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by

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Disentangling the firm growth process: evidence from a recursive panel VAR*

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Abstract

We attempt to describe the coevolution of employment growth, sales growth and growth of profits in a panel of French manufacturing firms 1996-2004. Our analysis entails 'recursive' panel vector autoregressions, whereby we impose the structure of employment growth leading to contemporaneous sales growth, which in turn is associated with contemporaneous growth of profits. We observe that whilst employment growth has a direct negative association with profit growth, there are indirect effects through which employment growth leads to sales growth which in turn has a large effect on profits growth. The net effect of employment growth is thus positive growth of profits. Counter to some 'replicator dynamics' theories of industrial development, profit growth is not followed by much subsequent growth of employment.

JEL codes: L25, L20

Keywords: Firm Growth, Panel VAR, Recursive VAR, Employment Growth, Industrial Dynamics

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1 Introduction

A major strand of the literature on firm growth econometrics (beginning with Gibrat's 'Law of Proportionate Effect') has sought to identify the determinants of growth rates. The typical regression framework has been to observe how firm growth (usually measured in terms of sales or employees) is influenced by variables such as firm size, age, innovative activity, multiplant structure or level of diversification (see Coad (2007c) for a survey). This literature has had a limited success, however, as Geroski bluntly summarizes: "The most elementary 'fact' about corporate growth thrown up by econometric work on both large and small firms is that firm size follows a random walk" (Geroski, 2000, p. 169). Instead firms appear to grow for a wide variety of reasons, and an idiosyncratic component in firm growth rates seems to dominate.

The approach taken in this paper is to take a closer look at the processes of firm growth. Firm growth can be seen as a multidimensional phenomenon, involving amongst others growth of employment, sales, and profits. These different variables shed light on different aspects of firm growth, as is evidenced by the fact that they are far from perfectly correlated between themselves (Delmar et al. (2003)). We therefore attempt to drive a wedge between these different indicators of firm growth, and aim to identify their growth patterns and their distinct influences upon each other as the firm grows. We thus view a growing firm as a multifaceted coevolving system subject to complex interactions. Panel VARs (vector autoregressions) are well-suited devices for investigations of this sort, and they have in fact been previously applied to investigations of firm growth. Stanca and Gallegati (1999) use reduced-form VARs to investigate the relationship between financial factors and investment, while Love and Zicchino (2006) use a more structural VAR specification to observe how the level of financial development influences dynamic investment behavior.

In Section 2 we present the database along with some summary statistics. Our regression methodology is discussed in Section 3. In Section 4 we present our main results, and conclude in Section 5.

2 Database and summary statistics

This research draws upon the EAE databank collected by SESSI and provided by the French Statistical Office (INSEE).[1,2] This database contains longitudinal data on a virtually exhaustive panel of French firms with 20 employees or more over the period 1989-2004. We restrict our

[1]The EAE databank has been made available to the author under the mandatory condition of censorship of any individual information.

[2]This database has already featured in several other studies into firm growth – see Bottazzi et al. (2005), Coad (2007d), and Coad (2007a).

analysis to the manufacturing sectors.[3] For statistical consistency, we only utilize the period 1996-2004 and we consider only continuing firms over this period. Firms that entered midway through 1996 or exited midway through 2004 have been removed. Since we want to focus on internal, 'organic' growth rates, we exclude firms that have undergone any kind of modification of structure, such as merger or acquisition. To start with we had observations for around 22'000 firms per year for each year of the period,[4] but at this stage we have a balanced panel of 8503 firms for each year.

In order to avoid misleading values and the generation of NANs[5] whilst taking logarithms and ratios, we now retain only those firms with strictly positive values for Gross Operating Surplus (GOS),[6] and employees in each year. This creates some missing values, especially for our growth of gross operating surplus variable (see Table 2). By restricting ourselves to strictly positive values for the gross operating surplus, we lose 13-14% of the observations in 1997 and 2000 whereas we lose about 26% of the observations in 2004.

In keeping with previous studies, our measure of growth rates is calculated by taking the differences of the logarithms of size:

$$GROWTH_{it} = log(X_{it}) - log(X_{i,t-1}) \tag{1}$$

where, to begin with, X is measured in terms of employment, sales, or gross operating surplus for firm i at time t.

