Trade and Efficiency of Manufacturing Industries in South Africa

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Abstract

This paper advances and empirically tests the hypothesis that trade raises input-oriented technical efficiency through cost saving practices that reduce cost inefficiencies. Using a primal and dual True-Fixed-Effects (TFE) stochastic frontier approach on a panel dataset comprising 28 manufacturing industries in South Africa between 1970 and 2016 at 3-digit level, it found average technical and cost efficiency values of 0.83 and 0.33 respectively indicating that the industries operated 33 percent above their cost minimizing level and could have reduced their input usage by 17 percent without compromising their output level. Empirical findings then confirmed a significant positive effect of import penetration and export intensity on technical efficiency that operates through reduction of cost inefficiencies. These findings do not only support our proposed hypothesis; they also corroborate the idea that competition from global trade forces local industries to rationalise their operations and give up production practices that are not consistent with the cost minimization objective. The Department of Trade and Industry (DTI) might find these results useful as they suggest that a less restrictive trade policy that promotes exports and imports has the potential to improve resource utilization within the manufacturing sector through downward cost adjustments.

Key Words: Stochastic Frontier Analysis, Manufacturing Industries, Import Penetration, Export Intensity

1.0 Introduction

The role of trade in explaining technical efficiency has been subject to debate for decades. On one hand, the argument raised by Corden (1974), Martin and Page (1983), Tybout (1992), Bernard *et al.,* (2003), Njikam (2003), Dai and Yu (2013) and Yahmeda and Dougherty (2017) among others is that trade raises productivity and efficiency through the import discipline hypothesis which posits that imports create a level of competition that forces domestic industries to operate efficiently to avoid perishing. The intuition behind this theoretical prediction is that, under market imperfections which are inherent in most developing countries, imports create a competitive environment[1] that eliminates monopoly powers (see Hansson, 1992). Empirical evidence supporting this claim includes Blalock and Veloso (2007), Yasar and Paul (2007) and Herrerias and Orts (2011). Lying on the other hand is the infant industry argument which claims that imports compromise technical efficiency if the bulk of industries in the importing country are too small to compete with those in exporting countries. Also, when the playing field is not level, the proliferation of imports from developed countries can make it difficult for producers in developing countries to survive on their home turf. Political economists make the case that unless governments make fiscal interventions to support

[1] The competitive environment created by imports forces producers to give up inefficient production practices that are inconsistent with the profit or output maximization or cost minimization objective.

and strengthen domestic industries, import penetration can displace domestic production as reported in Edwards and Jenkins (2015) for South Africa.

Equally important is the view held by proponents of open economy endogenous growth theory (Grossman and Helpman., 1991, Grossman and Helpman., 1995, Coe and Helpman., 1995) which proclaims that integration to global trade can improve productivity and efficiency growth through technological upgrades. Dollar (1992), Wha-Lee (1993), Sachs and Warner (1995), Harrison (1996) and Greenaway *et. al* (2002) provide evidence supporting this channel albeit at a macro-level. Another line of argument holds that exports can improve technical efficiency of exporting industries through specialization and learning by doing. This reasoning is close to the prediction raised by new trade models (see, for instance, Krugman, 1980), which is that producers exhibit increasing returns to scale so that increased trade allows existing producers to expand and raise their levels of efficiency. In line with this proposition, Feeney (1999) show that exporting producers grow faster than their non-exporting counterparts using sector specific learning by doing. Similar predictions are made by Roberts and Tybout (1997) based on a model with sunk costs of entry. Contrary to these predictions, Bernard and Jensen (1999) demonstrate that causality runs from productivity growth to exporting and not the other way round. These theoretical ambiguities clearly suggest that establishing the relationship between trade and technical efficiency is an empirical question.

Turning to empirical literature, the chain of evidence is not consistent across studies. One branch of evidence shows that the effect of imports on technical efficiency is positive citing increased competition and technological upgrades[2] as the key driving forces. Examples of such studies are Keller (2004), Nishioka and Ripoll (2012), Acharya and Keller (2009), Medda and Piga (2014), Piermartini and Rubínová (2014) and Pradeep *et al.* (2017). However, another branch of studies confirms that the effect of imports on technical efficiency can be negative and this branch comprises Shchetynin (2015). Despite an abundance of literature addressing this subject, there is a dearth of such studies in the context of South Africa.

Few available studies include Edwards, Rankin and Schoer (2008), Edwards and Jenkins (2015) and Fedderke, Shin, and Vaze (2012). However, these studies focus on the effects of trade variables usually imports and exports on either production or employment in South Africa's manufacturing sector and they do not explicitly focus on technical and cost inefficiency. Focusing on technical and cost efficiency is attractive in that it captures the economic reality that producers do not always produce at the maximum production possibility frontier due to technical inefficiencies caused by exogenous factors beyond their control. We therefore contribute to South Africa's literature on trade and manufacturing sector by focusing on input oriented-technical and cost inefficiency. The former defines technical efficiency as the rate at which industries can reduce their inputs without changing their output level while the latter compares the actual production costs with the cost minimization level.

