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On the heterogeneity of sectoral growth and structural dynamics: Evidence from Austrian manufacturing industries.

Werner Hölzl and Andreas Reinstaller*

Abstract

This paper studies the factors driving structural dynamics across Austrian manufacturing industries. Using a SVAR framework we identify sectoral labor productivity and demand shocks that are orthogonal to aggregate shocks. We analyze the sectoral impulse-response patterns and find that the effect of industry labor productivity shocks on industry output growth is quite heterogeneous. We devise a taxonomy that allows us to classify industries according to the effect productivity and demand shocks have on output growth. We also show that productivity shocks are quite heterogeneous not just across industries but also over time, whereas shocks to sectoral demand growth are more systematic. We test the taxonomy in a panel regression and are able to confirm our sector specific findings. Industry demand shocks and aggregate productivity and demand shocks lead always to an increase in industry output and industry employment.

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1 Introduction

Joseph Schumpeter's view on growth and structural change is probably best captured by the following quote:

> *"(...) industrial change is never harmonious advance with all elements of the system actually moving, or tending to move, in step. At any given time, some industries move on, others stay behind; and the discrepancies arising from this are an essential element in the structures which develop."* Schumpeter (1939), p. 101-102.

As the quote suggests from a Schumpeterian perspective heterogeneity in sectoral growth patterns should be considered a rather general and persistent characteristic of the process of economic growth. Harberger (1998) has provided empirical evidence for the uneven distribution of growth across industries. Some early studies on the dynamics of inter-sectoral structural change have combined the differential patterns of real cost reduction and productivity growth explored by Harberger with Engel's law stating that the income elasticity of demand for different types of commodities changes as over time income increases. Differential demand developments play a very prominent role for the heterogeneous development of industries in the pioneering empirical study by Svennilson (1954) or the multi-sectoral growth models advanced by Pasinetti (1981; 1993). In recent times this aspect has been ignored in most contributions on structural change.[1] The question this paper addresses therefore is to what extent sectoral patterns of growth do depend on differential developments in productivity growth *and* demand growth.

We devise an approach to identify both changes in sectoral productivity and demand growth from aggregate industry data, and explore their relative importance for sectoral output and employment growth. For this purpose we use structural vector autoregressive models (SVARs) with long-run restrictions. Based on the cumulated effects demand and productivity shocks have on sectoral output growth we devise a classification of industries. We also analyze whether the arrival of shocks to the growth of productivity and demand shocks is synchronous across sectors. We analyze then the robustness of the results obtained from a longitudinal analysis using dynamic panel methods for all industries. The paper is organized as follows. In Section 2 we discuss identification issues. In Section 3 we briefly review the data and discuss the specification and the estimation procedure. In Section 4 we present our results. The last section we discuss our results and provide directions for further research.

[1] Notable exceptions are for instance Echevarria (1997) and Kongsamut et al. (2001). See Silva and Teixeira (2008) for a comprehensive literature review

2 Theory and econometric strategy

Pasinetti (1981; 1993) has proposed a formal model of unbalanced growth where structural change is driven by two growth processes: the growth of productivity in each industry and the growth of demand in each industry. Both growth rates change as a consequences of learning processes. Shifts of productivity over time reflect technical change. Industry specific changes in the rate of demand growth reflect behavioral variations by agents who adapt their consumption as news about new products and changes in income arrive (see also Browning and Crossley, 2001). Therefore, industries expand or decline not only in dependence of the ability of firms to increase productivity growth through real cost reduction (e.g. process or organizational innovations), but also if they are able to capture a higher share of the demand for domestic products (e.g. through product innovations). In a related paper (Hölzl and Reinstaller, 2007) we show how sector specific SVARs can be specified and the long-run restrictions identified from Pasinetti's model. Here we restrict ourselves to summarize the main assumptions:

- Sectoral productivity growth and sectoral demand growth follow two distinct stationary stochastic processes. Unforeseen changes will show as 'innovations' or shocks to the rate of change of sectoral labor coefficients and sectoral consumption coefficients.
- In each sector there is a fixed-coefficient production technique selected from a set of alternative fixed-coefficient technologies (Pasinetti, 1981; Basu, 1996).
- In order to identify the SVAR model with long run restrictions we assume that the shocks to the growth rate of demand have no permanent effect on the growth rate of productivity.
- As observed labor productivity in a sector fluctuates pro-cyclically due to variations in the degree of capacity utilization (Basu, 1996) we need to control for business cycle fluctuations.
- If industries are small as compared to the aggregate economy a weighted combination of all productivity shocks outside a specific industry will correlate with the sectoral productivity shock. In order to identify the genuine sectoral productivity shock, we control for this "imported productivity"

Based on these assumptions we specify the sectoral structural VAR models (SVAR) with long run restrictions from which structural productivity and demand shocks are obtained (Blanchard and Quah, 1989) for each sector. [2] If both sector productivity and demand series are I(1) the data vector in the empirical model is given by $\hat{y}_{i,t} = [\Delta \hat{l}_{i,t}\ \Delta \hat{h}_{i,t}]'$ where

[2] The dynamic analysis in this paper is thus distinct from approaches that track changes in input-output coefficients (technological change) and changes and composition of final demand (see e.g. Korres (1996), Andreoso- O'Callaghan and Yue (2002)).

$\Delta\hat{l}_{i,t}$ corresponds to the sectoral growth rates of (hourly) productivity and $\Delta\hat{h}_{i,t}$ to the growth rates of worked hours gained by first differencing the logs of these series.[3] Accordingly, for each sector i we estimate a reduced form VAR(p) process

$$\hat{y}_{i,t} = \Psi_0 + \sum_{j=1}^{p} \Psi_j \hat{y}_{i,t-j} + \sum_{l=0}^{s} \Psi_{x,l} x_{t-l} + e_{i,t.} \qquad (1)$$

where Ψ_0 is a vector of parameters representing the intercept of the VAR, Ψ_j is the parameter matrix of the VAR and $\hat{y}_{i,t-j}$ are the *p* lags of the vector of endogenous variables, $\Psi_{x,l}$ is the parameter matrix of the influence of the exogenous variables $x_{t-l} = (\sigma^p_{x,t-l} \ \ \sigma^d_{x,t-l})'$ on the endogenous variables over horizon *s*. The exogenous variables are the contemporaneous business cycle and the aggregate productivity shock. Finally, $e_{i,t}$ is the vector of the reduced form disturbances of the VAR. If the VAR(p) is stable, then a related VMA(∞) representation exists and is given by

$$\hat{y}_{i,t} = \mu_i + \Phi_{i,x}(L)x_t + \Phi_i(L)\sigma_{i,t} \qquad (2)$$

where μ_i is a time-invariant mean of $\hat{y}_{i,t}$, *L* is the lag operator and $\Phi_i(L)$ is the long run multiplier matrix of the structural shocks in vector $\sigma_{i,t}$ where $\sigma^p_{i,t}$ and $\sigma^d_{i,t}$ are the structural shocks defined before. Additional to the assumption that the industry specific productivity shocks $\sigma^p_{i,t}$ and the demand shocks $\sigma^d_{i,t}$ are orthogonal with respect to each other, i.e. $\sigma^p_{i,t} \perp \sigma^d_{i,t}$, we also normalize them to have unit variance, $E(\sigma_{i,t}\sigma'_{i,t}) = I$. The coefficient matrix $\Phi_{i,x}(L)$ contains the effects that changes in the exogenous variable x_t have on the endogenous variables. In order to recover the structural shocks we impose the restriction $\Phi^{12}_i(1) = 0$, i.e. we impose $\Phi_i(1)$ to be lower triangular. This restriction captures the idea that demand shocks have no permanent effect on productivity. It is then possible to recover $\sigma_{i,t}$ from the reduced form disturbances $e_{i,t}$ of the VAR.