In keeping with previous work the growth rate distributions have been normalized around zero in each year which effectively removes any common trends such as inflation.[7]

2.1 Summary statistics

Table 1 presents some year-wise summary statistics for employment levels, which gives the reader a rough idea of the range of firm sizes in our dataset. Table 2 presents some summary statistics of the growth rate distributions. Figure 1 shows the unconditional growth rates distributions for our three variables of interest. These growth rates distributions are visibly

[3]More specifically, we examine firms in the two-digit NAF sectors 17-36, where firms are classified according to their sector of principal activity (the French NAF classification matches with the international NACE and ISIC classifications). We do not include NAF sector 37, which corresponds to recycling industries.

[4]22 319, 22 231, 22 305, 22 085, 21 966, 22 053, 21 855, 21 347 and 20 723 firms respectively.

[5]NAN is shorthand for Not a Number, which refers to the result of a numerical operation which cannot return a valid number value. In our case, we may obtain a NAN if we try to take the logarithm of a negative number, or if we try to divide a number by zero.

[6]GOS is sometimes referred to as 'profits' in the following.

[7]In fact, this choice of strategy for deflating our variables was to some extent imposed upon us, since I was unable to find a suitable sector-by-sector series of producer price indices to be used as deflators.

heavy-tailed.[8] This gives an early hint that standard regression estimators such as OLS, which assume Gaussian residuals, may perform less well than Least Absolute Deviation (LAD) techniques which are robust to extreme observations. We also observe that the distribution of growth rates of gross operating surplus has a particularly wide support, which would indicate considerable heterogeneity between firms in terms of the dynamics of their profits.

Table 3 shows the correlations between our indicators of firm growth. Spearman's rank correlation coefficients are also shown since these are more robust to outliers. All of the series are correlated between themselves at levels that are highly significant. However, the correlations are indeed far from perfect, as has been noted elsewhere (Delmar et al. (2003)). The largest correlation (0.3922) is between sales growth and growth of gross operating surplus. Although there is some degree of multicollinearity between these series, the lack of persistence in firm growth rates (despite a high degree of persistence of firm size) will, we hope, aid in identification in the regression analysis. Furthermore, the large number of observations will also be helpful in identification. Multicollinearity has the effect of making the coefficient estimates unreliable in the sense that they may vary considerably from one regression specification to another. With this in mind, we also explore the robustness of our results across several specifications.

3 Methodology

The reduced-form regression equation of interest is of the following form:

$$w_{it} = c + \beta w_{i,t-1} + \varepsilon_{it} \tag{2}$$

where w_{it} is an $m \times 1$ vector of random variables for firm i at time t. β corresponds to an $m \times m$ matrix of slope coefficients that are to be estimated. In our particular case, m=3 and corresponds to the vector (Empl. growth(i,t), Sales growth (i,t), GOS growth (i,t))'. ε is an $m \times 1$ vector of disturbances.

In this paper we impose some more structure to the regression model in (2), however. It seems reasonable to suppose that employment growth will have a 'within-the-period' effect on sales growth and also on growth of profits. This is because new employees will presumably start to add value to the firm from the first days at work. Similarly, it is meaningful to consider that sales growth has a 'within-the-period' effect on growth of profits, because a higher sales volume at roughly constant margins will lead automatically to a higher level of

[8] Bottazzi et al. (2005) present a parametric investigation of the distribution of sales growth rates of French manufacturing firms. In particular, they estimate the functional form of the growth rates density in terms of the Subbotin family of distributions (of which the Gaussian (normal) and the Laplace (symmetric exponential) distributions are special cases). They observe that, in the case of French manufacturing firms, the growth rates density is even fatter tailed than the Laplace.

profits. However, we will suppose that profits are not immediately reinvested in employment growth, for two reasons. First, we anticipate that there will be a certain time lag concerning the feedback channel of reinvesting profits into firm growth (i.e., firms will at least wait until the end of the annual exercise before finding out how much profit there is and deciding how to allocate it). Second, in any case the available evidence suggests that the growth of profits is not strongly associated with subsequent growth of sales or employment (Coad (2007d)). In addition, we suppose that any feedback from sales growth to employment growth (what we might call an 'accelerator theory' of firm growth) does not occur within the same period. In sum, our vision of the timeline of the firm growth process is broadly in agreement with previous findings using data on French manufacturing firms (Coad (2007b)) as well as on US manufacturing firms (Coad and Rao (2007)).

