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THE INCONSISTENCY OF COMMON SCALE ESTIMATORS WHEN OUTPUT PRICES ARE UNOBSERVED AND ENDOGENOUS

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ABSTRACT

This paper explores the inconsistency of common scale estimators when output is proxied by deflated sales, based on a common output deflator across firms. The problems arise when firms operate in an imperfectly competitive environment and prices differ between firms. In particular, we show that the scale estimates will tend to be downward biased in the production function case, under a wide range of assumptions about the pattern of technology, demand and factor price shocks. The result also holds for scale estimates obtained from cost functions. The empirical part of the paper presents various estimates of scale economies for a sample of Norwegian manufacturing plants. The findings provide some support for the hypothesis that the firms face an imperfectly competitive environment. The estimates suggests that there are significant markups and scale economies to the variable factors of production in our sample. However, the estimates of markups and scale economies presented in this paper are substantially lower than the results obtained by Hall (1988, 1990) and others using industry level data.

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1 Introduction

Scale economies and imperfect competition have for a long time been at the hart of the industrial organization literature. More recently, researchers in other fields of economics such as international trade, macro economics and growth theory, have focused their attention to the importance of increasing returns to scale and imperfect competition[1]. This interest in scale economies and imperfectly competitive behavior has been stimulated further by empirical research carried out by Hall (1988, 1990) and others[2]. This research suggests very substantial market power in U.S. manufacturing.

However, one problem with the empirical research just cited is that the estimated markup is critically dependent on the assumption of constant returns to scale[3]. If the firms in fact are operating with short run decreasing returns to scale, their markup estimates might be an artifact due to the erroneous assumption of constant returns. It is clear that estimating the scale economies relevant for the firms' price setting decisions requires firm level data, rather than the more aggregated data employed in the studies cited above.

Estimating scale economies from micro level data has a long history in

[1]See e.g. Krugman (1989) for an introduction to the recent research in trade theory and Mankiw (1990) for references to the macro economic literature. Recent research in growth and development economics, drawing on the theory of increasing returns and imperfect competition, is presented in *Quarterly Journal of Economics, May 1991.*

[2]See Domowitz et al. (1988) and Shapiro (1987).

[3]Abbott et al. (1988) have questioned the validity of the instruments used in Hall's regressions.

econometrics, but is still an unsettled research topic[4]. In particular, scale estimates obtained by estimating production functions tend to suggest substantial decreasing returns to scale (to all factors of production)[5]. On the other hand, it is well known that estimates of factor demand equations give results which imply increasing returns to scale[6].

The theoretical part of this paper shows that the practice of using deflated sales as a proxy for real output will tend to create a downward bias in the scale estimate obtained from production functions. This is so under a wide range of conditions if the firms face an imperfectly competitive environment. When estimating cost functions - which is closely related to estimating factor demand equations - we show that there will be a similar bias.

In the empirical part of this paper we provide an attempt to identify the scale elasticity, as well as other interesting parameters, from regressions of deflated sales on usual production function regressors when a demand change variable is introduced as an additional regressor. The point is that this re-

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[4]Abbott (1991, section 2) gives a brief discussion and further references to the literature.

[5]This proposition summarizes the studies which apply panel data; see e.g. Cuneo and Mairesse (1984), Griliches and Mairesse (1984, 1990). Cross sectional studies of production functions typically suggest increasing returns to scale; see e.g. Griliches and Ringstad (1971) and Ringstad (1974). There is a widely held view that scale estimates from cross sectional studies are upward biased as these studies do not account for persistent differences in efficiency between firms. This is an old issue which is much commented on in the literature. Discussions of the questions involved in comparing cross sectional and panel data studies of production functions are provided by e.g. Ringstad (1971), Mundlak (1978), Griliches and Mairesse (1990) and Mairesse (1990).

[6]Griliches and Hausman (1986) examine to what extent increasing returns to scale in the labour demand equation can be interpreted as errors in variables in the output variable.

gression will be a reduced form model, where the parameters are mixtures of supply and demand side parameters. Under suitable assumptions we are able to identify the scale elasticity to variable factors and other parameters of interest. We find that with our reinterpretation of the parameters, the estimates obtained by the cost function and the production function specification are highly consistent. Hence, one contribution of this paper is to provide a suggestion for reconciliation of results obtained from the two approaches to estimation of producer relationship.

The empirical part of this paper shows that the annual movements in total factor productivity at the plant level are highly correlated with the (industry-wide) demand change variable, in regressions where we do *not* impose assumptions about constant returns to scale (or perfect competition)[7].

[7]Hall (1990) has provided an extensive discussion of the possible explanations for the procyclical behavior of total factor productivity. Two explanations examined in great detail by Hall are market power and scale economies. Our results suggest that, at the micro level, the (apparent?) procyclical movements in productivity can not fully be accounted for by incorporating imperfect competition and scale economies into the model.

The empirical model presented in the second half of this paper is very similar to a model examined by Bartelsman, Caballero and Lyons (1991). Their main finding is that productivity at the industry level is highly correlated across industries, and in particular with changes in output aggregated across industries. The current paper identifies a similar pattern at the plant level. However, the interpretation we offer differ entirely from the interpretation of Bartelsman et al., who claim their finding suggests some kind of external economies. We interpret our finding as a result of the econometric problem created by replacing the unobserved movements in output with changes in deflated sales. Notice that Bartelsman et al. do not face a similar econometric problem since they could apply industry specific deflators which is their unit of observation. Unfortunately, we do not

Reinterpreting our estimated production and cost function parameters as reduced form parameters, suggest that the scale elasticity to variable factors alone are of the order 1.06 – 1.10, and the demand elasticities varies between -6 to -12.

Abbott (1991) has presented results supporting the perspective of the current paper. He had access to price data for individual firms (which we do not have). His analysis shows that prices differ significantly within the hydraulic cement industry in the U.S., also after adjustment is made for differences in output mix. Using individual deflators rather than industry wide deflators gives different, and in Abbott's terms, more plausible estimates of production function parameters and productivity changes[8].

This paper is organized as follows: Section 2 provides a general theoretical analysis of the problem created by using a common deflator when prices differ between firms, in terms of the omitted variable framework. It begins by examining the production function case, and then provides a discussion of the cost function case. Section 3 carries the analysis a step further in the production function case, by studying an explicit, complete framework of supply and demand. The asymptotic bias in the OLS scale estimator is derived as-

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have access to firm specific deflators.

[8]Though it must be added that Abbott's argument is somewhat incomplete in the production function case. Abbott argues that his estimated production function parameters should be close to the factors shares. He finds that using "correctly" deflated sales moves his estimates towards the observed factor shares. But it seems likely that his estimated production function parameters are biased due to the simultaneity between the residual and factor inputs.

suming orthogonality between the idiosyncratic productivity, markup, factor price and demand shocks. Some extensions are also considered. The empirical analysis is presented in section 4. Some final remarks are added in section 5.

