.3 %
Paper & Allied Prod.	51.1 %	43.4 %
Printing & Publishing	41.2 %	48.3 %
Chem. & Allied Prod.	61.1 %	35.5 %
Petroleum Refining	92.3 %	2.0 %
Rubber & Plastic Prod.	42.1 %	15.8 %
Durable		
Lumber & Wood Prod.	58.2 %	89.2 %
Furniture & Fixtures	59.7 %	45.3 %
Stone, Clay & Glass	82.2 %	18.7 %
Primary Metal Ind.	31.8 %	26.4 %
Fabricated Metal Prod.	84.6 %	65.6 %
Ind. Machinery,Comp.Eq.	55.3 %	0.4 %
Electric & Electr. Eq.	17.6 %	0.2 %
Transportation Equip.	0.6 %	2.4 %
Instruments	31.1 %	6.6 %
Misc. Manufacturing	7.6 %	14.8 %

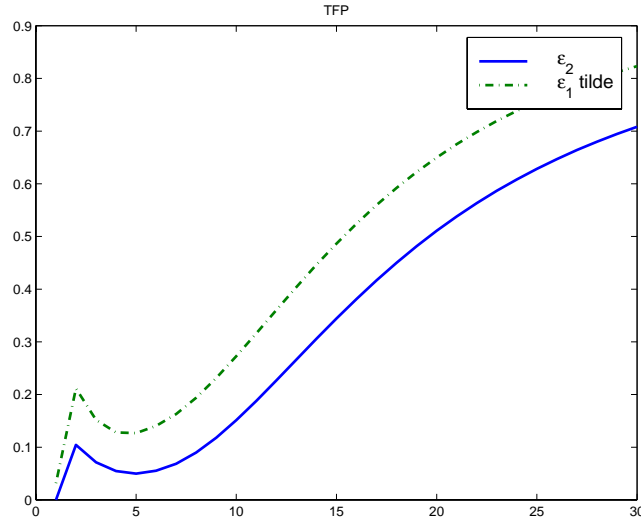
B Figures

Figure 1: Impulse Responses to Shocks ϵ_2 and $\tilde{\epsilon}_1$ in the (TFP, SP) VAR, Using U.S. Annual Observations (1948-2000)



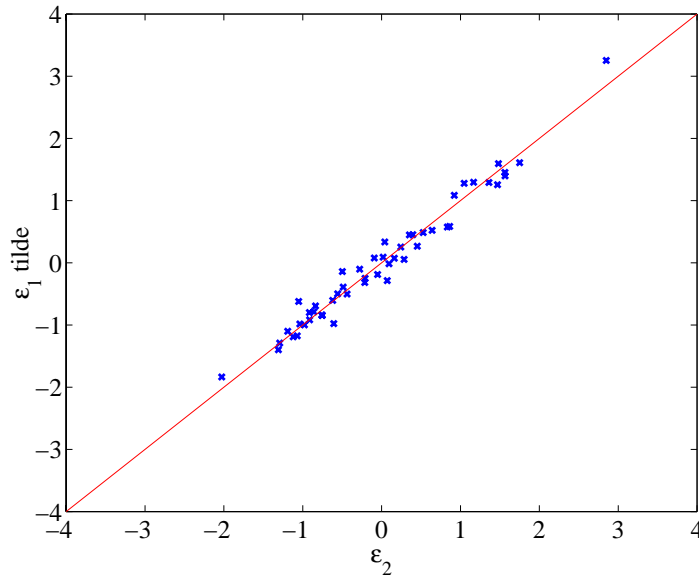
On each panel of this figure, the bold line represents the point estimate of the responses to a unit ϵ_2 shock (the shock that does not have instantaneous impact on TFP in the short run identification); the line with circles represents the point estimate of the responses to a unit $\tilde{\epsilon}_1$ shock (the shock that has a permanent impact on TFP in the long run identification). Both identifications are done in the baseline bivariate specification. The unit of the vertical axis is percentage deviation from the situation without shock. Dotted lines represent the 10% and 90% quantiles of the distribution of the IRF in the case of the short run identification, this distribution being the bayesian simulated distribution obtained by Monte-Carlo integration with 2500 replications, using the approach for just-identified systems discussed in Doan (1992).

