The dynamics of firm size and wage costs

The Danish manufacturing sector

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Abstract

This is a first draft presenting methodological considerations and preliminary results of a work in progress. As shown by previous empirical investigations and as discussed in many models, features of organizations such as human capital stock, management practices, organizational structure and organization of work do affect the relationship between employment, labour costs and performance. These effects play, presumably, different roles in firms acting in different industries and operating at different scales. We want to investigate if, and to what extent, these phenomena shape the relationship between employed workforce and output. In other terms, we are interested in investigating how the efficiency in the use of the labour input scales withe the size of the firm. Various methods for determining the relationship among such variables are then discussed and the heterogeneity of the relationship between value added and employment across industries in the Danish manufacturing sector is demonstrated.

1 Introduction

In this paper we investigate the relationship between firm size and a number of performance variables, with focus on value added, gross operating margin and wage costs. In this first draft, however, only the relationship between size (measured by employment) and value added are explored.

Many studies find that larger firms pay higher wages. The suggested explanations for this correlation, however, differ across studies. Some studies find that the higher wages are matched by higher performance in terms of revenue or productivity; but also that this higher productivity is not accounted for by observable human capital traits and so is often ascribed to "unobservable qualities" of employees at larger firms (Oi and Idson, 1999; Brown and Medoff, 1989). An alternative explanation for higher wages in firms that are performing well is the hypothesis of rent-sharing: managers of well performing firms choose to distribute the accrued rents across the whole workforce of the firm–to skilled and

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unskilled production workers as well as managers, administrative staff, technicians etc. This means paying wages higher than the market wage, higher than the marginal productivity of the employee and higher than incentives schemes justify (Brown and Medoff, 1989). One possible explanation is a social norm of fairness, which is equally hard to study empirically as the notion of unobservable qualities, but which is well-known from experimental economics (see for instance the discussion on the ultimatum game in chapter 3 of Bowles (2004)).

Other studies find that this wage premium is not accounted for by higher performance at larger firms. One explanation put forward for the wage premium observed in the absence of increased performance is that the premium arises from differences in organisational structure. This argument typically comes in two different forms.

In one form it is argued that employees receive higher compensation the higher their place in the organizational hierarchy based on social norms more than economic rationales (Simon, 1957). This means that firms with deeper hierarchies pay higher average wages. This is also referred to as monitoring costs: the increased wage costs arising from purchasing labour services with the sole aim of monitoring other employees. The cost of monitoring may even increase more than proportionally with the number of workers being monitored as larger organizations often also are more complex, making the monitoring task more expensive (Brown and Medoff, 1989). Beaumont and Harris (2003) presents a study of the role of hierarchies in explaining wages and find that the relevance of the effect differs across industries and is blurred by a number of other factors affecting wages, not least firm size and ownership structure.

A second reason why differences in organisational structure should lead to higher wages but not higher performance in larger firms is the assumption that larger firms offer inferior working conditions and therefore need to pay employees a premium. However Lallemand et al. (2007) discuss empirical evidence to the contrary, arguing that there is no indication that employees at larger firms face more impersonal working conditions, less autonomy or longer commutes. The question is however not completely settled. Recent research comparing work organisation across European countries (albeit studying neither wages nor performance) have found a relationship between work organisation and size (Holm et al., 2010; Arundel et al., 2007). These studies find that some aspects of work organisation, especially monotony and repetitiveness of tasks as well as work pace constraints, are more common in larger firms. Other characteristics of work organisation that arguable contribute to the intrinsic value of the job to employees, on the other hand, have a more complicated relation with the size of the firm.[1]

A recent study of the wage-size relationship in Italian manufacturing found that the size premium on wages at larger firms is not accounted for by higher productivity. This can be related to the change in the organisational structure–i.e. the balance of white and blue collar workers–observed when moving from smaller to larger firms which in turn affects average wages (Bottazzi and Grazzi, 2010). A similar explanation is put forward by Lallemand et al. (2007). The authors compare five European countries, including Denmark and Italy, and find that the wage premium arising from size is smaller in Denmark than in the

[1] Concrete examples are autonomy in the organisation of tasks and being subject to cognitively challenging tasks.

other four countries, although still significant. They suggest that for both Italy and Denmark much of the correlation between size and wage can be explained by differences in work organisation being correlated with firm size too. This explanations is in line with the one proposed by Bottazzi and Grazzi (2010).