2 The omitted variable bias

In this section we will provide a general analysis of the inconsistency of scale estimates when estimation proceeds by using deflated sales instead of output in production and cost function analysis. The analysis shows that if the (real, unobserved) prices are correlated with the included variables in the model, an omitted variable bias will arise. More specifically, we will argue that in the analysis of production functions, plausible assumptions suggest that commonly applied scale estimators will be downward biased. Also in the case of cost functions a similar bias of the scale elasticity will occur. To focus ideas we will carry out the argument in terms of panel data estimation of production relationships. That is to say, we will consider models in terms of growth rates, but the argument can easily be altered to be of relevance for pure cross sectional regressions. However, the biases will probably differ, as the *importance* of the various shocks considered below will be different in the cross sectional versus the time series dimension.

2.1 The production function case

Let us assume that the true production function relationship can be written

$$q = X\alpha_0 + u^q, \tag{1}$$

where q is a $(N \times 1)$ - vector of the growth in "real" output, X is a $(N \times L)$ matrix of the growth in inputs. α_0 is the $(L \times 1)$ vector of the parameters of interest, while u is assumed to be an orthogonal error term. N is the number of observations. The model in equation (1) is the familiar Cobb-Douglas production function, and the scale elasticity is defined as; $\epsilon \equiv \sum_{i=1}^{L} \alpha_{i0}$.

The estimated model is a slight modification to equation (1):

$$r = X\alpha + u^r, \tag{2}$$

where the left hand side variable now is r, which represents changes in deflated sales. The OLS estimator of the parameter vector α, assuming orthogonality of u^r, is

$$\hat{\alpha} = (X'X)^{-1}X'r. \tag{3}$$

Define the firm specific price relative to the deflator as π. Then the relationship between true output (q) and deflated sales is $\pi + q = r$. Focusing on the probability limit of $\hat{\alpha}$, and using this relationship, we obtain

$$\text{plim}_{N\to\infty}(\hat{\alpha}) = \alpha_0 + \text{plim}_{N\to\infty}[(X'X)^{-1}X'\pi)] + \text{plim}_{N\to\infty}[(X'X)^{-1}X'u^q]. \tag{4}$$

Both of the last two terms in equation (4) may have non-zero probability limits. The potential non-zero probability limit of the last term in equation (4) is referred to in the literature as the bias from the "transmission" of productivity shocks[9]. This problem will be neglected for the moment, as it has been discussed extensively in the existing literature. Let us focus on the second term on the right hand side of equation (4).

To examine the second term in equation (4), notice that it can be expressed as the OLS-estimate of the vector of $\delta's$ in the following auxiliary regression[10]:

$$\pi = X\delta + u^{\pi}, \tag{5}$$

where u^{π} is an orthogonal error term. The direction and the size of the bias in $\hat{\alpha}$ will depend on the sign and the magnitude of the δ-coefficients in the auxiliary model (5). That is to say, $\text{plim}_{N\to\infty}(\hat{\alpha}_i) = \alpha_{i0} + \delta_i$. Focusing on the bias in the estimated scale elasticity ($\hat{\epsilon} \equiv \sum_i \hat{\alpha}_i$), we have

$$\begin{aligned} \text{plim}_{N\to\infty}\hat{\epsilon} - \epsilon &= \text{plim}_{N\to\infty}\left(\sum_{i=1}^{L}\hat{\alpha}_i\right) - \sum_{i=1}^{L}\alpha_i \\ &= \sum_{i=1}^{L}\delta_i, \end{aligned} \tag{6}$$

where ϵ is the true scale elasticity. The question now is: Will there be a systematic relationship between the changes in the price a firm charges and the growth of the firm in terms of its *inputs*? A satisfactory analysis of the relationship between the price a firm charge and the size of the firm requires

[9]The literature dates back to Marschak and Andrews (1944). This simultaneity problem has been discussed by Mundlak and Hoch (1965) and Zellner et al. (1966) among others.

[10]This idea has been applied by Griliches (1957), and Griliches and Ringstad (1971, appendix C) to discuss other issues of specification bias in the estimation of production functions.

a more complete model which include the factors which determine the firm's price setting behavior and demand. The next section will provide a simple model incorporating these aspects into a complete formal framework. For the moment we will provide a more general, but less formal discussion.

Let us first consider the impact of idiosyncratic changes in (quality adjusted) factor prices. This case is simple, and suggests that firms which experience higher costs will, *cet. par.*, charge a higher price and loose market share. Hence, idiosyncratic changes in factor prices suggest a negative relationship between firms' price movements and the changes in input levels, i.e. $\sum_{i=1}^{L} \delta_i < 0$.

The next case to consider is the relationship between price and the level of inputs, when there are idiosyncratic productivity shocks. If efficiency levels differ between firms, it seems plausible that the more productive firm will have a larger market share, and also charge a lower price. If some firms experience productivity improvements beyond the average, they will probably, *cet. par.*, obtain a larger market share, measured in terms of (quality adjusted) output. However, more output does not necessarily imply more inputs when productivity improves. For the specific model in the next section, it turns out that the two effects - the larger market share versus higher productivity - exactly cancel out so that there is no systematic relationship between changes in price and variations in inputs. For that particular model, the larger market share obtained as a result of higher productivity (and there by a lower quality adjusted price) is just offset by the reduction in inputs per unit output, so that the movements in firms' inputs and the changes in output prices are uncorrelated. Beyond that particular model, we are not able to make any general predictions about the relationship between changes in relative prices and the growth of firms measured in terms of inputs, when the differences are due to idiosyncratic productivity movements. Consequently, the bias in the scale estimator related to changes in relative efficiency between firms can in general not be predicted from purely theoretical considerations, even if we are willing to impose "plausible" assumptions.

The last case we want to discuss here is the consequences of demand shocks. If there are scale economies, changes in firm size will affect the price a firm charges in an imperfectly competitive environment. With decreasing returns to scale, we would expect a firm which grows faster than the average, to increase its relative price, and *vice versa*. Hence, this case suggests positive (negative) δ-coefficients in the auxiliary equation (5) if there are negative (positive) scale economies. It follows that demand shocks will bias the estimated scale elasticity towards unity.