Figure 2: U.S.A.: Forecast Error Variance of TFP explained by ϵ_2 and $\tilde{\epsilon}_1$



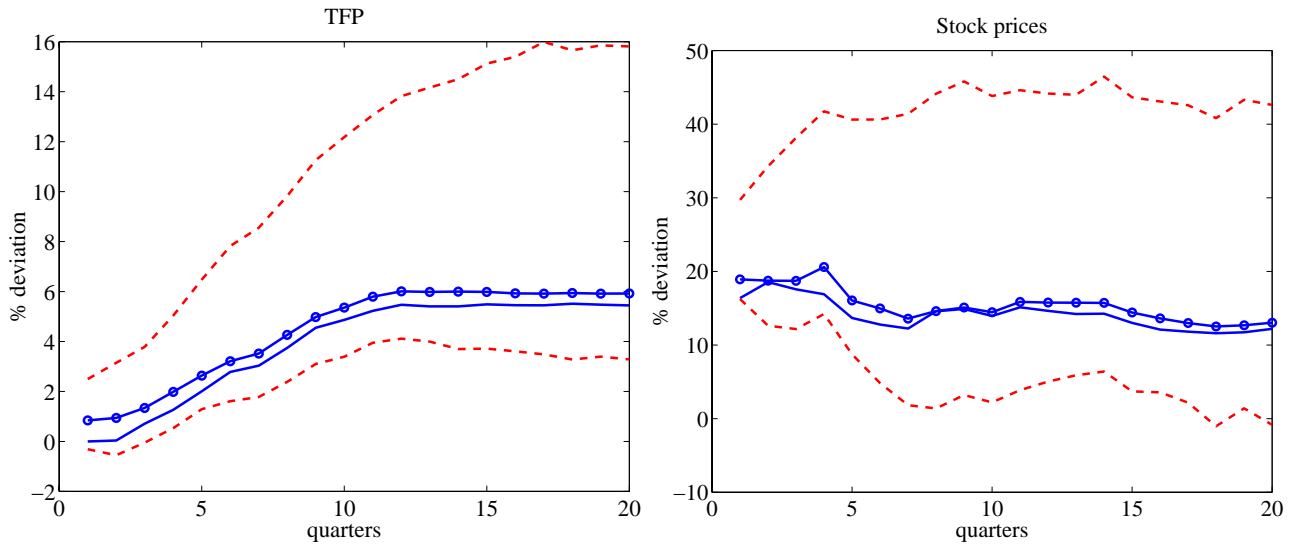
This figure displays the share of TFP forecast error variance attributed to ϵ_2 (the shock that does not have instantaneous impact of TFP in the short run identification) or to $\tilde{\epsilon}_1$ (the shock that has a permanent impact on TFP in the long run identification)(right panel), both in the baseline bivariate U.S. specification.

Figure 3: ϵ_2 Against $\tilde{\epsilon}_1$ in the (TFP, SP) VAR, Using U.S. Annual Observations (1948-2000)



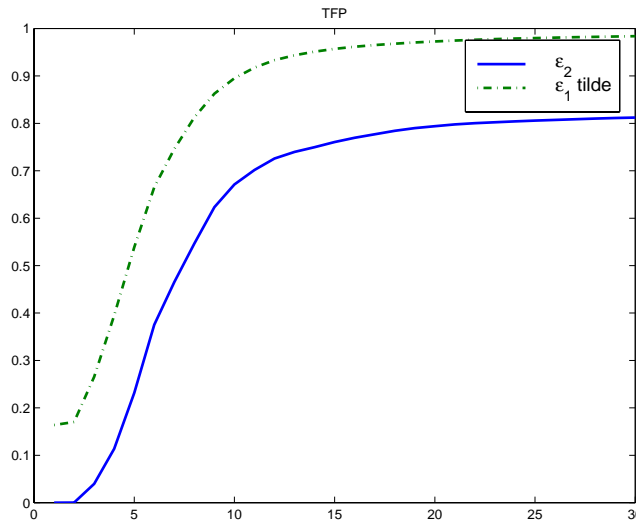
Each panel of this figure plots ϵ_2 against $\tilde{\epsilon}_1$. Both shocks are obtained from the baseline (TFP, SP) VAR, with 2 lags and one cointegrating relation. The straight line is the 45° line.

Figure 4: Japan: Impulse Responses of TFP and Stock Prices to ϵ_2 (solid line) and $\tilde{\epsilon}_1$ (circles) with One Cointegrating Relation in the (TFP, SP) VAR using confidence bands of the long run identification



