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# Do monetary and technology shocks move euro area stock prices?

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May 19, 2010

## Abstract

I use a Bayesian vector autoregressive (VAR) model to investigate the impact of monetary and technology shocks on the euro area stock market in 1987-2005. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. The identification method is flexible enough to study the effects of technology news shocks. The responses are consistent with the idea that news on technology improvements have an immediate impact on stock prices. These findings are robust to several modelling choices, including the productivity measure, omitted variables, and the identifying restrictions.

*Keywords:* monetary policy, technology shocks, news, stock prices, Bayesian VAR

*JEL-Codes:* E44, E52, G1, O33

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# 1 Introduction

The objective of this paper is to understand the underlying sources of movements in the euro area stock market. I address this issue by estimating a Bayesian VAR model on 1987-2005 data. The sample period covers the 1995-2003 episode when the stock market experienced a pronounced boom-bust cycle (see Figure 1). Stock prices tripled between 1995 and 2000, showing double-digit returns each year. The boom ended in early 2000 and stock prices declined thereafter by 60% until 2003.

Within the VAR framework, I consider monetary and technology shocks as underlying disturbances. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. Over the sample period, more than 22% of the variation in stock prices can be attributed to technology shocks while monetary shocks explain less than 5%. Moreover, technology shocks are responsible for almost all variation in stock prices during the boom-bust cycle of 1995-2003. In addition, I find a significant response of stock prices to technology news shocks. Finally, I show that these findings are robust to the inclusion of additional disturbances, such as government spending or oil price shocks.

To identify monetary and technology shocks, I use sign restrictions on impulse responses as in Canova and De Nicoló (2002) or Uhlig (2005). I prefer this approach to the long-run restriction method of Galí (1999) which builds on the assumption that technology shocks are the only source of long-run variations in productivity. First, Uhlig (2004) convincingly argues that there exist other shocks that may influence productivity in the long-run, such as permanent changes in capital income taxation or social attitudes to the workplace. And second, the sign restriction method is flexible enough to study the effects of technology news shocks on stock prices. Technology news shocks have only a delayed impact on productivity and are identified by Beaudry and Portier (2006) as being an important determinant of U.S. stock price movements. Furthermore, I can incorporate additional short or long-run restrictions into the framework.

Following Beaudry and Portier (2006), I interpret technology shocks as being the exogenous component of total factor productivity (hereafter 'productivity'). Technology improvements either raise productivity immediately or with a lag of a few quarters. This delayed impact is motivated by technology diffusion models in which firms need some time to adjust productive capacity, i.e. have to hire skilled workers and buy new machines. The most important aspect in such models is that the new technological opportunities are anticipated by economic agents and immediately incorporated into forward looking variables, in particular, stock prices. This results from the assumption that the current stock market value equals the discounted stream of expected firm profits which in turn are a function of future production possibilities.

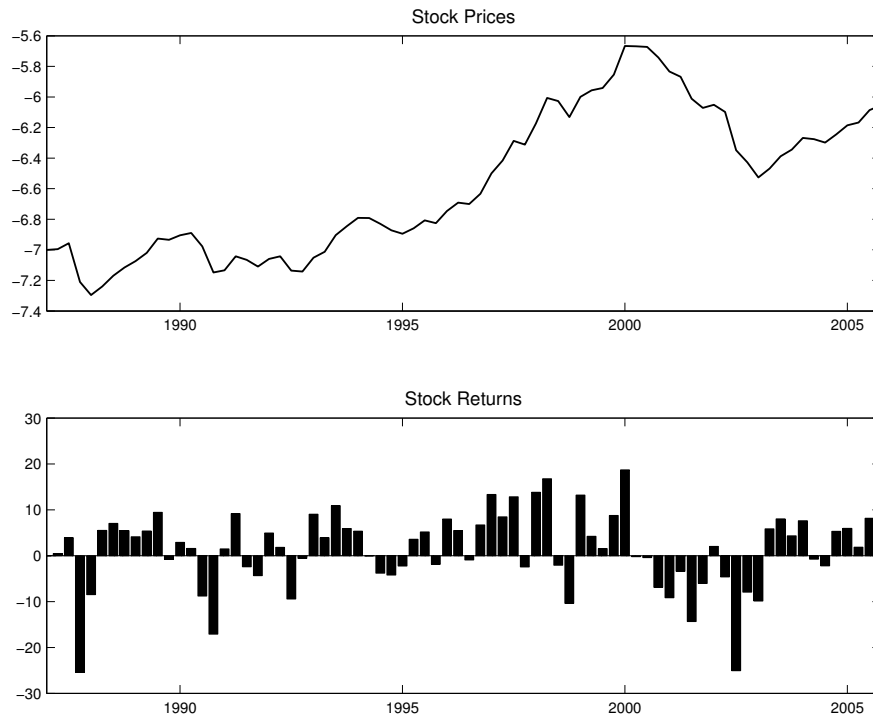


Figure 1: Euro area stock market data. Notes: All entries are log levels (upper panel) or percent (lower panel).

I incorporate monetary shocks into the analysis since it is not a priori clear to me why they should not have effects on real stock prices. Monetary shocks are changes in the stance of monetary policy that cannot be explained by a policy rule, i.e. the endogenous response of the policy interest rate to movements in real activity and inflation. Examples include the response to the stock market crash in 1987, the collapse of the Long-Term Capital Management hedge funds or the terrorist attacks on 9/11. Given the evidence of the monetary VAR literature that monetary disturbances influence the business cycle, they may have (temporary) effects on the discount factor or firm profits, and hence on the stock market. Moreover, the stock market boom of 1995-2000 was accompanied by falling nominal and real interest rates, raising the question if loose monetary policy has contributed to a stock market bubble. In addition, the end of the boom in 2000 coincided with a monetary tightening.

The rest of the paper is organized as follows. Section 2 outlines the Bayesian VAR and the identification strategy with sign restrictions. Section 3 reports the results, including an impulse response analysis and a forecast error variance as well as a historical decomposition. Moreover, I assess the plausibility of the estimated shocks and provide robustness checks. Finally, Section 4 concludes.

## 2 The empirical setup

### 2.1 Bayesian VAR model

A VAR is given by

$$Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + u_t, \quad (1)$$

where  $Y_t$  is a  $G \times 1$  vector of variables,  $A_i$  is a  $G \times G$  coefficient matrix for lags  $i = 1, \dots, p$ ,  $u_t$  is a  $G \times 1$  vector of residuals with covariance matrix  $\Sigma$ , and data are available for  $t = 1, \dots, T$ . Given the vector of structural shocks  $\epsilon_t$ , the residual vector can be written as  $u_t = B\epsilon_t$ , where  $E[\epsilon_t \epsilon_t'] = I$  and thus  $\Sigma = E[u_t u_t'] = BB'$ .

The vector  $Y_t$  contains an index for total factor productivity ( $tfp_t$ ), real GDP in per capita terms ( $y_t$ ), the GDP deflator ( $p_t$ ), a nominal short-term interest rate ( $i_t$ ), a monetary aggregate ( $m_t$ ), and real stock prices in per capita terms ( $s_t$ ). I consider all variables in log levels, except the interest rate, which is expressed in percent. By doing the analysis in levels, I allow for implicit cointegrating relationships between the variables. I do not include a constant or time trend and set the lag length to four.

