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New Evidence on News-Driven Business Cycles

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New Evidence on News-Driven Business Cycles

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Abstract:

We study the Beaudry and Portier (2006)-hypothesis of delayed-technology diffusion and news-driven business cycles. For German data on TFP and stock prices we find qualitatively similar empirical evidence. Quantitatively, however, an impulse response analysis suggests that a substantial part of the total TFP response is immediate rather than delayed. We relate this to disembodied technological change and noisy data on TFP. Nevertheless, we confirm the technology interpretation of structural shocks by showing that they are Granger-causal for data on patents granted by the German patent agency.

JEL: E32

Keywords: news, business cycles, TFP, structural VAR

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1 Introduction

In a recent paper, Beaudry and Portier (2006) have emphasized that stock prices may have relevant informational content for understanding macroeconomic fluctuations. New information, their argument goes, may alter expectations about future fundamentals. Forward looking variables such as stock prices will react to changes in expectations much earlier than the foreseen changes in fundamentals affect other macroeconomic time series. In particular, news about technological innovations may affect stock prices instantaneously, but due to an implementation lag, it may take some time until they actually alter total factor productivity (TFP). Thus, our understanding of expectations-driven macroeconomic fluctuations could be enhanced if news about expected changes in fundamentals could be properly identified from, among others, stock market data.

For this purpose, Beaudry and Portier (BP) suggest to use structural vector autoregressions (SVAR). Imposing different identifying restrictions on the estimated lag polynomial of a moving average (MA) representation (cf. Blanchard and Quah (1989)) yields a set of structural shocks for ready comparison. If similar shocks are found under different identifying assumptions, then the type of identifying assumption reveals important information about the way a specific shock hits the economy. This, in turn, allows inference on the validity of competing models and their assumptions.

For instance, in a bivariate vector autoregression for US TFP and stock prices, BP find two almost co-linear shocks under two polar identifying assumptions. The first identifying assumption imposes that there exists a shock which does not alter TFP in the short run, the alternative identifying assumption imposes that there exists a shock which does not alter TFP in the very long-run. The two co-linear shocks are consistent with the former but inconsistent with the latter. Hence, BP conjecture that they represent a technological innovation which affects TFP with considerable delay. However, this technological innovation affects stock prices immediately and may therefore cause expectations-driven fluctuations in consumption and investment.

The idea of a prominent role for technology-related news in macroeconomic fluctuations has recently given rise to quite a few other papers, e. g. Lorenzoni (2006) and Jaimovich and Rebelo (2006). It is therefore very interesting to investigate if the empirical finding of BP in favor of news-driven business cycles is a robust business cycle fact which can be documented for other countries and samples as well. Moreover, one would like to know if there is any kind of direct evidence which supports the interpretation of the identified shocks as being technology shocks.

In the first line of research, Beaudry and Portier (2005) took the lead by repeating their analysis with Japanese data. Here they came up with essentially the same finding as for the US: Two almost co-linear “technology” shocks under alternative identifying assumptions. In this paper, we look at Germany as a third country and present a similar, but slightly weaker piece of evidence: There is evidence of a gradually increasing response of TFP to certain shocks in excess of a clearly positive effect on impact. Therefore, if the identified shocks are indeed technological, the overall evidence is quite supportive of a stylized business cycle fact of delayed TFP response to technology shocks.

Going further, we test whether the identified shocks are rightly considered as technology shocks by confronting them with data on patents granted by or applied for at the German patent agency. For various measures of TFP and patents, we have very robust evidence that

the identified shocks Granger-cause patents. Conversely, the identified non-persistent shock in the SVAR-approach is not Granger-causal in any of the specifications we test. This seems to be fairly strong evidence for the hypothesis that the identified shock, which affects TFP on impact and with a delay, is indeed a technology shock.

The sequel of the paper is organized as follows: In section 2, we illustrate that the BP approach can be used to infer key model properties. We present a modified Long and Plosser (1983) model which allows for multi-period usage of capital goods. We compute stock prices as the discounted sum of expected returns to capital. We then show that a standard specification of TFP shocks has very different implications for the shocks identified in the Blanchard-Quah approach than a delayed-implementation specification. In section 3, we briefly illustrate the econometric approach and apply it to German data. We use three different measures of TFP in order to check the robustness of our results. Section 4 analyzes Granger-causality between the identified shocks and different measures of patents. Section 5 concludes.

2 The Model

We will illustrate the potential of the BP approach by considering two versions of the same model: One with a standard, instantaneous reaction of TFP to a technological innovation, the other with a delayed response. This is similar to BP (2005). However, their model assumes 100% depreciation on physical capital, which makes it difficult to model stock prices, since, essentially, firms shut down each period. Hence, BP (2005) do not consider stock prices but rather focus on bonds whose price is inversely related to the return on the (one-period) capital goods. By contrast, we use a model where the productive use of capital goods extends over many periods and stock prices are computed as the discounted sum of expected returns to capital.

The model is taken from Long and Plosser (1983). We aggregate their model to just a single sector, but extend its production technology to a multi-period setting. Specifically, investment goods I_t can be used for $p+1$ periods until they are completely worn out. The production elasticities of investment of period $t-\tau$ is given by a_τ and we can allow for any kind of depreciation schedule by securing $a_\tau > a_{\tau+1} \quad \forall \tau < p$. Labor input is L_t with production elasticity $b > 0$, so that constant returns imply $\sum_{\tau=0}^p a_\tau + b = 1$. Λ_{t+1} is TFP of period $t+1$ and production is given by

$$Y_{t+1} = \Lambda_{t+1} L_t^b \prod_{\tau=0}^p I_{t-\tau}^{a_\tau} \quad (1)$$

or (using small letters to denote logs)

$$y_{t+1} = b l_t + \sum_{\tau=0}^p a_\tau i_{t-\tau} + \lambda_{t+1}. \quad (2)$$

The representative agent has a standard intertemporal utility function with subjective discount factor $0 < \beta < 1$ and risk aversion captured by $\sigma > 1$. $\theta_t = e^{\eta_{2t}}$ is a stationary preference shock and the innovation η_{2t} is, for simplicity, white noise with unit variance.

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

Maximizing utility under the budget constraint

$$C_t + I_t = Y_t \quad (3)$$

yields first order conditions

$$\frac{I_t}{C_t} = \sum_{\tau=0}^p \beta^{\tau+1} a_\tau E_t \left[1 + \frac{I_{t+1+\tau}}{C_{t+1+\tau}} \right] =: \gamma + \sum_{\tau=0}^p \beta^{\tau+1} a_\tau E_t \left[\frac{I_{t+1+\tau}}{C_{t+1+\tau}} \right] \quad (4)$$

and

$$\theta_t L_t^\sigma = \beta b E_t \left[1 + \frac{I_{t+1}}{C_{t+1}} \right]. \quad (5)$$

Imposing stability, solving (4) forward and using (3) yields

$$C_t = (1 - \gamma) Y_t, \quad I_t = \gamma Y_t. \quad (6)$$

This is the policy function, since Y_t is a state variable. For labor, we compute

$$l_t = \ln L_t = \frac{1}{\sigma} \left(\ln \frac{\beta b}{1 - \gamma} - \eta_{2t} \right). \quad (7)$$

Inserting (6) into (1) we get

$$Y_{t+1} = \Lambda_{t+1} \gamma^a L_t^b \prod_{\tau=0}^p Y_{t-\tau}^{a_\tau}, \quad (8)$$

where $a := \sum_{\tau=0}^p a_\tau$. Setting $\kappa := a \ln \gamma + \frac{b}{\sigma} \ln \frac{\beta b}{(1 - \gamma)}$ and taking logs we get:

$$y_{t+1} = \kappa + \sum_{\tau=0}^p a_\tau y_{t-\tau} + \lambda_{t+1} - \frac{b}{\sigma} \eta_{2t} =: \kappa + a(L) y_{t+1} + \lambda_{t+1} - \frac{b}{\sigma} \eta_{2t} \quad (9)$$

$$y_t = \frac{\kappa}{1 - a} + \frac{\left(\lambda_t - \frac{b}{\sigma} \eta_{2t-1} \right)}{1 - a(L)} := \frac{\kappa}{1 - a} + A(L) \left(\lambda_t - \frac{b}{\sigma} \eta_{2t-1} \right), \quad (10)$$

where $a(L), A(L)$ are polynomials in the lag operator L and $a(0) = 0, A(0) = 1$.