2.2 Scale estimates from cost functions

A similar result to the inconsistency pointed in the production function case applies when estimating cost functions replacing real output with deflated sales. To make this argument as transparent as possible, we will stick to the "linear-in-variables" case[11].

$$c = W\gamma_0 + \beta_0 q + u^c \tag{7}$$

[11]That is, we consider the cost function corresponding to a Cobb-Douglas production function.

is assumed to be the true relationship. c is a $(N \times 1)$ - vector representing the growth in costs. W is a $(N \times K)$ matrix expressing the growth in the K factor prices for the N observations. q is growth in real output as above. β_0 is the parameter of interest. It is the inverse of the scale elasticity. Once more, we assume that we do not observe real output growth; q. The estimated model assumes the same relationship replacing output with deflated sales:

$$\begin{aligned} c &= W\gamma + \beta r + \tilde{u}^c \\ &= Z\lambda + \tilde{u}^c, \end{aligned} \tag{8}$$

where Z denotes the $(N \times (K+1))$ matrix obtained by adding the column of r to the W-matrix. λ is the $(K+1)$ column vector containing γ and β. It follows that the OLS-estimator, assuming orthogonality of $\tilde{u}^c$ is

$$\hat{\lambda} = (Z'Z)^{-1}Z'c \tag{9}$$

Using the expression $r - q = \pi$, we can rewrite equation (7):

$$\begin{aligned} c &= W\gamma_0 + \beta_0 r + \beta_0(q - r) + \tilde{u}^c \\ &= Z\lambda_0 - \beta_0\pi + \tilde{u}^c, \end{aligned} \tag{10}$$

where λ_0' is the true parameter values (γ_0', β_0). It follows that the probability limit of $\hat{\lambda}$ is given by

$$\text{plim}_{N\to\infty}(\hat{\lambda}) = \lambda_0 - \beta_0 \ \text{plim}_{N\to\infty}(Z'Z)^{-1}Z'\pi + \text{plim}_{N\to\infty}(Z'Z)^{-1}Z'\tilde{u}^c, \tag{11}$$

At this point we again neglect the last term in equation (11). The problem in focus here is the second term on the right hand side of equation (11). Once more we can obtain some intuition about this term by noting that $\text{plim}_{N\to\infty}(Z'Z)^{-1}Z'\pi$ can be thought of as the coefficient associated with the regression of π on Z. That is to say, the term $\text{plim}_{N\to\infty}(Z'Z)^{-1}Z'\pi$ is equal to the $\tilde{\delta}$-vector in the auxiliary regression

$$\begin{aligned}\pi &= Z\tilde{\delta} + v^{\pi} \\ &= W\tilde{\delta}_W + r\tilde{\delta}_r + v^{\pi}\end{aligned} \tag{12}$$

where v^{π} is an orthogonal error term. The question in focus is whether and how the scale coefficient will be biased, which is equivalent to ask about the significance and magnitude of the $\tilde{\delta}_r$-coefficient in the OLS-regression of the model in equation (12). Ruling out the unlikely case of inelastic demand, this coefficient will be negative. Notice that if we neglect the last term in equation (11), we have

$$\text{plim}_{N\to\infty}\hat{\beta} = \beta_0(1 - \tilde{\delta}_r) \tag{13}$$

It follows that the cost function estimates of the scale elasticity – equal to the inverse of $\hat{\beta}$ – will be biased upwards in the limit.

In passing, let us notice that the parameters associated with the factor prices will be biased downwards, as the movements in factor prices will tend to be positively correlated with the changes in relative price, π (i.e. $\delta_W > 0$).

3 Bias formulaes in an explicit model

In this section we will provide a more formal argument of the inconsistency of the scale estimate in the production function case. We will augment the production function model in equation (1) with a simple demand equation and a price setting rule. The demand function facing a firm "i" at time "t" can be expressed as follows:

$$Q_{it} = D_{it} P_{it}^{\eta}, \tag{14}$$

where D_{it} is a demand shifter. P_{it} is the price relative the general price level in the industry. η is the demand elasticity[12]. The environment we have in mind is an industry with horizontal product differentiation[13]. A finite η corresponds to product differentiation between the goods produced by the different firms in the industry[14]. If we employ the relationship between true output and deflated sales; $R_{it} = P_{it} Q_{it}$, equation (1) can be rewritten

$$Q_{it} = R_{it}^{\eta/(\eta+1)} D_{it}^{1/(\eta+1)} \tag{15}$$

[12]Such a demand system has been widely examined in the industrial organization and international trade literature under the label "the Spence-Dixit-Stiglitz-model". The characteristic feature of this formalization of monopolistic competition is that it leads to price elasticities which are constant and independent of the number of variants available, as expressed in equation (14). Tirole (1989, ch. 7.5) provides a discussion and further references to the micro foundations of this demand system.

[13]Vertical product differentiation is hidden in the possibility that Q_{it} can be an index capturing both the quantity and quality of the output.

[14]For a more elaborate discussion and further references on the econometric modelling of demand in industries with product differentiation, see Berry (1991).

We will assume that the firms apply a markup rule:

$$\frac{R_{it}}{C_{it}} = \frac{\mu_{it}}{\epsilon} \tag{16}$$

where R_{it} and C_{it} are (deflated) revenues and total (deflated) costs. μ_{it} and ϵ represent the markup and the scale elasticity.

Assuming cost minimization, we have that

$$C_{it} = W_{it}\left(Q_{it}/A_{it}\right)^{1/\epsilon}. \tag{17}$$

W_{it} is the deflated factor price. It is convenient to deflate the factor price with the same deflator as we used for the output price (P_{it}). A_{it} is the productivity level, while ϵ is the scale elasticity. Inserting equation (16) into equation (17), we get

$$R_{it} = \frac{\mu_{it}}{\epsilon} W_{it}\left(Q_{it}/A_{it}\right)^{1/\epsilon}. \tag{18}$$

Finally, we need the production function (cf. equation (1)). Sticking to the one input case[15], we have:

$$Q_{it} = A_{it} X_{it}^{\epsilon}. \tag{19}$$

Taking the logarithmic differences between the time "t" and "t-1" versions of equations (15), (18) and (19), we get the following system of equations:

$$\begin{aligned} \dot{q}_{it} &= \frac{1}{\eta+1}\dot{d}_{it} + \frac{\eta}{\eta+1}\dot{r}_{it}, \\ \dot{r}_{it} &= \dot{w}_{it} + (\dot{q}_{it} - u_{it}^{q})/\epsilon + u_{it}^{m}, \\ \dot{q}_{it} &= \epsilon\,\dot{x}_{it} + u_{it}^{q}, \end{aligned} \tag{20}$$

[15]Assuming either that there is a Leontief technology, fixed ratios between the factor prices or an appropriate input index has been constructed.

where we have introduced the notation that a dot above a lower case letter (e.g. $\dot{q}_{it}$), corresponds to the logarithmic differenced upper case variable $(\log(Q_{it}) - \log(Q_{i,t-1}))$. The variables u^q_{it} and u^m_{it} represent $\log(A_{it}) - \log(A_{i,t-1})$ and $\log(\mu_{it}) - \log(\mu_{i,t-1})$. That is, u^q_{it} corresponds to productivity shocks, while u^m_{it} captures deviations from a fixed markup rule[16].