[3] Using total hours worked in the place of employment allows accounting for e effects of labor hoarding and other manifestations of labor market rigidities, as well as changes in capacity, that do not influence productivity. Galí (1999) has first proposed this approach in the realm of business cycle research. It has been applied at the sector level by Kiley (1996). Alexius and Carlsson (2005) show that this method allows identifying productivity shocks accurately.

3 Data and estimation procedure

3.1 The data

The data are yearly data for Austrian manufacturing and cover the period 1971-1995. The labor productivity series is from the ISIS database of Statistics Austria. Labor productivity is an index of real production per hour worked. The index of total worked hours is derived from the productivity and the real production value also taken from the ISIS database. Sectoral employment data and gross production value were all taken from the Industrial Statistics of Statistics Austria. Hours worked was obtained from Biffl (2000). GDP was taken from the International Financial Statistics (IMF). The list of industries included in the study and their id number used throughout this paper as well as some summary statistics of the series used in our analysis are given in Table 1. The table also shows that the structure of Austrian manufacturing has considerably changed over the period of observation.

Table 1 about here.

3.2 Specification tests and estimation procedure

We first had to establish the order of integration of the time series used in the SVARs. As unit root tests have in general low power and our data consist of pooled time series we use panel unit root tests that have been proposed as a more powerful alternative to unit root tests on single time series. We use three different tests: The Levin-Lin-Chu test (Levin et al., 2002), the Im-Pesaran-Shin test (Im et al., 2003) and the Pesaran test (Pesaran, 2007). The test proposed by Im, Pesaran and Shin (IPS) allows for heterogeneous panels and the unit root test is based on the average of the individual ADF unit root tests computed from each single time series. The null hypothesis is that each individual time series contains a unit root while the alternative allows for some but not all of the individual series to have unit roots. The Levin, Lin and Chu test assumes that the AR coefficients for unit roots in particular are assumed to be the same across cross-sections. The null hypothesis is that each individual time series contains a unit root against the homogenous alternative that each time series is stationary. One major criticism of both these tests is that they require cross-sectional independence. To meet this criticism Pesaran's test relaxes this requirement. It is based on augmenting the ADF regression with the lagged cross-sectional mean and its first-difference to capture cross-sectional dependence. Analogous to the IPS test, the Pesaran test is consistent under the alternative that only a fraction of the series is stationary. The results of the unit root tests with a constant are given in Table 2. The hypothesis of a unit-root cannot be rejected for log productivity and log hours worked while it is clearly rejected for first differences by all three tests. These results are in line with unreported results on unit root tests for the individual sectoral time series.

Table 2 about here.

As the results of the unit root tests show that both series used in our analysis are integrated of the same order we need to carry out cointegration tests. We used four different panel cointegration tests: Pedroni's (1999; 2004) group rho and the group t tests, as well as Westerlund's (2005) group mean variance ratio and panel variance ratio statistics, which are all residual based. The null hypothesis is no cointegration. The pooled panel test has the alternative that the first order serial correlation coefficients are identical and not equal to 1 for all industries. The group tests test against the alternative that the first order serial correlation coefficients are heterogeneous across industries but not equal to one. We calculated the residuals using OLS. The results reported in Table 3 suggest that the null of no cointegration, cannot be rejected. This is consistent with unreported results for cointegration tests carried out for the individual sectoral time series. The results imply that we should use series in first differences in the sectoral VAR models and that no error correction is needed.

Table 3 about here.

We have used different information criteria and likelihood ratio tests to determine the optimal lag order for the panel unit root, the cointegration tests and the VARs. In general these tests seemed to favor models with lags for the endogenous variables ranging between one and four and lags for the exogenous variables with up to two lags. For, both for panel unit root and the panel cointegration tests it made no difference whether we used optimal lags or only one lag. However, as the series are short order selection criteria have very low power in indicating the exact lag order (Lütkepohl, 2005, p. 153). For this reason we rely on a heuristic argument for the lag selection for the VARs. The data have yearly frequency and the series are short. This makes a parsimonious model more appealing, and therefore we use a model with one lag for the endogenous variables and no lag for the exogenous variables for each sector in order to determine the productivity and demand shocks from its residuals. We have also run models with one lag of the exogenous variable, but results were almost identical.

In estimating the sectoral SVARs we proceed as follows: In a first step we extract productivity and demand shocks for the Austrian economy following the SVAR approach developed by Galí (1999). A number of contributions have provide robust evidence that the aggregate demand or non-technology shocks attained with his approach match business cycle shocks closely (Francis and Ramey, 2005; Galí, 2004). In the second step we use then the recovered aggregate demand shocks as control variable in the sectoral VARs, such that the resulting sectoral productivity and demand shocks will be orthogonal to the aggregate shocks. We then extract the structural shocks in productivity and demand for each sector.[4]

4 Results

4.1 Impulse response analysis and patterns in response

In order to study the factors driving the growth of sectoral output we computed the cumulated impulse-response functions for the growth rates of productivity and hours worked to a one standard deviation innovation for ten periods. The cumulated responses are then summed up to establish the cumulated impact of productivity and demand shocks on sectoral output growth. As the productivity is I(1) in all industries a one standard deviation productivity shock has ceteris paribus always a permanent and for all industries positive effect on productivity growth. The same holds true for the effect of a demand shock on the growth of hours worked. It has a permanent and positive effect as hours worked are also I(1) for all industries. Therefore, differences in sectoral development patterns depend on the combined effect of productivity and demand shocks on sectoral output growth. As the response patterns are heterogeneous across industries we classify them according to the effect shocks to the growth of productivity and demand have on sectoral output growth.

Table 4 about here.

There are five logically possible and economically meaningful combinations of how the different growth rates may react to productivity and demand shocks. The first four columns in Table 4 summarize them. For pattern 1 the cumulated effect of a productivity shock on productivity growth is lower than its negative effect on the growth of hours worked. Consequently, the joint effect on output growth is negative. Pattern 2 corresponds to the patterns postulated by Galí (1999) and Francis and Ramey (2005) for the aggregate economy. Here productivity shocks have a negative effect on the growth rate of hours worked, but a positive effect on output growth. In pattern 3 the cumulated effects of the productivity shock on the growth rate of productivity and hours worked sum up to a zero impact on output growth. In pattern 4 a productivity shock has no effect on the growth of hours worked and clearly a positive effect on output growth and in pattern 5 it increases the growth rate of hours worked and has a positive effect on output growth. Pattern 5 captures

[4] We also tested whether the shocks are independent of important macro-economic variables by means of an *F*-test with the null that the coefficients of the exogenous macro-economic factors are jointly equal to zero. We found that with the exception of two industries the sectoral productivity and demand shocks are not correlated with exogenous macro-economic factors.

the scenario the real business cycle literature claims to hold for the aggregate economy. Labor inputs, productivity and output growth are positively correlated.