Net profits are output minus labor and investment costs:

$$\Pi_{t+1} := Y_{t+1} - \frac{\partial Y_{t+1}}{\partial L_t} L_t - I_{t+1} = (1 - b - \gamma) Y_{t+1} \quad (11)$$

Let $SP_t := E_t \left[\sum_{\tau=1}^{\infty} \beta^{\tau} \Pi_{t+\tau} \right]$ be the stock price, i. e. the discounted sum of profits expected in period t . By definition, we have

$$SP_t := E_t \left[\sum_{\tau=1}^{\infty} \beta^{\tau} \Pi_{t+\tau} \right] = \beta E_t [\Pi_{t+1}] + E_t \left[\beta \sum_{\tau=1}^{\infty} \beta^{\tau} \Pi_{t+1+\tau} \right] = \beta E_t [\Pi_{t+1}] + \beta E_t [SP_{t+1}].$$

Log-linearizing this equation we get:

$$\begin{aligned} sp_t &\approx cns_t + (1-\beta) E_t \pi_{t+1} + \beta E_t sp_{t+1} \\ &= \frac{cns_t}{(1-\beta)} + (1-\beta) E_t \left(\sum_{\tau=0}^{\infty} \beta^{\tau} \pi_{t+1+\tau} \right) \\ &=: cns_{t1} + (1-\beta) \sum_{\tau=0}^{\infty} \beta^{\tau} E_t \left(A(L) \left(\lambda_{t+1+\tau} - \frac{b}{\sigma} \eta_{2t+\tau} \right) \right) \\ &=: cns_{t1} - \delta(L) \eta_{2t} + (1-\beta) \sum_{\tau=0}^{\infty} \beta^{\tau} (E_t A(L) \lambda_{t+1+\tau}), \end{aligned} \tag{12}$$

where $\delta(0) \neq 0$.

Let us now consider two different specifications for the stochastic processes driving the model. The standard specification would be a random walk for log TFP:

$$\lambda_t = \lambda_{t-1} + \eta_{1t} \tag{13}$$

Here, η_{1t} is assumed to be white noise with unit variance.

The alternative specification would specify a delayed response of log TFP to permanent technological innovations. Assume that log TFP is the sum of a random walk component ζ and a stationary process v . There are orthogonal, unit-variance-white noise innovations η_1 and η_3 to ζ and v , respectively. The η_3 innovation affects log TFP in the same period in which it becomes known, while we assume that the η_1 innovation affects TFP with a delay of one period. Thus, the stochastics are described by

$$\begin{aligned} \lambda_t &= \zeta_{t-1} + v_t \\ \zeta_t &= \zeta_{t-1} + \eta_{1t} \\ v_t &= \rho v_{t-1} + \eta_{3t}, \quad \rho < 1 \end{aligned} \tag{14}$$

To preserve the same number of shocks as under the standard specification, we assume that there is no preference shock in the delayed-response specification, $\eta_{2t} = 0 \quad \forall t$.

Under the standard specification we derive from (12)

$$\begin{aligned}
sp_t &\approx const_1 - \delta(L)\eta_{2t} + \tilde{A}(L)\lambda_t \\
\Delta sp_t &\approx \tilde{A}(L)(1-L)\lambda_t - \delta(L)(1-L)\eta_{2t} \\
&= \tilde{A}(L)\eta_{1t} - \delta(L)(1-L)\eta_{2t},
\end{aligned}$$

where $\tilde{A}(L)$ is a lag polynomial with $\tilde{A}(0) \neq 0 \neq \tilde{A}(1)$.

Hence, the moving average representation is given by

$$\begin{pmatrix} \Delta \lambda_t \\ \Delta sp_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \tilde{A}(L) & -\delta(L)(1-L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} =: C_1(L) \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix}. \quad (15)$$

Under the delayed-response specification we know

$$\begin{aligned}
sp_t &\approx const_2 + \tilde{A}(L)\zeta_t + \tilde{B}(L)v_t \\
&= const_2 + \tilde{A}(L)\zeta_t + \frac{\tilde{B}(L)}{1-\rho L}\eta_{3t}
\end{aligned}$$

with $\tilde{B}(0) \neq 0 \neq \tilde{B}(1)$. The moving average representation for the first differences is then given by

$$\begin{pmatrix} \Delta \lambda_t \\ \Delta sp_t \end{pmatrix} = \begin{pmatrix} L & \frac{(1-L)}{1-\rho L} \\ \tilde{A}(L) & \frac{\tilde{B}(L)}{1-\rho L}(1-L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{3t} \end{pmatrix} =: C_2(L) \begin{pmatrix} \eta_{1t} \\ \eta_{3t} \end{pmatrix}. \quad (16)$$

From (15) and (16) we infer that the first row of both $C_1(1)$ and $C_2(1)$ is $(1,0)$, while the first row of $C_1(0)$ and $C_2(0)$ are very different: $(1,0)$ and $(0,1)$, respectively. This implies that the identification of the structural shocks gives rise to different patterns, too, and these patterns can be used to infer what the true underlying model is. We will discuss this in detail in the next section.

3 The Econometric Approach

Consider empirical time series for log TFP and log stock prices, denoted λ_t and sp_t as before. We assume these are integrated of order one and cointegrated with each other, i. e. $(\Delta \lambda_t, \Delta sp_t)'$ is $I(0)$. Using Wold's decomposition theorem, $(\Delta \lambda_t, \Delta sp_t)'$ can be written in reduced form

$$\begin{pmatrix} \Delta \lambda_t \\ \Delta sp_t \end{pmatrix} = C(L) \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \quad \text{with} \quad C(L) := I + \sum_{i=1}^{\infty} C_i L^i \quad (17)$$

and in structural form

$$\begin{pmatrix} \Delta\lambda_t \\ \Delta sp_t \end{pmatrix} = D(L) \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \quad \text{with} \quad D(L) := \sum_{i=0}^{\infty} D_i L^i. \quad (18)$$

Identifying the structural shocks ε requires knowledge of D_0 . This matrix can be recovered from the estimated $C(L)$ matrices of the reduced form (17), if one restriction is imposed on the parameters of $D(L)$. We follow Beaudry and Portier (2005, 2006) by using two alternative assumptions, which we call the short-run and the long-run restriction. The former postulates that the (1,2) element of $D(0)$ is zero, i. e. the stock market shock ε_{2t} has no effect on TFP on impact. The latter postulates that the (1,2) element of $D(1)$ is zero, i. e. the stock market shock ε_{2t} has no long-run effect on TFP. Let us think of (18) as the representation obtained under the short-run restriction and let (19) be the representation obtained under the long-run restriction:

$$\begin{pmatrix} \Delta\lambda_t \\ \Delta sp_t \end{pmatrix} = \tilde{D}(L) \cdot \begin{pmatrix} \tilde{\varepsilon}_{1,t} \\ \tilde{\varepsilon}_{2,t} \end{pmatrix} \quad \text{with} \quad \tilde{D}(L) := \sum_{i=0}^{\infty} \tilde{D}_i \cdot L^i \quad (19)$$

If the empirical data were generated by the model of section 2 with standard specification, i. e. by equation (15), the impact matrix

$$C_1(0) = \begin{pmatrix} 1 & 0 \\ \tilde{A}(0) & -\delta(0) \end{pmatrix}$$

would already fulfill the short-run identifying assumption, hence, as structural shocks we would identify $\varepsilon_1 = \eta_1$, $\varepsilon_2 = \eta_2$. On the other hand, the long-run matrix is

$$C_1(1) = \begin{pmatrix} 1 & 0 \\ \tilde{A}(1) & 0 \end{pmatrix},$$

thus, we would immediately have $\tilde{\varepsilon}_1 = \eta_1$, $\tilde{\varepsilon}_2 = \eta_2$. The important point is that under both identifying assumptions we would find the same result for ε_1 and $\tilde{\varepsilon}_1$.