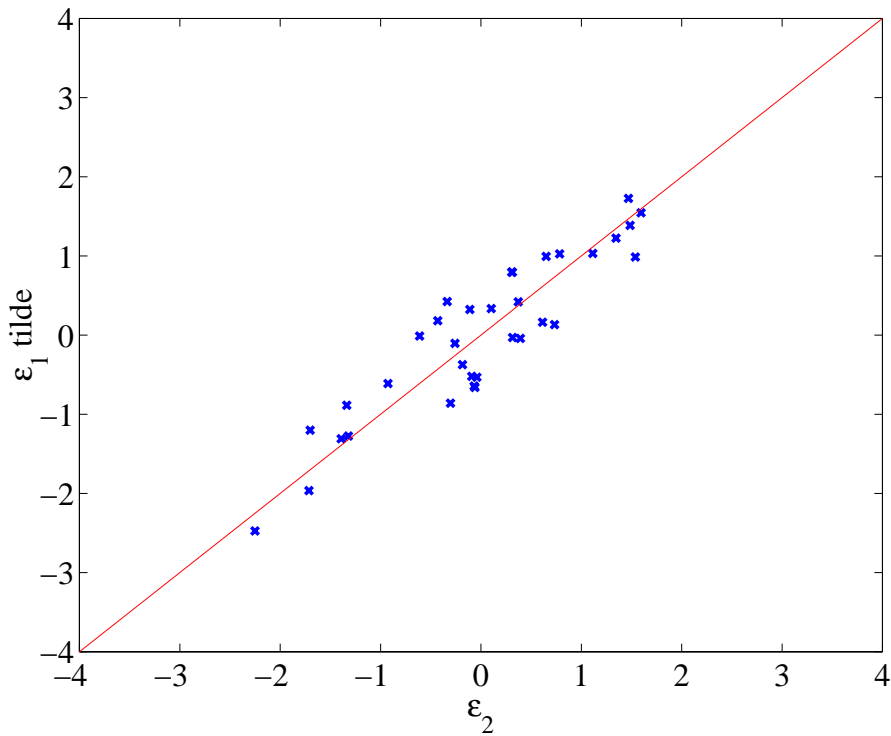
On each panel of this figure, the bold line represents the point estimate of the responses to a unit ϵ_2 shock (the shock that does not have instantaneous impact on TFP in the short run identification); the line with circles represents the point estimate of the responses to a unit $\tilde{\epsilon}_1$ shock (the shock that has a permanent impact on TFP in the long run identification). Both identifications are done in the baseline bivariate specification. The unit of the vertical axis is percentage deviation from the situation without shock. Dotted lines represent the 10% and 90% quantiles of the distribution of the IRF in the case of the long run identification, this distribution being the bayesian simulated distribution obtained by Monte-Carlo integration with 1000 replications, using the approach for just-identified systems discussed in Doan (1992).

Figure 5: Japan: Forecast Error Variance of TFP explained by ϵ_2 and $\tilde{\epsilon}_1$



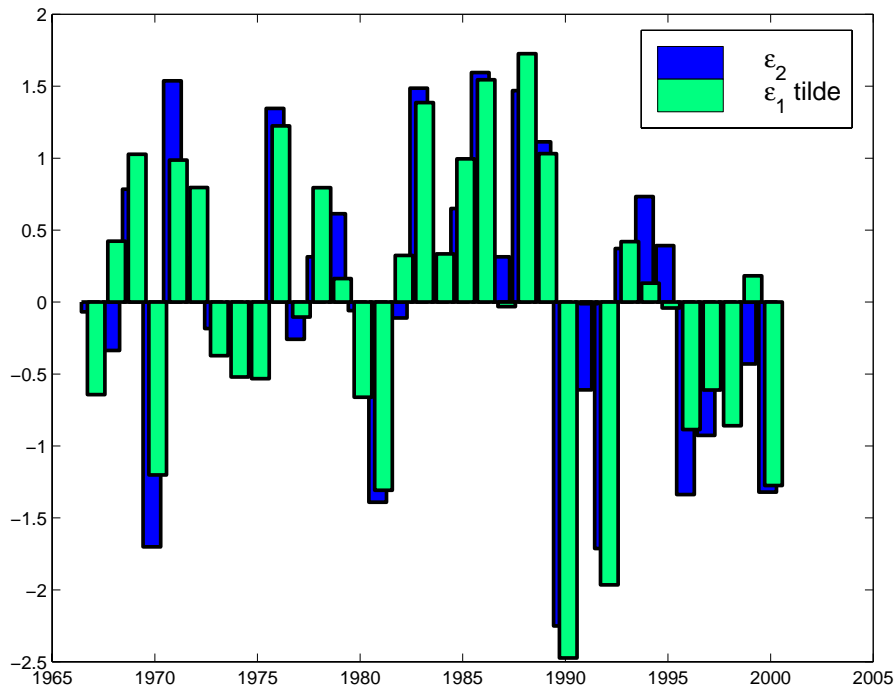
This figure displays the share of TFP forecast error variance attributed to ϵ_2 (the shock that does not have instantaneous impact of TFP in the short run identification) or to $\tilde{\epsilon}_1$ (the shock that has a permanent impact on TFP in the long run identification)(right panel), both in the baseline bivariate Japanese specification.

