Wirtschaftsuniversität Wien
Vienna University of Economics and Business Administration

Working Papers Series:

Growth and Employment in Europe: Sustainability and Competitiveness

Working Paper No. 38

SECTORAL AND AGGREGATE TECHNOLOGY SHOCKS: IS THERE A RELATIONSHIP?

Werner Hölzl and Andreas Reinstaller

June ,2004

This working paper series presents research results of the WU-Research Focus:
Growth and Employment in Europe, Sustainability and Competitiveness
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by

Werner Hölzl
Vienna University of Economics and Business Administration
Department of Economics (VWL-4)
Augasse 2-6
A-1090, Vienna, Austria
Tel.: +43-1-31336-4175
email: Werner.hoelzl@wu-wien.ac.at

and

Andreas Reinstaller
Vienna University of Economics and Business Administration
Department of Economics (VWL-7)
Augasse 2-6
A-1090, Vienna, Austria
Tel.: +43-1-31336-5254
email: Andreas.Reinstaller@wu-wien.ac.at

Abstract

We analyze sector specific shocks in productivity and demand in 19 manufacturing sectors of the Austrian economy. Based on a structural vector autoregressive (SVAR) model with long run restrictions developed by Gal\'i (1999) we extract technology and non-technology shocks from sectoral andaggregate data and study their patterns and relationship by means of a principal components analysis. We find a close association of sectoral and macroeconomic non-technology shocks but only a very weak association for technology shocks. Impulse-response analysis indicates that for almost all manufacturing sectors and the Austrian economy productivity growth rates experience an immediate increase to positive technology shocks while the hours worked decline. We therefore confirm Gal\'i's results on the level of manufacturing industries. Finally, we use the identified shocks as explanatory variables in fixed effect regressions on growth rates of employment, output and investment. We find that our shocks are closely associated to employment growth and output growth but not to growth in investment. The effect of technology shocks is different on the level of manufacturing industries and the aggregate economy.

Acknowledgements

We thank the participants of the FSP-Research seminar and the participants of the NOeG 2004 conference in Vienna for useful discussion and comments. All remaining errors and shortcomings are in our sole responsibility. This research project was supported by a research grant (project nr. 9800) from the Jubiläumsfonds der Oesterreichische Nationalbank (OeNB).

Keywords
Economic growth, business cycle, manufacturing industries, technology shocks, employment, SVAR

JEL
D24, E24, E30, O30

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Werner Hölzl and Andreas Reinstaller

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Address:
Vienna University of Economics and Business Administration, Department of Economics, Augasse 2-6, 1090 Vienna, Austria,
E-mail: Werner.Hoelzl@wu-wien.ac.at (*Hölzl*), areinst@wu.edu (*Reinstaller*).

JEL Codes: D24, L16, E24, E30, O30

1 Introduction

The question how business cycles relate to growth and changes in employment is controversial in economics. The view that the same impulses that drive economic growth lead also to business cycles was suggested by Schumpeter [27] and was taken up and developed by real business cycle theorists in the framework of neoclassical growth theory (see for instance Kydland and Prescott [20], Long and Plosser [21]). These models usually predict a positive co-movement between employment and technology shocks, so that fluctuations in employment and output are seen as a phenomenon driven by real shocks.

In recent times the relationship between technology shocks and employment growth has come under new scrutiny after the contribution of Galí [12]. He devised an empirical approach based on a SVAR model with long run restrictions to investigate the relation between (log) employment and (log) labor productivity. He showed that the basic prediction of the real business cycle (RBC) model of a positive correlation between productivity or technology shocks and employment growth is not observed empirically for the US. The second important finding was that non-technology shocks closely match the business cycle patterns in the US economy. Accordingly non-technology shocks may be considered the source of business cycles. These results were confirmed by other authors (e.g. Shea [28], Basu et al [4] Francis and Ramey [11] or Galí [13]). They are in line with predictions from New Keynesian theory that holds that business cycles are driven by nominal disturbances such as Galí's non-technology shocks. The responses to these shocks are determined by market imperfections and other factors inhibiting an immediate adjustment of economic agents to the perceived shocks (see Goodfriend and King [14]).

Overall Galí's empirical model is consistent with a broad class of theoretical models such as New Keynesian ones with sticky prices as well as dynamic general equilibrium models with habit formation or limited substitution possibilities between capital and labor. Galí for instance shows that the negative co-movement between hours and technology may be observed if firms set their prices before technology shocks arrive. In the short run firms will reduce hours while consumption will not increase. Francis and Ramey [11] present two dynamic general equilibrium models without price or wage rigidities that share the same prediction. They show that models based on habit formation in consumption and adjustment costs on investment and models with a Leontieff technology and labor saving technology shocks provide explanations for a negative response of hours to technology shocks.

All the listed empirical as well as theoretical studies investigate technology and non-technology shocks from a macroeconomic perspective.[1] The aggregated perspective neglects the fact that shocks are absorbed at a disaggregated level. Industry specific factors may induce quite different responses across industries, so that insights gained from aggregate analysis may not be taken for granted for sectors in an economy. Harberger [18] for instance illustrates in his seminal paper that growth is unbalanced. He showed that different economic sectors experience very different shocks to total factor productivity which give rise to heterogeneous patterns of sectoral growth. Therefore it is interesting to study whether the macroeconomic results of Galí hold at the industry level and how industry specific shocks are related to macroeconomic ones. This is the first aim of this paper. The second aim is to study the association of technology and non-technology shocks with important indicators for economic growth such as employment growth, output growth and investment growth. We believe this to be a more indicative strategy in order to uncover the relationships between growth and cycles in as it helps to dissect the relationship between responses to shocks at the disaggregated and the macroeconomic level. Our disaggregated perspective will focus on manufacturing industries.

The paper is organized as follows. The next section presents the empirical model used to identify the technology and non-technology shocks. Section three presents the data. The results are presented in section 4. We present first evidence regarding the relationship between sectoral and macroeconomic shocks. Then we investigate the effect of the shocks on the growth rates of employment, production and investment both on the sectoral and the macroeconomic level. Concluding remarks close the paper.

2 Identifying technology and demand shocks with structural VARs: the empirical model

Our approach to extract genuine technology and non-technology shocks from aggregate sectoral data follows the identification strategy proposed by Galí [12]. It draws on a SVAR model with long run restrictions originally introduced by Blanchard and Quah [5]. This method has two advantages:

1. Two kinds of shocks are extracted as opposed to TFP analysis. This allows to consider two kinds of impulse mechanisms, the real business cycle mechanism starting from stochastic fluctuations in productivity and a second mechanism based on non-technology shocks. It is often argued that additional shocks are essential to capture the business cycle phenomenon (Stadler [29]).

[1]Exception are the studies by Basu et al. [4] and Burnside et al. [6], who use sectoral Solow residuals to study aggregate productivity growth.

2. This method enables us to circumnavigate the problems of interpretation of total factor productivity (Felipe and Fisher [10], Carlaw and Lipsey [7]). Total factor productivity (TFP) is usually used in the calibration exercises of RBC-theorists. TFP is derived as residual in growth accounting and has more than one interpretation. The most popular is that TFP measures technological change (e.g. Barro [3] or Prescott [26]), others interpret it as free lunch (e.g. Jorgenson and Griliches [19]), while the most daunting is the interpretation of TFP as measure of ignorance and measurement error (e.g. Griliches [15]). This suggests, that it is an advantage that the technology shocks we estimate are not based on Solow residuals.

The key assumptions entertained by Galí are that capital labor ratios and effort per hour determining labor input follow stationary stochastic processes, whereas the technology shock is assumed to have a unit root. Only technology shocks can have a permanent effect on the level of labor productivity. We apply this identification strategy to sectoral series of productivity and hours for Austrian manufacturing. The logs of productivity $\hat{l}_{i,t}$ and of worked hours $\hat{h}_{i,t}$ on the sectoral level can be represented as a VMA(∞) process determined by technology and non-technology shocks. Assuming that sectoral time series are integrated of order one, it is necessary to use first differences to achieve stationarity. Accordingly, for each industrial sector i we define $\hat{\mathbf{y}}_{i,t} = \begin{bmatrix} \Delta\hat{l}_{i,t} \\ \Delta\hat{h}_{i,t} \end{bmatrix}$ and write

$$\hat{\mathbf{y}}_{i,t} \quad = \quad \mathbf{\Phi}_i(L)\sigma_{i,t}, \tag{1}$$

where L is the lag operator, the $\sigma_{i,t} = \begin{bmatrix} \sigma_{s_{i,t}} \\ \sigma_{d_{i,t}} \end{bmatrix}$ are the vectors of technology and non-technology (demand) shocks in each period. $\mathbf{\Phi}_i(L) = \sum_{\ell=0}^{\infty} L^{\ell}\mathbf{\Phi}_{i,\ell}$ is the long run multiplier matrix of these shocks, $\Delta\hat{l}_{i,t}$ and $\Delta\hat{h}_{i,t}$ are the first differences of the logs of productivity and hours. The technology and non-technology shocks are assumed to be orthogonal, and to have unit variance, $E[\sigma_{i,t}\sigma'_{i,t}] = \mathbf{I}$. As every VMA process has a VAR representation, they can be extracted from the residuals $e_{i,t}$ of

$$\hat{\mathbf{y}}_i, t = \mathbf{\Psi}\hat{\mathbf{y}}_{i,t-1} + e_{i,t}$$

which is a VAR(1) process. For this purpose we must find the $\mathbf{\Phi}_{i,0}$, so that

$$\mathbf{\Phi}_{i,0}^{-1} e_{i,t} = \sigma_{i,t}, \tag{2}$$

transforms the reduced form shocks of the VAR(1) into the genuine shocks of the VMA(∞) process, as shown by Blanchard and Quah [5, p.657] or Hamilton [17, p.324ff.]. The Choleski decomposition underlying the transformation of VAR(1) residuals into VMA(∞) shocks requires a restriction to be imposed on the matrix of long run multipliers. We assume that