If, conversely, the empirical data were generated by the delayed technology specification, the impact matrix would be

$$C_2(0) = \begin{pmatrix} 0 & 1 \\ \tilde{A}(0) & \tilde{B}(0) \end{pmatrix}.$$

In this case, the identifying assumptions imply that $\varepsilon_{1t} = \eta_{3t}$, $\varepsilon_{2t} = \eta_{1t}$, whereas under the long-run restriction we have

$$C_2(1) = \begin{pmatrix} 1 & 0 \\ \tilde{A}(1) & 0 \end{pmatrix}$$

and hence $\tilde{\varepsilon}_{1t} = \eta_{1t}$, $\tilde{\varepsilon}_{2t} = \eta_{2t}$. Under this model, we would thus not find the same result for ε_1 and $\tilde{\varepsilon}_1$, but rather we would find that $\varepsilon_2 = \tilde{\varepsilon}_1$. Therefore, if the empirical analysis suggests that $\varepsilon_2 \approx \tilde{\varepsilon}_1$ we may infer that a model with delayed technology response is more appropriate than a standard specification. We now turn to an investigation of this issue for German data.

3.1 Data description

As in Beaudry and Portier (2006), three different TFP variables are calculated: the standard Solow residual, the Solow residual adjusted for variable capital utilization and a TFP measure following the methodology of Groth et al. (2004) and Oulton (2001).

We have quarterly data from 1970(1) to 2005(2). The simple TFP measure (without capital utilization) is computed from data on GDP, hours worked and annual capital stock data interpolated with constant within year quarterly growth rates. Under the assumption of constant returns to scale, the observed quarterly labor share is used as the production elasticity of labor. The log of this measure is denoted TFP_D1. Modifying the capital stock data by multiplying with the capacity utilization rate in manufacturing gives a second measure of TFP whose log is denoted TFP_D2.

Computation of the third TFP measure (TFP_D3) takes several criticisms of the standard Solow residual into account. Quality aspects are considered when measuring labor input. Under the assumption of perfect competition, the quality of work is reflected by wages. Therefore, quality adjusted labor input L_t can be constructed as

$$\hat{L}_t = \sum_{i=1}^n \left(\frac{s_{it} + s_{it-1}}{2} \right) \cdot \hat{h}_{it}, \quad (20)$$

where hatted variables are growth rates, n constitutes the number of employee categories, s_{it} describes output contribution and h_{it} working hours of group i in period t . In the case of Germany, relevant data in terms of gross earnings exist for salaried employees of the service and manufacturing sectors, and in terms of gross wages for wage earners of manufacturing and agriculture. From microdata, four categories of labor input can be distinguished.

The concept of capital input does not refer to the capital stock but uses a measure of capital services. Different types of assets are weighed by their rental prices to represent the value of services which can be realized at perfect competition. Rental prices MP of asset type j in period t are, in principle, computed as

$$MP_{j,t} = T_{j,t} \cdot \left[\left(r_{j,t} + \delta_j - \hat{p}_{j,t} \right) \cdot p_{j,t} \right], \quad (21)$$

where $r_{j,t}$ are opportunity costs, δ_j is depreciation and $T_{j,t}$ expresses taxation and investment allowances¹.

¹ As in Oulton (2001) dwellings are excluded from buildings because dwellings may not conform with strict profit maximizing behavior. Depreciation rates for machinery and buildings are assumed to be 13% and 2.5%. Market prices of both assets result from the ratio of nominal and real values of the respective gross fixed capital formation. Rates of return are computed by the ratio of gross operating surplus and capital stock value. The tax factor is disregarded due to lack of adequate data.

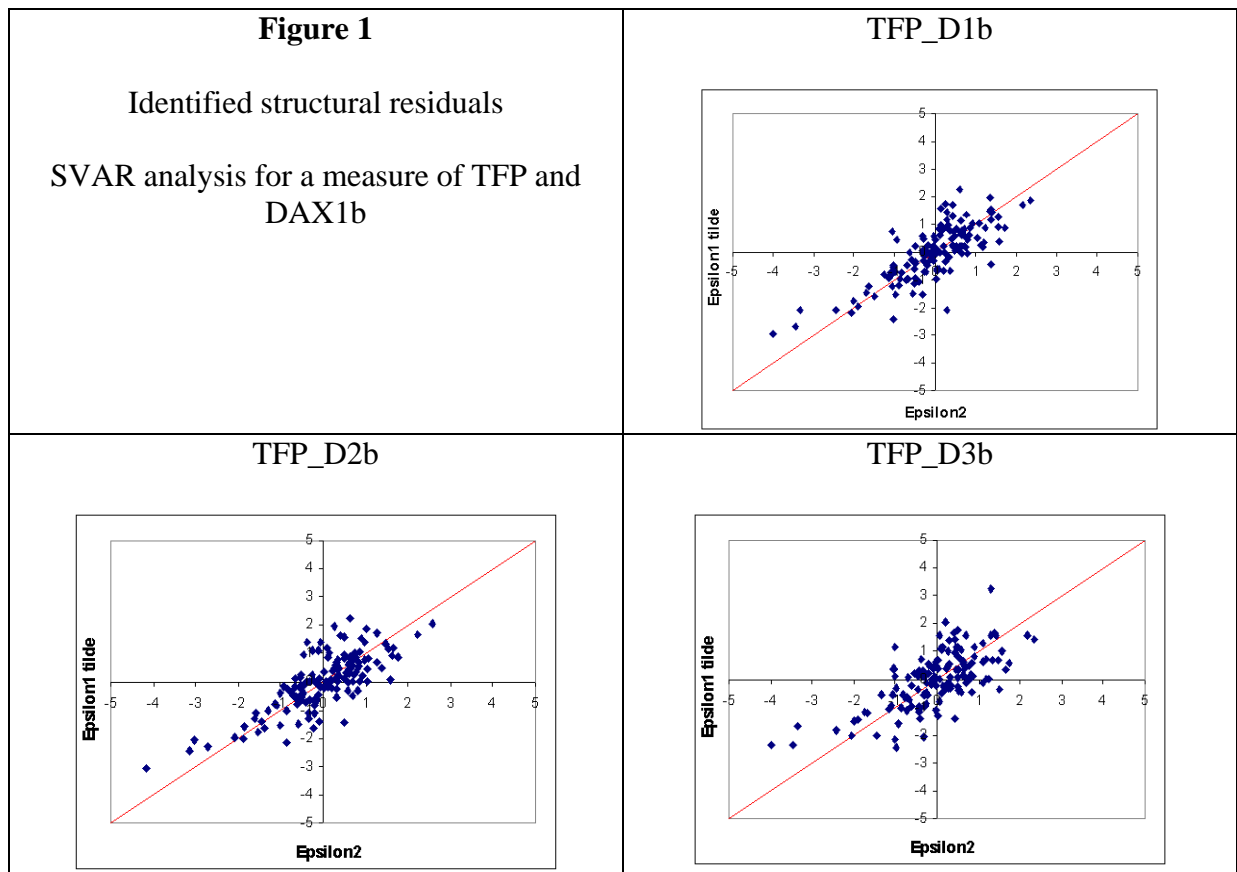
Stock prices are approximated using the German stock market index DAX deflated by the GDP deflator. We follow Beaudry and Portier (2006) and transform into per-capita values by dividing through the number of employees. The log of the resulting series is denoted DAX1. See the appendix for time series graphs of the constructed series TFP_D1, TFP_D2, TFP_D3 and DAX1.

3.2 Testing, Estimation, Identification

The analysis of German data requires particular care due to the change in the territorial definition which took effect in the first quarter of 1991. As unit root and cointegration tests are severely affected by structural breaks, we exploit the fact that the break point is known and that time series for West Germany and reunified Germany overlap in the first years of the nineties. In particular, the level of West German time series is still available in the first quarter of 1991, while growth rates for unified Germany are available since the second quarter of the same year. We construct time series without a unification break by applying the growth rates for unified Germany to West German levels in the first quarter of 1991 and denote the break-adjusted series TFP_D1b, TFP_D2b, TFP_D3b and DAX1b.