Figure 6: ϵ_2 Against $\tilde{\epsilon}_1$ in the (TFP, SP) VAR, Japanese Annual Data



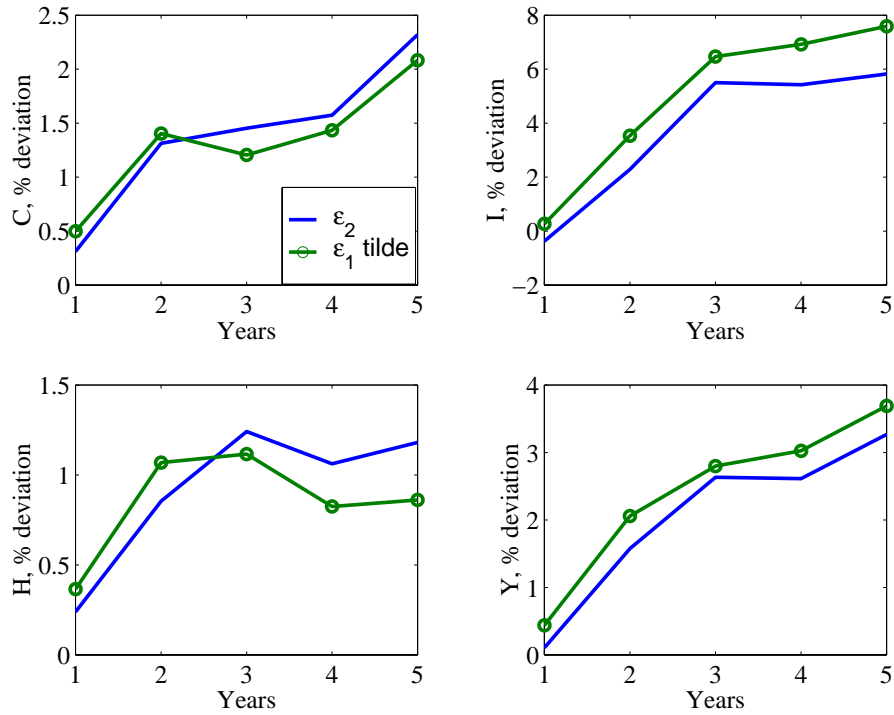
This figure plots ϵ_2 against $\tilde{\epsilon}_1$. Both shocks are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation. The straight line is the 45° line.

Figure 7: Estimated ϵ_2 and $\tilde{\epsilon}_1$ in the (TFP, SP) VAR, Japanese Annual Data



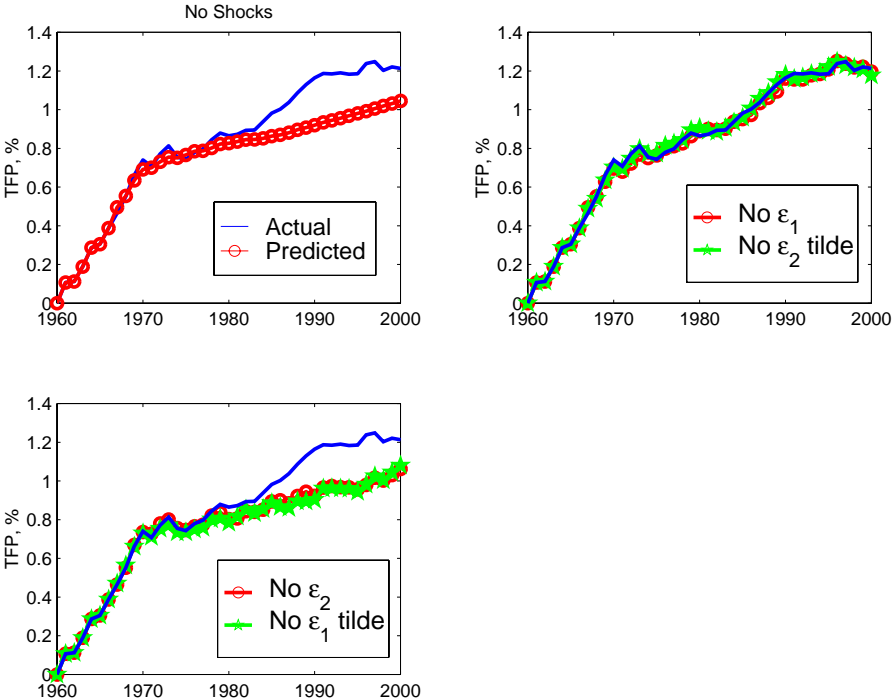
This figure plots ϵ_2 and $\tilde{\epsilon}_1$. Both shocks are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation.