$\sum_{\ell=0}^{\infty} \mathbf{\Phi}_{i,\ell}(1,2) = 0$. This is equivalent to say that the assumed unit root in the productivity growth series is not influenced permanently by non-technology shocks. Francis and Ramey [11] show that this identification scheme performs very well in extracting genuine technology shocks from the data. Hall-Evans tests carried out on our shocks (reported below) support this view also for the sectoral context.

A recent debate has questioned Galí's identification scheme. Uhlig [30] for instance argues that other shocks such as changes in income capital taxation may influence labor productivity in the long run. Christiano, Eichenbaum and Vigfusson [8] question whether hours worked should enter the SVAR model in first differences. For US data there is no clear evidence of an unit root in employment. In this case - so their argument - using hours in first differences is likely to distort the estimated response of hours to technology shocks. Galí [13] counters this criticism by showing with US data that innovations to the capital income tax rate are uncorrelated with his technology shocks. Furthermore, while acknowledging that US employment data may not be characterized by an unit root, he shows that for employment data for Euro area this is not the case. Therefore hours should enter the SVAR in first differences for the Euro area. Galí's findings are confirmed by unit root tests carried out on the Austrian macroeconomic series for hours worked and productivity.

3 The data

The data are yearly data for Austrian manufacturing and cover the period 1971-1995. Due to changes in industry classification comparable data is not available for later years. The labor productivity series is from the ISIS database of Statistics Austria. The labor productivity is an index of real production per hour worked. The index of worked hours are derived from the labor productivity and the real production value also taken from the ISIS database (Appendix A.1 provides the details of the derivation of the series). Sectoral employment, gross production and investment data were all taken from the Industrial Statistics of Statistics Austria. Hours worked at the aggregate level were obtained from Biffl [2]. The GDP deflator, government expenditures and quasi money were taken from the International Financial Statistics (IMF). Real GDP and real investment in machinery at the aggregate level were taken from the WIFO database.

4 Results

We estimated a VAR(1) for each sector i and extracted the technology and non-technology shocks from its residuals. The modulus of the VAR(1) matrix $\mathbf{\Psi}_i$ was less than 1 for each of the VARs estimated indicating that they were stable and covariance stationary, so that the assumption of a VMA(∞) representation is vindicated. The series of (log) productivity and (log) hours for each sector where tested for unit roots. ADF tests (including a trend with a SIC based lag selection) did not reject the null of a unit root in the levels for the productivity series, but did reject it when applied to the first differences. In a few cases where results were ambiguous further DF-GLS tests confirmed the difference stationarity of the series. We proceeded in a similar way for the hours series, which were also all difference stationary with exception of two industries (ID 16 and 17). In a similar way we tested the macro series of labour productivity and hours for a unit root and found that both were first-difference stationary.[2]

4.1 Technology and non-technology shocks at the aggregate and the sectoral level

Impulse responses Figures 1 and 2 show the estimated impulse-responses of the logs in productivity and hours to a one standard deviation innovation for the whole economy and for one representative industry (iron and metal products). The confidence levels were obtained by bootstrapping (see Amisano and Giannini [1, chapter 5.3]). The impulse response patterns are similar for most other industries.[3] In the Austrian economy and most sectors the productivity growth rate experiences an immediate *increase* in response to a positive technology shock (upper left quadrant in the figures), while the hours growth rate *decreases* for almost all sectors (upper right quadrant). By definition non-technology shocks do not have an impact on productivity (lower left quadrant), while non-technology shocks have in all cases a permanent effect on hours worked (lower right quadrant). Technology shocks have a negative impact on hours, which reduces the base for employment in the different sectors. The impulse responses for aggregate data show a weak negative effect of technology shocks on hours worked. The two sectors where hours respond to a technology shock as RBC theory would postulate are foundries (14) and machinery & steel constructions (16), with the effect being larger for the latter. The impulse response functions for one of these industries is shown in figure 3. A possible explanation is that demand in these sectors is highly price elastic and competition international, so that productivity gains which translate into lower prices attract foreign demand, which in turn leads to an increase in employment. This is not implausible for these export oriented sectors. What is also apparent is that some declining sectors such as the mining or the leather producing sectors and processing industries such as the petroleum industry, basic metal prod-

[2]VAR and unit root statistics are not reported here. Tables can be obtained from the authors.

[3]All impulse-response figures are available upon request.

ucts, stone and ceramic or glass and glass product manufacturing respond with a stronger reduction in hours to technology shocks.

The responses of log productivity to non-technology shocks are zero out of the restriction imposed in the structural VAR. Positive non-technology innovations have a positive and lasting impact on the growth of hours worked in each sector. The responses are slightly more accentuated for most of the industries which display stronger response to technology shocks.

(Figures 1,2 and 3 about here)

Hall-Evans tests Hall [16] and Evans [9] claim that technology shocks as computed by growth accounting are correlated with other exogenous shocks that are not related to technology. We examine whether the technology and non-technology shocks that we derived pass their tests. We consider innovations in the inflation, money supply and government spending as exogenous disturbances. As we use yearly data, two kinds of tests are used: The first looks whether there is a contemporaneous correlation between our shocks and other exogenous influences. We use an F-test to look whether there is a strong correlation. The second test checks whether our shocks are Granger-caused by the exogenous disturbances. In order to do this, we regress technology (non-technology shocks) on a constant and two lags of each of log per capita government spending, log GDP deflator and log per capita nominal money. We use an F-test whether these variables Granger-cause the technology and the demand shock.

(Table 1 about here)

Table 1 reports the tests for each of the industries. MS indicates the macro shocks. A correlation between exogenous disturbances and technology shocks is rejected for all manufacturing industries and the economy as a whole. Causality cannot be rejected for clothing (20). That means that we cannot reject the hypothesis that the shocks indeed are technology shocks. The non-technology shocks show also a weak contemporaneous correlation with the exogenous disturbances. However, the causality test shows that the non-technology shocks are 'caused' to a larger extent by exogenous disturbances, as we find that Granger-causality cannot be rejected for 6 industries at the 10 percent level. This suggests that we were able to identify genuine technology shocks.

4.2 Principal components in technology and non-technology shocks

Principal components analysis (PCA) is a multivariate statistic technique which transforms a set of k indicators on l statistical units into a reduced set of variables explaining a significant proportion of the variability of the original set of data. The components obtained trough PCA are uncorrelated, linear combinations of the original variables with unit variance. This procedure is equivalent to an extraction of eigenvectors from the correlation matrix of the data, where the eigenvectors with the largest eigenvalues also explain the largest part of the observed variance in the data.

It is our purpose here to find out how the identified technology shocks in each industry contribute to the total observed variance throughout all industrial sectors, or vice versa, which shocks are best explained by which components. For this purpose we have calculated the squared correlation between each component and a sectoral shock indicating the proportion of variation in data series σ_{k_i}, $k = s, d$ explained by component c_j. This measure is of particular interest, as it allows a componentwise explanation of the shocks.