Given the absence of structural breaks, a standard Augmented Dickey Fuller (ADF) test is used to check for unit roots. We cannot reject the null hypothesis in any case (cf. Table A1 in the appendix), thus, we will treat all variables as $I(1)$. To test for a long-run equilibrium relationship of technology and stock market prices we apply the Johansen trace test with an orthogonal trend, cf. Table A2 in the appendix. We can reject the null of no cointegration with DAX1b for all versions of the TFP variable. This gives rise to the specification of bivariate vector error correction models (VECM) whose coefficient estimates are used to compute the reduced form moving average representation. For the estimation results, see the appendix.

Going through the identification under both the short- and the long-run restriction, we find for all three measures of TFP a pronounced positive correlation between ε_2 and $\tilde{\varepsilon}_1$, cf. Figure 1. The correlation is about 0.78 for TFP_D1b and TFPD2b; it is 0.68 for TFP_D3b. While this falls short of the almost perfect co-linearity found by Beaudry and Portier (2005, 2006) for Japan and the US, it certainly tends to favor a delayed-technology-diffusion hypothesis over the standard model.

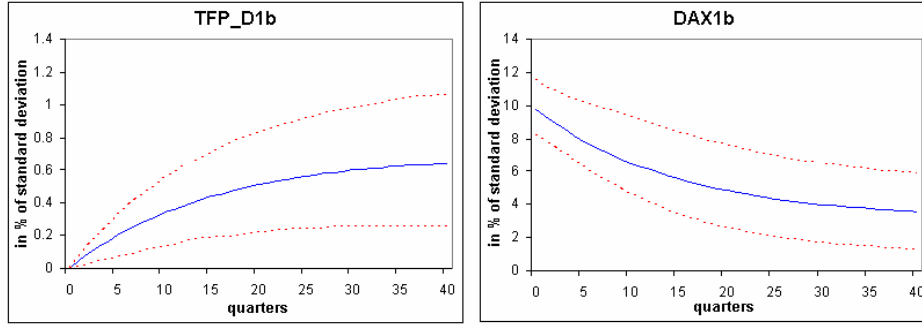


To explore this issue further, let us look at impulse response functions. We focus here on the basic TFP-version TFP_D1b (without capital utilization) – the results for TFP_D2b (with capital utilization) are very similar. The quality-adjusted TFP-measure TFP_D3b will be discussed separately.

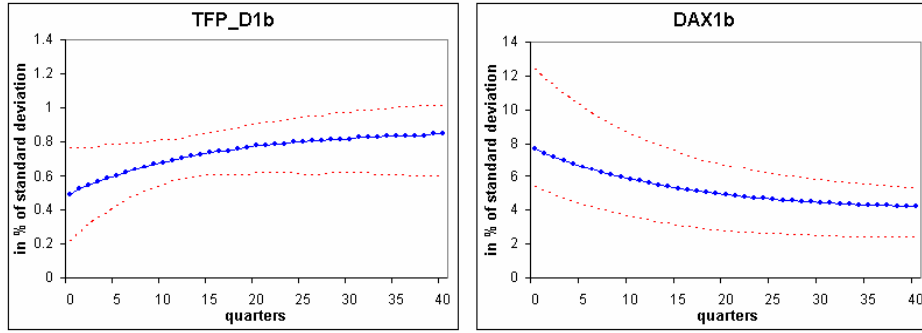
The upper panel in Figure 2 shows the impulse responses of the levels of TFP and stock prices to ε_2 , i. e. the structural shock identified by the requirement that it does not have an immediate effect on TFP. This shock has a strong immediate effect on stock prices, but about 60% of this effect melts away over the next ten years. If this shock was a gradually diffusing technology shock, then the interpretation of the upper panel would state that stock markets receive new information on a technological innovation, which slowly increases TFP. Stock markets anticipate future profits and prices rise. But as the innovation diffuses through the economy, competition reduces profits again and stock prices adjust to the lower level of remaining future profits. (Note that in BP (2006) the impulse response of stock prices rises quickly in the first two or three quarters and stays virtually constant thereafter. It is not clear how a higher level of profits can be maintained over the long run if the economy is competitive).

Figure 2: Impulse-response functions for TFP_D1b and DAX1b¹

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



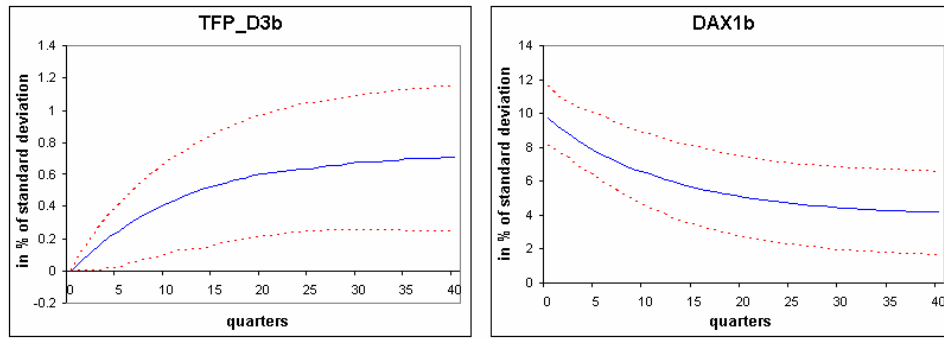
In the lower panel of Figure 2 we see the response to the shock $\tilde{\varepsilon}_1$ identified under the restriction that the other shock $\tilde{\varepsilon}_2$ must not affect TFP in the long-run. If $\tilde{\varepsilon}_1$ and ε_2 were perfectly co-linear, then the impulse responses in the lower panel of Figure 2 should be equal to those in the upper panel. This, however, is not the case. Unlike ε_2 , the shock $\tilde{\varepsilon}_1$ is allowed to have an instantaneous effect on TFP. If we consider merely the point estimates, the instantaneous effect is substantial and equals about 60% of the long-run effect. Nevertheless, about 40% of the innovation seems to diffuse gradually. The impulse response of stock prices is slightly weaker on impact – a result which is well in line with the interpretation that part of the technological innovation diffuses rather quickly so that competition brings profits back to normal faster than with a more delayed technology diffusion.

Results for TFP_D2b are very similar, see the appendix. For the quality-adjusted TFP-measure TFP_D3b, however, we find that there is virtually no gradual diffusion of technology to TFP, the effect of $\tilde{\varepsilon}_1$ on TFP and stock prices (lower panel of Figure 3) is almost instantaneous and virtually constant over time. Consequently, there is a large difference between the impulse responses in the upper and lower panel of Figure 3. Given our discussion on Figure 2, this is not completely surprising, since we knew already that the correlation between ε_2 and $\tilde{\varepsilon}_1$ is lower for the quality adjusted measures than for the two standard measures. So does this latter finding, which is based on methodologically more appealing construction of TFP, constitute evidence against the delayed-diffusion model?

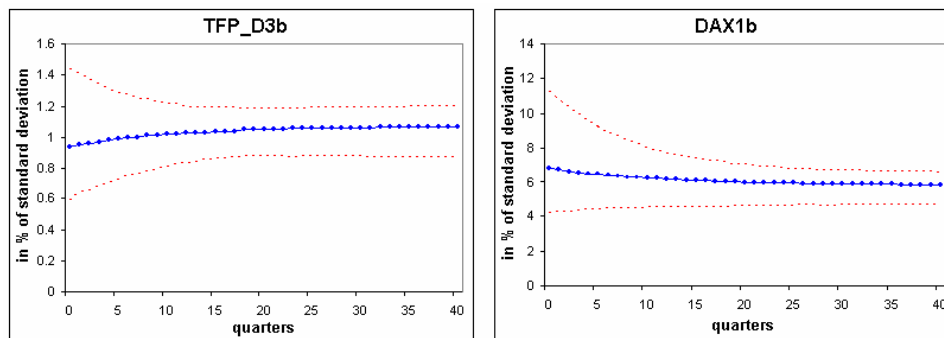
¹ Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

Figure 3: Impulse-response functions for TFP3 and DAX¹

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



Not necessarily. Note that technological innovations are typically embodied in either physical or human capital. In fact, this may precisely be the reason why technology diffuses somewhat slowly: It is not the mere existence of an idea, which increases standard measures of TFP, but its implementation in new machinery or its communication in terms of schooling and training and both requires time. Now, as long as a standard measure of TFP is used, advances in the quality of labor and capital are incorrectly attributed to TFP and our SVAR exercises show the gradual diffusion of a new idea into the production factors. With a quality-adjusted measure of TFP, however, our measure comprises just those technological innovations which need not be embodied in either production factor. As far as we can see, there is no compelling reason why such innovations should not be able to diffuse much faster (and possibly almost instantaneously) than embodied technical progress.