We have carried out a hierarchical cluster analysis using the point estimates of the cumulated sectoral impulse response to a shock after ten periods to develop our taxonomy. We have applied the angular separation measure to calculate the similarity of responses across sectors and computed the clusters with the complete linkage algorithm (Gordon, 1999, p. 21; p.78). The resulting classification of industries is stable with respect to the use of the alternative minimum sum of squares cluster algorithm. Four out of the five possible classes were identified using our data. The last column of Table 4 shows to which class each industry is attributed. The cluster analysis has identified the petroleum industry (id 2) and the chemical industry (id 5) as outliers. Their impulse responses match pattern 4 where hours worked respond neutrally to a productivity shock with an overall positive impact on output growth. However, the size of the cumulated effects is much higher and therefore the cluster analysis identifies these industries as a group on its own.

Figure1 about here

Figure 1 summarizes the relative importance of productivity and demand shocks for output growth in each of the four classes identified with the cluster analysis. The box plots show the cumulated values of the point estimates of the sectoral impulse response functions on which the cluster analysis has been performed. The general characteristics of the identified industry groups matching patterns 1 and 3 are that productivity shocks do not lead to an output expansion. Group 1 contains mostly declining industries. In these two groups expanding demand is the main cause for changes to the sectoral rate of output growth. In group 1 productivity shocks even lead to a permanent decline in the sectoral output growth rate. As the cumulated effect on productivity growth is positive, changes in productivity favor the reduction of labor input. Productivity improvements in these groups seem therefore to favor cut employment. The same holds true also for group 3, even though the cumulated effect of productivity shocks on hours are not as pronounced as in group 1 so that the joint effect of a productivity shock on productivity and demand growth on the rate of output growth is almost neutral. The general characteristics of the industries in the groups matching pattern 2 and 4 is that productivity improvements increase the sectoral rate of output growth. In these sectors productivity and demand shocks are potential sources of output growth.

If we compare the results of this innovation accounting exercise in Table 4 with Table 1 we see that more than half of the industries grouped under pattern 1 were declining industries, such as the mining (id 1), the leather producing (id 12) and the leather processing (id 13) industry. For all the industries in this group a productivity improvement has contractionary effects. A shock to the rate of productivity growth reduces the demand for labor more than it increases the growth of output. This is most likely due to rationalization and downsizing of activities. Productivity increases in these industries translate into lower costs, and if the industry was not shrinking then output growth was mostly driven by an expanding demand. The industries in group three consists of two industries that have experienced an above average increase in real output (electrical equipment id 19, paper processing id 7), and one that has shrunk over the observation period (stone & ceramics id 3). In these industries the observed expansion or contraction of real output as shown in Table 1 was exclusively driven by demand changes. To summarize, in the industries in groups 1 and 3 productivity improvements translated into cost reductions through their effect on employment, but where overall real output growth or contraction was driven by a demand expansion.

The picture is different for the industries grouped under patterns 2 and 4. All industries in these groups except for one have experienced substantial growth in real output over the observed period. In the industries in group 2 productivity shocks reduce ceteris paribus labor inputs. However, the total effect of a productivity shock is to increase output growth. Hence, they over-compensate the negative effect a reduction of labor input would have on output growth. In group 4 on the other hand the effect on labor input is on average zero, and a productivity shock therefore translates directly into a positive effect on output growth. In these two groups both demand innovations and productivity improvements drive output growth. This implies that in these industries potentially negative effects of the sectoral demand shrinking in the long run, can be (partly) o set by productivity improvements.

Overall, the classification exercise in this section shows that the transmission mechanisms of productivity and demand shocks into sectoral output are different across sectors, and that both changes in demand as well as changes in sectoral productivity have to be taken into account in order to better understand what drives the long-run development of industries.

4.2 Principal component analysis

In the previous section we classified industries in terms of their estimated response to productivity and demand shocks. In this section we want to verify to what extent the shocks are synchronized across industry groups. We use principal components analysis (PCA) as tool of analysis (Jackson, 1991). In case shocks are synchronous across industries and within industries we should be able to identify two or three principal components that explain a large fraction of the variation in the data. This would not be the case if heterogeneity over time and across industries was high.

Productivity shocks The results for the PCA on productivity shocks are summarized in Table 5. The first principal component accounts for 24.33% of the correlation of productivity shocks across industries. It reflects a common structural effect on productivity growth. However, there is a larger number of industries (seven out of nineteen) for which this first component does not explain much of the variation.

Table 5 about here.

Component c_2 suggests a contrasting pattern of innovations in productivity between the food and tobacco (11) and the machinery and steel construction industries (16) on the one side and the chemical (5) and the leather processing industries (12), foundries (14), the non-metal (15), the transportation equipment (17) and the iron and metal products (18) industries on the other side. The patterns of innovation in these two contrasting subgroups reflect a positive correlation within the two groups and a negative correlation between the groups, but it is not clear what may be the cause for this as the two groups are composed of quite heterogeneous industries. Similar difficulties of interpretation arise for the remaining components. Productivity shocks vary unevenly across sectors suggesting that innovation-possibility frontiers that shape productivity growth are largely industry-specific.

Demand shocks The results for the PCA on demand shocks are displayed in Table 6. Almost all industries (except mining, petroleum and leather processing) share one principal component c_1, which accounts for 38.17% of the correlation of demand shocks across industries and between twenty and more than eighty percent of the correlation in the shocks to the growth rate of hours worked in each industry. This is surprising given that we have controlled for the aggregate effects in the sectoral demand shocks. This suggests that sector specific demand developments are less idiosyncratic than productivity shocks. The first component is likely to capture the shift from demand for manufacturing goods to services, which is related to the general effect of income growth. Exceptions are mining (for which the component explains just slightly more than 10%), the oil and refinery, the leather producing and the leather processing industries.

Table 6 about here.

General changes in demand affect all sectors, but some industries decline while others grow. This is a possible interpretation of components c_2 and c_3. The second component seems to reflect the contrasting development between some intermediate industries related to basic good production (1, 2) and the consumer good sector (11, 12, 13, 21) on the one hand and some intermediate and capital goods industries on the other hand (3, 6, 14, and 18). Component c_3 is related to component c_2 and captures the contrast between some sectors growing above industry average (11, 19) and others growing below the industry average (14, 15, 21). All remaining components are difficult to interpret and are likely to reflect industry specific variation.

To sum up, the timing of productivity and demand shocks as well as their direction are very unsystematic across sectors. This is especially the case for productivity shocks. Demand shocks seem to be more systematic across industries. This implies that despite its importance for sectoral output growth technical progress is much more industry-specific, whereas changes in the rate of growth of sectoral demand are more systematic across sectors and over time.

4.3 The impact of productivity and demand shocks on Austrian manufacturing industries

The following regression analysis has the goal of providing a robustness test of the results of the impulse-response analysis and the sectoral classification we derived in Section 4.1. In order to do so we use standard industry groupings (capital, intermediate and consumer goods industries) to study the heterogeneity of responses as well as the groupings based on the typology of responses presented in Table 4. We go further and account also for the influence of aggregate productivity and demand shocks. According to Galí(1999; 2004) aggregate demand shocks should capture primarily the influence of the business cycle, while aggregate productivity shocks should be interpreted as aggregate non-cyclical labor productivity improvements. In fact, aggregate labor productivity shocks are nothing else than a weighted sum of all sectoral technology shocks that have a permanent influence on aggregate labor productivity. We estimate the following equation:

$$y_{i,t} = x'_{i,t}\,\beta_1 + z'_t\,\beta_2 + \eta_1 + v_{i,t}$$

where $y_{i,t}$ denotes the growth rate of the industry in employment or output terms in industry i at time t, $x'_{i,t}$ is the vector of industry specific productivity and demand shocks and z'_t is the vector of aggregate productivity and demand shocks. The error term consists of industry components η_i and an idiosyncratic term, $v_{i,t}$. The econometric challenge is to consistently estimate β_1 and β_2. To overcome the source of endogeneity related to the correlation with unobserved time-invariant industry-specific omitted variables it is standard practice to apply the 'within-group' transformation by using the fixed effect estimator. Using industry dummies allows for heterogeneous intercepts and enables to identify unobservable time-variant factors.