Technology shocks The results for the PCA on technology shocks are summarized in table (2). It is evident that the heterogeneity in the data is very high. The first principal component accounts for only 21,69% of the total variance across industries. Manufacturing industries do not appear to synchronize in technological development. The results give evidence for a hypothesis of differential potential for innovation which leads to an unbalanced development in productivity (see also Harberger [18] and Pasinetti [24]). For thirteen out of nineteen industries the first component is among the components explaining the largest part in their variance ranging from eighteen to sixty percent. Even though this component explains a large part of the variance in most industries it does not explain any variance in the observed macroeconomic technology shock. This suggests, that aggregate productivity shocks are not associated with the most important component affecting the productivity development in almost all manufacturing sectors. However, closer inspection shows that components c_2 and c_3 do account for some major part in variance in the macro shock and together they explain about 25% of the variance in technology shocks across all industries. Analysis of sectoral growth rates revealed that these components can be interpreted as the contrast between expanding and declining industries. The association of macroeconomic technology shocks with with sectoral developments in manufacturing is weak. This suggests that that technological development is to a large extent sector specific (see also Malerba [23]). The evidence suggests that macroeconomic developments in labor productivity are more closely related to the non-manufacturing sectors in the Austrian economy than to the developments in the manufacturing industries.

Non-technology shocks The results for the PCA on non-technology (demand) shocks are displayed in table 3. They are quite different from the evidence on technology shocks. Almost all industries (except mining, petroleum and leather processing) share one principal component c_1, which accounts for 45.16% of the total variance across industries and for thirty to eighty percent of the industry variances. Furthermore, this component explains a large part of the variance in the macroeconomic non-technology shocks. This is a strong indication that sectoral non-technology shocks are correlated to their macroeconomic couterpart. This is the main difference from the PCA analysis of technology shocks, where we found much more heterogeneity. General macroeconomic non-technology shocks seem to affects all sectors, while there are still industry specific effects of expansion and decline. This is a possible interpretation for components c_2, c_3, and c_4. Component c_2 seems to reflect a contrasting development between intermediate industries (related to basic good production) and the consumer goods sector on the one hand and more competitive intermediate good industries and the capital good sector on other hand. Most other components seem to be either idiosyncratic to some groups of industries (e.g. c_6 to basic goods sector) or to single industries.

(Table 2 and 3 about here)

Long and Plosser [22] carried out a similar exercise with monthly US data. They found that a common aggregate disturbance in output had significant explanatory power for industrial outputs, but that its influence was very modest. The shocks identified by Long and Plosser were the residuals of a VAR model with (logs) of monthly output growth and seasonal means across industries. Even though one should be careful to compare Long and Plosser's analysis with ours, our results suggest that Long and Plosser's residuals were not genuine technology shocks. The VAR residuals they use for their analysis are likely to be combinations of different shocks. This might be the reason why their sectoral output shocks share one large component. If their residuals contain technology *and* non-technology shocks, then the latter might be the cause for their finding. The shocks derived with the SVAR approach are more parsimonious and allow to distinguish between two different types of shocks. Our results suggest that business cycles in Austrian manufacturing are not driven by aggregate technology shocks. They can also be interpreted as evidence against the validity of RBC arguments for

Austria, as RBC models require large symmetric shocks (Stadler [29]). The heterogeneity of technology shocks suggests that if there are large symmetric shocks they are likely to be demand shocks.

4.3 The effect of technology and non-technology shocks on economic growth

The analysis in the previous section analyzed the link between aggregate and sectoral shocks in technology and demand. In this section we look at the impact of these shocks on growth by studying employment, output, and investment growth both at the sectoral and at the macroeconomic level. We study whether the influence of the shocks is homogenous across industries and the relationship between manufacturing and the aggregate economy. For this purpose we use fixed effect regressions which allow for industry specific intercepts at the sectoral level. At the macroeconomic level we use OLS. In order to check for possible heterogeneity at the industry level we report our results for broader industry groupings.

The impact on employment growth From the discussion of impulse-responses it should be clear that we expect a negative correlation between technology shocks and employment growth and a positive correlation between non-technology shocks and employment growth.

(Table 4 about here)

Table 4 displays the regression results for the manufacturing industries. We find a negative relationship between technology shocks and employment growth and a positive relationship between non-technology shocks and employment growth. Also, the lagged demand shocks and technology shocks show the expected sign, although they are not statistically significant. The r^2 is high, that means industry-specific technology and demand shocks are important determinants of employment dynamics at the level of manufacturing industries. These regressions therefore summarize our impulse response analysis. This result confirms the impulse-response analysis. The separate regressions for the capital goods, intermediate goods and consumer goods sectors in table 4 confirm that there is a nearly uniform response in terms of employment to technology and non-technology shocks. We conclude that employment dynamics in the manufacturing industries are guided to a large extent by technology and demand shocks. Technology shocks reduce and non-technology shocks increase hours worked.

At the macroeconomic level we find no negative relationship between total employment growth and technology shocks. The regression results in column 2 in table 5 show there is a positive, although not statistically significant, contemporaneous association. The non-technology shocks are correlated contemporaneously with employment growth. Overall the shocks explain less variation at the macroeconomic level than at the level of manufacturing industries.

(Table 5 about here)

The impact on output growth. Let us now consider the growth of production. True demand shocks should be correlated with the growth rate of production. Technology shocks may or may not influence the growth of production value. Taking into account the models considered by Galí [12] and Francis and Ramey [11] a technology shock should lead to a delayed response of output. As the delay should be different across the industries we expect that technology shocks are less correlated with the growth rate of the gross production value than non-technology shocks.

(Table 6 about here)

Table 6 presents the regression results for output growth at the industry level. Table 5 reports in column 3 the results for the aggregate economy. We used the gross production value at the industry level and GDP at the aggregate level as this is consistent with the theory of production (Basu et al [4]). Non-technology shocks are as expected uniformly positive and highly correlated with the growth rate of production. Interestingly, the correlation between demand shocks and the growth rate of the gross production value is highest for the capital goods industries but very strong also for the intermediate and the consumer goods industries. Technology shocks show a more differentiated picture. The correlation is significant and positive for capital goods industries, but significant and negative for the intermediate goods industries. The negative coefficient is puzzling but most likely associated with the negative effect of technology shocks on employment. For consumer goods industries technology shocks seem not to be associated with the growth rate of production. Technology shocks lead to heterogeneous responses across the industries. Overall, the regression suggests that the non-technology shocks we identified are *demand* shocks.

At the macroeconomic level we find a very strong relationship of GDP growth with both technology and demand shocks. In terms of r^2 the shocks we identified are able to explain a large part of GDP growth. Again as for employment growth, we observe a different association of technology shocks with output growth at the macroeconomic level, the association is similar as in the capital goods industries. The positive lagged effect of technology shocks and the negative lagged effect of non-technology shocks shows again the difference between the behavior of the aggregate economy and the manufacturing sector.

The impact on investment growth. The association between investment growth and technology shocks is highly interesting. On the one hand, one can think of technology shocks causing higher investment through their effect on the long run value of the firm, but on the other hand the causation which runs from technology shocks to investment via a vintage effect is equally plausible. These are two conflicting hypotheses, that can be tested empirically. We use investment into machinery as the indicator for investment growth, as investment in structures and vehicles are less to be associated with technology shocks, at least in the manufacturing sector.

Table 7 presents the regression results for the growth rate of investment at the level of manufacturing industries. The explanatory power in terms of r^2 is much lower than for employment and output growth. There is a statistically significant negative association of investment growth with technology shocks, which is driven by the consumer goods sector and the capital goods sector. A speculative interpretation of this surprising result is that productivity advances are generated primarily by capital goods that are also increasing capital productivity. This needs to be tested more rigorously. The positive association of non-technology shocks is less surprising. If the non-technology shocks are interpreted as demand shocks, this result suggests that higher demand leads to capacity expansions. However, bear in mind that demand shocks and technology shocks do explain very little of the observed investment growth. Column 4 in table 5 reports the results for the aggregate economy. No coefficient is significant. However, again we observe no negative effect of technology shocks on investment growth.

(Tables 7, 8, 9 and 10 about here)

Let us now consider the other direction of causality. Table 8 reports tests of the causality running from investment to non-technology shocks and table 9 for the causality from investment growth to technology shocks. For both we observe a strong contemporaneous association which is in line with the findings before. A contemporaneous negative effect between investment and technology shocks can be explained on the basis of adjustment costs. For the consumer goods sector we find that lagged investments leads to negative technology shocks. However in terms of explained variation the findings are again very weak. A similar picture is present on the macroeconomic level as table 10 shows. No coefficient is significant and we observe again a positive relationship between technology shocks and investment growth, however the r^2's are extremely modest. We conclude that there is only a very weak relationship between investment growth and technology shocks both on the aggregate level and on the level of manufacturing industries.

5 Discussion and conclusion

We find that Galí's results on the impact of technology and non-technology shocks on hours worked and labor productivity are well supported by the Austrian data at the aggregate *and* the sectoral level. The identified sectoral technology shocks are shown to be genuine in so far as they do not to correlate with other exogenous macroeconomic disturbances. The impulse-response analysis for each sector shows that hours worked permanently and negatively responds to positive technology shocks, while positive demand shocks positively affect the growth of employment in each sector. These findings are robust across industries and are at odds with the Real Business Cycle literature, which postulates a positive co-movement between technology shocks and employment. Also the aggregate evidence leads support to New Keynesian theories that emphasize adjustment delays due to prices rigidities, technological complementarities (say if the assumption of Leontief technologies is valid in the short run) or consumer habits.