Within the stochastic frontier analysis literature, few studies on technical efficiency and trade such as Andersson and Stone (2017) have done so using the Battese and Coelli (1995) time-varying decay stochastic frontier model which does not distinguish between time-invariant heterogeneity from time-varying inefficiency and as a result have an implication of generating biased

[2] Reallocation effects of trade affect the *level* of productivity and efficiency. In fact, Lucas (1988) and Young (1991) note that much of the literature predicts that trade affects the level of productivity. However, Grossman and Helpman (1991) & Lee (1993) show that technological upgrades and knowledge sharing through trade can affect the *growth* of productivity and efficiency.

technical efficiency scores of industries by treating unobserved heterogeneity as inefficiency. We therefore contribute empirically by applying the True-Fixed-Effects stochastic frontier model developed by Greene (2005) which improves early time-varying decay models by separating time-invariant heterogeneity from time-varying technical inefficiency. This issue is relevant in our case where time-invariant industry-specific effects are likely to be correlated with production inputs, labour and capital. We then use the within transformation proposed by Wang and Ho (2010) to avoid the incidental parameters problem associated with the likelihood dummy variable approach of estimating the true-fixed effects model. In the estimation procedure unlike most previous studies, we use lags rather than contemporaneous values to circumvent the endogeneity problem inherent both in the stochastic frontier analysis and in the technical inefficiency model. We also control for other macroeconomic variables as an attempt to isolate the impact of trade on technical efficiency.

For policy purposes, our analysis helps to answer several debates concerning South Africa's integration to global trade and the performance of local industries. Most important, we help to resolve the widely discussed conundrum related to the consequences of export and import competition on technical efficiency of domestic industries as South Africa is becoming more open to global trade. Long-held judgments about the rising competition suggest that imports displace domestic production and destroy jobs but we very know little concerning how they relate on technical and cost efficiency of manufacturing industries.

The rest of the paper is organised as follows: section 2.0 comprises a theoretical framework, 3.0 outlines the methodology, 4.0 presents and interprets the empirical findings while concluding remarks are given in section 5.0.

Theoretical Framework

The objective here is to link international trade with technical efficiency and it is often standard to first define the key concepts. International trade is the exchange of goods and services across international boundaries while technical efficiency[3] refers to the rate at which inputs can be reduced with a given output level. Within the technical efficiency literature, technical efficiency is broadly measured using either parametric or non-parametric methods. Parametric methods encompass the stochastic frontier analysis (SFA) applied in Wang and Wong (2012) and Andersson and Stone (2017). This technique was developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977).

Non-parametric methods on the other hand rely on linear programming techniques particularly the data envelopment analysis (DEA). The DEA is a deterministic linear programming technique which makes it inherently difficult to purge the effect of the decision-making unit (DMU) from those outside the control of the DMU when measuring efficiency. In contrast, the SFA considers measurement errors and other exogenous effects that are beyond the control of the DMU. Our analysis relies on secondary manufacturing data which is mulled by measurement error as well as production noise which necessitates the use of a stochastic frontier model.

The SFA is a parametric technique that uses standard production function methodology. The approach explicitly recognises that production function represents technically maximum feasible output level for a given level of inputs. Common ordinary least squares (OLS) regression production functions fit a function through the centre of the data and assumes that all producers are efficient.

[3] One can also focus on other versions of efficiency that include X-efficiency, profit efficiency, scale efficiency, cost efficiency and allocative efficiency.

Deterministic production frontiers extensively used by Bjurek *et al.,* (1990) on the other hand fit a frontier function over the data and assume absence of noise in data. SFA production frontiers represent a mix of these two approaches and it is grounded in micro-economic theory of production.

Accordingly, the SFA assumes that a typical producer often referred to as the decision making unit, thrives either to maximise output or profit subject to specific constraints that can include existing technology, funds available for investment, the number of people to be employed and so on. Achievement of this objective is assumed to be affected by a combination of internal factors (such as skill, organizational structure, level of motivation) which can be controlled by the decision making unit or external factors such as the macroeconomic environment (trade policy, monetary and fiscal policies etc.) which are normally beyond the control of the decision making units. In this paper, we seek to establish how trade affects the macroeconomic environment through for example increased competition for domestic producers. This, in theory, can have an influence on the firm's optimization decisions and consequently the level of technical efficiency.

From a technical point of view, it is important to distinguish between input-oriented and output-oriented technical efficiency. Input-oriented technical efficiency seeks to establish the margin by which producers can minimise their input usage with fixed output, in other words without changing the level of output. Output-oriented technical efficiency on the other hand seeks to establish the margin by which producers can increase their level of output with fixed inputs and the existing technology. These two concepts are illustrated in Figure 1 in which output (Y) is produced using a combination of inputs (X). The productivity frontier is given by the curve Y=f(X) which means point A is technically inefficient as it is positioned below the maximum possible output frontier. Focusing on A, the technical inefficiency point, a producer can move towards the maximum possible output frontier in two ways. The first route is to increase output up to point B with fixed inputs N. This route defines output-oriented (OO) technical efficiency. The second route is to hold output constant and reduce inputs from point N to point M in order to operate at point C which is input-oriented (IO) technical efficiency.

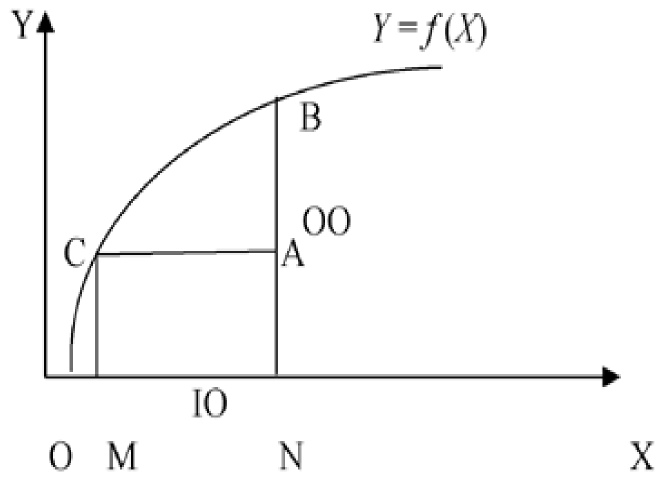


Figure 1: Input and Output-Oriented Technical Efficiency

In this paper, focus is on input-oriented technical efficiency since manufacturing output is usually pre-determined by demand. In other words, manufacturing output is usually exogenously given and focusing on input-oriented technical efficiency allows us to determine how much the manufacturing industries can reduce their inputs without changing the exogenously given output level. The theoretical question therefore boils down to how trade affects input-oriented technical efficiency.