We employed a number of specification tests to select the appropriate estimator. First, we used an *F*-test to check whether fixed effects are warranted. The test statistics are reported in the row headed F_{fix} in Tables 7 and 8. We tested for group wise heteroscedasticity using a modified Wald test in the residuals of the fixed effect regression model, following Greene (2000, p. 597). The resulting test statistic is $\chi^2(N)$ distributed, where *N* is the number of cross sectional units. The statistics are reported in the row headed *W* in Tables 7 and 8. We used two tests to test for autocorrelation. The first test is for autocorrelation in panel-data models as proposed by Wooldridge (2002 p. 282-283). The test statistic is distributed as *F(1, N – 1)*, where *N* is the number of cross sectional units. The test statistics are reported in the row headed F_{ar} in Tables 7 and 8. The second test is the LM test proposed by Baltagi and Li (1995). The test statistic is distributed as χ_1^2 and reported in the row headed LM_{ar} in Table 7 and 8. Overall results of the tests suggested the use of fixed effect regression with panel-corrected standard errors Beck and Katz (1995) and Prais-Winsten correction, where use is made of an estimated autocorrelation to transform the data, when the autocorrelation tests required this. The resulting estimators are either a fixed effect estimator with panel-corrected standard errors (PCSE) or an estimated generalized least squares estimator (EGLS).[5]

Table 7 presents the regression results for the pooled manufacturing sector and the three industry groupings for employment and output growth. Table 8 reports the results using the industry grouping identified by the impulse response analysis earlier in this paper (see Table 4). The four sector groupings are of different size: Pattern 1 contains 5 industries, Pattern 2 contains 5 industries and patterns 3 and 4 contain 3 and 4 industries, respectively. Two industries were not considered. The mining industry was excluded because it is no true manufacturing industry and the oil and petroleum industry because it is an outlier. All coefficients reported in Table 7 and 8 are linear combinations of contemporaneous and of once lagged shocks.

Table 7 and 8 about here.

Let us first consider first employment growth equations listed in columns 2 to 5 in Table 7. Industry-specific productivity shocks are as expected negatively associated with employment growth. The coefficient is statistically significant at the 1% level for manufacturing as a whole and the three industry groupings. Industry-specific demand shocks (DS) are as expected uniformly positively associated with employment growth. The association is significant for all industry groupings. Aggregate productivity (APS) and aggregate demand shocks (ADS) are both positively associated with employment growth. The effect of ADS and APS is approximately of the same magnitude for the capital goods and the intermediate goods sectors, while the coefficients on APS is more then double of the size of the ADS coefficient for the consumer goods sector. For the output growth equations reported in columns 6 – 8 in Table 7, we found that industry-specific demand shocks (DS) are again as expected uniformly positive and highly correlated with the growth rate of production. The association between demand shocks and the growth rate of the gross production value is highest for the capital goods industries but highly significant also for the intermediate and the consumer goods

[5] For those equations where the autocorrelation tests provided conflicting information we also ran regression without correcting for autocorrelation. The results (not reported here) were in the rage of the results in Tables 7 and 8 and those obtained by using the bias corrected fixed effect estimator.

industries. Industry-specific productivity shocks (PS) present a more differentiated picture. The correlation is significant and positive for capital goods industries but insignificant and negative for the intermediate goods industries.

Also for consumer goods industries and the overall manufacturing sectors there is no statistically significant association between productivity shocks and output growth. Industry-specific demand shocks lead to quite homogeneous responses while productivity shocks lead to heterogeneous responses across industries groupings with regard to output growth. This can easily be explained on the basis that positive demand shocks lead to more demand, while the effect of productivity shocks is not that clear cut. The effect of productivity shocks on the growth rate of output depends on the price elasticity of demand and by implication on the market structure. With a price-inelastic demand a reduction of prices through industry competition can even lead to negative effects on the gross production value. APS and ADS are positive for the industries as a whole and for all industries. They are also significant with the exception of APS in the intermediate goods industries.

Let us next turn to the regression analysis of the classification identified by the impulse response analysis presented earlier in this paper. Here we group the sectors into four different groups based on the impulse response analysis as reported in Table 4. Let us first consider the sectoral productivity shocks (PS) and the sectoral demand shocks (DS). As expected we find that sectoral demand shocks are positively related to both employment growth and output growth. For PS (industry-specific productivity shocks) we find that the results confirm our impulse-response analysis. In line with the results reported in Table 4 we find for pattern 1 a negative effect of productivity shocks on both employment growth and output growth, for pattern 2 we report a negative coefficient in the employment growth equation and a positive coefficient for output growth. Pattern 3 is characterized by a negative coefficient for PS in the employment growth equation and an insignificant coefficient in the output growth equation. The results for pattern 4 confirm the results in Table 4. The main difference between the results for standard industry groupings and our classification is that we are able to obtain clear cut results for the sectoral productivity growth. For the standard industry groupings in Table 7 we obtain in general a negative coefficient of PS in the employment growth equations and an insignificant or positive coefficient for the output equations, while the results in Table 8 suggest that one can say much more on the relationship between productivity shocks and employment and output growth. As pattern 1 can be interpreted to contain primarily declining industries and pattern 4 to contain primarily expanding industries, and we find that the effect of PS is quite different for these two industries groupings, we take this as indication that PS has a different impact on growing and declining industries. This is likely to be related to the price elasticity of demand. With a price-inelastic demand competition can lead to a negative effect on the gross production value, if the reduction of price is larger than the increase of quantities sold. This story is likely to hold for pattern 1. The sectors in pattern 4, on the other hand, are likely to be characterized by a price-sensitive demand that compensates for the labour saving effects of the technology shocks.

Regarding aggregate shocks (ADS and APS) we find that these carry a positive but not in all cases statistically significant sign for both the employment growth and output growth equations. In particular ADS is not significant for the output growth equation for patterns 1 and 3. APS is not significant for the output growth equation for pattern 3. If we interpret pattern 1 to capture declining industries and pattern 3 to capture primarily expanding industries then it is interesting to see that the importance of APS and ADS is reversed. For pattern 1 we record larger coefficients for APS than for ADS for both the employment growth and the output growth equation, while for pattern 4 it is the opposite: The coefficients on ADS are larger the coefficients for APS. For the other two groupings the coefficients are largely of the same order of magnitude.