I estimate the VAR on quarterly data for the period 1987-2005 and provide a summary of the data sources in Appendix A. For stock prices, I use the Dow Jones EURO STOXX Net Return index (which includes dividends), deflated by the GDP deflator and transformed in per capita terms by dividing by the civilian labor force. The index is available from STOXX Limited and was introduced in 1987, which determines the sample period. To obtain quarterly data, I average daily figures. Data on real GDP, the GDP deflator, the interest rate and the civilian labor force come from the Area-wide Model (AWM) database. I use the civilian labor force to transform real GDP into per capita terms. Moreover, monetary data (M1) are from the OECD Main Economic Indicators (MEI) database.

To construct the productivity index, I obtain data on the capital stock ( $K_t$ ) from the AWM database and on annual total hours worked ( $H_t$ ) from the EU KLEMS Growth and Productivity Accounts. The EU KLEMS database is updated until 2005, which limits my sample period. Moreover, I use the interpolation method of Fernández (1981) to obtain quarterly figures on hours, using real GDP and total employment as indicator series. The latter series is from the AWM database. Furthermore, the EU KLEMS database provides data on labor and capital compensation, which I use to calculate an average labor share ( $\bar{\alpha} = 0.66$ ) for the sample period. Finally, I construct a measure of (log) total factor productivity as  $tfp_t = \log(GDP_t/H_t^{\bar{\alpha}}K_t^{1-\bar{\alpha}})$ , where  $GDP_t$  denotes real GDP.

For estimation and inference, I employ a Bayesian approach. In particular, I use a weak Normal-Wishart prior for  $(A, \Sigma)$  as in Uhlig (2005), while shocks are identified per sign restrictions following Canova and De Nicoló (2002). I take a joint draw from  $(A, \Sigma)$  and derive an orthogonal decomposition of  $\Sigma = BB' = PDP'$  using the eigenvalue-eigenvector decomposition.  $P$  is a matrix of eigenvectors,  $D$  is a diagonal matrix with eigenvalues on the main diagonal and  $B = PD^{1/2}$ . Given that for any orthonormal matrix  $Q$ , i.e.  $QQ' = I$ ,  $\Sigma = BQQ'B' = \hat{B}\hat{B}'$  is an admissible decomposition, I can construct a large number of candidate impulse matrices  $\hat{B}$ . I generate orthonormal matrices using the multiple of the basic set of Givens matrices as  $Q = \prod_{m,n} Q_{m,n}(\theta)$  with  $Q_{m,n}(\theta)$  being  $G(G-1)/2 = 15$  bivariate rotation matrices of different elements of the VAR:  $\theta = \theta_1, \dots, \theta_{15}$ , the rows  $m, n$  are rotated by the angle  $\theta_i$ . I provide an example for  $Q_{m,n}(\theta)$  in Appendix B. To exhaust the range of possible decompositions, I do not use a grid search method as in Canova and De Nicoló (2002) but follow Peersman (2005) and draw the parameters  $\theta_i$  from a uniform distribution on the interval  $[0, \pi]$ . Finally, I calculate the associated responses for each candidate draw and keep it if all the restrictions are satisfied. Otherwise, I discard it. Based on the draws kept, I calculate the statistics of interest.

## 2.2 Identifying sign restrictions

Sign restrictions on impulse responses are frequently used to identify monetary shocks in VAR models and widely accepted (see, e.g., Faust, 1998; Canova and De Nicoló, 2002; Uhlig, 2005; Scholl and Uhlig, 2008, among others). These authors impose a small number of uncontroversial restrictions on the sign of impulse responses for selected variables while being agnostic with respect to the responses of others. This procedure allows them to rule out ‘price or liquidity puzzles’ by construction. Consistent with this literature, I impose that a positive interest rate shock has a negative effect on the monetary aggregate and the GDP deflator. I do not restrict the response of real stock prices to leave the question at hand open. Furthermore, I set the horizon for the sign restrictions equal to three, i.e. the restrictions are binding on impact and for the following two quarters. This horizon is within the range used in related studies and rules out short-lived deviations from a policy rule.

Furthermore, I identify two technology shocks. A technology shock that immediately impacts on productivity. And a technology news shock where the effect of the technology improvement on productivity is delayed by two quarters. The results are robust to variations in this time period. Contrary to other sign restrictions approaches (see, e.g., Dedola and Neri, 2007; Peersman and Straub, 2009, among others), I do not restrict the response of any other variable. In particular, I do not require a positive response of real GDP. Given that Basu et al. (2006) obtain

Table 1: Sign restrictions on impulse responses

Shocks	Variables	Horizon in quarters
Monetary	$p_{t+j} \leq 0, i_{t+j} \geq 0, m_{t+j} \leq 0$	$j = 0, \dots, 2$
Technology	$tfp_{t+j} \geq 0$	$j = 0, \dots, 7$
Technology news	$tfp_{t+j} = 0$ $tfp_{t+j} \geq 0$	$j = 0, 1$ $j = 2, \dots, 9$

Notes: Horizon 0 denotes the initial response.  $p$  = GDP deflator;  $i$  = interest rate;  $m$  = monetary aggregate;  $tfp$  = total factor productivity.

evidence in favor of a contractionary effect of technology improvements in the short-run, this appears reasonable. I set the horizon over which productivity has to respond positively equal to eight quarters, consistent with the conventional wisdom that technology improvements have persistent effects on productivity.

Table 1 summarizes the sign restrictions. I impose all restrictions either as  $\leq$  or  $\geq$ , while I implement a zero restriction as 'approximate equality constraint' following Kilian and Murphy (2009). That is, the restriction does not have to hold literally but the response has to be at least close to zero. In particular, I accept a draw if the response is within the interval  $\pm 0.00005$ . Furthermore, I identify a monetary and in addition either a technology or technology news shock at the same time to ensure orthogonality between them.

### 3 The results

#### 3.1 Dynamic responses to monetary and technology shocks

I show the responses to monetary as well as technology shocks in Figures 2 and 3, respectively. In both cases, the figure plots the median of the posterior distribution, together with the area between the 16th and 84th percentiles, calculated at each horizon between 0 and 30 quarters after the shock. I construct 250,000 candidate responses, leaving me with about 1,500 draws that satisfy the restrictions. An acceptance ratio of 0.6% is compatible with related studies.

By construction, the monetary aggregate and the GDP deflator fall in response to positive interest rate shocks. Moreover, both responses are persistent. The response of the interest rate, however, becomes insignificant once I remove the restriction, suggesting that the monetary policy authority reverses course immediately after the shock. Furthermore, productivity and real