Figure 8: Response of Consumption, Investment, Output (Defined as $C + I$) and Hours to ϵ_2 and $\tilde{\epsilon}_1$ in the (TFP, SP) VAR, Japanese Annual Data



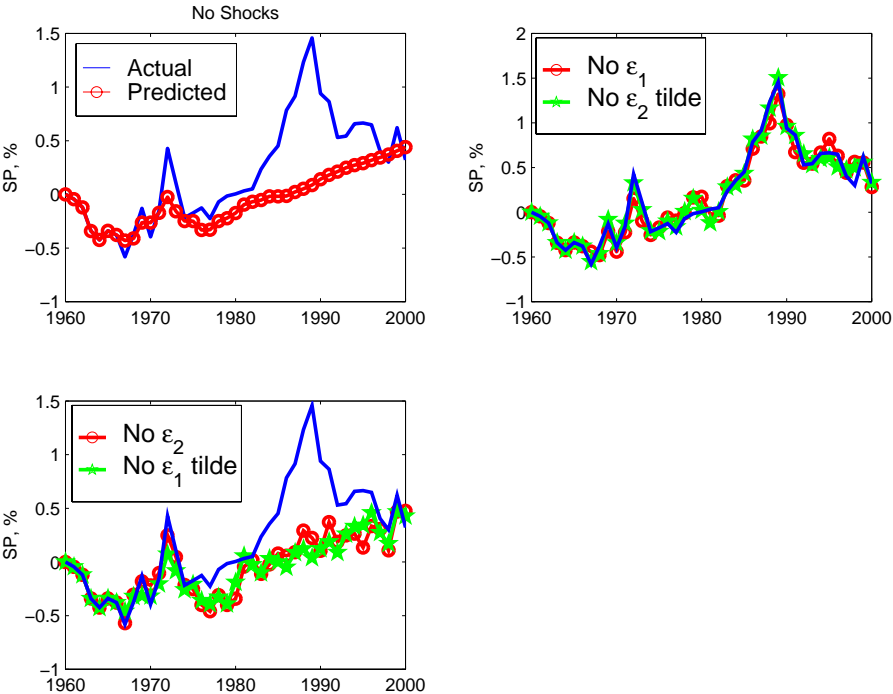
This figure displays the response of consumption, Investment, Output (Defined as $C + I$) and Hours to a unit ϵ_2 shock (the shock that does not have instantaneous impact on TFP in the short run identification) or to a unit $\tilde{\epsilon}_1$ (the shock that has a permanent impact on TFP in the long run identification). The unit of the vertical axis is percentage deviation from the situation without shock (See the main text for more details).

Figure 9: Historical Decomposition of the TFP path, Whole Sample, (TFP, SP) VAR, Japanese Annual Data



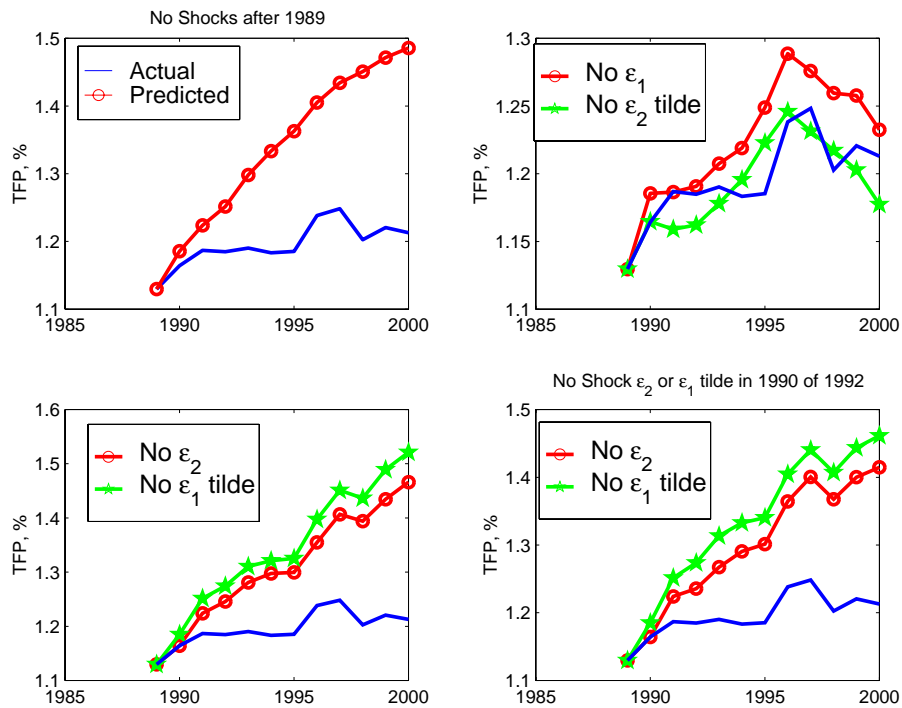
This figure plots the decomposition of TFP into movements explained by some various combinations of structural shocks (See the main text for more details). Results are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation.