We do not include any dummy control variables (such as industry dummies) in the VAR equation because we anticipate that, if indeed there are any temporal or sectoral effects at work, then dummy variables will be of limited use in detecting these effects. Instead, we suspect that the specificities of individual years or sectors may have non-trivial consequences on the structure of interactions of the VAR series, and these cannot be detected through the use of appended dummy variables alone. We explore the influence of sector of activity in the next section. Furthermore, since previous work on this dataset has not observed any dependence of sales growth on size (Bottazzi et al. (2005)), we do not attempt clean the series of size dependence before applying the VAR. However, we explore how our results change across firm size groups in detail in Section 4.

The VAR regression equations we have in mind effectively correspond to a series of m individual OLS regressions (Stock and Watson (2001)). One problem with OLS regressions in this particular case, however, is that the distribution of firm growth rates is typically exponentially distributed and has much heavier tails than the Gaussian. In this case OLS may provide unreliable results, and we would prefer Least Absolute Deviation (LAD) estimation.

A further reason why OLS (and also LAD) estimation of equation (2) is likely to perform poorly is if there is unobserved heterogeneity between firms in the form of time-invariant firm-specific effects in the *growth rates* series (i.e. firm-specific components that are still visible after taking differences of size). In the event that these 'fixed effects' are correlated with the explanatory variables, then OLS (and LAD) estimates will be biased. One way of doing accounting for these fixed effects would be to introduce a dummy variable for each firm and to include this in the regression equation to obtain a standard 'fixed-effects' panel data model. The drawback with this, however, is that the inclusion of lagged dependent variables can be a source of bias for fixed-effect estimation of dynamic panel-data models. The intuition is that the fixed effect would be in some sense 'double-counted' if the dependent variable is included in the regression equation at time t and also at at previous times due to the lag structure (this problem is known as 'Nickell-bias' after Nickell (1981)). Nickell-bias is often observed to be rather small, however, and so its practical importance is a matter of debate.

This 'Nickell-bias' problem can be dealt with by using instrumental variables (IV) techniques, such as the 'System GMM' estimator (Blundell and Bond (1998)).[9] The performance of instrumental variables estimators, however, depends on the quality of the instruments. If the instruments are effective then the estimates will be relatively precisely defined. If the instruments are weak, however, the resulting estimates will be biased, and the confidence intervals will be implausibly small (Murray (2006)). This is likely to be the case in this study because it is difficult to find suitable instruments for firm growth rates because they are characteristically random and lack persistence (see the discussion in Geroski (2000) and Coad (2007d)). IV estimation of a panel VAR with weak instruments can thus lead to imprecise estimates, even in datasets with large numbers of observations.

Binder et al. (2005) present a panel VAR model which can include firm-specific fixed effects but that does not require the use of instrumental variables. The model is estimated using Quasi-maximum-likelihood optimization techniques. They propose the following model:

$$w_{it} = (I_m - \Phi)\mu_i + \Phi w_{i,t-1} + \epsilon \tag{3}$$

where μ corresponds to the firm-specific fixed effects and Φ is the $m \times m$ coefficient matrix to be estimated. ϵ is the usual vector of disturbance terms. BHP (2005) present evidence from Monte Carlo simulations that demonstrates that their estimator is more efficient (i.e. the estimates have lower standard errors) than IV GMM. The drawback with the BHP estimator for this particular application, however, is that it assumes normally distributed errors (whereas the distributions of firm growth rates are approximately Laplace-distributed).

The approach taken in this paper is that any firm-specific component has been largely removed by the fact that we are dealing with growth rates (i.e., differences) rather than size levels. In unreported regressions we compared results obtained from OLS and fixed-effect regressions, and we interpreted the similarity of the results obtained as an indication that firm-specific components in growth rates are not a major phenomenon.[10] Instead the non-Gaussian nature of the growth rate residuals seems to us to be a more pressing econometric issue than any firm-specific component in growth rates, and as a result our estimator of choice

[9] The panel VAR studies by Stanca and Gallegati (1999) and Love and Zicchino (2006) mentioned in the introduction use the system GMM estimator.

[10] If individual effects are unjustly omitted from a regression, the resulting OLS coefficient estimates will be biased upwards (Bond (2002)). Fixed-effect regression results, on the other hand, are likely to be downward-biased in short panels (Bond (2002)). In unreported regressions we observed that coefficient estimates from OLS and FE regressions were quite similar, although admittedly we did observe some differences concerning autocorrelation dynamics of the VAR series (for more on growth rate autocorrelation, see Coad (2007a)). We therefore conclude that time-invariant firm-specific effects in growth rates are not a major problem in this particular context.

is the LAD estimator, which is best suited to the case of Laplacian error terms.