Assuming that the system of equations in (20) describes the economic environment facing our firms, we can examine the bias in the production function estimate of the scale elasticity. Let us first focus on *the "omitted (price) variable bias"*, caused by omitting the individual price from the production function (i.e. using the common deflator). The *"transmission" bias*, due to the correlation between the variable input(s) and the productivity shock will be incorporated into the analysis below. We can express the omitted variable bias in the scale estimate obtained from the production function where deflated sales has replaced real output:

[16] In the case of price setting firms, with a finite number of firms, the deviations from a fixed markup rule will be related to a firm's market share. That is, $u^m_{it} \sim$ the deviation in the firm's market share from the mean market share, see Klette (1990, ch. 4). In the case of vertical product differentiation, the markups might be correlated with the quality of the firms' output. See Tirole (1989, ch. 7.5.1) for discussion and references. One can argue that u^m_{it} will develop in the time dimension depending on the firm's innovative history. E.g. an idiosyncratic productivity shock might lead the innovative firm to charge a higher markup, as discussed by Arrow (1962) in the competitive case and by Kamien and Schwartz (1982) in the oligopolistic case. The pattern of variations in u^m_{it} will be more complex if the firm takes into consideration intertemporal dependence in demand or production economies (cf. Tirole, ch. 1.1.2). Finally, notice that u^m_{it} also will capture deviations from a common scale elasticity across firms and over time. To keep our problem tractable, we will assume that u^m_{it} fulfills some suitable orthogonality conditions.

$$\text{plim}(\hat{\epsilon}) - \epsilon = \text{plim}\left[\frac{\sum_{i,t}\dot{x}_{it}(\dot{r}_{it} - \dot{q}_{it})}{\sum_{j,s}\dot{x}_{js}^2}\right], \tag{21}$$

where the sums in the numerator and denominator should be carried out over all observations, both across firms and over time. The probability limit is taken with respect to the number of observations[17].

Solving the system of equations in (20) with respect to $\dot{x}_{it}$ and $(\dot{r}_{it} - \dot{q}_{it})$, in terms of the supply shocks (w_{it}, u_{it}^q and u_{it}^m) and the demand shock ($\dot{d}_{it}$), we find that

$$\dot{r}_{it} - \dot{q}_{it} = \frac{1}{\epsilon(\eta+1)-\eta}\left[\epsilon(\dot{w}_{it} + u_{it}^m) + (1-\epsilon)\dot{d}_{it} - u_{it}^q\right], \tag{22}$$

and

$$\dot{x}_{it} = \frac{1}{\epsilon(\eta+1)-\eta}\left[\dot{d}_{it} - (\eta+1)u_{it}^q + \eta(\dot{w}_{it} + u_{it}^m)\right]. \tag{23}$$

Inserting equations (22) and (23) into equation (21), the bias can be expressed

$$\begin{aligned}\text{plim}(\hat{\epsilon}) - \epsilon = &\\ &\left\{\text{plim}\,\frac{1}{N}\sum_{i,t}\left[\dot{d}_{it} - (\eta+1)u_{it}^q + \eta(\dot{w}_{it} + u_{it}^m)\right]\right.\\ &\qquad\left.\times\left[\epsilon(\dot{w}_{it} + u_{it}^m) + (1-\epsilon)\dot{d}_{it} - u_{it}^q\right]\right\}\\ &\times\left\{\text{plim}\frac{1}{N}\sum_{j,s}\left[\dot{d}_{js} - (\eta+1)u_{js}^q + \eta(\dot{w}_{js} + u_{js}^m)\right]^2\right\}^{-1}.\end{aligned} \tag{24}$$

[17]In practice, we might want to allow for a non-trivial time structure of the productivity shocks, by e.g. incorporating time dummies into the equation. In that case, the relevant limit to consider is with respect to an increasing number of firms.

N is the number of observations. To obtain some intuition about this expression, let us assume that all the factor price, productivity, price setting and demand shocks are orthogonal. Then the inconsistency of $\hat{\epsilon}$ can be expressed in terms of the variances

$$\text{plim}(\hat{\epsilon}) - \epsilon = \frac{\epsilon\eta(\sigma_w^2 + \sigma_m^2) + (\eta+1)\sigma_q^2 + (1-\epsilon)\sigma_d^2}{\eta^2(\sigma_w^2 + \sigma_m^2) + (\eta+1)^2\sigma_q^2 + \sigma_d^2}. \tag{25}$$

$\sigma_w^2, \sigma_m^2, \sigma_q^2$ and σ_d^2 are the variances of the factor prices, the "markup-disturbance" (u^m), the productivity shocks and demand shocks.

Notice first that as the elasticity of substitution (represented by $-\eta$) between the differentiated goods in the industry tends to infinity, the bias from neglecting the price differences will vanish. This situation corresponds to the standard case with no product differentiation. The important point is that if there is no horizontal product differentiation in the industry, there is no scope for differences in *quality adjusted* prices. In this case, differences in sales corresponds to differences in inputs (costs), so sales is a valid measure for quality adjusted output[18]. This is essentially a perfectly competitive situation.

Equation (25) shows that if the demand shocks dominates, the bias will be $1-\epsilon$. That is to say, pure demand shifts will bias the scale estimate towards unity. Below, we will show that this results survives if we take into consideration that productivity shocks are "transmitted" to inputs (cf. footnote 10).

[18]This argument has been used to justify quality adjustment of an input price on the basis of changes in the cost of producing the input. See the discussion between Gordon and Triplett in Foss (1982, ch. 4 and 5).

Only if there are both decreasing returns to scale *and* the demand shocks dominate will there be an upward bias in the scale estimate. If there are increasing returns to scale, demand shocks will also contribute to a downward bias in the scale elasticity. Presence of the various supply shocks will all tend to bias the scale elasticity downwards. Notice that with a fairly high elasticity of substitution between the goods in the industry, or a scale elasticity close to unity, the magnitude of the inconsistency due to demand shocks will tend to be dwarfed by the supply shocks.

So far, we have disregarded the bias due to "transmission" of productivity shocks. That is, there will in general be an additional term in equation (21) due to the correlation between the productivity shocks u^q and the changes in of inputs. An explicit expression for this term can be obtained as follows. Assuming orthogonality between the various shocks, it follows by using equation (23), that

$$\text{plim}\frac{\sum_{it}\dot{x}_{it}u^q_{it}}{\sum_{ls}\dot{x}^2_{ls}} = -\frac{(\eta+1)\sigma^2_q}{\eta^2(\sigma^2_w+\sigma^2_m)+(\eta+1)^2\sigma^2_q+\sigma^2_d}. \tag{26}$$

This equation expresses the *upward bias* to the scale estimate caused by the "transmission bias" alone. Surprisingly, the positive "transmission bias" exactly cancels the "omitted (price) variable" bias, for our particular model. Adding the right hand side of equations (25) and (26), the total bias can be written

$$\text{plim}(\hat{\epsilon}) - \epsilon = \frac{\epsilon\eta(\sigma^2_w+\sigma^2_m)-(\epsilon-1)\sigma^2_d}{\eta^2(\sigma^2_w+\sigma^2_m)+(\eta-1)^2\sigma^2_q+\sigma^2_d}. \tag{27}$$

It is now clear that idiosyncratic productivity shocks will *not* create any bias. Furthermore, the presence of idiosyncratic productivity shocks will tend to reduce the bias caused by demand, costs or markups shocks. This is evident since a larger variance in productivity shocks does not affect the the numerator, while it increases the denominator in equation (27).

