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Total factor productivity estimation for Polish manufacturing industry- A comparison of alternative methods

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Abstract: The concept of total factor productivity (TFP) and its measurement have been of interest to researchers for more than half a century, and are intensively discussed topics in debate on economic growth[1]. This chapter discusses the different problems related to methodologies for estimating TFP at the establishment (sector and firm) levels. These include simultaneity and selection bias, deflated input and output values, and endogeneity of product choice. It then describes existing techniques for overcoming these methodological problems - specifically, it is shown that these are addressed at sector level by computing TFP using a semi parametric technique at the establishment level. A manufacturing sector data is used at three levels of aggregation for Poland for the period 1995 to 2007; the results indicate significant TFP growth and also intensive dynamic changes to productivity over time. The results from three different techniques - index measures (non-parametric), parametric production function estimation (General Method of Moment - GMM) and production function – to account for endogeniety (semi-parametric) provide consistent results. This suggests that the estimates are sensitive to the technique and definitions of variables used, and indicate the biases related to traditional TFP estimations.

JEL classification: L6, D2

Key words: Total Factor Productivity, Manufacturing

[1] See Edwards (2001), Henry and Sasson (2008) , Bonfilioli (2007)

1 Introduction

The origins of Total Factor Productivity (TFP) analysis can be traced back to Farrell (1957) and Solow (1957). From a microeconomics perspective, productivity is understood as the fraction of output that is not explained by the amount of inputs used for production (see Comin, 2008). There are three main sources of productivity growth: technical change; allocative efficiency; and changes to the scale of operations.[2] Farrell (1957) defined allocative efficiency as the company's ability to use inputs in their optimal proportions given their respective prices and the production technology available.[3] Technical efficiency has been defined as the firm's ability to obtain the maximal output from a given set of inputs while scale efficiency refers to productive scale size or optimal productive scale (see Coelli, Rao and O'Donnell, and Battese, 2005). Significant improvements to data econometrics software that occurred in the mid- 1990s renewed interest in firm-level TFP analysis. Productivity can be measured using parametric or non-parametric methods. Traditional parametric methods for computing TFP which assume a certain shaped production function curve suffer from simultaneity and endogeneity problems.[4] Several methodologies have been proposed to account for these methodical problems such as Fixed Effects (FE) estimations, Instrumental Variables and Generalized method of moments (GMM). However, since these techniques provide poor performance estimators, semi-parametric techniques were pioneered by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP). These techniques are applicable at firm-level.

This chapter provides an empirical overview of the measurement of TFP accounting for input and output choices. Also this chapter aims to obtain more accurate estimates of TFP growth for manufacturing sectors by taking account of methodological issues at the establishment level. I discuss possible bias and inconsistency of results from the three econometric techniques: TFP index measure (non-parametric), parametric production function estimation (GMM) and proposed semi-parametric estimations. The Polish manufacturing sector presents an interesting case since it

[2] See Fare, Grosskopf, Norris, Zhang (1994), Coelli, Rao, O'Donnell, and Battese (2005) The analysis of productivity is strictly connected to efficiency measurements. Efficiency measures estimate the distance of a company or industry from the theoretical optimal at the production frontier.

[3] Allocative efficiency can be calculated using either: i) the input-oriented base (cost efficiency) or ii) the output oriented base (revenue efficiency). It is rarely calculated from a profit-maximizing perspective. For instance, Färe, Grosskopft and Lovell (1994) use DEA to measure profit efficiency along with a hyperbolic measure of technical efficiency. Kumbhakar (1987) in his stochastic frontier framework decomposes profit efficiency into three: input-allocative efficiency, output-allocative efficiency and input-orientated technical efficiency.

[4] This problem, as highlighted in Marschak and Andrews (1994) and Wedervang (1965), is a recently developed methodology.

has been under- researched, and also has suffered significant restructuring in the period 1995 and 2007.[5]

The chapter is organized as follows. Section 2 provides an overview of the TFP methodology. Section 3 provides a review of the literature on TFP studies in Poland and CEE countries. Section 4 discusses the estimation methodology and data used, and presents the empirical results for the manufacturing industry. The chapter concludes in Section 5

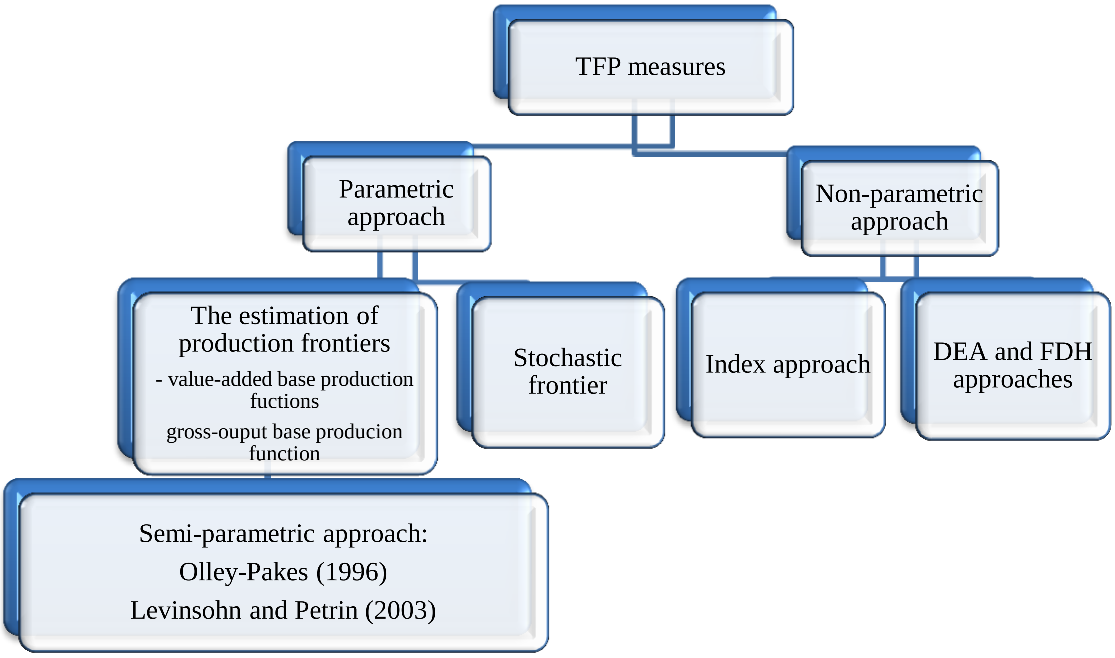
2. Productivity measures

Discussions of economic growth highlight certain factors, such as the resources of capital and labour, technical progress, investments in human capital, and their efficient usage, that lead to higher economic performance (see Krugman, 1990 and Stiglitz, 2002). Efficient resources use and efficient technical processes are contributors to productivity. This section describes the techniques used to measure TFP and the advantages and disadvantages of these techniques, and also how the output and input measures impact on TFP measurement.

The literature suggests ways to measure productivity using both parametric and non-parametric approaches (Figure 1), methods derived from the concepts of maximization of production for a given input and minimization of cost function(s), or maximization of revenue.

[5] Since 1990 tariffs have gradually been reduced, largely as a result of the need to align with EU requirements. (Kochanowicz, Kozarzewski, Woodward, 2005). Since 1995, the process of accession to the EU has gathered momentum, mainly related to legal regulation (Sadowska-Cieslak, 2000). In 2004, Poland became a member of the EU. In view of future accession to the Euro-zone, the requirements of Stage 2 for Poland are the basic conditions of wage flexibility, a prudent fiscal and monetary stance, and financial system soundness. Poland should adhere to the new exchange rate mechanism ERM2, which requires near parity between Polish currency and the euro within a +/-15% margin, to be maintained for at least 2 years prior to qualifying for Stage 3 of European Monetary Union (Lane, Milesi-Ferretti , 2006). The Privatization Act of 1990 ensured that privatization took place, but the first government sell-off was the Kruszwica manufacturing company, producers of oil products in 1996. In 1996, the government agreed to privatize the Polish energy sector and the larger commercial bank in Poland (see Bekeart, Campbell, 2002c).

Figure 1 Measuring Total Factor Productivity Growth



Source: Author's analysis based on Beveren (2007), Coelli, Rao, O'Donnell, and Battese (2005), Eberhardt and Helmers (2010) Abramovitz (1990), Coelli, Rao, O'Donnell, and Battese (2005), Simar, Daraio, and Eeckaut (2008)

2.1 Parametric approaches

The parametric approach estimates the production function by employing two different methods: estimation of production frontiers, and stochastic frontier approach.[6] This approach defines production as a functional form with the parameters on inputs estimated econometrically using sample data.

Estimation of production frontiers

In order to estimate production frontiers, it is necessary to express a production function with respect to inputs as the explanatory variable and an algebraic function form. A production function is expressed as $y = f(x_1, x_2, ..., x_n)$ where output (y) and input (x_i) and i=1, …, n are n-number of inputs.[7] There are many different mathematical forms of the production function as proposed in the literature, such as: Cobb-Douglas, Normalized Quadratic, Constant Elasticity of

[6] See Abramovitz (1990), Coelli, Rao, O'Donnell, and Battese (2005), Simar, Daraio, and Eeckaut (2008) and Eberhart and Helmers (2010)

[7] The input might be classified into five main categories, namely: capital (K), labour (L), energy (E), material inputs (M) and purchased services (S).

Substitution (CES), and Generalized Leontief (see Appendix 2 Table 1). However, the most common functional form in the applied economics literature is the linear Cobb-Douglas (CD) function.[8] This form is also supported via a standard neo-classical production function $y = f(L, K)$ where L denotes labour and K denotes capital stock. In order to implement a linear regression framework, the parameter of production function must be in linear form.[9] To implement the Cobb-Douglas function requires the logarithms of both sides of the function. This mathematical transformation yield is the Cobb-Douglas function form as described as:

$$\ln(Y) = \ln(\beta_o) + \sum_{i=1}^{N} \beta_i \ln(x_i) \quad (1)$$

where x_i is expressed as L-labour and K-capital.

The measure of output to estimate productivity can be defined in two ways: as gross output, or as gross value-added. In the Cobb-Douglas framework, there is a gross-output base production function which includes the parameters of material inputs (M), labour (L), and capital stock (K). The value-added base production function includes the two parameters labour and capital stock (see Bruno, 1984, Eberhardt and Helmers 2010). The value-added base production function is described as

$$Y = \beta_o K^{\beta_K} L^{\beta_L} \quad (2)$$

where Y is value added, β_o is the Hicksian neutral efficiency level which is unobservable to the researcher,[10] K is the capital stock, L is the labour, β_L is the proportion of labour usage in production and β_K is the proportion of capital usage in production. In order to obtain the linear estimation equation, a logarithmic transformation must be made thus:

$$\ln(Y_{jt}) = \ln(\beta_o)_{jt} + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) \quad (3)$$

where j – individual unit (e.g. country, firm, industry sector), t =1,.., T - time subscription.

Beveren (2007) and Eberhardt and Helmers (2010) discuss output size (Y_{jt}), labour (L_{jt}) and capital stock (K_{jt}). Researchers do not observe productivity term (w_{jt}) compared to firm's managers in the estimating equation as,

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + w_{jt} + \varepsilon_{jt} \quad (4)$$

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[8] See Dowrick, Duc-Tho Nguyen (1989), Abramovitz (1990), Gasiorek, Augier and Varela, (2005), Felipe (1997), Smarzynska (2002), Eberhardt and Helmers (2010), Beveran (2007), Danka-Borsiak, 2011)

[9] For instance, the parameters in the linear former form can be estimated using the method of ordinary least squares (OLS), GMM, Generalized Least Squares Method (GLS) (see Gasiorek, Augier and Varela, 2005, Dowrick, Duc-Tho Nguyen, 1989, Baumol , 1989, Abramovitz, 1990, Smarzynska 2002, Danka-Borsiak, 2011, Glick and Rogoff, 1992 and Edwards, 1998).

[10] It can be observed by company managers or company owners.

where $\varepsilon_{jt} + w_{jt} + \alpha_0$ is equal to $\ln\beta_o, \alpha_0$ measures the mean efficiency level across firms and over time, ε_{jt} identifies measurement error and random noise[11] and w_{jt} is a productivity term (TFP)

Both terms w_{jt} and ε_{jt} are part of the estimation residual. Therefore in order to find the value of the TFP parameter, it is necessary to estimate the empirical equation (1) to obtain the values of β_L and β_K (respectively $\hat{\beta}_L$ and $\hat{\beta}_K$) and subscript its values as follows:

$$\hat{w}_{jt} = \ln(Y_{jt}) - \hat{\beta}_L \ln(L_{jt}) - \hat{\beta}_K \ln(K_{jt}) \ (5)$$

The procedure for estimating TFP from the gross-output base production function is similar to the estimation for the value-added base production functions. The only difference is that there is an additional parameter M_{jt} which is material inputs hence the estimation equation is

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + \beta_M \ln(M_{jt}) + w_{jt} + \varepsilon_{jt} \ (6)$$

and value of TFP is calculated as

$$\hat{w}_{jt} = \ln(Y_{jt}) - \hat{\beta}_L \ln(L_{jt}) - \hat{\beta}_K \ln(K_{jt}) - \hat{\beta}_M \ln(M_{jt}) \ (7).$$

Coelli, Rao, O'Donnell, and Battese (2005) introduced a discussion of an industry-specific knowledge of technological developments to the broader topic of the transmission bias problem by. The transmission bias problem deals with situations when input is not independent of the omitted productivity effect, resulting in biased and inconsistent coefficient estimates $\hat{\beta}_L$ and $\hat{\beta}_K$.

According to Eberhardt and Helmers's (2010) and Beveren's (2007) discussions, the transmission bias problem can be developed on the basis of equation (4). If $\ln\beta_o = \varepsilon_{jt} + w_{jt} + \alpha_0$, then estimation residual

$$\gamma_{jt} = w_{jt} + \varepsilon_{jt} = w^*_{jt} + \varepsilon_{jt} + \eta_j + \upsilon_t \ (8)$$

where ε_{jt} is a measurement error, w_{jt} is a productivity term (TFP)

The above description of the production estimation assumes the measurement error to be serially uncorrelated, but the possibility of a correlation between ε_{jt} and the observable inputs (L, K) suggests the presence of a time trend. Therefore, it is necessary to assume common shocks for all firms, and to split the productivity shock w_{jt} into three elements; a common shock for all firms (υ_t), a firm-specific shock (η_j), and w^*_{jt} an actual productivity shock (see Eberhardt and Helmers, 2010). A common shock across firms (υ_t) includes macroeconomic shocks, or/and

[11] The estimation results of ε_{jt} will be in the implementation of stochastic frontier.

overall ‘technological progress’ which affect all firms and industries. These common shocks and average processes are specified for t=2... T where υ_1=0 implies that α_0 represents average productivity in the base period t=1. On the other hand, the firm-specific elements (η_j) represent the permanent deviation of firm j from the reference firms’ average productivity in the base year. Hence, the estimation equation is written as:

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + w^*_{jt} + \varepsilon_{jt} + \eta_j + \upsilon_t \quad (9)$$

A transmission bias problem occurs in the moment when the firms decide on their choice of inputs (L, K) based on the realized firm-specific productivity shock (w^*_{jt}). Company managers usually have good market intuition so they can predict the direction of market trends. Also, managers can directly observe deviations in production that occur in the industry sector in which their companies operate. This adjustment to shocks in firm’s policy operations can cause input changes.[12] Thus, they cover both types of productivity shocks: the firm-specific elements and the common shock across firms. These are observed by firms but not by researchers (see Beveren, 2007). If researchers do not observe these shocks then the effect of inputs K and L on output Y cannot be separated from firm-specific productivity shock (w^*_{jt}). Thus, β_K and β_L are not identified. Even knowing the ‘true’ population distributions of the data, unbiased and consistent estimates of the input coefficients are not obtainable (see Eberhardt and Helmers, 2010:6). This analysis of firm-specific productivity shocks (w^*_{jt}) suggests that ‘transmit’ to input choices is a particular problem of ‘transmission bias’ and does not include productivity. It is strictly linked to aspects such as: selection bias (endogeneity of attrition) and endogeneity of input choices (simultaneity bias).[13]

Firstly, there is a selection problem caused by omitting firms’ entry or exit over the sample period (see Olley and Pakes, 1996). The probability of firm exit is a function of unobserved productivity (η_j and υ_t) and observed capital stocks (Beveren, 2007). Lower levels of capital and productivity mean a higher probability that firms will be bankrupt in the case of a negative productivity shock. In contrast, firms survive and stay in the market if they have access to higher levels of capital, and higher productivity. There are two types of firms: survivors with high capital stocks and losers with small capital stocks. In this case, survivors with high capital and high skills, creating higher profits, have a greater probability to survive compared to losers which are

[12] For instance, during a financial crisis times many firm decides to reduce an operation cost though labour redundancies or reduction in investment of fixed assets.

[13] See Olley and Pakes (1996), Beveren (2007), Levinsohn and Petrin (2003), Eberhardt and Helmers (2010).

characterized by lower survivor probability (see Beveren, 2007). Selection bias (endogeneity of attrition) causes problematic correlation between ε_{jt} and the observable inputs (K_{jt}) so that the capital coefficient estimate is biased downwards ($\hat{\beta}_K < \beta_K$).

The second problem is simultaneity bias (endogeneity of inputs) which is caused by a correlation between ε_{jt} and the observable inputs (X_{jt}), if the firms 's prior beliefs about ε_{jt} influence its choice of inputs. A traditional OLS estimation method requires independence between the independent variables and the error term.[14] Thus, the results of the OLS estimation in equation (9) are biased through induced endogeneity between labour and the productivity shock. The labour coefficient estimate is biased upwards ($\hat{\beta}_L > \beta_L$) (see Eberhardt and Helmers, 2010, p. 8). However, if the company maximizes profit, a positive productivity shock raises the marginal product of capital and labour with the assumption of constant factor prices. The firm's expansion can cause increased use of inputs which will drive down marginal products. On the other hand, in the case of a negative productivity shock, and unobserved productivity, and since the choice of inputs is likely to be correlated with the residual, the situation is reversed and OLS produces biased estimators ($\hat{\beta}_M > \beta_M$, $\hat{\beta}_K < \beta_K$) (see De Loecker, 2007 and Beveren, 2007). According to Eberhardt and Helmers (2010:8) the sources of transmission bias are related to the attenuation bias. This acts as a downward bias on the factor input coefficients ($\hat{\beta}_L < \beta_L$, $\hat{\beta}_K < \beta_K$). The capital equation is defined as:

$$K_{jt} = K^*_{jt} + \varepsilon_{jt} \quad (10)$$

where K^*_{jt} is the true capital stock and ε_{jt} is a measurement error hence the production function is

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K^*_{jt}) + \varsigma_{jt} \quad (11)$$

where ς_{jt} is a measurement error.

The combination of equations (10) and (11) results in the production function estimation:

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + (\varsigma_{jt} - \beta_K \varepsilon_{jt}) \quad (12).$$

Then, observed capital stock K_{jt} is negatively correlated with the error term in parentheses. If productivity is described as follows:

$$w_{jt} = g(w_{jt-s}) + \zeta_{jt} \quad (13)$$

[14] When X_{jt} is random and is correlated with the random disturbance ε_{jt} then $E(X_{jt}\varepsilon_{jt}) \neq 0$. This makes the moment condition invalid and results in biased estimators (see Hill, Griffiths and Lim, 2007, Wooldridge, 2006)

where g(.) is some function of past productivity and ζ_{jt} is the idiosyncratic productivity shock in period t.

Hence, L_{jt} and K_{jt} are assumed to be endogenous with respect to firm productivity levels, L_{jt} to be predetermined, K_{jt} to be endogenous with respect to ζ_{jt} and the productivity shock ζ_{jt} to be strictly exogenous with respect to the productivity level (see Eberhardt and Helmers, 2010).

Table 1 presents a summary of the methodological problems related to parametric TFP estimations in firm-level analysis. Note that these methodological problems have been addressed in productivity analyses at firm level, but not at sector level.

Table 1: TFP Estimation and methodological problems

Origin of the bias	Definition	Direction of the bias	References
selection bias (endogeneity of attrition)	correlation between ε_{jt} and the observable inputs (K_{jt})	Biased downward ($\hat{\beta}_K < \beta_K$).	Eberhardt & Helmers (2010) Beveren (2007) Olley & Pakes (1996) Wedervang (1965)
simultaneity bias (endogeneity of inputs).	correlation between ε_{jt} and the observable inputs (x_{jt}) if firms 's prior beliefs about ε_{jt} influence its choice of inputs	Biased upward/downward $\hat{\beta}_L > \beta_L$ or $\hat{\beta}_L < \beta_L$ Biased upward $\hat{\beta}_M > \beta_M$ Biased downward $\hat{\beta}_K < \beta_K$	Eberhardt & Helmers (2010) Beveren (2007) De Loecker (2007) Levisohn & Melitz (2002)

Note: The other methodological problems are defined with respect to estimation of productivity, such as input price bias and multi-product firms (Beveren 2007, De Locker 2007, Levisohn and Melitz 2002). There are not significant in the sector-level analysis. *Source:* Eberhardt and Helmers (2010) and Beveren (2007)

There are several solutions to endogeneity of input choices and the selection problem related to unobserved productivity. One solution to unobserved heterogeneity and endogeneity problems is the use of fixed effect models. However, Eberhardt and Helmers (2010) suggest that for firm-level data, fixed effects cannot solve these problems, given the continued existence of a contemporaneous correlation between firm-specific productivity shocks (w^*_{jt}) and the firm's input choices. Other solutions include implementing instrumentations using input price data (Beveren, 2007:8) or using 'dynamic panel estimators' with efficient 'own instruments'. 'Dynamic panels' were introduced by Arellano and Bond (1991) and Blundell and Bond (1998). The dynamic empirical specification includes lagged terms of the dependent and independent variables and allows computation of the long-run coefficients by considering 'common factor restrictions'. Alternatively, *structural estimators* can be used to solve these methodological problems. Structural estimators are used by Olley and Pakes (OP) (1996), Levinsohn and Petrin (LP) (2003) and Ackerberg, Caves and Frazer (2006).

The OP approach is designed to solve endogeneity of attrition and input choice. The endogeneity problem is incorporated into the production function equation through an investment function (I_{jt}). An investment function is used as a proxy for unobserved productivity (w_{jt}). The capital stock function is described as:

$$K_{jt+1} = (1-\delta)K_{jt} + I_{jt} \quad (14)$$

where δ is the depreciation rate and I_{jt} denotes firm j's investment in physical capital at time (t).

In this situation, an investment policy function depends on unobserved productivity and physical capital $I_{jt}(K_{jt}, w_{jt})$.[15] The estimation production function procedure has two steps. The first includes regression of output (Y_{jt}) on labour input (L_{jt}) and nonparametric function of firm-specific productivity (ϕ (K_{jt}, I_{jt}). Hence the estimation equation is defined as:

$$\ln(Y_{jt}) = \alpha_0 + \beta_L \ln(L_{jt}) + \beta_L \ln(K_{jt}) + \phi_{jt}(I_{jt}, K_{jt}) + \psi_{jt} \quad (15)$$

where ψ_{jt} is an error term.

Because it is a 'partially -linear' equation, it can be estimated using semi-parametric methods. The proxy for firm-specific productivity is computed as

$$\phi_{jt}[\ln(I_{jt}), \ln(K_{jt})] = \beta_0 + \beta_K \ln(K_{jy}) + f_{jt}[(\ln(I_{jt}), \ln(K_{jt})] \quad (16)$$

Equation (16) represents average productivity level, capital input and inverted investment function proxy for productivity term (w_{jt}). Moreover, $\phi_{jt}(.)$ is approximated by a higher order polynomial in $\ln(I_{jt})$ and $\ln(K_{jt})$.[16]

In the second step, according to Olley and Pakes (1996), it is necessary to consider including the probability of survival of firm j (P_{it}) in the next period t+1. The higher probability

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[15] Conditional on functional form restrictions: the investment function is continuous in K_{jt} and w_{jt}, and provided investment is positive (I_{jt}>0). The inverse function is $w_{jt} = f_t[\ln(I_{jt}), \ln(K_{jt})]$. The $f_{jt}(.)$ takes account of changes in state variables I_{jt}, K_{jt} where labour L_{jt} is assumed to be exogenous with respect to ψ_{jt} is an error term.

[16] For instance, Arnold (2005) provides examples of 3rd and 4th order polynomials. Yasar, Raciborski and Poi (2008) assume 2nd order polynomial series in age, capital and investment.

of surviving might be linked to higher productivity of firm j.[17] Moreover; firms with higher capital stock will be more likely to survive in the market despite low productivity than companies with smaller capital stock (see Yasar, Raciborski and Poi, 2008:2).[18] Then an expectation of productivity shocks based on the previous year's productivity can be defined as:

$$E(w_{jt+1} / w_{jt}, \chi_{it+1}) = g[P_{jt}, \phi_{jt} - \beta_k \ln(K_{jt})] \quad (16)$$

This expected productivity shock is required to calculate the second stage estimation equation such as

$$\ln(Y_{jt+}) - \hat{\beta}_L \ln(L_{jt+1}) = \beta_K \ln(K_{jt+1}) + g\left(\hat{\phi}_{jt}(I_{jt}, K_{jt}) - \beta_K \ln(K_{jt}), \hat{P}_{it}\right) + \varsigma_{it} + \gamma_{jt} \quad (17)$$

where γ_{jt} is the error term, $g(.)$is approximated by a higher order polynomial[19] in $\hat{\phi}_{jt}(I_{jt}, K_{jt}) - \beta_K \ln(K_{jt})$ and $P_{it} = \Pr\{\chi_{i,t+1} = 1\}$.[20] In order to obtain the correct value for β_K, it is necessary to apply non-linear least squares in equation (17).[21] After obtaining the correct value of the coefficient on different inputs following the procedure in equation (6), it is possible to obtain the value of TFP (see Eberhardt and Helmers, 2010:9).