This paper aims to analyse the wage-size relationship in Danish manufacturing using individual level data to construct highly detailed indicators of work organisation; and to judge whether the evidence corresponds to the results by Bottazzi and Grazzi (2010) and Lallemand et al. (2007).

2 Data

The preliminary analysis presented here makes use only of firm level data from the General Firmastatistik database, which is based on numerous government registers and maintained by Statistics Denmark. The database contains all Danish firms with non-negligible activity from 1999 to 2006. We pool all years and use only manufacturing firms (NACE, rev. 1 classes 15 to 37) and only firms with at an employment of at least 20 full time equivalent (FTE) employees.[2]

Removing all firms with less than 20 FTE employees entails removing about 80 percent of all firms in any given year. However, these firms only account for a small share of total FTE employment. This share is quite stable at 14 percent across years. The result of this censoring is an unbalanced panel in which a few firms pop in and out as they cross the 20 FTE employment threshold as well as a number of firms that only are present in few years. Thus the panel is censored to only include firms for which there are at least four observations and for which all observations are continuous. This decreases the number of firms in the panel from 3,624 to 2,290 and the number of observations from 17,023 to 14,406. The year 1999 is lost prior to censoring as a number of lagged variables are created and the panel thus includes the 7 years 2000 to 2006.

All variables in nominal values in the database are deflated to 2005 values using the price index for the Danish domestic supply of goods, which is publicly available from Statistics Denmark at `www.statistikbanken.dk`. In the present paper only two variables are used: FTE employment and value added.

2.1 Descriptives

Table 1 shows descriptive statics for the two variables in the panel. Over the seven years 2000-2006 firm mean size grows both in terms of employment and output but median size does not keep up and this is reflected in the standard deviations increasing more than proportionally with the means. I.e. over the seven years the heterogeneity of size has increased.

In the regression analyses reported below the variables will be ln-transformed and the descriptive statistics for these transformed variables are reported in table 3 page 12. The tendency for increasing standard deviation is much weaker in the transformed data indicating that the increasing standard deviation is an effect due to the multiplicative nature of the growth process.

A final piece of descriptive statistics is the correlograms presented in figures 1 and 2 page 16. The first figure plots the autocorrelation of logarithmically

[2]This threshold means that the definition of "non-negligible activity" has no practical consequence.

	Real value added			FTE employment		
Year	Mean	Median	Std. dev.	Mean	Median	Std. dev.
2000	62.80	23.03	238.0	124.6	54	276.4
2002	71.20	23.36	282.9	134.2	51	454.5
2004	73.71	24.03	315.8	131.4	49	444.0
2006	79.53	25.60	328.8	139.1	55	445.0

Real VA in millions of DKK at 2005 prices.

DKK is pegged to the Euro at 7.46 DKK per Euro with a band of ±2.25%.

Table 1: Descriptives for select years

transformed real value added and FTE employment. Both variables exhibit strong autocorrelation even with a lag length of 6 years (the maximum allowed for by the data). In contrast, the autocorrelations of the first differences of these two variables, reported in figure 2, are very close to zero at all lag lengths.

3 Models

The traditional way of estimating the responsiveness of one variable to changes in another is to estimate elasticities using a log-log specification. However, the panel data used here also allows for a dynamic specification where firm level changes relative to previous year are used to estimate elasticities.

An estimated elasticity of unity means that the variables change in proportion to each other, while an elasticity greater than unity, i.e. an elastic relationship, implies that a change in one variable is associated with a more than proportional change in the other variable. Thus if wage costs are elastic with respect to employment while value added has unit elasticity this indicates diseconomies of scale: value added only increases proportionally to employment while wage costs increase more than proportionally. It is of course also possible that both wage costs and value added are at the same time elastic or inelastic and the interpretation of the result then depends on the relative magnitude of the estimates.

3.1 The relationship

$L_{i,t}$ denotes FTE labour input in firm i at time t and $V_{i,t}$ denotes real value added for firm i at time t. Equation 1 specifies how these two variables are assumed to be related. The model carries the implicit assumption that only the short run is being studied as far as labour intake is the input factor that is adaptable in the short run. When $\alpha = 1$ equation 1 suggests that value added is related to input by a scalar. However, other studies have shown that performance in large firms is disproportionately weak ($\alpha < 1$) so it should be studied whether α is indeed equal to unity.

$$V_{i,t} = \beta L_{i,t}^{\alpha} \tag{1}$$

The size relationship in equation 1 suggests that the relationship between changes in labour input and value added is as specified in equation 2. In the analyses of later sections elasticity estimates based on equation 1 will be referred to as estimates based on the static relationship while estimates based on equation 2 are referred to as based on the dynamic relationship.