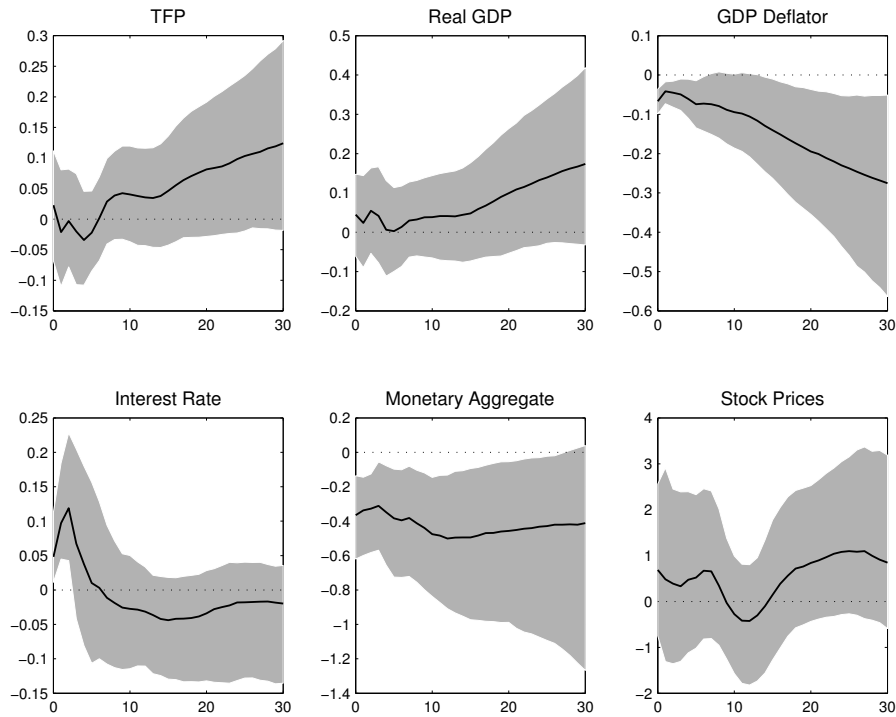


Figure 2: Monetary shocks. Notes: I show the median response, together with the area between the 16th and 84th percentiles. Entries are percent; horizontal axis denotes quarters after the shock.

GDP display an insignificant response over all horizons which is consistent with monetary neutrality, both in the short and long-run. Overall, these findings are similar to those of Uhlig (2005). ‘Contractionary’ monetary shocks do not necessarily have to contract real GDP. In Section 3.6, I show that this conclusion is robust to tighter identifying restrictions, such as fixing the impact response of productivity and real GDP to zero. Most important, I draw the same conclusion for the impact of monetary shocks on real stock prices. There is no evidence of a contractionary effect of a monetary tightening on the real stock price index.

I identify technology shocks as having a positive impact on productivity for two years throughout, enough to induce a permanent upward shift in the level of productivity. Moreover, the response of real GDP is persistently positive as well, while interest rates and the GDP deflator tend to fall. In addition, there is no effect on the monetary aggregate. These findings are compatible with conventional wisdom and insensitive to an alternative productivity measure that adjusts for time-varying capacity utilization. I discuss this issue in Section 3.5. Finally, the response of real stock prices is positive and significant on impact and for most of the following ten quarters. This coincides with the idea that improvements in productivity are accompanied by stock market booms.



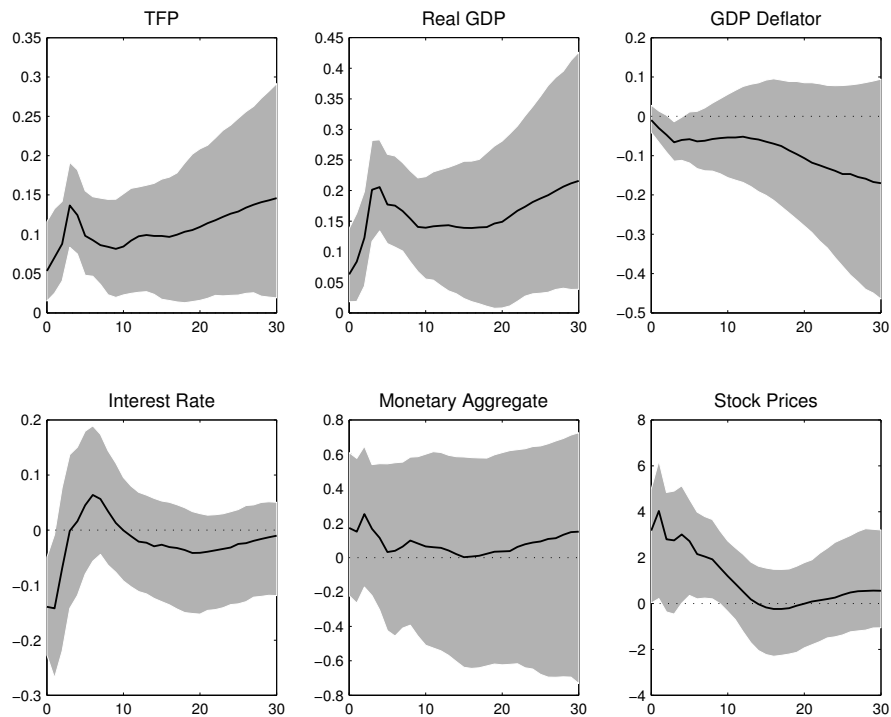


Figure 3: Technology shocks. Notes: See Figure 2.

### 3.2 Explanatory power of the shocks

Before presenting the responses to the technology news shocks in Section 3.4, I investigate the explanatory power of monetary and technology shocks by means of a forecast error variance and a historical decomposition. Moreover, I assess their plausibility in Section 3.3.

I follow Fry and Pagan (2007) and perform the analysis on the basis of one particular draw from the posterior distribution. In particular, I choose that draw which produces impulse responses that are as close as possible to the median responses. This procedure retains the orthogonality between the shocks while it has the desirable property that variance shares sum exactly to one. Moreover, it preserves the consensus view that the median is a good summary statistic. I have checked that the selected draw indeed produces responses that are similar to those generated by the median of the posterior distribution (see Appendix C, Figures 11 and 12) so that the conclusions of the previous section are not altered.

Figure 4 shows the estimated historical series for both the monetary (upper panel) and the technology shocks (lower panel). As we can see from the monetary series, the stance of monetary policy in the euro area is tight around 1992-93 and in the early 2000s. In addition, the series displays the responses to the terrorist attacks on 9/11 and financial market turmoils in 2002-03.

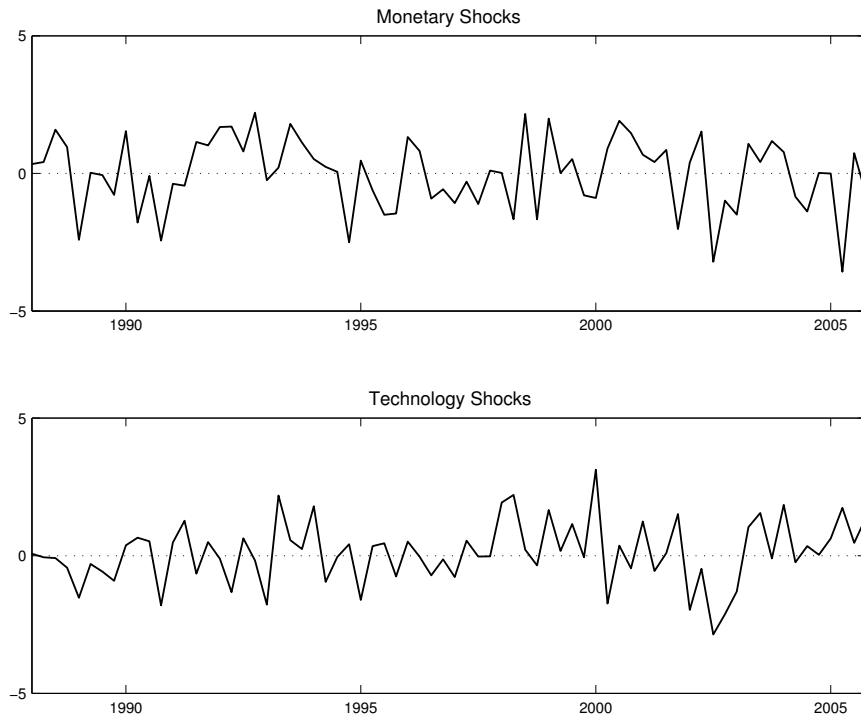


Figure 4: Estimated monetary and technology shocks. Notes: Entries are percent.