Figure 10: Historical Decomposition of the SP path, Whole Sample, (TFP, SP) VAR, Japanese Annual Data



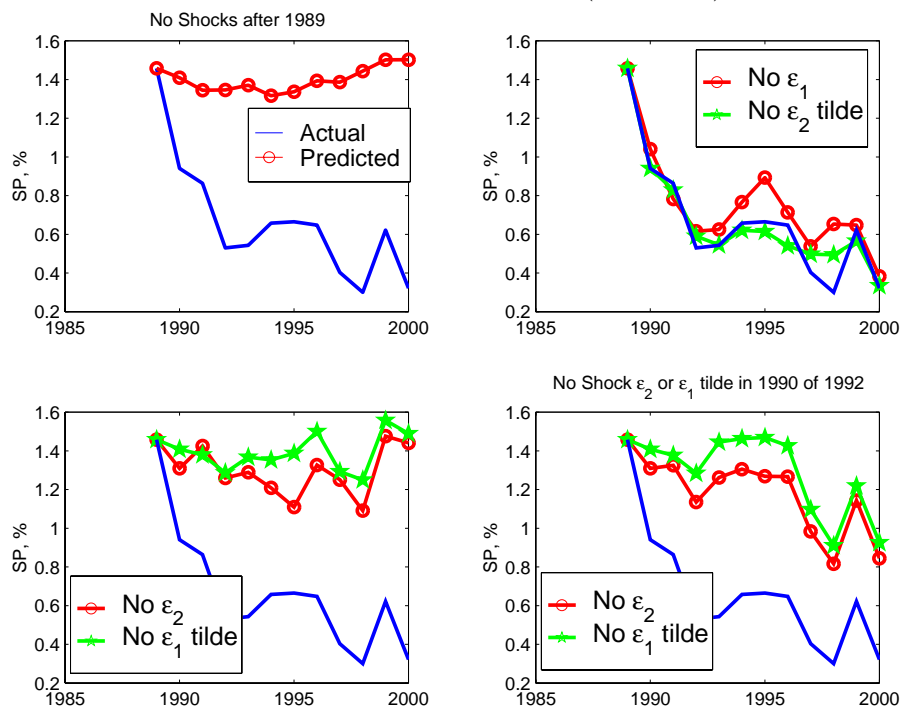
This figure plots the decomposition of SP into movements explained by some various combinations of structural shocks (See the main text for more details). Results are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation.

Figure 11: Historical Decomposition of the TFP path, 1990's, (TFP, SP) VAR, Japanese Annual Data



