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Endogeneity Corrected Stochastic Frontier with Market Imperfections

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Abstract

This work provides a method of endogeneity corrected stochastic frontier for efficiency and productivity growth estimation in presence of product and labour market imperfections. The imperfections generate efficiency losses and hence affect the productivity estimates. A modified frontier function based on Cobb-Dauglus form that represents in terms of residue per unit of capital helps estimating the terms containing product and labour market imperfections. To correct the endogeneity issue for input selection, the estimation involves three-stages approaches. First, by applying Battese and Coelli (1992) error component model, the one-sided error is estimated. Second, the Levinsohn and Petrin (2003) approach is applied on the frontier values to estimate efficiency parameters that eliminates the input selection bias by using material cost as a proxy. Third, the endogeneity corrected technical efficiency is recovered from the modified one-sided error. The analysis of three-digit level of Indian industrial data across 17 major states for the period 2008-2016 portrays a strong presence of product and labour market imperfections. While the product market efficiency has deteriorated a bit at the aggregate level, it shows a marginal improvement in the allocative efficiency for the labour market. However, the efficiency level varies across industries. The productivity growth derived by adding the components of efficiency changes is similar to the Solow residual growth.

JEL Code: D24, F16, L11

Key words: Stochastic Frontier Model, market imperfections, productivity growth

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1 Introduction

A firm producing in a organised setting typically may enjoy a certain degree of market power and may face some degree of labour market rigidity. The equilibrium under such market imperfections are deviated from the Pareto optimum, and hence suffers from efficiency losses. Any change in such market conditions affecting the economic losses and gains would essentially influence efficiency and productivity estimates. This paper attempts to offer a method of accounting for such efficiency change in the presence of product and labour market imperfections and their influences on the total factor productivity growth using the stochastic frontier approach. The standard frontier approach does not account for such efficiency changes and address the endogeneity issue in the estimation simultaneously. When the market conditions are imperfect in either product or labour markets, the equilibrium product price does not equate to the marginal cost, and the workers are not paid according to their value of marginal products. The extent of deviations and resultant economic losses depend on the producer's market and workers' bargaining powers, and thus generates an efficiency loss from two sources - market inefficiency and allocative inefficiency. The SFA usually deals with labour market inefficiency (known as allocative efficiency), but ignores this issue linked to the product market to a large extent. Such efficiency losses must be accounted for the better understanding of the sources of inefficiencies and their relative contribution to the productivity growth and would essentially inform policy markers to make changes for the desired efficiency outcomes. Moreover, the existing research does not offer a suitable method to account for such changes, specially when prices and wage information are not directly available at the dis-aggregate level.

The concern for market imperfections both in the product and factor markets is growing in the context of productivity estimation in the recent years (Kutlu and Sickles, 2012; Maiti, 2013). A dis-aggregated level of industry information shows that a limited number of firms enjoys sufficient market power and some of them has appeared as 'super-stars' in the market (Dorn et al., 2017; Kehrig and Vincent, 2017). They must be competing with the rivals in such market strategically. It is further evident that the degree of market imperfections, measured in terms of mark-up, varies across firms or industries, and has increased in a number of countries in the recent years (De Loecker and Eeckhout, 2018). Using a similar dis-aggregated information over 43 countries, the study finds that an average mark-up exceeds one during 2016 and ranges from 2.84 (Denmark) to 1.19 (Portugal). Applying a different data-set, Weche and Wambach (2018) and Calligaris et al. (2017) account for almost similar results. In 33 advanced economies, Diez et al. (2018) observed that the mark-ups have been rising steadily since the 1980s and at an accelerated pace since the mid-2000s. While De Loecker and Eeckhout (2017) revealed that gains in the profit share is reflected in the increased mark-ups, Barkai (2019) did not support the rise of profit share. The profit earned by the 'super-stars' firms due to the product market imperfection illicit workers to negotiate a pie out of it. The recent studies revealed that the workers enjoy a certain degree of bargaining power in many countries, for example, 0.12 to 0.4 in Europe and Asia, (Dobbelaere, 2004; Maiti, 2013). At the same time, a large volume of literature suggests that the unionization rates and labour's bargaining power might have been declined as a result of trade integration and growing automation (Dani, 1997; Elsby et al., 2013; Jayadev, 2007; Piketty and Zucman, 2014; Dorn et al., 2017; Carmody et al., 2017; Acemoglu and Restrepo, 2018; Maiti, 2019).

A reform measure in the industrial and labour policies of an economy is sought to raise the competitiveness that improves efficiency gain, and, hence, contribute to the residual growth or, broadly speaking, total factor productivity growth. It is noteworthy to mention that the reform measures usually affect either product or labour market conditions, and thereby influence their respective bargaining positions. This must change the distributive share of cost-price margin between the producer and workers (Rodrik, 1997, 1995; Slaughter, 2001; Ahsan and Mitra, 2014; Maiti, 2019). Therefore, market imperfections that affect efficiency gain cannot be ignored in the estimation of productivity growth and its decomposition. Therefore, a growing interest is to identify the issues that are affecting the productivity growth under the complex market environment so that the policy makers could manipulate the market conditions effectively to accelerate the level. The productivity growth should be assumed to be driven by not only pure technological progress, scale change and technical efficiency change but also the efficiency changes from the labour and product market environments.

Broadly speaking, what contributes to the productivity growth under market imperfections remains a 'black-box'. Whether the efficiency change in the market conditions should be included in the total factor productivity derivation does not have uniform approach. One view suggests that the productivity is a proxy for technology change and hence all other distortions should be eliminated from the residual growth (Maiti, 2013). The other view takes a stand that any factor contributing to the efficiency change should be part of total factor productivity growth (Kumbhakar and Lovell, 2003). But, they do not seem to be much different. However, there has been growing interest among the scholars and practitioners estimating various efficiencies and their relative contribution to the productivity growth. The standard frontier approach offers a technique to account for allocative efficiency that arises from factor mis-allocation, and its contribution to the productivity growth (Kumbhakar and Lovell, 2000; Kumbhakar and Wang, 2006). While estimating allocative efficiency, they hardly pay an attention to the product market imperfections, except Karakaplan and Kutlu (2019a) who applied the Herfindahl–Hirschman

Index on Stevenson stochastic frontier model to estimate market power, but did not estimate efficiency losses arising out from the market dynamics. Any measure of allocative efficiency accounting for the deviation of factor payment from value of marginal productivity or factor share from its elasticity, as is done in Kumbhakar and Parmeter (2009), would suffer from a bias if the product market imperfection is ignored. Because, the factor payment is heavily dependant upon the product market condition and the mark-up. Instead of ignoring it, if the efficiency loss due to the product market imperfections is taken out from the allocative inefficiency, one can account for an actual estimate of allocative efficiency as well as the marginal contribution of both factor and product market imperfections on the efficiency loss separately, and productivity changes on top of technology change, technical change, and scale change. This has precisely been the attempt of this paper. The approach used here far different from Karakaplan and Kutlu (2019a) and Shee and Stefanou (2015) both in terms of approach and purposes. On the other hand, Orea and Steinbuks (2018) offered an approach to estimate the market power, but ignored factor market imperfections and endogeneity issue.

Availability of large-scale data in the recent years has encouraged scholars to undertake a decomposition analysis of productivity growth into various components. The conventional theory and practice reply heavily on the assumption of perfect competition while investigating the dynamics of productivity growth in the literature. But, the anecdotal evidences do not support its prevalence in reality to a large extent. The Stochastic Frontier Approach (SFA) is quite popular among the scholars and practitioners for accounting various sources of efficiency changes and their contribution to the productivity growth. While a standard econometric approach assumes that the firm always utilises its technology optimally, SFA does not believe so, and, hence, offers a method of estimating technical inefficiency by accounting for the distance of actual production from the best practice comparator. Hence, this paper relies on the same approach while accounting for the efficiency losses from market imperfections. In addition, the standard estimates of efficiency change and productivity growth using either econometric or frontier approaches suffer from endogenity bias for the input selection. A part of productivity can be seen while selecting an input and hence it generates a endogenity bias in the estimation. This issue has been well-addressed in the literature on econometric approaches (Levinsohn and Petrin, 2003; Ackerberg et al., 2015). Recently, Shee and Stefanou (2015) followed Levinsohn-Petrin approach to offer endogeneity corrected method of stochastic frontier for productivity estimates. But, they (1) ignored the issues of market imperfections and (2) did not estimate the productivity growth as per the Levinsohn-Petrin method. So, this paper attempts to improve further by accounting for the efficiency losses from the product and labour market imperfections as well as by correcting endogeneity bias, as prescribed by Levinsohn and Petrin (2003). Unlike econometric approach, SFA can potentially face endogeneity issue with technology choice and technical efficiency and hence it becomes quite challenging task. However, scholars have attempted to address the issue of endogeneity with technical efficiency and technology choice (Karakaplan and Kutlu, 2017b; Amsler et al., 2017; Karakaplan and Kutlu, 2019b).