$$\frac{V_{i,t}}{V_{i,t-1}} = \left(\frac{L_{i,t}}{L_{i,t-1}}\right)^{\alpha} \tag{2}$$

3.2 OLS models

Equations 1 and 2 suggest that the elasticity (α) of output (real value added) with respect to labour input (FTE employment) can be estimated with either of the two models specified below.

$$\ln V_{i,t} = \ln \beta_1 + \alpha_1 \ln L_{i,t} + \epsilon_{1,i,t} \tag{Model 1}$$

$$\ln \frac{V_{i,t}}{V_{i,t-1}} = \alpha_2 \ln \frac{L_{i,t}}{L_{i,t-1}} + \epsilon_{2,i,t} \tag{Model 2}$$

Both of these two models can be estimated by OLS on the full unbalanced panel. However, it is unreasonable to expect that the scale parameter β is the same across all firms, not least as all manufacturing firms are pooled in the panel. Thus it it is hypothesised that the scale parameter, β, is firm specific. This has implications for model 1 but not model 2, where the differencing cancels out the firm specific effect. Thus the intercept term in model 1 is substituted with firm fixed effects and the result is model 3, which will also be estimated with OLS.

$$\ln V_{i,t} = \ln \beta_{3,i} + \alpha_3 \ln L_{i,t} + \epsilon_{3,i,t} \tag{Model 3}$$

The epsilons of models 1, 2 and 3 are classic error terms. Model 3 can be seen as a generalization of model 1 where η_i is allowed to diverge from zero in $\epsilon_{1,i,t} = \epsilon_{3,i,t} + \eta_i$ (whereby $\epsilon_{1,i,t}$ is of course no longer a classic error term).

3.3 Panel GMM

It is practically unavoidable that the level variables for employment and output at a given firm will both exhibit autocorrelation. And while the presence of a trend in evolution at the aggregate level does not mean that the same trend is present for individual firms, it does arouse suspicion. Below, a consistent control for the autoregressive effects will be undertaken using a dynamic panel technique.

The hypothesized size relationship modified for AR(1) effects becomes equation 3 and the associated regression models become models 4 and 5. Notice that the scale parameter of model 4 does not carry an i subscript. The technique used to estimate model 4 (and 5) includes first differencing the models so that the scale parameter is removed anyway.

$$V_{i,t} = \beta L_{i,t}^{\alpha} V_{i,t-1}^{\rho} \tag{3}$$

$$\ln V_{i,t} = \ln \beta_4 + \alpha_4 \ln L_{i,t} + \rho_4 \ln V_{i,t-1} + \epsilon_{4,i,t} \tag{Model 4}$$

$$\ln \frac{V_{i,t}}{V_{i,t-1}} = \alpha_5 \ln \frac{L_{i,t}}{L_{i,t-1}} + \rho_5 \ln \frac{V_{i,t-1}}{V_{i,t-2}} + \epsilon_{5,i,t} \qquad \text{(Model 5)}$$

Models 4 and 5 are to be estimated using the generalized method of moments (GMM) estimator first outlined in Arellano and Bond (1991) and further developed in Arellano and Bover (1995). It is often referred to as the dynamic panel estimator and this use of "dynamic" should not be confused with the distinction made between models 1 and 2 above. See Bun and Windmeijer (2010); Blundell and Bond (1998) for further discussions on the dynamic panel data method and Bond (2002); Blundell et al. (2000) for more user oriented expositions.

In models 4 and 5 $\epsilon_{i,t} = \eta_i + \upsilon_{i,t}$, and the following "standard assumptions" are made:

$$E(\eta_i) = 0,\ E(\upsilon_{i,t}) = 0,\ E(\eta_i \upsilon_{i,t}) = 0 \text{ for } i = 1, \ldots, N \text{ and } t = 2, \ldots, T \qquad (4)$$

and

$$E(\upsilon_{i,t}\upsilon_{i,s}) = 0 \text{ for } i = 1, \ldots, N \text{ and } \forall t \neq s \qquad (5)$$

The assumption in 5, no autocorrelation, is important and should be tested. Arellano and Bond (1991) suggest a test for autocorrelation (the m_2 test) in connection with the dynamic panel method though later research has questioned its usefulness (Jung, 2005). The software package used for the analyses presented in the current paper allows for direct application of a version of the m_2 test to balanced data and this is used as a preliminary gauge of violations of 5. Therefore the dynamic panel method will be applied to both the full panel and a balanced panel. The panel is balanced by removing all firms not present in all seven years.