Principal components analysis was used to identify common components in variance of extracted shocks. The analysis delivered a number of interesting results, that strengthen the results from the IR analysis:

1. The results support the idea that business cycles are not driven by technology shocks in the manufacturing sectors.
2. Heterogeneity in technology shocks was much higher than in non-technology shocks. In fact, the sectoral non-technology shocks shared their first principal component with the macroeconomic demand shock. Non-technology shocks are quite uniform for the macro-economic and the sectoral level.
3. There is only a weak association between macro-economic and sectoral technology shocks in manufacturing industries. This supports the view that the development of labor productivity follows a "mushroom" pattern, as found by Harberger [18] for the US industries and Peneder [25] for Austria and other EU countries.

The effects of technology and non-technology shocks to indicators of growth confirmed the interferences form impulse response analysis. There is a strong relationship of non-technology shocks with employment and output growth and a very weak relationship with investment growth. The findings for technology shocks however, showed marked differences for the manufacturing industries and the aggregate economy. We did not find the a negative effect on employment growth by technology shocks.

The main policy conclusions that can be drawn from our analysis are twofold. Based on the the finding that hours worked are negatively associated to technology shocks in almost all manufacturing sectors (and to a lesser extent at the aggregate level) it follows that if this is not compensated by demand growth sectoral employment tends to shrink. This suggests that on the one hand increasing the sectoral mobility of the workforce should be an important policy goal to avoid unemployment. On the other hand, if other sectors cannot compensate the negative effects of technological change on employment then reductions of working hours is probably a feasible solution. In fact, during the period we studied the reduction in working hours together with the expansion of employment in non-manufacturing sectors can explain the aggregate result that the negative response of hours worked to technology shocks did not translate into negative effects on employment growth. Supply side policy measures such as technology policies oriented towards product innovations may be able to offset the need to reduce working hours, as competition in product variety reduces the pressure to increase labor productivity and demand saturation is avoided. But a detailed discussion of this is beyond the scope of this paper. Even more so as our results suggest that further research needs to take into account the service sector.

Acknowledgements: We thank the participants of the 2004 conference of the Austrian Economic Association (NOeG) for helpful comments and discussions. This research project was supported by a research grant (project nr. 9800) of the Jubiläumsfonds der Österreichische Nationalbank (OeNB).

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A Data appendix

Table 11 lists the industries used in the empirical research. Industries 8 and 9, the film industry and sawmills were excluded due to incomplete data.

(Tables 11 and 12 about here)

A.1 The extraction of working hours

Statistik Austria does not provide data on hours worked for the industries. However they provide indices of productivity per hour worked for the industries. An index of hours worked can be obtained from this index by using the index of physical production. As real labor productivity per hour is defined as $\alpha = \frac{Y}{H}$, where Y is real output and H is total hours, total hours can be obtained by $H = \frac{Y}{\alpha}$, where Y is the index of production. An index of hours per worker can also be obtained in a similar fashion.

A.2 Industry specific deflators

As the Austrian statistical office does not provide data on real production values or specific output-deflators, the indices of physical production and nominal production values were used to calculate the desired industry-specific deflators. The current value of production for the quantity produced in 1995 was calculated for each year by multiplying the nominal production with the index of production (100 = 1995). Industry-specific output-deflators were then obtained by dividing the current value of the quantity produced in 1995 by the nominal production value in 1995.

B Tables in text

Table 1: Hall-Evans-tests

	technology shocks						non-technology shocks					
	Correlation			Granger Causality			Correlation			Granger Causality		
	r^2	F-test	p-value	r^2	F-test	p-value	r^2	F-test	p-value	r^2	F-test	p-value
1	0.04	0.27	0.85	0.08	0.23	0.96	0.13	0.95	0.44	0.22	0.76	0.61
2	0.06	0.40	0.75	0.22	0.77	0.60	0.09	0.62	0.61	0.25	0.91	0.51
3	0.17	1.33	0.29	0.40	1.81	0.16	0.05	0.31	0.81	0.51	2.82	0.05
4	0.20	1.57	0.23	0.20	0.67	0.68	0.06	0.40	0.76	0.31	1.22	0.35
5	0.13	0.92	0.45	0.36	1.47	0.25	0.04	0.27	0.85	0.53	3.07	0.03
6	0.05	0.34	0.80	0.20	0.66	0.68	0.11	0.78	0.52	0.46	2.31	0.08
7	0.23	1.91	0.16	0.34	1.38	0.28	0.25	2.15	0.13	0.62	4.30	0.01
10	0.16	1.18	0.35	0.34	1.37	0.29	0.03	0.21	0.89	0.42	1.91	0.14
11	0.20	1.54	0.24	0.28	1.03	0.44	0.33	3.07	0.05	0.48	2.46	0.07
12	0.19	1.50	0.25	0.32	1.24	0.34	0.24	2.00	0.15	0.51	2.72	0.05
13	0.04	0.23	0.87	0.29	1.11	0.40	0.17	1.26	0.32	0.22	0.74	0.62
14	0.11	0.77	0.52	0.31	1.22	0.35	0.06	0.37	0.77	0.32	1.24	0.34
15	0.06	0.41	0.75	0.41	1.82	0.16	0.04	0.30	0.83	0.32	1.24	0.34
16	0.11	0.77	0.52	0.19	0.63	0.70	0.04	0.28	0.84	0.62	4.28	0.01
17	0.10	0.69	0.57	0.11	0.33	0.91	0.07	0.50	0.69	0.35	1.44	0.26
18	0.16	1.21	0.33	0.20	0.67	0.67	0.03	0.16	0.92	0.34	1.34	0.30
19	0.05	0.31	0.82	0.46	2.27	0.09	0.03	0.22	0.88	0.25	0.91	0.51
20	0.12	0.88	0.47	0.17	0.54	0.77	0.09	0.63	0.60	0.43	2.05	0.12
21	0.17	1.32	0.30	0.11	0.34	0.91	0.04	0.28	0.84	0.33	1.29	0.32
MS	0.11	0.78	0.52	0.13	0.39	0.88	0.11	0.78	0.52	0.32	1.24	0.34

Table 2: **Proportion of variance accounted for by component c_i in sectoral technology shocks (TS) by principal component (squared correlation $[r(c_i, \sigma_i)]^2$). Sectors and macro-shock.** Legend: (EV) eigenvalue, (ExV) explained Variance, (Cum) cumulated ExV, (Prop.Var) Proportion of variance explained by bold marked components, numbers in first column give the industry IDs, MS the macro shock. All components with EV $\geq$ 1.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	Prop. Var.
EV	4.34	3.32	1.88	1.84	1.41	1.30	1.10	1.01	
ExV	21.69%	16.60%	9.39%	9.18%	7.04%	6.51%	5.50%	5.04%	
Cum	21.69%	38.29%	47.68%	56.86%	63.90%	70.41%	75.91%	80.95%	
1	0.0917	0.0260	**0.1987**	**0.1802**	0.0000	**0.1100**	0.0366	0.0688	0.4888
2	0.0084	0.0103	**0.3114**	**0.4003**	0.0182	0.0141	0.0226	0.0023	0.7118
3	**0.4263**	0.0957	0.0466	0.0600	0.0307	0.0004	**0.1982**	0.0012	0.6245
4	**0.3964**	0.0363	**0.1108**	0.0322	0.0604	**0.1234**	0.0196	0.0399	0.6305
5	0.0639	**0.4330**	**0.1985**	0.0505	0.0099	0.0054	0.0613	0.0007	0.6315
6	**0.2353**	0.0111	0.0364	**0.2595**	**0.2286**	0.0453	0.0000	0.0000	0.7234
7	0.0560	0.0105	**0.3143**	**0.2591**	**0.1432**	0.0739	0.0182	0.0337	0.7166
10	**0.3143**	0.0224	0.0050	0.0151	0.0031	0.0408	0.0038	0.0641	0.3143
11	**0.3533**	**0.1757**	0.0725	**0.1031**	0.0085	**0.1089**	0.0196	0.0342	0.7410
12	**0.3440**	**0.1553**	**0.1008**	0.0310	**0.1763**	0.0259	0.0572	0.0209	0.7764
13	**0.2032**	**0.2905**	0.0041	0.0022	**0.2425**	0.0044	0.0192	0.0490	0.7362
14	0.0150	**0.4984**	0.0120	0.0057	0.0357	0.0721	**0.1137**	0.0319	0.6121
15	0.0481	**0.2662**	0.0003	0.0409	0.0433	0.0634	0.0560	**0.3440**	0.6103
16	**0.1837**	**0.2239**	0.0203	0.0028	0.0067	**0.1564**	**0.2189**	0.0050	0.6103
17	0.0001	0.2778	0.1315	0.2053	0.0028	0.0656	0.1510	0.0158	0.7828
18	**0.2249**	**0.3147**	0.0130	0.0574	**0.2403**	0.0048	0.0393	0.0030	0.7799
19	**0.2909**	0.0282	**0.1346**	**0.1074**	0.0833	**0.2189**	0.0385	0.0007	0.7518
20	**0.6045**	0.0418	0.0010	0.0226	0.0548	**0.0890**	0.0061	0.0002	0.6935
21	**0.4658**	**0.0980**	0.0159	0.0000	0.0082	0.0480	0.0020	0.0022	0.5638
MS	0.0114	**0.3046**	**0.1504**	0.0009	0.0109	0.0316	0.0192	**0.2896**	0.7446