Furthermore, I conclude from an investigation of the technology series that technology innovations behave similarly to real stock returns over the sample period (see also Figure 1, lower panel). There is a number of large positive shocks during the late 1990s as well as the early 2000s, while the years 2002-03 are associated with negative disturbances. Moreover, the correlation between the series is 0.48. These findings support my idea that stock prices are driven by technology innovations.

I report in Figure 5 how the estimated monetary and technology shocks contribute to historical movements in euro area stock prices. The upper panel plots the actual data, together with the estimated deterministic component or baseline projection. I obtain the baseline projection from a counterfactual simulation that no shocks occur during the sample period. Thus, the baseline projection mirrors the initial conditions, summarized in the first four data points. In the lower panel, I plot that part of the estimated stochastic component that I attribute to monetary and technology shocks, respectively.

As we can see from the lower panel, monetary policy mostly contributes positively to developments in euro area stock prices over the sample period. This finding is particularly evident after 1995 when the contribution of monetary shocks is always positive. However, their impact appears to be small when compared to technology shocks. While their effect on stock prices is

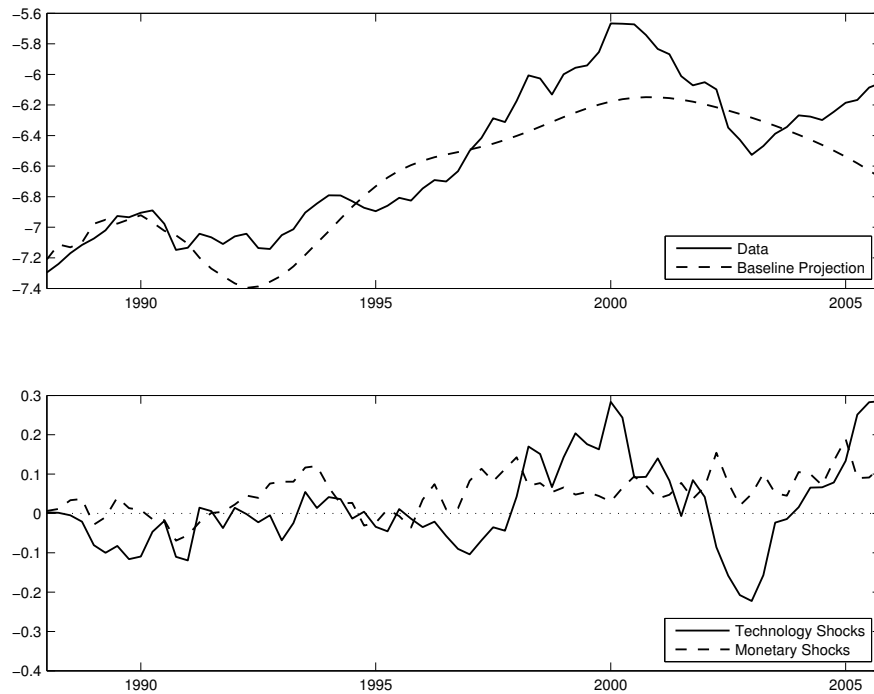


Figure 5: Historical decomposition of euro area stock prices. Notes: Entries are log levels.

moderate in the first part of the sample, technology disturbances are responsible for about half of the deviation from the baseline projection in 2000 and nearly all in 2002-03. These results suggest that the pronounced boom-bust cycle in euro area stock markets in 1995-2003 is to a large extent due to technology disturbances.

In order to quantify the importance of monetary and technology shocks for historical movements in stock prices and other variables, I conduct a historical business cycle variance decomposition and report the results in Table 2. The entries in the table refer to the fraction of the variance in variables that can be accounted for by the shocks, obtained from the counterfactual simulation that only a single shock occurs. Before constructing the variance shares, I apply the Hodrick-Prescott (HP) filter to the series resulting from the counterfactual simulation to emphasize fluctuations at business cycle frequencies.

I find an important role for technology shocks in explaining business cycle variations in stock prices. About 22% of the variation can be attributed to such shocks, hence they are more important than monetary shocks that explain less than 5%. Moreover, I identify technology shocks as an important driver of fluctuations in real GDP, explaining roughly 18% of the variation. In contrast, monetary shocks are responsible for a mere 2%. These findings are different from those of Galí (1999) who finds no role for technology in explaining aggregate fluctuations.

Table 2: Historical business cycle variance decomposition

Shocks	Variable					
	$tfp_t$	$y_t$	$p_t$	$i_t$	$m_t$	$s_t$
Monetary	7.29	2.05	6.06	2.99	15.45	4.58
Technology	15.13	17.89	3.99	9.52	18.66	22.31
Other	77.58	80.06	89.95	87.49	65.89	73.11

Notes: Entries are percent. Statistics are calculated on HP-filtered series.  $tfp$  = total factor productivity;  $y$  = real GDP;  $p$  = GDP deflator;  $i$  = interest rate;  $m$  = monetary aggregate;  $s$  = real stock prices.

However, they are consistent with Dedola and Neri (2007), Enders et al. (2008) or Peersman and Straub (2009) who all build their analysis on identifying sign restrictions. Of course, I cannot rule out that this difference is the result of other factors, like the choice of the sample period.

I end this part by presenting the forecast error variance decomposition in Table 3. The variance decomposition is based on the impulse responses of the previous section (i.e. on the chosen draw, not on the median). The entries in the table refer to the fraction of the variance in the forecast error that can be attributed to monetary, technology and other shocks, respectively. The forecast horizon is 30 quarters. I perform the exercise to provide insights about the predictive ability of the shocks over a long-term horizon rather than over the business cycle as in case of the business cycle variance decomposition.

Table 3 shows that more than 20% of the variability in real GDP can be accounted for by technology shocks, confirming such shocks as a main driver of aggregate fluctuations. Monetary shocks, however, explain only 10% of the variance in the forecast error of real GDP. Most important, technology shocks contribute around 12% to the variance in the forecast error of real stock prices. This number is smaller than the 22% coming from the business cycle decomposition but larger than the 6% that can be attributed to monetary shocks. Furthermore, across all variables between 68% and 89% of the variance in the forecast error is neither explained by monetary nor by technology shocks. These numbers are not unusual, given that shocks are identified on the basis of sign restrictions alone. In particular, technology shocks contribute not more than 18% to the variability in productivity even though I identify technology shocks as having a persistent effect on productivity. The same statistic obtained from the long-run restriction approach of Galí (1999) would be, nearly by construction, considerably larger. I return to this issue in Section 3.6.

Table 3: Forecast error variance decomposition

Shocks	Variable					
	$tfp_t$	$y_t$	$p_t$	$i_t$	$m_t$	$s_t$
Monetary	10.69	10.31	21.35	1.98	7.47	6.25
Technology	18.15	20.82	2.15	8.17	7.87	11.91
Other	71.16	68.87	76.50	89.85	84.66	81.84

Notes: Entries are percent. The horizon is 30 quarters. See notes to Table 2 for abbreviations.