We also base our inference upon standard errors obtained using the computationally intensive 'bootstrapping' resampling technique (see Efron and Gong (1983) for an introduction).

4 Analysis

Regression results for two and three-lag models are presented in Table 4.[11]

We begin by commenting on the autocorrelation coefficients obtained from our dataset (shown along the 'diagonals'). A negative autocorrelation exists for each of the growth series, with the smallest autocorrelation coefficient being obtained for employment growth and the largest coefficient being for growth of profits. However, we acknowledge that this observed negative autocorrelation may be an artefact of the composition of our dataset. Whilst other studies focusing on large firms have found positive autocorrelation, our present investigation contains data on a relatively large number of small firms, which may explain the negative autocorrelation (Coad (2007a)).

Employment growth has a large effect on sales growth, and the bulk of this relationship appears to be contemporaneous. Sales growth appears to have a statistically significant feedback effect on employment, but the magnitude of this effect is rather small. Instead, we observe a very large association of sales growth with growth of profits. The contemporaneous coefficient is around 1.9, which implies that a 1 percentage point increase in the growth rate of sales is associated with a 'within-the-period' increase in the growth rate of profits of about 1.9 percentage points.

The direct association between employment growth and contemporaneous or subsequent growth of profits appears to be negative. This negative influence of employment growth is more than offset by the indirect influence via sales growth, however. In other words, when we hold sales growth constant, adding extra employees increases the cost burden to a firm. Employment growth, however, leads to sales growth, which in turn generates profits, such that the overall impact of employment growth on growth of profits is large and positive. This tradeoff between the direct and indirect effects of employment growth on growth of profits can be identified in our 'recursive VAR' specification, but could not be detected in earlier reduced-form VAR models (Coad (2007b), Coad and Rao (2007)).

We also observe very little in the way of feedback from growth of profits to growth of employment or sales. This is perhaps surprising when we consider that a number of theoretical contributions have supposed that 'selection pressures' ensure that the profitable firms grow whilst unprofitable firms decline (and eventually exit). This principle of 'growth of the fitter'

[11]Including a fourth lag did not change our results very much.

can be found in the discussions in Alchian (1950) and Friedman (1953), as well as being formalized in the 'replicator dynamics' models in Nelson and Winter (1982) and Metcalfe (1994). The evidence presented here is not in line with this vision of industrial development (see also Coad (2007d) for a more focused analysis applying panel-data IV-GMM techniques).

We also explore how our results vary across industries by comparing the results from four particular sectors: precision instruments, basic metals, machinery and equipment, and textiles. These sectors have been chosen to represent the different sectors of Pavitt's taxonomy of industries (Pavitt (1984)); that is, science-based industries, scale-intensive industries, specialized supply industries, and supplier-dominated industries respectively.[12] The results from this sectoral disaggregation exercise are presented in Table 5. Generally speaking, our main findings appear to hold at a disaggregated (sectoral) level of aggregation.

In addition, we consider how our findings vary across different firm size classes (for the sake of space these results are not reported here). Although there is some variation across size groups, our findings obtained from the aggregate analysis appear to be relatively robust.

5 Conclusion

We apply a vector autoregression to French firms in order to describe the comovements of three firm growth variables: growth of employment, sales and profits. We opt for a 'recursive' panel VAR specification in which employment growth contributes to contemporaneous sales growth, which in turn contributes to contemporaneous growth of profits. Among our results we observe that employment growth has a negative direct association with profits growth (i.e., controlling for sales growth), although this is more than offset by a strong positive indirect of employment growth leading to sales growth, which in turn increases profits. The 'ploughback' effect of growth of profits being associated with subsequent growth of sales or employment is relatively small, in contrast to some theoretical conjectures.

[12]The sectors we study are NAF 33 (manufacturing of medical, precision and optical instruments, watches and clocks), NAF 27 (manufacturing of basic metals), NAF 29 (manufacturing of machinery and equipment, nec.) and NAF 17 (manufacturing of textiles).