In theory, economists provide three main avenues through which trade can possibly affect productivity (see Salim, 2003, Islam et al., 2016). The first channel proposed by Grossman and Helpman (1991), Coe and Helpman (1995) and Coe *et al*. (2009) and empirically supported by Apergis *et al.* (2009), Nishioka and Ripoll (2012), Acharya and Keller (2009), Medda and Piga (2014), Piermartini and Rubínová (2014), Pradeep *et al.* (2017), Behera *et al*. (2012) and Bloom *et al.* (2016) is that trade allows technology transfers across international borders and it is this technological diffusion and upgrade that fosters productivity growth in tradable industries. This idea is tied in open economy endogenous growth theories in which imports and exports are given a role to play as transmitters of embodied innovation. Technology uptake however leads to a shift of the existing production possibility frontier which makes endogenous growth theories less useful in explaining the movement of industries within a production possibility frontier. The second explanation provided by Melitz (2003), Hossain and Karunaratne (2004), Rodrik (1995) and Horn *et al.,* (1995) is that trade affects overall productivity by allowing the exiting of inefficient firms and expansion of efficient ones combined with the within-industry reallocation of firms. The third mechanism posits that trade increases productivity growth through economies of scale.

In this paper, we hypothesize that exports and imports (which proxy the level of integration into the global economy) are associated with global competition which forces domestic manufacturing industries to rationalise their operations by avoiding resource overuse and reducing cost inefficiency. This hypothesis is closely related to the import-discipline hypothesis raised in Levinsohn (1991) and Melitz (2003) where imports eliminate market power of firms and create a competitive market environment which ultimately improves efficiency. Much of their evidence relies on firm-level data and the import-disciple hypothesis is confirmed by a significant negative effect of import penetration measures on firm-level mark-ups. In this paper, our hypothesis is that import penetration and export intensity expose domestic industries to external competition which forces them to improve their levels of technical efficiency through cost reduction. In other words, competition emanating from the global market forces domestic industries to realign themselves with the cost minimum level by cutting unnecessary production costs that stem from an overuse of resources. If inputs are overused by W percent, total costs are increased by W percent so survival of firms facing competition from exporting and importing depends on how much they are able to cut back on costs. A reduction in cost inefficiency consequently raises their levels of technical efficiency levels.

Testing our hypothesis follows two steps. First, we estimate a model in which technical efficiency scores of manufacturing industries are regressed against trade variables and a set of controls. We then, in the second stage, estimate a specification in which cost efficiency scores are regressed against trade variables in order to determine whether trade affects technical efficiency through improvements in cost efficiency within a stochastic frontier framework. Application of the SFA on cost efficiency is based on the duality theory which posits that the cost function contains information that allows one to derive information regarding the corresponding production function. With SFA, the frontier cost function defines minimum costs given output level, input prices and the existing production technology. Failure to attain the cost frontier implies the existence of technical and/or allocative inefficiency.

Assumed here is that[4] a typical industry in South Africa's manufacturing sector sets the objective of minimizing costs in order to produce a given output level[5]. This is a reasonable assumption since, as mentioned earlier, industrial output is usually pre-determined by demand. The same producer is also assumed to be technically inefficient (i.e. operating below the production possibility frontier) but allocatively efficient. This second proposition makes it easy for us to link technical and cost inefficiency. For cost inefficiency, additional costs might arise from an overuse of inputs while cost savings might arise from the elimination of inefficiency by avoiding an excess usage of resource inputs. For producer i, the cost minimisation problem under input-oriented inefficiency takes the form:

$$\min \boldsymbol{w}' z \quad \text{s.t.} \quad y = f(\boldsymbol{z}e^{-u}) \quad (1)$$

where z and $\boldsymbol{w}$ are vectors of inputs and their corresponding prices respectively, y is the observed or actual output and u captures inefficiency. Algebraically from equation (1), the first order conditions (FOCs) are given by:

$$f_i(\boldsymbol{z}e^{-u}) \Big/ f_i(\boldsymbol{z}e^{-\theta}) = w_j / w_1, \quad j = 2, \dots, J \quad (2)$$

where $u \geq 0$ represents input-oriented technical inefficiency which essentially captures the extent to which input resources are being overused by the producer in producing a given output level y. One can alternatively interpret this as the extent to which the use of inputs can be reduced by the producer without reducing the level of output y. The marginal product (i.e. the change in output arising from an additional input) of the input $\boldsymbol{z_j}e^{-u}$ is given by $f_j(\cdot)$ which represents the partial derivative of $f(\cdot)$ w.r.t $\boldsymbol{z_j}e^{-u}$. The FOCs for $(J-1)$ equations in equation (2) can be used to derive the J input demand functions which take the form:

$$\boldsymbol{z_j}e^{-u} = \sigma_j(\boldsymbol{w}, y) \quad j = 1, \dots, J \quad (3)$$

From equation (3), the cost function C* can be formulated as:

$$C^*(w, y) = \sum_j w_j z_j e^{-u} \quad (4)$$

which is a minimum cost function of the following problem:

$$\min_{z_j e^{-\theta}} \boldsymbol{w}\boldsymbol{z_j}e^{-u} \quad \text{s.t.} \quad y = f(\boldsymbol{z}e^{-u}) \quad (5)$$

The frontier cost function denoted by $C^*(\cdot)$ provides the minimum cost given the prices of inputs $\boldsymbol{w}$ and actual output level y. Noteworthy is that this cost function $C^*(\cdot)$ reflects the cost of effective units of all inputs z. Put differently, it is the cost of producing output y when all inputs z are used effectively. As a result, $\boldsymbol{w}\boldsymbol{z_j}e^{-u}$, the minimum cost, would be less than $\boldsymbol{w}'z$ actual cost.