### 3.3 Are the identified shocks plausible?

Before proceeding, I assess the plausibility of the approach by subjecting the estimated monetary and technology shocks to additional tests. If both shocks reflect exogenous innovations to monetary policy and productivity, then they should be uncorrelated to other exogenous shocks or lagged endogenous variables. In detail, I investigate whether the government expenditure to GDP ratio, the Hamilton (1996) oil shock measure, and the nominal short-term interest rate Granger-cause the estimated shocks. Similar testing procedures are developed in Hall (1988) and Evans (1992) (so called 'Evans-Hall' tests) and frequently used in the literature (see, e.g., Francis and Ramey, 2005; Fisher, 2006, among others). The three variables are considered because they are associated with business cycle fluctuations but not related to technology improvements. Moreover, Hoover and Perez (1994) and Bernanke et al. (1997) point out that peaks in oil prices and policy interest rates often coincide, making it difficult to distinguish between oil and monetary shocks.

The data on government expenditures and oil prices are from the AWM database. Furthermore, Hamilton calculates his oil shock measure by taking the difference between the quarterly oil price and the maximum oil price of the preceding four quarters. He sets the value to zero in case the difference is negative. Though Hamilton (1996) convincingly argues in favor of such an asymmetric oil price measure, I consider the quarterly change in oil prices as an alternative. The Granger causality test is based on a regression of the estimated monetary and technology shocks on a constant and four lags of the government expenditure to GDP ratio, the oil shock measure, and the interest rate. I also add the contemporaneous value for the oil shocks since I do not expect that they respond to technology improvements within the period. Moreover, interest rates enter the regression in first differences to ensure stationarity.

Table 4: Granger causality tests

Shocks	Variable			$R^2$	$\bar{R}^2$
	Government expenditure	Hamilton oil shocks	Interest rate		
Monetary	0.9809	0.1234	0.6722	0.19	0.00
Technology	0.6888	0.1995	0.3055	0.16	0.00

Notes: Entries are probabilities from a F-test. The F-test is based on the regression of the identified shocks on a constant and four lags of the variables. For the oil shocks, I also include the current value. The null hypothesis is that all of the coefficients on the variable in question are jointly equal to zero.

I show the results in Table 4. For both shocks, the explanatory power of the set of variables is low. The  $R^2$  is 0.19 for the regression involving the monetary shocks and 0.16 for the technology shocks while the adjusted  $\bar{R}^2$  is zero in both cases. Furthermore, there is no evidence that any of the variables Granger-causes the two shock series. I cannot reject the null hypothesis that all of the coefficients on the variable in question are jointly equal to zero at conventional significance levels for any variable. I obtain the lowest probability values for the oil shocks (0.12 and 0.19 for the monetary and technology shocks, respectively). But even then the significance is above 10 percent. Moreover, these numbers do not significantly change when I replace the oil shock measure by the quarterly change in oil prices (see Appendix C, Table 5). In this case I do not include the oil price contemporaneously to avoid endogeneity problems.

Hence, the Granger causality test supports my interpretation of the shocks as exogenous innovations to monetary policy and productivity. Given the fact that technology innovations coming from traditional long-run restriction methods or Solow residual regressions often fail ‘Evans-Hall’ type tests, this is encouraging.

### 3.4 Dynamic responses to technology news shocks

As an extension, I provide evidence on the effects of technology news shocks on stock prices. By construction, technology improvements no longer raise productivity immediately but with a delay of two quarters. Such a shock process is not easily supported by the data and I have to increase the number of candidate draws considerably. Less than 0.1% of the candidates are accepted. Figure 6 shows the results. As in Figure 2, I report the median of the posterior distribution, together with the area between the 16th and 84th percentiles, based on about 1,500 draws that fulfill the restrictions.

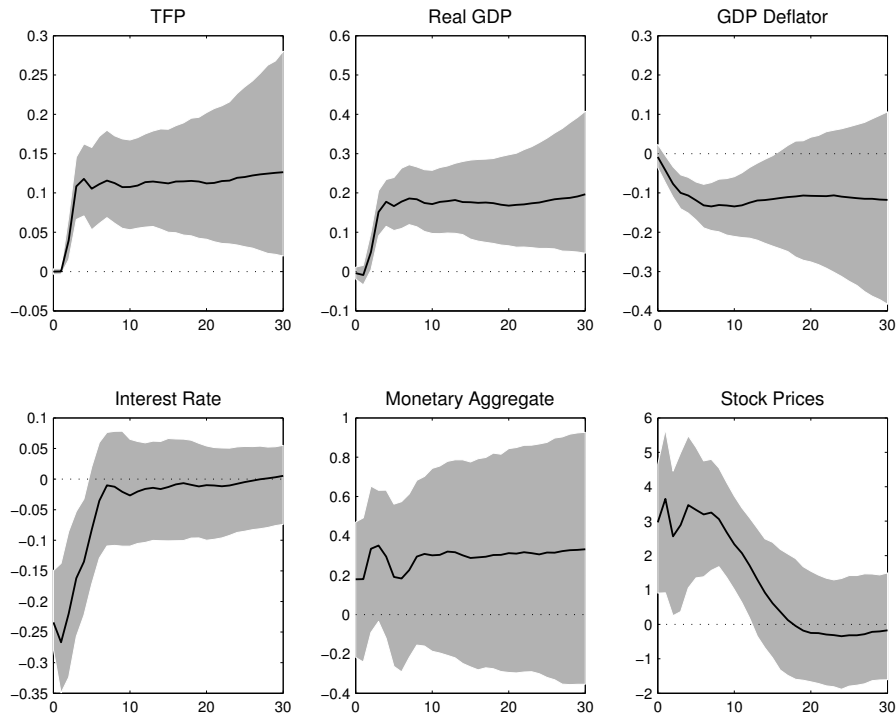


Figure 6: Technology news shocks. Notes: See Figure 2.

The exercise produces the following results. First, real GDP responds to the technology improvement only after productivity has increased, consistent with the notion that production capacities adjust slowly. Second, the GDP deflator as well as interest rates and monetary aggregates react immediately and display responses that are comparable to those in Figure 3. Moreover, stock prices show a large and positive response on impact, reflecting the anticipated increase in productivity. The response is significantly above zero for three years after the shock. Thus, stock prices (and all other variables, except productivity and real GDP) respond instantaneously to the news about the technology improvement with the actual increase in productivity having little or no effect. Third, the posterior distribution is less dispersed, probably due to the additional restrictions, leading to tighter confidence bands. Overall, the findings are consistent with the predictions of the class of diffusion models outlined in the introduction.