The positive association of employment and output growth with APS and ADS suggests that technical change in other sectors of the economy (most likely in sectors that are somehow vertically related) has a positive effect on the employment performance in manufacturing industries. This can be considered as evidence for a positive cumulative effect of labor productivity growth. Own productivity increases lead to a reduction of employment, while labor productivity improvements in other sectors lead to an increase of employment. The magnitude of the coefficient on aggregate productivity shocks is at first surprisingly high, but can be explained on the basis of our method of calculating sectoral productivity shocks. We orthogonalize sectoral shocks to aggregate shocks, therefore all improvements related to inputs, especially materials should show up in the aggregate productivity shocks if these inputs lead to labor productivity improvements in more than one sector. This mirrors also the findings of productivity studies that use the KLEMS framework that inputs from other industries (materials, energy) are important drivers of sectoral productivity growth (e.g. Jorgenson et al. 1987).

The positive association of aggregate demand shocks mirrors business cycle influences. It is interesting to see that the coefficient of ADS is much larger for capital goods industries (sectoral typology) than for the intermediate goods and the consumer goods industries. This seems to mirror the conventional wisdom that investment plays an important role in business cycles. However, it should be noted that the coefficient on APS for the capital goods sector is of comparable magnitude as the other sectors. Moreover, the results in Table 8 suggest that this may related to the fact that most of the capital intensive industries are also sectors that fit into pattern 4 -thus they are expanding sectors in Austrian manufacturing.

Table 9 and 10 about here.

In order to check the robustness of our results we employed also a dynamic fixed effect specification:

$$y_{it} = y_{it-1}\alpha + x'_{it}\,\beta_1 + z'_t\,\beta_2 + \eta_i + v_{it}\,,$$

where y_{it} denotes the growth rate of the industry in employment or output terms in industry *i* at time *t*, y_{it-1} is the lagged dependent variable, x'_{it} is the vector of industry specific productivity and demand shocks and z'_t is the vector of aggregate productivity and demand shocks. The error term consists of an industry components η_i and an idiosyncratic term, v_{it}. As it is well known that the dynamic fixed effect estimator is biased, we use the bias corrected version of the fixed effect estimator as proposed by Kiviet (1995). In particular, we use the bias correction procedure proposed by Bruno (2005). The use of this estimator is suggested by the Monte Carlo results obtained by Judson and Owen (1999) for panels with a small cross-sectional and a small time dimension. Their results are encouraging insofar, as they found that the bias on the dependent variables is reduced substantially. As we use this estimator primarily as robustness check for the signs and magnitudes of the β_1 and β_2 this is important for our interpretation of the results. The results are in Tables 9 and 10. Overall the results show that the estimates obtained with the bias corrected fixed effect estimator are quite close in magnitude and significance to the results documented in Tables 7 and 8.

The coefficients obtained using the dynamic panel estimator are usually smaller and have a slightly lower statistical significance than those reported before. The most important differences the lower significance levels for aggregate shocks for the standard industry groupings: ADS no longer carries a statistically significant coefficient for both the employment growth and the output growth equations for the consumer goods industries and looses also statistical significance for the output equation in the case of intermediate goods sectors. For the sectoral typologies the results are less dramatic. Only APS in the case of pattern 4 looses statistical significance. Overall the results are quite robust.

5 Concluding remarks

The aim of this paper was to analyze the impact innovations in productivity and demand have on output growth and employment in the Austrian manufacturing industry using a SVAR approach with long run restrictions. We have devised a classification of industries based on the cumulated effects demand and productivity shocks have on sectoral output growth. Four out of five possible patterns are found in the data. This shows that changes to the rate of productivity growth are not equally important for all industries. For some, demand changes seem to be more important than productivity growth.

After controlling for aggregate effects we find that productivity shocks do not correlate very strongly across sectors, and common factors do explain only a rather limited fraction of this correlation. Demand shocks, on the other hand, present a more systematic picture, even after controlling for aggregate effects. A principal components analysis on the industry-specific shocks shows that productivity shocks are much more heterogeneous than demand shocks. Industry-specific demand shocks share a large first principal component indicating that demand shocks synchronize to a much higher degree across sectors than productivity shocks even though they are orthogonal to the aggregate demand shock. The second finding of this paper is therefore that productivity developments are largely industry-specific, while sectoral demand is more related to secular economy-wide patterns of income development and changes in preferences.

The robustness of our classification was confirmed by a panel regression analysis. In the panel regressions we included also aggregate labor productivity and demand shocks. Aggregate demand shocks showed uniformly a positive influence. More surprisingly also aggregate productivity shocks had a positive influence on most sectors. This result can be considered as evidence for a positive Schumpeterian effect of labor productivity growth, as it suggests that technical change in other sectors of the economy has a positive effect on the employment performance in manufacturing industries. For most of the sectors we find that own permanent labor productivity increases lead to a reduction of employment, while permanent labor productivity improvements that affect all sectors have a positive effect on sectoral employment.

Further research is clearly needed. In order to study whether or not our results are driven by the specificities of manufacturing industries in general and Austrian manufacturing in particular, the analysis should be expanded to include the service sector and a larger set of countries.

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Tables in the text

Table 1: Summary statistics: changes in % in Austrian Manufacturing, 1971-1994.

id	real output	employment	hourly labor productivity	hours worked	industry grouping
Avg. all industries	91.75	-25.81	212.89	-51.49	
(1) mining	-32.2	-75.54	281.12	-82.21	
(2) oil & refinery	-32.38	-37.28	102.52	-59.57	intermediate goods
(3) stone & ceramics	-18.13	-28.01	163.31	-46.21	intermediate goods
(4) glass & glass prod.	156.51	-24.93	403.76	-38.75	intermediate goods
(5) chemical ind.	208.55	-19.42	327.43	-39.99	intermediate goods
(6) pulp & paper	150	-39.72	490.77	-51.95	intermediate goods
(7) paper processing	183.86	-15.23	274.77	-33.29	intermediate goods
(10) wood processing	125.06	-1.36	169.71	-16.56	consumer goods
(11) food & tobacco	107.07	-23.38	210.98	-33.41	consumer goods
(12) leather producing	-26.47	-59.31	126.21	-63.17	consumer goods
(13) leather processing	-16.70	-67.4	179.94	-73.73	consumer goods
(14) foundries	40.69	-46.44	217.87	-55.74	capital goods
(15) metal ind. except steel	95.96	-47.15	340.9	-55.55	capital goods
(16) machinery & steel constr.	83.74	3.04	130.99	-20.45	capital goods
(17) transportation equipment	158.36	-1.35	231.09	-21.97	capital goods
(18) iron and metal products	135.56	-25.07	285.79	-38.94	capital goods
(19) electrical equip., appliances & components	267.05	10.41	341.26	-16.82	capital goods
(20) textiles except clothing	-10.23	-62.89	207	-70.76	consumer goods
(21) clothing	41.63	-59.94	95.82	-65.47	consumer goods

Table 2: Panel unit root tests

	$\ln p$	$\ln h$	$\Delta \ln p$	$\Delta \ln h$
Im-Pesaran-Shin, W-stat	0,91	3,75	-6,25	-6,52
	(0,82)	(1,00)	(0,00)	(0,00)
Levin-Lin-Chu, t-stat	-1,40	0,42	-4,18	-5,71
	(0,10)	(0,66)	(0,00)	(0,00)
Pesaran, Z-stat	1,05	5,60	-4,59	-3,44
	(0,85)	(1,00)	(0,00)	(0,00)

Notes: The Levin-Lin-Chu test assumes common unit root processes (see Levin, Lin and Chu, 2002). The Im-Pesaran-Shin test (Im, Pesaran and Shin, 2003) and the Pesaran (2003) test assume individual unit root processes. P-values are given in parentheses. $\ln p$ is the log of productivity and $\ln h$ is the log of hours.