The issue with technical efficiency is dealt with the approach followed by (Shee and Stefanou, 2015), that incorporated an instrument in the error correction model. Building on Shee and Stefanou (2015), this paper has modified a bit to account for efficiency losses due to product and labour market imperfections. Although the standard practice is to consider translog production (Greene, 2005) in the frontier approach, this paper confines to the use of Cobb-Dauglas production function in order to exploit the relationship between the factor share (available in the observed dataset without the exact price information) and factor elasticities. The difference between them can be represented by the degree of product and labour market imperfections. In order to do so, a bit of flexibility in the production function specification has been sacrificed. Moreover, the corrective measure of endogeneity, as prescribed by Levinshion and Petrin (2003), can be implemented effectively using value-added approach. In our specification, two factors of production (i.e., labour and capital) are considered, where labourers can form union to extract a rent from the surplus. Similarly, the product market is also not perfectly competitive. Under these two imperfections, the production function is reduced and represented in terms of labour share so that the degree of imperfections (both in the product and labour markets) can be estimated. To run the frontier method, the residue per unit of capital arising out of a Cobb-Dauglus specification, a bit different form of production function from the standard one, has appeared as dependent variable. And, the terms containing market and bargaining powers including other state variables are included in the set of independent variables. The estimation of the model involves three-stages approach. In the first stage, the Battese and Coelli (1992) error component model has been applied on the modified production function that offers the estimates of one-sided error. Since the level of technical efficiency, derived from the estimate of one-sided error, can be endogeneosuly related to the input choice, the material costs is used as a proxy variable and combined with capital in the form of third-order polynomials. By adding the estimated one-sided error, the frontier level of outputs are derived. In the Second stage, the frontier value is regressed on the terms containing market and bargaining powers along with capital. The terms are directly derived from the reduced form of production function. The Levinsohn and Petrin (2003) approach is executed to eliminate the endogeneity bias of input selection from the productivity estimate by using material cost as the proxy variable. The regression coefficients are used to estimate efficiency losses from mark-up and bargaining power of workers as well as return to scale. The residual change from this expression is represented as technological change. This is different from (Shee and Stefanou, 2015), who consider time dummy in the first stage for the estimation of technical progress. This technique does not seem to have been followed. After eliminating the stochastic two-sided error term, the one sided error is re-calcuated in the stage III by taking the deviation of the original output from the combined value of predicted value and the estimated term of technology change found in the stage II.

The model is applied on the three-digit level of Indian industrial data across 17 major states for the period 2008-2016. The efficiency losses from the market imperfections have been accounted for using the estimated parameters representing mark-up and bargaining power that are derived from the estimated model. This allows us to estimate the contribution of product market and allocative efficiencies in the total factor productivity growth. It shows that these two terms containing market efficiencies vary substantially across industries. The model shows five components of efficiency changes on the productivity growth, which is unique feature of the study. We find that there has been a substantial improvement of productivity growth during 2008-2016 in the post-financial crisis period. Overall, while an improvement of allocative efficiency has contributed positively to the total factor productivity growth, the market efficiency has deteriorated marginally. However, this varies widely across industries. This supports observations found in other studies Jayadev (2007); Maiti (2019). The combined efficiency changes representing the total factor productivity growth follow the similar pattern of Solow residual, the productivity estimate as per the growth accounting method.

There exists a parallel tradition of research, which acknowledges the change in factor and product market conditions affecting the measure of productivity growth (Hall, 1988; Domowitz et al., 1988; Harrison, 1994; Konings et al., 2001, 2005). They mostly confined to the parametric approach and looked at the product market imperfections only. Dobbelaere (2004) estimated the price-cost mark-up and workers' bargaining power among 18 manufacturing industry and found that sectors with higher workers' bargaining power typically show higher price-cost margins in Belgium. (Abraham et al., 2009) applied a similar methodology to estimate the mark-up and worker's bargaining power across manufacturing in Belgium. Using the similar approach, Maiti (2013) estimated a level of technology growth after eliminating both the product and labour market distortions for Indian economy during 1998-2005. This tradition of literature mainly relied on the econometric approaches. None of these works dealt with the technical efficiency than arises from sub-optimal use of the existing technology. Unfortunately, the literature on stochastic frontier largely ignores this issue for a long-period. However, this received growing attention in the recent literature Kutlu and Sickles (2012); Orea and Steinbuks

(2018); Karakaplan and Kutlu (2019a). The present framework is different from them. While Kutlu and Sickles (2012); Orea and Steinbuks (2018) focused to measure the market power only, (Karakaplan and Kutlu, 2019a) concentrated on scaled Stevenson stochastic frontier model for the same.

The rest of the paper has been organized as follows. The empirical framework of estimation of mark-up and bargaining powers of labourers showing marketing and allocative efficiencies and the resultant TFPG have been discussed in section 2. The results derived from this framework are discussed in section 3. Section 4 ends up with concluding remarks.

2 Empirical Framework

While a production function simply describes transformations of inputs into outputs, the unexplained part of output is defined as residue. The rate of residual change is often treated as total factor productivity growth in the literature. But, it contains explained and unexplained parts. While this part is mainly assumed to be influenced by technology, technical efficiency and economies of scale, this could also be affected by the market conditions (Maiti, 2013). What portion of the change is influenced by the change in technology, technical efficiency and scale economies, and how much of it is due to the efficiency change from market competitiveness and factor allocations are of our interest here. The SFA estimates efficiency changes that contribute to the measure of productivity growth. The existing literature (Battese and Coelli, 1992; Kumbhakar and Lovell, 2000; Greene, 2005; Kumbhakar et al., 2009; Orea and Álvarez, 2019; Klein et al., 2020) has offer various alternatives and rich models to account for some of the inefficiencies using cross-section and panel data at the dis-aggregate level. A set of recent literature on SFA (Shee and Stefanou, 2015; Karakaplan and Kutlu, 2017b; Amsler et al., 2017) further improved by addressing the endogeneity bias from factor selection for the estimation of productivity under different circumstances. Following this tradition, this study attempts to account for efficiency losses from the product and labour market imperfections along with other sources and their changes over time.

The standard SFA defines that a production unit is assumed to be technically inefficient if a higher level of output is technically attainable for a given level of inputs. If Y_{it} is the actual output produced by i-th firm at t-th period with reference to the potential level (i.e., best possible or frontier) output Y^*_{it}, the output-oriented technical inefficiency can be specified as (Battese and Coelli, 1992):

$$lnY_{it} = lnY^*_{it} + v_{it} - u_{it}; i = 1, ..., N; t = 1, .., T \tag{1}$$

Here, the last two terms respectively represent the double-sided and single-sided errors. While the single-sided error corresponds to technical inefficiencies, the two-sided error links to the level of technology. The random error term, v_{it}, follows standard normal distribution, $v_{it} \sim N(0, \sigma_v^2)$. On the other hand, u_{it} captures a short-fall of production from its frontier given inputs. Hence, the term u_{it} follows either half-normal (Aigner et al., 1977) or truncated normal distribution (Stevenson, 1980). Battese and Coelli (1992) considered a truncated normal distribution. Here, it is assumed to follow a truncated distribution as $u_{it} \sim N^+(0, \sigma_u^2)$ (Battese and Coelli, 1992; Kumbhakar and Lovell, 2000). Both the terms are assumed to be distributed independently.