An interesting extension of the preceding analysis is to consider the case where u_{it}^m and u_{it}^y are correlated. What we have in mind, is that a firm which experiences a positive productivity shock might not fully pass it over to consumers by lowering its price[19] . This corresponds to a positive correlation between u_{it}^m and u_{it}^y. When $u_{it}^m = u_{it}^q/\epsilon$ a productivity shock is fully offset by a change in the markup, as can be seen from equation (18). The consequence of allowing for a non-zero correlation between the productivity and the markup shocks, is to add a new term $-(\eta\epsilon + \epsilon)\ \mathrm{Cov}(u_{it}^m, u_{it}^q)$ to the numerator of equation (27). An additional term will also appear in the denominator of equation (27), equal to $-2\eta(\eta+1)\ \mathrm{Cov}(u_{it}^m, u_{it}^q)$. If there is a positive correlation between u_{it}^m and u_{it}^q, the additional term in the numerator is positive. The new term in the denominator is negative. Consequently, the total effect on the bias in the scale estimator from correlations between productivity movements and markup changes can not be identified without further assumptions.

[19]Cf. the discussion in footnote 15. Menu costs, as discussed in the macro literature, could cause such price setting behavior. See e.g. Mankiw (1990) for further references.

4 Towards consistent estimates of the scale elasticity

In this section we will show how we can identify the scale elasticity from regressions of deflated sales on usual production function regressors when we add the demand shock variable into the regression. There are two major points: The basic idea is that with observations on changes in aggregate demand and individual sales, we can infer the changes in real output (as a function of the demand elasticity) when we employ the simple demand structure presented in the previous section. The second point is that the parameters in the augmented regressions will be reduced form parameters, which are mixtures of supply and demand parameters. However, we present various specifications of our model which permits identification of the structural parameters.

4.1 Common, misspecified estimating equations

Let us start by explicitly stating the estimating equations for what we claim are (potentially) misspecified models. The models considered are the Cobb-Douglas production function and a cost function. We have also estimated a semi-parametric version of a model presented by Hall (1990). All these estimated models provide inconsistent estimates of the scale elasticity when deflated sales are used to replace output, as discussed above. In the next section we will show that after adding a demand shift variable, we can reinterpret the parameters, and identify the scale elasticity and other parameters of interest.

Following common practice, we have estimated a production function with deflated sales as the dependent variable (cf. equations (1) and (2)). The estimating equation in this case is

$$\dot{r}_{it} = \beta_1^r(\dot{m}_{it} - \dot{l}_{it}) + \beta_2^r(\dot{e}_{it} - \dot{l}_{it}) + \beta_3^r \dot{l}_{it} + \beta_4^r \dot{k}_{it} + u_{it}^r. \quad (28)$$

The variables $\dot{m}_{it}, \dot{l}_{it}$ and $\dot{e}_{it}$ refer to materials, labour and energy. Notice that, if we neglect the inconsistency issue for the moment, this transformation of the variables imply that β_3^r corresponds to the scale elasticity of the *variable factors.*

The next case to consider is the cost function approach (cf. equations (7) and (8)). For the cost function, the estimating equation is

$$\dot{x}_{it} = \beta_1^x \dot{r}_{it} + \beta_2^x \dot{k}_{it} + u_{it}^x. \quad (29)$$

The dependent variable in this equation is a cost weighted average of the variable inputs:

$$\dot{x}_{it} \equiv \sum_{j \in \{L,M,E\}} s_{it}^j \dot{x}_{it}^j, \quad (30)$$

where s_{it}^j is the cost share of factor j. This is a slight modification of the common specification of the cost function. We have used the observed shares (in variable costs) – while the common practice is to use estimated shares – in front of the factor price terms in the cost function[20]. The inverse of β_1^x in

[20]This approach highlights the similarity, as well as the difference in terms of stochastic

equation (29) could be interpreted as the scale elasticity of variable inputs if output replaced deflated sales.

We have also considered a model which relates the growth in deflated sales – rather than output – to the cost-weighted input measure, growth in capital inputs and a residual[21]:

$$\dot{r}_{it} = \tilde{\beta}_1^r \dot{x}_{it} + \tilde{\beta}_2^r \dot{k}_{it} + \tilde{u}_{it}^r. \tag{31}$$

As stated by Hall (1990), the $\tilde{\beta}_1^r$ parameter can be interpreted as a scale parameter. That is to say, if we neglect the problem of replacing output by deflated sales, the specification in equation (31) implies that the $\tilde{\beta}_1^r$ parameter can be interpreted as the scale parameter of *variable inputs*. However, this estimating equation suffer from the same problem as the production function and the cost function, in that there is an omitted variable bias associated with the discrepancy between the growth in the individual price relative to the applied deflator.

4.2 Reduced form models

In the model presented in section 3, we were able to express the quality adjusted output in terms of deflated sales (cf. equation (20)). We will split the demand changes into an idiosyncratic part (u_{it}^d) and a component which

specification, between the production function, the factor demand and the cost function approach to production econometrics.

[21]This is a slight modification – using gross output rather than value added – to a model considered by Hall (1990). Notice that equation (28) is equal to equation (31) if we replace $\tilde{\beta}_1^r \dot{x}_{it}$ by $\beta_1^r(\dot{m}_{it} - \dot{l}_{it}) + \beta_2^r(\dot{e}_{it} - \dot{l}_{it}) + \beta_3^r \dot{l}_{it}$ in the latter equation.

vary over time but is common across firms within an industry (d_{It} ; 'I' refer to the industry to which firm 'i' belongs).

$$\dot{q}_{it} = \frac{\eta}{\eta+1}\dot{r}_{it} + \frac{1}{\eta+1}(\dot{d}_{It} + u^d_{it}). \tag{32}$$

Using this equation, and replacing $\dot{r}_{it}$ by $\dot{q}_{it}$ in equation (28), we get

$$\dot{r}_{it} = \frac{\eta+1}{\eta}\left[\beta^r_1(\dot{m}_{it} - \dot{l}_{it}) + \beta^r_2(\dot{e}_{it} - \dot{l}_{it}) + \beta^r_3\dot{l}_{it} + \beta^r_4\dot{k}_{it}\right] - \frac{1}{\eta}\dot{d}_{It} + v^r_{it}. \tag{33}$$

v^r_{it} is a composite mean-zero error term. Similarly in the cost function case; substituting $\dot{q}_{it}$ for $\dot{r}_{it}$ in equation (29), and employing equation (32), we get

$$\dot{x}_{it} = \frac{\eta\beta^x_1}{\eta+1}\dot{r}_{it} + \beta^x_2\dot{k}_{it} + \frac{\beta^x_1}{\eta+1}\dot{d}_{It} + v^x_{it}. \tag{34}$$

Lastly, replacing $\dot{r}_{it}$ in equation (31) by $\dot{q}_{it}$, and using equation (32):

$$\dot{r}_{it} = \frac{\eta+1}{\eta}\left(\tilde{\beta}^r_1\dot{x}_{it} + \tilde{\beta}^r_2\dot{k}_{it}\right) - \frac{1}{\eta}\dot{d}_{It} + \tilde{v}^r_{it}. \tag{35}$$

Notice that in the models presented in equations (33) – (35) both the η- and the production/cost function parameters of interest are identified.