A second structural estimator was proposed by Levinsohn and Petrin (2003). This structural estimator utilizes intermediate input demand as a proxy for productivity (w_{jt}).[22] The production function is estimated as:

$$\ln(o_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + \beta_M \ln(M_{jt}) + w_{jt} + \varepsilon_{jt} \quad (18)$$

where M_{jt} is intermediate inputs, and $\ln(o_{jt})$ gross output is the dependent variable.

The LP is a two-step procedure similar to the OP method. In this case instead of an investment function, there is an intermediate inputs function. This intermediate inputs function

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[17]In this mode, a productivity is assumed to follow 1st order Markov process which is described as follows $w_{jt+1} = E(w_{jt+1} / w_{j,t}) + \varsigma_{jt+1}$ where ς_{jt+1} represents the component which assumes that there is no correlation between productivity and capital in period t+1 (see Beveren, 2007).

[18] Following Yasar, Raciborski and Poi (2008), a firm j will decide to operate in the market, then $\chi_{j,t} = 1$ or exit the market, then $\chi_{j,t} = 0$. Hence, everything depends on some threshold (state variable) which is subject to capital stock $K_{j,t}$. This requires the followed rules for $\chi_{j,t} = 1$ if $\Omega_{j,t} \geq \Omega_{jt}(K_{j,t})$ and $\Omega_{j,t}$ is assumed to follow a 1st-order Markov process.

[19] Yasar, Raciborski and Poi (2007) assume a second-order polynomial, then Beveren (2007) and Arnold(2005) provide high-order polynomials.

[20] As Beveren (2007) suggests that a probability (P_{jt}) can be obtained by estimating a Probit model.

[21] This procedure has been implemented in many studies of productivity (see Eberhardt and Helmers, 2010, Yasar, Raciborski and Poi, 2007, Arnold, 2005).

[22] There are two reasons for this proxy. Firstly, a firm has to choose the intermediate inputs at time t on the knowledge about the level of productivity w_{jt}. Secondly, intermediate inputs are readily available in most firm-level datasets since value-added is commonly constructed from gross output and intermediate inputs (see Eberhardt and Helmers, 2010, Gasiorek, Augier and Varela, 2005)

depends on unobserved productivity and physical capital.[23] The first stage is an estimation of the production function to obtain values for $\hat{\beta}_L$ and $\hat{\zeta}_{jt}$ as

$$\ln(o_{jt}) = \beta_L \ln(L_{jt}) + \zeta_{jt}[\ln(K_{jt}), \ln(M_{jt})] + \varepsilon_{jt} \quad (19)$$

$$\zeta_{jt}[\ln(K_{jt}), \ln(M_{jt})] = \beta_0 + \beta_K \ln(K_{jt}) + \beta_L \ln(M_{jt}) + f_t[\ln(K_{jt}), \ln(M_{jt})] \quad (20)$$

where ε_{jt} is an error term.

Similarly, to identify Olley and Pakes's (1996) approach, the second stage of Levinsohn and Petrin's (2003) application is to obtain β_K by estimation equation (25).

$$\ln(o_{jt}) - \hat{\beta}_L \ln(L_{jt}) = \beta_K \ln(K_{jt}) + \beta_M \ln(M_{jt}) + g(\hat{\zeta}_{jt-1} - \beta_o - \beta_K \ln(K_{j,t-1}) -$$
$$\beta_m \ln(M_{jt-1})) + \xi_{jt} + \varepsilon_{jt} (21)$$

With the 'structural estimators' option (see Ackerberg, Caves and Frazer, 2006) there is a problem related to identifying the correct labour coefficient β_L, because labour demand L_{jt} is a function of the proxy for the productivity variable (w_{jt}).[24] The other solution to the endogeneity problem is "structural foundations" to the dynamic panel data estimators proposed by Bond and Söderborn (2006). Because both these estimation techniques cannot be implemented in sector-level analysis I discuss them only briefly here.

Stochastic frontier approach (SFA)

Stochastic frontier is an alternative method for estimating the production frontier and assumes a given functional form for the relationship between inputs and outputs.[25] The analysis of SFA originated with Aigner and Chu (1968) through the implementation of a Cobb-Douglas production function in the firm-level analysis:

$$\ln(Y_j) = \alpha_0 + \sum_{i=1}^{N} \beta_i \ln(x_i) - u_j \quad (22)$$

where j=1,…n (i-th companies), Y_j-the output of the j-th firm, x_i-vector for i-th inputs, u_j-non-negative random variable associated with technical inefficiency.

[23] The inverse function is a proxy for unobserved productivity follow way is $w_{jt} = f_t[\ln(K_{jt}), \ln(M_{jt})]$

[24] In this case investment or the intermediate input functions used to proxy for unobserved productivity have the functional form as $m_{jy} = h_t[w_{jt}, \ln(K_{jt}), \ln(L_{jt})]$.

[25] See Fecher and Perelman (1989), Nishimizu and Page (1982), Bauer (1990), Coelli, Rao, Donnell and Battese (2005) and Simar, Eeckaut and Daraio (2008), Battese, Coelli (1992)

The concept suggests that the whole production function will be moved down if the firm lacks the ability to obtain maximum output from given inputs (u_j). A negative sign of this random variable suggests a downward shift. Then the entire concept of SFA expands through the development of symmetric random error (γ_{jt}) as:

$$\ln(Y_j) = \alpha_0 + \sum_{i=1}^{N} \beta_i \ln\left(x_{ij}\right) - u_j + \gamma_j \quad (22)$$

where γ_{jt} is statistic noise, u_j is technical inefficiency, j is individual unit (firms), i -1,.. n number of inputs[26].

Simar (1992) and Hall-Härdle-Simar (1995) implement this stochastic model in panel analyses through the data generating process. As Schmidt and Lovell (1979) propose, this approach can be implemented in a Cobb-Douglas form with two inputs:

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) - u_{jt} + \gamma_{jt} \quad (23)$$

where γ_{jt}-statistical noise, u_j-technical inefficiency, j – individual unit (firms), i -1,.. n number of inputs, K –capital stock and L-labour.

However as Førsund, Love and Schmitdt (1980) and Kumbhaker and Lovell (2000) point out, the main weakness of the SFA is the difficulty to decompose individual residuals in two components (γ_{jt} and u_j) and compute the value of the productivity term. On the other hand, cross-firm data provide a solution[27] because the individual performance of each producer can be traced over a time period sequence which is impossible in a sector-level analysis.

2.2. Non-parametric approaches

The non-parametric approach includes three forms of productivity estimations: Index numbers, Data Envelopment analysis (DEA) and Free Disposability estimators (FDE)[28].

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[26] $u_{ji} \geq 0$ and $\gamma_{ji} \in IR$ for all j-individual unit (firms), i =1,.. N number of inputs, $u_{ji} \approx N^{+}(\mu, \sigma_u^2)$, $\gamma_{ji} \approx N(0, \sigma_\gamma^2)$

[27] However, there has been important progress in the area of stochastic frontier models, such as semi-parametric methods (see Park, Sickles, Simar, 1998), estimation of mean technical efficiency, prediction of firm-level technical efficiency, alternative functional forms and the dynamic stochastic approach (see Ahn, Good, Sickles 1999,2000, Hultberg, Nadri, Sickles,1999).

[28] Index numbers (Divisia index, Malmquist index, Hick-Moorsteen index), Data Envelopment analysis (DEA):constant returns to scale, the variable returns to scale and Free Disposability estimators (FDE) (see Simar, Eeckaut and Daraio, 2008, Coelli, Rao, Donnell and Battese, 2005)

Index approach

A description of the index approach emphasizes the significant separation between *TFP index* and *measurement of changes in TFP* [29]. While the empirical literature of *TFP index numbers* is much diversified, the aim of this section is to focus on various index numbers in the microeconomics panel analysis (sector- or firm level aggregation).

TFP index can be divided into three methods: the Hicks-Moorsteen Index, TFP Index based on the profitability ratio and Malmquist TFP Index[30].

The Divisia Index Numbers are defined as the difference in output and input growth rates. The formula for this index is:

$$T\dot{F}P = \dot{Y} - \dot{G} \quad (24)$$

where $\dot{G} = \sum_i \frac{W_i}{C} x_i \quad \dot{Y} = \frac{d \ln Y}{dt}$ where Y is observed output, G is an aggregate measure of observed input usage, W_i is the price of the i-th inputs, x_i is the observed use of the i-th inputs, C is the observed cost, t is time.[31]

The Hicks-Moorsteen Index[32] is the ratio of output and input growth rates which is another way of computing growth difference. This index follows the formula:

$$TFP = \frac{Growth\_in\_output}{Growth\_in\_input} = \frac{Output\_quantity\_index}{Input\_quantity\_index} \quad (25)$$

The Hicks-Moorsteen index can be formulated for two types of inputs - capital and labour - in a form of Cobb-Douglas function. This type of index has been used to analyse Polish manufacturing sectors (see Danka-Borsiak, 2011 and Jakubiak, 2002). The productivity determination formula is:

$$TFP_{jt} = \frac{Y_{jt}}{K_{jt}^{\beta_K} L_{jt}^{\beta_L}} \quad (26)$$

where j-th is individual (sector, firm), t is time period, β_K and β_L represents the cost of inputs[33].

[29] Index numbers are implemented to measure price and quantity changes across time and across individuals (such as firms, industries, regions, countries). Measurement of TFP changes uses index numbers such as Price Index Numbers (e.g. Laspeyres, Paasche, Fisher, Tornqvist indexes). The quantity index induces the direct approach and indirect approach where direct approach includes Laspeyres, Paasche, Fisher, and Tornqvist indexes (see Coelli, Rao, Donnell, Battese, 2005:90). Input and output quantity indexes are implemented individually in TFP index numbers.

[30] TFP Index can be developed by applying two different approaches: output-orientated TFI indices and input-orientated TFP indices.

[31] See Baumol (1988), Hulten (1973), Christensen and Jorgenson (1970), Gouyette and Perelman (1997) and Denne Fuss Waverman (1981)

[32] This index is attributed to Hick (1961) and Moorsteen (1961).

[33] If a firm is minimizing cost, then it will set β_K and β_L as the respective input cost-share. Also the productivity measures might be transformed into logarithmic form and calculated as $\ln(TFP_{i,t}) = \ln(Y_{i,t}) - \beta_{i,t}\ln(L_{i,t}) + (1-\beta_{i,t})\ln(K_{i,t})$ where labour share in production $\beta_{i,t}$ - is expressed as a

These indexes are used to compute technical change and efficiency changes because they contain no information on price changes (see Coelli, Rao, Donnell and Battese, 2005).

The third approach is the TFP index based on the profitability ratio. The TFP index formula is

$$TFP_t = \frac{(R_t / R_{t-n}) / Output\_price\_index}{(C_t / C_{t-n}) / Input\_price\_index} \quad (27)$$

where R_t and R_{t-n} are revenues respectively for two different periods s and t, C_t and C_{t-n} are the costs of s given firms in periods t and t-n.

The Malmquist TFP Index is based on computing a distance function[34]. This index can include both output-orientated TFI indices and input-orientated TFP indices. This index is constructed to measure the radial distance of the observed output and input vectors in two different periods (s and t), relative to a reference technology. The Malmquist output-orientated TFP indices maximize the level of output to produce goods by using a given input amount and known technology[35]. The Malmquist input-orientated TFP indices maximizes the level of input to produce goods by using a given output amount and known technology (see Coelli, Rao, Donnell and Battese, 2005).

The output-orientated Malmquist productivity index is given as:

$$m_0(Q_{t-n}, Q_t, X_{t-n}, X_t) = \left[m_0^{t-n}(Q_{t-n}, Q_t, X_{t-n}, X_t) * m_o^t(Q_{t-n}, Q_t, X_{t-n}, X_t)\right]^{0.5} \quad (28)$$

where quantities are defined respectively t-n and t for Q_{t-n} and Q_t production outputs, then X_t and X_s are inputs for two periods s and t and the prices of inputs are W_t and W_s[36].

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ratio of total labour compensations to gross value added, L-labour measures, K-physical capital stock measures under the assumption of a constant returns to scale (see Jakubiak, 2002).

[34] The distance function is useful for describing the technology in a way that makes it possible to measure productivity. This concept was proposed by Malmquist (1953) and Shephard (1953). The distance function allows for a description of a multi-input and multi-output production technology without the need to specify a behavioural objective such as cost-minimization or profit-maximization (Coelli, Rao, O'Donnell, and Battese, 2005:47). For instance, an input distance function characterizes the production technology by looking at a minimal proportional contraction of the input vector, given the output vector. Then an output distance function considers a maximal proportional expansion of the output vector, given the input vector (Coelli, Rao, O'Donnell, and Battese, 2005:47).

[35] A similar result is obtained for the Malmquist input index based and the output index, when the distance function for periods s and t is a translog function with identical second-order parameters, then the total Malmquist output index of a geometric mean of the period-t and period-s is $m_i(Q_s, Q_t, X) = \left[m_i^s(Q_s, Q_t, X) * m_i^t(Q_s, Q_t, X)\right]^{0.5} = \prod_{n=1}^{N}\left[\frac{X_{i,t}}{X_{i,t-n}}\right]^{(\varpi_{i,t}+\varpi_{i,t-n})/2}$ - Törnqvist input quantity index when ϖ_{it} and ϖ_{is-n} are input cost-shares in periods t and s respectively, n- different inputs.

[36] (32) where d_0^s - is a notation for a distance function in period s. Malmquist productivity index for period s is $m_0^{t-n}(Q_{t-n}, Q_t, X_{t-n}, X_t) = d_0^{t-n}(Q_t, X_t) / d_0^{t-n}(Q_{t-n}, X_{t-n})$ Then, a period-t Malmquist productivity index based on period t-technology $m_0^t(Q_{t-n}, Q_t, X_{t-n}, X_t) = d_0^t(Q_t, X_t) / d_0^{t-n}(Q_{t-n}, X_{t-n})$ (33) where d_0^t - is notation for a distance function in period t.[36] Taking into account both Malmquist productivity index for both period s and t, the Malmquist TFP index is defined as the geometric average of these two indices.

Malmquist input oriented productivity index had similar procedure to be constructed as an output-orientated TFI indices. Malquist input-orientated index can be defined for two periods t-n and t as:

$$m_i\,(Q_{t-n}, Q_t, X_{t-n}, X_t) = \left[m_i^{t-n}(Q_{t-n}, Q_t, X_{t-n}, X_t) * m_i^t(Q_{t-n}, Q_t, X_{t-n}, X_t)\right]^{0.5} \quad (29)$$

where quantities are defined respectively t-n and t for Q_{t-n} and Q_t as production outputs, then X_t and X_s are inputs for two period s and t and prices of inputs are W_t and W_s.

The Malmquist productivity index can be decomposed into two parts which allows measures of efficiency change and technical change[37]. Definitely, there is an open question about the properties of a return to scale and what Malmquist TFP index captures. For instance, if a constant return to scale is valid then there are two main sources of productivity growth, efficiency change and technical change. On the other hand, Caves, Christensen and Diewert (1982a) do not make any assumptions about the economic scale in relation to the Malmquist TFP index (see Färe, Grosskopf and Love, 1994 and Fare, Grosskopf and Margiritis, 2006).

There is a large micro-firm-economics literature with regards to a fourth source of productivity growth, that is an multi-output and multi-input firms – output mix effect (OME) and the input mix effect (IME) (see Raa 2005 and Fare, Primont 2003)[38]. However, because it is not a part of possible sector analysis it is not investigated here in more details.

The measures in changes in TFP have also been broadly discussed in the literature[39]. The most popular approaches are the Hick-Moorsteen and Törnqvist to compute changes in TFP[40]. This approach is formulated as equation for two different period s and t as:

[37] Malmquist productivity index is given as $m_0(Q_{t-n}, Q_t, X_{t-n}, X_t) = \left[m_0^{t-n}(Q_{t-n}, Q_t, X_{t-n}, X_t) * m_o^t(Q_{t-n}, Q_t, X_{t-n}, X_t)\right]^{0.5}$ Through implementation of equations (32) and (33) then Malmquist TFP index is $m_0(Q_{t-n}, Q_t, X_{t-n}, X_t) = \left[\frac{d_0^{t-n}(X_t, Q_t)}{d_0^{t-n}(X_{t-n}, Q_{t-n})} * \frac{d_o^t(X_t, Q_t)}{d_o^t(X_{t-n}, Q_{t-n})}\right]^{0.5}$ where $\frac{d_0^t(X_t, Q_t)}{d_0^{t-n}(X_t, Q_t)}$ is an efficiency $= \frac{d_0^t(X_t, Q_t)}{d_0^{t-n}(X_t, Q_t)} * \left[\frac{d_0^{t-n}(X_t, Q_t)}{d_0^t(X_t, Q_t)} * \frac{d_o^t(X_{t-n}, Q_{t-n})}{d_o^t(X_{t-n}, Q_{t-n})}\right]^{0.5}$ change and $\left[\frac{d_0^{t-n}(X_t, Q_t)}{d_0^t(X_t, Q_t)} * \frac{d_o^t(X_{t-n}, Q_{t-n})}{d_o^t(X_{t-n}, Q_{t-n})}\right]^{0.5}$ is a technical change. As Coelli, Rao, Donnell and Battese (2005:109-110) pointed out, the Malmquist output index based on technology in period s with an arbitrarily selected input vector x is defined as $m_0(Q_{t-n}, Q_t, X) = d_0^{t-n}(Q_t, X) / d_o^{t-n}(Q_{t-n}, X)$, hence, the similar way Malmquist output index can be defined for period-t . Then, if the distance function for periods s and t is as a translong function with identical second- order parameters, then the total Malmquist output index of a geometric mean of the period-t and period-s is as $m_o(Q_{t-n}, Q_t, X) = \left[m_0^{t-n}(Q_{t-n}, Q_t, X) * m_0^t(Q_{t-n}, Q_t, X)\right]^{0.5}$ - Törnqvist output index

[38] The interesting approach of Balk (2001) shows that three main sources of productivity growth are technical change (shift in the production technology), efficiency change (firm's ability to use the available technology) and scale efficiency change.

[39] See Coelli, Rao, O'Donell and Battese (2005), Caves Christensen and Diewert (1982), Jakubiak (2002)

[40] It is also be defined as Fisher index (see Coelli, Rao, O'Donell and Battese , 2005 and Caves Christensen and Diewert, 1982)

$$\Delta TFP_{t-n,t} = \ln\left[TFP_{t-n,t}\right] = \ln\left[{Output\_Index_{t-n,t}} \middle/ {Input\_Index_{t-n,t}}\right] = \ln[Output\_Index_{t-n,t}] - \ln[Input\_Index_{t-n,t}]$$

(30) where t and t-n-periods [41].

The Hick-Moorsteen approach is more intuitive than Törnqvist index. The utilization of Törnqvist index is done as follows:

$$\ln\left[TFP_{st}\right] = \frac{1}{2}\sum_{m=1}^{M}(r_{is} + r_{it})(\ln Q_{mt} - \ln Q_{ms}) - \frac{1}{2}\sum_{n=1}^{N}(s_{ns} + s_{nt})(\ln X_{nt} - \ln X_{ns}) \quad (31)$$

where r_s is the revenue share of output, s_s is cost shares for inputs, s and t different periods, m-th output commodities and k denotes the k-th input commodities.

DEA and FDH approaches - a linear programming procedure

DEA and FDH are the other approaches that do not have an assumption about the fixed form of a production function. They are not based on a relationship between factors and outputs.

The DEA approach basic model was introduced by Charnes, Cooper and Rhodes (1978). DEA method is commonly used to evaluate the efficiency of a number of producers by comparing each producer with the "best" producers on the market[42]. The "best" producers on the market define an optimal efficient point. Each producer is described as a decision making unit (DMU) in a linear programming procedure for frontier analysis of inputs and outputs. The DEA approach is defined through the following perspectives: input or output orientation, constant or variable returns scale, price information and allocative efficiency, non-discretionary variables and bad or undesirable outputs. The one method to solve a linear programming calculation is to add the convexity constraint (convex cone) with regards to these different perspectives. However, these constraints might be not always provide a full description of the real economy (for instance in the case of constant return to Scale for manufacturing sector) [43].

2.3 Summary of weakness and strengths across TFP measures

Several problems and drawbacks might be pointed out in utilizing the parametric approaches to calculate the production frontier. The main problems are linked to statistical

[41] It can be two different individuals (such as two different firms, sectors and countries).
[42]See Afriat (1972), Färe, Grosskopf and Logan (1983), Banker, Charnes and Cooper(1984), Simar and Wilson (2002)
[43] The assumption of Constant Return to Scale is not always appropriate. Firms are not always operating at optimal scale because of imperfect competition, government regulations and financial constraints. The other issue is that it is an input-oriented model. In this case of sectors, the idea is that it is simply utilization of input which causes technical inefficiency with output levels treated as given. However, it is possible to analyse technical efficiency with maximization of output with input levels held constant (see Coelli, Rao, O'Donnell, and Battese 2005).

problems for a deterministic frontier to predict the correct value of residuals, and the stochastic frontier in its ability to distinguish noise from efficiency (see Simar, Eeckaut and Daraio, 2008)[44]. Moreover, it is less plausible to be able to implemented multiple-output or multiple-input situations in the aggregated-sector data analysis. On the other hand, the parametric approach can easily interpret estimation parameters. All non-parametric models capture the distance from the most efficient utilization of inputs to maximalization of output or minimalization of the cost production that is defined through a distance function section. These approaches do not have an assumption about the fixed form of a production function as such, and moreover they are not based on a relationship between factors and outputs. However, in order for simple computation, they then have to introduce certain constraints with regards to economy of scale or input or output orientation. In this case, a semi-parametric approach seems to be a solution, which is laid between parametric and nonparametric ways of measuring TFP. This approach allows for controlling of problems with bias that comes out through parametric techniques. The bias problem connects to 'transmit' to input choices, selection bias and an endogeneity of input choices (see Table 1).

In order to summarise and compare all different TFP techniques for conducting the empirical analysis, following Coelli, Rao, O'Donnell, and Battese (2005) and Kathuria, Raj and Sen (2011), six key parameters are defined in Table 2.

Table 2: Weakness and strengths for different TFP measures

Parameters	Semi-parametric	Parametric		Non-parametric	
		The estimation of production frontier	Stochastic Frontier	Index approach	DEA/FDH
Specification of function Form	Required may in incorrect	Required may in incorrect	Required may in incorrect	Required	Not required
Outliers	Not as sensitive	Not as sensitive	Not as sensitive	Sensitive	Inaccurate efficiency assessment
Sample Size	Moderate sample size is required	Moderate sample size is required	Large sample	Small sample size adequate	Small sample size adequate
Prevalence of high collinearity among inputs	Possible misleading interpretations	Possible misleading interpretations	Possible misleading interpretations	?	Better discriminat ion
Noise/Measurem ent errors	?	Affected but less than DEA	Strong distributional assumptions	Sensitive	Highly sensitive
Statistical Testing	Possible	Possible	Possible	Not	Possible

[44] Especially, a situation of many outliers or too-large residuals ε_j might be problematic in identifying the correct value of productivity.

				possible	but complex

Source: Coelli, Rao, O'Donnell, and Battese (2005) and Kathuria, Raj and Sen (2011)

2.4. Data issues for productivity analysis

A review of TFP measures suggested that there are three categories of variables required for productivity calculations. These variables are: output quantities, input quantities, and prices of output and inputs. In this section, I will answer the problem how a selection of output and inputs measures has impact on TFP measuring?

Starting with output quantities, two different categories are considered; single-output firms and multiple-output firms[45]. This choice is especially important for firm-level analysis. I do not further elaborate on this issue because the analysis of productivity is focused on the manufacturing sector and thus in this case the output is computed at the arrogated level.

However, it is important to choose an appropriate measure of output. One choice is between gross output and gross value-added.[46] The empirical literature has argued strongly for using value-added as the measures of production.[47] Diewert (2002) suggests that costs of intermediate input may have significant differences across industries so in this mater it more advisable to use value-added measure for output. Similarly, Hossain and Kaunahara (2004) argue that the use of gross output in the model might diminish the role of capital and labour in productivity growth. According to Kathuria, Raj and Sen (2011) TFP growth based on value added measure is greater than that of output based, and this upward bias is created by not including cost of intermediate goods and services. On the other hand Norsworthly and Jang (1992) suggests that usage of gross-output as a measure of output might help avoid the problem of distortion of technology, which can be caused by removing the effect of changes in prices of purchased raw-materials inputs from the costs of production. Other researchers are of the same view (Rao, 1996a, Ray, 2002 and Trivedi, 2004), which indicates that production analysis without investigation of material inputs does not provide the overall picture. In the case of this analysis both measure of output (gross output and gross value-added) were used to compute TFP for manufacturing sector.

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[45] In the case of single-output firm, the output is measured by the number of units produced. The situation for multiple-output firms is more complicated to calculate the output. In this case it is important to specified methodology to calculate the price of inputs and products (see Coelli, Rao, O'Donnell, and Battese, 2005).

[46] Gross output is defined as the sum of the value of outputs of all the firms belonging to the sector. Gross value-added is a measure of the total value of net output of the entire sector outputs that is used as an intermediate input into the sector itself (see Coelli, Rao, O'Donnell, and Battese, 2005:156).

[47] See Coelli, Rao, O'Donnell, and Battese (2005), Balakrishnan and Pushpangadan (1994, 1998), Godar (1986), Ahluwalia (1991), Diewet(2000), Hossain and Kaunahara (2004)

The other issue is to make a proper adjustment from the nominal value aggregate into real value using an appropriate price index. Here there are two methods to be used: single deflation method or double deflation method. Single deflation includes adjustment through output price, while double deflation is related to both output and input prices changes. As long as the proportion between changes in input and output prices is constant, the results of TFP calculation are the same for both deflation methods. If the input price growths faster than output price that island deflation calculation of TFP will obtains a downward biased compare to double deflation computations (Coelli, Rao, O'Donnell, and Battese, 2005, Kathuria, Raj and Sen, 2011).