The production function has been specified as $Y_{it}^* = A_{it} f(X_{it}; \beta)$, where X_{it} represents a vector of input quantities used by i-th firm at t-th period. β denotes a vector of unknown parameters to be estimated to derive various inefficiencies and A_{it} represents the (unobserved) production shock component. Although a large number of frontier analysis considers translog form of production function for its flexibility, a Cobb-Dauglus form is assumed here for its specific property that shows a clear relationship between the factor elasticities and factor share in the presence of market imperfections. This essentially helps to include the parameters influencing the degree of market imperfections respectively in both product and labour markets from the one that prevails with perfect competition. Then, the frontier output takes the form of Cobb-Dauglus function as $Y_{it}^* = A_{it} L_{it}^{\beta_L} K_{it}^{\beta_K}$. Taking logarithm of the production function and replacing Y_{it}^* in equation (1), we write

$$y_{it} = a_{it} + \beta_L l_{it} + \beta_K k_{it} + v_{it} - u_{it} \tag{2}$$

Lower-case letters represent logarithmic form of the variables. Here, β_L and β_K represent respectively labour and capital elasticities, and t is the proxy for exogenous technical change. In order to estimate them, the truncated distribution of error terms is taken into the log-likelihood form. The function is numerically iterated to find out the parameters using actual observations that offers maximum value. The log-likelihood estimation is undertaken with a set of constraints to ensure positive variances. This allows us to estimate jointly the model parameters along with the technical inefficiencies using the distance function approach from the frontiers (Shee and Stefanou, 2015). It is now important to test the existence of one-sided error in the model. Since such one-sided specification does not exist, one reduces it to a generalised standard OLS model. A generalised log-likelihood ratio is constructed with a null-hypothesis for not having one-sided distribution with the log-likelihood values of restricted OLS against that of the restricted SFA (Battese and Coelli, 1992).

Using the above-mentioned approach, one can estimate the parameters along with the technical inefficiencies. But, the inefficiencies arising out of market imperfections in product and labour markets cannot be estimated directly using the above-mentioned specification. The market imperfections do not only affect the market price but also deviate the elasticities from the level that exists in the competitive environment . The extent of deviation is the key to account for the degree of market imperfections and we would exploit Cobb-Dauglas properties to account for such deviation. It is noteworthy to mention that the dis-aggregated level of price and wage information are not often available. In this case, one would prefer to derive them econometrically (Maiti, 2013). For the sake of simplicity, we shall deal with the terms of market imperfections first and then efficiency estimation.

2.1 Market Imperfections

Let us confine into the production function that defines envelope and ignore other terms for the time being. If the production function is assumed to be homogeneous of degree $1+\lambda$ for factors, then it follows that $\beta_L + \beta_K = 1 + \lambda \geq 0$. If $\lambda \geq (= \leq 0)$, the production function exhibits increasing (zero and decreasing) returns to scale. By replacing β_K from (2), we get

$$y_{it} = a_{it} + \beta_L(l_{it} - k_{it}) + (1+\lambda)k_{it} \tag{3}$$

This expression suggests that the level of output is influenced by technology shock (a_{it}), labour elasticity (β_L) and economies of scale (λ). Rearranging the terms, the Solow residual can be derived. The residual (SR_{it}) is defined output minus labour contribution in terms of per unit of capital. Since this term contains output, it is monotonically related to technology shock (two-sided error) and technical inefficiency (one-sided error). This is shown as follows:

$$SR_{it} \equiv (y_{it} - k_{it}) - \beta_L(l_{it} - k_{it}) = a_{it} + \lambda k_{it} \tag{4}$$

Note that one can run this regression model to estimate labour elasticity along with technology and scale parameters. But, the underlying assumptions would be that perfect competition prevails both production and labour markets. In reality, it may not be true and anecdotal evidences show that the production takes place under imperfect market conditions. SFA offers an technique to estimate allocative inefficiency in the presence of factor market imperfections by taking the deviation of actual factor shares from the factor elasticities (Kumbhakar and Lovell, 2003). But, this cannot offer a correct account of the allocative inefficiencies. Because, the actual input share is not only influenced by the input price but also affected by the output price. If the product market is influenced by a market power, the share would be lower. Let us try to estimate the part of efficiency loss influenced by the product market power that separates out from the allocative inefficiency accurately.

If the imperfection only prevails in the product market, the wage is not paid according to the value of marginal physical products. Rather, it is equivalent to the marginal value of revenue products. Then, the labour share would be different from its elasticity. If the price over marginal cost is defined by mark-up μ, then we find that $\beta_L = \mu s_L^M$, where $\mu = \frac{P}{MC}$. Here, s_L^M represents the labour share when the product market is alone imperfect. Since, the firm tends to raise the price over the marginal cost, the labour share would be lower than that of perfect competition, depending upon the degree of market power, and the residue tends to rise.

On the other hand, when the imperfections prevail both in the product and labour markets, a rise of bargaining power of workers tends to take away a part of surplus from the producer. The union derives a relatively higher wage than that in the competitive wage depending on their bargaining power. So, the relative strength of bargaining power and mark-up would ultimately determine the distribute share of workers in the market. Formally, we can capture the relationship between the labour share and its elasticity in terms of using the mark-up and bargaining power. Let us assume that $\bar{L}$ is the total workers available in the economy,w_0 is the alternative wage for workers outside the firm and θ is the bargaining power of the union, the union wage can be derived from the following Nash bargaining expression:

$$\max_{w,L} \Omega = (Lw + (\bar{L} - L)w_0 - \bar{L}w_0)^{\theta}(PY - wL)^{1-\theta}$$

Where, P is the price of output Y, $\bar{L}$ is the total labour supply, mark-up $\mu = \frac{e}{e-1}$ and price elasticity $e = \frac{P}{Y}\frac{\partial Y}{\partial P}$. Differentiating the expression with respect to wage and employment, substituting $\frac{\partial (PY)}{\partial L} = \frac{P\partial Y}{\mu \partial L}$, and then rearranging the terms, we get:

$$\beta_L = \mu s_L^U + \mu \frac{\theta}{1-\theta}(s_L^U - 1) \tag{5}$$

Where s_L^U represents actual labour share in the presence of both product and labour market imperfections. Note that when $\theta = 0$ and $\mu = 1$, then $s_L^U = \beta_L$. For any value, $\mu > 1$ and $\theta > 0$, we find that $\beta_L \neq 0$. When $\mu > 1$ and $\theta = 0$, we find that $S_L^U = S_L^M$ and when $\mu > 1$ and $\theta > 0$ we find that $S_L^U \neq S_L^M$. So, the deviation between labour elasticity and labour share cannot give us the correct account of allocative inefficiency.

It is to be noted that the labour union tries to bargain a pie of the surplus created by the firm in the presence of imperfection. While a rise of μ reduces labour share, θ raises it. The difference between the actual labour share and elasticity would essentially be captured by the values of θ and μ in this case. And, the efficiency losses can be decomposed into the losses arising out from product market and labour market imperfections separately

(Dobbelaere, 2004; Maiti, 2013). We can write that $s_L^U - s_L = (s_L^U - s_L^M) - (s_L - s_L^M)$. After substituting the share solved above, we get $s_L^U - \beta_L = (s_L^U - \frac{\beta}{\mu}) - \frac{(\mu-1)}{\mu}\beta_L$. This captures the deviation of labour share under imperfections from that under perfect competition, and higher the value of μ the lower would be the deviation. So, $s_L^U - \beta_L$ that capture the deviation of labour share from its elasticity, and can be defined as allocative efficiency. However, it cannot account for the actual figure. To capture it accurately, we shall take the deviation $s_L^U - s_L^M = s_L^U - \frac{s_L}{\mu}$. After substituting β_L taken from (5), this gives us the allocative inefficiency as follows: $s_L^U - s_L^M = \left(\frac{\theta}{1-\theta}\right)(1 - s_L^U); \in (0,1)$. Note that this difference must be zero when $\theta = 0$ and rises with θ. There must be a maximum level of θ (say, $\hat{\theta}$ for which the allocative inefficiency would be one). At this level of inefficiency, we find that $\hat{\theta} = \frac{1}{2-s_L^U}$. Since the s_L^U can take value one maximum, then the $\hat{\theta}$ shows value one. This is its maximum permissible value. In order to convert the inefficiency to efficiency term, it can be subtracted from one. Then, the allocative efficiency is expressed as:

$$AE = 1 - \left(\frac{\theta}{1-\theta}\right)(1 - s_L^U); \in (0,1) \tag{6}$$

Higher the value of θ or s_L^U, lower would be allocative efficiency (AE). This is similar to what was proposed by Kumbhakar and Parmeter (2009), with a different specification.