### 3.5 Controlling for time-varying capacity utilization

As a first sensitivity check, I investigate whether the results depend on the specification of the productivity index. The literature does not provide a unique answer to the question how to best measure productivity. For example, O'Mahoney and Timmer (2009) control for changes in the

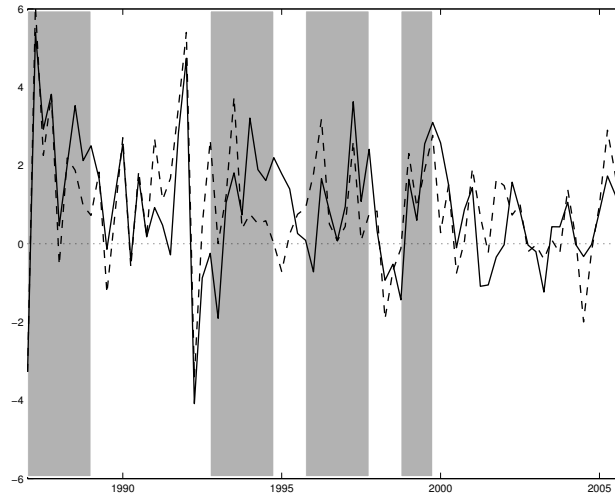


Figure 7: TFP measures. Notes: All entries are annualized quarterly growth rates. Solid line: unadjusted TFP; dashed line: TFP adjusted for time-varying capacity utilization. The shaded areas represent CEPR expansions.

composition of labor and capital. Moreover, Basu et al. (2006) construct a productivity series for the U.S. from disaggregated data while taking time variations in the utilization of labor and capital into account. Most of these adjustments, however, are either beyond the scope of this paper or not applicable because the relevant data are not available for the euro area. Here, I focus on the role of time-varying capacity utilization since it appears to be an important factor in Beaudry and Portier (2006) as well as Basu et al. (2006). Moreover, I have data on the usage of capital in the manufacturing sector and thus can proxy for variations in the utilization of the whole economy capital stock for which no data are available. I obtain the series from the OECD MEI database. I construct the adjusted (log) total factor productivity series as  $tfp_t^A = \log \left( GDP_t / H_t^{\bar{\alpha}} (CU_t K_t)^{1-\bar{\alpha}} \right)$ , where  $CU_t$  is the rate of capacity utilization.

Figure 7 plots the adjusted productivity measure (dashed line), together with the unadjusted series (solid line). For comparability, I show annualized quarterly growth rates. To demonstrate the cyclical behavior of both series, Figure 7 displays the euro area expansions as dated by the Centre for Economic Policy Research (CEPR) (shaded area). The dates are available on the CEPR homepage and provided in Appendix A. The CEPR defines an expansion as a prolonged period of increasing growth of real GDP, where the starting (ending) point is the point of minimal (maximal) growth. As you can see, the unadjusted productivity measure is highly pro-cyclical. Troughs and peaks in the series often coincide with starting and ending points of expansions. Furthermore, the correlation of productivity with annualized quarterly real GDP growth (not shown here) is about 0.95. Correcting for time-varying capacity utilization, how-



ever, makes productivity less pro-cyclical. This results from the fact that capacity utilization itself is highly pro-cyclical. In this case, starting and ending points of expansions are often preceded by troughs and peaks in productivity and the correlation with real GDP growth declines to 0.72. Of course, this correlation is still high and adjusted productivity is not counter-cyclical as in Basu et al. (2006). A possible explanation is that I do not (and simply cannot) control for unobserved labor effort as they do. Despite this drawback, the exercise is useful to examine the robustness of my previous results.

Do the responses to a technology improvement change when productivity is corrected for variations in the utilization of capital? Figure 8 provides an answer. Essentially, all of the variables show responses that are similar to those reported in Figure 3. However, the positive response of real GDP is delayed by about one year and I cannot rule out a negative response on impact. This is consistent with the findings of Basu et al. (2006), who demonstrate that if capacity utilization is taken into account, technology improvements lead to a fall in hours worked and reduced utilization of capital in the short-run with real GDP being unchanged for some time. Moreover, this finding casts doubt on identification schemes which build on the assumption that real GDP immediately increases when technology improves (see, e.g., Dedola and Neri, 2007; Peersman and Straub, 2009, among others). Finally, the response for stock prices is not as sharp at the short end as before but still significantly above its initial level over the medium-term.

### **3.6 Comparing the sign restrictions to short and long-run restrictions**

As a second sensitivity check, I assess whether imposing additional short and long-run restrictions leads to qualitative changes in the impulse responses. In particular, I do not allow for a contemporaneous response of productivity and real GDP to monetary shocks and require that technology shocks account for at least half of the variation in productivity at a horizon of 30 quarters. I impose the latter restriction on the forecast error variance share. Essentially, these additional restrictions move my identification scheme towards short and long-run restriction approaches.

My motivation for fixing the initial responses of productivity and real GDP to zero is the following. As you can see in Figure 2, both variables as well as real stock prices tend to increase after positive interest rate shocks (though not significantly) which is counterintuitive. Hence, I find it worth investigating if this finding is sensitive to the relatively weak identifying assumptions made. A delayed response of real GDP to monetary shocks is often assumed in the monetary VAR literature. Furthermore, I justify the restriction on the variance share as follows. It is difficult to find a decomposition of the covariance matrix that supports a large contribution

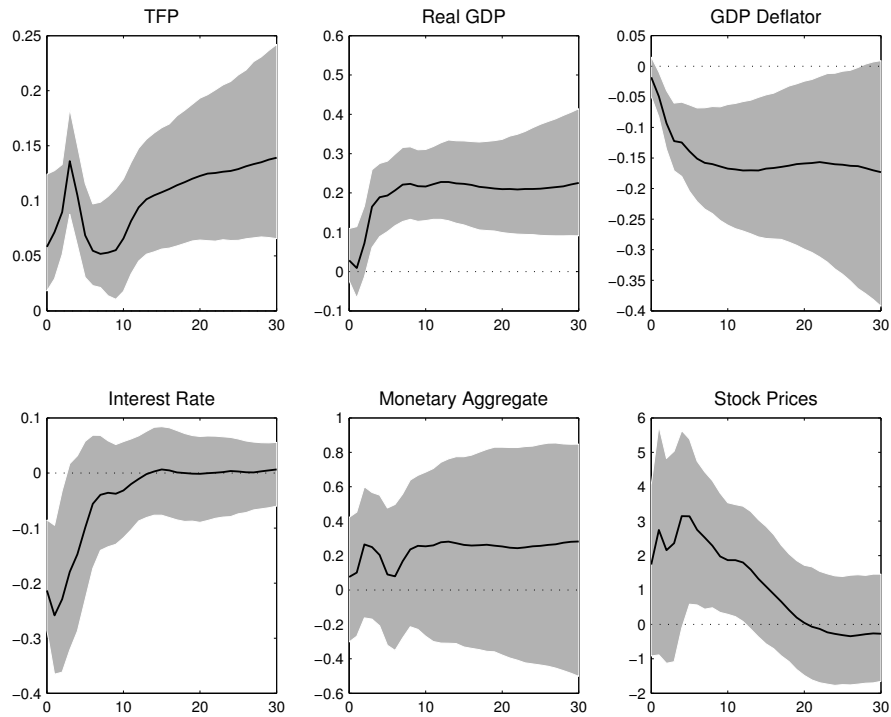


Figure 8: Technology shocks when controlling for time-varying capacity utilization. Notes: See Figure 2.

of technology shocks to long-run movements in productivity when shocks are identified on the basis of sign restrictions alone. Therefore, among the draws that satisfy the set of restrictions, I extract those that are associated with exceptionally large and permanent effects on productivity. Of course, the horizon of 30 quarters (the ‘long-run’) as well as the 50 percent threshold (‘large’) are to some extent arbitrary but the results of this exercise appear robust to variations in both.