Table 3: Panel cointegration tests

	Pedroni group-rho	Pedroni group-t	Westerlund group mean variance ratio	Westerlund panel variance ratio
OLS	6,40	2,70	86,62	42,97
	(1,00)	(1,00)	(1,00)	(1,00)

Notes: *p*-values are given in parentheses. OLS on demeaned data.

Table 4: Potential response patterns and classification trough cluster analysis

Pattern	Effect productivity shock on productivity growth	Effect productivity shock on growth of hours	Effect productivity shock on output growth	Effect demand shock on output growth	Identify through cluster analysis (industry id)
	(1)	(2)	(3)	(4)	(5)
1	+	-	-	+	1,10,12,13,21
2	+	-	+	+	6,11,15,18,20
3	+	-	0	+	3,7,19
4	+	0	+	+	4,14,16,17
5	+	+	+	+	no observation

Notes: The +,- and 0 signs in the other columns summarize the permanent effect of a one standard deviation shock on the sectoral growth rate mentioned in the heading of each column. The numbers in column 5 correspond to the industry ids listed in Table 1.

Table 5: Principal components: proportion of variation of productivity shocks accounted for by principal component c_j and the related component load

	c_1		c_2		c_3		c_4		c_5		c_6		c_7		Prop.var.	PC
Eigenvalue	4.478224		2.94		2.04		1.71		1.53		1.23		1.14			
Explained variation	23.57%		15.47%		10.73%		9.02%		8.03%		6.45%		5.98%			
Cumulated	23.57%		39.04%		49.76%		58.78%		66.81%		73.26%		79.25%			
industry id	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load		
(1)					**0.35**	0.60							**0.12**	0.35	0.47	c_3
(2)					**0.12**	0.35	**0.58**	0.76							0.71	c_4
(3)	**0.47**	0.68			**0.13**	-0.36									0.59	c_1
(4)	**0.26**	0.51	**0.17**	-0.42	**0.16**	0.40			**0.11**	0.33					0.71	c_1
(5)	**0.11**	0.34	**0.39**	0.62	**0.17**	0.41					**0.12**	0.35			0.79	c_3
(6)	**0.23**	0.48			**0.15**	0.38	**0.20**	0.45			**0.16**	0.39			0.59	c_1
(7)			**0.23**	0.48	**0.10**	-0.31	**0.25**	-0.50			**0.13**	0.36			0.61	c_4
(10)	**0.34**	0.58													0.34	c_1
(11)	**0.28**	0.53	**0.29**	-0.54	**0.18**	-0.42									0.75	c_2
(12)	**0.50**	0.70					**0.10**	-0.31	**0.16**	-0.40					0.66	c_1
(13)	**0.35**	0.59									**0.22**	-0.47	**0.17**	0.41	0.74	c_1
(14)			**0.41**	0.64					**0.14**	0.37	**0.18**	-0.42			0.73	c_2
(15)			**0.16**	0.39					**0.11**	0.33					0.26	c_2
(16)	**0.18**	0.42	**0.15**	-0.39			**0.11**	-0.33	**0.18**	0.43	**0.14**	-0.37			0.76	c_5
(17)			**0.16**	0.40	**0.32**	-0.56	**0.06**	0.25					**0.17**	-0.42	0.65	c_3
(18)	**0.34**	0.58	**0.44**	0.67											0.78	c_2
(19)	**0.27**	0.52			**0.24**	-0.49			**0.29**	0.54					0.80	c_5
(20)	**0.41**	0.64	**0.19**	-0.43					**0.12**	-0.34					0.72	c_1
(21)	**0.54**	0.73													0.54	c_1

Notes: The bold numbers are the squared correlation ($(r(c_i, \sigma_j))^2$) which gives the proportion of variation of the series of industry-specific shocks σ_i explained by component c_j. For the components listed this proportion is larger than 10%, other components were dropped. The numbers in the first column give the industry IDs and the related description. The last two columns give the proportion of the total variation of the shocks in an industry the reported components explain (Prop.Var.) and the most important component for each industry (PC) respectively. All components reported have an eigenvalue larger than 1

Table 6: Principal components Proportion of variation of demand shocks accounted for by principal component c_i and the related component load

	c_1		c_2		c_3		c_4		c_5		c_6		Prop.Var..	PC
Eigenvalue	7.25		2.63		1.85		1.61		1.41		1.11			
Explained variation	38.17%		13.84%		9.74%		8.48%		6.44%		5.87%			
Cumulated	38.17%		52.01%		57.74%		66.22%		73.64%		79.51%			
industry id	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load	$r(c_i, \sigma_i)^2$	ev. load		
(1)			**0.48**	0.69	**0.16**	0.40	**0.15**	0.39					0.80	c_2
(2)			**0.21**	0.46			**0.50**	0.71					0.71	c_4
(3)	**0.39**	0.63	**0.18**	-0.42			**0.11**	-0.32					0.67	c_1
(4)	**0.63**	0.80					**0.10**	0.32					0.73	c_1
(5)	**0.75**	0.87											0.75	c_1
(6)	**0.54**	0.73	**0.12**	-0.34									0.66	c_1
(7)	**0.47**	0.69							**0.23**	-0.48	**0.14**	-0.37	0.84	c_1
(10)	**0.19**	0.43			**0.18**	-0.43			**0.24**	0.49	**0.12**	0.35	0.55	c_5
(11)	**0.26**	0.51	**0.14**	0.38	**0.28**	-0.53	**0.17**	-0.41					0.85	c_3
(12)			**0.28**	0.53			**0.10**	-0.32			**0.17**	0.41	0.55	c_2
(13)			**0.34**	0.58			**0.13**	-0.36			**0.10**	0.31	0.58	c_2
(14)	**0.24**	0.48	**0.19**	-0.44	**0.37**	0.60							0.79	c_3
(15)	**0.40**	0.64			**0.19**	0.43			**0.24**	0.49			0.83	c_1
(16)	**0.58**	0.76											0.58	c_1
(17)	**0.30**	0.55							**0.21**	-0.46	**0.29**	0.54	0.80	c_1
(18)	**0.52**	0.72	**0.16**	-0.40									0.69	c_1
(19)	**0.24**	0.49			**0.15**	-0.39							0.38	c_1
(20)	**0.75**	0.86											0.75	c_1
(21)			**0.38**	0.61	**0.26**	0.51							0.75	c_2

Notes: See Table 5 for details.