In the presence of product market imperfection on the other hand, we have seen that the labour share would be lower than the share under perfect competition. Because $\mu > 1$ implies that $P > mc$ (marginal cost) and, then, the output is produced at a lower level than the optimum one (when perfect competition prevails). Hence, there is an efficiency loss and this can be termed as product market inefficiency. To normalise it, the inefficiency is defined as $\beta = 1 - \frac{1}{\mu}; \in (0,1)$. By subtracting it from one, one can convert this into market efficiency term (ME) as follows:

$$ME = 1 - \beta = 1 - \left(1 - \frac{1}{\mu}\right); \in (0,1). \tag{7}$$

where, β and μ are monotonically related. Note that if $\mu \longrightarrow 1$, then $\beta \longrightarrow 0$ and $ME \longrightarrow 1$. And, if $\mu \longrightarrow \infty$, then $\beta \longrightarrow 1$ and $ME \longrightarrow 0$. So, lower the value of μ, lower is the efficiency loss and higher is value of ME.

Replacing β_L by s_L^U, the expression (4) in the presence of labour and product market imperfections can be represented as:

$$SR_{it} \equiv (y_{it} - k_{it}) - s_L^U(l_{it} - k_{it})$$

$$= \frac{a_{it}}{\mu} + \left(1 - \frac{1}{\mu}\right)(y_{it} - k_{it}) + \frac{\theta}{1-\theta}(1 - s_L^U)(l_{it} - k_{it}) + \frac{\lambda}{\mu}k_{it} \tag{8}$$

Assume that $\beta = \left(1 - \frac{1}{\mu}\right), b = a/\mu, LR_{it} = (y_{it} - k_{it}), BR_{it} = (1 - s_L^U)(l_{it} - k_{it}), \eta = \frac{\theta}{1-\theta}, \gamma = \frac{\lambda}{\mu}$. Substituting these terms, we rewrite the expression as

$$SR_{it} = \beta LR_{it} + \eta BR_{it} + \gamma k_{it} + b_{it} \tag{9}$$

This should be treated as modified production function in our case and can be used to estimate the inefficiencies along with the degrees of product and labour market imperfections econometrically without using the price information. Note that β and $\eta(1 - s_L^U)$ respectively give product market and allocative inefficiencies. And, $\beta \times LR$ and $\eta \times BR$ account for amount of losses in the residue due to the presence of product and labour market imperfections respectively. Therefore, this looks a standard expression for the application of the Stochastic Frontier Model. One can, in principle, apply the error component model (Battese and Coelli, 1992). But, this cannot address the endogeneity issue.

2.2 Efficiency and Productivity Estimation

Adding the technical efficiency and random disturbance terms, shown in equation (2), to the modified production function (6), we get the following expression.

$$SR_{it} = \beta LR_{it} + \eta BR_{it} + \gamma k_{it} + b_{it} + v_{it} - u_{it} \tag{10}$$

Under *ceteris peribus*, SR is monotonic and positively related to y. So, v and u would follow the similar relationship with SR that exists with y. Note that the production function expressed here is different from the standard one (Shee and Stefanou, 2015). The dependent variable is presented as the residue per unit of capital. Frontier approach can be applied to estimate the parameters, which would essentially be used to derive the efficiency contribution by components. The approach suggested by (Battese and Coelli, 1992) can be applied to estimate the parameters of this equation using panel data that helps to derive the level of efficiencies. The parameters can be derived by running fixed effect panel regression and using the standard SFA model. But, they would not offer unbiased figures. Because, both technology (b_{it}) and technical inefficiency term (u_{it}) can be correlated for the input choice. Hence, such SFA model cannot be directly applied to estimate the efficiency parameters because of this endogeneity issue with factor choice.

3 Estimation: Endogeneity and Application of SFA

The application of simple error component model, developed by Battese and Coelli (1992), cannot offer unbiased estimates of parameters because of the endogeneity issue with the factor selection. If a producer observes a part of its productivity, its choices of input tend to be highly affected, leading to a simultaneity problem in the stochastic production frontier estimation. The input choices are likely to be correlated with the components of productivity (two-sided error) and technical inefficiency (on-sided error) terms that are observed by the producer. Recently, Shee and Stefanou (2015) applied to the same model and corrected the endogeneity issue in the productivity estimation, using the approach developed by (Levinsohn and Petrin, 2003). But, they ignored market imperfection terms. Moreover, (Karakaplan and Kutlu, 2017b) criticised by arguing that both the one-sided and two-sided errors can be influenced by the input choice. Hence, the terms containing technology level as well as technical efficiency in simple regression seem to be suffered from endogeneity bias. The issues of endogeneity in production function estimation are well documented in the literature Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg et al. (2015). The most traditional approaches to addressing endogeneity in production function estimation is to employ a model with instrumental variables and fixed effects. But, they are problematic on both theoretical and empirical grounds. Olley and Pakes (1996) dealt with the endogeniety issue by using gross investment as an instrument, while (Levinsohn and Petrin, 2003) applied intermediate inputs as a means to control for the unobserved shocks. The literature on frontier approach took this up after a long. (Kutlu, 2010) provided a maximum likelihood model that enables estimation of producer specific cost (or technical) efficiencies when some of the frontier regressors are correlated with the two-sided error term. Thereafter, the works of (Karakaplan and Kutlu, 2017b) and (Karakaplan and Kutlu, 2017a) applied this technique to solve the endogeneity problem with both sided errors in the cross-sectional and panel data settings by using gross investment as an instrument. Essentially, to deal with the endogeneity with technical efficiency, the gross investment has been considered in the study as a proxy variable and tried to eliminate the bias using a log-likelihood estimation method. However, the gross investment as a proxy does not offer a better solution. Because, many firms under-report the investment figures and hence often get zero value. It creates invertibility problem in the estimation. As a result, the approach offered by Levinsohn and Petrin (2003), who suggested inputs as proxy variables, is much preferred. Following this recommendation, Shee and Stefanou (2015) applied energy as a proxy for the productivity shocks with an assumption that the market environment is assumed to be competitive and firms face common input and output prices.

In the present case, the input selection can be correleted to the one-sided error (u_{it}) and two-sided error ($b_{it} + v_{it}$), where b_{it} is a transmitted component and v_{it} is a pure stochastic component. In order to deal with the factor selection and simultaneity, a proxy variable, material costs, used here, unlike Kutlu and Sickles (2012) and Karakaplan and Kutlu (2017b), has been treated separately for one-side and two-sided error terms. The estimation is done in three stages. In stage 1, the error correction model has been run to estimate one-sided error (say, $\tilde{u}_{it}$ that represents the technical inefficiency, where the material costs is included as an instrument variable. This would handle the simultaneity issue with one-sided error terms, and (Shee and Stefanou, 2015) has applied the same strategy. In stage II, the frontier values of the dependent variable (say, $SR^{*}it$ is derived by adding the estimated one-side error term derived in stage 1) to SR_{it}. The semi-parametric approach, followed by (Levinsohn and Petrin, 2003), has been executed to take care of the endogeneity with the transmitted component of two-sided error while estimating the regression coefficients. The residual change from this regression offers the corrected figure of endogeneity corrected technology term ($\hat{b}_{it}$). The predicted value of the dependent variable is denoted as SR_{it}^{**}. In stage III, the revised estimate of one-sided error (say, $\hat{u}_{it}$) is recalculated by subtracting the actual SR_{it} from the predicted value of dependent variable (i.e., $\hat{SR_{it}}$) and technology estimate ($\hat{b}_{it}$) received in the stage II. The exponential terms of the one-sided error gives us the endogeneity corrected technical inefficiency ($exp(-\hat{u}_{it})$). This is substantially different from (Shee and Stefanou, 2015), where both terms for technology level and technical efficiency are estimated in the first stage.