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Table 1: Summary statistics after cleaning the data (number of employees)

	Mean	Std. Dev.	10%	25%	Median	75%	90%	obs.
1996	101.01	235.79	25	32	45	86	190	8503
2000	106.16	234.71	27	34	47	93	200	8503
2004	104.35	238-96	25	33	47	92	200	8503

Table 2: Summary statistics for the growth rate series

	Mean	Std Dev	10%	25%	50%	75%	90%	obs
1997								
Empl. growth	0.0000	0.1352	-0.1049	-0.0437	-0.0096	0.0417	0.1156	8489
Sales growth	0.0000	0.2314	-0.1759	-0.0740	-0.0038	0.0785	0.1803	8503
GOS growth	0.0000	0.8068	-0.7630	-0.3152	0.0043	0.3191	0.7675	7383
2000								
Empl. growth	0.0000	0.1333	-0.1168	-0.0526	-0.0117	0.0466	0.1317	8503
Sales growth	0.0000	0.2084	-0.1708	-0.0800	-0.0077	0.0752	0.1845	8503
GOS growth	0.0000	0.7988	-0.7688	-0.2995	-0.0029	0.3232	0.7550	7323
2004								
Empl. growth	0.0000	0.1295	-0.1157	-0.0373	0.0164	0.0475	0.1050	8502
Sales growth	0.0000	0.2191	-0.1763	-0.0729	-0.0002	0.0810	0.1779	8503
GOS growth	0.0000	0.8603	-0.8465	-0.3151	0.0176	0.3257	0.8312	6276

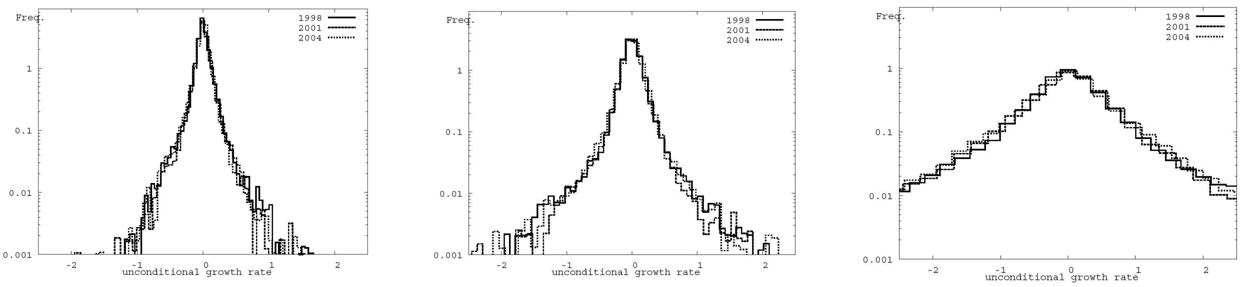

Figure 1: Distribution of the unconditional growth rates of our sample of French manufacturing firms. Left: employment growth. Centre: sales growth. Right: growth of gross operating surplus. Note the log scale on the y axis.

Table 3: Matrix of contemporaneous correlations for the indicators of firm growth. Conventional correlation coefficients are presented first, followed by Spearman's rank correlation coefficients.

	Empl. growth	Sales growth	GOS growth	Prod. growth
Empl. growth	1.0000			
p-value	0.0000			
obs.	67978			
(Sp. Rank)	1.0000			
(p-value)	0.0000			
Sales growth	0.3710	1.0000		
p-value	0.0000	0.0000		
obs.	67978	68024		
(Sp. Rank)	0.3294	1.0000		
(p-value)	0.0000	0.0000		
GOS growth	0.0754	0.3922	1.0000	
p-value	0.0000	0.0000	0.0000	
obs.	56554	56594	56594	
(Sp. Rank)	0.0750	0.4738	1.0000	
(p-value)	0.0000	0.0000	0.0000	

Table 4: LAD estimation results. Standard errors (and hence t-statistics) obtained from 1000 bootstrap replications.