I show the responses to monetary and technology shocks under the extended set of restrictions in Figures 9 and 10, respectively. It seems that fixing the initial responses for productivity and real GDP to zero after a monetary shock hardly alters the findings of Section 3.1. Though both variables have now the tendency to fall in the short-run, they do so by little. Moreover, the response of the real stock price index is not affected. In contrast, restricting variance shares has consequences. The posterior distribution is less dispersed than those in Figure 3. Given that only 7% of the posterior draws satisfy the long-run restriction, this is not surprising. Specifically, the responses for productivity, real GDP and the GDP deflator display tight confidence bands. Moreover, the subset of technology shocks which is associated with exceptionally large and permanent effects on productivity increases productivity growth, not only the level of productivity. As a consequence, the median response for stock prices shifts upwards, suggesting a

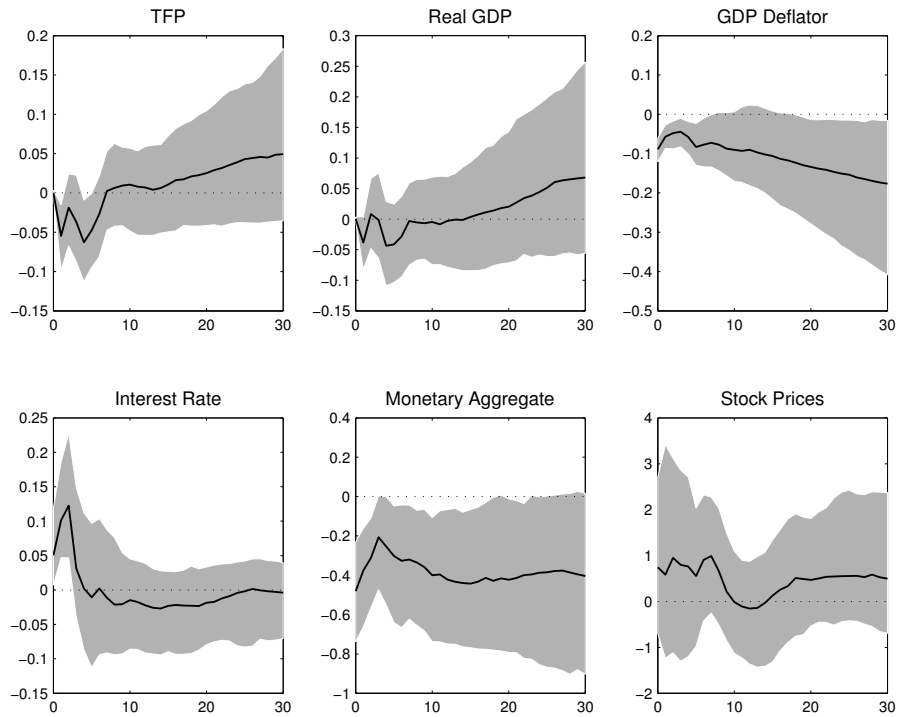


Figure 9: Monetary shocks when fixing the initial TFP and real GDP response to zero. Notes: See Figure 2.

permanent impact of changes in productivity growth on the level of stock prices. This finding coincides with the result of the long-run restriction approach of Beaudry and Portier (2006).

## 4 Conclusion

In this paper, I provide evidence on the impact of monetary and technology shocks on real stock prices using a Bayesian VAR model for the euro area. I achieve identification by imposing sign restrictions on impulse responses as in Canova and De Nicoló (2002) or Uhlig (2005). The results suggest an important role for technology shocks, but not monetary shocks, in explaining variations in stock prices. Over the sample period, technology shocks account for more than 22% of the movements in stock prices while monetary shocks contribute less than 5%. Specifically, the pronounced boom-bust cycle of 1995-2003 can almost completely be attributed to technology shocks. I also find a significant response of stock prices to technology news shocks.

Furthermore, I investigate the robustness of these findings with respect to (a) an alternative measure of productivity which adjusts for time-varying capacity utilization and (b) the inclusion of additional short and long-run restrictions. Moreover, I show that monetary and

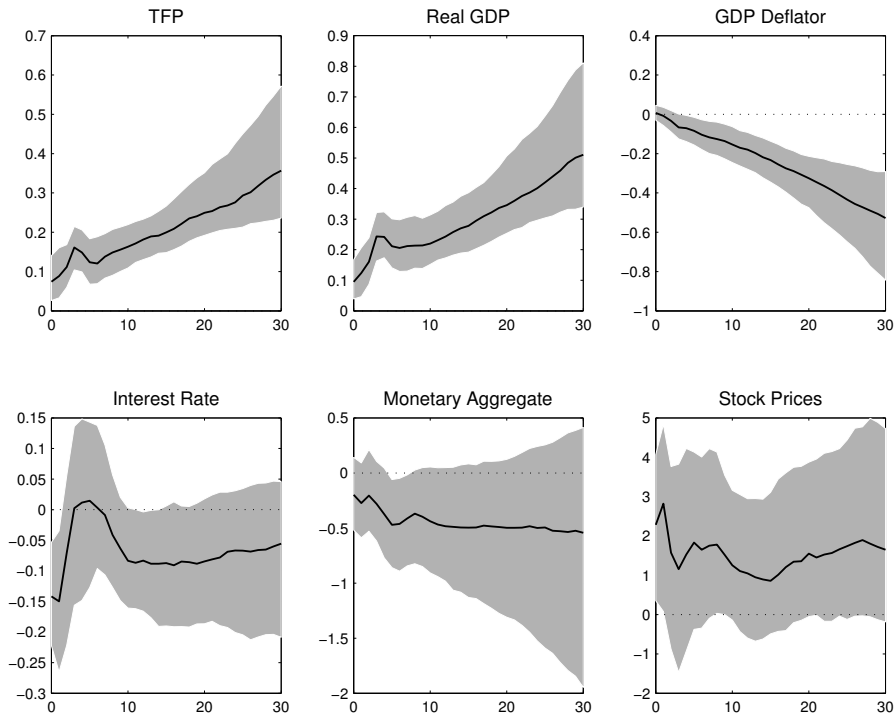


Figure 10: Technology shocks when requiring a large contribution to long-run TFP changes. Notes: See Figure 2.

technology shocks are not correlated with omitted variables and shocks, such as government spending or oil prices.

This last result leads me to conclude that the estimated shocks are plausible while the identification strategy is at the same time less dogmatic than those typically found in the literature. Moreover, I show how to combine short and long-run as well as sign restrictions in a convenient way. In particular, the use of zero restrictions, not only on impact but for an extended horizon, allows me to study the effects of anticipated shocks. An exercise which has been rarely undertaken yet. Needless to say, such a framework can be applied to anticipated shocks other than technology news shocks.

Finally, the analysis offers an explanation for the stylized fact that real stock returns and inflation are negatively correlated. Given the evidence of this paper that, first, real stock prices are to a large extent driven by technology shocks and, second, the conditional correlation of real stock returns and inflation is negative for technology shocks, I conclude that the correlation pattern in the data is to a certain degree the result of technology disturbances. This appears particularly relevant for the late 1990s when a series of positive technology shocks hit the euro area economy, leading to positive real stock returns and low inflation rates. Moreover, the anal-

ysis helps to understand why the stock market boom of 1995-2000 coincided with a period of falling interest rates. Rather than being the source of this boom, falling interest rates reflected an improved trade-off between output and inflation due to enhanced technology.