Table 3: **Proportion of variance accounted for by component c_i in sectoral demand shocks (DS) by principal component. Sectors and macro-shock.** All components with EV $\geq$ 1.

	c_1	c_2	c_3	c_4	c_5	c_6	Prop. Var.
EV	9.03	2.31	1.45	1.26	1.14	1.03	
ExV	45.16%	11.57%	7.25%	6.29%	5.68%	5.16%	
Cum	45.16%	56.73%	63.98%	70.27%	75.95%	81.11%	
1	0.0843	**0.5938**	0.0204	0.0172	0.0317	**0.1019**	0.6957
2	0.0052	**0.2900**	**0.4251**	0.0025	0.0803	0.0422	0.7151
3	**0.4274**	**0.2006**	0.0174	0.0320	0.0771	0.0125	0.6280
4	**0.6952**	0.0064	0.0047	0.0055	0.0686	0.0265	0.6952
5	**0.6951**	0.0146	0.0325	0.0322	0.0242	0.0151	0.6951
6	**0.5550**	**0.1401**	0.0303	0.0000	0.0007	0.0007	0.6951
7	**0.5713**	0.0304	0.0277	**0.1271**	0.0361	**0.1077**	0.8061
10	**0.4663**	0.0113	0.0019	0.0005	0.0250	**0.3214**	0.7877
11	**0.4937**	0.0546	0.0035	**0.1236**	**0.1226**	0.0634	0.7400
12	**0.1076**	**0.1384**	0.0916	**0.1757**	0.0089	**0.1453**	0.5670
13	0.0080	**0.3029**	**0.4119**	0.0064	0.0229	0.0221	0.7148
14	**0.3675**	**0.1489**	0.0213	**0.1542**	0.0505	0.0947	0.6706
15	**0.4565**	0.0156	0.0245	**0.3216**	0.0483	0.0069	0.7781
16	**0.5524**	0.0064	0.0009	0.0222	**0.1389**	0.0293	0.6913
17	**0.5562**	0.0014	0.0520	0.0406	0.0929	0.0050	0.5562
18	**0.8080**	0.0517	0.0022	0.0102	0.0350	0.0005	0.8080
19	**0.6516**	0.0076	0.0008	0.0509	0.0313	0.0296	0.6515
20	**0.8472**	0.0149	0.0524	0.0006	0.0028	0.0005	0.8472
21	**0.3268**	**0.2721**	0.0230	**0.1216**	0.0268	0.0061	0.7206
MS	**0.3566**	0.0122	**0.2053**	0.0131	**0.2114**	0.0006	0.7733

Table 4: Employment growth and technology and non-technology shocks at the level of manufacturing industries: 1976-1995

	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
ts_t	-0.013	-0.009	-0.012	-0.017
	[7.89]***	[3.23]***	[5.48]***	[4.77]***
ts_{t-1}	-0.003	0.001	-0.005	-0.004
	[1.67]*	[0.38]	[2.45]**	[1.03]
ts_{t-2}	0	0.003	0	0.001
	[0.18]	[1.01]	[0.09]	[0.14]
ds_t	0.022	0.022	0.021	0.025
	[14.25]***	[8.34]***	[10.39]***	[7.00]***
ds_{t-1}	0.015	0.017	0.011	0.017
	[9.75]***	[6.78]***	[5.53]***	[4.80]***
ds_{t-2}	0.004	0.006	0.002	0.005
	[2.71]***	[2.03]**	[0.76]	[1.53]
Observations	380	120	120	120
industries	19	6	6	6
r^2	0.51	0.54	0.63	0.49

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%; industry specific intercepts not reported.

Table 5: Economic growth and technology and non-technology shocks at the macroeconomic level

	Employment growth	gdp growth	Investment growth
ts_t	0.003	0.012	0.035
	[1.71]	[5.33]***	[1.24]
ts_{t-1}	0.003	0.005	0.015
	[1.67]	[1.95]*	[0.72]
ts_{t-2}	0.002	-0.001	-0.014
	[0.89]	[0.44]	[0.74]
ds_t	0.004	0.012	0.023
	[2.19]**	[5.28]***	[1.14]
ds_{t-1}	0.001	-0.006	-0.017
	[0.66]	[3.09]***	[0.73]
ds_{t-2}	0.001	0.001	0.006
	[0.55]	[0.33]	[0.35]
Observations	21	21	19
years	$1975-95$	$1975-95$	1977-1995
r^2	0.36	0.84	0.34

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: The growth of output and technology and non-technology shocks at the level of manufacturing industries: 1976-1995

	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
ts_t	0.002	0.02	-0.011	-0.002
	[0.62]	[4.40]***	[1.90]*	[0.34]
ts_{t-1}	0.002	0.006	0.001	0.007
	[0.61]	[1.38]	[0.13]	[1.41]
ts_{t-2}	0.003	0.004	0.001	0
	[1.05]	[0.95]	[0.12]	[0.06]
ds_t	0.041	0.061	0.024	0.029
	[14.09]***	[13.79]***	[4.42]***	[6.18]***
ds_{t-1}	0	0.002	-0.005	0.005
	[0.06]	[0.38]	[0.99]	[0.99]
ds_{t-2}	0.001	0.003	-0.001	-0.001
years	[0.18]	[0.56]	[0.10]	[0.17]
Observations	380	120	120	120
industries	19	6	6	6
r^2	0.37	0.68	0.2	0.29

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%; industry specific intercepts not reported.

Table 7: The growth of investment in machinery and technology and non-technology shocks at the level of manufacturing industries: 1976-1995

	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
ts_t	-0.04	-0.055	-0.017	-0.05
	[2.26]**	[1.63]	[0.48]	[2.04]**
ts_{t-1}	-0.012	-0.056	-0.009	0.005
	[0.72]	[1.76]*	[0.25]	[0.21]
ts_{t-2}	0.03	0.037	0.052	0.015
	[1.76]*	[1.17]	[1.53]	[0.62]
ds_t	0.047	0.049	0.058	0.043
	[2.71]***	[1.52]	[1.72]*	[1.76]*
ds_{t-1}	0.031	0.041	0.043	0.038
	[1.82]*	[1.34]	[1.26]	[1.57]
ds_{t-2}	-0.002	0.076	-0.013	-0.041
	[0.10]	[2.26]**	[0.38]	[1.67]*
Observations	380	120	120	120
industries	19	6	6	6
r^2	0.06	0.14	0.06	0.11

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%; industry specific intercepts not reported.

Table 8: Non-technology shocks and the growth of investment in machinery at the level of manufacturing industries: 1975-1995

	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
inv_t	0.435	-0.005	0.567	0.835
	[2.88]***	[0.02]	[2.22]**	[2.41]**
inv_{t-1}	0.114	-0.259	0.394	0.13
	[0.75]	[1.09]	[1.54]	[0.37]
inv_{t-2}	0.065	-0.438	0.217	0.356
	[0.42]	[1.75]*	[0.85]	[1.09]
Observations	418	132	132	132
industries	19	6	6	6
r^2	0.02	0.03	0.05	0.05

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%; industry specific intercepts not reported.

Table 9: Technology shocks and the growth of investment in machinery at the level of manufacturing industries: 1975-1995

	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
inv_t	-0.366	-0.462	-0.1	-0.929
	[2.43]**	[1.94]*	[0.39]	[2.70]***
inv_{t-1}	-0.078	0.16	-0.028	-0.706
	[0.52]	[0.69]	[0.11]	[2.04]**
inv_{t-2}	0.14	-0.014	0.39	0.008
	[0.93]	[0.06]	[1.53]	[0.02]
Observations	418	132	132	132
industries	19	6	6	6
r^2	0.02	0.04	0.02	0.07

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%; industry specific intercepts not reported.