After this short discussion related to output measurement, I described measurement issue with respect to inputs. The input quantities might be classified into five main categories: capital (K) labour (L), energy, material inputs (M) and purchased services.

The most customary methods to measure labour are number of persons employed, number of hours of labour input, number of full-time equivalent employees and the total wages and salaries bill (see Coelli, Rao, O'Donnell, and Battese, 2005). Among all these instruments, the number of hours worked is the most accurate measure; however, it is also necessary to take the contracts of employees into account (full-time or part-time employees). For instance, wages and salaries are required for making adjustments for differences in employees' earnings in different firms. Even if these firms are in the same sectors, employee benefits might be different because of firm location (i.e in a capital city or local town). The other measures, such as number of persons employed, face the problem of constructing a proper measure of full-time and part-time employees in an individual company (see Coelli, Rao, O'Donnell, and Battese, 2005, p. 142)[48].

Capital input (K) is the most challenging data to obtain for calculating productivity. The capital input mainly includes three categories, namely capital stock; capital services and capital cost (see Coelli, Rao, O'Donnell, and Battese, 2005). The main problem is how to determine a value of capita stock, measurement of capital services and used costs of capital. There are several methods to measure the value of capital stock, such as the perpetual inventory method (PIM), replacement value, sale price of fixed assets or book value of fixed assets. However each of measures has its own drawbacks. For instance, in the PIM method, if the capital input is given as a measure of total service flows from various capital assets for a given enterprise, then assets are generally seen as fixed assets (such as machinery, equipment) (see Mahadevan, 2003). As Kathuria, Raj and Sen (2011) pointed out, perpetual inventory method (PIM) does not address the problem of capacity utilization. Other measures, such as replacement value or sale price of fixed

[48] Still these measures suffer from a limitation in terms of quality of employees: skilled and unskilled workers (see Mahadevan, 2003 and Kathuria, Raj and Sen, 2001).

assets suffer from a lack of data availability. Furthermore book value method might not provide the accurate data of physical stock of machinery and equipment used because of off-balance transaction (e.g. equipment leasing).

Lastly energy, material (M) and purchased services are significant categories of input. As there is a lack of proper data, it is not possible to obtain the details. Thus, it is necessary to aggregate the data (see Coelli, Rao, O'Donnell, and Battese, 2005)[49].

3. Review of empirical productivity literature of Poland and CEE

I now turn to a brief review of work carried out in measuring productivity in Poland in the past two decades. This section focuses especially on Manufacturing sector productivity analysis. Firstly, I review empirical studies which analyse the case of Poland, then secondly I investigate the empirical productivity studies for Central Eastern European Countries (CEE) as a whole, which include Poland in their country sample.

To my knowledge I have found 24 papers which discussed productivity in Poland as single country studies. These can be groups into three categories: productivity analyses of the whole economy, analyses of the manufacturing sector-level, and analyses of the firm-level.

All productivity analyses of the whole economy use a parametric approach via the estimation of production frontiers to measure productivity[50]. A majority of these empirical studies focused on examining the effect of catch-up, FDI-spillover effects, privatization effects and trade liberalization effects. They found a positive productivity growth between 1 and 4 percentage points. The only exception was Broek and Koln's (2000) empirical study which pointed out negative productivity growth of -0.7% (see Table 3). Sector and firm level analyses of polish manufacturing confirm also this positive trend in productivity growth[51]. In addition, the results for productivity suggests that manufacture sectors is more labour intensive than capital intensive because the output elasticity to labour input is between 0.55 and 0.7 (Table 3).

On the other hand, the empirical studies at sector level compute a productivity growth between 3.6 and 5.5% which is higher than results from the whole-economy analysis (see Table 3). Apart from implementation of a parametric approach on sector-level analysis (see Dańska-

[49] The majority of data is available in a nominal form; hence it is necessary to calculate a deflator.
[50] Eight empirical studies: Piatkowski (2005), Kolasa and Żółkiewski (2004), Rapacki (2002), De Broek and Koln (2000), Żółkiewski(2003), Welfe (2003), Gradzewicz,Kolasa (2004), Czyżewski (2002)
[51] Nine sector-level studies: Woodward, Binkiewicz, Cukrowski, Gorynski and Jakubiak (2005), Marczewski and Szygieslki (2005), Barbone, Marchetti and Patenosto (1996), Kolasa and Żółkiewski (2004), Jakusiak (2002,2006), Pawlik (2006), Bradley and Zaleski (2003), Dańska-Borsiak(2011), Five firm-level analysis: Marczewski and Szczygieski (2005), Hagemejer (2006), Cullmann and Von Hischhausen (2006), Kotowski and Zagoździński (2005), Pinto, Belka and Krajweski (1993)

Borsiak, 2011 and Kolasa and Żółkiewski, 2004), researchers use other techniques to measure productivity: an index approach (see Jakusiak, 2002, 2006) and partial productivity measures such as a labor productivity (see Woodward, Binkiewicz, Cukrowski,Gorynski and Jakubiak, 2005, Marczewski and Szygieslki, 2005, Barbone, Marchetti and Patenosto, 1996, Pawlik, 2006, Bradley and Zaleski, 2003).

Table 3: Description of main empirical studies about Polish productivity

Source	Method of TFP calculation	Period	Output elasticity with respect to labor input	Size	TFP number
Kolasa, Żółkiewski(2004)	Parametric approach- the estimation of production frontier by followning Shaikh (1974) and Harrigan's (1997) procedure.	1992-2002	α= 0.55 (Gradzewicz,Kolasa, 2004)- GK α= 0.56 (Czyżewski, 2002)-CZ α= 0.7 (Kolasa, Żółkiewski, 2004)-KZ	whole economy and manufacturing sector (21 sectors)	GK-3.1% CZ-3.4% KZ-3.6%
Rapacki (2002)	Parametric approach- the estimation of production frontier	1992-2002	α= 0.65	whole economy	4%
De Broek, Koln (2000)	Parametric approach- the estimation of production frontier	1992-1998 1980-1998	α= 0.65	whole economy	-0.7% -0,49%
Żółkiewski (2003)	Parametric approach- the estimation of production frontier	1991-2001		whole economy	2,6%
Welfe (2003)	Parametric approach- the estimation of production frontier	1992-1998		whole economy	1%
Jakubiak (2002,2006)	Non-Parametric approach-TFP index measure	1994-2002	Labour share in production is revenue-based, expressed as a ratio of total labor compensations to value added	Manufacturing (19 sectors)	5,5%
Kolasa (2003)	Parametric approach- the estimation of production frontier	1994-2002		Manufacturing (21 sectors)	66% relative to Germany*
Monnikhof and Van Ark (2002)	Labour productivity: Gross output per person Value Added per Person	1996		Manufacturing	25.4% relative to German productivity*
Piatkowski (2005)	Non-parametric approach index measures Labour productivity	1995-2000	Average share labour compensation in GDP- 55,9%	Whole economy	3,97%
Dańska-Borsiak(2011)	Parametric approach- the estimation of production frontier-Dynamic Panel GMM	1998-2007		Manufacturing (22 sectors)	Positive growth

*Notes:**Germany =100. *Source:* Author's analysis based on Kolasa, Żółkiewski (2004), Rapacki (2002), De Broek, Koln (2000), Żółkiewski (2003), Welfe (2003), Jakubiak (2002), Kolasa (2003), Monnikhof and Van Ark (2002), Piatkowski (2005), Dańska-Borsiak (2011)

Similar to sector-level analysis of productivity, the majority of researchers used partial productivity measures to investigate productivity on firm-level; however there are some exceptions such as the semi-parametric approach taken by Olley and Pake (1996), Hagemejer (2006) and the stochastic frontier and DEA analysis offered by Cullmann and Von Hischhausen (2006). It is worth mentioning that the partial productivity measures can lead to misrepresentation of firm and sector performance (see Kathuria, Raj and Sen, 2011). For instance improvement in labor productivity could be caused by changes in scale economies (see Mahadevan, 2004).

An investigation of the empirical productivity studies for Central Eastern European Countries (CEE) which include in their country sample Poland, reveals this to be a not as intensively researched area (13 studies)[52]. A majority of the empirical studies employed labor productivity measures and focused on examining the effect of catch-up, trade liberalization and FDI effects.

In sum, this review indicates that it is just few studies that investigating productivity in Poland and majority of them usage the partial productivity measures or parametric frontier approach.

4. Methodology and Data for sector-level measures analysis

4.1 Manufacturing sector-level data and variables construction

Manufacturing sector level data

Data was obtained from Statistical Yearbook of Industry from the Polish Central Statistical Office (CSO)[53]. According to the Polish Classification of Activities and *NACE rev. 1.1* the industry is divided into main three divisions: *Mining and quarrying, Manufacturing* and *Electricity, Gas and Water supply,* while *Manufacturing* division is itself divided into 22 sections (Table 2 in Appendix 3). This research was conducted between 1995 and 2007. Selecting this period allows for consistency of data. Since 1995

[52] Sector level analyses include Monnikhof and van Ark (2002), Van Ark Bart (1999), Havlik (2004), Piatkowski and Van Ark (2004), Stephan (2004). On the other hand, firm-level analysis consider Torlak (2004), Majcen, Radosewic and Rojec (2003), Damijan, Majcen, Rojec and Knell (2001), Gersl, Rubene and Zumer (2007), Wziatek-Kubiak, Jakubik and Antczak (2004), Claessens, Djankov and Pohl (1997), Zukowsa-Gagelmann (2001), Tonini and Jongeneel (2006)

[53] All companies in Poland receive a REGON number and they are obliged to provide simplified balance sheet reports and cash flows statement. Based on this data, CSO calculated indicators for manufacturing sectors. Data regarding the financial management of companies include economic entities keeping accounting ledgers and employing more than nine employees. The basic company activity is defined in accordance with in accordance with the Polish Classification of Activities (PKD) and *NACE Rev. 1.1*.

Polish manufacturing data analyses have been made to comply with EUROSTAT's *"Nomenclature des Activités de Communauté Européenne –NACE rev. 1.1*" through a decree of the Polish Council of Ministers. Also 2007 was chosen because for two years after publication the Polish Statistic Office continue to correct and update their data[54].

Variables construction

Input quantities and output aggregates are required in this analysis to compute TFP. Also required are definitions for the value of output, capital, intermediate inputs consumption and investments, comparable over time and across industries. The definition of variables and the deflator used are provided later in this section.

Output

There are essentially three indicators to describe the output in Polish manufacturing sector.[55]

[54] However, these corrections can happen for periods even longer than 2 years. Manufacturing data for period between 1995 and 2005 were available in hard copy which allowed these corrections over this longer period to be more visible.

[55] It is important to analyse the output aggregates for sector analysis: sold production, gross output, gross value added , value of sold production and industrial production . All four categories expressed in million zloty (the Polish currency). However, there is a problem with the data availability for value of sold production and industrial production and as a result there are three indicators.

Table 4: Description of output variables

Notation	Variable description
Gross output *(gu)*	This variable includes 1) revenues from the sale of self-manufactured products; 2) margins realized on the sale of commodities purchased for re-sale; 3) the value of products in the form of settlements in kind; 4) products designated for increasing the value of own fixed assets; and 5) the changes in inventories of finished goods and work in progress.* This variable in expressed in million zlotych.
Gross value added *(gva)*	This variable is a measure of the net total value of output-mainly a portion of gross output manufactured in industry minus the value of intermediate consumption. This variable in expressed in million zlotych.
Sold production *(s)*	This measure includes products designated for increasing the value of own fixed assets, and the changes in inventories of finished goods and work in progress. [56] Also sold production includes the value of finished products sold (regardless of whether or not payments due were received from them), semi-finished products and parts of own production, the value of paid work and services rendered, lump-sum agent fees in the case of concluding an agreement on commission terms and full agent fees in the case of concluding an agency agreement. This variable in expressed in million zlotych.

Notes: Gross output definition according to CSO is slightly different than commonly understood. As Coelli, Rao, O'Donnell, and Battese (2005:156) gross output is defined as the value of the total outputs of all the firms belonging to a particular sector. *Source:* Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Inputs quantities

In this subsection, I provide the definitions and explore concerns regarding these definitions for the input quantities for the followed categories such as capital (K), labour (L), energy (E) and material inputs (M).

Capital

The measure of capital input has been widely discussed in the theoretical and empirical literature. As mentioned in previous subsection 2.4, this discussion has not lead to agreement with a correct measure of capital. Most studies in the Polish manufacturing sector do not use the Perpetual Inventory Method (PIM method), as the Polish Central Statistical Office (CSO) does not provide information on the accumulated depreciation of capital on manufacturing sector level. Hence, PIM method could not be used in the TFP computation. In this case, inputs of physical capital (K) are defined by a gross value of fixed assets (*gvfa*) in thousand zloty. Data for this category is available for the period between 1995-2007 for all divisions, sections and sectors.

[56] Labour cost defines as the sum of gross wages and salaries, non-wage related expenditures is not provided for the 22 sectors. It can be problem to do calculation in the case of sold production or gross output.

Labour

As was mentioned in previous subsection 2.4, the number of persons employed is the most common measure of Labour in empirical analyses of productivity. This type of labour measure is also widely used in polish manufacturing studies (see Dańska-Borsiak, 2011 and Jakubiak 2002, 2006). According to Polish Central Statistical Office (CSO) at the sector level this labour measure might be defined in three ways: the average salary of full-time paid employees, employment, as of 31 XII and average number of employed persons in the industry (see Table 5)[57].

Table 5: Description of labour indicators

Average salary of full-time paid employees *(ape)*	This measure includes seasonal and temporary employees and part-time paid employees in terms of full-time paid employees (expressed in thousands zlotych)
Employment, as of 31 XII (*em31_*)	Full-time paid employees (including seasonal and temporary employees) and part-time paid employees in their primary job without converting them into full-time paid employees (expressed in thousands zlotych)
An average number of employed persons in the industry(*em*)	This measures is is obtained after converting part-time paid employees to full-time paid employees excluding employers own-account workers and agents (expressed in thousands zlotych)

Source: Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Material inputs

The other input is a material input (M). In CSO's data it may be defined as intermediate consumption (*ic*)[58]. Intermediate consumption includes the value of

[57] The Polish Central Statistical Office (CSO) provides other labour measures for sector level analyses, such as the number of hours of labour and the total wages- and salaries bill. The number of hours of labour has been defined via the three main indicators as: i) total work-time paid, the time that an employee remains at the disposal of employer in the workplace, place of employment or other place designated for performing work (measured in hours per paid employee) ii) Paid regular work-time (measured in hours-per-paid employee) and iii) Paid overtime work-time p (measured in hours per paid employee). The total wages and salaries bill is defined as the average monthly (nominal) wages and salaries paid to each employee. This includes the following categories: personal wages and salaries, excluding wages and salaries of a person engaged in outwork and apprentices and persons employed abroad, payment from profit and balance surplus in co-operatives, annual extra wages and salaries for employees of budgetary sphere entities, fee paid to selected groups of employees for performing work in accordance with a labour contract (this index is expressed in million zlotych). Among these four labour indicators, total work-time paid and employed persons in industry are not available for all subsectors for the whole period. Total work-time paid is obtained for the period between 1995 and 2007. For 1996, the data are not available for sections with id numbers manufacturing of tobacco products, publishing, printing and reproduction of recorded media products, manufacturing of office machinery and apparatus and Recycling.

[58] This variable is expressed in million zloty.

consumed materials (fuels etc.), raw materials, energy, technological gases, outside services, financial intermediation services etc. This definition of intermediate consumption also includes purchased services (S).

Proxy for unobserved productivity shocks (Investments and Intermediate consumption)

Lastly, it is worth mentioning indicators that are useful for the semi-parametric estimation to be a proxy for computing unobserved productivity shock. For Olley and Pakes' (1996) approaching the data for investment function was required. In CSO's data, there are five different indicators (see Table 6)[59].

Table 6: Description of investments indicators

Total investments *(i)*	This category is described as an investment outlays. This indicator includes financial or tangible outlays to create a new fixed asset or improvement of existing capital asset items, or initial investments for j-th manufacturing sector. This variable is expressed in mln zloty
Total investments in fixed assets (*ifa*)	This category is defined as investment outlays on fixed asset include building and structures, machinery, technical equipment and tools, transport equipment for j-th manufacturing sector. This variable is expressed in mln zloty
Total investments in fixed asset building (*ifab*)	This category is defined as investment outlays on buildings, real estates and constructions for j-th manufacturing sector. This variable is expressed in mln zloty
Total investments in fixed asset transport (*ifat*)	This category is defined as investment outlays on transport equipment and machineries for j-th manufacturing sector. This variable is expressed in mln zloty
Total investments in fixed asset machinery (*ifam*)	This category is defined as an investment outlays on equipment and machinery. This variable is expressed in mln zloty

Source: Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Similar to Olley and Pakes'(1996) approach, Levinsohn and Petrin's (2003) analysis requires an additional variable to provide a proxy for unobserved productivity, such as a material input. Material input can be measured through three variables from CSO's data: an intermediate consumption (*ic*), a consumption of electricity (*cel*) and a direct consumption of electricity (*dce*) (expressed in TJ)[60].

[59] Data for all categories of investment indicators are not available for a whole period. Between 2001 and 2007 the data does not exist for 33 Recycling and 26 Manufactory of office machinery and computer.

[60] Intermediate consumption (*ic*) is expressed in million zloty; consumption of electricity (*cel*) and a direct consumption of electricity (*dce*) are expressed in TJ. Data for a consumption of electricity and a direct consumption of electricity are available since 1999.

Price deflator

The CSO's dataset did not provide a consistent measure for input deflator. The common deflator was implemented as price indices of sold production of industry. According to CSO's database this deflator is classified in the line to NACE classification (one-digit, two-digits and three-digits). As Greenstreet (2007) and Eberhardt and Helmers (2010) pointed out, the single deflated price indicator is an inappropriate measure for all parameters, such as output, investments, physical capital[61].

4.2. Sector productivity methodology

This methodology has two main methodological subsections: the first is for *TFP measures on level* and the second describes the methodology for *measurement of changes in TFP*. Because of potential problem of misrepresenting the performance of firms in the manufacturing sector through partial productivity measures, this analysis focuses on TFP measures (see Coelli, Rao, O'Donnell, and Battese, 2005).

TFP measures on level

In this paper, TPF is estimated using parametric, semi-parametric and non-parametric approaches. *The estimation production frontier* is utilized in the parametric method, the proposed new '*proxy for semi-parametric approach'* by Olley Pakes (1996) and Levinsohn and Petrin (2003) for cross-sector analysis and *Index approach-Hicks-Moorsteen* methodology in the non-parametric approach. These methods were chosen because they seem to be correct for estimating Polish manufacturing data, as there is not large number of observations points, and also that this data is suspect to serious noise caused through intensive process of economic transformation since 1990.[62] Other

[61] All variables were deflated to 1995 prices level. All variables were expressed in logarithm form for production estimation. For instance, ln(s) is expressed as ls. The same rule was expressed to other variables.

[62] According to the Privatization Act of 1990, the most of the state enterprises were converted into state-owned corporations. This process was called 'corporatization' or 'commercialization'. In these state-owned corporations the employees have a right to elect one-third of the Board of Directors and the other two-thirds being selected by the owners of the corporation. Another method of privatization was called liquidation (See Kochanowicz, Kozarzewski, Woodward,2005). The liquidation method involved the transfer of the assets of an enterprise into a new company, provided that a majority of the employees became owners in the company. Small and medium-sized enterprises were privatized in that way. However, some small and medium-sized firms were privatized by public auction, with the State arranging

parametric approaches such as stochastic frontier analysis required a large samplem while the other non-parametric approach-DEA is highly sensitive to a noise in the data (see Table 2).

The estimation production frontier

I used a parametric estimation of the production frontier to estimate sector efficiency for Polish manufacturing. The procedure follows Beveren's (2007) study. I estimated the Cobb-Douglas production function with two inputs: labour (L) and capital (K) for two different bases: gross-output base and value-added base in equations (32) and (34).

Value-added base

The estimation equation is form is followed as:

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + w_{jt} + \varepsilon_{jt} \text{ (32)}^{63}$$

where j – individual industry sectors, t =1,.., T time periods , Y_{jt}-gross value added, L_{jt}-labour will be expressed by three different indicators (*em, em31_ ,ape*) and K_{jt} is physical capital stock (*gvfa*), α_0- measures the mean efficiency level across sectors and over time , ε_{jt} identifies measurement error and random noise, w_{jt} a productivity term (TFP).

In order to solve the TFP parameter, it is necessary to estimate the empirical equation (45) to obtain the values of β_L and β_K (respectively $\hat{\beta}_L$ and $\hat{\beta}_K$) and the subscripted values:

$$\hat{w}_{jt} = \ln(Y_{jt}) - \hat{\beta}_L \ln(L_{jt}) - \hat{\beta}_K \ln(K_{jt}) \text{ (33)}$$

for the bank financing for the buyers (this is known as 'direct privatization'). The Polish government received $1.4 was received in 1994, in $2.5 billion was obtained, $2 billion by this foreign direct the first half of 1996, while , in the first half of 1998 $5 billion was obtained (see Bekeart, Camplbell (2002c). Since the Round Table in 1989 the justice system was reformed. In 1992 Poland implemented the "Little Constitution" which amended the Constitution of 1952. This amendment allowed for the separation of powers and secured the position of the court system. The courts system has since been composed of the Supreme Court, the Chief Administrative Court (10 branches), the military courts and the common courts. In 1997 the new Constitution of the Republic of Poland was introduced and then a new Criminal Code in 1997 and new Company Code in 2001 (Kochanowicz, Kozarzewski and Woodward , 2005). At the beginning of transformation, Poland had a fixed exchange rate. In May 1991 Poland introduced crawling peg regime. In 1994 and 1995 the band of acceptable exchange rate fluctuations was widened. Then in 1998 the National Bank of Poland (NB) began to move full-blown exchange rate regime reform. In April 2000 the float exchange regime was fully adopted World Bank (2002).

[63] For cross-time analysis the estimation equation is $\ln(Y_t) = \alpha_o + \beta_L \ln(L_t) + \beta_K \ln(K_t) + w_t + \varepsilon_t$

Gross-output base

The gross-output base method is similar to a value-added base production function with an addition parameter M_{jt} which measured material inputs.

The estimation equation is defined as:

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + \beta_M \ln(M_{jt}) + w_{jt} + \varepsilon_{jt} \quad (34)$$

where j – individual industry sectors, t =1,.., T time periods, Y_{jt} - is expressed as gross output (*gu*) or sold production (*s*), L_{jt} -labour will be expressed by three different indicators (*em, em31_ ,ape*) and K_{jt} is physical capital stock (*gvfa*), α_0 - measures the mean efficiency level across sectors and over time, ε_{jt} identifies measurement error and random noise, w_{jt} a productivity term (TFP), M_{jt} is intermediate consumption (*ic*).

The value of TFP is computes as:

$$\hat{w}_{jt} = \ln(Y_{jt}) - \hat{\beta}_L \ln(L_{jt}) - \hat{\beta}_K \ln(K_{jt}) - \hat{\beta}_M \ln(M_{jt}) \quad (35)$$

This methodology has been used on three level of data aggregation: Total Manufacturing[64], the main three divisions (Electricity, gas, stem and hot water supply, Manufacturing, and Mining and quarrying), and then lastly, calculations are done for 22 manufacturing sectors (see Table 2 in Appendix 3). Estimations for Total Manufacturing and each of three divisions have a cross-time character for the period between 1995 and 2007. And the TFP estimation for 22 manufacturing sectors is two-dimension panel analysis (time and sectors).

In order to calculate the estimation production frontier, the OLS and Fixed Effects estimators (FE)[65] and 'Dynamic panels' GMM estimation[66] were employed. These techniques were used in order to solve the problem of endogenity of input choices and a selection problem (see details in Section 2.1 and Beveren, 2007 and Danka-Borsial, 2011). For instance the dynamic empirical speciation included lagged terms of the dependent and independent variables to compute the long-run coefficients.

[64] This category includes all three divisions: 1) Electricity, gas, stem and hot water supply, 2) Manufacturing, and 3) Mining and quarrying.

[65] The fixed effect estimator is implemented in panel data when there is a matrix with respect to two dimensions (time- years and individual- sectors). Moreover random effect estimator might not be implemented because the data were not implemented randomly.

[66] The GMM results are going to be obtained by using the *xtabond2* command with first differences and System GMM (see Blundell and Bond 1998). For time-series analysis the *gmm* command is used. There are two weak instrument average monthly gross wages (*aw*) and total work- time paid (*twt*). Both instruments seem to be strongly related with labour input, however, less related with explanatory variable.

Also the method of moments (GMM) compared to other methods (OLS, FE) control the seeming persistent simultaneity bias by modelling a dynamic process. The estimation of production frontier is conducted via comparing results for implementing different proxy for output and inputs (see Section 2.1).

Proposed proxy for semi-parametric approach by Olley Pakes (1996) and Levinsohn and Petrin (2003))

A problem of endogenity of input choices and a selection problem are not solved through different econometric techniques implemented in the estimation of the production frontier. This section describes the *structural estimators* to solve these methodological problems on the sector panel analysis. This methodology cannot be used for cross-time analysis for estimation TFP for Total of Manufacturing and each of division analysis.