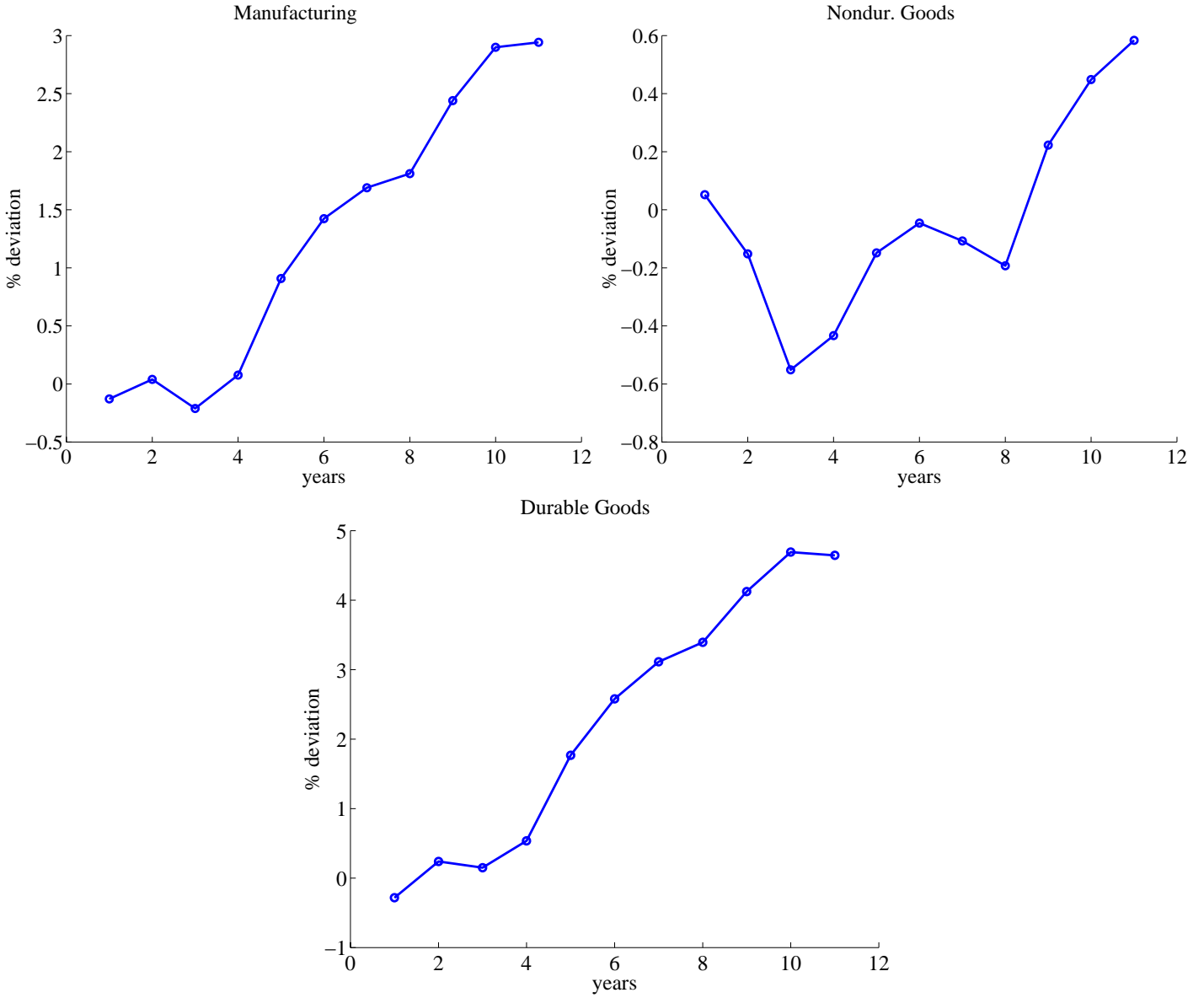
This figure plots the decomposition of TFP into movements explained by some various combinations of structural shocks (See the main text for more details). Results are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation.

Figure 12: Historical Decomposition of the SP path, 1990's, (TFP, SP) VAR, Japanese Annual Data



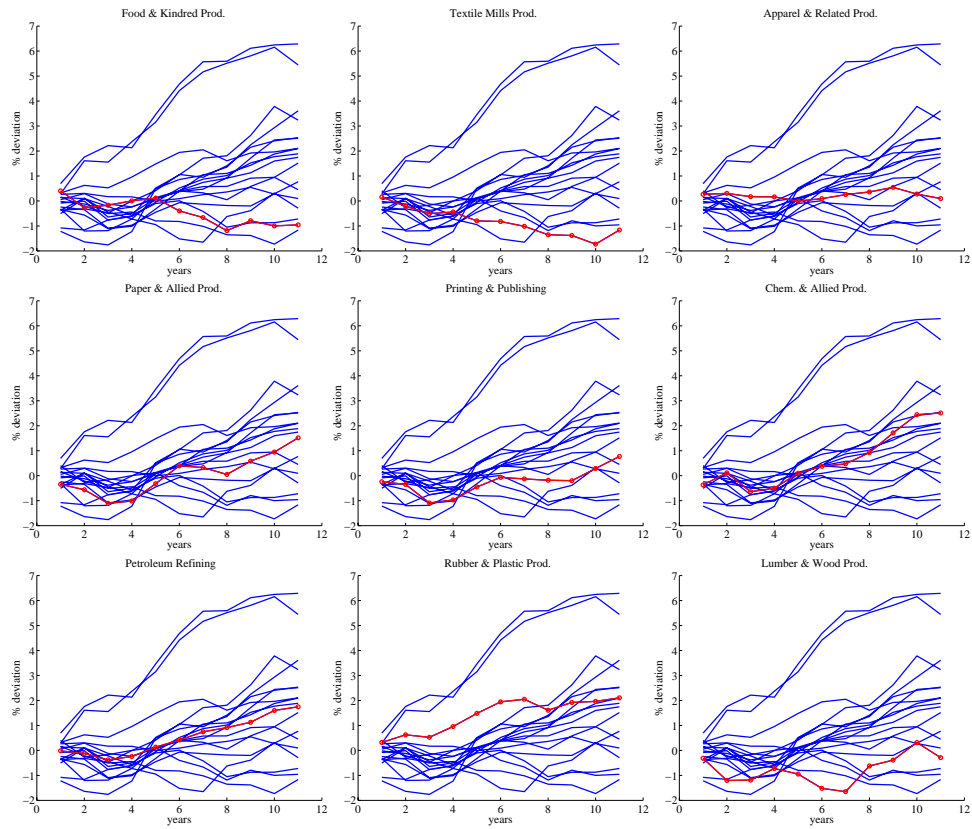
This figure plots the decomposition of sP into movements explained by some various combinations of structural shocks (See the main text for more details). Results are obtained from the baseline (TFP, SP) VAR, with 6 lags and one cointegrating relation.