The general idea of Arellano and Bond's GMM estimator is to re-write the model in first differences so that firm specific effects are differenced out (cf. earlier, the beta parameter in equation 3 could be given an i subscript to account for η_i). The differenced lag of the endogenous variable on the right hand side is then substituted by a number of instruments. Define the Δ operator as $\Delta x_t \equiv x_t - x_{t-1}$ and the differenced version of model 4 can be written as equation 6 (the following exposition of the technique relates to model 4 but the same treatment is applied to model 5).

$$\Delta \ln V_{i,t} = \alpha_4 \Delta \ln L_{i,t} + \rho_4 \Delta \ln V_{i,t-1} + \Delta \upsilon_{4,i,t} \qquad (6)$$

The instruments employed for $\Delta \ln V_{t-1}$ can be levels of the endogenous variable lagged at least two periods in order not to be correlated with the error ($\Delta \upsilon_{4,i,t}$), that is, for observations referring to later years there will be more lags available as instruments. The use of these instruments entails the $\frac{(T-1)(T-2)}{2}$ moment restriction of equation 7.

$$E(\ln V_{i,t-s} \Delta \upsilon_{4,i,t}) = 0; \text{ for } t = 3, \ldots, T \text{ and } 2 \leq s \leq t-1 \qquad (7)$$

The regressor ($\Delta \ln L$) can also be used as an instrument. If the variable is strictly exogenous, then all lags and leads can be used as instruments at any t but if it is predetermined, i.e. weakly exogenous (if current shocks to the dependent variable affects future values of the instrument) then only lagged values of the instrument can be used. In the former case (strict exogeneity) the $T(T-2)$ moment restriction of equation 8 apply.

$$E(\ln L_{i,s} \Delta \upsilon_{4,i,t}) = 0;\ \text{for } t = 3, \ldots, T \text{ and } 1 \leq s \leq T \tag{8}$$

But if $\ln L$ is rather predetermined then there are only $\frac{(T+1)(T-2)}{2}$ additional moment restriction, as specified in equation 9:

$$E(\ln L_{i,t-s} \Delta \upsilon_{4,i,t}) = 0;\ \text{for } t = 3, \ldots, T \text{ and } 1 \leq s \leq t-1 \tag{9}$$

Based on these moment restrictions the parameters for model 4 can be estimated with GMM but there is widespread agreement in the literature (see earlier references) that the instruments in levels are often weak instruments for the variable of interest (i.e. the first difference of the lagged dependent variable). This is especially so when the autoregressive parameter, ρ, is close to unity or when the variance of $\eta_{4,i}$ is large relative to the variance of $\upsilon_{4,i,t}$.

Thus an extension is employed where a system of two equations is estimated. One equation is the differenced model with level instruments (the one discussed so far) while the other is the model in levels with differenced instruments. For $\Delta \ln L$ to be used as in instrument in the level equation it is necessary that it is not correlated with the firm specific effects, $\eta_{4,i}$. This further assumption (in addition to the "standard assumptions" in 4 and 5 above), is referred to as the "initial conditions assumption", as it follows from the restriction that the initial value of $\ln L$ is not correlated with the firm specific effects:

$$E(\eta_{4,i} \Delta \ln L_{i,2}) = 0 \text{ for } i = 1, \ldots, N \tag{10}$$

The result is the $T-2$ moment restriction of equation 11 for the level equation. Many methodological contributions (cf. earlier references) consider application of the differenced endogenous variable as instrument in the level equation but in practice it is very rare in panel data that the dependent variable is not correlated with the subject specific effects.

$$E(\upsilon_{4,i,t} \Delta \ln L_{i,t}) = 0;\ \text{for } t = 3, \ldots, T \tag{11}$$

Summing up on the above, which moment conditions to use (7, 8, 9 and 11) depends on the assumptions made regarding the instruments. Notice that it is preferable to use the system GMM estimator rather than the difference GMM estimator (i.e. to include restrictions 11). In the following all available lags will be used as instruments and the estimation procedure will be two step GMM, where the optimal weights for the moment restriction is estimated in the first step.