It is assumed that the input choice is correlated with transmitted component of technology term, b_{it}, and one-sided error, u_{it}, but uncorrelated with stochastic component of two-sided error terms, v_{it}. In stage I, the material cost is employed as a proxy for the unobserved productivity term and specified as a function of technology and capital.

$$m_{it} = m_{it}(b_{it}, k_{it}) \tag{11}$$

Under the assumption of strict monotonicity condition, the technology can be expressed in terms of inverted equation as follows:

$$b_{it} = b_{it}(m_{it}, k_{it}), \tag{12}$$

Substituting (13) into (10), we can express:

$$SR_{it} = \beta LR_{it} + \eta BR_{it} + \phi_t + v_{it} - u_{it} \tag{13}$$

Where $\phi_t = \gamma k_{it} + b_{it}(m_{it}, k_{it})$

A time-varying technical inefficiency is estimated in this stage using the Battese and Coelli (1992) error component model. In order to address the endogeneity issue with one-sided error here, a third-order polynomial is approximated in k_{it} and m_{it} in place of $\phi_t(m_{it}, k_{it})$, where $\phi_{it} = \sum_{i=0}^{3}\sum_{j=0}^{3-i} c_{ij}k_{ij}e_{ij}$. After taking out the estimated value of one-sided error term (say, $\tilde{u}_{it}$), the residue, the SR_{it}^{*} is derived that represents the frontier values. Here, the exponential value of one-sided error represents the technical inefficiencies.

$$SR_{it}^{*} = SR_{it} + \tilde{u}_{it} = \beta LR_{it} + \eta BR_{it} + \phi_t + v_{it} \tag{14}$$

Note that SR^*_{it} is frontier function and contains two-sided error only.

In stage II, the semi-parametric method, followed by Levinsohn and Petrin (2003), is applied to estimate the coefficients of free variables, the proxy input and the state variable (capital) in the expression (15). The identification of coefficients is proceeded by assuming that capital is a state variable and does not instantaneously adjust to the unexpected part of productivity shock, although it might adjust to the transmitted part. Formally, this notion can be entailed by assuming that productivity is governed by an exogenous first-order Markov process

$$p(b_{it}|\{b_{i\tau}\}_{\tau=0}^{t-1}, I_{it-1}) = p(b_{it}|b_{it-1}) \tag{15}$$

where, I_{it-1} is the firm's information set at $t-1$. According to this, we assume that firms, realizing the value of b_{it-1} at $t-1$, form expectations of productivity at t and infers that the distribution of b_{it} will be $p(b_{it}|b_{it-1})$. Hence, one could decompose b_{it} into its conditional expectation given the information available to the firm at $t-1$ and a residual term. So, we obtain

$$b_{it} = E(b_{it}|b_{it-1}) + \varepsilon_{it} \tag{16}$$

Where ε_{it} is a random variable.

It is also further assumed that the random part of productivity is uncorrelated with the capital, leading to the following two moment conditions:

$$E[\varepsilon_{it} + v_{it}]k_{it} = E[\varepsilon_{it}k_{it}] + E[v_{it}]k_{it} = 0$$

$$E[\varepsilon_{it} + v_{it}]m_{it-1} = E[\varepsilon_{it}m_{it-1}] + E[v_{it}]m_{it-1} = 0$$

The former one suggests that capital stock in period t is determined by investment decisions from previous periods and does not respond to the current period productivity change. The second condition reveals that the last period choice of input is uncorrelated with the productivity change.

Using a locally weighted least squares regression, the coefficients of free variable can be estimated first from (15).

$$SR^*_{it} - \hat{\beta}LR_{it} - \hat{\eta}BR_{it} = \phi_t + v_{it} \tag{17}$$

In the next stage, the coefficient of state variable is estimated. Hu et al. (2020) proposed a generalized method of moment (GMM), a more flexible and straightforward technique to apply, for the estimation. By applying the similar GMM technique, one can estimate the parameters of capital with initial values γ^*_k. For any candidate values, we rewrite (15) to yield

Substituting (17) into (18), we can express:

$$SR^*_{it} - \hat{\beta}LR_{it} - \hat{\eta}BR_{it} - \gamma^* k_{it} - E[b_{it}|b_{it-1}] = \varepsilon_{it} + v_{it} \tag{18}$$

Given the initial values γ^*_e, one gets the estimate $\widehat{b_{it} + v_{it}}$ from equation (18) and this is expressed as below:

$$\widehat{b_{it} + v_{it}} = SR^*_{it} - \hat{\beta}LR_{it} - \hat{\eta}BR_{it} - \gamma^* k_{it} \tag{19}$$

Since $E[b_{it}|b_{it-1}]$ is unknown, one can estimate it from (17). The estimate can be expressed as follows:

$$\hat{b}_{it-1} = \hat{\phi}_{it-1} - \gamma^* k_{it-1} \tag{20}$$

A local least squares regression, non-parametric kernel-based estimation method, is used to estimate this (Li and Racine, 2007; Pagan and Ullah, 1999). This will help to estimate the residue. So, by regressing on $\widehat{b_{it} + v_{it}}$ by $\hat{b}_{it-1}$, we can compute the residue as $\hat{\varepsilon}_{it} + v_{it}(\gamma^*)$ by using (19). We run a local quadratic kernel-based estimation that weights the observations closest to the point of evaluation more heavily. Thereafter, GMM criteria is employed to estimate (γ^*). The problem is specified as:

$$\min_{\gamma}[\sum_i \sum_t (\varepsilon_{it} + v_{it})^2] \tag{21}$$

where, $\widehat{\varepsilon_{it} + v_{it}} = SR^*_{it} - \hat{\beta}LR_{it} - \hat{\eta}BR_{it} - \gamma^* k_{it} - E(b_{it}|b_{it-1})$. The moment condition represents the distance between the observed moments and zero. So, both the estimated stage co-coefficients and the predicted values from the local least square regression are then combined in the GMM estimation routine to estimate the co-coefficients of the capital and the proxy. The bootstrap approach is introduced to estimate the standard errors, where the observed data are used to approximate the true population distribution of the data. The residue derived from this stage can be expressed as follow:

$$\hat{b}_{it} = SR^*_{it} - \hat{\beta}LR_{it} - \hat{\eta}BR_{it} - \hat{\gamma}k_{it} \tag{22}$$

Running a fixed effect panel regression of time (t) on b_{it} and eliminating stochastic term, we derive $\hat{b}^*_{it}$ And, this would give the endogeneity corrected technological change.

In the stage III, the estimated value of predicted value, say $\hat{SR}_{it}$ from the stage II represents the SR free from two-sided error. The deviation of SR_{it} from combined figure of $\hat{SR}^*_{it}$ and $\hat{b}^*_{it}$ represents the revised estimate of one sided error, where $\hat{u}_{it} = \hat{SR}^*_{it} + \hat{b}^*_{it} - SR_{it}$. The exponential value of the revised estimate shows the endogeneity corrected technical inefficiency.

Therefore, in the presence of market imperfections, this model allows us to decompose the residue into five components - technology change, economies of scale and technical inefficiency, and market and allocative inefficiencies. Following Nishimizu and Page (1982) and Kumbhakar et al. (2009), the efficiency change can be derived using the estimated parameters and by adding then total factor productivity growth for a specific period can be calculated as follows:

- Technical efficiency change (TEC): $\dot{e}^{(-\hat{u})}$
- Technological change (TC): $\dot{\hat{b}}^{*}$
- Scale Efficiency change (SEC): $\frac{\lambda}{\mu}\dot{k}$
- Allocative efficiency change (AEC): $[1-\eta].\dot{BR} = \left[1 - \frac{\theta}{1-\theta}(1-s_L^U)\right](\dot{l}-\dot{k})$
- Market efficiency change (MEC): $[1-\beta]\,\dot{LR} = \left[1 - \left(1 - \frac{1}{\mu}\right)\right](\dot{y}-\dot{k})$

By adding the above five components, we find the total factor productivity growth as:

$$TFPG = TC + TEC + SEC + AEC + MEC \tag{23}$$

It should be mentioned that $\dot{x}$ (where x represents a variable showing the change in the efficiency) denotes rate of change over time. The TFPG can be compared with the Solow residual to investigate the extend that the current method captures the variation of residual growth.