4.3 The data sources and variable construction

The data source used in this analysis is the annual census carried out by The Division of Manufacturing Statistics in The Central Bureau of Statistics of Norway. Aggregate numbers and definitions for the census are reported in NOS (several years. See also Halvorsen et al. (1991)). We have employed an unbalanced sample of annual observations for the period 1983-89 (inclusive) for 4 industry groups producing "Metal products, machinery and equipment". The sample includes only establishments with at least 5 employees. Plants with incomplete reports for the variables needed in the estimation have been eliminated, but no other cleaning has been carried out. Summary statistics for the employed sample is reported in table 1.

All variables are in first differences. In all models, we have applied a Tornquist index for the variable inputs, i.e. the shares are constructed as the average share for the two years used to construct the growth rates. The output measure is gross output adjusted for duties and subsidies. Labour inputs are represented by man hours. Price deflators for gross production (at seller prices), materials, energy and capital (at buyer prices) are taken from the Norwegian National Accounts. Wage payments comprise salaries and wages in cash and kind, other benefits for the employees, taxes and social expenses levied by law.

The capital input variable employed is based on investment figures and the total reported fire insurance value for buildings and machinery. The annual movements are obtained by assuming geometric depreciation at a 3 percent annual rate, and that investment takes about a year to become productive[22]. This last assumption is imposed also to reduce biases caused by the possibility that investments respond to contemporaneous productivity

[22]An examination of the fire insurance values and a comparison with the investment figures reveal much noise in the fire insurance values. We have constructed a simple filter to pool the two sources of information about movements in the capital stock. Essentially the filter identifies the level of the capital stocks from the fire insurance values. Extreme fire insurance values have been eliminated.

shocks.

Unfortunately, we do not have access to demand side variables which could be employed to model the demand shift variable in equations (33) – (35). Instead, we have used the (weighted) average growth in deflated sales across all firms in each (5-digit) industry, as our proxy for demand changes. In the appendix, we have shown that one assumption which would justify our approach is that the growth rate in the aggregate output deflator represents a (weighted) average of the unobserved growth rates in the individual output prices.

We are well aware that we do encounter an identification problem here. That is to say, we can not rule out that the "demand shifter" in fact captures common supply shocks, rather than common demand shocks. I.e. correlation in the residuals across firms in the same industry could be due to common technological shocks, which would be correlated with the average expansion of sales for the firms in the industry[23]. However, we will assume that the large fluctuations in the *annual growth* rates in average sales in our sample, is *dominated* by demand shifts. One should keep in mind that the Norwegian

[23]Abbott et al. (1988) have argued that correlation between the production function residuals and variables capturing changes in demand could be due to common variations in capacity utilization of capital and labour. Bartelsman, Caballero and Lyons (1991) have attempted to argue that the correlation in the production function residuals across *industries* can be interpreted as evidence for the existence of external economies related to both supply and demand. See also Shapiro (1987), Hall (1988, 1990) and Caballero and Lyons (1991) for further discussion of the interpretation of movements in the production function residual correlated across industries, and the correlation between these movements and changes in aggregate demand.

economy entered a severe recession in 1987.

4.4 Other econometric issues

For both the cost function models (cf. equations (30) and (34)) and the semi-parametric models (cf. equations (31) and (35)), we have both carried out OLS and instrumental variable regressions. The instrumental variable used are changes in the number of employees. The motivation for using an IV-approach is twofold: First, it seems likely that the number of employees is less responsive to short term changes in productivity, as compared to manhours, materials and energy in the production function and semi parametric models. Similarly, in the cost function case we believe that the number of employees is less affected by temporary shifts in productivity relative to deflated sales. If these claims are true, the orthogonality assumption on the error term is more appropriate using changes in employees as an instrument. Notice that permanent differences in productivity between firms, or random walk changes in productivity, will not cause any simultaneity bias, as all variables are expressed in terms of (annual) growth rates.

Second, any measurement errors in the input index will cause a bias in the OLS regression. Measurement errors might be introduced if we are using weights which randomly deviate from the correct shares when constructing the input index, as well as for a variety of other reasons. If these measurement errors are uncorrelated with changes in employment, using the IV-approach will remove the bias due to errors of measurement in the input variables.

4.5 The Results

Table 2 reports the results obtained from estimating the production function in equation (28), as well as a model where the production function is augmented by adding the constructed demand shock variable as an explanatory variable. The main result to notice is that the demand shock variable is highly significant. However, rather than elaborating on these estimates, we will notice that the semi parametric model which aggregates the variable inputs by means of a Tornquist index performs uniformly better in terms of the RMSE; see table 3 – 6. Also, the scale estimates obtained by the semi parametric model are likely to be more consistent, as we are able to instrument the variable inputs (manhours, energy, materials) which are likely to be correlated with high frequency movements in productivity buried in the residual. In what follows we will focus on the semi parametric model, instead of the standard production function model.

Tables 3-6 summarize the main results for each industry group separately. The first two columns in each of the four tables, refer to estimation of the semi parametric model in equation (31). Columns 3 and 4 present results obtained from the cost function (cf. equation (29)), which is essentially the same regression but with a reshuffling of the left hand side and right hand side variables. The last two columns provide results from estimated models augmented by including the constructed demand shock variable in the regression.

One should notice that the reported RMSE-values refer to the root mean square prediction error of deflated sales, rather than the prediction error of the different dependent variables. This is done in order to facilitate comparisons between the various (non-nested) models.

The first column in table 3 gives an estimate around 0.91 (standard error equal to 0.007) of what is traditionally interpreted as the scale elasticity of the variable inputs. The estimated constant term suggests an average productivity decline around -1 percent per year (same as the reported TFP-figure in table 1).

The estimated coefficient for capital growth has the wrong sign, but is not significant. The insignificance of capital is a results which we obtain throughout our estimations. Our belief is that with the available quality of our capital measures, it is not possible to trace the annual changes in capital services. We will add further comments on this problem in the final section of the paper.

As we compare the results from the various models, only one of the estimated scale parameters deviates significantly from the results just reported. That is the scale estimate obtained by OLS estimation of the cost function. The scale estimate is 1.13 (=1/0.883), and it is very precisely estimated. However, when we instrument growth in deflated sales by the growth in number of employees, the estimated scale coefficient declines to 0.93 (same as the result obtained in column 2, as we would expect, since the results reported in column 2 is obtained using the same instruments and the rest of the model is essentially the same). There are two reasons why we will place greater trust in the (higher) IV-estimate of the sales coefficient. First, random measurement errors in deflated sales will cause a downward bias in the estimated sales coefficient (and thereby an upward bias in the scale elasticity)

[24]. Second, a similar bias will arise due to the (negative) correlation between sales and the cost function error term, which incorporates the productivity movements with a negative sign. As discussed above, our instrument is likely to remove at least some of these biases.