## A The data

I use data from five different sources which are all accessible through the web: the Area-wide Model database (<http://www.eabcn.org/area-wide-model>), the EU KLEMS Growth and Productivity Accounts (<http://www.euklems.net/>), the OECD Main Economic Indicators database (<http://www.oecd.org>), STOXX Limited (<http://www.stoxx.com/index.html>), and the CEPR (<http://www.cepr.org/Data/euroCOIN/recession/>). The estimation period is 1987Q1-2005Q4. To obtain quarterly data, I average daily figures and convert yearly series using interpolation methods.

### *Area-wide Model database (series are quarterly):*

Real GDP in millions of euro with reference year 1995, seasonally adjusted, YER

GDP deflator with reference year 1995, seasonally adjusted, YED

Whole-economy capital stock in millions of euro with reference year 1995, KSR

Nominal short-term interest rate in percent, STN

Civilian labor force in thousands of persons, LFN

Total employment in thousands of persons, LNN

Government expenditure to GDP ratio, GEN\_YEN

Oil prices in U.S. dollars, POILU

### *EU KLEMS Growth and Productivity Accounts (series are yearly):*

Total hours worked by employees in millions of hours, H\_EMPE

Labor compensation in millions of euro, LAB

Capital compensation in millions of euro, CAP

### *OECD Main Economic Indicators database (series are quarterly):*

Monetary Aggregate M1 in billions of euro, seasonally adjusted, EA6003DSA

Rate of capacity utilization in percent, manufacturing, seasonally adjusted, EA2961DSA

### *STOXX Limited (series is daily):*

Dow Jones EURO STOXX Net Return index (including dividends)

### *CEPR Expansion dates:*

Jan 1988 - Feb 1989, Nov 1992 - Oct 1994, Nov 1995 - Nov 1997, Oct 1998 - Nov 1999

## B Rotation matrices

In the context of my six variable VAR a  $6 \times 6$  Givens matrix  $Q_{3,4}(\theta_{10})$  has the form

$$Q_{3,4}(\theta_{10}) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \cos(\theta_{10}) & -\sin(\theta_{10}) & 0 & 0 \\ 0 & 0 & \sin(\theta_{10}) & \cos(\theta_{10}) & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

i.e. the matrix is the identity matrix in which the (3,4) and (4,3) elements are replaced by the sine terms and  $\theta_{10}$  lies within  $[0, \pi]$ . Accordingly, I replace the (3,3) and (4,4) elements by the cosine terms. To construct  $Q$ , I use the multiple of the basic set of Givens matrices:  $Q = Q_{1,2}(\theta_1) \times Q_{1,3}(\theta_2) \times \dots \times Q_{5,6}(\theta_{15})$ .

## C Additional tables and figures

Table 5: Granger causality tests with oil price

Shocks	Variable			$R^2$	$\bar{R}^2$
	Government expenditure	Oil price	Interest rate		
Monetary	0.8673	0.1354	0.6101	0.17	0.00
Technology	0.7741	0.1208	0.2449	0.16	0.00

Notes: Entries are probabilities from a F-test. The F-test is based on the regression of the identified shocks on a constant and four lags of the variables. The null hypothesis is that all of the coefficients on the variable in question are jointly equal to zero.

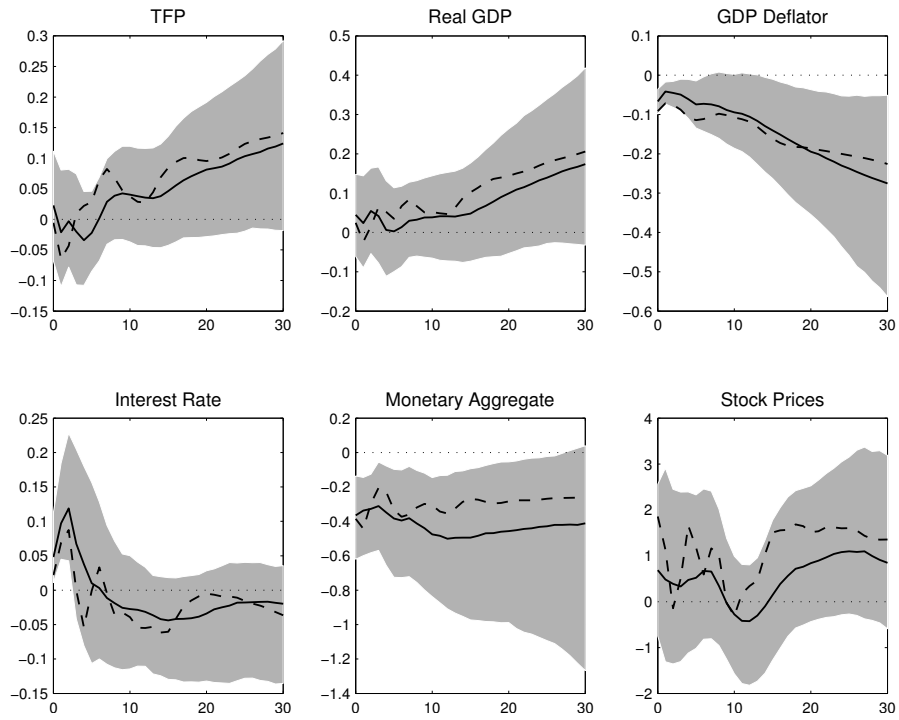


Figure 11: Monetary shocks with responses under single draw restriction.

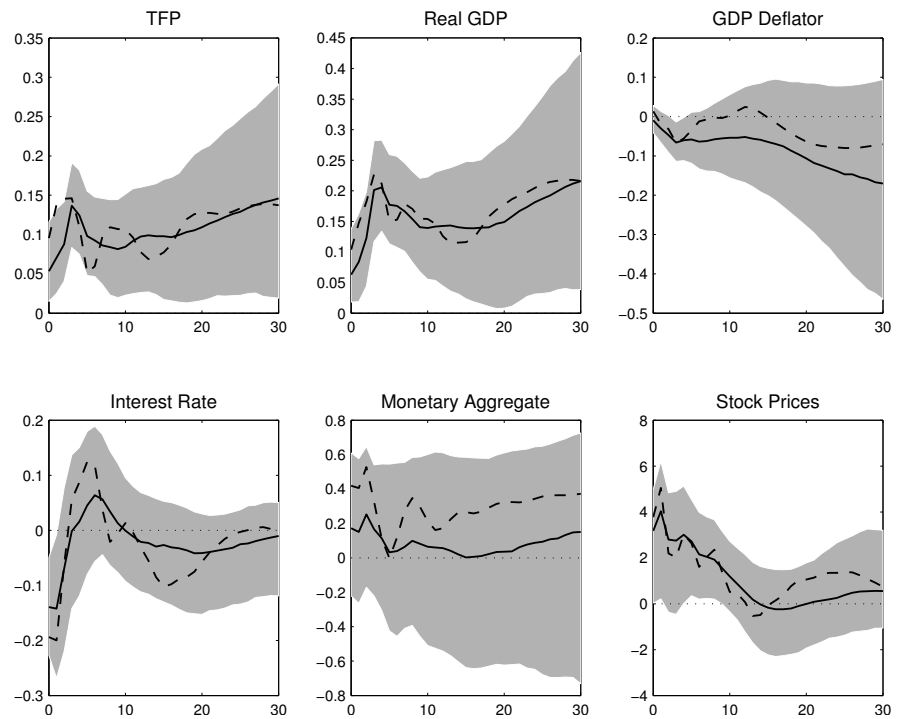


Figure 12: Technology shocks with responses under single draw restriction.



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