Cobb-Douglas function is also implemented to estimate TFP for 22 manufacturing sectors. The estimation is carried out by employing a proposed semi-parametric approach for sector analysis which is based on two well-known firm-level methods by Oley and Pakes (1996) and Levinsohn and Petrin (2003). Both method are addressed to the potential simultaneity bias in production function estimation and employ different proxies for estimating unobserved productivity shocks. Olley and Pakes' (1996) procedure uses a proxy through an investment function and then Levinsohn and Petrin (2003) use intermediate inputs. As firm-level analysis of productivity suggested, the lack of correction for potential endogeneity of attrition and simultaneity bias can cause the downward bias on coefficients of inputs. If the manufacturing sector data were computed on the basis of individual firms' performance, it seems rational to implement semi-parametric approach on at this establishment level through consideration of exit/entry of firms (a 'survivor' function).

Sector semi-parametric approach based on Olley Pakes' (1996) study

First, Olley and Pake's (1996) method implementation for sector level data is presented. This technique is computed by employing two ways of calculating Olley and Pake's (1996) approach through *no-built-in* and *user-developed commands*[67].

A user-developed command (*opreg*) was introduced by Yasar, Raciborski and Poi (2008)[68]. Yasar, Raciborski and Poi's (2008) employs Olley and Pake's (1996) technique. Their approach has a significant assumption about unknown $g(.)$ and $\phi(.)$ functions which are approximated by second order polynomials and capture a productivity shocks. As the results of data limitation there is one state variable in analysis (a logarithmic form of capital stock) which allows one to compute the probability of survival by firms (P_{it}). For instance, if a firm j exists on a market then probability of surviving is "1" ($P_{j,t} = 1$) if the capita stock threshold ($\Omega_{j,t}$) is above certain minimum value of capital which allows company to survive as $\Omega_{j,t} \geq \Omega_{jt}(K_{j,t})$. Otherwise the firm leaves the market and then $P_{j,t} = 0$ if $\Omega_{j,t} < \Omega_{jt}(K_{j,t})$. In this matter the capita stock threshold is linked to changes in firm's investment policy. Any productivity shock is transferred into investment size and then into likelihood of the firm to survive. Hence the proxy for unobserved productivity might be defined through investment outlays (I_{jt})[69]. Based on the investment policy, these two unknown functions $g(.)$ and $\phi(.)$ are defined as:

$$\phi[\ln(K_{j,t}),\ln(I_{jt})] = c_0 + c_1\ln(K_{j,t}) + c_2\ln(I_{j,t}) + c_3(\ln(K_{j,t}))^2 + c_4(\ln(I_{j,t}))^2 + c_5(\ln(I_{j,t}))(\ln(K_{j,t}))$$

(36) where the c's are parameters estimated along with other model parameters[70].

To compute probability of surviving requires providing the variable which indicates a firm's exit (1 indicates the firms exit and 0 indicates that a firm survives). Because CSO's sector data does not have individual information for numbers of exit happens for individual firms. In order to measure this effect, I construct a proxy for

[67] Both ways are used to estimate Olley and Pake's (1996) approach are calculated on different level of sector level aggregation similar to previous parametric approaches which will aid the computation of the production function by utilizing three different types of production outputs.

[68] This command (*opreg*) is provided in STATA software package.

[69] This variable is also in log form. There are five different possible proxies for investments in sector data which are defined in the previous section (*i, ifab, ifat, ifam, ifa*).

[70] The formula is followed for g(.) function $\phi[\ln(K_{j,t}),\ln(I_{jt})] = a_0 + a_1\ln(K_{j,t}) + a_2\ln(I_{j,t}) + a_3([\ln(K_{j,t}))^2 + a_4(\ln(I_{j,t}))^2 + a_5(\ln(I_{j,t}))]$ where parameters are estimated along with other model parameters.

probability of firm's exit indicators based on an aggregate data regarding the number of active firms. This firm's exit variable is on/off indicators. If the number of active companies will drop by 10% compared to the previous year, then firm's exit indicators equal "1", otherwise "0". In other word, "1" is defined as a "good year" for a company to survive to the next year with 90% probability to operate in this sector. On the other hand, "0" is defined as "bad year" for company to survive.

A *non-built-in command* employed Arnold's (2005) nonlinear second stage. A *non- built-in command,* allows calculating higher order polynomials (3th and 4th order) as the proxy for unknown $g(.)$ and $\phi(.)$ functions. It can allow obtaining better estimation results. Moreover, this technique allows us to calculate this approach with survival probability function and it is similar to the implementation of Yasar, Raciborski and Poi's (2008) implementation of Olley and Pake's (1996) technique.

Sector semi-parametric approach based on Levinsohn and Petrin's (2003) study

Lastly, a semi parametric approach based on Levinsohn and Petrin (2003)'s procedure is used via STATA's user-developed command (*levpet*). This command estimates production functions using intermediate inputs to control for unobservable productivity shocks. This estimation technique is similar to Olley and Pakes' approach with regards for computing survivor productivity function. Levisohn and Petrin (2003) demonstrate a case where there is a correlation between capital, labours and the productivity shocks[71]. Again, it is a two-step method using bootstrapping methods to obtain standard error and test statistics (Wooldrgide, 2004). The unknown functions are proxies by third-degree polynomials, to capture the effect of unobserved shocks. In this case the usage of materials, such as energy consumptions or materials cost, are included to capture the proxy for unobserved technological shocks. Moreover, the extensions can be easily implemented in a General Method of Moment's framework (GMM) for Levisohn and Petrin's (2003) procedure[72]. This analysis was made for three different proxies for unobserved productivity shocks such as an intermediate consumption (*ic*), a consumption of electricity (*cel*) and a direct consumption of electricity (*dce*). Moreover,

[71] The parameter for labour will tend to be overestimated. The parameters for capital will tend to be underestimated.

[72] It is important to add that all variables are assumed to be in logarithms.

the linear combinations of two of these three different variables were added to the estimation equations.

This methodology is used for TFP calculations for 22 manufacturing sectors (see Table 2 in Appendix 3). In a similar way to a parametric analysis, the estimation of the semi-parametric production frontier is conducted through a comparison of results based on different proxy for output and inputs (see Section 4.1).

Index approach

According to literature review, the majority of studies for Poland and CEE countries used the parametric estimation production frontier and nonparametric-index approach (see Table 3). It therefore seems to be rational to compare results of the implemented productivity measuring method in the literature for this case with my own finding.

Because the index approach- Hicks-Moorsteen Index, with two factors (labour and capital) was used to compute TFP in the Polish manufacturing sector (see Jakubiak, 2002, 2006), I decided to follow this index methodology as benchmark for a comparison with the semi-parametric analysis results.

The Hicks-Moorsteen Index for capital (K) and labour (L) is expressed in a "natural' logarithm form (see Jakubiak, 2002, 2006) as

$$\ln(TFP_{j,t}) = \ln\left(Y_{j,t}\right) - \beta_K \ln\left(K_{j,t}\right) - \beta_L \ln\left(L_{j,t}\right) \quad (37)$$

where t-time periods, j –sector unites β_K and β_L are taken directly from the observed data based on input's cost-share, K_t is gross value of fixed assets (*gvfa*) and output Y_t is a gross value added (*gva*), L_t -number of employees.[73]

Following Jakubiak's methodology with assumption of constant return to scale, ($\beta_K + \beta_L = 1$) where β_L is defined a labour share in production with revenue-base expressed as a ratio of total labor compensations to gross value added and $\beta_K = 1 - \beta_L$.

[73] Polish Central Statistical Office offers three different proxies for labour, this TFP index will be calculated on the base of these three labour indexes (*em, em31_, ape*). In addition the labour stock can be divided into non-manual labour (skilled) and manual labour (unskilled). However, there is a lack of data to calculate labour share in production with respect to different categories of labour.

Measurement of changes in TFP (ΔTFP_{it})

The measurement of changes in TFP is calculated in two ways separately, for a parametric and semi-parametric approach, and then for an index approach.

Measurement of changes in TFP for parametric and semi-parametric approach estimation

After computing coefficients in production function from estimating a parametric/semi-parametric approach, TFP can then be determined as residual. In this case TFP growth is computed as follows:

$$\ln(\frac{TFP_{j,t}}{TFP_{i,s}}) = \ln(TFP_{j,t}) - \ln(TFP_{j,s}) \quad (38)$$

Where j is manufacturing sector, t- is second period and s-is first period[74].

Measurement of changes in TFP for index approach

The formula for measuring changes in TFP is the natural logarithms form, as detailed below (see Jakubiak, 2002, 2006):

$$\ln(\frac{TFP_{i,t}}{TFP_{i,s}}) = \ln(\frac{Y_{i,t}}{Y_{i,s}}) + \beta_{i,t}\ln(L_{i,t}) + (1-\beta_{i,t})\ln(K_{i,t}) - \beta_{i,s}\ln(L_{i,s}) + (1-\beta_{i,s})\ln(K_{i,s}) \quad (39)$$

where the labour share in production $\beta_{i,t}$ is expressed as a ratio of total labor compensations to output, L-number of employees, K- physical capital stock[75].

To summarise, the parametric approach and nonparametric-index approach are estimated on three different data aggregation levels[76]. As the semi-parametric applications cannot be used on cross-time data, this estimation is conducted for manufacturing sector panel of 22 sectors in the Manufacturing division (see Table 2 in Appendix 3). The variables and theirs measure are described in Section 4.1.

[74] In the cross-time analysis I do not consider sector units.

[75] In the case of "aggregate data" such as sector data or country data, aggregates take the form of "value aggregates at constant prices" or "constant prices series".

[76] A first level of data aggregation: Total Manufacturing (NACE one-digit classification). which includes all three divisions: Electricity, Gas, Stem and Hot water supply, Manufacturing and Mining and Quarrying. A second level of data aggregation: three divisions (NACE two-digit classification) Electricity, Gas, Stem and Hot water supply, Manufacturing and Mining and quarrying. A last level of data aggregation (NACE three-digit classification) is 22 manufacturing sectors in Manufacture division.

4.5. Empirical productivity results for sector level analysis

The analysis of TFP is presented on three different data aggregations; calculating TFP for Total Manufacturing (NACE one-digit classification)[77], the main three divisions such as Electricity, Gas, Stem and Hot water supply, Manufacturing and Mining and Quarrying (NACE two-digit classification). Lastly, calculations are done for 22 manufacturing sectors (NACE three-digit classification).

4.5.1 Empirical productivity results for Total Manufacturing

Estimation productivity results for Total Manufacturing are presented in two perspective TFP level analysis and the dynamics of productivity. The time-series for total manufacturing considers the period between 1995 and 2007 and a summary statistics are presented in Appendix 4 in Table 3[78].

TFP of Total Manufacturing is computed through the parametric approach and index approach. The parametric estimation production frontier is presented, followed by the non-parametric approach estimations.

The parametric estimation production frontier is computed on value-added base and gross-output based.

Value-added base is estimated via an equation

$$\ln(Y_t) = \alpha_o + \beta_L \ln(L_t) + \beta_K \ln(K_t) + \varepsilon_{jt} \quad (39)$$

where t-years, Y is gross value added (*gva*), L is proxy via three different labour indicators (*em* , *em31_*, *ape*) and K is proxy via gross value of fixed assets.

Gross-output based is estimated via an equation

$$\ln(Y_t) = \alpha_o + \beta_L \ln(L_t) + \beta_K \ln(K_t) + \beta_M \ln(M_t) + \varepsilon_t \quad (40)$$ [79]

where t-years, Y is gross output (*gu*) and a sold production (*s*), L is a proxy via three different labour indicators (*em* , *em31_*, *ape*) and K is proxy via gross value of fixed assets, M is an intermediate consumption (*ic*).

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[77] This category includes all three divisions: Electricity, gas, stem and hot water supply, Manufacturing and Mining and quarrying.

[78] All proxies for labour have a similar value on average and similar proxies of production such as sold production (*s*) and gross output (*gu*). The analysis of trends suggests that for the period between 1995 and 2007, all outputs proxies (*s, gu, gva*) and capital proxies (*gvfa*) have an upward rising trend. However, in the case of labour, between 1995 and 2005 they declined in employment of labour by all three proxies (*em31_, em_, ape*). Especially since 1997 this decline was very rapid. Since 2005, the slow upward trend is noticed for all three indicators of labour. This decline of labour might be caused by the reduction of number of firms for representative periods.

[79] Both of these equations were computed on the basis of equations (32) and (34) from Section 4.2.

All variables for estimation equations (39) and (34) in Section 4.2 are characterized by the stationary process according testing by Dickey-Fuller GLS regressions. The data are estimated via two econometrics techniques OLS and IV instruments.

Value added base estimation and *Gross-output base estimation* of OLS technique detects an autocorrelation problem via the Durbin-Watson test and Breusch-Godfrey test for higher-order serial correlation[80]. The data did not suggest any problems of heteroscedasticity via implementing both the Breusch-Pagan/Cook-Weisberg Test and Koenker tests. In order to correct the problem, the independent variable lags are introduced to the equation and the second problem was corrected by the Huber-White Robust Standard Errors. As the results of existence of the problem of endogeneity[81], IV estimations are computed with two instruments; monthly gross wages (*aw*) and total work- time paid (*twt*)[82]. Both instruments are weak because in certain ways they are linked to an independent variable – the labour indicator. Also the Wu-Hausman test confirmed the necessity to implement these instruments. *Value added base estimation* results are not statistically significant[83] (see Table 4 in Appendix 4). The results for gross-output based results are presented in Table 7 and 8.

Table 7: Production function estimates for Total Manufacturing for gross output (*gu*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS (*em*)	13	0.65*	0.36** (0.1)	0.66*
IV reg	13	0.65*	0.36***	0.66*
OLS (*em31_*)	13	0.59*	0.22***	0.59*
IV reg	13	0.61*	0.22***	0.64*
OLS (*ape*)	13	0.50*	0.36**(0.066)	0.63*
IV reg	13	0.50*	0.36***	0.63*

Notes: *** the statistical significant level is more than 10 percent ** the statistical significant level is equal to and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()- provided the value of probability to accept or reject hypothesis of significant [84], F-statistics confirm an overall statically significant at 5 percentages significant level *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

[80] Also estimations suffer for minor multi-collinearity problems.
[81] There are a possibility of correlation between independent variables and error terms.
[82] The instruments were transformed into logarithm.
[83] The statistical significant level is 10 percentages.
[84] The information was provided if the probability was closed over the edge of statistical signification.

There are essentially four statistical significant results from calculating the production function (see Table 7 and 8)[85]. An estimation parametric production function shows the elasticity of output with respect to labour and capital is significant different from zero in Total Manufacturing sector. The labour coefficient is between 0.73 and 0.50 and capital coefficient is between 0.66 and 0.6 (see Table 7 and 8). These findings are consistent with other TFP results for the Polish market (see Table 3 in Section 3). It is worth noticing that using two different labour indicators: the average paid employment of full-time paid employees (*ape)* and an average number of employed persons (*em*) provided these major different results of the labour intensity by 0.2 percentage points (see Table 7 and 8). The average paid employment of full-time paid employees (*ape*) is a more accurate measure than is more broadly used in the empirical studies for Polish manufacturing sectors (see Kolasa and Żółkiewski 2004 and Dańska-Borsiak, 2011). The estimation results for labour index (*ape)* suggested that the manufacturing sector in Poland is more capital intensive then labour intensive (see Table 8).

Table 8: Production function estimates for Total Manufacturing for sold production (*s*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS (*em*)	13	0.73*	0.45** (0.057)	0.64*
IV reg	13	0.72**	0.46**	0.70*
OLS (*em31_*)	13	0.68*	0.26*** (0.13)	0.55*
IV reg	13	0.71*	0.25***	0.61*
OLS (*ape*)	13	0.56*	0.44**(0.062)	0.60*
IV reg	13	0.56*	0.44**(0.062)	0.60*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal to and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, F-statistics confirm an overall statically significant, ()- provided the value of probability to accept or reject hypothesis of significant F-statistics confirm an overall statically significant at 5 percentages significant level, *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years).[86]

Table 9 describes a relation between TFP computing via parametric or non-parametric methods. A non-parametric Hicks-Moorsteen Index approach is found on the

[85] These results in the Table 7 and 8 are highlighted by the blue colour. This result indicates the coefficient is statistically significant at 10 percentages level.

[86] Wu-Hausman test confirms that instruments should not be used in three cases of estimation production i) gross output (*gu*) and average paid employment (*ape*), ii) sold production (*s*) and average number of employed (*em*) and, iii) sold production (*s*) and average number of employed (*ape*) (see Table 7 and 8). Especially, it is important in the case of last estimation with the usage of sold production (*s*) and average number of employed (*ape*) because the result cannot be considered under the further analysis.

base of growth accounting framework and in this analysis the equation is taken from Jakubiak's (2002, 2006) studies:

$$\ln(TFP_t) = \ln(Y_t) + \beta_t \ln(L_t) + (1-\beta_t)\ln(K_t) \quad (41)$$

where t is year, labour share in production is β_t expressed as revenue-based, expressed as a ratio of total labor compensations to gross value added (*gva*), L_t -labour index is measured by three different proxies (*ape*, *em* and *em31_*), K_t is physical capital stock (*gvfa*) and Y_t is proxy for output (*gva*) .

Table 9 presents a high degree of correlation across the nonparametric indexes (a blue colour in the table) employed between 0.99 and 1 and representatively a fairly high degree of correlation is between TFP parametric approaches between 0.9829 and 0.9906 (a green colour in the table). This result in Table 9 suggests that there is not a large impact through different measures of labour inputs on TFP value, but the methods themselves might have significant impact on TFP performance. The reason of this low correlation between different techniques of TFP (an orange colour in the table) may be that the estimation period of the parametric method assumed the constant value of coefficient in the production function. This suggests that it is sensible to use other productivity methods, such as a semi-parametric approach for further analysis with sector panel data. Overall, this suggests a high degree of consistency across the results, though with some differences.

Table 9: Correlation of productivity estimates across methodologies

	TFP_{ape}	$TFP_{\_em}$	$TFP_{\_em31}$	TFP_{s_ape}	TFP_{s_em}	TFP_{gu_ape}	TFP_{s_em}
TFP_{ape}	1						
$TFP_{\_em}$	0.99	1					
$TFP_{\_em31}$	*0.99	1	1				
TFP_{s_ape}	*0.156	*0.146	*0.146	1			
TFP_{s_em}	0.032	*0.0215	*0.0217	*0.9905	1		
TFP_{gu_ape}	*0.101	*0.0904	*0.0906	*0.9882	*0.9829	1	
TFP_{s_em}	-0.046	-0.056	-0.056	*0.9723	*0.9906	*0.9838	1

Note: TFP calculation will be based on gross output (*gu*) and sold production (*s*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t) - \hat{\beta}_M \ln(M_t)$ where L is define the average paid employment of full-time paid employees (*ape)* or an average number of employed persons (*em*), K is material input (*gvfa)* and M is intermediate consumption (*ic)* . Basing on this estimation equation a four TFP indexes are as TFP_{s_ape}, TFP_{gu_ape}, TFP_{gu_em} and TFP_{s_em} respectively for each labour proxy and output.*-statically significant level is 5 percentages. Notation for non-parametric Hicks-Moorsteen Index approach for different proxy indicators (*ape*, *em* and *em31_*) are TFP_{ape}, $TFP_{\_em}$ and $TFP_{\_em31}$. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years).

TFP dynamic is investigated through trend analysis of changes in TFP (see Figure 2 and 3). The changes in TFP for both implemented parametric and non-parametric techniques illustrated an upward trend for the estimation period between 1995 up to 200 (see Figure 2 and 3). However, the trend is more rapid in the case of nonparametric approach (see Figure 3). The graphs show clearly that there is not a significant difference in using a different set of data to calculate productivity with certain types of techniques (parametric or non-parametric), although without it is different than correlation matrix analysis pointed out earlier. This result also confirmed the pattern of economy transmission from implementation of significant government–economics reforms at the beginning of 90s which caused a significant drop in productivity, followed by an upward speed-up effect after firms adjust to the new opened economy and start progressing faster (see Figure 2 and 3).

Figure 2 TFP growth measures by parametric approach for Total Manufacturing in Poland for a period between 1995 and 2007.

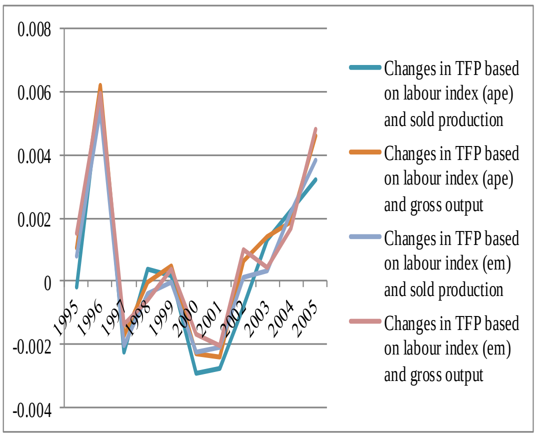
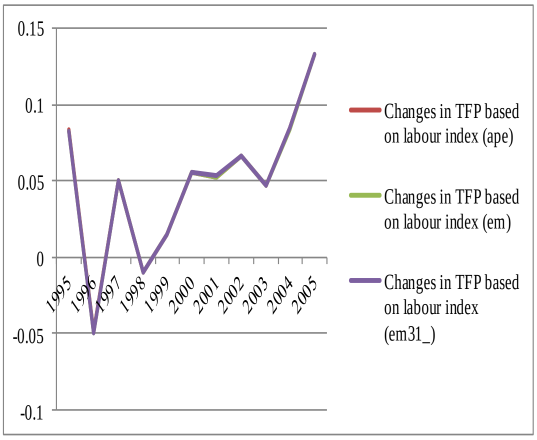


Figure 3 TFP growth measures by non-parametric for total manufacturing in Poland a period between 1995 and 2007



Source: Author's own calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

4.5.2 Empirical productivity results for three main divisions such as Electricity, gas, stem and hot water supply, Manufacturing and Mining and quarrying

In this section, I analyse the estimation results for the three divisions *Mining and quarrying, Electricity, Gas, Steam and Hot water supply* and *Manufacturing* (according to NACE classification C,D,E). The period of analysis is between 1995 and 2007 for each division. Similar to the analysis in previous section, the analysis was done using a proxy for production and labour indicators. The summary statistics are presented in summary statistic tables for each division (see Table 5, 6 and 7 in Appendix 4.).

Empirical productivity results for Mining and quarrying

The time-series analysis for Mining and quarrying has two parts: a TFP level analysis and a trend analysis of productivity dynamics.

The TFP level analysis based its computation on equation (39) and (40) from Section 4.1. Compared to the above analysis of trends among different indicators to calculate TFP, almost all indicators had a downward trend[87] apart from the number of active companies[88]. Moreover, all variables are stationary according to the Dickey-Fuller GLS regressions test. Similar to previous analysis and calculations, the following econometric techniques were used in the OLS and IV regression (*ivreg* and *ivreg2*-two

[87] The labor proxy indicators (*ape, em, and em31_)* drop around 60 percentages, while production proxy (*s, gu* and *gva*) and capital indicator (*gvfa*) decreased between 30 to 40 percentages. However, there was a positive peak for production proxies (*s, gu* and *gva*) and capital indicator (*gvfa*) in 1997.

[88] This result suggests that there were processes of defragmentation of large mining companies during this period. A number of active firms increase by 100 percentages.

stage least squares, 2SLS)[89]. Diagnostic tests point out there is no problem of autocorrelations or multicollinearity. Nevertheless, problems of heteroscedasticity were noticeable, something which was corrected.[90] There were not any statistical significant findings for regressing value-added basis production function. Similar to previous findings, the estimation of gross-output basis production function provided significant results estimation with respect to three proxies of labour (*ape*, *em* and *em31_*) which are presented in Table 10.

Table 10: Production function estimates for Mining and quarrying for gross output (*gu*)

Method	N	Labour β_L	Material β_M	Capital β_K
IV reg (2 SLS) (*em*)	13	0.48*	0.22*	0.21***(0.106)
IV reg (2 SLS) (*em31_*)	13	0.51*	0.21*	0.21**(0.102)
IV reg (2 SLS) (*ape*)	13	0.47*	0.22*	0.20***(0.112)

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[91]- provided the value of probability to accept or reject hypothesis of significant. F-statistics confirm an overall statically significant. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

The labour coefficient is between 0.47 and 0.51 and the capital coefficient is between 0.20 and 0.22. It is important to notice that there is not a large difference between using different labour indicators (*em31_*, *ape* and *em*) (see Table 10). The finest statistical results are for employment, as of 31 XII (*em31_*) and gross output (*gu*) (a blue colour in the table). In contrast to the previous analysis for total manufacturing, mining and quarrying are more labour intensive than capital intensive (see Table 10 and Appendix 4 Table 8).

Table 11 presents a correlation matrix across the parametric and non-parametric methodologies.

[89] The IV regression was used in order to eliminate the problem of endogeneity via the use of two instruments: monthly gross wages (*aw*) and total work-time paid (*twt*). The instruments were transformed into logarithms. Moreover, the Wu-Hausman test confirmed it was necessary to implement instruments for all estimated data.

[90] Autocorrelation diagnostic tests are Durbin-Watson test and Breusch-Godfrey test for higher-order serial correlation). Breusch-Pagan/Cook-Weisberg is a test to check hypothesis of homoscedasticity

[91] The information was provided if the probability was closed over the edge of statistical signification.