Table 7: Industry growth and productivity and demand shocks: sector groupings, EGLS

Dependent variable	Employment growth				Output growth			
	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
PS	-0.016***	-0.009***	-0.012***	-0.026***	-0.002	0.021***	-0.01	-0.001
	(-8.21)	(-2.88)	(-4.61)	(-6.88)	(-0.39)	(4.58)	(-1.53)	(-0.12)
DS	0.028***	0.027***	0.025***	0.030***	0.030***	0.046***	0.015**	0.021***
	(13.04)	(8.88)	(9.95)	(8.93)	(8.74)	(10.93)	(2.30)	(4.88)
APS	0.018***	0.021***	0.011***	0.026***	0.021***	0.017***	0.011	0.024***
	(6.73)	(4.98)	(3.41)	(6.58)	(4.68)	(3.04)	(1.41)	(4.21)
ADS	0.014***	0.022***	0.012***	0.012***	0.014***	0.022***	0.013**	0.008**
	(6.58)	(6.28)	(4.69)	(3.98)	(3.83)	(4.45)	(2.04)	(1.92)
industry dummies	y	y	n	y	y	y	y	y
Prais Winsten Transformation	y	n	y	y	y	y	y	y
Observations	399	126	126	126	399	126	126	126
industries	19	6	6	6	19	6	6	6
F_{fix}	8.82***	6.33***	1.63	6.09***	5.74***	2.20*	8.76***	4.33***
W	561.50***	57.42***	199.20***	71.15***	707.03***	80.59***	70.59***	123.66***
LM_{ar}	496.58***	1.75	10.46***	0.17	32.36***	22.53***	0.86	17.00***
F_{ar}	32.81***	3.13	15.52**	40.95***	5.53**	0.51 78.16***	0.30	
R^2	0.58	0.65	0.57	0.58	0.50	0.72	0.43	0.47

Notes: Estimated GLS estimator based on Prais-Winsten transformation with panel-corrected standard errors. Independent variables: PS are industry productivity shocks, DS are industry demand shocks, APS are aggregate productivity shocks and ADS are aggregate demand shocks. All regressions were run with contemporaneous and lagged shocks. The reported coefficients, statistics and significance levels are based on the linear combination of contemporaneous and one year lagged shocks. Absolute value of z statistics (based on panel-corrected standard errors) in brackets. The mining industry was excluded from the sector groupings, as it is no manufacturing industry. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 8: Industry growth and productivity and demand shocks: sector typologies

Dependent variable	Employment growth				Output growth			
group	1	2	3	4	1	2	3	4
PS	-0.033***	-0.010***	-0.017***	-0.001	-0.016**	0.007**	-0.001	0.027***
	(-7.84)	(-3.04)	(-8.15)	(-8.44)	(-2.44)	(2.00)	(-1.48)	(3.69)
DS	0.034***	0.033***	0.022***	0.031***	0.024***	0.033***	0.014**	0.037***
	(8.65)	(6.98)	(10.05)	(9.60)	(4.06)	(9.88)	(2.14)	(5.16)
APS	0.021***	0.016***	0.010***	0.015***	0.036***	0.017***	-0.001	0.017*
	(5.00)	(3.61)	(3.50)	(4.68)	(5.09)	(5.16)	(0.14)	(1.76)
ADS	0.015***	0.014***	0.012***	0.025***	0.004	0.015***	0.008	0.021***
	(4.64)	(4.00)	(4.77)	(7.43)	(0.76)	(6.03)	(1.20)	(2.82)
industry dummies	y	y	y	y	y	y	y	n
Prais Winsten Transformation	y	y	n	y	y	y	y	y
Observations	105	105	63	84	105	105	63	84
Industries	5	5	3	4	5	5	3	4
F_{fix}	8.24 ***	5.93***	9.64***	4.84***	2.79**	8.41***	16.17***	0.79
W	27.10***	25.20***	3.97	27.01***	210.31***	54.81***	38.00***	5.88
F_{ar}	45.26***	11.00**	5.23	8.00*	0.121	3.26	8.27	6.84*
LM_{ar}	12.62***	5.34**	3.36*	12.47***	8.21***	25.46***	10.71***	13.84***
R^2	0.63	0.55	0.81	0.69	0.45	0.74	0.56	0.55

Notes: Estimated GLS estimator based on Prais-Winsten transformation with panel-corrected standard errors. Independent variables: PS are industry productivity shocks, DS are industry demand shocks, APS are aggregate productivity shocks and ADS are aggregate demand shocks. All regressions were run with contemporaneous and lagged shocks. The reported coefficients, statistics and significance levels are based on the linear combination of contemporaneous and one year lagged shocks. Absolute value of z statistics (based on panel-corrected standard errors) in brackets. For sector typologies see Table 4. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 9: Industry growth and productivity and demand shocks: sector groupings, dynamic panel

Dependent variable	Employment growth				Output growth			
	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector	Manufacturing sector	Capital goods sector	Intermediate goods sector	Consumer goods sector
lagged	-0.312***	-0.242**	0.350***	-0.302***	0.093*	-.123	-0.184**	-0.122
dependent	(6.16)	(3.08)	(4.05)	(3.72)	(1.74)	(-1.56)	(2.02)	(1.40)
PS	-0.012***	-0.006**	-0.009***	-0.023***	-0.001	0.024***	-0.008	-0.001
	(-5.90)	(-2.02)	(-3.58)	(-4.85)	(-0.37)	(4.37)	(-1.33)	(-0.03)
DS	0.024***	0.024***	0.020***	0.026***	0.027***	0.052***	0.011*	0.019***
	(12.98)	(9.80)	(8.07)	(6.44)	(7.66)	(8.11)	(1.78)	(3.54)
APS	0.016***	0.018***	0.009***	0.026***	0.19***	0.019***	0.007	0.023***
	(7.08)	(5.44)	(3.13)	(5.34)	(4.56)	(3.02)	(0.91)	(3.48)
ADS	0.010***	0.018***	0.009***	0.007	0.012***	0.025***	0.009	0.007
	(5.12)	(4.99)	(2.98)	(1.39)	(3.08)	(3.67)	(1.06)	(1.13)
industry dummies	y	y	y	y	y	y	y	y
Observations	399	126	126	126	399	126	126	126
industries	19	6	6	6	19	6	6	6

Notes: Bias corrected LSDV estimators for the standard autoregressive panel data model using the bias approximations in Bruno (2005). The Arellano-Bond estimator is used to initialize the bias correction procedure. Independent variables: PS are industry productivity shocks, DS are industry demand shocks, APS are aggregate productivity shocks and ADS are aggregate demand shocks. All regressions were run with contemporaneous and lagged shocks. The reported coefficients, statistics and significance levels are based on the linear combination of contemporaneous and one year lagged shocks. Absolute value of z statistics in brackets. The confidence levels were obtained by bootstrapping standard errors using 50 draws. The mining industry was excluded from the sector groupings, as it is no manufacturing industry. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 10: Industry growth and productivity and demand shocks: sector typologies, dynamic panel

Dependent variable	Employment growth				Output growth			
group	1	2	3	4	1	2	3	4
lagged	0.287***	0.322***	0.012	0.212**	0.079	-0.152*	0.012	0.003
dependent	[2.93]	[3.67]	[0.11]	[2.22]	[0.90]	[-1.95]	[1.16]	[0.02]
PS	-0.029***	-0.074*	-0.017***	0.002	-0.015**	0.009*	-0.009	0.027***
	[-5.44]	[-1.94]	[-7.12]	[0.46]	[-1.96]	[1.72]	[-1.16]	[2.60]
DS	0.029***	0.020***	0.022***	0.028***	0.022***	0.034**	0.013*	0.037***
	[6.74]	[6.73]	[7.79]	[8.62]	[3.78]	[7.28]	[1.81]	[4.01]
APS	0.021***	0.014***	0.011***	0.017***	0.035***	0.020***	-0.001	0.017
	[3.66]	[3.52]	[3.43]	[3.71]	[3.87]	[3.60]	[-0.14]	[1.46]
ADS	0.010**	0.011***	0.012***	0.021	0.003**	0.018***	0.007	0.021**
	[1.98]	[2.85]	[4.20]	[5.65]	[0.44]	[3.80]	[0.75]	[2.26]
industry dummies	y	y	y	y	y	y	y	y
Observations	105	105	63	84	105	105	63	84
Industries	5	5	3	4	5	5	3	4