4 Efficiency Change and Productivity Growth of Indian Economy: 2008-2016

4.1 Indian Growth: An overview

Before presenting the key results, let us highlight an overview of the economic growth of the economy. Since the economic reform was initiated in the early 1990s, Indian economy has maintained a high growth rate, which has often exceeded the rate of Chinese economy. But, this has been slowed down after the Global Economic Crisis in late 2000s. According to the World Bank Development Indicators, while GDP grew roughly at 5% during the latter half of 1980s, it reached up to 9.7% in 2010, and then declined to around 7.2% in 2018. However, the contribution of secondary sector in the GDP has slowly gone up from 20% in 1970 to 28.4% in 2010 and then 29.29% in 2017. The recent research has tried to establish whether such growth is driven by the productivity growth. If so, what are the contributory forces and how does the market evolved in the post-crisis?

For a long time, the Indian economy could not achieve a decent growth during the early planning era. After the independence in 1947, the country relied on strategies for the achievement of self-reliance, by putting particular focus on import substitution and large-scale home-based industrialization polices. But, such strategy for industrialization, by protecting the national economy from outside world, could not push up the economic growth, and hence was responsible for the industrial deceleration experienced for more than a decade during mid-1960s to late 1970. As a result, such approach have been severely criticised by many scholars Bhagwati et al. (1975); Dutt (1984). Gradually, India had started liberalizing her industrial, trade and national development policies since mid-1985. When the foreign exchange reserves came down to a critically low level, the crisis hit the economy badly in the early 1990s and the inflation caught the double-digits, the economy started liberalising overall economic policies in all fronts. The gradual reduction of trade barriers, dis-investment in public sector, de-reservation of small-scale industries, de-licensing the industrial activities, private sector expansion, reduction of the barriers on foreign capital, financial sector autonomy, exchange rate convertibility and similar reform measure were undertaken to improve the growth rate by raising competitiveness and efficient of resources Bhagwati and Srinivasan (2002). So, the principal philosophy behind such reform policies had been to promote competitiveness so that it reduces market imperfections and encourages the optimal use of labour and other resources. This essentially contributed to an acceleration of productivity growth Maiti (2019).

The predominant view is that the institutional reforms and better infrastructure required to reap the benefits from economic reform were lacking for productivity improvement (Nin-Pratt et al., 2010; Hasan et al., 2012). This apart, the Industrial Disputes Acts, 1947 that fueled labour market rigidity was identified one of the root problems for Indian growth acceleration by number of scholars (Besley and Burgess, 2004; Hasan et al., 2007; Aghion et al., 2008). The recent deceleration of economic growth in the late 2000s and early 2010s was largely driven by the global financial crisis and its allied complications in the other sectors (Prasad and Reddy, 2009). The crisis was originated from the financial sector and hence forced to change the functioning of the sector and to bring down the addition regulations imposed on the financial transactions including deposits and loans (Eichengreen and Gupta, 2013). In addition, the crisis has instigated to make changes of various other policy on the industrial rules and regulations, labour laws etc that have a clear implication on the level of competitiveness and labour market rigidity. This set of literature clearly suggested that the degree of competitiveness and labour market rigidity have definite implications on the productivity growth of Indian economy. Hence, the role of market and resource allocations influenced by these policy change should not be ignored while investing the productivity growth of the economy.

4.2 Efficiency and Productivity Estimates

The estimation of productivity and efficiencies in the presence of market imperfections requires a dis-aggregated level of industrial statistics. The dis-aggregated level information of Indian industries for the organised or formal manufacturing sector is compiled by the Annual Surveys of Industries, a organ of Central Statistical Organisation, Government of India. The frequent changes in the coding for providing statistics, specifically, at the firm levels bind us to use the data for relatively a shorter period, 2008-2016. Last, the industrial coding has been substantially revised on 2008. As per the latest definition, three-digit level of industrial statistics over the major states of India available during the period has compiled in this study. This would allow us to investigate the pace of reconstruction of Indian manufacturing in the post-financial crisis period. The three-digits industries are grouped into nine groups. Within each group, the industries are producing close complementary or substitutes. Some industries are eliminated from the study due to lack of sufficient observations during this period. Industries having more than 200 observations are kept. The number of observations across the major industries have been presented in Table 1.

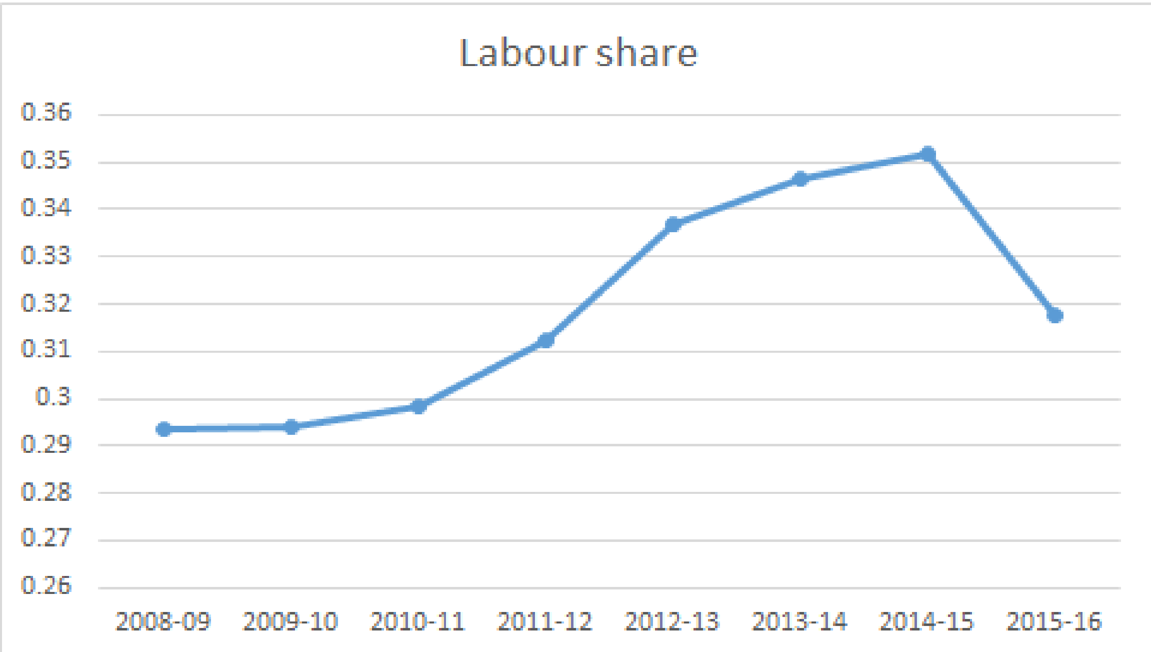
Therefore, our analysis has been confined to the analysis for the period from 2008 to 2016, which covers eight years and nine industries in the post-crisis period. The world economy including India was badly affected by the global economic crisis 2008, but has gradually overcome in the next couple of years. Hence, it could be perfect case study to investigate sources of efficiency changes and their relative contribution to the productivity growth during the recovery period. Using the three-stage approach, the model parameters have been estimated and the terms containing degree of market imperfections as well as efficiencies are estimated as per the above-mentioned methodology.

Table 1: Industry Division

Industry Code (NIC 2008)	Industry Name	Abbreviation	Observations (Nos)
10+11+12	Food Products, Beverages and Tobacco	Foods	432
13+14+15	Textiles, Textile Products, Leather and Footwear	Textile	352
16+17+18	Wood and wood products, Pulp, Paper, Paper products, Printing	Wood	280
19+20+21	Coke, Refined Petroleum Products and Nuclear fuel , Petroleum , Chemicals	Chemicals	360
22+23	Rubber and Plastic Products and Non-Metallic Mineral Products	Non-metallic	360
24	Basic Metals	Basic metals	208
26+27	Computer, Electrical and Optical Equipment	Electrical	576
29+30	Transport Equipment	Transports	240
28+31 +32+33	Furniture, Other Manufacturing, recycling	Others	448
All	All Manufacturing	All	3664