3.4 Assumptions about the instruments

The previous description of the estimator focussed on model 4 but the estimation of model 5 follows the same lines. Two GMM estimations of model 4 are carried out: the regressor is certainly correlated with the subject specific effects so only the difference GMM will be employed. It is likely that the regressor is predetermined (i.e. that current shocks to output ($\ln V$) will affect future values of the input variable ($\ln L$)), implying that moment restrictions 7 and 9 are to be used. However, it is also possible that the correct assumption is for the

Model	Estimation technique	Panel dataset: Full	Balanced
Static			
1	OLS: pooled	1.049(0.003)	
3	OLS: fixed effects	0.865(0.011)	
4	GMM: diff., exog.	0.802(0.021)	0.854(0.019)
4	GMM: diff., pred.	0.531(0.069)	0.515(0.084)
Dynamic			
2	OLS: pooled	0.764(0.014)	
5	GMM: sys., exog.	0.777(0.015)	0.782(0.015)
5	GMM: sys., pred.	0.779(0.017)	0.782(0.017)
	Firms	2,290	1,525
	Observations	14,406	10,675

Elasticity of value added to changes in FTE employment.
S.E. in parentheses.

Table 2: Estimated elasticities by data, model and technique

regressor to be strictly exogenous so this model is estimated too (using moment restrictions 7 and 8).

For model 5, however, it is reasonable to expect that the regressor (employment growth, $\ln \frac{L_{i,t}}{L_{i,t-1}}$) is not correlated with the firm effects, as it is already differenced, and thus the superior system GMM can be used. As with model 4, model 5 is estimated under both the assumption that the regressor is predetermined (using the correlaries of restrictions 7, 9 and 11) and under the assumption that it is strictly exogenous (using the correlaries of restrictions 7, 8 and 11).

In the following section four estimations of model 4 and four of model 5 are reported. The difference being 1) whether the regressor-cum-instrument is assumed to be strictly exogenous or predetermined and 2) whether or not the data is further trimmed in order to balance the data and check for autocorrelation in the errors. Notice also that only model 5 can be estimated as a system of two equations while only the difference equation can be used for model 4. Furthermore the results of estimating models 1, 2 and 3 with OLS are presented.

4 Results

Table 2 presents the results from estimating models 1 through 5. The table has two columns of estimates and it is split into an upper panel and a lower panel. The top panel reports estimated elasticities based on the static cross section specification (e.g. α_1 in model 1 page 5) while the bottom panel reports estimated elasticities based on the dynamic specification (e.g. α_2 in model 2 page 5). The most interesting estimates are those of the first column, which are based on the full panel. Those in the second column are based on a reduced, balanced panel that allows for testing for autocorrelation in the residuals. The estimates in the second column are included to demonstrate that reducing the panel has limited effects on the estimates.

All estimates in table 2 are several standard errors below or above unity. The only technique that results in an elasticity greater then unity is naive pooled OLS applied to the static model ($\hat{\alpha}_1 = 1.049$). Simply adding fixed effects to control for firm idiosyncrasies brings the elasticity down well below unity ($\hat{\alpha}_3 = 0.865$). When applying Arellano and Bond's GMM estimator to control for serial correlation the estimate goes down even further: to $\hat{\alpha}_4 = 0.802$ when assuming that the instruments are exogenous and to 0.531 when assuming that the instruments are predetermined. Notice, though, that these estimates are based solely on the differenced equation with level instruments, and such estimates have been shown to have downward bias.[3]

For the dynamic specification, on the other hand, the estimated elasticity is very robust. The three estimates are all within one standard error of each other. For the GMM estimates of the dynamic model (model 5) it was argued that the system of two equations can be applied; i.e. differencing model 5 and using the original variables as instruments as well as using the differenced variables as instruments in the original specification of model 5.[4] Therefore the estimates attained by model 5 do not suffer from the downward bias of the estimates attained through model 4.

As noted earlier it is assumed that there is no serial correlation in the errors when undertaking the GMM estimation and therefore the balanced data has been tested for such effects. The test was applied up to a lag of 4 (which is the maximum allowed for by the data) and neither of the estimates for model 4 show any signs of autocorrelated residuals. But for model 5 both estimations show serial correlation in the residuals at lag 2 and 4 at 5 percent significance. This implies that 5 is violated and that the moment restrictions of 7 should not be used. Model 5 has therefore also been estimated using only restrictions 8 and 11 and the result is an estimated elasticity of 0.787 with a standard error of 0.015.[5] This is slightly higher than the other estimates presented in table 2 but by less than one standard error. The result of the test for serial correlation in the residuals does not change but this is less of a problem for this estimation.