Table 11: Correlation of productivity estimates across methodologies

	TFP_{ape}	TFP_{em}	TFP_{em31}	TFP_{s_ape}	TFP_{s_em}	TFP_{gu_ape}	TFP_{gu_em}	TFP_{s_em31}
$TFP_{\_em}$	1*	1						
TFP_{em31}	1*	1*	1					
TFP_{s_ape}	0.33*	0.33*	0.33*	1				
TFP_{s_ape}	0.33*	0.33*	0.33*	0.96*	1			
TFP_{gu_ape}	0.33*	0.33*	0.33*	1*	0.99*	1		
TFP_{gu_ape}	0.33*	0.33*	0.33*	0.99*	1*	0.99*	1	
$TFP_{s\_em31\_}$	0.32*	0.32*	0.32*	0.99*	0.98*	0.98*	0.98*	1
TFP_{gu_em31}	0.41*	0.41*	0.41	0.98*	0.99*	0.99*	0.998*	0.97*

Notes: TFP calculation will be based on gross output (*gu*) and sold production (*s*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t) - \hat{\beta}_M \ln(M_t)$ where L is define the average paid employment of full-time paid employees (*ape*) or an average number of employed persons (*em*), employment, as of 31 XII (*em31_*), K is material input (*gvfa*) and M is intermediate consumption (*ic*) . Notation for non-parametric Index approach for three labour indicators (*ape*, *em* and *em31_*) are TFP_{ape} , $TFP_{\_em}$ and $TFP_{\_em31}$.*-statically significant level is 5 percentages. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

According to the results in the Table 11, there is a high degree of correlation employed across all nonparametric indexes (a blue colour in the table) and the same situation across parametric indexes (a green colour in the table). The correlation between the nonparametric and parametric approach is between 0.3 - 0.4 (an orange colour in the table). It suggests that there are differences between usages of different TFP calculation methods.

An initial trend analysis of TFP level suggests that there are no changes in the TFP trends over time for Mining and Quarrying (especially via implementing the parametric approach) between 1995 and 2007 (see Appendix 4 Figure 1). It can be caused by the reduction of operating and active firms during this period. This sector was under intensive transitions reforms via privatization process. The dynamic process analysis is presented on Figure 4 and 5.

Figure 4 TFP growth measures by parametric approach for Mining and Quarrying in Poland for a period between 1995 and 2007.

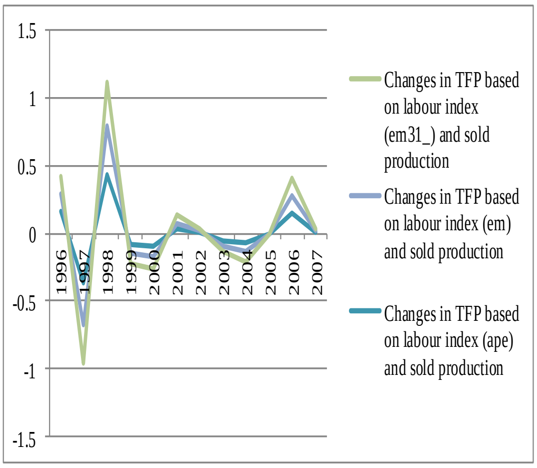
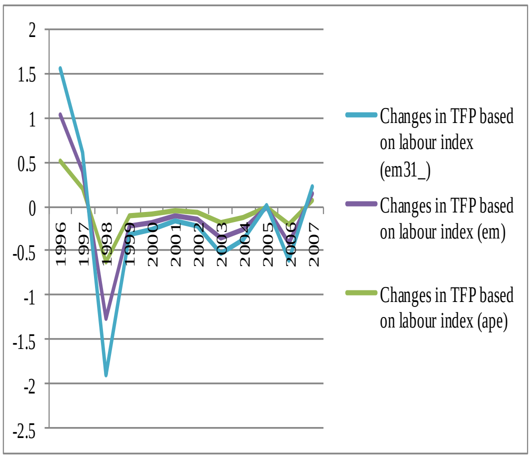


Figure 5 TFP growth measures by non-parametric for Mining and Quarrying in Poland a period between 1995 and 2007



Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

The changes in TPF for both implemented parametric and non-parametric techniques illustrated a downward trend in the transmission period at the beginning of 90s and then slow upward trend after the adjustment period. However it can be noticed that there are fluctuations in productivity for the Mining and Quarrying sector.

Empirical productivity results for Electricity, gas, steam and hot water supply (EGSW)

The analysis for Electricity, gas, steam and hot water supply (EGSW) includes the time-series analysis of TFP level and trend analysis of productivity dynamics.

Almost all indicators of TFP level have an upward trend apart from labour measures.[92] According to the results of Dickey-Fuller tests, all variables are stationary. The analysis of (EGSW) followed the previous analysis of Manufacturing and Mining and quarrying by implementing the econometric techniques.[93] Among all the econometric techniques only the results derived from implementing a IV regression 2

[92] The labor proxy indicators (*ape, em, and em31_)* drop around 5 percentages, and then production proxy (*s, gu* and *gva*) and capital indicator (*gvfa*) decreased between 30 percentages. However, there was a positive peak for production proxies (*gu*) and capital indicator (*gvfa*) in 1997 and 1995.

[93] Econometrics techniques are OLS, and IV regression (*ivreg* and *ivreg2*-two stage least squares, 2SLS). Moreover, the same instruments are used (monthly gross wages (*aw*) and total work- time paid (*twt*)) and the same diagnostic tests - Wu-Hausman test, serious autocorrelations (Durbin-Watson test and Breusch-Godfrey test for higher-order serial correlation) and heteroscedasticity test (Breusch-Pagan/Cook-Weisberg Test reject hypothesis of homoscedasticity). Because the multicolliniarity problem is defined, the lagged variable of independents variables in employed in estimation.

SLS were statistically significant for sold production (*s*) and employment, as 31 XII (*em31_*) (see Table 12).

Table 12: Production function estimates for Electricity, gas, steam and hot water supply (sold production)

Method	N	Labour β_L	Material β_M	Capital β_K
IV reg (2 SLS) (*em31_*)	13	0.45*	0.39*	0.88*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[94]- provided the value of probability to accept or reject hypothesis of significant. *Source*: Author's own calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 12 shows that compared to previous results for Mining division, the EGSW division is most capital intensive. The size of coefficient on capital is double compared to Mining division. This possibly points to the fact that the firms in this division are moving towards a more capital intensive production process. The elasticity of labour is slightly smaller than for Mining division, however is also lower than the coefficient on labour for Total Manufacturing.

Table 13 presents the correlation matrix which analyses the relation between results of nonparametric and parametric measures. This result suggests that both methods are strongly linked with each other (correlation around 0.8). In other word, both methods might be replaced in this matter.

The initial analysis of the TFP level trend suggests that there was a slight decrease in TFP over time for this division between 1995 and 2007, especially in the period of intensive transformation in between 1995 up to 1998. This pattern is also confirmed by trend analysis of changes in TFP (see Figure 6 and 7).

[94] The information was provided if the probability was closed over the edge if statistical signification.

Table 13: Correlation of productivity estimates across methodologies

	TFP_{ape}	TFP_{em}	TFP_{em31}	TFP_{s_em31}
TFP_{ape}	1			
TFP_{em}	1*	1		
TFP_{em31}	1*	1*	1	
TFP_{s_em31}	0.8288*	0.8288*	0.8291*	1

Notes: TFP calculation will be based on sold production (*s*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t) - \hat{\beta}_M \ln(M_t)$ where L is define as an employment, as of 31 XII (*em31_*), K is material input (*gvfa)* and M is intermediate consumption (*ic)* . Notation for non-parametric Index approach for three labour indicators (*ape*, *em* and *em31_*) are TFP_{ape}, $TFP_{\_em}$ and $TFP_{\_em31}$.*-statically significant level is 5 percentages. *Source:* Author's own calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Figure 6: TFP growth measures by parametric approach for EGSW in Poland for a period between 1995 and 2007.

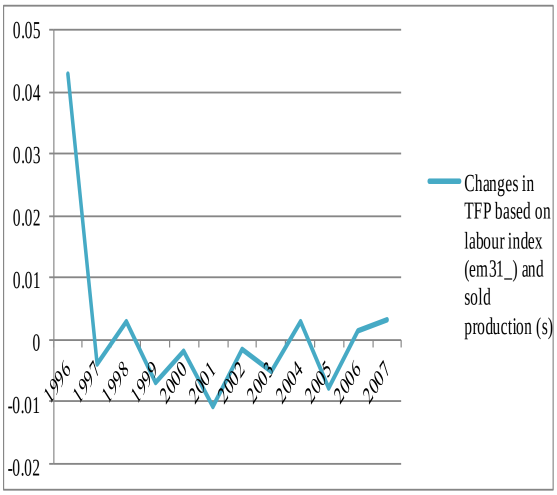
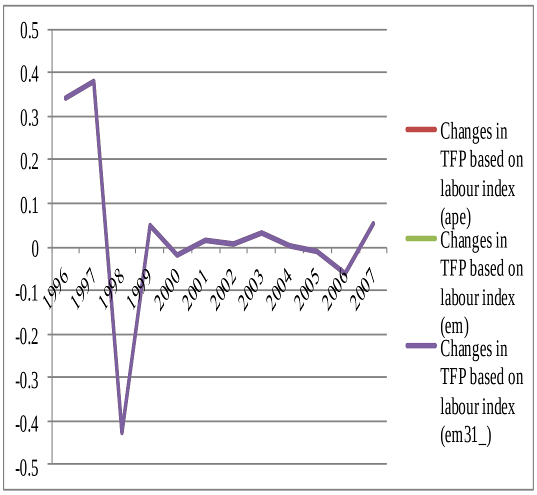


Figure 7: TFP growth measures by non-parametric approach for EGSW in Poland a period between 1995 and 2007



Source: Author's own calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

The changes in TFP for both implemented parametric and non-parametric techniques illustrate a downward trend for the estimating period. This possibly points to the facts that the firms in this division were strongly impacted by the transformation in Poland, illustrated by sharp downward trend at the beginning of the estimation period between 1995 and 1998. This effect was more fully captured by a nonparametric approach which suggested that the cost of capital played an important role. Then there are upward trends for both types of measures between 1998 and 2007 which can pick up the fact of the firm's positive adjustment to changes in economy. In other word, firms that were survivors of the transformation period expanded their operations and took over the market share of those who left. However, it seems that this process was more volatile for this division than for either Total Manufacturing or Mining division.

Empirical productivity results for Manufacturing

Estimated productivity results for manufacturing division are presented in two perspectives TFP level analysis and the dynamics of productivity for the period between 1995 and 2007.

All variables to compute TFP are stationary, according to the Dickey-Fuller GLS regressions test. The following econometric techniques were implemented in the analysis OLS, and IV regression (2SLS). Similar to previous analysis the IV regression made use of two instruments: monthly gross wages (aw), and total work- time paid (twt) to eliminate the problem of endogeneity.[95] Diagnostic tests identify an autocorrelation and multicollinearity problem.[96] In order to correct this, the lags of independent variables were included in the estimation equation. There were no significant statistical results for regressing the gross value added measure (*gva*) for production function. Gross-output basis estimation of TFP with usage of sold production *(s)* and gross output (*gu*) were presented results in Table 12 and 13.

Table 12 Production function estimates for Manufacturing Industry for sold production (*s*)

Method	N	Labour β_L	Material β_M	Capital β_K
reg (OLS) (*em*)	13	0.635*	0.712*	0.434*
IV reg (2 SLS) (*em31_*)	13	0.627*	0.535*	0.289*
reg (OLS) (*ape*)	13	0.544*	0.596*	0.279*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[97]- provided the value of probability to accept or reject hypothesis of significant. *Source:* my own calculations on estimating the sector data from Polish CSO.

[95]The instruments were transformed into logarithms. The Wu-Hausman test confirmed the necessity to implement instruments for estimation of proxy of output (gu).
[96] Diagnostics tests: Durbin-Watson test and Breusch-Godfrey test for higher-order serial correlation. For all sample of data, problems of heteroscedasticity was not noticeable. Breusch-Pagan/Cook-Weisberg Test reject hypothesis of homoscedasticity.
[97] The information was provided if the probability was close to the edge of statistical signification.

Table 13: Production function estimates for Total Manufacturing for gross output (*gu*)

Method	N	Labour β_L	Material β_M	Capital β_K
IV reg (2 SLS) (*em*)	13	0.507*	0.698*	0.368*
IV reg (2 SLS) (*em31_*)	13	0.443*	0.675*	0.234*
reg (OLS) (*ape*)	13	0.3897*	0.679*	0.393*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages. ()- provided the value of probability to accept or reject hypothesis of significant *Source:* Author's calculations on estimating the sector data from Polish CSO

Table 12 and 13 shows that the elasticity of capital is relatively lower than that of labour, implying that the labour plays more a significant role in the production process. The labour coefficient is between 0.64 and 0.9 and capital coefficient is between 0.43 and 0.23. Manufacturing is more a labour intensive than capital intensive. This result seems to be consistent with other studies in Poland for manufacturing (see Kolasa and Żółkiewski 2004 and Dańska-Borsiak, 2011). Also, the size of coefficients on inputs is seemed to be consistent across of the use of different labour indicators.

In order to investigate the differences between methods of calculating TFP a correlation matrix is presented in Table 14.

Table 14 Correlation of productivity estimates across methodologies

	TFP_{ape}	TFP_{em}	TFP_{em31}	TFP_{gu_ape}	TFP_{s_em31}
TFP_{ape}	1				
TFP_{em}	0.9983*	1			
TFP_{em31}	0.9998*	1*	1		
TFP_{gu_ape}	0.1233*	0.1056*	0.1052*	1	
TFP_{s_em31}	0.3569*	0.3509*	0.3512*	0.5531*	1
TFP_{s_em31}	0.1551*	0.1373*	0.1364*	0.9535*	0.40501*

Notes: TFP calculation will be based on sold production (*s*) and gross-output(gu) and follows the equation (40) where labour is define as the average paid employment of full-time paid employees (*ape)* or an average number of employed persons (*em*), employment, as of 31 XII (*em31_*), capita is material input (*gvfa)* and M is intermediate consumption (*ic)* . Parametric estimations are done via IV instrument (2SLS). Notation for non-parametric Index approach for three labour indicators (*ape*, *em* and *em31_*) are TFP_{ape}, $TFP_{\_em}$ and $TFP_{\_em31}$.*-statically significant level is 5 percentages. *Source:* my own calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

According to the results of the correlation matrix there is a high degree of correlation across among all nonparametric indexes employed around 0.9 (blue colour in table), which suggests that usage of different labour measures does not affect TFP results. The correlation between the nonparametric and parametric approaches result is also positive, which suggests that both type of techniques provide a similar direction with respect to measuring TFP.

The initial analysis of TFP suggests that, according to both parametric and non-parametric measures for computation of TFP, there were indeed significant drop at the middle of 90s. Also the change in TFP shows this major decline in this period in Figure 8 and 9 which is similar to previous finding in two other divisions (*Electricity, gas, steam and hot water supply* and *Mining and quarrying)*. Also the number of companies is lowest in 1998, which indicates the intensive process of transformation in this sector. Without substantial government subsidiaries, publicly own companies did not manage to survive the pressure from the open market after 1998.

TFP growth for the non-parametric approach and parametric approach was calculated in the same way as in the previous section. Between 2003 and 2007 there are upward trends for both types of measures. However, upward trends were more rapid in the case of the nonparametric approach between 2004 and 2007 (see Figure 8 and 9). This result might suggest that Polish companies introduced a different strategy after reducing employment rate. The labour measures reached the bottom in 2003, when companies moved into introduction of new products in the strategy of competition through an increase of investment which lead to an upward trend in productivity (Wziątek-Kubiak, Jakubiak, Antczak, 2004). In other words, this upward trend might point out the fact of slow recovery by companies after significant economy reconstructions. Lastly, Figures 8 and 9 demonstrate that there is no difference in using a different set of data to calculate productivity with certain types of techniques (parametric or not parametric), which confirms correlation analysis (see Table 14).

Figure 8 TFP growth measures by parametric approach for Manufacturing division in Poland for a period between 1995 and 2007.

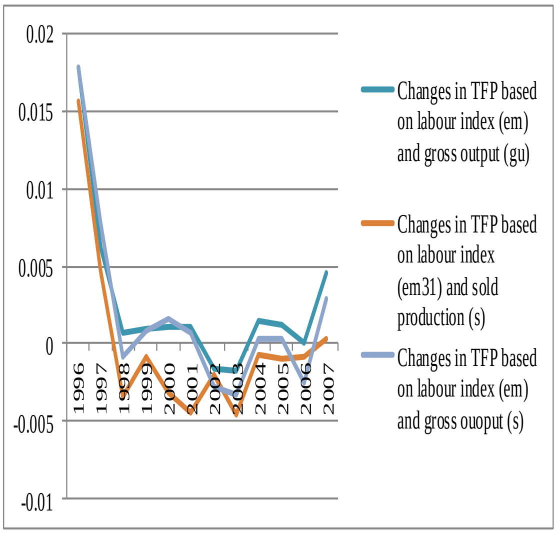
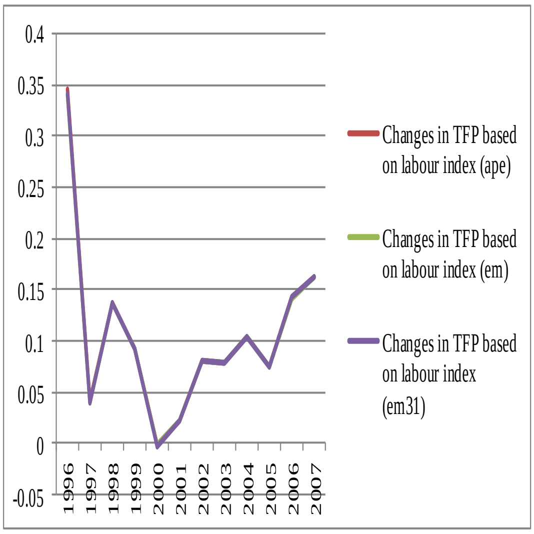


Figure 9 TFP growth measures by non-parametric for Manufacturing division in Poland a period between 1995 and 2007



Notes: Parametric estimations are done via IV instrument (2SLS). Notation for non-parametric Index approach for three labour indicators. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

4.5.3 Empirical productivity results for 22 manufacturing sectors (NACE three-digit classification)

Estimation productivity results for manufacturing division are presented in two perspectives: TFP level analysis and the dynamics of productivity for the period between 1995 and 2007 for 22 sectors from manufacturing division (see Appendix 3 Table 2). In this section, the techniques utilized are parametric approach of estimation production frontier (OLS, Fixed Effect estimator, and Dynamic Panel GMM), the Index approach-Hicks-Moorsteen Index and proxy for semi-parametric approach for sector level based on Olley Pakes'(1996) and Levinsohn and Petrin's (2003) methodology. Parametric approach of estimation production frontier and proxy for semi-parametric approach for sector level based are computed on two bases: value-added basis and gross-output basis.

Value added base estimation

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + \varepsilon_{jt} \quad (42)$$

where Y is gross value added (*gva*) L is proxy via three different labour indicator (*em* , *em31_*, *ape*), K is a gross value of fixed assets (*gvfa*), j-is sector, t-year.

Gross-output base estimation

$$\ln(Y_{jt}) = \alpha_o + \beta_L \ln(L_{jt}) + \beta_K \ln(K_{jt}) + \beta_M \ln(M_{jt}) + \varepsilon_{jt} \quad (43)$$

where Y is gross output (*gu*) and a sold production (*s*), L is proxy via three different labour indicator (*em , em31_, ape*), K is proxy via gross value of fixed assets (*gvfa*), M is an intermediate consumption (*ic*), j-is sector, t-year.

In order for the utilization of the semi-parametric approach, additional key variables need to be included, such as a proxy for investments (*i, ifa, ifab, ifat, ifam*) and consumption of electricity (*ce* and *dce*) (see Appendix 4. in Table 7). [98]

The analysis of summary statistics suggests that employment, as of 31 XII (*em31*) and the average number of employed persons in industry *(em)* have a similar value on average, with a similar dispersion (see Appendix 4. in Table 7). The remained labour measures - the average paid employment of full-time paid employees *(ape)* was less than 10% on average in comparison to other labour measures. For production, the proxy for sold production (*s*) and gross output (*gu*) has similar results on average. [99]

Analysis of outliers suggests that the majority of outliers were accumulated between 1995 and 2001 for key variables to compute productivity. The Manufacture of food products and beverages seems to be more clearly outllyingg with almost four-times higher results for productions and employment on average compared to summary statistics for the sector panel. A similar situation is recycling which lied much more above the average results for summary statistics for the panel.[100]

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[98] There are between 286 and 279 observations for the period between 1995 and 2007 which is presented in a summary statistics table (Appendix 4 in Table 7). Some key variables such as *i, ifa, ifab, ifat, ifam* are available for all periods between 2001 and 2007 apart from two sectors (33 Recycling and 26 Manufactory of office machinery and computer). On the other hand, a consumption of electricity (*ce*) and direct consumption of electricity (*dce*) data has only been obtained since 1999. The data available for the other key variables were all the proxies for outputs (*s, gu, gva*), proxy for capital (*gvfa*) and all three proxies (*em31_, em_, ape*) for the period between 1995 and 2007.

[99] The analysis of summary statistics utilized in the semi-parametric approach suggested wider dispersion between sectors. The two sectors of 22 have similar results on average as the whole panel (Manufacture of pulp and paper and Manufacture of basic metals). Almost the same sector stayed above the average in comparison to the panel results, plus an additional sector of Manufactured motor vehicles, trailer and semi-trailers. Alternatively the Manufacturing of furniture sector moved to the group below. It suggests that there are discrepancies between the grounds (different sectors) two times larger than within groups over the time for key variables to estimate productivity (*s,gva,gu,ape,em, em31_,gvfa, and ic*). The key variables to estimate the semi-parametric (*i, ifa, ifam, ifab, ifat, ce, dce*) approach have even less dispersions within sectors than the other one. The graphic descriptions of data via implementing box graphs confirm previous results about dispersions between sectors over time. The other suggestions about existences of outliers were confirmed.

[100] It is worth analysing the summary statistics by the changes in key variables by sector. There are three messages from this analysis. Firstly, there are only three sectors among all 22 sectors which have similar results to the average result for the whole panel (Manufacture of wood and wood, straw and wicker products, Manufacture of pulp and paper, Publishing, printing and reproduction of recorded media). Moreover, there is a significant dispersion between sector 12 of 22 (Manufacture of tobacco products, Manufacture of textiles , Manufacture of wearing apparel and furriery , Processing of leather and manufacture of leather products , Manufacture of coke, refined petroleum products, Manufacture of office machinery and apparatus , Manufacture of electrical machinery and apparatus , Manufacture of radio, television and communication equipment and apparatus, Manufacture of medical, precision and optical

The analysis of trends suggests that for the period between 1995 and 2007, all different measures of outputs had an upward rising trend over time. Between 1995 and 2005 all three measures of labour, measures of capital (*gvfa*) and measures of consumptions of electricity had a constant trend. The measures of investments have upward trends between 1995 up to 1999 and then between 2002 and 2007, with a small drop in 2002. All variables, apart from the measures of consumption of electricity seemed to have normal distributed data with a longer left tail.

The analysis of predictions by drawing the estimation line showed clearly that the best estimation across-time and across sections is for output in sold production (*s*), all three labour measures and capital measure.[101] The relationship between output measures, capital measure and labour measures seemed to be linear, a trend which is confirmed by the bubble graphs with respect to three years; 1995, 2000 and 2007 (see Figures 2 and 3 in Appendix 4). Moreover, it seems that a majority of variables have normally distribution data over time and cross-sections (see Figure 4 in Appendix 4). However, there are some disturbances in the case of labour measures, sold production and gross output (see Figures 2, 3, 4 in Appendix 4). Especially since 1997, this decline was very rapid. Since 2005, the slow upward trend is noticed for all three indicators of labour.[102] The analysis cross sector over time shows that majority of sectors have a positive trend (see Figures 2 and 3 in Appendix 4).

Panel estimators are created on the assumption that by combining the data from different groups, it will allow improvements in efficiency in parameters estimation. Under this assumption, if there are similarities in the processes generating the data in the different groups then in this case because N (number of sector) is larger than T (number of years) I will treat the data as a set of cross section regression: $y_{it} = \alpha_t + \beta_t^{'} x_{it} + u_{it}$ and $u_{it} \sim N(0, \sigma_t^2)$ (44) where t-time units, j-sector units

This estimation freely allows differences over time with a strong assumption of independence both over-time and over-units. However, one issue is that because of a

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instruments, Manufacture of motor vehicles, trailer and semi-trailers , Manufacture of other transport equipment, Recycling) which have results below the panel average (between 70 to 8 percentages of average results) then on the other hand, 7 of 22 (Manufacture of food products and beverages, Manufacture of chemicals and chemical products, Manufacture of rubber and plastic products, Manufacture of other no-metallic mineral products, Manufacture of basic metals, Manufacture of metal products, Manufacture of furniture) sectors have results above the average panel results.

[101] The gross output with respect to the labour proxy and capital proxy was reasonable. However, in both cases there were problems in 1998 with respect to these two output proxies and capital proxy, because data was accumulated in the left part of the graph. The worst estimation prediction was done with respect to Gross Value Added, especially with the labour proxy (*ape*).

[102] In 2004 Poland accessed UE.

small amount of time observations, this model needs to be kept as a static model. Also, the number of individuals are higher than the number of years (N>T) thus it seems it is more of a cross-sector analysis then cross-time. Because of this (not enough observations) it is impossible to perform the test for stationarity. [103]In order to get better a picture about the data, the Fisher's test of unite root was implemented which assumes that all series are non-stationary under the null hypothesis against the alternative that at least one series in the panel is stationary.

This sector panel data analysis employs the following econometrics techniques: OLS, and IV regression. The problem of endogeneity was eliminated though implementing the IV regression and the Dynamic Panel GMM regression. Lastly, the proxy for semi-parametric approach on sector level is used which is based on Olley and Pake's (1996) method and Levinsohn and Petrin (2003)'s procedure. [104]

All these econometric techniques required diagnostic testing. The diagnostic tests were included in this analysis. Firstly, it is necessary to test for omitted variables by the Ramsey Reset Test, in order to analyse the problem of serious autocorrelation Arellano-Bond (1991)[105], to test for autocorrelation and serial correlation in linear panel-data, the models by David M. Drukker were implemented. Three tests for heteroscedasticity were used: Breusch-Pagan / Cook-Weisberg, Szroeter's test for homoscedasticity and Cameron and Trivedi's decomposition of the IM test. Moreover, the test for cross-section dependence, the Pesaran (2004), in macro panel data was used, and the data was analysed with respect to the multicolliniarity problem and normal distribution. Lastly, I carefully analysed the pattern for residuals, unit-specific effects and slope heretogeneity. The last two were especially crucial for a correct analysis of a panel with a fixed number of observations for individuals and time period. The unit heterogeneity was analysed via implementing the Hausman test and the Breush-Pagan

[103] The Levin-Lin-Chow test and Pesaran (2007) panel unit root test for multiple variables and lags are employed to analyse this effect on panel data.