Before we continue the discussion of the scale estimates, notice that the "demand shifter" is highly significant when introduced into the regressions, suggesting that the firms do not face perfectly elastic demand curves (cf. columns 5 and 6). If we assume that changes in average sales capture demand shocks, we can go a step further. Using equations (34) and (35), we can identify the demand elasticity from column 5 and 6 in table 3. Simple calculations show that the two models implies a demand elasticity around -6.2. We can also identify the scale elasticity from the two set of estimates, which turn out to be about 1.10 in both cases. The same calculations for the other industries are reported in table 6.

The results for the other industries are very similar to the findings discussed above. In particular we find that after taking into consideration the demand equation facing the firms, the results are almost identical across the two estimated models. The findings are also quite similar across industries. Our results suggest significant, but not large, scale economies in all industries. The results suggests that the firms face a less than perfectly elastic demand curve, with a demand elasticity around - 6 to - 12. (However, we have not provided confidence intervals for the estimates of the demand elasticities.).

[24]This bias was pointed out by Friedman (1955), and was labelled the "regression fallacy". This discussion was one of the first examinations of the consequences of random measurement errors in the regressors.

5 Final remarks

This paper has identified some problems of interpretation of the production function parameters when deflated sales is used instead of true output as the dependent variable. The problems arise in situations when the firms compete in an imperfectly competitive environment, where prices will reflect idiosyncratic differences in cost. The basic insight is that a firm experiencing a cost improvement beyond the industry average, will be inclined to undercut its competitors price and thereby expand its market share. However, since the firm will have a below average change in price, the expansion in sales will be less than proportional to the growth in output. It follows that replacing changes in real output by growth in deflated sales will introduce a bias in the standard approaches to estimation of production parameters.

Our paper also provides some empirical results from a production function model, augmented by incorporating average, industry wide sales into the estimating equation. Alternative specifications are carried out. We provide one interpretation of the results along the lines outlined in the theoretical part of the paper. Our findings suggest that the firms in our sample face downward sloping demand curves with significant, but moderate price elasticities. The results suggest some scale economies to the variable factors.

One problem with our findings is the non-significance of capital in our models. As the equations are in first differences, this result is consistent with the general experience with these kind of data. The usual explanation is simple: The quality of our capital measures is to poor to identify the annual variations in capital services. Two key problems in this respect are variations in capacity utilization and investment lags. These issues rises the question of how we should incorporate capital into our models. Does capital have positive (shadow) price only when the firm operates at full capacity? And closely related; how does the firm incorporate the shadow price of capital into its pricing decisions? We believe that a more satisfactory solution to these questions requires an explicit dynamic model of investment behavior, incorporating uncertainty [25].

The question raised about the measurement of the capital inputs takes us to another serious problem with the results presented above. That is, we have just provided *one interpretation* of the variable we have termed the "demand shock variable" (the movements in deflated, industry wide sales). It is not unlikely that this variable will be correlated with changes in the utilization of capital[26]. If such correlation is present, the "demand shock" coefficient is a mixture of the true demand shock coefficient and the capital coefficient. It follows that the true demand elasticity is higher than the estimates presented above, - and that the correct scale coefficient is consequently lower.

We also suspect that changes in the capital services are picked up by movements in the variable inputs (particularly energy) in our production function regressions, and by the deflated sales variable in the cost function regressions. In both cases the result will be an upward bias in the scale

[25] See Eden and Griliches (1991) for an analysis of some of the issues which arise in a dynamic setting which emphasizes the importance of capacity choice and uncertainty.

[26] This is the point stressed by Abbott et al. (1988). Notice that unobserved movements in labour effort and output (maintenance) - buried in the residual - might also be correlated with this "demand shock variable".

coefficent, reinforcing the tendency stated above.

Another interpretation of the correlation between the production function residuals and aggregate sales is examined by Bartelsman et al.(1991). They point out that the correlation between production function residuals and aggregate sales could be due to external economies in demand and supply[27]. A long list of theoretical models suggesting such externalities have been presented, ranging from R&D-externalities to "thick market effects"[28]. To this list one could add measurement problems with the input and output deflators. If these measurment errors are correlated across the units of observation, this problem will show up as correlation in the production function residuals (also at the industry level).

We have not been able to unravel the different causes of the correlation between the production function residuals and movements in aggregate sales. The present paper has rather taken one extreme position by assuming that "the demand shock" variable captures *only* what is intended by its label. This interpretation of our findings has provided us with estimates of scale economies and market power (demand elasticities) which are substantially higher than what is usually obtained (or assumed) in panel data studies of production, but much lower than recent estimates obtained by Hall (1988, 1990) and others. To the extent that our demand shock variable also captures the other factors listed above, the correct interpretation of our results would

[27]Their analysis is carried out at the industry level, but the same mechanisms are potentially operating at the firm level, studied here.

[28]See Bartelsman et al. (1991) and Caballero and Lyons (1991) for references to the literature.

be closer to the mainstream panel data studies, and even further away from the recent results of Hall and others.

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Appendix

In this appendix we will show that if the growth rate of the industry wide price deflator is a (weighted) average of the changes in the firm specific prices, the common component in changes in demand can be constructed as the (weighted) average of the growth in sales for the firms in the industry.

Using the relationship $\dot{r}_{it} = \dot{q}_{it} + \dot{\pi}_{it}$ and equation (32), we have that

$$\dot{q}_{it} = \dot{d}_{It} + \eta\dot{\pi}_{it} + u^d_{it}, \tag{36}$$

where $\dot{\pi}_{it}$ is the growth in the price of firm 'i' between 't' and 't-1', relative to the growth in the aggregate price level in the industry. Assuming we have weights (w_{it}) such that $\sum_{i\in I} w_{it}\dot{\pi}_{it} = 0$, we have that:

$$\begin{aligned} \sum_{i\in I} w_{it}\dot{q}_{it} &= \sum_{i\in I} w_{it}(\dot{d}_{It} + \eta\dot{\pi}_{it} + u^d_{it}) \\ &= \dot{d}_{It}, \end{aligned} \tag{37}$$

where $\dot{d}_{It}$ is the average demand shock in the industry I. It follows that if we have the appropriate weights, the common demand shifter can be constructed from the weighted mean of the growth in deflated sales.

Table 1: Summary statistics for the four industry groups in the applied sample. Period 1983-89.

Industry:	381		382		383		384	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
# Obs.	3945		2542		1174		2445	
Output (*)	0.004	0.326	0.014	0.363	0.011	0.339	-0.001	0.393
TFP (*)	-0.009	0.144	0.004	0.178	-0.004	0.141	0.000	0.164
Labour (*)	-0.005	0.316	-0.010	0.331	0.003	0.270	-0.010	0.365
Capital (*)	0.026	0.162	0.024	0.164	0.041	0.217	0.016	0.138
Dmd.shift (*)	-0.002	0.088	0.032	0.102	-0.005	0.140	0.016	0.104
Rev./v.cost	1.124	0.142	1.102	0.173	1.104	0.135	1.092	0.115
Lab.shr. (**)	0.431	0.141	0.441	0.165	0.393	0.131	0.387	0.165
Enrg.shr.(**)	0.025	0.022	0.019	0.018	0.013	0.011	0.019	0.017
#Empl./plant	30.8	50.5	73.3	195.4	76.4	175.1	58.7	110.1

Note: Variables indicated by (*) refer to annual growth rates. The cost shares for energy and labour, indicated by (**), refer to shares in variable costs.
Industry 381: Manufacture of metal products, except machinery and equipment
Industry 382: Manufacture of machinery
Industry 383: Manufacture of electrical apparatus and supplies
Industry 384: Manufacture of transport equipment

Table 2: Production function estimates with and without demand shock variable (average deflated sales) included in the regression. Cf. equation (28). All industries.