It would seem that the preferred method of estimating the elasticity of value added to changes in FTE employment is model 5 estimated by Arellano and Bond's two step systems GMM using only the regressor as instrument. As already argued this instrument can be assumed to be strictly exogenous. Therefore the appropriate moment restrictions are 8 and 11.

The GMM estimates of models 4 and 5 presented in table 2 are argued to be methodologically flawed but they will nevertheless be applied to 2-digit industry level data in the following section along with the preferred method for comparison. It must thus be kept in mind that these estimates of elasticity based on the static model are downward biased while the estimates based on the dynamic

[3]This downward bias is demonstrated by e.g. Blundell and Bond (1998) and more resent research has suggested that it might not even be enough to apply the system specification to correct for the bias (Bun and Windmeijer, 2010).

[4]This may be a bit confusing since model 5 is already expressed in differences. "Levels" refers to the specification in page 6 while "differences" refers to the differencing undertaken as part of the Arellano and Bond methodology. The differenced equation with level instruments for model 5 is thus the second difference of log real value added regressed on the second difference of log FTE employment and instruments in first differences.

[5]0.795 with S.E. 0.017 for the balanced data.

model are partially based on incorrect moment conditions. The downward bias of model 4 seems to be greatest when the instruments are assumed to be predetermined so they are assumed to be exogenous. In model 5 this assumption does not seem to have great consequence and the instruments will be assumed to be exogenous here too.

5 Industry level

Table 4 page 13 contains the results of estimating the elasticity of real value added to changes in FTE employment in the two digit industries of the Danish manufacturing sector. There are three columns of estimates corresponding to the estimation techniques chosen in the previous section. All are estimated using the Arellano and Bond dynamic panel data technique (two stage generalized method of moments). The first column of results are based on model 4, the static model, using lags of the dependent variable and both lags and leads of the regressor as instruments to control for autoregressive effects. This means that the moment restrictions of equations 7 and 8 are used.

It was argued that in model 5, the dynamic model, it is reasonable to assume that the dependent variable is uncorrelated with the firm specific error and thus the estimator can be applied in the system specification, where also the moment restrictions of equation 11 are used. These are the estimates of the second column. As tests reject the hypothesis of no serial correlation in the errors of this model, however, the assumption of equation 5 is violated and the moment restrictions of 7 cannot be used in the estimation. This results in the estimates of the third column.

A few of the industries have very few observations and these are indicated by a dagger (†). The number of firms and the number of observations in each industry are reported in table 5 along with the associated two digit code in NACE rev. 1.

5.1 Results

Abstracting from the industries flagged by a dagger there are still some differences among the industries. The most inelastic industry is the manufacturing of textiles, where value added increases by only 0.421 percent when employment increases by one percent (according to the estimates of the third column).

Which industry has the most elastic relationship differs by estimation technique but according to the second and third columns the only two sectors with elasticities greater than unity are the manufacturing of radio and communications equipment and the manufacturing of medical and optical instruments.

The estimates of the second and third columns are generally in close agreement but the estimates of the first column differs for several industries. It was expected that the estimates of the first column would be downward biased but on some occasions, e.g. manufacturing of pulp and paper, the estimate in the first column is relatively high. The estimates of the second column are generally slightly lower than the estimates in the last column indicating that, for the data employed here, the violation of the assumption in 5 produces downward bias.

For comparison the elasticities of real wage costs to changes in FTE employment have also been computed and the results are presented in table 6 page 15.

The technique used is the same as in the third column of table 4. When the elasticity of wage costs is greater than the elasticity of value added there is indication of diseconomies of scale: wage costs rises faster then value added when FTE employment increases. The opposite case is an indication of economies of scale: output rises faster than wage costs as employment is increased.

The two industries in which output was found to be elastic also exhibit economies of scale (manufacturing of radio and communications equipment and manufacturing of medical and optical instruments). But also others, e.g. manufacturing of metal products, have elasticity of wage costs several standard errors lower than the elasticity of value added. At the other end of the spectrum there are also a number of industries exhibiting clear diseconomies of scale. In industries such as manufacturing of textiles, manufacturing of wearing apparel and manufacturing of chemicals the elasticity of wage costs is noticeably higher than the elasticity of value added. Wearing apparel is the only industry, with a acceptable number of observations, in which wage costs are estimated to be elastic.

It is difficult to guess at a cause for the heterogeneity of elasticities without further information. It is possible that elasticity is not constant over size and it is also possible that elasticity varies depending on whether employment is growing or declining. Thus the continuation of this research will entail the estimation of additional elasticities–including elasticities for other performance measures, e.g. margin as well as distinguishing between elasticity with respect to different categories of labour.