[104] For IV estimation STATA's command *ivreg* and *ivreg2*-two stage least squares, 2SLS were used with two instruments monthly gross wages (*aw*) and total work- time paid (*twt*). The instruments were transformed into logarithm. Wu-Hausman test confirmed that it is necessary to implement instruments for all the estimated data. This GMM analysis was obtained by using the *xtabond2* command for panel analysis with two possible weak instrument average monthly gross wages (*aw*) and total work- time paid (*twt*). For the Semi-parametric approach I decided to implement two ways of calculating Olley and Pake's (1996) approach: no-built-in and user-developed commands. A user-developed command (*opreg*) was introduced by Yasar, Raciborski and Poi (2008). Levinsohn and Petrin (2003)'s procedure uses the semi parametric approach which will be implemented in sector level data by STATA's user-developed command (*levpet*). The parameter for labour will tend to be overestimated. The parameters for capital will tend to be underestimated.

[105] This test is not appropriate for fixed-effects regressions for dynamic models, assuming those are done via a mean-deviation transformation.

LM test for random effects. While the slope heterogeneity could be tackled by the Hausman-style Swamy test, in this case the panel was not large enough.

There was a need at the beginning of the diagnostic problems to describe the pooled OLS estimations. All estimations suffered the problems of hetoroskedasticity, cross-section dependence, non-normal distributed data (Appendix 4 Figure 4) and a small problem of multicolliniarity. However, the estimation with the proxy for production - sold production or gross output had a more significant problem of multicolliniary than gross-value estimation. Moreover, the data suffered from the autocorrelation problem. The Ramsey Rest test showed the problem of omitted variables for most of the estimations for Sold production and Gross Output, apart from one which was Gross output and Average employed person in the industry (*em*). The Fisher's test of unite root confirmed that at least one series in the panel was stationary for all estimations of Gross Value Added, Gross Output with Average employed person in the industry (*em),* and Sold production with the average paid employment of full-time paid employees (*ape).* All the models were corrected for hetescedasticity and autocorrelation.[106]

There are two solutions which were implemented in sector data after the hypothesis of cross-section independence was rejected.

One way to solve this problem was by introducing the common trend cross time, which measures by yearly dummy variables. This trend showed that there was a common pattern with respect to productivity for all manufacturing sectors in Poland. All regression showed that all yearly dummy variables were overall joint. The significant exceptions were the production estimation for Sold production (*s*) and average number of employed persons in the industry (*ape*). Furthermore, introducing dummy yearly variables reduced the problem of multicolliniarity and increased the individual statistical significance for each variable for all regressions. However, the Ramsey Reset Test pointed out problems of omitted variables which I corrected by implementing sector dummy variables. Moreover, it seemed to be sensible to also include the sector-level dummy variables that could present a different impact of sector on productivity. For all estimations in respect to different proxies for labour and production, these dummy variables were statistically significant and all other variables were also statistically

[106] Autocorrelation was corrected by Cochrane Orcutt procedure for production estimation of Gross output, the rest was corrected by Prais-Winsten procedure and herescedasticity via robust variance estimations.

significant. Additionally, dummy variables for sector and years reduced the problem of autocorrelations. According to the information criteria (BIC – Bayesian information criterion and AIC – Akaike's information criterion) among all Pooled OLS estimations with both type of dummy variables, there are results with lower scores than the other. The best results were provided for gross value added (*gva*) and an average number of employed persons in industry (*em*). The results for Pooled OLS estimations with two types of dummy variables were presented in Tables 15 - 17.

The second solution of instrumental variables was also used in order to analyse common unobserved factors, and in addition to remove the problem of endogeneity (see Table 15 - 17).

Both tests for unit heterogeneity confirmed the existence of the problem.[107] Moreover, it is noticeable in the results in Table 15 - 23 that the unit dummies only capture all level effects which do not include the omitted time-invariant variables. In other words, there are differences in sectors, which are coming from different initial conditions in period zero. It was necessary to implement FE estimations. Because of the fact that in this case it is a small T there was no point in estimating the mean group estimator (Swamy random-coefficients model). However, the FE model did not fix the problem of non-normal distribution of residuals and a lack of randomness of residuals. It seemed there was still a problem of endogeneity, something which might be solved by an implementation of GMM. In this model a "first difference GMM" was used. This is an augmented version outlined by Arellano and Bond (1995) and fully developed by Blundell and Bond (1998)[108].

During this analysis of panel data, the GMM procedure was conducted by one and two step approaches. Due to a small number of sectors in this sample, the lists of endogenous variables (proxy for labours) were included with a second lag. This second lag was required due to its not correlating with the current error term as compared to the first lag. Moreover, a small size of panel caused the Sargan test of exogenous instruments to be weak[109]. All estimation results were presented in Table 15 - 17.

[107] Hausman test and Breush-Pagan LM test for random effects

[108] All conditions for employing this econometrics techniques were passed with regards to AR(1) process of error terms.

[109] The estimation for Gross value added (*gva*) with combination of each of these different proxies for labour (*ape, em, em31_*) were implemented by using both one and two step procedures. The estimation results were similar with regards to different labour proxy (see Table 15-17). Also these estimations included two sets of instruments (*gvfa, em,* or *em31_* or *ape*). Then a one-step procedure was implemented for Gross output (*gu*) and Sold production (*s*) except for estimation with labour proxy for average paid employed (*ape*) which was estimated by two step procedure with two types of instruments

The last step of the data analysis was done though implementation of Olley and Pakes'(1996) approach and Levinsohn and Petrin's (2003) analysis on sector -level analysis. In order to capture the productivity shocks, there were five different possible proxies for investments for use in of Olley and Pakes'(1996) approach (*i, ifab, ifat, ifam, ifa*)[110](see Table 10 in Appendix 4). These results suggest that investment outlays on fixed asset building (*i)* and investment outlays on fixed assets (*ifab)* provide the correct estimation with significant statistical results for a majority of the labour measures and output. The other investment proxies did not obtain significant statistical results on the highest significance level. The non-survival correction though Yasar, Raciborski and Poi's (2008) approach did not bring a statistical significant change.

Table 15: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross value added (*gva*) and an average number of employed persons in industry (*em*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.61*	-	0.33*
IV reg	299	0.65*	-	0.33*
Fixed Effects	299	0.65*	-	0.33*
GMM	299	0.34*	-	0.41*
OP	285	0.44*	-	0.418*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[111]- provided the value of probability to accept or reject hypothesis of significant. OP- semi-parametric estimation through investment outlays on fixed assets *(ifa)* , GMM- Dynamic Panel GMM *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

as lags of endogenous variables (*gvfa* and *ape*). The rest of the estimation was estimated using one type of instrument as lags of endogenous variable such as (*gvfa*).

110 All investment variables were utilized in the logarithmic form. Yasar, Raciborski and Poi's (2008) implementation of Olley and Pake's (1996) technique assumed unknown $g(.)$ and $\phi(.)$ functions and are approximated by second order polynomials. Compared to Yasar, Raciborski and Poi's (2008) work, in this analysis, there is just one state variable which is a logarithmic form of capital stock K_{jt} (*gvfa*). The significant statistical results at the significant levels 5 percentages and 10 percentages for Olley and Pake's (1996) technique were used for all possible investment proxies.

111 The information was provided if the probability was closed over the edge of statistical signification.

Table 16: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross output (*gu*) and an average number of employed persons in industry (*em*)

Method	N	Labour β_L	Material β_M	Capital β_M
OLS	299	0.09*	0.027*	0.87*
IVreg	299	0.11*	0.17*	0.88*
Fixed Effects	299	0.11*	0.018***(0.24)	0.85*
GMM	299	0.146*	0.0723**(0.1)	0.88*
OP	285	0.107*	0.0598**(0.068)	0.85*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[112]- provided the value of probability to accept or reject hypothesis of significant. OP- semi-parametric estimation through investment outlays on fixed assets *(ifa),* GMM- Dynamic Panel GMM. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 17: Production function estimates for manufacturing sector data (22 manufacturing sectors) for sold production (*s*) and an average number of employed persons in industry (*em*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.12*	0.86*	0.0724*
IVreg	299	0.11*	0.89*	0.057*
Fixed Effects	299	0.11*	0.85*	0.05*
GMM	299	0.146*	0.88*	0.072**(0.056)
OP	285	0.113*	0.84*	0.078*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[113]- provided the value of probability to accept or reject hypothesis of significant (l)-Linear regression with panel-corrected standard errors was implemented, OP- semi-parametric estimation through investment outlays on fixed assets *(ifa)* , GMM- Dynamic Panel GMM. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Estimations based on value-added show that the labour coefficient is between 0.34 and 0.61 and the capital coefficient is between 0.33 and 0.42. These results confirmed that manufacturing sectors are more labour intensive than capital intensive, apart from FE estimation (see Table 15 and Appendix 4 Tables 11 and 12).[114] These results are in the same line in the other publications about the manufacturing sector (see Gradzewicz, Kolasa, 2004, Czyżewski, 2002, Kolasa, Żółkiewski, 2004). On the other hand, gross output base estimation suggests that material and materials have a larger

[112] The information was provided if the probability was closed over the edge of statistical signification.

[113] The information was provided if the probability was closed over the edge of statistical signification.

[114] Table 11 in Appendix 4.4 shows similar results to previous estimations with respect to other labour measures (ape) that production is more impacted by labour intensive than capital. With respect to labour proxy (em31_and ape) the labour coefficient is between 0.3 and 0.75 and capital coefficient is between 0.27 and 0.44.apart from FE was the results are slightly different than other techniques (see Table 12 in Appendix 4.4).

impact on production in comparison to labour and capital (Table 16 and Appendix 4 Table 13, 14).[115]

In the case of estimations based on value added and sold production it seems that FE, GMM and Olley and Pake's method reduces the effect on the bias on coefficient because of endogeneity of attribution and simultaneity bias (especially downward bias on capital coefficient and upward bias on material coefficient). In contrast, for the estimation based on gross-output, the results for FE, GMM and Olley and Pake's methods did not provide statistically significant results (see Table 15, 16 and 17).

Lastly, the semi-parametric approach based on Levinsohn and Petrin (2003)'s procedure was implemented in sector level data. This procedure allows controlling for unobservable productivity shocks, which is similar to Olley and Pakes approach. However, it requires an additional variable to be a proxy for unobserved productivity, such as a material input or consumption of electricity. Based on CSO's data, there are three possible variables which were utilized in the estimation: intermediate consumption (*ic*) (expressed in mln zloty), a consumption of electricity (*cel*) (expressed in TJ) and a direct consumption of electricity (*dce*) (expressed in TJ) [116]. Moreover, data was estimated by using one or two intermediate inputs or combinations of them[117]. All the estimation results are presented in Tables 18 and 19. Table 19 present results of estimations based on the single proxy for productivity shocks.

[115] According to the information criteria (BIC- Bayesian information criterion and AIC – Akaike's information criterion) it seems that Pooled OLS estimation with both types of dummy variables results in higher scores than the other (Table 13 in Appendix 4). The labour coefficient is between 0.09 and 0.12 and capital coefficient is between 0.025 and 0.17. These results are similar to the previous Gross Output estimation and suggest that material has a larger impact on production compared to labour and capital. These results confirmed that manufacturing is more labour intensive than capital intensive. The results for FE, GMM and Olley and Pake's methods did not provide statistically significant results (see Table 14 in Appendix 4). The labour coefficient is between 0.062 and 0.11 and capital coefficient is 0.028. These results are similar to previous Gross Output estimations and suggested that material has a larger impact on production compared to labour and capital and manufacturing is more labour intensive than capital intensive. Moreover, the results for FE, GMM and the semi-parametric approach based on Olley and Pake's methods did not provide statistical significant results (Table 15 in Appendix 4). The labour coefficient is between 0.136 and 0.062 and capital coefficient is 0.0281 to 0.076. These results are similar to the previous Gross Output and Sold production estimations and suggest that materials have a larger impact on production in comparison to labour and capital and that manufacturing is more labour intensive then capital intensive. Furthermore, the results for GMM did not provide statistically significant results.

[116] These variables were in the form of logarithm.

[117] An intermediate consumption (*ic*) is in logarithmic form. For estimation for sold production and gross output only one proxy variable can be used because of the limitation of the command. Moreover, as a previous GMM estimation did not bring any positive effect on the estimations, GMM was not utilized in this Levinsohn and Petrin (2003)'s procedure.

Table 18: Production function estimates for manufacturing sector data (22 manufacturing sectors) for different output measures and three different labour measures (*em, em31_, ape*) via Levinsohn and Petrin (2003)'s procedure.

Intermediate consumption proxy/Labour proxy	N	Labour β_L	Capital β_K	Materials β_M
Gross value added (*gva*)				
ic dce em	299	0.348*	0.35*	-
*ic dce em31_*	299	0.348*	0.355*	-
ic dce ape	299	0.325*	0.342*	-

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[118]- provided the value of probability to accept or reject hypothesis of significant. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 19: Production function estimates for manufacturing sector data (22 manufacturing sectors) for different output measures and three different labour measures via Levinsohn and Petrin (2003)'s procedure.

Intermediate consumption proxy/Labour proxy	N	Labour β_L	Capital β_K	Materials β_M
Gross value added (*gva*)				
ic em	299	0.307*	0.418*	-
*ic em31_*	299	0.307*	0.42*	-
ic ape	299	0.284*	0.42*	-
dce em	207	0.3*	0.456*	-
*dce em31_*	207	0.29*	0.46*	-
dce ape	207	0.26*	0.47*	-
cel em	207	0.3*	0.46*	-
*cel em31_*	207	0.29*	0.46*	-
cel ape	207	0.26*	0.47*	-
Sold production (*s*)				
dce em	207	0.22*	0.65*	0.143***(0.44)
cel em	207	0.22**(0.08)	0.65*	0.143***(0.3)
Gross output (*gu*)				
dce em	207	0.21**(0.07)	0.59*	0.19***(0.198)
*dce em31_*	207	0.22**(0.053)	0.565*(0.084)	0.19***(0.644)
cel em	207	0.21*	0.58*	0.19***(0.399)
*cel em31_*	207	0.22*	0.56*	0.192***(0.479)

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[119]- provided the value of probability to accept or reject hypothesis of significant. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 18 shows results of the estimation on double proxies for productivity shocks. The Levinsohn and Petrin (2003)'s technique presented different results than

[118] The information was provided if the probability was closed over the edge if statistical signification.
[119] The information was provided if the probability was closed over the edge if statistical signification.

previous estimations. The labour coefficient is between 0.3 and 0.21 and capital coefficient is 0.42 to 0.65. It is impossible to say anything about a material impact on production compared to labour and capital. However, these results suggest that manufacturing is more a capital intensive than labour intensive. A semi-parametric approach based on Levinsohn and Petrin's (2003) method was calculated though a six different combinations proxy for productivity shocks. The most reliable and statistically significant results were provided by using as a proxy for productivity shock intermediate consumption (*ic*).

To summarize, there are notable differences between using different labour indicators (*em31_*, *ape* and *em*), and implementation of different proxies for outputs provide slightly different results in the estimation coefficient for labour and capital, apart from the semi-parametric approach based on Levinsohn and Petrin (2003)'s procedure. However, for the majority of the estimation results using different estimation techniques, the estimation output supported that manufacturing is more labour intensive than capital intensive. Also, estimation results for Gross Output and Sold production suggest the significant impact of materials on production[120] (see Table 15-19 and Appendix 4 Table 11-16). The previous analyses for Total Manufacturing and Manufacturing division are consistent with this panel of manufacturing sector analysis results. It is also visible that the semi-parametric approach reduces the effect of bias on coefficient because of an endogeneity of attribution and a simultaneity bias (see Figure 10 and 11).

The next step is important to see the link between different methods of calculating TFP with respect to different output measures. The correlations table across the parametric and non-parametric TFP measures are provided in Tables 20 and Appendix 4 Tables 17 and 18.

[120] Moreover, the estimation results for GMM did not provide statistically significant results in a majority of cases, and a similar problem is that FE estimation and Olley Pake's estimations.

Figure 10. Distribution function across parametric and semi-parametric measures of TFP

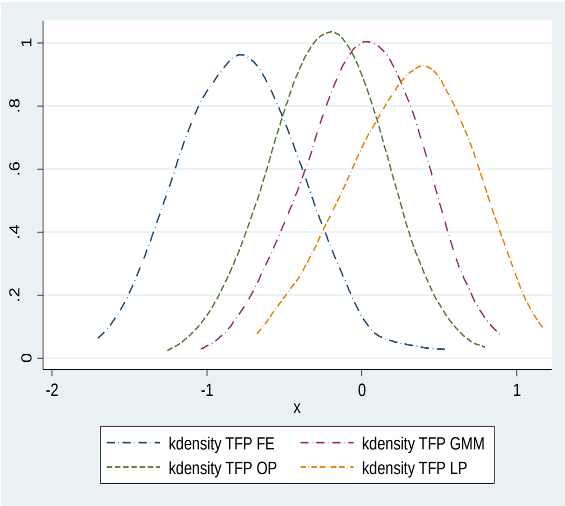
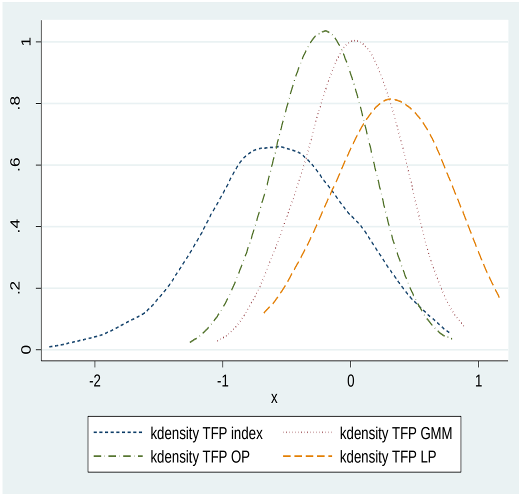


Figure 11. Distribution function across parametric, nonparametric and semi-parametric measures of TFP



Sources: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 20: The comparison between parametric and non-parametric measures for TFP based on Gross Value Added (*gva*) and Average number of employed persons in industry (*em*)

	TFP_{em}	TFP_{ols}	TFP_{IVreg}	TFP_{FE}	TFP_{GMM}	TFP_{OP}	TFP_{LP}
TFP_{em}	1						
TFP_{ols}	0.346*	1					
TFP_{IVreg}	0.3395*	0.992*	1				
TFP_{FE}	0.3256*	0.9944*	0.9996*	1			
TFP_{GMM}	0.5742*	0.9198*	0.8740*	0.8787*	1		
TFP_{OP}	0.5576	0.9198*	0.8740*	0.8787*	0.9816*	1	
TFP_{LP}	0.2962*	0.7772*	0.6919*	0.7070*	0.9465*	0.9097*	1

Note: TFP calculation will be based on gross value added (*gva*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t)$ where L is define as Average number of employed persons in industry (*em*) , K is material input (*gvfa*), the estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations productivity shock by using intermediate consumption *(ic)*. Notation for non-parametric Index approach for average number of employed person in industry (*em*) is $TFP_{\_em}$ *-statically significant level is 5 percentages. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

The correlation between the nonparametric and parametric approach is between 0.57-0.21 across different labour measures (first column in the tables). The analysis of correlation between different semi-parametric and parametric TFP indexes showed that they are very strongly correlated around 0.9, which is expected because they are estimated on the base of production frontier. Table 21 presents statistically significant estimation results for gross-output basis with respect to three labour measures and two production estimations (sold production *(s)* and gross output *(gu)*).

Table 21: The comparison between parametric and non-parametric measures for TFP Correlation of productivity estimates across methodologies for gross-output basis estimations

Gross Output *(gu)*			Sold production *(s)*			
	TFP_{em}	TFP_{ols}		TFP_{em}	TFP_{ols}	TFP_{IVreg}
TFP_{em}	1		TFP_{em}	1		
TFP_{ols}	-0.0858*	1	TFP_{ols}	-0.0563*	1	
TFP_{IVreg}	-0.0933*	0.999*	TFP_{IVreg}	-0.0668*	0.999*	1
TFP_{FE}			TFP_{FE}	-0.0688	0.999*	1
Gross Output *(gu)*			Sold production *(s)*			
	TFP_{ape}	TFP_{ols}		TFP_{ape}	TFP_{ols}	TFP_{IVreg}
TFP_{ape}	1		TFP_{ape}	1		
TFP_{ols}	-0.074 *	1	TFP_{ols}	-0.074*	1	
TFP_{IVreg}	-0.074	1*	TFP_{IVreg}	-0.074*	1*	1
TFP_{FE}			TFP_{FE}	-0.0728	0.9996*	1
Gross Output *(gu)*			Sold production *(s)*			
	$TFP_{em31\_}$	TFP_{ols}		$TFP_{em31\_}$	TFP_{ols}	TFP_{IVreg}
$TFP_{em31\_}$	1		$TFP_{em31\_}$	1		
TFP_{ols}	-0.0972*	1	TFP_{ols}	-0.0972*	1	
TFP_{IVreg}	-0.0960	1*	TFP_{IVreg}	-0.0960	1*	1
TFP_{FE}			TFP_{FE}	-0.0633	0.9998*	0.9998*

Notes: TFP calculation will be based on gross value added (*gva*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t) + \hat{\beta}_M \ln(M_t)$ where L is defined as the average paid employment of full-time paid employees (*ape)* or an average number of employed persons (*em*), employment, as of 31 XII (*em31_*), K is material input (*gvfa),* the estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations productivity shock by using intermediate consumption *(ic)*. Notation for non-parametric Index approach for three labour indicators (*ape*, *em* and *em31_*) are TFP_{ape}, $TFP_{\_em}$ and $TFP_{\_em31}$ *-statically significant level is 5 percentages. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry, Polish Central Statistical Office (CSO) (various years)

The correlation matrix analysis for gross-output base estimations suggests that there is a high degree of correlation among all parametric indexes employed between 0.99 and 1. On the other hand, the correlation between the nonparametric and parametric approaches seems to be negative which is in contrast to value added base estimation correlation results. One consideration is that the majority of econometrics techniques for correcting the problems of endogeneity provided not statistically significant results for gross-output base estimation. In this matter it seems to be wise to implement value added base estimation for further analysis in Chapter 5.

In this part of analysis, I investigate the dynamics of productivity for the period between 1995 and 2007 for 22 sectors from the manufacturing division. The initial analysis of TFP trends shows the positive trends in all sectors across-time (see Figure 12, 13 and Appendix 4 Figure 5).

Figure 12. Value added base estimation for TFP trends across time for an average number of employed person in industry and Gross Value Added

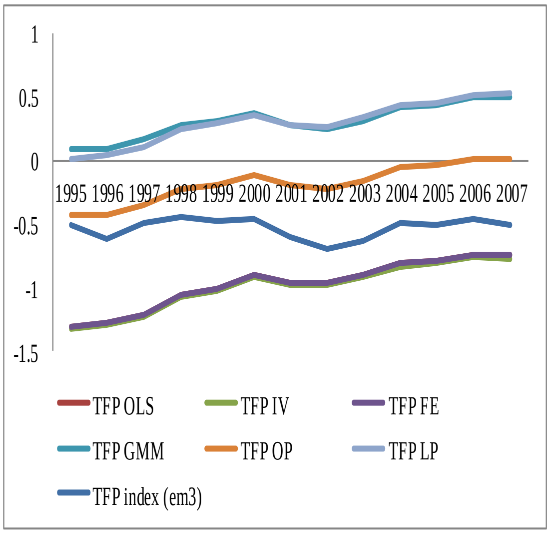
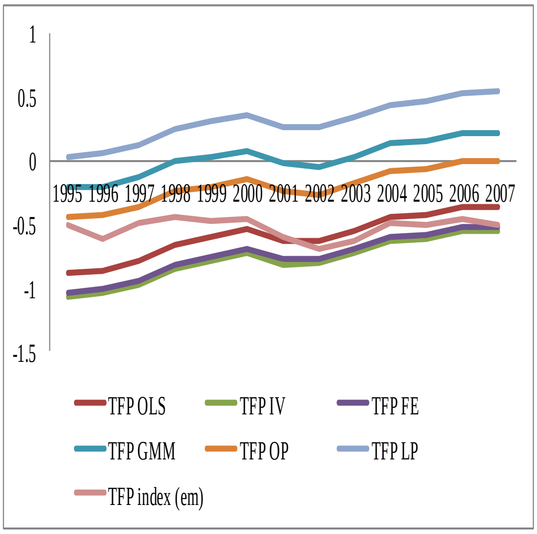


Figure 13. Gross output base estimation for TFP trends across time employment, as of 31 XII and Gross output



Notes: Estimation for Olley and Pake's method includes an investment outlays on fixed assets buildings (*ifab*). The Levinsohn and Petrin's approach was utilized for TFP calculations productivity shock by using intermediate consumption *(ic).Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

There are significant dispersions between sectors, as shown though calculating an average mean for each sectors (see Figure 14 and 15). However, the overall patterns of TFP is the same for parametric, and slightly different with respect to the non-parametric approach.[121] Similar to an analysis with respect to gross value-added there is

[121] A calculation for TFP with utilization of Gross Output, similar to the last calculation for TFP with respect to Gross Value Added, and the average paid employment of full-time paid employees *(ape)*, have readily constant trends for all sectors. This is in contrast to the same estimation with respect to employment, as of 31 XII *(em31)* and the average paid employment of full-time paid employees *(ape)*

some significant dispersion between sectors, and the trend is different for the parametric and non-parametric approaches for employment (see Appendix 4 Figure 6).