The bargaining power between firm owners and workers is reflected on the movement of labour share. It registers that the labour share at the aggregate level has marginally raised from 0.29 in 2008-09 to 0.31 in 2011-12 and then jumped sharply upto 0.35, followed by a drop in the next year. The market conditions must have changed during this period a bit along with a gradual recovery from financial crisis after 2008 (see Fig 1). At the industry level, the average labour share ranges from 0.22 in chemicals to 0.37 in textiles (see Table 2). Following the three-stage estimation techniques mentioned above and then applying the formula shown in (11), the mark-up and bargaining power are derived from the estimated regression co-efficient and presented in table in 2. The estimated values for β and η, the coefficients of LR and BR, are presented in the third and fourth columns respectively. Note that all the estimated values are statistically significant at 1% level. Again, using the estimated regression co-efficient, the marketing efficiency (ME) and allocative efficiency have been calculated and reported in fifth and sixth column in the table. The mark-up (μ), derived from the estimated β, reveals that they are greater than one for all the sectors and vary, however, from 5.65 (electrical sectors) to 1.19 (non-metalic sector). Combining all industries, the average mark-up counts for 2.52 during this period. It essentially suggests that the firms in the all industries enjoy a certain degree of market power that allow them to raise the market price over the marginal cost. Similarly, the measure of labour bargaining power (θ), derived from estimated values of η, accounts for the relatively low figures and ranges from 0.09 (in textiles and non-mentalic sectors) to 0.19 (in chemicals sector). The average bargaining power of workers employed in all industries shows 0.14 during the same period. It suggests that the workers too hold a bit of bargaining power, thought it is very low. In the presence of market powers of firms and workers, the market and allocative efficiencies are essentially less than one. The level of market efficiency (ME) varies from 0.28 (in electrials) to 0.81 (in transports). On the other hand, the allocative efficiencies (AE) are much better ME, and it varies from 0.82 (in chemicals) to 0.94 (in textiles). Therefore, both product and labour markers are found imperfect and the industries are facing substantial efficiency losses as a result of the imperfections.

Figure 1: Labour Share of Indian Industries from 2008 to 2016



Note: ASI

Table 2: Mark-up, Bargaining power and Efficiencies

Industry	Labour share	β	η	Markup (μ)	Bargaining power (θ)	ME	AE
Food	0.27	0.35***	0.12***	1.53	0.11	0.65	0.91
Textiles	0.37	0.52***	0.10***	2.08	0.09	0.47	0.94
Wood	0.31	0.52***	0.17***	2.09	0.14	0.54	0.89
Chemicals	0.22	0.29***	0.23***	1.41	0.19	0.71	0.82
Non-metallic	0.25	0.16***	0.10***	1.19	0.09	0.84	0.92
Metals	0.25	0.62***	0.20***	2.62	0.17	0.38	0.85
Electrical	0.33	0.82***	0.17***	5.65	0.16	0.28	0.88
Transport	0.30	0.22***	0.17***	1.28	0.14	0.78	0.88
Other	0.34	0.70***	0.13***	3.31	0.12	0.30	0.91
All	0.30	0.60	0.15	2.52	0.13	0.40	0.90

Note: ME - Market Efficiency $(1-\beta)$, AE - Allocative Efficiency $[1-\eta(1-s_L^U)]$, *** represents significance at 1% level.

In order to investiage the dynamics in the post crisis period, the efficiency changes have been estimated. Since the strong presence of market imperfections both in the product and labour markets are found, the efficiency changes in the product markets (MEC) and labour markets (AEC) are estimated along with the scale efficiency change (SEC), technical efficiency change (TEC) and technological change (TC). Following the discussion above, these are estimated and presented in Table 3. While the market efficiency level has improved in some industries (textiles, woods, chemicals, electrical and metals), it registers a marginal deterioration in the other industries (foods, non-metallic, transports and others). The sectors which registered a increase in market efficiency have experienced a rise of competitiveness. The level of competitiveness has deteriorated in the rest of industries. On the whole, it registers a marginal drop of 0.02% during 2008-16, suggesting that the efficiency loss from product market imperfections have increased a bit. On the other hand, there is an efficiency gain from labour market allocation in textiles, chemicals, non-metallic, transport and others. In the other industries, this has deteriorated that represents a rise of labour market rigidity. On the whole, the allocative efficiency has improved by 0.27% in the same period. These results seem to suggest that the efficiency loss from labour market imperfection has improved a bit while this has declined marginally for the product market imperfections.

While the efficiency changes from these two accounts along with other sources are calculated, the total productivity growth registered a substantial improvement in the industries (except food and other allied sectors). The productivity growth accounts for 3.72% during 2008-16 in the Indian manufacturing. However, the growth rate varies significantly across the sectors (see Table 3). It registers the highest growth in the chemical sector (5.64%) and textiles (8.09%) respectively, and negative growth (-0.17%) in food allied industries. More importantly, the Solow residual (SR) that captures the productivity growth using growth accounting method, presented in table 3, does not show substantially different from the figures estimated using decomposition method. While the growth accounting method registers 4.03% productivity growth, this method reveals only 3.72%, which is marginally different. Therefore, the method provided here does not only show the sources of productivity growth but also account for the figure similar to the growth accounting method.

Table 3: Percentage Change of Efficiency and Productivity during 2008-2016

Industry	MEC	AEC	SEC	TEC	TC	TFPG	SR
Food	-0.47	-2.44	-1.31	-0.04	4.10	-0.17	2.62
Textiles	1.09	3.75	-0.19	0.003	3.43	8.09	5.10
Wood	0.34	-0.72	0.47	-0.02	3.42	3.49	4.79
Chemicals	1.83	1.37	-1.25	-0.001	5.64	7.56	6.38
Non-metallic	-1.08	1.60	-1.25	0.001	3.06	2.33	2.33
Metals	0.67	-2.33	-0.04	0.08	5.32	3.71	6.85
Electrical	0.25	0.23	0.98	0.04	3.13	4.63	6.24
Transport	-1.13	2.98	-0.28	-0.03	3.46	4.99	4.42
Other	-1.04	-3.04	1.00	0.14	3.12	0.19	2.0
All	-0.02	0.27	0.23	0.06	3.18	3.72	4.03

Note: Technical efficiency change (TEC): $\dot{e}^{(-\hat{u})}$; Technological change (TC): $\dot{\hat{b}}^{*}$; Scale Efficiency change (SEC): $\frac{\lambda}{\mu}\dot{k}$; Allocative efficiency change (AEC): $[1-\eta]\dot{BR}$; Market efficiency change (MEC): $[1-\beta]\,\dot{LR}$

5 Concluding Remarks

The paper attempts to account for the efficiency loss from product and labour market imperfections and their relative contribution on the productivity growth using board industry classifications during 2008-16 for Indian economy. This paper offers an endogeneity corrected decomposition method to account for product and labour market efficiency changes along with scale efficiency change, technical efficiency change and technological change using a standard stochastic frontier approach. The estimation is undertaken using threesteps approach. First, the error component model, using (Battese and Coelli, 1992), is applied to account for technical inefficiency using production function with proxy variable for the productivity. Second, the semi-parametric approach, using (Levinsohn and Petrin, 2003) technique, is applied to estimate the terms representing market imperfections, scale parameters and technology level. Material cost has been used here as a proxy variable. Finally, the term representing technical efficiency has been recovered from the residue. The approach followed here similar to (Shee and Stefanou, 2015), but is very much different from the way endogeneity issue dealt with and the estimate of technical efficiency and technical change derived. The results indicate that the product and labour markets are imperfects. The efficiency changes from such losses affect the estimates of total factor productivity. While the contribution from product product efficiency has deteriorated a bit at the aggregate level, the same from the labour market has improved during the study period. The total factor productivity growth, combining all the efficiency changes, have been found similar to the Solow residual change, applying the growth accounting method.

References

Abraham, F., Konings, J., and Vanormelingen, S. (2009). The effect of globalization on union bargaining and price-cost margins of firms. *Review of World Economics*, 145(1):13–36.

Acemoglu, D. and Restrepo, P. (2018). Artificial intelligence, automation and work. Technical report, National Bureau of Economic Research.

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Aghion, P., Burgess, R., Redding, S. J., and Zilibotti, F. (2008). The unequal effects of liberalization: Evidence from dismantling the license raj in india. *American Economic Review*, 98(4):1397–1412.

Ahsan, R. N. and Mitra, D. (2014). Trade liberalization and labor's slice of the pie: Evidence from indian firms. *Journal of Development Economics*, 108:1–16.

Aigner, D., Lovell, C. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, 6(1):21–37.

Amsler, C., Prokhorov, A., and Schmidt, P. (2017). Endogenous environmental variables in stochastic frontier models. *Journal of econometrics*, 199(2):131–140.