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	$\ln V_{i,t}$			$\ln L_{i,t}$		
Year	Mean	Median	Std. dev.	Mean	Median	Std. dev.
2000	10.278	10.059	1.003	4.221	3.989	0.917
2002	10.290	10.056	1.038	4.214	3.932	0.942
2004	10.303	10.087	1.046	4.151	3.892	0.984
2006	10.374	10.150	1.073	4.226	4.007	0.943

Table 3: Descriptives for select years

Industry	Model 4	5	5
All	0.802(0.021)	0.777(0.015)	0.787(0.015)
Food and beverages	0.865(0.040)	0.830(0.020)	0.826(0.022)
Tobacco†	0.319(0.448)	0.111(0.056)	0.090(0.037)
Textiles	0.572(0.011)	0.418(0.024)	0.421(0.050)
Wearing apparel	0.862(0.031)	0.601(0.094)	0.684(0.069)
Leather and shoes†	1.738(1.547)	0.229(0.049)	0.229(0.049)
Wood products	0.834(0.029)	0.717(0.026)	0.724(0.031)
Pulp and paper	0.906(0.005)	0.669(0.009)	0.715(0.043)
Printing and Publishing	0.708(0.034)	0.509(0.030)	0.514(0.034)
Refined petroleum†	0.281(1.511)	0.235(0.495)	0.247(0.494)
Chemicals	0.755(0.005)	0.509(0.015)	0.515(0.021)
Rubber and plastic	0.689(0.026)	0.721(0.023)	0.750(0.029)
Other non-metallic products	0.680(0.025)	0.723(0.031)	0.736(0.036)
Basic metals	0.739(0.005)	0.700(0.003)	0.635(0.026)
Metal products	0.908(0.038)	0.882(0.026)	0.906(0.029)
Machinery	0.731(0.044)	0.830(0.031)	0.859(0.033)
Electronic components†	0.552(0.282)	0.561(0.117)	0.744(0.100)
Other electronic	0.919(0.029)	0.542(0.006)	0.566(0.011)
Radio and communications	0.803(0.009)	1.129(0.007)	1.111(0.016)
Medical and optical instrum.	0.634(0.061)	1.116(0.034)	1.120(0.054)
Motor vehicles	0.780(0.007)	0.857(0.018)	0.844(0.007)
Other transport	0.939(0.011)	0.725(0.023)	0.735(0.013)
Furniture and n.e.c.	0.935(0.040)	0.826(0.035)	0.828(0.039)
Recycling†	0.035(1.079)	0.568(0.642)	1.105(0.281)
Restrictions used:	7, 8	7, 8, 11	8, 11

Elasticity of value added to changes in FTE employment.
S.E. in parentheses. †: industry with few observations, cf. table 5.

Table 4: Elasticity of VA for 2-digit manufacturing industries

Industry	NACE rev. 1	Firms	Observation
Full panel dataset		2,290	14,406
Balanced panel		1,525	10,675
Food and beverages	15	226	1,411
Tobacco	16	6	37
Textiles	17	61	371
Wearing apparel	18	24	143
Leather and shoes	19	4	23
Wood products	20	114	710
Pulp and paper	21	53	318
Printing and Publishing	22	177	1,086
Refined petroleum	23	3	18
Chemicals	24	71	452
Rubber and plastic	25	147	934
Other non-metallic products	26	95	599
Basic metals	27	46	301
Metal products	28	364	2,295
Machinery	29	414	2,702
Electronic components	30	13	80
Other electronic	31	89	538
Radio and communications	32	39	239
Medical and optical instrum.	33	91	569
Motor vehicles	34	36	229
Other transport	35	32	195
Furniture and n.e.c.	36	182	1,137
Recycling	37	3	19

Table 5: No. firms and observations in 2-digit industries

Industry	Elasticity
All	0.836(0.010)
Food and beverages	0.881(0.013)
Tobacco†	0.328(0.022)
Textiles	0.718(0.029)
Wearing apparel	1.024(0.005)
Leather and shoes†	0.838(0.078)
Wood products	0.798(0.017)
Pulp and paper	0.889(0.023)
Printing and Publishing	0.759(0.023)
Refined petroleum†	1.439(0.290)
Chemicals	0.870(0.012)
Rubber and plastic	0.849(0.016)
Other non-metallic products	0.837(0.028)
Basic metals	0.658(0.012)
Metal products	0.831(0.015)
Machinery	0.840(0.017)
Electronic components†	0.697(0.037)
Other electronic	0.745(0.004)
Radio and communications	0.833(0.011)
Medical and optical instrum.	0.883(0.026)
Motor vehicles	0.828(0.002)
Other transport	0.876(0.004)
Furniture and n.e.c.	0.770(0.025)
Recycling†	1.075(0.216)

Elasticity of wage costs
to changes in FTE employment.
S.E. in parentheses.
†: industry with few observations, cf. table 5.
Estimated with model 5 using the correlaries of 8 and 11.