Figure 14 Parametric and Non-parametric approach value added base for an average number of employed persons in industry (em) cross sectors

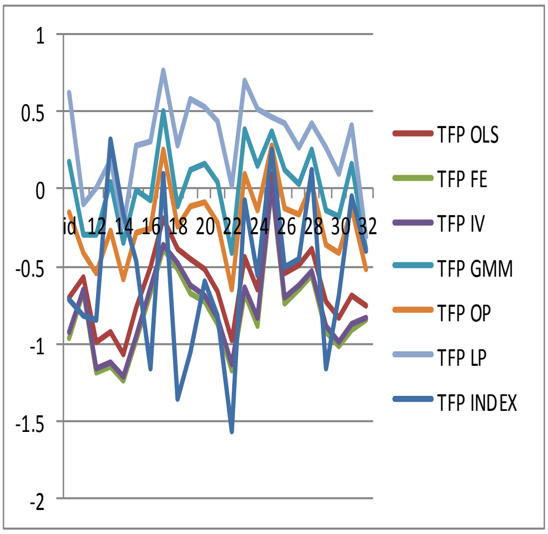
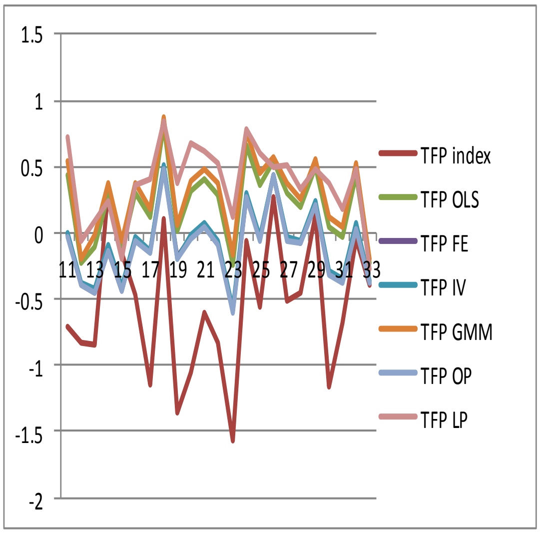


Figure 15 Parametric and Non-parametric approach value added base for the average paid employment of full-time paid employees (ape) cross sectors



Notes: Estimation for Olley and Pake's method includes an investment outlays on fixed assets buildings (*ifab*). The Levinsohn and Petrin's approach was utilized for TFP calculations productivity shock by using intermediate consumption *(ic). Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years**)**

A dynamics of productivity for the period between 1995 and 2007 for 22 sectors from manufacturing division shows the positive trends in all sectors across-time with a significant disturbance in the beginning of 90s (see Figure 16 and Appendix 4 Figure 8). There is an inconsistency between parametric and non-parametric techniques' results, and it seems that a semi-parametric –approach better-predicts productivity shocks and is in the same direction with TFP index in the end of period than parametric computations (see Figure 16). Also this result seems to present more of the dynamics in TFP changes compared to previous studies of Polish manufacturing (see Jakubiak, 2002, 2005).

Figure 16 Mean of changes in TFP index over period 1995 and 2007 for an

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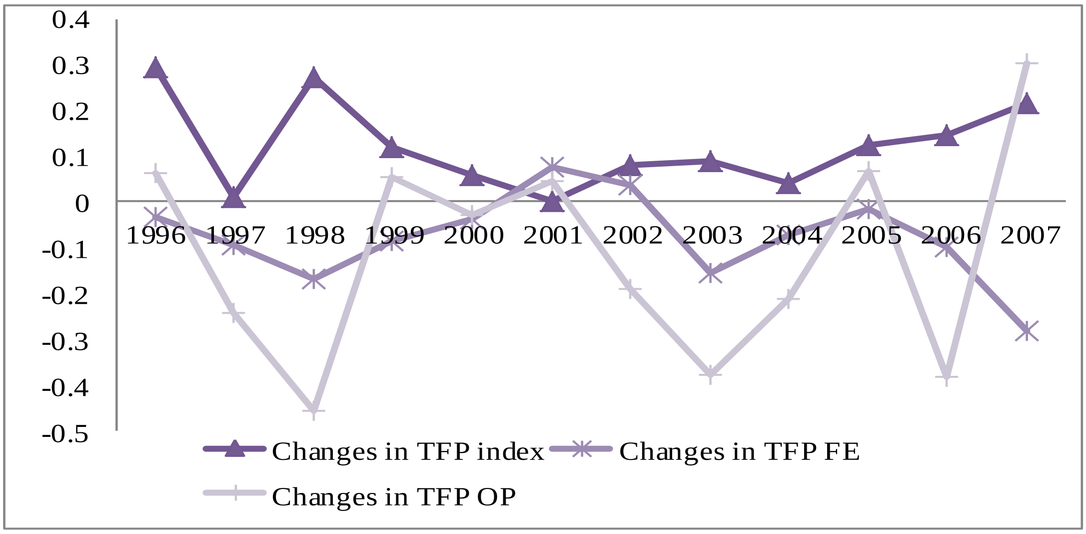
where the trend is positive. A calculation for TFP with utilization of sold production showed a positive trend (see Appendix 4.4 Figure 6).

average number of employed persons in industry (em)



Notes: TFP calculation will be based on gross value added (*gva*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t)$ where L is define as Average number of employed persons in industry (*em*) , K is material input (*gvfa*), the estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. Notation for non-parametric Index approach for three labour indicators (*em31_*) is TFP index *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

According to gross-output base estimation for sold production and gross output, there is no difference in patterns between different labour measures (see Appendix 4 Figure 8). By contrast, in the case of the gross value added estimation, there are differences in patterns between all different techniques and labour measures (Appendix 4. Figure 8). Compared to the previous analysis of the Manufacturing division, these results for 22 manufacturing sectors presented the small and significant impacts of measures of inputs and outputs in productivity estimations.

6. Conclusion

The concept of TFP has been intensively discussed in the literature since the 1950s work on Solow model adaptation. This chapter gave an empirical overview of measurement of TFP and pointed out the problems of simultaneity of input choice and endogeneity of attrition within parametric estimations, at both the level of sector aggregation and at firm-level. The literature suggests various econometrics methods to overcome these issues for firm-level analysis, but not for sector aggregation.

In this paper, TFP was computed across time cross-time, and for manufacturing sector aggregation and output and input choice for Polish manufacturing sectors for the period between 1995 and 2007. The cross-time analysis was implemented for Total manufacturing, with respect to three divisions: mining and quarrying, manufacturing and electricity, gas and water supply. The panel analysis was used with respect to 22 manufacturing sectors according to NACE rev 1.1 classifications. I used three different econometric techniques to compute TFP: TFP index measure (non-parametric), parametric production functions estimation (GMM) and proposed semi-parametric estimations.

The evolution of industry TFP over the sample period shows an upward trend at the establishment level which it seems to be consistent with existing literature about the Polish manufacturing sector. Also, the elasticity of labour is relatively higher than that of capital, implying that the labour plays a significant role in the production process and should be taken into account in policy recommendations for further transformation of Polish manufacturing sector into more capital intensive economy. The exception is found in the results for Mining and quarrying division; this division is the most capital intensive. Moreover, the results for the value added base seems to be more consistent and statistical significant than the gross-output base. It seems also that there is not a large impact through different measures of labour inputs for division’s analysis and Total Manufacturing. On the other hand, there are small and significant impacts of measures of labour inputs into productivity estimations for panel of 22 manufacturing sectors. Among the three measures of labour, the average number of employed persons in industry *(em)* provides the most consistent results for TFP calculation. Also this measure includes a broader definition of labour input in Polish manufacturing sector data.

Furthermore, this chapter introduces the concept of semi-parametric techniques on sector level data to overcome the traditional biases, specifically through an implementation techniques by Olley Pakes (1996) and Levinsohn and Petrin (2003). It is also apparent that a semi-parametric approach reduces the effect of endogeneity of attribution and a simultaneity bias on the coefficient.

The changes in TFP for both the parametric and non-parametric techniques seem to be consistent. The illustration of TFP changes followed a downward trend over the estimating period (1995-2007) for the majority of sectors and then an upward trend. These results seem to reflect the transformation period for the Polish economy. This effect was more captured by a nonparametric approach, which might suggest that the cost of capital paid an important role. Then there were upward trends for both types of measures between 1998 and 2007, which could reflect the fact that firms that survived the transformation period were able to expand their operation and take over the market share of leavers. It seems that this process was also more volatile for *Electricity, gas, steam and hot* water supply division than for the *Total Manufacturing* and *Mining division*.

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Appendix 2

Table 1: Different function types and function forms

Function type	Function form
Linear	$Y = \beta_o + \sum_{i=1}^{N} \beta_i X_i$
Cobb-Douglas	$Y = \beta_o \prod_{i=1}^{N} X_i^{\beta_i}$
Normalised Quadratic	$Y = \beta_o + \sum_{i=1}^{N} \beta_i X_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{s=1}^{N} \beta_{is} \left(\frac{X_i}{X_N} \right) \left(\frac{X_s}{X_N} \right)$
Translog [122]	$Y = \exp \left[\beta_o + \sum_{i=1}^{N} \beta_i \ln(X_i) + \frac{1}{2} \sum_{i=1}^{N} \sum_{s=1}^{N} \beta_{is} \ln(X_i) \ln(X_s) \right]$
Generalized Leontief	$Y = \sum_{i=1}^{N} \sum_{s=1}^{N} \beta_{is} (X_i X_s)^{1/2}$
Constant Elasticity of Substitution (CES)	$Y = \beta_o \left(\sum_{i=1}^{N} \beta_i X_i^{\gamma} \right)^{1/\gamma}$

Notes: X –inputs and Y – is output *Source:* Coelli, Rao, O'Donnell, and Battese (2005, p. 211)

[122] The Cobb-Douglas can be transferred to the translog if all β_{is} =0 Coelli, Rao, O'Donnell, and Battese (2005:211)

Appendix 3
Table 2: NACE Rev 1.1 Classification

NACE Rev 1.1. classification		**Sector name**
D		**Manufacturing**
DA	15	Manufacture of food products and beverages
DA	16	Manufacture of tobacco products
DB	17	Manufacture of textiles
DB	18	Manufacture of wearing apparel and furriery
DC	19	Processing of leather and manufacture of leather products
DD	20	Manufacture of wood and wood, straw and wicker products
DE	21	Manufacture of pulp and paper
DE	22	Publishing, printing and reproduction of recorded media
DF	23	Manufacture of coke, refined petroleum products
DG	24	Manufacture of chemicals and chemical products
DH	25	Manufacture of rubber and plastic products
DI	26	Manufacture of other non-metallic mineral products
DJ	27	Manufacture of basic metals
DJ	28	Manufacture of metal products
DK	29	Manufacture of machinery and equipment n.e.c
DL	30	Manufacture of office machinery and computers
DL	31	Manufacture of electrical machinery and apparatus
DL	32	Manufacture of radio, television and communication equipment and apparatus
DL	33	Manufacture of medical, precision and optical instrument, watches and clocks
DM	34	Manufacture of motor vehicles, trailer and semi-trailers
DM	35	Manufacture of other transport equipment
DN	36	Manufacture of furniture, manufacturing n.e.c
DN	37	Recycling

Source: Nomenclature des Activités de Communauté Européenne –NACE rev. 1.1

Appendix 4

Table 1: Summary statistics of key variables for Total Manufacturing estimation

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Output (*s*)-Sold production	13	3393.789	699.061	2444.327	4833.289
Output (*gu*)-Gross output	13	3530.072	740.599	2518.189	5023.559
Output (*gva*)-Gross value added	13	1074.355	152.529	845.121	1376.251
Labour (*ape)*- average paid employment	13	2986	278.065	2639.1	3461.1
Labour (*em31_*) employment as of 31.XII	13	3243.931	364.712	2872.1	3761.3
Labour (*em*) average number of employed persons	13	3261.754	357.419	2902.2	3756.9
Capital (*gvfa*)-gross value of fixed assets	13	3171.715	278.065	2385.337	3605.171
Intermediate consumption (*ic*)	13	382321	151407.9	167306.8	667822.2

Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 2: Production function estimates for Total Manufacturing for Gross Value Added (*gva*)

Method	N	Labour β_L	Capital β_K
OLS (*lem*)	13	0.825***	0.44***
IV reg	13	0.83***	0.71***
OLS (*lem31_*)	13	0.825***	0.44***
IV reg	13	0.62***	0.87***
OLS (*lape*)	13	0.43***	0.83***
IV reg	13	0.44***	0.82***

Notes: *** the statistical significant level is more than 10 percentages, F-statistics confirm an overall statically significant, *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 3: Summary statistics of key variables for Mining and quarrying

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Output (*s*)-Sold production	13	166.8665	30.21372	137.7781	242.8817
Output (*gu*)-Gross output	13	167.3175	30.47456	138.6274	244.6555
Output (*gva*)-Gross value added	13	96.92588	15.45262	79.91848	136.23
Labour index (*ape)*- average paid employment	13	251.0923	70.61401	180.3	374.4
Labour index (*em31_*) employment index as of 31.XII	13	243.1615	64.70289	180.3	357.1
Labour index (*em*) average number of employed persons	13	252.3615	70.36403	181.8	375.3
Capital index (*gvfa*)-gross value of fixed assets	13	243.7129	78.96773	153.8615	398.027
Intermediate consumption (*ic*)	13	382321	151407.9	167306.8	667822.2

Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 4: Summary statistics of key variables for Manufacturing

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Output (*s*)-Sold production	13	3084.176	799.1115	2003.48	4719.723
Output (*gu*)-Gross output	13	3225.341	846.7752	2071.203	4927.007
Output (*gva*)-Gross value added	13	877.9339	164.4074	627.701	1207.702
Labour (*ape)*- average paid employment	13	2489.677	247.7364	2206.3	2820.9
Labour (*em31_*) employment as of 31.XII	13	2761.185	291.2405	2440	3177
Labour (*em*) average number of employed persons	13	2763.092	268.8381	2466.7	3125.7
Capital (*gvfa*)-gross value of fixed assets	13	1778.759	280.2049	1214.865	2278.668
Intermediate consumption (*ic*)	13	337980.5	137213	144350.2	599551.9

Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 5: Summary statistics of key variables for Electricity, gas, stem and hot water supply

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Output (*s*)-Sold production	13	303.1133	35.147	245.491	345.67
Output (*gu*)-Gross output	13	307.9619	36.85568	248,6221	352.4416
Output (*gva*)-Gross value added	13	129.0698	13.2997	107.015	144.6913
Labour (*ape)*- average paid employment	13	245.2308	23.89468	213.4	277.8
Labour (*em31_*) employment as of 31.XII	13	239.5846	17.6222	215.2	269.2
Labour (*em*) average number of employed persons	13	246.3	23.64734	214.8	278.2
Capital (*gvfa*)-gross value of fixed assets	13	1101.407	155.4572	933.436	1510.782
Intermediate consumption (*ic*)	13	32423.12	12488.14	14419.8	51491.3

Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 6: Production function estimates for Mining and quarrying for sold production (*s*)

Method	N	Labour β_L	Material β_M	Capital β_K
IV reg (2 SLS) (*em*)	13	0.47*	0.21**	0.21***(0.141)
IV reg (2 SLS) (*em31_*)	13	0.50*	0.20**	0.20***(0.11)
IV reg (2 SLS) (*ape*)	13	0.47*	0.22**	0.20***(0.12)

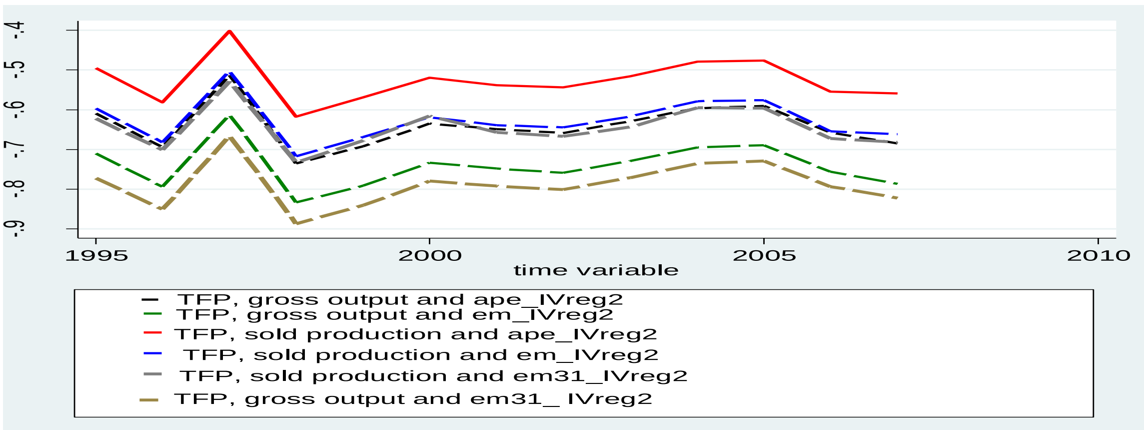
Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages. () - provided the value of probability to accept or reject hypothesis of significant F-statistics confirm an overall statically significant *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 7: Summary statistics of key variables for 22 manufacturing sectors

Variables	N	Mean	Standard Deviation	Minimum	Maximum
Output (*s*)-Sold production	286	143.276	140.4394	4.786	839.987
Output (*gu*)-Gross output	286	149.403	146.3796	5.867	918.7378
Output (*gva*)-Gross value added	286	41.089	33.10877	1.763	193.7204
Labour (*ape)*- average paid employment	286	112.799	98.29436	4.1	510.5
Labour (*em31_*) employment as of 31.XII	286	125.078	108.9049	4.7	562.1
Labour (*em*) average number of employed persons	286	125.184	107.2068	4.7	549.7
Capital (*gvfa*)-gross value of fixed assets	286	86.290	74.80458	1.345	385.852
Intermediate consumption (*ic*)	286	15288.44	17795.08	0.164	122382.9
Investment outlays (i)	279	9.138	8.6534	391.8	41.717
Investment outlays on fixed assets (ifa)	279	1262.741	1249.598	16.4	6780.9
Investment outlays on fixed asset buildings (ifab)	279	2.601	2.642	0.412	14.117
Investment outlays on fixed asset transports (ifat)	279	0.5447	0.6668	0.0106	3.80
Investment outlays on fixed asset machinery (ifam)	279	5.858	5.589631	0.059	26.555
Consumption of electricity (cel)	198	15288.44	16.3257	0.026	83.905
Direct consumption of electricity (dce)	198	1842.818	2503.23	2	11104

Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

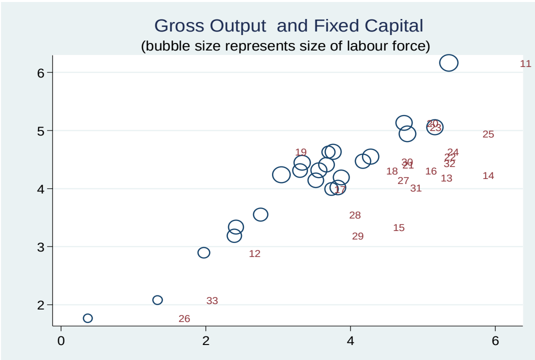
Figure 1: TFP index by parametric methods by IV instrumental regression for Mining and Quarrying in Poland a period between 1995 and 2007



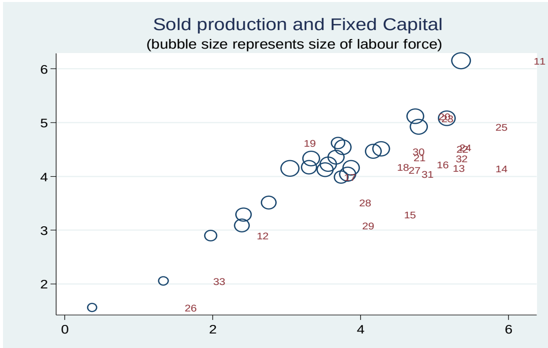
Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Figure 2: The relation between output, labour input and capital for year 1995, 2000 and 2007

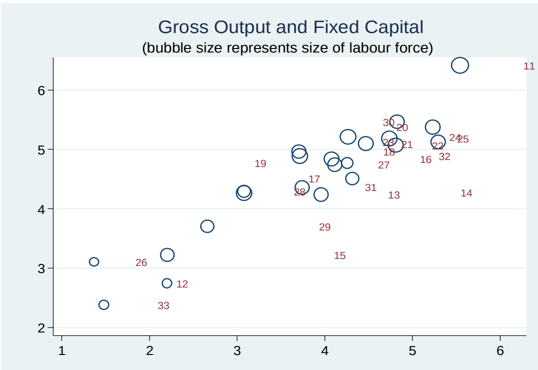
Gross Output and Fixed Capital for 22 sectors in Poland in 1995



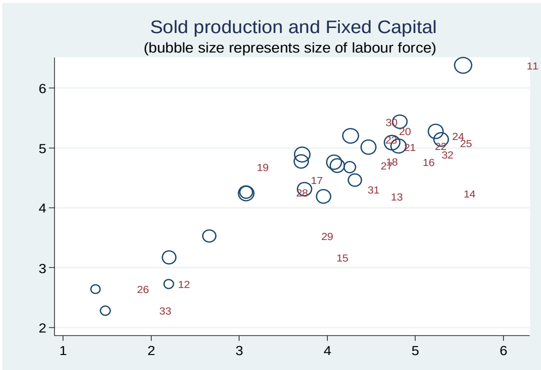
Sold production and Fixed Capital for 22 sectors in Poland in 1995



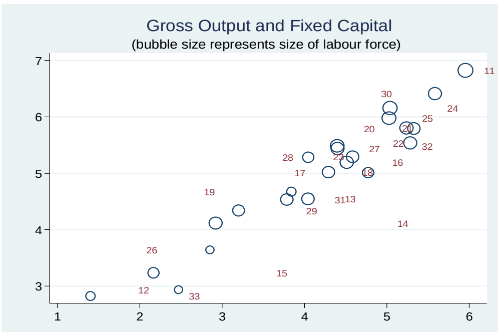
Gross Output and Fixed Capital for 22 sectors in Poland in 2000



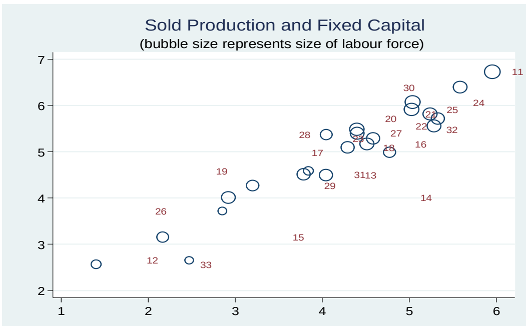
Sold production and Fixed Capital for 22 sectors in Poland in 2000



Gross Output and Fixed Capital for 22 sectors in Poland in 2007



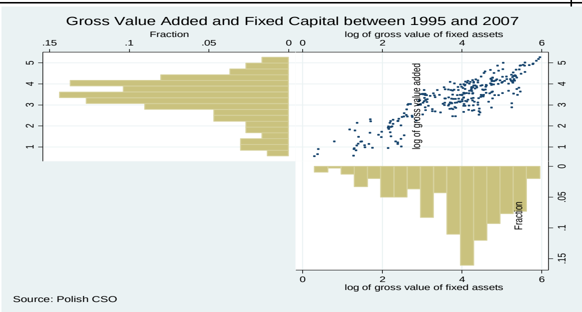
Sold production and Fixed Capital for 22 sectors in Poland in 2007



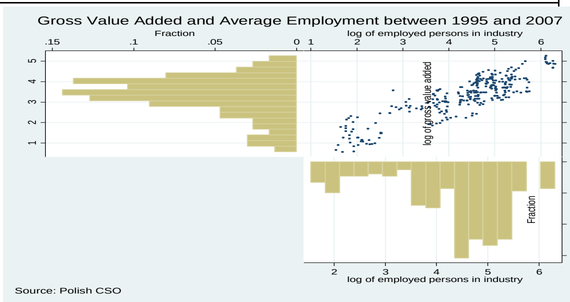
Notes: An analysis was employed with respect to other labour measures and provides similar results. *Source:* Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years). Labour is measured by an average number of employed person in industry

Figure 3: The relation between output, labour and capital inputs with regards to inputs distributions

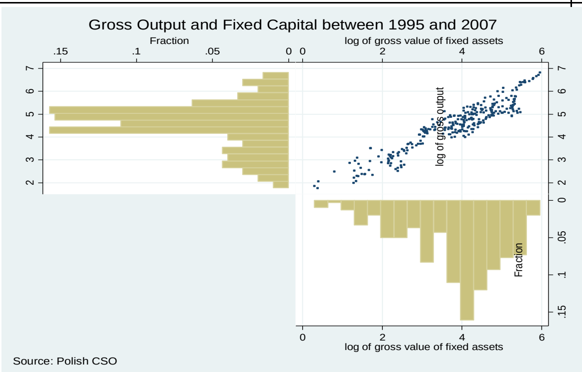
Gross Value Added and Gross value of fixed asset between 1995 and 2007



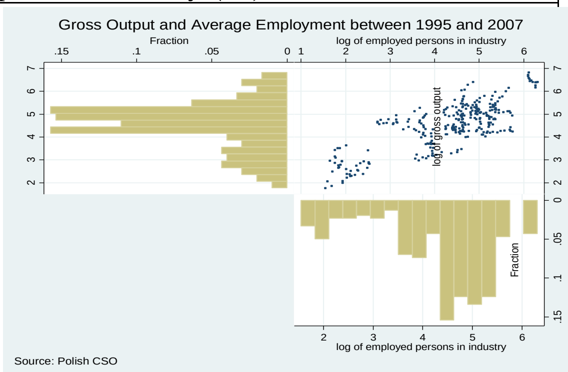
Gross Value Added and an average number of employed persons in industry *(em)* between 1995 and 2007