Barkai, S. (2019). Declining labor and capital shares. *Journal of Finance, Forthcoming.*

Battese, G. and Coelli, T. (1992). Frontier production function. *Technical Efficiency.*

Besley, T. and Burgess, R. (2004). Can labor regulation hinder economic performance? evidence from india. *The Quarterly journal of economics*, 119(1):91–134.

Bhagwati, J. and Srinivasan, T. N. (2002). Trade and poverty in the poor countries. *American Economic Review*, 92(2):180–183.

Bhagwati, J. N., Srinivasan, T. N., et al. (1975). Foreign trade regimes and economic development: India. *NBER Books.*

Calligaris, S., Criscuolo, C., and Marcolin, L. (2017). Digital and market transformations. Technical report, Discussion paper, OECD Report.

Carmody, K. et al. (2017). Superstar firms and the falling labor share. *Econ Focus*, (2Q):9–9.

Dani, R. (1997). Has globalization gone too far? washington. *DC Institute for International Economics.*

De Loecker, J. and Eeckhout, J. (2017). The rise of market power and the macroeconomic implications. Technical report, National Bureau of Economic Research.

De Loecker, J. and Eeckhout, J. (2018). Global market power. Technical report, National Bureau of Economic Research.

Diez, M. F., Leigh, M. D., and Tambunlertchai, S. (2018). *Global market power and its macroeconomic implications.* International Monetary Fund.

Dobbelaere, S. (2004). Estimation of price-cost margins and union bargaining power for belgian manufacturing. *International Journal of Industrial Organization*, 22(10):1381–1398.

Domowitz, I., Hubbard, R., and Petersen, B. (1988). Market structure and cyclical fluctuations in u.s. manufacturing. *The Review of Economics and Statistics*, 70(1):55–66.

Dorn, D., Katz, L. F., Patterson, C., Van Reenen, J., et al. (2017). Concentrating on the fall of the labor share. *American Economic Review*, 107(5):180–85.

Dutt, A. K. (1984). Stagnation, income distribution and monopoly power. *Cambridge journal of Economics*, 8(1):25–40.

Eichengreen, B. and Gupta, P. (2013). The financial crisis and indian banks: Survival of the fittest? *Journal of International Money and Finance*, 39:138–152.

Elsby, M. W., Hobijn, B., and Şahin, A. (2013). The decline of the us labor share. *Brookings Papers on Economic Activity*, 2013(2):1–63.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of econometrics*, 126(2):269–303.

Hall, R. E. (1988). The relation between price and marginal cost in us industry. *Journal of political Economy*, 96(5):921–947.

Harrison, A. (1994). Productivity, imperfect competition and trade reform. *Journal of international Economics*, 36(1-2):53–73.

Hasan, R., Mitra, D., and Ramaswamy, K. V. (2007). Trade reforms, labor regulations, and labor-demand elasticities: Empirical evidence from india. *The Review of Economics and Statistics*, 89(3):466–481.

Hasan, R., Mitra, D., Ranjan, P., and Ahsan, R. N. (2012). Trade liberalization and unemployment: Theory and evidence from india. *Journal of Development Economics*, 97(2):269–280.

Hu, Y., Huang, G., and Sasaki, Y. (2020). Estimating production functions with robustness against errors in the proxy variables. *Journal of Econometrics*, 215(2):375–398.

Jayadev, A. (2007). Capital account openness and the labour share of income. *Cambridge Journal of Economics*, 31(3):423–443.

Karakaplan, M. and Kutlu, L. (2017a). Handling endogeneity in stochastic frontier analysis. *Economics Bulletin*, 39(2):889–901.

Karakaplan, M. U. and Kutlu, L. (2017b). Endogeneity in panel stochastic frontier models: an application to the japanese cotton spinning industry. *Applied Economics*, 49(59):5935–5939.

Karakaplan, M. U. and Kutlu, L. (2019a). Estimating market power using a composed error model. *Scottish Journal of Political Economy*, 66(4):489–510.

Karakaplan, M. U. and Kutlu, L. (2019b). School district consolidation policies: endogenous cost inefficiency and saving reversals. *Empirical Economics*, 56(5):1729–1768.

Kehrig, M. and Vincent, N. (2017). Growing productivity without growing wages: The micro-level anatomy of the aggregate labor share decline. *Economic Research Initiatives at Duke (ERID) Working Paper*, (244).

Klein, N., Herwartz, H., and Kneib, T. (2020). Modelling regional patterns of inefficiency: A bayesian approach to geoadditive panel stochastic frontier analysis with an application to cereal production in england and wales. *Journal of Econometrics*, 214(2):513–539.

Konings, J., Cayseele, P. V., and Warzynski, F. (2005). The effects of privatization and competitive pressure on firms' price-cost margins: Micro evidence from emerging economies. *Review of Economics and Statistics*, 87(1):124–134.

Konings, J., Van Cayseele, P., and Warzynski, F. (2001). The dynamics of industrial mark-ups in two small open economies: does national competition policy matter? *International Journal of Industrial Organization*, 19(5):841–859.

Kumbhakar, S. C. and Lovell, C. K. (2003). *Stochastic frontier analysis*. Cambridge university press.

Kumbhakar, S. C. and Parmeter, C. F. (2009). The effects of match uncertainty and bargaining on labor market outcomes: evidence from firm and worker specific estimates. *Journal of Productivity Analysis*, 31(1):1–14.

Kumbhakar, S. C., Tsionas, E. G., and Sipiläinen, T. (2009). Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. *Journal of Productivity Analysis*, 31(3):151–161.

Kumbhakar, S. C. and Wang, H.-J. (2006). Estimation of technical and allocative inefficiency: A primal system approach. *Journal of Econometrics*, 134(2):419–440.

Kumbhakar, S. L. and Lovell, K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.

Kutlu, L. (2010). Battese-coelli estimator with endogenous regressors. *Economics Letters*, 109(2):79–81.

Kutlu, L. and Sickles, R. C. (2012). Estimation of market power in the presence of firm level inefficiencies. *Journal of Econometrics*, 168(1):141–155.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341.

Li, Q. and Racine, J. S. (2007). *Nonparametric econometrics: theory and practice*. Princeton University Press.

Maiti, D. (2013). Market imperfections, trade reform and total factor productivity growth: theory and practices from india. *Journal of Productivity Analysis*, 40(2):207–218.

Maiti, D. (2019). Trade, labor share, and productivity in india's industries. In *Labor Income Share in Asia*, pages 179–205. Springer.

Nin-Pratt, A., Yu, B., and Fan, S. (2010). Comparisons of agricultural productivity growth in china and india. *Journal of Productivity Analysis*, 33(3):209–223.

Nishimizu, M. and Page, J. M. (1982). Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in yugoslavia, 1965-78. *The Economic Journal*, 92(368):920–936.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):263–97.

Orea, L. and Álvarez, I. C. (2019). A new stochastic frontier model with cross-sectional effects in both noise and inefficiency terms. *Journal of Econometrics*, 213(2):556–577.

Orea, L. and Steinbuks, J. (2018). Estimating market power in homogenous product markets using a composed error model: application to the california electricity market. *Economic Inquiry*, 56(2):1296–1321.

Pagan, A. and Ullah, A. (1999). *Nonparametric econometrics*. Cambridge university press.

Piketty, T. and Zucman, G. (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly Journal of Economics*, 129(3):1255–1310.

Prasad, A. and Reddy, C. P. (2009). Global financial crisis and its impact on india. *Journal of Social Sciences*, 21(1):1–5.

Rodrik, D. (1995). Has globalization gone too far?(washington, dc: Institute of international economics, 1997); and raghav gaiha," does agricultural growth matter in poverty alleviation?". *Development and Change*, 26:2.

Rodrik, D. (1997). Has globalization gone too far? number 57 in peterson institute press.

Shee, A. and Stefanou, S. E. (2015). Endogeneity corrected stochastic production frontier and technical efficiency. *American Journal of Agricultural Economics*, 97(3):939–952.

Slaughter, M. J. (2001). International trade and labor–demand elasticities. *Journal of international Economics*, 54(1):27–56.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of econometrics*, 13(1):57–66.

Weche, J. P. and Wambach, A. (2018). The fall and rise of market power in europe. *ZEW-Centre for European Economic Research Discussion Paper*, (18-03).