Figure 13: U.S. Sectoral TFP Responses To a Stock market Innovation ϵ_2



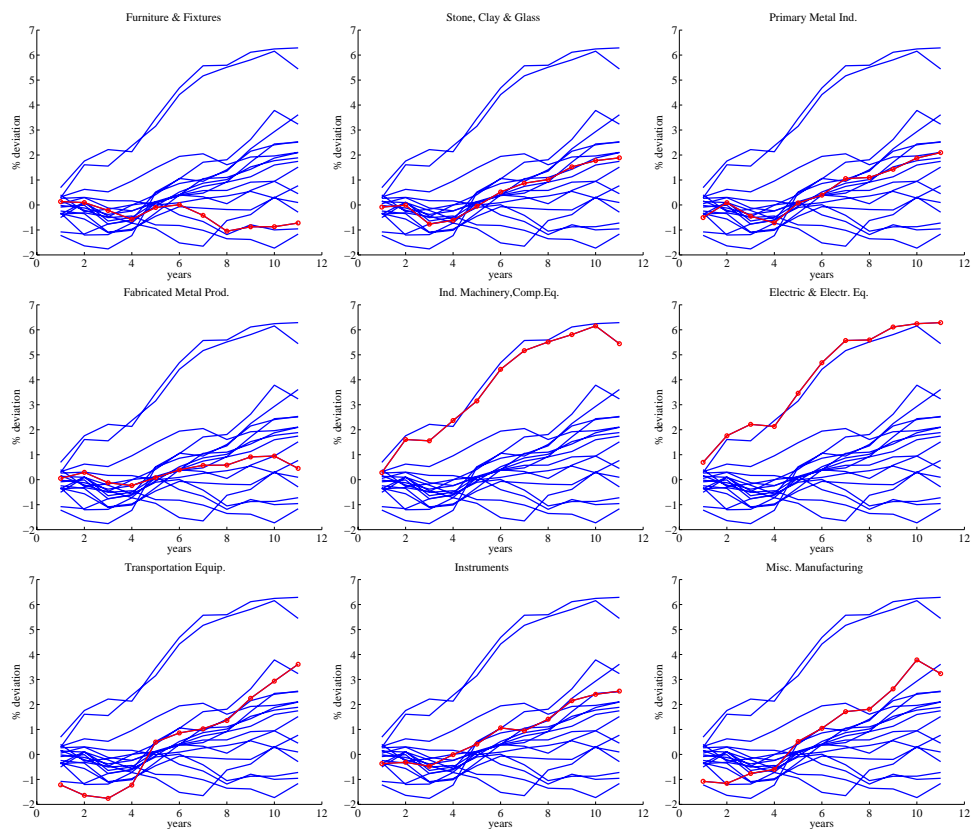
This figure displays the response of Sectoral TFP to a unit ϵ_2 shock (the shock that does not have instantaneous impact on aggregate TFP in the short run identification). The unit of the vertical axis is percentage deviation from the situation without shock (See the main text for more details).

Figure 14: U.S. Sectoral TFP Responses To a Stock market Innovation ϵ_2 , 2-digit level (a)



This figure displays the response of Sectoral TFP to a unit ϵ_2 shock (the shock that does not have instantaneous impact on aggregate TFP in the short run identification). The unit of the vertical axis is percentage deviation from the situation without shock (See the main text for more details).

Figure 15: U.S. Sectoral TFP Responses To a Stock market Innovation ϵ_2 , 2-digit level (b)



This figure displays the response of Sectoral TFP to a unit ϵ_2 shock (the shock that does not have instantaneous impact on aggregate TFP in the short run identification). The unit of the vertical axis is percentage deviation from the situation without shock (See the main text for more details).