Table 10: Technology shocks and non-technology shocks and demand shocks at the macroeconomic level: 1979-1995

	Technology shock	Technology shock	Non-technology shock	Non-technology shock
inv_t	4.536		3.969	
	[1.15]		[1.01]	
inv_{t-1}	0.052	0.569	-0.061	0.391
	[0.02]	[0.17]	[0.02]	[0.12]
inv_{t-2}	3.136	1.784	1.119	-0.065
	[0.92]	[0.55]	[0.33]	[0.02]
Observations	17	17	17	17
R-squared	0.11	0.02	0.07	0

Notes: Absolute value of t statistics in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: List of industries

KS	Industry (German)	Industry (English)
1	Bergwerke	mining
2	Erdöl	oil and refinery
3	Stein-Keramik	stone and ceramics
4	Glas	glass and glass products
5	Chemie	chemical industries
6	Papiererzeugung	manufacture of pulp and paper
7	Papierverarbeitung	paper processing
10	Holzverarbeitung	wood processing
11	Nahrungs- und Genussmittel	food and tobacco
12	Ledererzeugung	leather producing
13	Lederverarbeitung	leather processing
14	Giesserei	foundries
15	NE-Metall	metal industry except steel
16	Maschinen-Stahlbau	machinery and steel constructions
17	KFZ	transportation equipment
18	Eisen-Metal	iron and metal products
19	Elektroindustrie	electrical equipment, appliances and components
20	Textilindustrie	textiles except clothing
21	Bekleidungsindustrie	clothing

Table 12: Industry grouping

Code	Description	Industries (KS)
1	capital goods industries	14,15,16,17,18,19
2	intermediate goods industries	2,3,4,5,6,7
3	consumer goods industries	10,11,12,13,20,21

C Figures in text

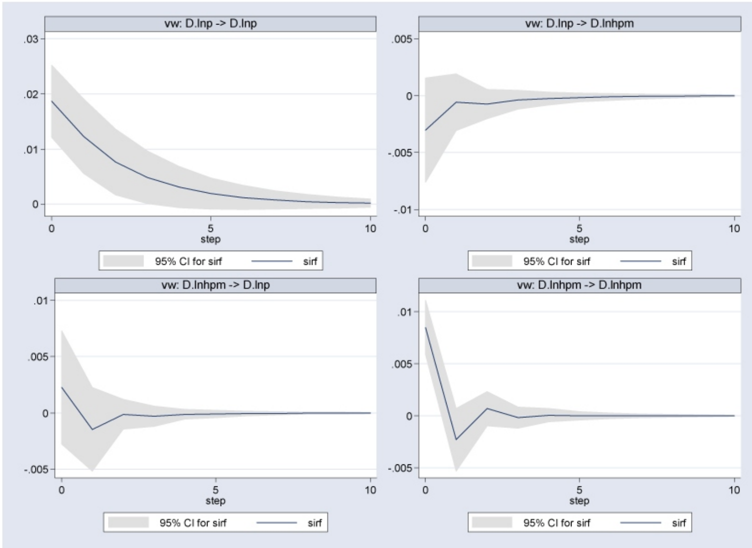

Figure 1: Aggregate impulse responses for the entire economy. The response of hours worked to technology shocks is weak and near zero.

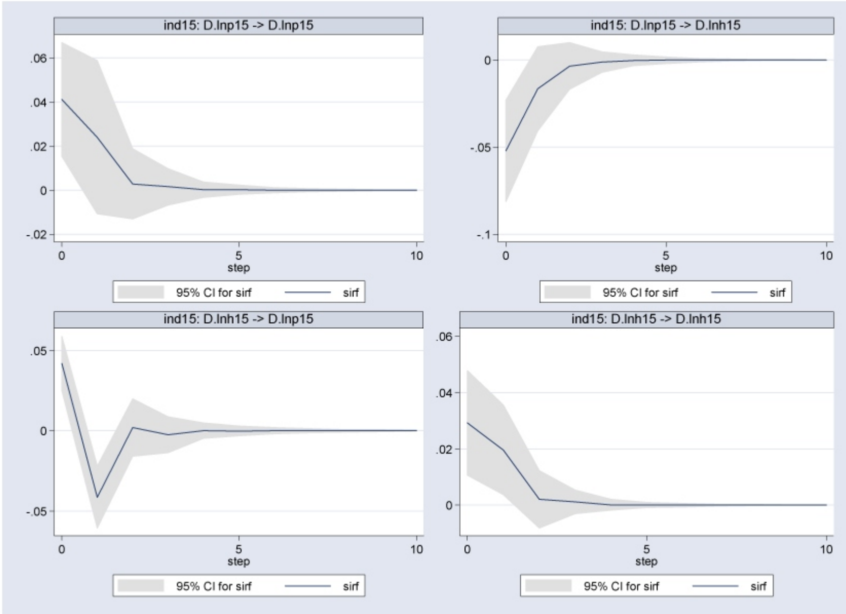

Figure 2: Impulse response for the metal industry (except steel) (ID 15). The impulse response patterns shown for this industry are representative for most other industries. Technology shocks have a negative long run impact on hours worked.

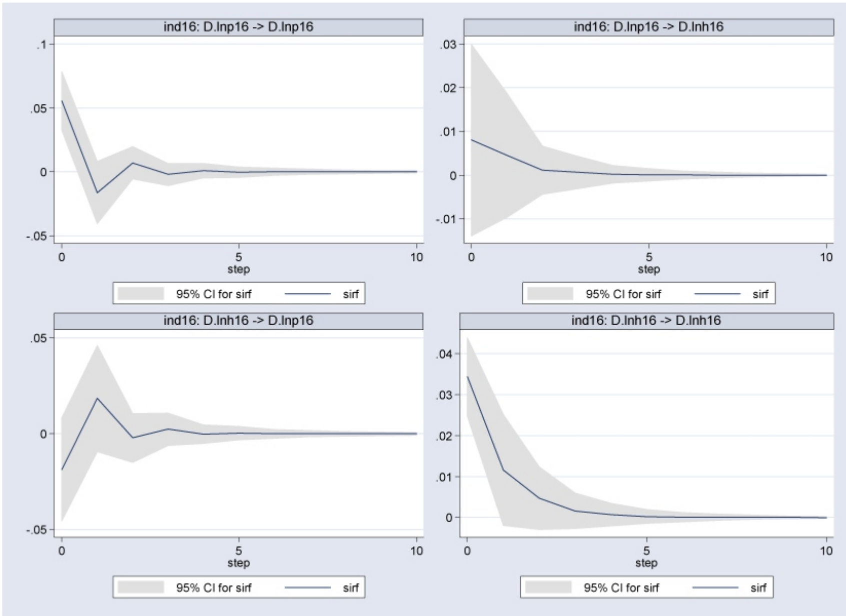

Figure 3: Impulse response for machinery and steel construction (ID16). Together with the machinery and steel constructions industry (ID16) the impulse response patterns correspond to "pathological" cases, where technology shocks have a positive long run impact on hours worked.

D The extraction of technology and non-technology shocks from the VAR residuals

As the VMA(∞) process in equation (1) contains non-observable technology and non-technology shock parameters, it is necessary to rewrite it as an VAR(1) process (omitting the subscript i identifying each sector) of the form

$$\begin{aligned} \hat{\mathbf{y}}_t &= \mathbf{\Psi}\hat{\mathbf{y}}_{t-1} + e_t = \mathbf{\Psi} L \hat{\mathbf{y}}_t + e_t \\ &= (\mathbf{I} - \mathbf{\Psi} L)^{-1} e_t. \end{aligned} \tag{3}$$

Here the e_t's are the reduced form shocks. They are linear combinations of technology and non-technology (demand) shocks σ_{dt} and σ_{st} in equation (1). The inverse $(\mathbf{I} - \mathbf{\Psi} L)^{-1}$ represents the estimated accumulated responses to the observed shocks, as $(\mathbf{I} - \mathbf{\Psi} L)^{-1} \approx \mathbf{I} + \mathbf{\Psi} L + (\mathbf{\Psi} L)^2 + ... + (\mathbf{\Psi} L)^n$, with $n \to \infty$.[4] Taking out the lag operator we can rewrite equation (3) as:

$$\hat{\mathbf{y}}_t = \mathbf{I} e_t + \mathbf{\Psi} e_{t-1} + \mathbf{\Psi}^2 e_{t-2} + ... + \mathbf{\Psi}^n e_{t-n}. \tag{4}$$

Comparing the first terms in equations (1) and (4) we get by definition $\mathbf{I} e_t = \mathbf{\Phi}_0 \sigma_t$, which leads to equation (2). It gives us the shocks from the residuals of the VAR.