INDUSTRY	381		382		383		384	
Labour	0.854 (.009)	0.843 (.009)	0.814 (.014)	0.800 (.014)	0.934 (.018)	0.925 (.018)	0.845 (.011)	0.838 (.011)
Materials	0.470 (.006)	0.465 (.006)	0.400 (.008)	0.394 (.008)	0.502 (.012)	0.500 (.012)	0.554 (.007)	0.550 (.007)
Energy	0.060 (.005)	0.056 (.005)	0.070 (.009)	0.065 (.009)	0.024 (.011)	0.021 (.011)	0.085 (.008)	0.083 (.008)
Capital	-0.005 (.005)	-0.004 (.005)	-0.013 (.008)	-0.011 (.008)	-0.022 (.022)	-0.020 (.022)	0.004 (.004)	0.004 (.003)
Demand shock		0.233 (.030)		0.282 (.040)		0.112 (.034)		0.172 (.035)
Const.	-0.009 (.003)	-0.009 (.003)	0.007 (.004)	-0.003 (.004)	-0.002 (.005)	-0.002 (.005)	-0.002 (.004)	-0.005 (.004)
R2	0.75	0.75	0.68	0.69	0.78	0.78	0.80	0.80
RMSE	0.163	0.162	0.206	0.204	0.161	0.160	0.178	0.177

Note: Standard errors in parentheses.
Industry 381: Manufacture of metal products, except machinery and equipment
Industry 382: Manufacture of machinery
Industry 383: Manufacture of electrical apparatus and supplies
Industry 384: Manufacture of transport equipment

Table 3: Estimation results for the models in equations (29), (31), (34) and (35).
Industry 381: Manufacture of metal products, except machinery and equipment.

	BASIC MODELS:				AUGMENTED MODELS:	
Model: Equation:	Semi.param. (31)		Cost fct. (29)		Semi.p. (35)	Cost f. (34)
Estimation method:	OLS	IV	OLS	IV	IV	IV
Inputs	0.907 (.007)	0.930 (.010)			0.923 (.010)	
Deflated sales			0.883 (.007)	1.075 (.012)		1.083 (.012)
Capital	-0.005 (.004)	-0.005 (.004)	0.007 (.004)	0.006 (.005)	-0.005 (.004)	0.005 (.005)
Demand shock					0.161 (.027)	-0.174 (.030)
Const.	-0.007 (.002)	-0.007 (.002)	0.008 (.002)	0.007 (.002)	-0.007 (.002)	0.007 (.003)
RMSE	0.146	0.146	0.163	0.146	0.145	0.145

Note: Numbers in parentheses are standard errors. RMSE refers the root mean square prediction error of deflated sales as implied by the model.

Table 4: Estimation results for the models in equations (29), (30), (34) and (35).
Industry 382: Manufacture of machinery

	BASIC MODELS:				AUGMENTED MODELS:	
Model:	Semi.param.		Cost fct.		Semi.p.	Cost f.
Equation:	(31)		(29)		(35)	(34)
Estimation method:	OLS	IV	OLS	IV	IV	IV
Inputs	0.865 (.010)	0.912 (.015)			0.905 (.015)	
Deflated sales			0.871 (.010)	1.096 (.018)		1.105 (.019)
Capital	-0.007 (.007)	-0.006 (.007)	0.003 (.007)	0.007 (.007)	-0.005 (.007)	0.006 (.007)
Avg.defl. sales					0.167 (.036)	-0.185 (.041)
Const.	0.005 (.004)	0.005 (.004)	-0.002 (.004)	-0.005 (.004)	-0.005 (.007)	0.001 (.004)
RMSE	0.180	0.181	0.207	0.181	0.180	0.180

Note: Numbers in parentheses are standard errors. RMSE refers the root mean square prediction error of deflated sales as implied by the model.

Table 5: Estimation results for the models in equations (29), (30), (34) and (35). Industry 383: Manufacture of electrical apparatus and supplies

	BASIC MODELS:				AUGMENTED MODELS:	
Model: Equation:	Semi.param. (31)		Cost fct. (29)		Semi.p. (35)	Cost f. (34)
Estimation method:	OLS	IV	OLS	IV	IV	IV
Inputs	0.957 (.013)	0.989 (.019)			0.981 (.019)	
Deflated sales			0.850 (.012)	1.011 (.020)		1.020 (.020)
Capital	-0.023 (.020)	-0.022 (.020)	0.015 (.019)	0.023 (.020)	-0.021 (.020)	0.021 (.020)
Avg.defl. sales					0.084 (.031)	-0.085 (.032)
Const.	-0.002 (.004)	-0.003 (.004)	0.005 (.004)	0.003 (.004)	-0.002 (.004)	0.002 (.004)
RMSE	0.147	0.148	0.163	0.148	0.147	0.147

Note: Numbers in parentheses are standard errors. RMSE refers the root mean square prediction error of deflated sales as implied by the model.

Table 6: Estimation results for the models in equations (29), (30), (34) and (35). Industry 384: Manufacture of transport equipment

	BASIC MODELS:				AUGMENTED MODELS:	
Model: Equation:	Semi.param. (31)		Cost fct. (29)		Semi.p. (35)	Cost f. (34)
Estimation method:	OLS	IV	OLS	IV	IV	IV
Inputs	0.913 (.009)	0.919 (.013)			0.912 (.013)	
Deflated sales			0.903 (.008)	1.088 (.015)		1.096 (.016)
Capital	0.005 (.003)	0.005 (.003)	-0.005 (.003)	-0.005 (.004)	0.005 (.003)	-0.006 (.003)
Avg.defl. sales					0.139 (.032)	-0.152 (.036)
Const.	0.001 (.003)	0.001 (.003)	-0.002 (.003)	-0.002 (.004)	-0.001 (.003)	0.001 (.004)
RMSE	0.165	0.165	0.182	0.165	0.164	0.164

Note: Numbers in parentheses are standard errors. RMSE refers the root mean square prediction error of deflated sales as implied by the model.

Table 7: Point estimates of the demand and scale elasticities as implied by the results in table 3-6, columns 5 and 6.

Model:	Semi param.		Cost function	
Industry	Demand	Scale	Demand	Scale
381	-6.2	1.10	-6.2	1.10
382	-6.0	1.09	-6.0	1.09
383	-11.9	1.07	-12.0	1.07
384	-7.2	1.06	-7.2	1.06