[4] There are several other assumptions which are important in the measurement of cost efficiency using the duality theory. Firstly, industries are input price takers; that is they have no control over the prices of labour, capital and intermediate inputs. Secondly, input factors prices are assumed to be strictly positive in order to ensure that the solution to the cost minimisation problem lies within the solution space. Thirdly and associated with the second assumption, it is further assumed that industries cannot produce a positive output with zero costs. Fourth, at least one input is required to produce output. Fifthly, input factor prices and production costs are linearly and positively correlated. Sixth, input factor prices and total production costs change proportionally. This assumption technically implies that the cost function is homogenous of degree one in factor input prices. Lastly, production costs cannot decrease when output is increasing.

[5] A producer can be cost inefficient due to technical or allocative inefficiency. In this analysis, the producer is assumed to be technically inefficient but allocatively efficient. Relaxing the allocative efficiency assumption would make interpretation of the inefficiency component less clear cut.

Relating actual cost (C^a) with the unobservable minimum cost (C^*) requires making use of the Shephard's lemma to equation (4) as follows:

$$\partial C^* / \partial w_j = z_j e^{-u} \quad (6)$$

$$\Rightarrow \quad \partial \log C^* / \partial \log w_j = \frac{w_j z_j e^{-u}}{C^*} = \frac{w_j z_j}{w' z} \equiv S_j \quad (7)$$

Hence,

$$w_j z_j e^{-u} = C^* \cdot S_j \quad \text{or} \quad z_j e^{-u} = \frac{C^* \cdot S_j}{w_j} \qquad (8)$$

Actual costs are then expressed as:

$$C^a = \sum_j w_j z_j = C^* \exp(u) \quad (9)$$

$$\Rightarrow \quad \log C^a = \log C^* (w, y) + u \ (10)$$

Equation (10) says that the logarithm of actual costs increases by u because all inputs are overused by u. Our argument here is that exporting and importing increases pressure on domestic industries which forces them to cut back on costs in order to operate at the minimum cost level. For estimation purposes, a stochastic term, v, is added to account for modelling errors. Adding this stochastic term together with panel subscripts, $i =$ industry and $t =$ time yields:

$$\begin{aligned} \log C_{it}^a &= \log C^*(w_{it}, y_{it}) + v_{it} + u_{it} \\ &= \alpha_0 + \sum_j \alpha_j \log w_{j,it} + \alpha_y \log y_{it} + v_{it} + u_{it} \end{aligned} \qquad (11)$$

where u_{it} measures the extent to which industry i operates above its cost frontier in period t. At the empirical level, there are several contentious issues in the stochastic frontier literature both for production and cost functions. The first issue relates to whether the analysis should be conducted using a one-step or two-step procedure. In the two-step approach, one estimates the production frontier, for example, by regressing output on factor inputs usually labour and capital omitting variables that affect technical efficiency. In the second step, the generated technical efficiency scores are regressed on explanatory variables that are believed to be relevant sources of technical efficiency of the DMU. The problem with the two-step approach is that it lacks consistency in the way it treats the distribution of the inefficiency component. In the first stage when estimating the frontier regression, the technical inefficiency component is assumed to be identical and independently distributed. However, in the second stage, the same inefficiency component is assumed to depend on other explanatory variables. Wang and Schmidt (2002) show that this two-step procedure is, as a result, biased and recommend the use of a one-step procedure where determinants of technical efficiency are incorporated directly in the maximum likelihood estimation. This is the approach used in this study.

Another issue in the stochastic frontier literature relates to the choice of the functional form[6]. Available functional forms include the Cobb-Douglas, Generalized Production Function due to Zellner and Revankar (1969), the Transcendental production function due to Halter (1957) and the Translog specification. Among these variants in empirical literature, the commonly assumed functional forms are the Cobb-Douglas and the Translog specifications. Each of these two functional forms is not without its own limitations. The advantage of the former is that it has universally smooth and convex isoquants. However, its demand elasticities and factor shares are assumed to be constant for given input prices. The criticisms that the Cobb-Douglas specification is too restrictive and that it represents only one of the three neoclassical production stages have generally motivated most empirical applications to assume a more flexible functional form which is the Translog.

Notwithstanding the flexibility of the Translog specification, the price to be paid for its flexibility is that it is not globally convex as is the Cobb-Douglas model. Also, it is generally challenging to impose an appropriate curvature on a Translog model. Despite these criticisms, the Translog and the Cobb-Douglas specifications continue to be widely used in the stochastic frontier literature and a common practice in literature is to estimate both specifications and then conduct relevant statistical tests to determine the form which best suits the data.

Empirical Application

Annual data spanning the periods 1970 and 2016 are applied. Selection of this sampling period is guided by data availability. The main data source of our empirical analysis was the South African Standardised Industrial (SASI) database and it currently covers the period 1970 – 2016. The SASI database provides input, output, price and trade variables for 45 industries and 28 of these 45 industries are manufacturing. Here, we rely on the 28 3-digit level manufacturing industries classified according to the International Standard Industrial Classification (ISIC), Rev.2. We focus on manufacturing industries as they are largely tradable and sensitive to trade changes. An ideal situation was to use firm level data which adequately captures firm optimization behaviour. However, such data are not available for long horizons hence we have relied on industry level data that are based on the assumption that all firms in a given industry behave homogenously. The same assumption is assumed in Parades (1994), Ocampo (1994), Jenkins (1995), Sun *et al.,* (1999) in the case of Chinese manufacturing industries more recently Suatmi *et al.,* (2017). The industries included in our analysis are listed in Table 7 and 8 attached in appendixes for brevity.