The multiplier matrix $\mathbf{\Phi_0}$ is extracted from the VAR(1) matrix $\mathbf{\Psi}$ through the following decomposition. Due to the orthonormality imposed on the shocks σ_{s_t} and σ_{d_t} it must be that

$$\text{Cov(ee')} = \mathbf{\Phi}_0 \mathbf{\Phi}_0'. \tag{5}$$

We call this covariance matrix $\mathbf{\Sigma} = \mathbf{\Phi}_0 \mathbf{\Phi}_0'$. Comparing equations (1) and (4) and by recalling equation (2) we can say that

$$\mathbf{\Phi}_1 \text{L} \sigma_t = \mathbf{\Psi} \text{L} e_t \to \mathbf{\Phi}_1 \text{L} \sigma_t = \mathbf{\Psi} \mathbf{\Phi}_0 \text{L} \sigma_t \to \mathbf{\Psi} = \mathbf{\Phi}_1 \mathbf{\Phi}_0^{-1}$$

and in general for any lag

$$\mathbf{\Psi}^\ell = \mathbf{\Phi}_\ell \mathbf{\Phi}_0^{-1}.$$

Finally, the resulting equation taking account of all lags is

$$\sum_{\ell=0}^{\infty} \mathbf{\Psi}^\ell = \sum_{\ell=0}^{\infty} \mathbf{\Phi}_\ell \mathbf{\Phi}_0^{-1}. \tag{6}$$

For easier handling we may introduce the following definitions:

$$\sum_{\ell=0}^{\infty} \mathbf{\Psi}^\ell = [\mathbf{I} - \mathbf{\Psi}]^{-1} := \mathbf{R}(1) \quad \text{and} \quad \sum_{\ell=0}^{\infty} \mathbf{\Phi}_\ell := \mathbf{C}(1).$$

[4]The matrix $(\mathbf{I} - \mathbf{\Psi} L)$ is of course non-singular, i.e. $(\mathbf{I} - \mathbf{\Psi} L)(\mathbf{I} - \mathbf{\Psi} L)^{-1} = \mathbf{I}$

Taking equation (6) we write

$$\mathbf{R}(1) = \mathbf{C}(1)\mathbf{\Phi}_0^{-1},$$

or

$$\mathbf{C}(1) = \mathbf{R}(1)\mathbf{\Phi}_0. \tag{7}$$

As $\mathbf{R}(1)$ and $\mathbf{\Sigma}$ from equation (5) are known, it is possible to find $\mathbf{C}(1)$ by post-multiplying the left part of (7) with its inverse

$$\mathbf{R}(1)\mathbf{\Phi}_0\mathbf{\Phi}_0'\mathbf{R}(1)' = \mathbf{R}(1)\mathbf{\Sigma}\mathbf{R}(1)' = \mathbf{C}(1)\mathbf{C}(1)'.$$

Due to the restriction that non-technology shocks do not affect long run productivity growth, $\sum_{\ell=0}^{\infty} \mathbf{\Phi}_\ell(1,2) = \mathbf{C}(1)_{12} = 0$ we can carry out a lower triangular Choleski decomposition to get $\mathbf{C}(1)$. By plugging this result back into equation (7) and finding the solution to $\mathbf{R}(1)^{-1}\mathbf{C}(1)$, the matrix of long run multipliers of the exogenous shocks $\mathbf{\Phi}_0$ results. The multiplication of the inverse of this matrix with the series of residuals from the estimation of (3) as shown in equation (2) gives then the series of technology and non-technology shocks. The factorization procedure described in this appendix is implemented in the *Eviews* and *STATA* packages, which we used both to derive our results.

E Additional figures: Impulse response functions for all industries

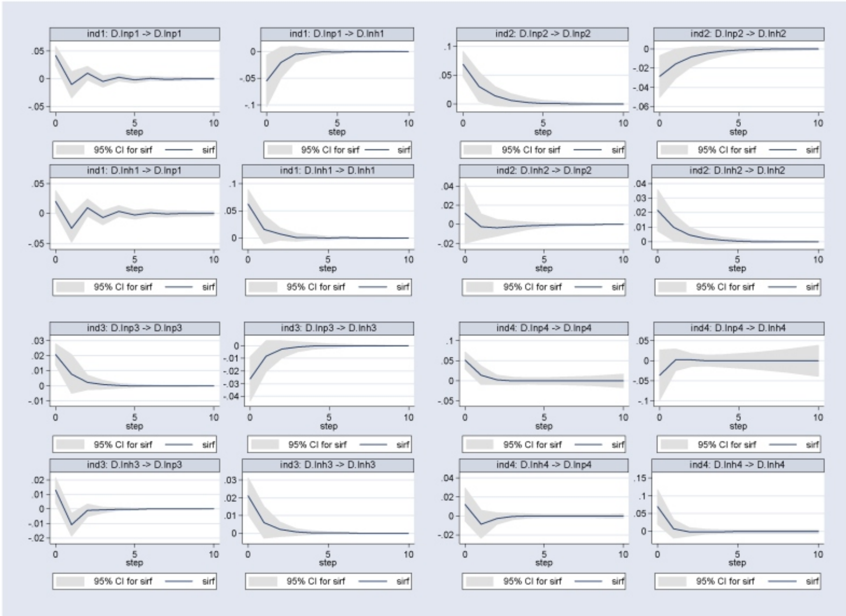

Figure 4: Impulse response functions industries 1-4.

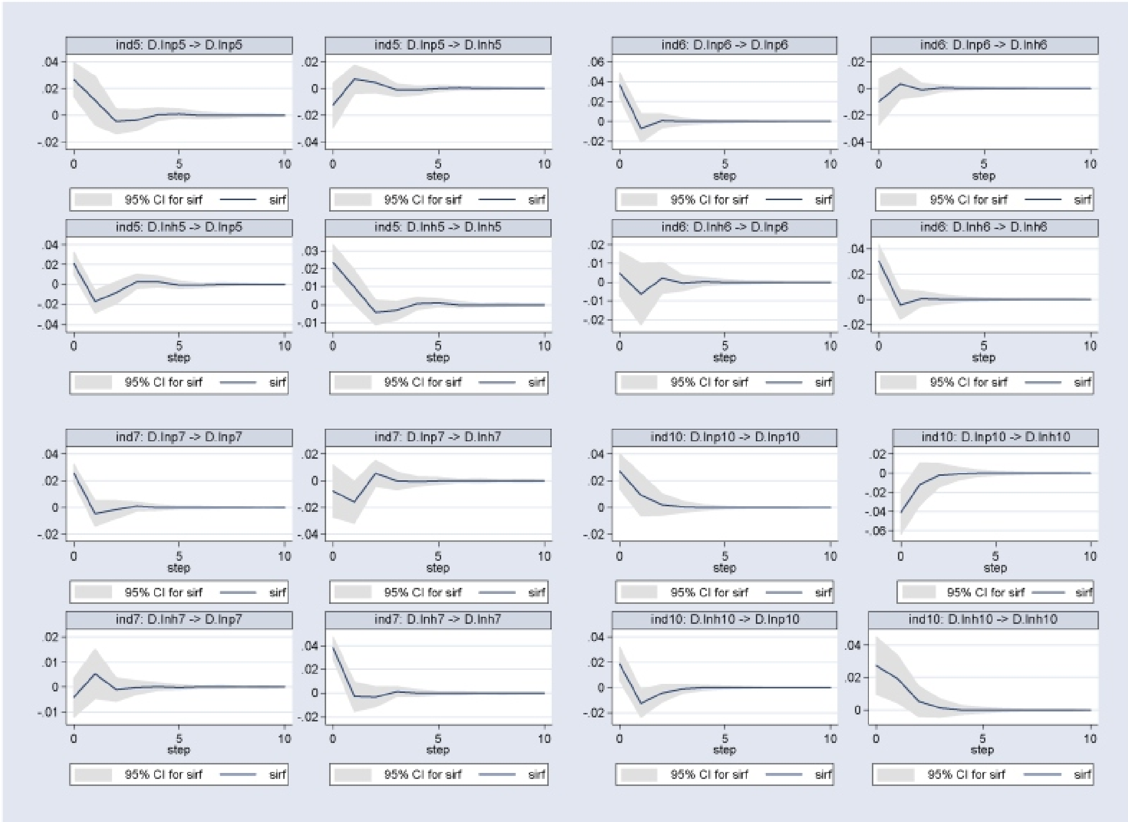

Figure 5: Impulse response functions industries 5,6,7 and 10.