w_t	β_t			β_{t-1}			β_{t-2}			β_{t-3}				
	Empl. gr.	Sales gr.	GOS gr.	Empl. gr.	Sales gr.	GOS gr.	Empl. gr.	Sales gr.	GOS gr.	Empl. gr.	Sales gr.	GOS gr.	R^2	obs
Empl. gr.				**-0.0216**	**0.0581**	**0.0021**	**0.0119**	**0.0260**	**0.0013**				0.0087	40924
				-4.39	14.12	3.26	2.94	8.21	2.18					
Sales gr.	**0.5034**			**0.1718**	**-0.1351**	0.0009	**0.0705**	**-0.0661**	-0.0002				0.0669	40924
	40.86			18.58	-16.20	0.78	8.74	-9.97	-0.19					
GOS gr.	**-0.4232**	**1.8622**		**-0.3063**	**0.6388**	**-0.3546**	**-0.1603**	**0.2294**	**-0.1495**				0.1734	38083
	-14.07	79.22		-12.51	25.59	-42.99	-6.52	10.08	-23.20					
Empl. gr.				**-0.0230**	**0.0590**	**0.0026**	0.0001	**0.0331**	**0.0021**	**0.0172**	**0.0263**	0.0014	0.0108	32392
				-4.33	13.57	3.54	0.03	8.29	2.86	3.78	6.34	1.93		
Sales gr.	**0.4960**			**0.1741**	**-0.1356**	0.0000	**0.0798**	**-0.0737**	-0.0005	**0.0335**	-0.0119	-0.0020	0.0676	32392
	37.95			16.62	-15.35	0.02	8.70	-9.73	-0.39	4.64	-1.95	-1.51		
GOS gr.	**-0.4273**	**1.8893**		**-0.3384**	**0.7276**	**-0.3966**	**-0.1931**	**0.3684**	**-0.2140**	**-0.1068**	**0.1221**	**-0.1019**	0.1817	30143
	-12.76	76.41		-9.90	23.56	-38.88	-5.96	13.61	-24.33	-4.08	5.22	-12.38		

Table 5: LAD estimation results. Standard errors (and hence t-statistics) obtained from 1000 bootstrap replications.

w_t	β_t			β_{t-1}			β_{t-2}				
	Empl. gr.	Sales gr.	GOS gr.	Empl. gr.	Sales gr.	GOS gr.	Empl. gr.	Sales gr.	GOS gr.	R^2	obs
NAF 33: Medical, precision and optical instruments											
Empl. gr.				0.0809	**0.0762**	0.0068	0.0005	**0.0760**	0.0023	0.0269	1235
				1.89	2.31	1.67	0.02	2.33	0.67		
Sales gr.	**0.5398**			**0.1443**	**-0.1272**	-0.0040	**0.1612**	-0.0414	0.0008	0.1017	1235
	9.46			2.35	-2.57	-1.01	3.59	-0.96	0.16		
GOS gr.	**-0.3911**	**1.8653**		**-0.4603**	**0.8061**	**-0.3686**	-0.1660	0.1901	**-0.1109**	0.1945	1151
	-2.08	10.32		-2.33	4.40	-6.64	-1.22	1.27	-2.78		
NAF 27: Basic metals											
Empl. gr.				0.0097	**0.0685**	-0.0047	0.0028	0.0099	-0.0033	0.0095	1006
				0.25	3.16	-1.29	0.06	0.46	-0.89		
Sales gr.	**0.4873**			0.0259	**-0.1089**	-0.0026	0.0219	-0.0602	0.0008	0.0378	1006
	3.08			0.39	-2.97	-0.39	0.53	-1.49	0.12		
GOS gr.	-0.3308	**1.9209**		0.0451	0.4086	**-0.3816**	-0.0036	**0.3234**	**-0.1424**	0.1730	934
	-0.95	13.10		0.21	1.92	-6.05	-0.02	2.16	-2.49		
NAF 29: Machinery and equipment											
Empl. gr.				-0.0111	**0.0372**	0.0003	0.0028	0.0149	0.0017	0.0042	4129
				-0.63	3.57	0.12	0.17	1.58	1.00		
Sales gr.	**0.6474**			**0.2658**	**-0.2560**	**0.0096**	**0.0856**	**-0.1262**	0.0003	0.0905	4129
	16.50			7.72	-9.61	2.21	2.83	-5.43	0.08		
GOS gr.	**-0.3151**	**1.9174**		**-0.3425**	**0.7749**	**-0.4238**	**-0.2511**	**0.2066**	**-0.1606**	0.2043	3795
	-2.76	30.53		-3.55	9.31	-15.02	-2.73	3.08	-7.79		
NAF 17: Textiles											
Empl. gr.				-0.0141	**0.0735**	0.0022	-0.0104	**0.0621**	-0.0022	0.0172	2571
				-0.80	4.94	0.83	-0.70	5.58	-0.99		
Sales gr.	**0.4708**			**0.1621**	-0.0658	-0.0014	**0.0436**	-0.0065	-0.0062	0.0466	2571
	9.18			4.75	-1.71	-0.25	2.15	-0.27	-1.24		
GOS gr.	**-0.4078**	**1.8807**		**-0.3351**	**0.7079**	**-0.4073**	**-0.2531**	**0.2984**	**-0.1649**	0.1941	2347
	-2.68	18.78		-2.77	5.67	-9.84	-2.34	3.19	-5.49		