Notes: Bias corrected LSDV estimators for the standard autoregressive panel data model using the bias approximations in Bruno (2005). The Arellano-Bond estimator is used to initialize the bias correction procedure. Independent variables: PS are industry productivity shocks, DS are industry demand shocks, APS are aggregate productivity shocks and ADS are aggregate demand shocks. All regressions were run with contemporaneous and lagged shocks. The reported coefficients, statistics and significance levels are based on the linear combination of contemporaneous and one year lagged shocks. Absolute value of z statistics in brackets. The confidence levels were obtained by bootstrapping standard errors using 50 draws. For sector typologies see Table 4, * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

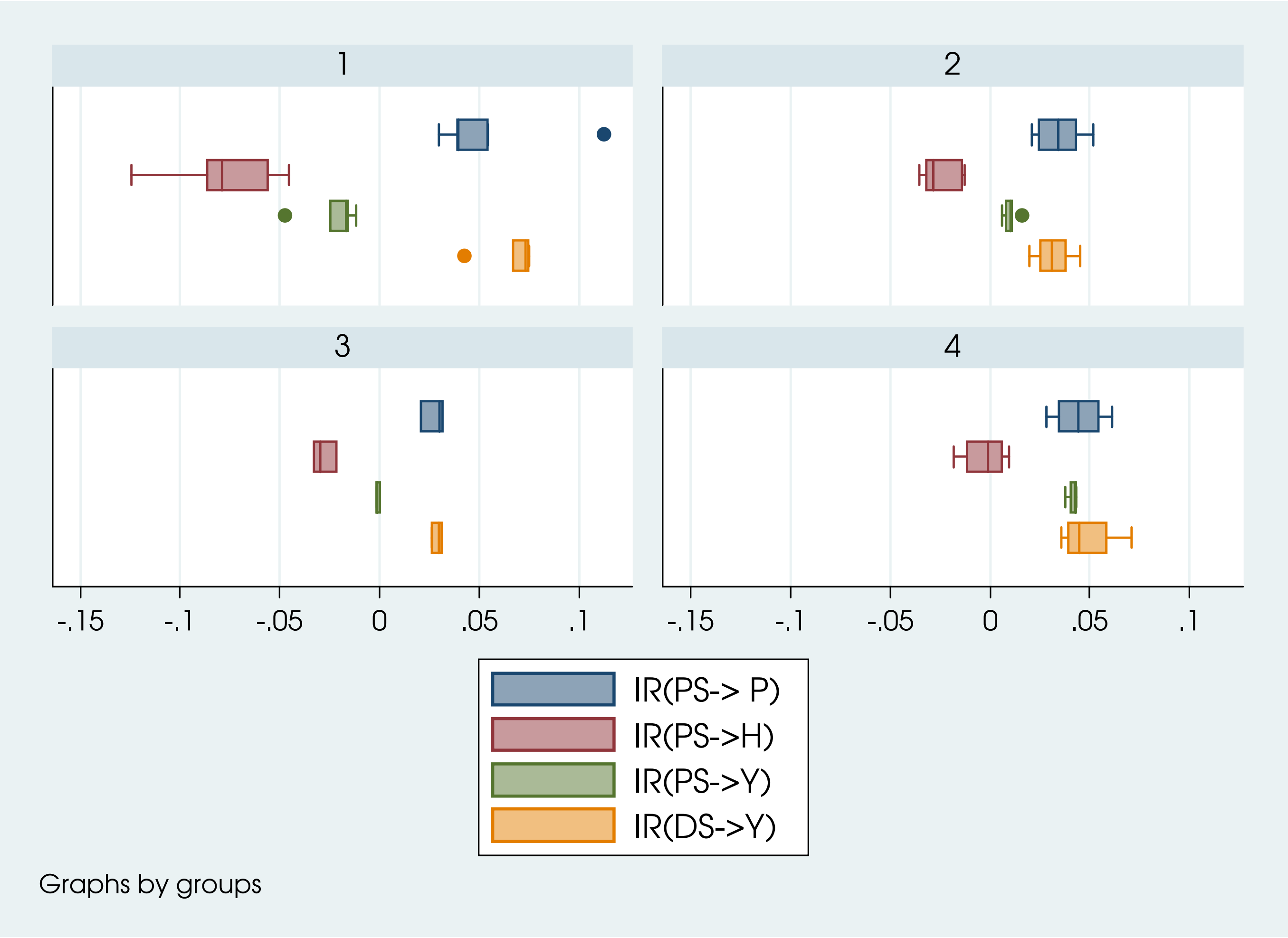
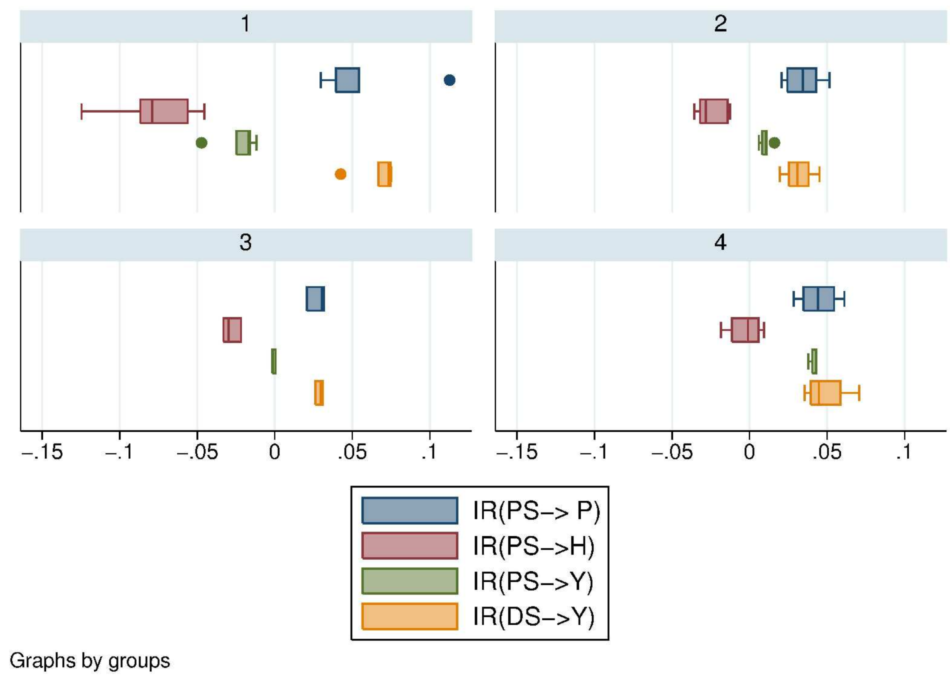


Figure 1: Box plots for the industry groupings as identified by the cluster analysis. The numbers on top of each plot correspond to the numbering of patterns in Table 4. PS= productivity shock, DS= demand shock, P= productivity, H= hours, Y= output growth. Industries 2 and 5 are omitted.



Box plots for the industry groupings as identified by the cluster analysis. The numbers on top of each plot correspond to the numbering of patterns in Table 4. PS= productivity shock, DS= demand shock, P= productivity, H= hours, Y= output growth. Industries 2 and 5 are omitted.
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