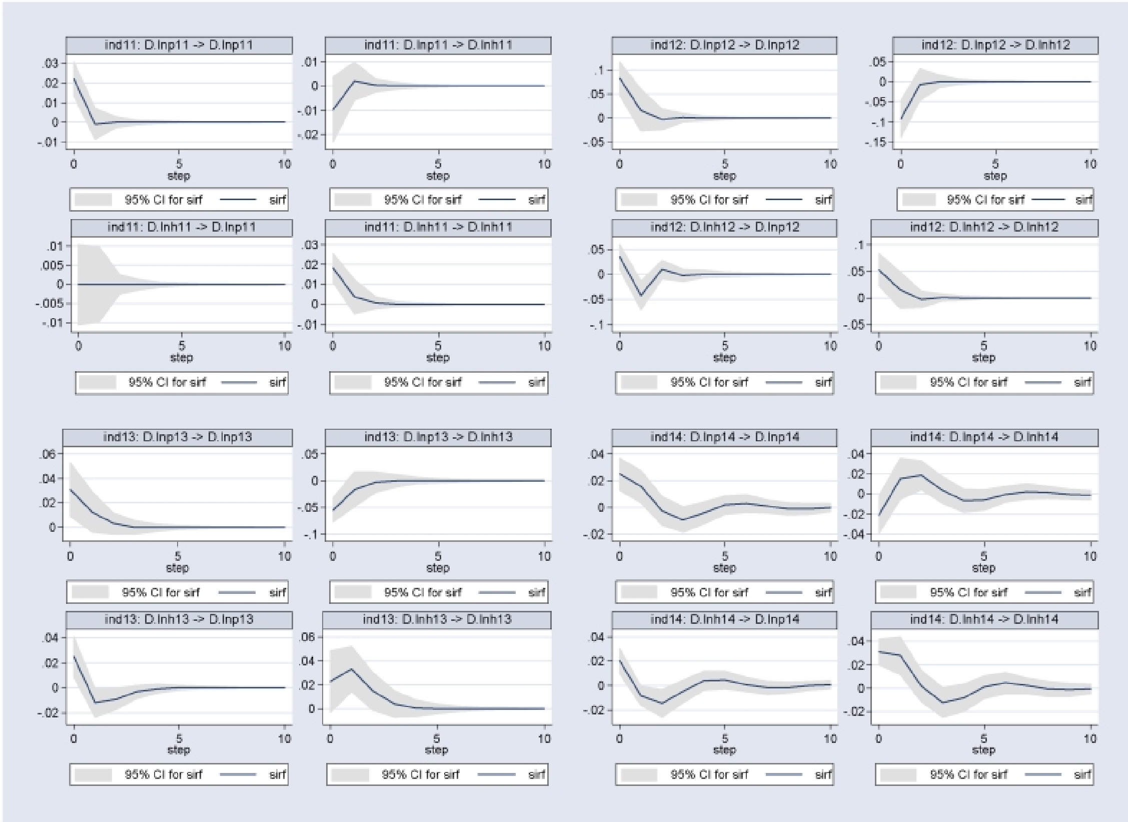

Figure 6: Impulse response functions industries 11-14.

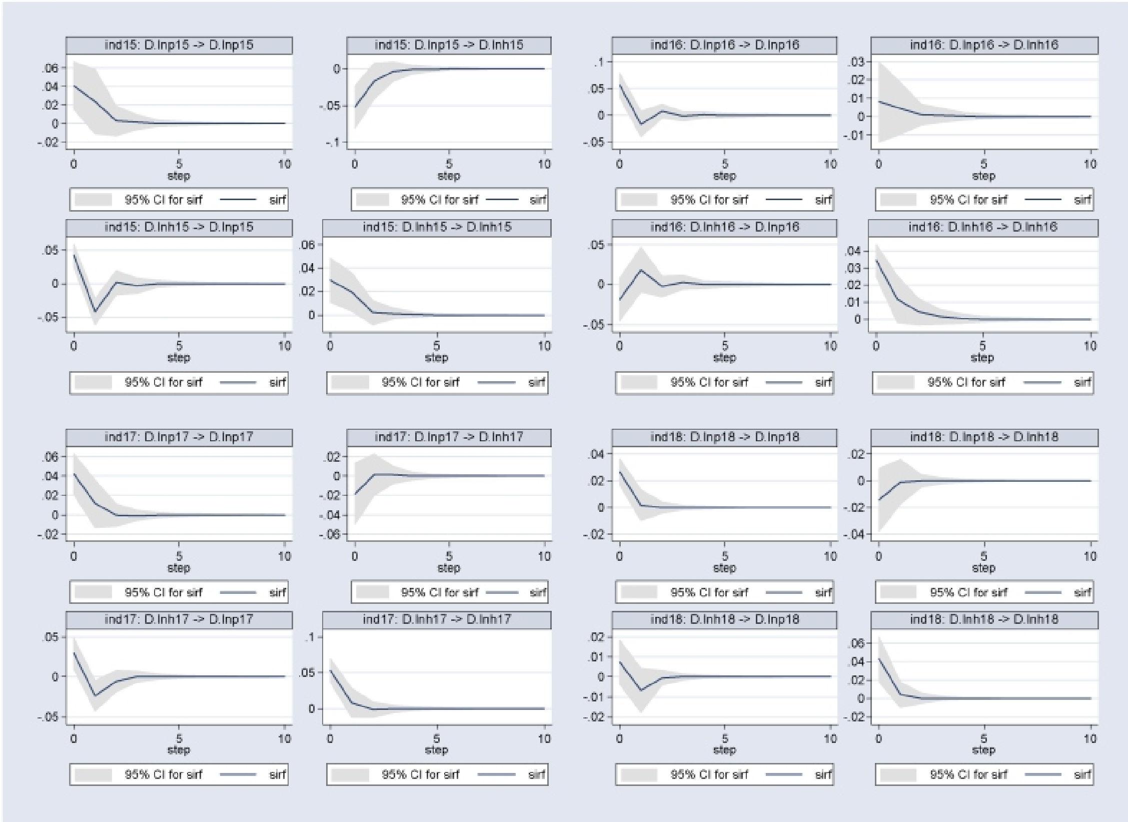

Figure 7: Impulse response functions industries 15-18.

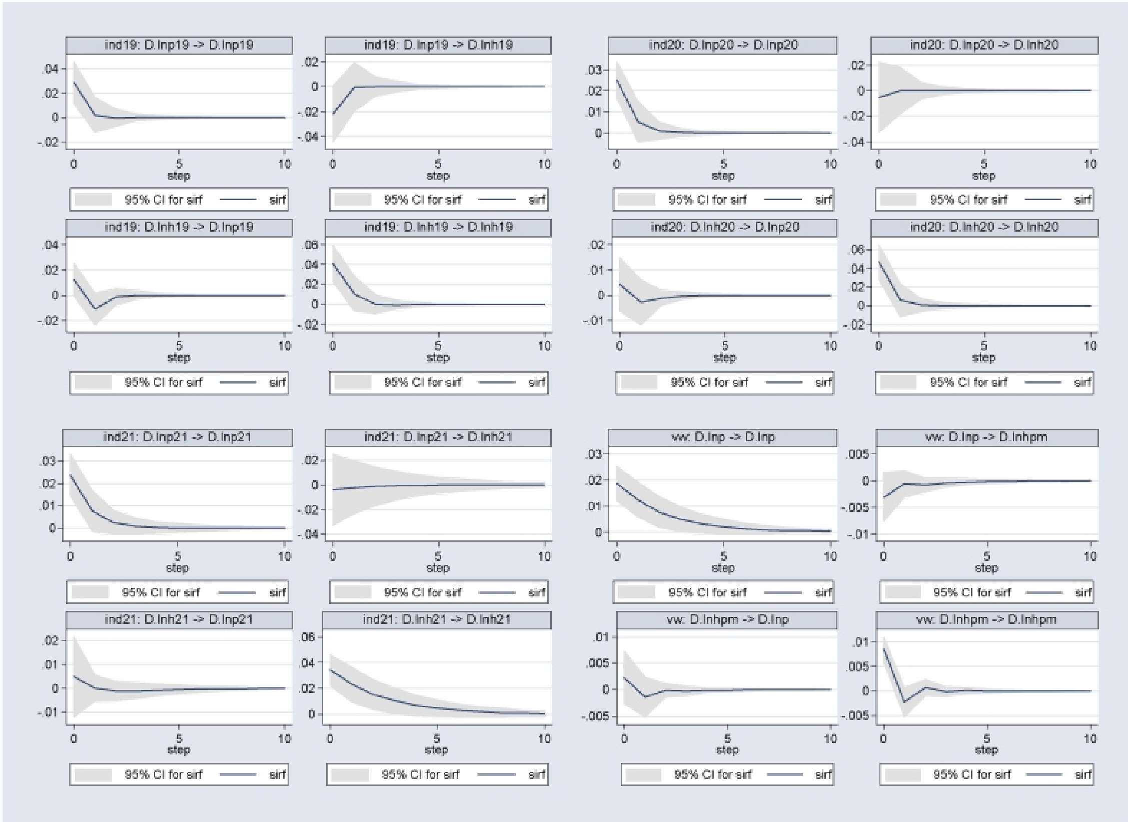

Figure 8: Impulse response functions industries 19, 20, 21 and aggregated shocks.