One might object to the above argument on the grounds that the quality-adjusted TFP-measure is different from standard measures, but captures nevertheless many movements in TFP in a similar way. If most technological innovations are indeed embodied in either labor or capital (or both), then one would expect that a quality-adjusted TFP-measure has little resemblance with standard measures. However, two counterarguments may be advanced: On the one hand, sticky factor prices may induce incomplete quality adjustment. On the other hand, TFP, being computed as a residual, is a measure of our ignorance (Abramovitz (1962)) and probably includes many non-technology developments which also affect production. Both standard and quality-adjusted measures of TFP share these unknown components and may therefore look more similar than they should.

¹ Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

4 Granger Causality

We are thus left with the question if the shocks ε_2 and $\tilde{\varepsilon}_1$ are predominantly technological in nature. So far this is merely an interpretation suggested from a simple economic model which assumed the existence of technology shocks (and assumed away all kinds of other shocks). We will now confront our candidates for technology shocks with data on technological innovations, namely the number of patents granted by the German patent agency. We will also look at data on patent applications.

These data have recently been published by Jungmittag und Grupp (2006) for 1850-1913 and 1950-1999. The data are yearly and given our earlier analysis we are just interested in the subsample 1970-1999. We aggregate the SVAR shocks by summing the quarterly values to annual frequency. We will first look at the number of granted patents. There are two measures available: the number of patents granted to German applicants (PGG) and the total number of patents granted (PGT).

It is, of course, an open issue, when exactly technological innovations become publicly known. Any invention which seeks patent protection has to be described in the patent application. By German law, this description must be sufficiently detailed to be understood by a knowledgeable person. The patent agency will publish the patent application not later than 18 months after it has been submitted. This can be long before a decision has been reached and a patent granted or refused. Hence, technological innovations are, in general, publicly known before a patent is granted.

The natural hypothesis to test for is thus a possibly causal effect of innovations on granted patents. If the technology-interpretation of the identified shocks ε_2 and $\tilde{\varepsilon}_1$ is correct, then these shocks might Granger-cause patents. Also, patents should not Granger-cause ε_2 and $\tilde{\varepsilon}_1$ since the patent applications (with technical descriptions) are already known before the patent agency decides on granting a patent.

We proceed by estimating bivariate VARs for one of the two measures of granted patents and one of the six ε_2 and $\tilde{\varepsilon}_1$ shocks identified under the three TFP measures. The lag length of the VAR is determined by the Schwarz criterion. Throughout, the chosen lag length is one.

Table 1 contains the main results. In each cell, there are two p-values. In the upper left corner we give the p-value for the hypothesis that the shock does not Granger-cause granted patents, while in the lower right corner we test the null that granted patents do not Granger-cause the shock. For all specifications, we find that the shock is indeed Granger-causal for granted patents (usually at the 1% level of significance), while the converse seems not to be true.

Table 1: Granger Causality Tests
Shocks suspected to be technological

		PGG	PGT
TFP1	ε_2	0.006 0.945	0.006 0.120
	$\tilde{\varepsilon}_1$	0.003 0.774	0.009 0.162
TFP2	ε_2	0.013 0.952	0.009 0.179
	$\tilde{\varepsilon}_1$	0.008 0.897	0.010 0.144
TFP3	ε_2	0.007 0.878	0.005 0.152
	$\tilde{\varepsilon}_1$	0.002 0.752	0.005 0.052

Upper left corner: P-value for null: Row variable does not Granger-cause column variable.

Lower right corner: P-value for null: Column variable does not Granger-cause row variable.

Note that the tests in Table 1 are not independent. In fact, the statistics are probably highly correlated, and hence the evidence is not quite as suggestive as it may appear. But nevertheless we can safely state that Granger-causality seems to be a robust feature of the data which is found across all specifications of TFP, for both measures of patents and for both identifying assumptions.

Table 2: Granger Causality Tests
Shocks suspected to have no permanent effect on TFP

		PGG	PGT
TFP1	ε_1	0.378 0.801	0.815 0.963
	$\tilde{\varepsilon}_2$	0.172 0.889	0.083 0.358
TFP2	ε_1	0.544 0.697	0.715 0.639
	$\tilde{\varepsilon}_2$	0.341 0.846	0.249 0.367
TFP3	ε_1	0.086 0.748	0.267 0.354
	$\tilde{\varepsilon}_2$	0.199 0.838	0.086 0.619

Upper left corner: P-value for null: Row variable does not Granger-cause column variable.

Lower right corner: P-value for null: Column variable does not Granger-cause row variable.

The shocks ε_1 and $\tilde{\varepsilon}_2$ were assumed to have only a transitory effect on TFP. Thus they should not be interpreted as inventions but rather as temporary effects such as changes in motivation, strikes, variation of capital utilization etc. Hence, we would expect that ε_1 and $\tilde{\varepsilon}_2$ do not Granger-cause patents, nor are Granger-caused by patents. Table 2 shows that indeed all tests give insignificant test statistics.

Apart from granted patents, data on patent applications are available: Applications from German applicants (PAG) and total applications (PAT) These data are certainly less informative, because only between one-third and one-fifth of the applications are successful,

hence many of the applications do apparently not represent inventions. Also, PAG is very strongly skewed due to a few observations in the late 1990s, when patent applications were increasing tremendously. Therefore, any kind of inference is very difficult for PAG and we have focused on PAT. We do not report the results in detail, but they are available upon request. Suffice it to say that no Granger-causality can be found between PAT and any of the identified shocks. This is what one would expect if inventors try to keep their inventions secret as long as possible, but the inventions are disclosed after submitting the patent application. (Recall that the time lag between submission and disclosure is at most 18 months, if it is shorter, it may well fall within the same year.)

One might criticize our procedure of simply aggregating quarterly shocks to yield annual frequency. In order to check for a possible temporal aggregation bias, we estimate the bivariate VARs also with annual data. Moreover, the frequency conversion may serve as a test of the robustness of our results. We thus recalculate the time series TFP_D1b, TFP_D2b, TFP_D3b and DAX1b with annual data.

Looking at the results of the Johansen trace test, we now do not find evidence for cointegration, in marked contrast to our results with quarterly data. This is an immediate contradiction, since cointegration for the quarterly series would imply that the annual series are also cointegrated. In view of the relatively low p-values of the Johansen test statistics for annual data one may thus suspect that the Johansen tests for annual data suffer from low power. We therefore reverse the test procedure by testing for the null hypothesis of cointegration using the Shin (1994) test. This test is also not able to reject the null hypothesis and this finding is robust for various choices of the truncation lag. Consequently, there is still no convincing evidence against the view that TFP and stock market prices are cointegrated.

We therefore redo the analysis in complete analogy to our handling of quarterly data. All relevant results for VECM estimation and impulse response analysis are presented in the appendix, as they are qualitatively very similar to the quarterly results. The resulting annual structural residuals can then be used in Granger causality tests which are not subject to temporal aggregation bias. The results are given in Tables 3 and 4. Basically, the conclusions from the earlier tests are unaltered. In most cases, the identified technology shocks are Granger-causal for granted patents and in the few cases where this is not the case, the p-values are very close to 5%. The converse is not true, i. e. nowhere are granted patents Granger-causal for the technology shocks. Moreover, there is no causality in either direction between granted patents and the non-technology shocks. Hence the available indicators indicate that the SVAR analysis correctly identifies technology and non-technology innovations for the German economy.