Apart from listing the industries included in our analysis, Tables 7 and 8 also show the average import penetration and export intensity respectively in SA's manufacturing sector for the period 1970 – 2016. The 28 3-digit industries are ranked according to the average ratios and it is easy to identify those that face stiff competition from imports and those that participate more in export markets. Starting with importation, professional and scientific equipment, machinery, TV, radio and communication equipment and rubber industries face high import penetration ratios. Competition from imports is moderate in industries such as basic chemicals, textiles, non-ferrous metals, clothing, glass and other manufacturing and relatively low in printing and publishing, beverages, tobacco and coke and petroleum products.

[6] The implication for empirical analysis is that, when estimating the technical inefficiencies of different producers, it is important that they are estimated with respect to the appropriate technology (Kumbhakar *et al*., 2015).

Model Specification

Hypothesis 1: Trade Variables affect Technical Efficiency

The first hypothesis requires us to estimate a stochastic frontier model in a primal approach in order to determine whether technical efficiency of industries is related to import penetration and export intensity. Empirically, the stochastic frontier analysis in panel data can take different forms that include the distribution free time-invariant technical inefficiency models (Schmidt and Sickles, 1984), time-varying technical inefficiency models (Cornwell, Schmidt and Sickles, 1990, Lee and Schmidt, 1993, Kumbhakar, 1990, Battese and Coelli, 1992) and the True-Fixed and Random effects (Greene, 2005). For the purpose of our empirical analysis, we apply the true-fixed effects stochastic frontier model based on its attractive feature of separating invariant-industry heterogeneity from time varying technical inefficiency. The true-fixed effects stochastic frontier model considered here is based on two functional forms, the flexible Translog and the restrictive Cobb Douglas specification. In specifying the stochastic frontier model, it is essential to note that inputs can be endogenous in a production function given that output can also influence employment and capital decisions. Because addressing endogeneity of inputs in a stochastic frontier framework is still at infancy, we attempt to deal with this endogeneity problem by lagging the right hand-side variables so that output y can be endogenously determined in period t given the constraints inherited from the previous period. The estimated Translog model takes the following form.

$$\begin{aligned}\log(\mathrm{Y})_{it} = {} & \delta_i + \beta_1 \log(\mathrm{L})_{it-1} + \beta_2 \log(\mathrm{K})_{it-1} + \beta_3\, 0.5 \log(\mathrm{K})_{it-1}{}^2 + \beta_4\, 0.5 \log(\mathrm{L})_{it-1}{}^2 \\ & + \beta_5 [\log(\mathrm{K}) \log(\mathrm{L})]_{it-1} + \beta_6 \mathrm{Year}_{t-1} + \beta_7 [\log(\mathrm{K})(\mathrm{Year})]_{it-1} + \\ & \beta_8 [\log(\mathrm{L})(\mathrm{Year})]_{it-1} + 0.5 * \beta_9 \mathrm{Year}_{t-1}{}^2 + \beta_{10} \log(\mathrm{I})_{it-1} \\ & + \beta_{11}\, 0.5 \log(\mathrm{I})_{it-1}{}^2 + \beta_{12} [\log(\mathrm{I}) \log(\mathrm{L})]_{it-1} + \beta_{13} [\log(\mathrm{I}) \log(\mathrm{K})]_{it-1} \\ & + \beta_{14} [\log(\mathrm{I}) \log(\mathrm{Year})]_{it-1} + \varepsilon_{it} \qquad (11)\end{aligned}$$

$$\varepsilon_{it} = V_{it} - U_{it}$$
$$V_{it} \sim IID\ N(0, \psi^2) \quad U_{it} \sim IID\ F_u(\sigma)$$

$$i = 1, \ldots, 28 \ \&\ t = 1970, \ldots, 2016$$

where subscripts i and t signify industry and year respectively, Y denotes real value added, L is labour measured by the number of workers, K is the capital variable measured by gross fixed capital stock[7], I denotes the value of intermediate inputs, $Year$ is a trend variable included to capture the possibility of frontier shifts i.e. technical changes and its squared term accommodates non-monotonic technical changes. The trend variable is interacted with input factors to capture Hicks non-neutral technical change (Wang & Wong, 2012). If the null hypothesis $\beta_3 = \beta_4 = \beta_5 = \beta_7 = \beta_8 = \beta_9 = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = 0$ is not rejected at 5% level, then the Translog specified in equation (1) will collapse to a Cobb Douglas specification of the following form.

$$\log(\mathrm{Y})_{it-1} = \delta_i + \beta_1 \log(\mathrm{L})_{it-1} + \beta_2 \log(\mathrm{K})_{it-1} + \beta_3 \log(\mathrm{I})_{it-1} + \beta_4 \mathrm{Year}_{t-1} + \varepsilon_{it} \quad (12)$$

[7] Capital stock figures for the main sectors of the South African economy are produced by the Reserve Bank using a perpetual-inventory method (PIM).

$$\varepsilon_{it} = V_{it} - U_{it}$$

$$V_{it} \sim IID\ N(0, \psi^2)\ \ U_{it} \sim IID\ F_u(\sigma)$$

$$i = 1, \ldots, 28\ \&\ t = 1970, \ldots, 2016$$

where year is a time trend variable included to capture Hicks-neutral technological progress. Based on economic theory, β_1, β_2 and β_3 are expected to be positive indicating that labour, capital and intermediate inputs raise output. Importantly, the two components of the composite error term; V_{it} and U_{it} in equations (11) and (12) are independently distributed. The technical inefficiency component represented by U_{it} is distributed according to F_u which is defined over $\mathbb{R}^+$ with σ.