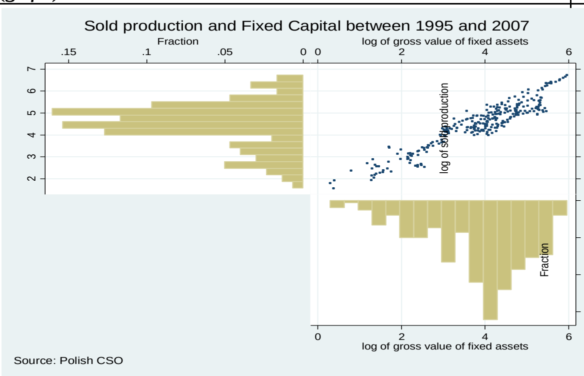
Gross Output and Gross value of fixed assets (*gvfa*) between 1995 and 2007



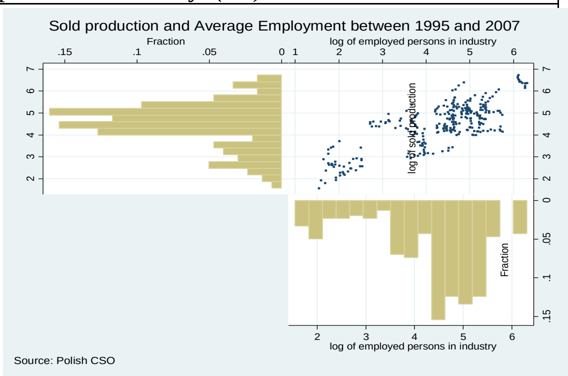
Gross Output and average number of employed persons in industry *(em)* between 1995 and 2007



Sold production and Gross value of capital fixed (*gvfa*) between 1995 and 2007



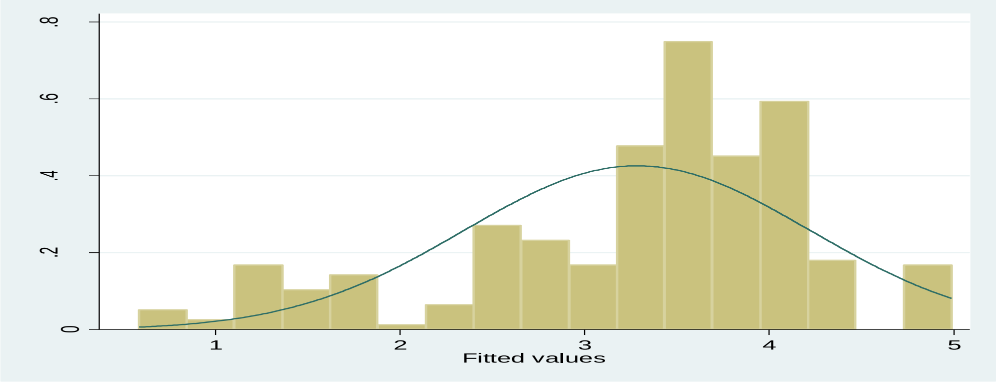
Sold production and average number of employed persons in industry *(em)* between 1995 and 2007



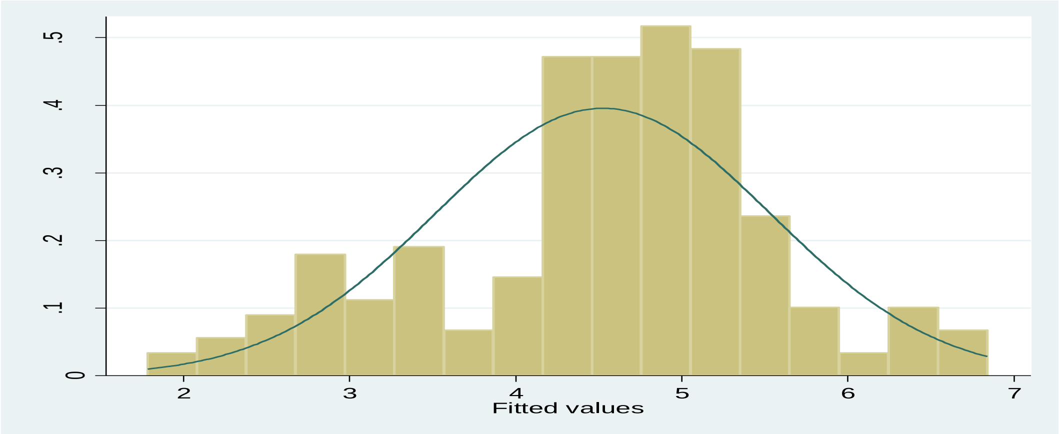
Notes: An analysis was employed with respect to other labour measures and provides similar results.
Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Figure 4: The residual distributions for production functions with regards to output measures

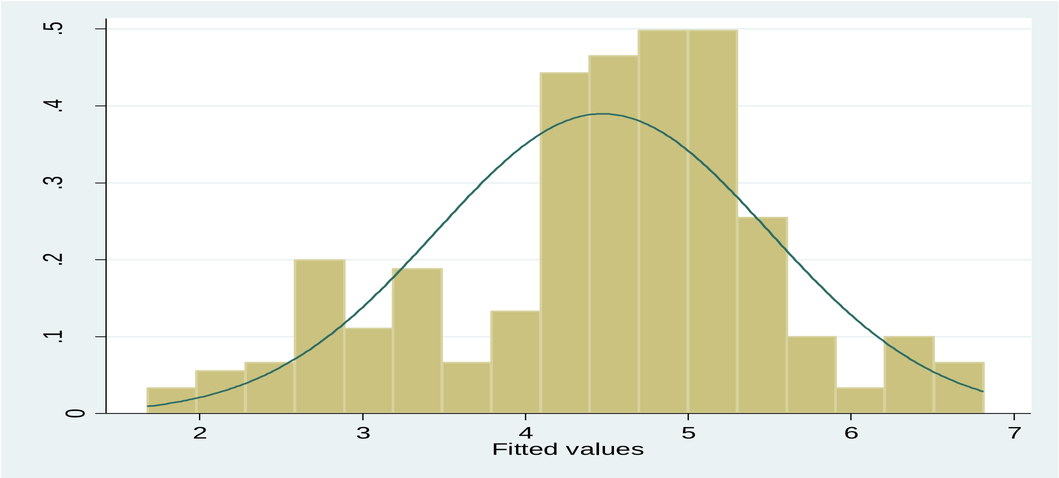
Residual plot graph for production functions estimating for Gross Value Added and an average number of employed person (*em*) between 1995 and 2007



Residual plot graph for production functions estimating for Gross Output and an average number of employed person (*em*) between 1995 and 2007



Residual plot graph for production functions estimating for Sold production and an average number of employed person (*em*) between 1995 and 2007



Notes: An analysis was employed with respect to other labour measures and provides similar results. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years). Labour is measured by an average number of employed person in industry

Table 8: Production function estimates for manufacturing sector data (22 manufacturing sectors) for different output measures and three different labour measures (*em, em31_, ape*) via Olley and Pake's (1996) technique

Output proxy/Labour proxy/ Investment proxy	N	Capital β_K	Labour β_L	Materials β_M
gva/em/ifa	285	0.445*	0.404**(0.056)	-
gva/em/ifab	285	0.44*	0.418*	-
gva/em/ifat	285	0.25**(0.052)	0.311*	-
gva/em/ifam	285	0.23**(0.09)	0.44*	-
gva/em31_/ifab	285	0.411*	0.44*	-
gva/em31_/ifat	285	0.25**(0.086)	0.312*	-
gva/em31_/ifa	285	0.435*	0.445*	-
gva/ape/ifab	285	0.396*	0.456*	-
gva/ape/ifa	285	0.4**(0.068)	0.463*	-
gu/em/ifab	285	0.06**(0.068)	0.107*	0.85*
s/em31_/ifab	285	0.076*	0.114*	0.83
s/em31_/ifam	285	0.059**(0.078)	0.117*	0.826*
s/em/ifab	285	0.078*	0.113*	0.837*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[123] - provided the value of probability to accept or reject hypothesis of significant. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 9: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross value added (*gva*) and an average number of employed persons in industry at 31.12. (*em31_*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.7*	-	0.28*
IVreg	299	0.75*	-	0.28*
Fixed Effects	299	0.75*	-	0.27*
GMM	299	0.3*	-	0.43*
OP	285	0.44*	-	0.41*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[124]- provided the value of probability to accept or reject hypothesis of significant. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

[123] The information was provided if the probability was close to the edge of statistical signification.
[124] The information was provided if the probability was close to the edge of statistical signification.

Table 10: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross value added (*gva*) and an average employed (*ape*).

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.51*	-	0.34*
IVreg	299	0.443*	-	0.4*
Fixed Effects	299	0.456*	-	0.4*
GMM	299	0.3*	-	0.437*
OP	285	0.456*	-	0.396*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[125]- provided the value of probability to accept or reject hypothesis of significant. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 11: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross output (*gu*) and an average number of employed persons in industry at 31.12. (*em31_*)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.106*	0.86*	0.025*
IVreg	299	0.11*	0.875*	0.0175*
Fixed Effects	299	0.12*	0.873*	0.158***(0.3)
GMM	285	0.0965*	0.88*	0.047***(0.25)

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[126] - provided the value of probability to accept or reject hypothesis of significant.
Source: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 12: Production function estimates for manufacturing sector data (22 manufacturing sectors) for gross output (*gu*) and an average employed (ape)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.062*	0.89*	0.028*
IVreg	299	0.061*	0.89*	0.028*
Fixed Effects	299	0.061*	0.89*	0.028**(0.08)
GMM	299	0.11*	0.82*	0.0057***(0.87)

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[127]- provided the value of probability to accept or reject hypothesis of significant. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 13: Production function estimates for manufacturing sector data (22 manufacturing sectors) for sold production (*s*) and an average number of employed persons in industry at 31.12. (*em31_*)

[125] The information was provided if the probability was close to the edge of statistical signification.
[126] The information was provided if the probability was close to the edge of statistical signification.
[127] The information was provided if the probability was close to the edge of statistical signification.

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.136*	0.85*	0.068*
IVreg	299	0.131*	0.88*	0.051*
Fixed Effects	299	0.0621*	0.89*	0.0281*
GMM	299	0.0865*	0.89*	0.0146***(0.25)
OP	285	0.114*	0.83*	0.076*

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[128]- provided the value of probability to accept or reject hypothesis of significant (l)-Linear regression with panel-corrected standard errors was implemented. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 14: Production function estimates for manufacturing sector data (22 manufacturing sectors) for sold production (*s*) and an average employed (ape)

Method	N	Labour β_L	Material β_M	Capital β_K
OLS	299	0.094*	0.86*	0.0795*
IVreg	299	0.083*	0.9*	0.062*
Fixed Effects	299	0.13*	0.88*	0.049*
GMM	285	0.129*	0.886*	0.0497***(0.85)

Notes: *** the statistical significant level is more than 10 percentages ** the statistical significant level is equal and less than 10 percentages * the statistical significant level is equal and less than 5 percentages, ()[129] - provided the value of probability to accept or reject hypothesis of significant (l)-Linear regression with panel-corrected standard errors was implemented. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

[128] The information was provided if the probability was close to the edge of statistical signification.
[129] The information was provided if the probability was close to the edge of statistical signification.

Table 15: Correlation of productivity estimates across methodologies for Gross Value Added (*gva*) and Average number of employed persons in industry at 31.12 (*em31*)

	$TFP_{em31\_}$	TFP_{ols}	TFP_{IVreg}	TFP_{FE}	TFP_{GMM}	TFP_{OP}	TFP_{LP}
$TFP_{em31\_}$	1						
TFP_{ols}	0.2112*	1					
TFP_{IVreg}	0.2173*	0.99*	1				
TFP_{FE}	0.2112*	1*	0.9999*	1			
TFP_{GMM}	0.5463*	0.4981*	0.4918*	0.4981*	1		
TFP_{OP}	0.5466	0.7815*	0.7779*	0.7815*	0.9258*	1	
TFP_{LP}	0.3*	0.6089*	0.6005*	0.6089	0.9552*	0.9208*	1

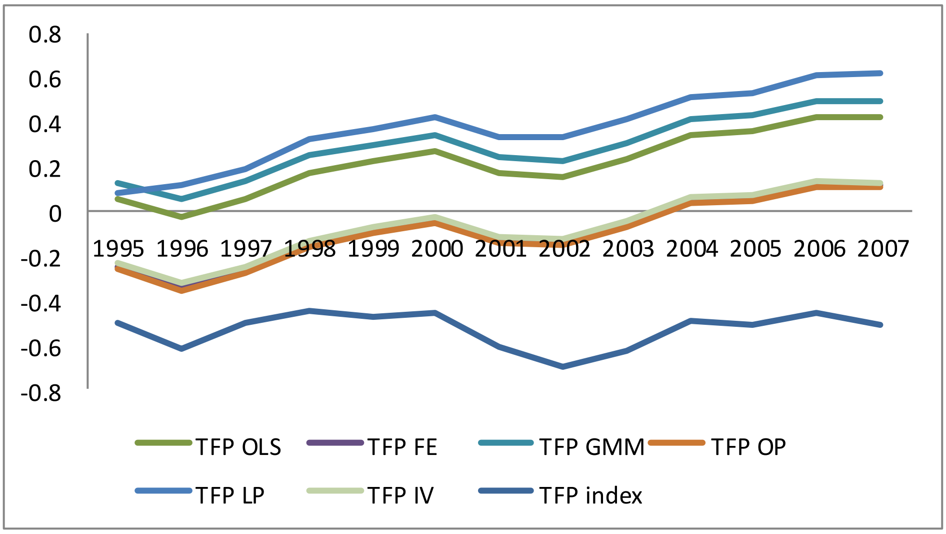
Note: TFP calculation will be based on gross value added (*gva*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t)$ where L is define as an Average number of employed persons in industry at 31.12 (*em31_*), K is material input (*gvfa),* the estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations of productivity shock by using intermediate consumption *(ic)*. Notation for non-parametric Index approach for Average number of employed persons in industry at 31.12 (*em31*) is TFP_{em31} *-statically significant level is 5 percentages. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Table 16: Correlation of productivity estimates across methodologies for Gross Value Added (*gva*) and Average paid employed (*ape*)

	TFP_{ape}	TFP_{ols}	TFP_{IVreg}	TFP_{GMM}	TFP_{OP}	TFP_{LP}
TFP_{ape}	1					
TFP_{ols}	0.5936	1				
TFP_{IVreg}	0.6262	0.9738	1			
TFP_{GMM}	0.6161	0.9698	0.9997	1		
TFP_{OP}	0.5887	0.9984	0.9597	0.9545	1	
TFP_{LP}	0.6156	0.9679	0.9996	1	0.9523	1

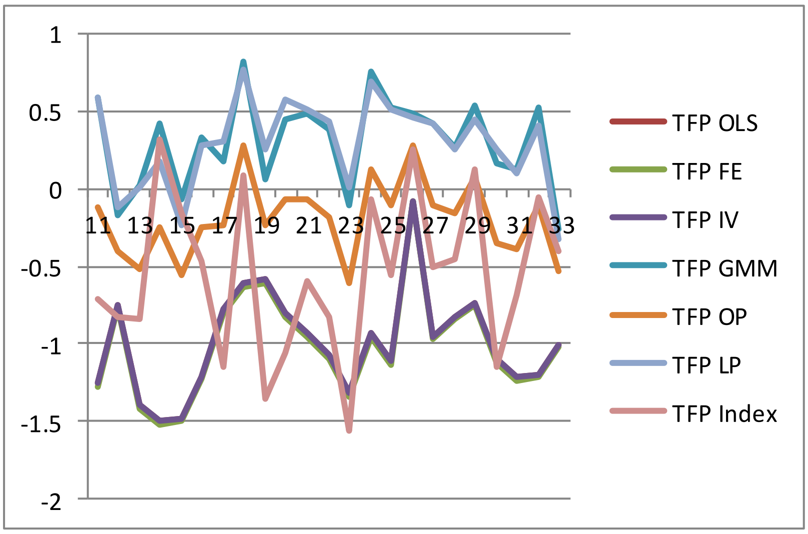
Note: TFP calculation will be based on gross value added (*gva*) and follows the equation $TFP_t = \ln(Y_t) - \hat{\beta}_L \ln(L_t) - \hat{\beta}_K \ln(K_t)$ where L is define as an average paid employed (*ape*), K is material input (*gvfa)*, the estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations of productivity shock by using intermediate consumption *(ic)*. Notation for non-parametric Index approach for an average paid employed (*ape*) is TFP_{ape} *-statically significant level is 5 percentages. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years)

Figure 5: Gross output base estimation for TFP trends across the average paid employment of full-time paid employees (ape) and sold production



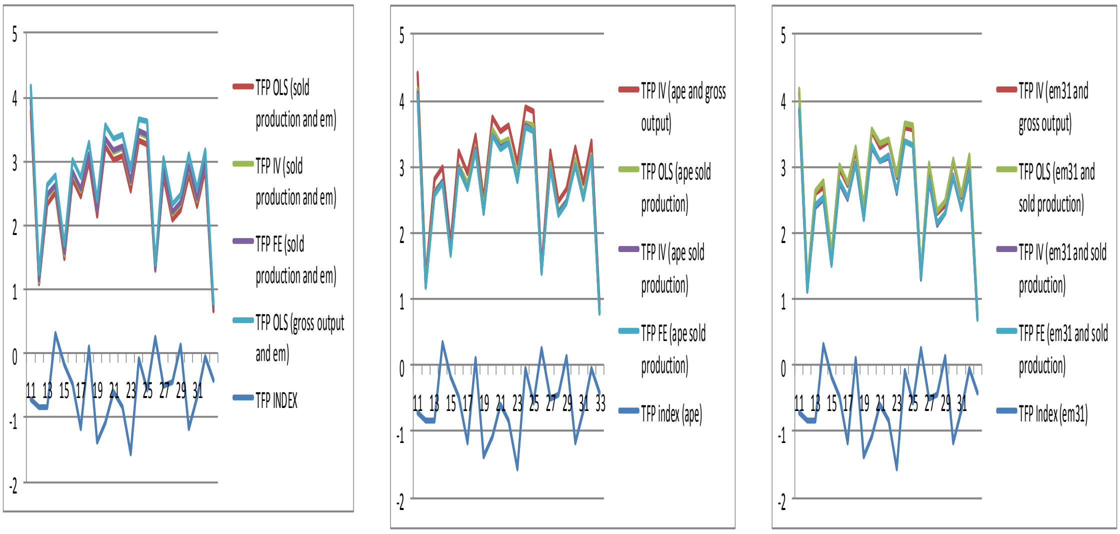
Notes: The estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations of productivity shock by using intermediate consumption *(ic)*. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years**)**

Figure 6: Parametric and Non-parametric approach value added base cross for employment, as of 31 XII *(em31)* cross sectors



Notes: The estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations productivity shock by using intermediate consumption *(ic)*. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years**)**

Figure 7: Parametric and Non-parametric approach value added base cross sectors

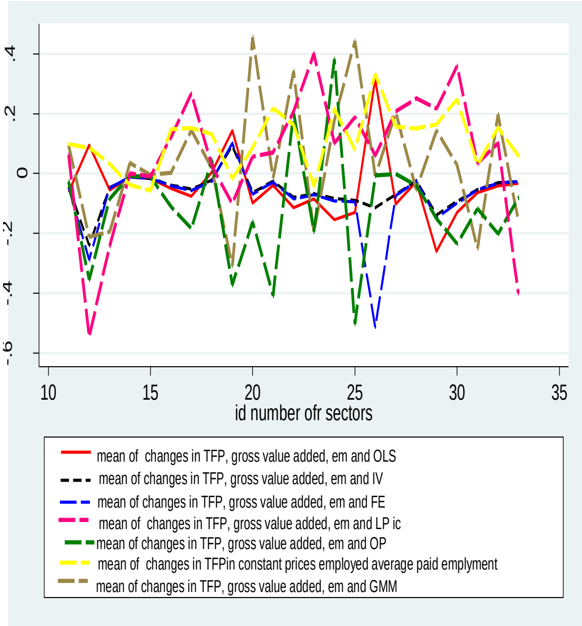


Notes: The estimation for Olley and Pake's method only included an investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations of productivity shock by using intermediate consumption *(ic)*. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years**)**

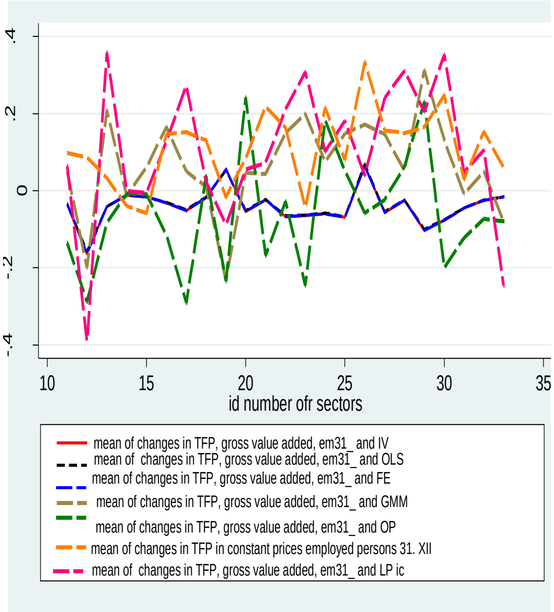
Figure 8: Trend of TFP growth for period between 1995 and 2007 for 22 manufacturing sectors

TFP growth measures by parametric approach and nonparametric approach for a gross value added and an average number of employed persons in industry (em).

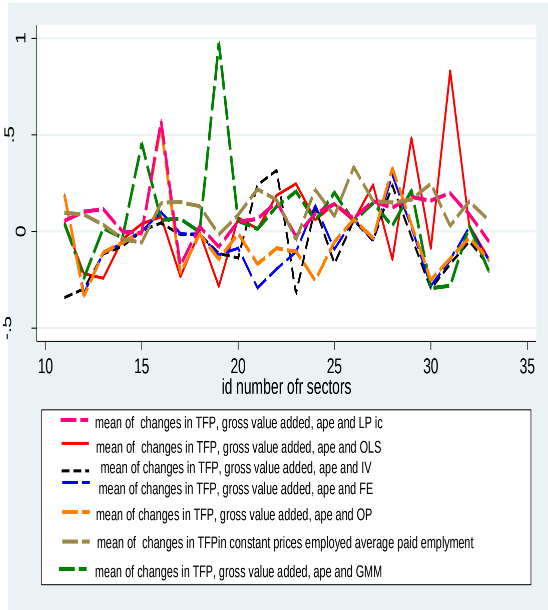
TFP growth measures by parametric approach and nonparametric approach for a period between 1995 and 2007 for a gross value added and employment, as f 31 XII(em31).



TFP growth measures by parametric approach and nonparametric approach for a gross value added and the average paid employment of full-time paid employees (ape).



TFP growth measures by parametric approach for a gross output and all labour measures.



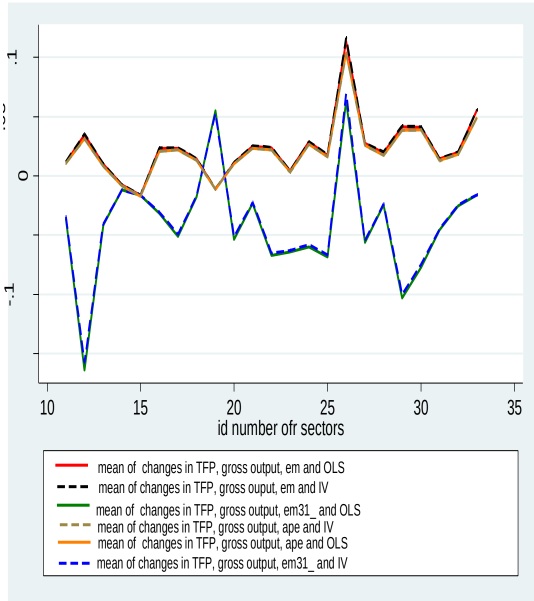


Figure 9: TFP growth measures by parametric approach and nonparametric approach 2007 for a sold production and all labour measures.

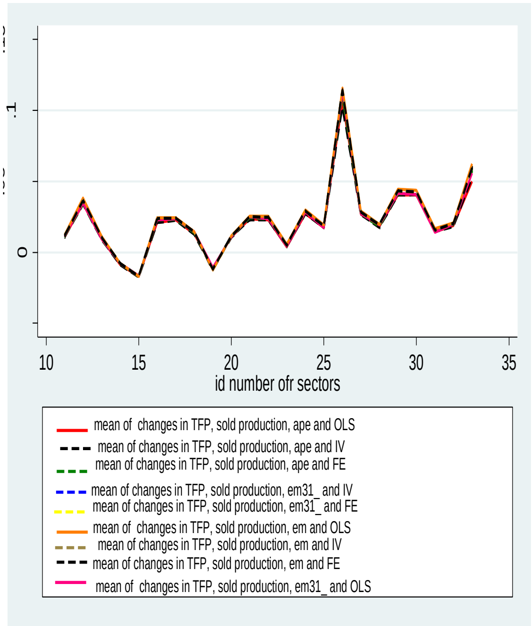


Figure 10: TFP growth measures by nonparametric approach for a gross value added and all three labour measures.

Notes: The estimation for Olley and Pake's method only included investment outlays on fixed assets buildings (*ifab*) because this proxy provided the best possible statistical results for all different labour proxies. The Levinsohn and Petrin's approach was utilized for TFP calculations of productivity shock by using intermediate consumption *(ic)*. *Source*: Author's calculations on estimating the sector data from Statistical Yearbook of Industry from Polish Central Statistical Office (CSO) (various years**)**