Table 3: Granger Causality Tests (identified shocks from annual VECM)
Shocks suspected to be technological

		PGG	PGT
TFP_D1b	ε_2	0.060 0.895	0.037 0.313
	$\tilde{\varepsilon}_1$	0.051 0.814	0.036 0.632
TFP_D2b	ε_2	0.050 0.731	0.029 0.223
	$\tilde{\varepsilon}_1$	0.015 0.826	0.016 0.263
TFP_D3b	ε_2	0.028 0.662	0.033 0.142
	$\tilde{\varepsilon}_1$	0.020 0.372	0.067 0.052

Upper left corner: P-value for null: Row variable does not Granger-cause column variable.

Lower right corner: P-value for null: Column variable does not Granger-cause row variable.

Table 4: Granger Causality Tests (identified shocks from annual VECM)
Shocks suspected to have no permanent effect on TFP

		PGG	PGT
TFP_D1b	ε_1	0.397 0.836	0.351 0.446
	$\tilde{\varepsilon}_2$	0.417 0.999	0.3800 0.945
TFP_D2b	ε_1	0.136 1.000	0.190 0.701
	$\tilde{\varepsilon}_2$	0.636 0.762	0.463 0.488
TFP_D3b	ε_1	0.221 0.500	0.421 0.236
	$\tilde{\varepsilon}_2$	0.357 0.880	0.281 0.687

Upper left corner: P-value for null: Row variable does not Granger-cause column variable.

Lower right corner: P-value for null: Column variable does not Granger-cause row variable.

5 Conclusions

The purpose of this study was to provide further evidence on the BP-hypothesis of delayed-technology diffusion and news-driven business cycles. For German data on TFP and stock prices we find qualitatively the same result as BP do: A high correlation between a shock with permanent effects on TFP in the long run and – under a different identification scheme - a shock which has an immediate effect on stock prices but does not affect TFP on impact.

The correlation is less pronounced, though, as in BP's analysis for US and Japanese data. Also, the impulse response analysis suggests that for Germany a substantial part of the total TFP response is immediate rather than delayed. Using a quality-adjusted measure of TFP, there is almost no delayed diffusion any more. This suggests that the delayed diffusion is

confined to embodied technological change. Disembodied technological innovations seem to have immediate effects on TFP. But since the share of disembodied technological progress in total technological progress may be small, the relatively large size of the quality-adjusted TFP measure suggests, that each measure of German TFP may actually contain a fairly large part of unexplained non-technology influences, i. e. our ignorance about the true nature of what we measure as TFP may be fairly large. It may therefore be the case that noise in TFP data is responsible for the immediate reaction of standard TFP measures in the impulse response analysis.

Given possibly noisy data on TFP, we then checked how well the identification of technology shocks in the SVAR approach worked. The answer seems to be: Surprisingly well. Shocks suspected to be technology shocks are Granger-causal for the number of patents granted by the German patent agency, while shocks without permanent effect on technology are not. This result is very robust across different specifications, measures and identification schemes. It may therefore be the case that the SVAR approach is able to separate the true, permanent technology shocks from transitory noise which also affects measured TFP. Under this interpretation, our results are quite supportive for BP's news-driven business cycle hypothesis.

6 Appendix

Results for quarterly data:

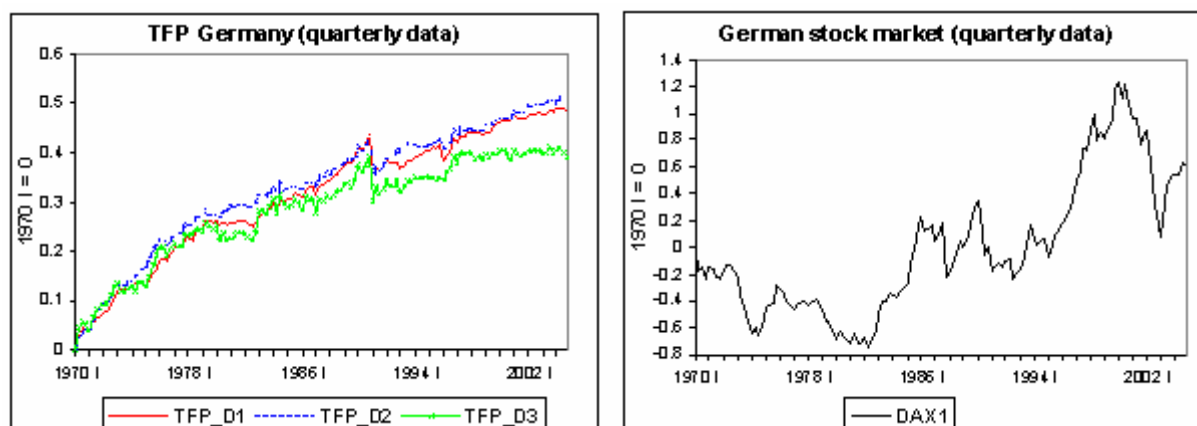


Table A1

ADF test					
Variable	Level / 1st diff.	Lags	Test statistics	Critical value (5%)	p-value
TFP_D1b	Level	0	-2.55	-3.44	0.3041
	1st diff.	0	-14.00	-3.44	0.0000
TFP_D2b	Level	1	-2.64	-3.44	0.2643
	1st diff.	0	-15.86	-3.44	0.0000
TFP_D3b	Level	1	-1.70	-3.44	0.7483
	1st diff.	0	-15.11	-3.44	0.0000
DAX1b	Level	0	-2.60	-3.44	0.2810
	1st diff.	0	-10.34	-3.44	0.0000

Table A2

Johansen trace test						
Variables	Lag length (1st diff.)	Trend in error correction term (EC) / Orthogonal Trend (OT)	Hypothesis	Test statistics	Critical value (5%)	p-value
TFP_D1b & DAX1b	0	OT	$r = 0$	16.24	15.49	0.0385
			$r = 1$	1.08	3.84	0.2991
		EC	$r = 0$	19.69	25.87	0.2420
TFP_D2b & DAX1b	1	OT	$r = 0$	19.29	15.49	0.0128
			$r = 1$	2.08	3.84	0.1491
		EC	$r = 0$	24.10	25.87	0.0817
TFP_D3b & DAX1b	0	OT	$r = 0$	15.57	15.49	0.0487
			$r = 1$	1.58	3.84	0.2089
		EC	$r = 0$	19.78	25.87	0.2372

Estimation results of coefficients in VECM {TFP_D1b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D1b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.021* \\ 0.203* \end{pmatrix} \begin{pmatrix} 1.000 & -0.220* \end{pmatrix} \begin{pmatrix} TFP_D1b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.046* \\ -0.399* \end{pmatrix} cnst + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	65.91	0.3432
Heterosc.	9.99	0.9322
Non-Normal.	69.54	0.0000

Implied SVAR coefficients¹

short-run restriction:

$$D_0 = \begin{pmatrix} 0.0080* & 0.0000 \\ -0.0003 & 0.0979* \end{pmatrix}$$

long-run restriction:

$$\tilde{D}_0 = \begin{pmatrix} 0.0049* & -0.0063* \\ 0.0766* & 0.0609* \end{pmatrix}$$

¹ * =significant at the 5% level.

Estimation results of coefficients in VECM {TFP_D2b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D2b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.023* \\ 0.194* \end{pmatrix} \begin{pmatrix} 1.000 & -0.187* \end{pmatrix} \begin{pmatrix} TFP_D2b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} -0.287* & 0.000 \\ 2.241* & 0.141 \end{pmatrix} \begin{pmatrix} \Delta TFP_D2b_{t-1} \\ \Delta DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.046* \\ -0.346* \end{pmatrix} cns + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	55.33	0.5753
Heterosc.	16.34	0.5690
Non-Normal.	58.09	0.0000

Implied SVAR coefficients¹

short-run restriction:

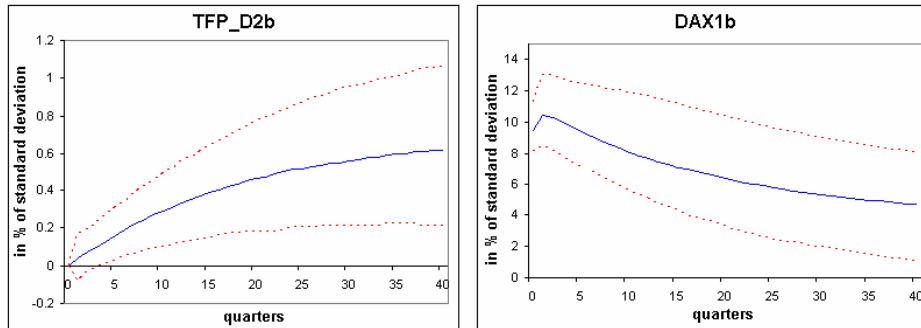
$$D_0 = \begin{pmatrix} 0.0081* & 0.0000 \\ 0.0075 & 0.0947* \end{pmatrix}$$

long-run restriction:

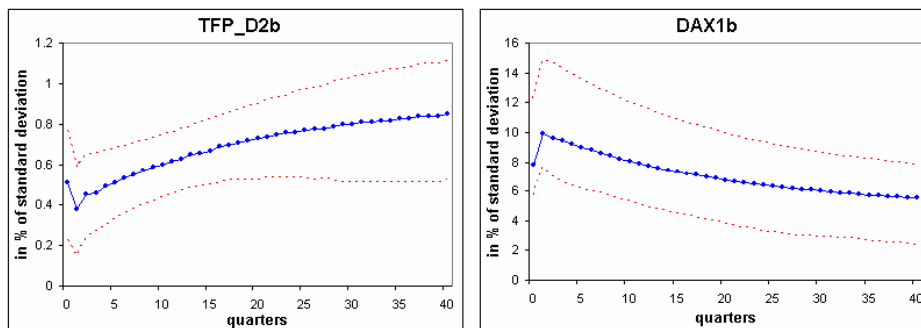
$$\tilde{D}_0 = \begin{pmatrix} 0.0051* & -0.0063* \\ 0.0783* & 0.0537* \end{pmatrix}$$

Impulse-response functions²

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



¹ * =significant at the 5% level.

² Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

Estimation results of coefficients in VECM {TFP_D3b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D3b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.033* \\ 0.258* \end{pmatrix} \begin{pmatrix} 1.000 & -0.186* \end{pmatrix} \begin{pmatrix} TFP_D3b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.060* \\ -0.436* \end{pmatrix} cnst + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	74.70	0.1292
Heterosc.	14.12	0.7215
Non-Normal.	58.89	0.0000

Implied SVAR coefficients¹

short-run restriction:

$$D_0 = \begin{pmatrix} 0.0129* & 0.0000 \\ 0.0021 & 0.0974* \end{pmatrix}$$

long-run restriction:

$$\tilde{D}_0 = \begin{pmatrix} 0.0094* & -0.0088* \\ 0.0681* & 0.0697* \end{pmatrix}$$

¹ * =significant at the 5% level.

Results for annual data:

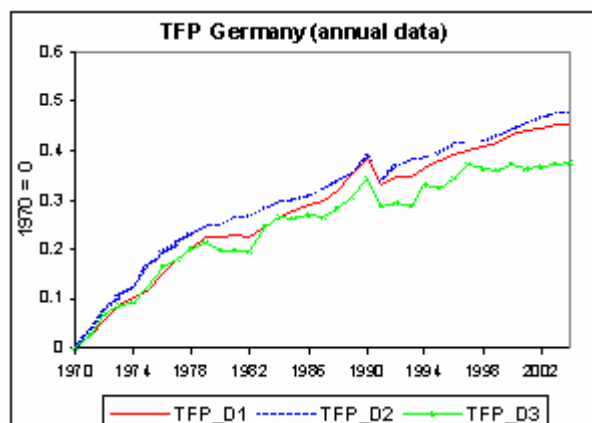


Table A3

ADF test

Variable	Level / 1st diff.	Lags	Test statistics	Critical value (5%)	p-value
TFP_D1b	Level	1	-2.16	-3.55	0.4970
	1st diff.	0	-3.12	-2.95	0.0344
TFP_D2b	Level	1	-2.38	-3.55	0.3847
	1st diff.	0	-2.75	-2.95	0.0763
TFP_D3b	Level	0	-2.04	-3.55	0.5578
	1st diff.	0	-5.01	-2.95	0.0003
DAX1b	Level	1	-3.01	-3.55	0.1437
	1st diff.	0	-3.94	-2.95	0.0048

Table A4

Johansen trace test

Variables	Lag length (1st diff.)	Trend in error correction term (EC) / Orthogonal Trend (OT)	Hypothesis	Test statistics	Critical value (5%)	p-value
TFP_D1b & DAX1b	1	OT	$r = 0$	12.00	15.49	0.1570
		EC	$r = 0$	18.32	25.87	0.3227
TFP_D2b & DAX1b	1	OT	$r = 0$	12.29	15.49	0.1435
		EC	$r = 0$	17.52	25.87	0.3769
TFP_D3b & DAX1b	0	OT	$r = 0$	14.39	15.49	0.0729
		EC	$r = 0$	17.93	25.87	0.3485

Table A5

Shin test (LM test statistics for TFP_D1b & DAX1b)				
		Lagged differences		
		2	4	6
Lag truncations	2	0.140	0.116	0.054
	4	0.112	0.103	0.061
	8	0.127	0.124	0.160
Critical value at the 5% level: 0.314 No linear trend assumption under null hypothesis				

Table A6

Shin test (LM test statistics for TFP_D2b & DAX1b)				
		Lagged differences		
		2	4	6
Lag truncations	2	0.138	0.109	0.049
	4	0.112	0.096	0.072
	8	0.127	0.125	0.113
Critical value at the 5% level: 0.314 No linear trend assumption under null hypothesis				

Table A7

Shin test (LM test statistics for TFP_D3b & DAX1b)				
		Lagged differences		
		2	4	6
Lag truncations	2	0.127	0.062	0.042
	4	0.103	0.057	0.043
	8	0.131	0.117	0.165
Critical value at the 5% level: 0.314 No linear trend assumption under null hypothesis				

Estimation results of coefficients in VECM {TFP_D1b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D1b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.035 \\ 0.700* \end{pmatrix} \begin{pmatrix} 1.000 & -0.226* \end{pmatrix} \begin{pmatrix} TFP_D1b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.418* & 0.011 \\ -2.601 & 0.346* \end{pmatrix} \begin{pmatrix} \Delta TFP_D1b_{t-1} \\ \Delta DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.079* \\ -1.336* \end{pmatrix} cns + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	8.40	0.5894
Heterosc.	6.75	0.6636
Non-Normal.	2.37	0.6680

Implied SVAR coefficients¹

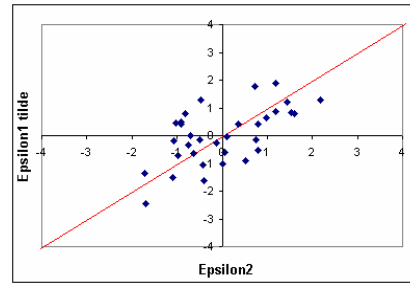
short-run restriction:

$$D_0 = \begin{pmatrix} 0.0084* & 0.0000 \\ 0.0296 & 0.1492* \end{pmatrix}$$

long-run restriction:

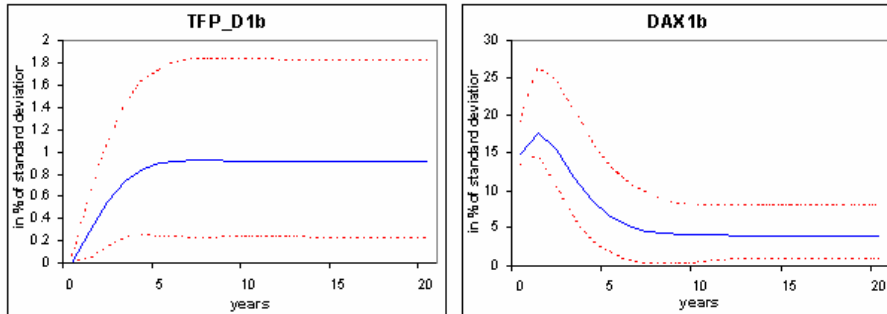
$$\tilde{D}_0 = \begin{pmatrix} 0.0067* & -0.0051* \\ 0.1134* & 0.1013* \end{pmatrix}$$

Identified shocks

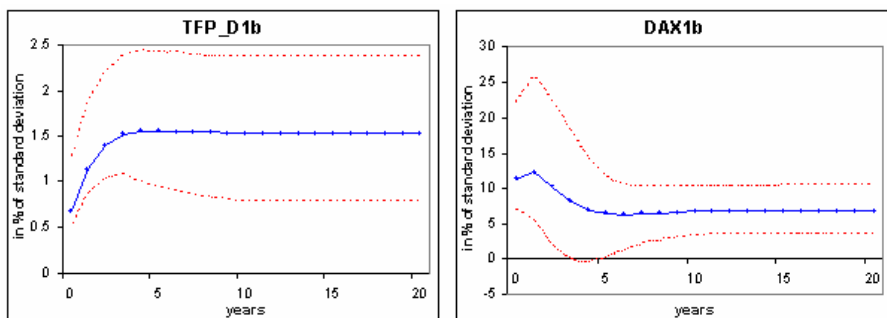


Impulse-response functions²

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



¹ * =significant at the 5% level.

² Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

Estimation results of coefficients in VECM {TFP_D2b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D2b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.036^* \\ 0.777^* \end{pmatrix} \begin{pmatrix} 1.000 & -0.222^* \end{pmatrix} \begin{pmatrix} TFP_D2b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.491^* & -0.007 \\ -0.698 & 0.339^* \end{pmatrix} \begin{pmatrix} \Delta TFP_D2b_{t-1} \\ \Delta DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.079^* \\ -1.516^* \end{pmatrix} cns + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	5.60	0.8479
Heterosc.	4.96	0.5690
Non-Normal.	3.67	0.4526

Implied SVAR coefficients¹

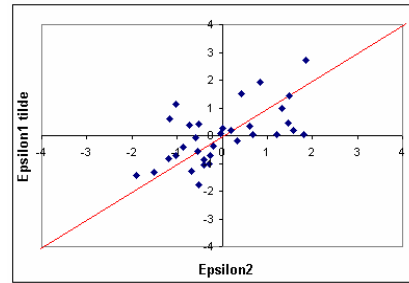
short-run restriction:

$$D_0 = \begin{pmatrix} 0.0078^* & 0.0000 \\ 0.0292 & 0.1506^* \end{pmatrix}$$

long-run restriction:

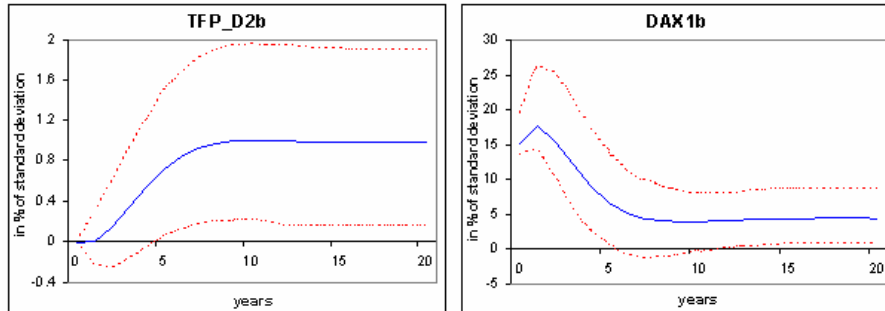
$$\tilde{D}_0 = \begin{pmatrix} 0.0062^* & -0.0047^* \\ 0.1145^* & 0.1021^* \end{pmatrix}$$

Identified shocks

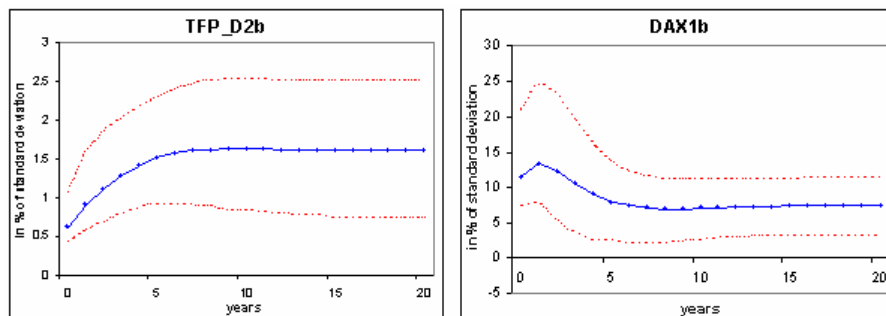


Impulse-response functions²

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



¹ * =significant at the 5% level.

² Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

Estimation results of coefficients in VECM {TFP_D3b, DAX1b}¹

$$\begin{pmatrix} \Delta TFP_D3b_t \\ \Delta DAX1b_t \end{pmatrix} = \begin{pmatrix} -0.064* \\ 0.677* \end{pmatrix} (1.000 \quad -0.142*) \begin{pmatrix} TFP_D3b_{t-1} \\ DAX1b_{t-1} \end{pmatrix} + \begin{pmatrix} 0.099* \\ -0.880* \end{pmatrix} cnst + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Test type	Test statistics	p-value
Autocorr.	14.84	0.3889
Heterosc.	8.3675	0.4976
Non-Normal.	3.46	0.4832

Implied SVAR coefficients¹

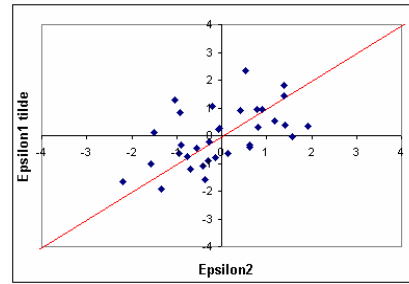
short-run restriction:

$$D_0 = \begin{pmatrix} 0.0159* & 0.0000 \\ 0.0657* & 0.1530* \end{pmatrix}$$

long-run restriction:

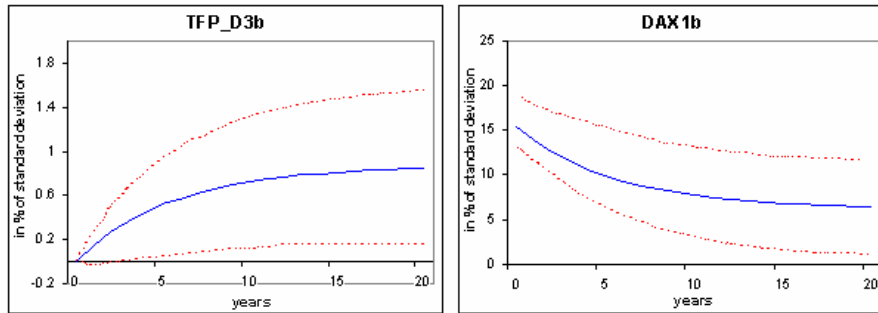
$$\tilde{D}_0 = \begin{pmatrix} 0.0133* & -0.0087* \\ 0.1388* & 0.0919* \end{pmatrix}$$

Identified shocks

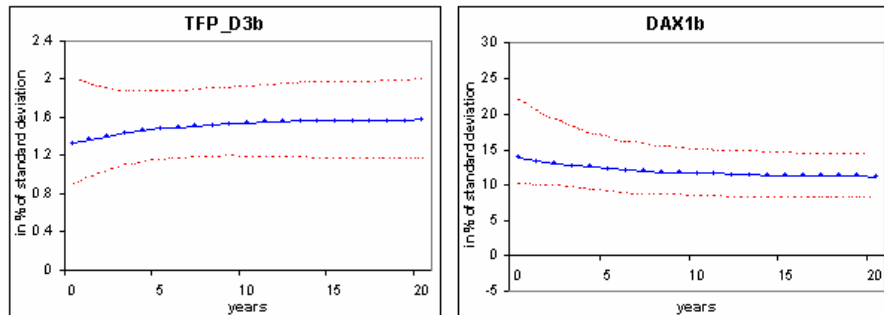


Impulse-response functions²

a) Short-run restriction (response to ε_2):



b) Long-run restriction (response to $\tilde{\varepsilon}_1$):



¹ * =significant at the 5% level.

² Confidence intervals are obtained by 2500 replications with the bootstrapping procedure of Hall (1992). They represent the 95% quantiles.

7 References

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