Table 6: Elasticity of WC for 2-digit manufacturing industries

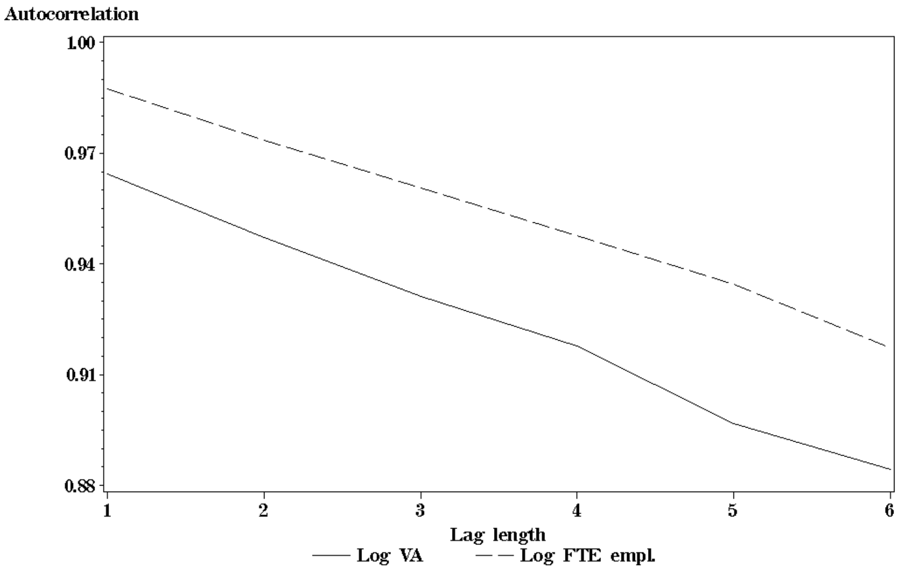

Figure 1: Correlogram for $\ln V_{i,t}$ and $\ln L_{i,t}$

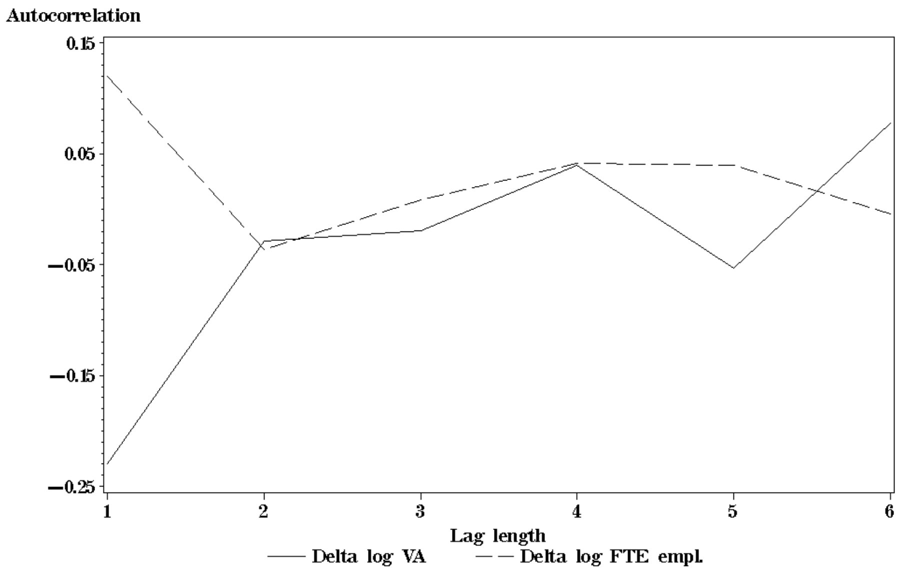

Figure 2: Correlogram for $\ln \frac{V_{i,t}}{V_{i,t-1}}$ and $\ln \frac{L_{i,t}}{L_{i,t-1}}$