To avoid the incidental parameters problem that may arise if estimation is done via the use of industry-specific dummy variables, we follow the recommendation proposed by Wang and Ho (2010) of estimating equations (11) and (12) via the within transformation so that the final specification is without δ_i. From equation (12), the within estimator results in:

$$\hat{\delta}_i = \frac{1}{T}\sum_{t=1}^{T}(\log(\mathrm{Y})_{it} - \hat{\beta}_1 \log(\mathrm{L})_{it-1} - \hat{\beta}_2 \log(\mathrm{K})_{it-1} - \hat{\beta}_{10} \log(\mathrm{I})_{it-1} + \hat{c}_{it})$$

$$i = 1, \ldots, 28$$

where parameters $\hat{\beta}$ &$\hat{c} = E(u_{it} \,|\hat{\beta},\ \hat{c})$ are consistently estimated using the maximum likelihood (ML) technique. The main interest lies in estimating the impact of trade on technical efficiency and we split trade into two parts, export intensity and import penetration[8].

The challenge however is to disentangle the effects of these trade components on technical efficiency from those of other macroeconomic variables that may explain variation in both trade and technical efficiency. As an attempt to isolate the effect of trade and circumvent the associated endogeneity problem, we follow two approaches simultaneously. One is to control for an array of other macroeconomic variables that may jointly influence trade and technical efficiency of the manufacturing industries and such factors include government expenditure (% of GDP) to capture the fiscal policy stance, total credit by the financial sector (% of GDP) to capture the monetary policy stance, real effective exchange rate to capture economic competitiveness, computer services (% of commercial services) to capture technological progress and access to market information and electricity consumption to capture energy use. The second approach is one used by Following Wang and Wong (2012) of lagging regressors so that we can establish how a change in each regressor in the current period affects technical efficiency in the subsequent period. With these considerations, the technical inefficiency effects are then derived from the following baseline model.

$$U_{it} = \delta_0 + \delta_1 \mathrm{Imp}_{it-1} + \delta_2 \mathrm{Exp}_{it-1} + \delta_3 \mathrm{Gexp}_{t-1} + \delta_4 \mathrm{Cred}_{t-1} + \delta_5 \mathrm{Elec}_{it-1} + \delta_6 \mathrm{Comp}_{t-1} + \delta_7 \log REER_{t-1} + w_{it} \qquad (13)$$

$$i = 1, \ldots, 28 \qquad t = 1970, \ldots, 2016$$

[8] An industry's export intensity is the exports of the industry as a percentage of its output. Import penetration on the other hand is calculated as the ratio of imports to total domestic demand (production plus imports minus exports) for the total manufacturing sector and industry groupings of South Africa.

where Imp and Exp represent import penetration and export intensity respectively included to capture the effect of trade on technical efficiency, Gexp is government expenditure (% of GDP), Cred denotes total credit by the financial sector (% of GDP), Elec is electricity consumption (% of GDP), Comp signifies computer services (% of commercial services) and REER represents the real effective exchange rate. Note that Gexp, Cred, Elec, Comp and REER do not have the subscript i. This is because they are economy wide variables which vary over time but not across industries. To the extent that literature is inconclusive regarding the effects of trade on technical efficiency, either sign is expected on Imp and Exp. We also consider another variant of equation (13) in which we interact trade variables with government expenditure in order to capture the fiscal intervention to moderate trade effects. The government intervention in trade is well documented in Rodrik (2004). For example, governments might embark on an expansionary fiscal policy to level the playing field for industries participating in global markets. The variant with interactions takes the following form:

$$U_{it} = \delta_0 + \delta_1 \mathrm{Imp}_{it-1} + \delta_2 \mathrm{Exp}_{it-1} + \delta_3 \mathrm{Gexp}_{t-1} + \delta_4 \mathrm{Cred}_{t-1} + \delta_5 \mathrm{Elec}_{t-1} + \delta_6 \mathrm{Comp}_{t-1} + \delta_7 \log REER_{t-1} + \delta_8 \mathrm{Imp}_{it-1} * \mathrm{Gexp}_{t-1} + \delta_9 \mathrm{Exp}_{it-1} * \mathrm{Gexp}_{t-1} + w_{it} \quad (14)$$

$$i = 1, \dots, 28 \qquad t = 1970, \dots, 2016$$

where δ_8 and δ_9 capture how the impact of import penetration and export intensity increase or decrease with an expansionary fiscal policy respectively. We estimate the frontier equation and the technical inefficiency model using the maximum likelihood technique simultaneously to avoid the persistent bias observed in Wang and Schmidt (2002) that arises if estimation proceeds in two stages. It is important to test the suitability of the stochastic frontier analysis over the general production function with normal errors. To achieve this, we compute the likelihood ratio test statistic as recommended by Kumbhakar, Wang and Horncastle (2015). The Likelihood Ratio test statistic is computed from the formula,

$$-2[L(H_0) - L(H_1)$$

where $L(H_0)$ and $L(H_1)$ represent the log-likelihood values computed from restricted ordinary least squares (OLS) model[9] and the unrestricted stochastic frontier model respectively with one degree of freedom representing the imposed restriction. Critical values for the mixed distribution are obtained from Kodde and Palm (1986). Technical efficiency scores were then computed via Jondrow *et al*. (1982).

$$TE_{it} = \exp(-U_{it})$$

Hypothesis 2: Trade variables affect technical efficiency through improvements in cost efficiency

Similar to the primal approach, the first methodological step here was to conduct a likelihood ratio (LR) test in order to determine the functional form that best suits the data. The LR test involves estimation of both the restricted specification (the Cobb-Douglas) and the unrestricted specification (the Translog). From equation (11), a Cobb-Douglas specification with cost inefficiency takes the following form:

[9] In STATA, this is achieved through the generalized linear model

$$\log(\widetilde{TC})_{it} = \alpha_i + \alpha_y \log y_{it} + \alpha_l \log(\widetilde{wL})_{it} + \alpha_k \log(\widetilde{wK})_{it} + \alpha_t \text{Year}_t + v_{it} + u_{it} \quad (15)$$

$$v_{it} \sim N(0, \sigma_v^2), \quad u_{it} \sim N^+(u, \sigma_{uit}^2)$$

$$i = 1, \dots, 28 \qquad t = 1970, \dots, 2016$$

where;

$$\widetilde{TC} = \left(\frac{TC}{wN}\right), \qquad \widetilde{wL} = \left(\frac{wL}{wN}\right), \qquad \widetilde{wK} = \left(\frac{wK}{wN}\right)$$

TC represents total costs, wK is the price of capital, wL is the price of labour, wN is the price of intermediate inputs while Year is a trend variable included to capture technical progress that might cause cost frontier shifts[10]. Note that wN divides TC, wK and wK to ensure that the linear homogeneity condition holds.

Intuitively, v_{it} and u_{it} are assumed to be independent of each other. The former is the usual error term while the latter represents the cost inefficiency term. By assumption, the error term, v_{it} is normally distributed with a mean of zero and a constant variance while the cost inefficiency term, u_{it}, follows, in this paper, a truncated normal distribution with a non-zero mean as proposed by Stevenson (1980) and a constant variance. The truncated normal distribution ensures that the mode of inefficiency varies significantly which is realistic in the present case given market imperfections that make the production environment less competitive.[11] The Translog specification, on the other hand, takes the following form:

$$\begin{aligned}\log(\widetilde{TC})_{it} = {} & \alpha_i + \alpha_y \log y_{it} + \alpha_l \log(\widetilde{wL})_{it} + \alpha_k \log(\widetilde{wK})_{it} + \frac{1}{2}\alpha_{yy} \log y_{it} \log y_{it} \\ & + \frac{1}{2}\alpha_{ll} \log(\widetilde{wL})_{it} \log(\widetilde{wL})_{it} + \frac{1}{2}\alpha_{kk} \log(\widetilde{wK})_{it} \log(\widetilde{wK})_{it} \\ & + \alpha_{lk} \log(\widetilde{wL})_{it} \log(\widetilde{wK})_{it} + \alpha_{ly} \log y_{it} \log(\widetilde{wL})_{it} + \alpha_{ky} \log y_{it} \log(\widetilde{wK})_{it} \\ & + \alpha_t \text{Year}_t + \frac{1}{2}\alpha_{tt} \text{Year}_t \, \text{Year}_t + \alpha_{lt} \log(\widetilde{wL})_{it} \text{Year}_\text{t} + \alpha_{kt} \log(\widetilde{wK})_{it} \text{Year}_\text{t} \\ & + \alpha_{yt} \log y_{it} \text{Year}_\text{t} + v_{it} + u_{it} \qquad (16)\end{aligned}$$

$$v_{it} \sim N(0, \sigma_v^2), \quad u_{it} \sim N^+(u, \sigma_{uit}^2)$$

$$i = 1, \dots, 28 \qquad t = 1970, \dots, 2016$$

---

10 An alternative way of capturing cost frontier shifts is to include m-1 time dummies. However, with a long time dimension, this leads to over parameterization.

11 Half-normal and exponential distributions proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) respectively might suit cases where producers are operating in a competitive market environment so that the majority of producers are forced to operate efficiently. Reality is however that the market environment is characterised by market imperfections which cause most producers to operate inefficiently.

Technically, the log-likelihood value from restricted specification (the Cobb Douglas) is denoted by $\mathrm{L(H_0)}$ and that from the unrestricted specification (the Translog) is represented by $\mathrm{L(H_a)}$. The likelihood ratio test statistic is then given by:

$$\text{LR statistic} = -2[L(H_0) - L(H_a)]$$

Alternatively, we can employ the Wald test for joint significance in which the null hypothesis; $\alpha_{yy} = \alpha_{ll} = \alpha_{kk} = \alpha_{lk} = \alpha_{ly} = \alpha_{ky} = \alpha_{yt} = \alpha_{tt} = \alpha_{lt} = \alpha_{kt} = 0$, against the alternative hypothesis; $\alpha_{yy} \neq \alpha_{ll} \neq \alpha_{kk} \neq \alpha_{lk} \neq \alpha_{ly} \neq \alpha_{ky} \neq \alpha_{yt} \neq \alpha_{tt} \neq \alpha_{lt} \neq \alpha_{kt} \neq 0$. The null hypothesis that the Cobb-Douglas specification is the preferred form is rejected if the test statistic is greater than the 5 percent critical chi-square value. Failure to reject the null hypothesis would imply a collapse of the Translog specification in equation (16) into a Cobb-Douglas form specified in equation (15). The cost inefficiency specification linking trade variables with cost inefficiency is then specified as:

$$u_{it} = \delta_0 + \delta_m \log imp\_p_{it-1} + \delta_x \log exp\_i_{it-1} + \delta_g \mathrm{gc}_{it-1} + \delta_r \log reer_{it-1} + \delta_c \mathrm{cr}_{it-1} + \delta_t \log tot_{it-1} + \delta_{inf} \mathrm{pcm}_{it-1} \quad (17)$$

$$i = 1, \ldots, 28 \qquad t = 1970, \ldots, 2016$$

Equation (17) is the equation of interest and it shows how the share of imports ($\log imp\_p_{it-1}$) and exports ($\log exp\_i_{it-1}$) on output correlate with the conditional cost inefficiency mean of the 28 three-digit level manufacturing industries in the subsequent year controlling for a number of macroeconomic variables. Import penetration and export intensity variables are lagged once as an attempt to circumvent the endogeneity problem since an industry's cost efficiency levels might influence its import penetration and export intensity. In addition, when faced with competition either from export intensity or import penetration, producers usually adjust their production costs with a delay hence the use of a lag captures this phenomenon. The dependent variable is cost inefficiency so a positive sign represents a negative effect on cost efficiency.

To improve estimation efficiency and avoid confusing the effect of imports and exports with those of other factors, we control for a number of macroeconomic variables namely the real effective exchange rate, government expenditure to capture the fiscal policy stance, credit extended to the private sector to capture financial developments, terms of trade to capture the external environment and the price cost margin to proxy domestic competition. The real exchange rate, in neoclassical sense, is a relative price of tradable to non-tradable goods and has important implications on the cost structure of manufacturing industries (Dhasmana, 2013. Vaz and Baer, 2014, Baltar, 2016). A depreciation (appreciation) of the local currency makes it expensive (cheaper) for manufacturing industries to import intermediate imports which eventually reduces (increases) production costs. Empirically, the real effective exchange rate is used and an increase signals an appreciation of the local currency relative to a basket of other currencies.

Government expenditure is essential because the fiscal policy has important implications on production costs of manufacturing industries in many respects. Firstly, an expansionary fiscal policy increases the cost of borrowing by reducing the supply of loanable funds when financed by domestic borrowing. The high cost of borrowing in turn affects total production costs particularly when industries rely on credit from banks. The second channel is when the government's fiscal policy builds infrastructure which reduces the cost of doing business. Government expenditure in this study, sourced from the South African Reserve Bank, is expressed as a percentage of GDP.

Credit to the private sector is included to capture financial developments as most governments normally level the playing field for exporting and importing industries with an access to cheap financial credit. In this sense, the effect of credit on total costs of manufacturing industries hinges on whether the cost of borrowing is high or low. When the cost of borrowing is high, one expects a significant effect on total costs while the opposite could be true when the cost of borrowing is low. Private sector credit, obtained from South African Reserve Bank, is measured here as a percentage of GDP. Favourable terms of trade, such as an increase in export prices, can act as an incentive for exporters to increase supply. Since the demand for labour is a derived one, firms are likely to employ more workers to take advantage of favourable terms of trade particularly if the increase in export prices is perceived to be permanent. This eventually leads to an increase in total costs of production hence a positive sign is expected in the cost inefficiency specification. Data on terms of trade (including gold) are obtained from the South African Reserve Bank.

Finally, one of the theoretical channels advanced in this analysis is that imports and exports create a level of competition that forces domestic industries to eliminate cost inefficient practices in order to survive foreign competition. However, domestic firms are also subject to domestic competition and failure to control for this domestic competition might overstate the foreign competition effect of imports and exports. A customary proxy for domestic competition at industry level is the price-cost margin otherwise known as the Lerner index and it takes the following form:

$$\mathrm{PCM} = \frac{\mathrm{VA_{it}} - \mathrm{wL_{it}}}{\mathrm{S_{it}}}$$

where PCM denotes price-cost margin, VA is added, wL is total wages and S represents sales. An increase in the price cost-margin signals weak competitive pressure or an increased market power and weak competition in economics usually comes with a reluctance to engage in cost efficient practices. In this regard, the price-cost margin is expected to have a positive sign.

To test the suitability of the cost frontier model over a normal cost regression model, a likelihood ratio test is conducted[12] with 2 restrictions (Kumbhakar et al., 2015) and the following LR test is computed:

$$\text{LR statistic} = -2[L(H_0) - L(H_a)]$$

where $L(H_0)$ and $L(H_a)$ represent the log-likelihood values computed from a restricted linear regression model and the unrestricted cost frontier model respectively with two degrees of freedom representing the imposed restrictions. Critical values for the mixed distribution are obtained from Kodde and Palm (1986). If the null hypothesis of no inefficiency is not rejected, then the cost frontier will reduce to a total cost function estimable by Ordinary Least Squares (OLS) with normal errors.

Total costs (TC) are the dependent variable in the cost frontier equation. By measurement, they are a sum of expenditure on intermediate inputs, labour and capital. Expenditure on labour is the total number of workers employed in each industry multiplied by the real remuneration per employee. Expenditure on capital is measured by real gross domestic fixed investment and expenditure on intermediate inputs is total real output minus real value added in million Rands deflated using 2010 prices. The price of labour (wL) is proxied by real remuneration per employee (2010=100). The price of intermediate inputs (wN) which is used to normalise total costs, labour and

[12] An alternative and common way of testing the suitability of the cost frontier model is one which defines the total variance as; $\sigma^2 = \sigma_u^2 + \sigma_v^2$ so that $\gamma = {\sigma_u^2}/{\sigma^2}$ approximates the proportion of variance in σ^2 attributed to cost inefficiencies. This approach is however misleading and inappropriate because the variance of u is not equal to σ_u^2 (see Kumbhakar, Wang and Horncastle, 2015).

capital prices is measured by the real intermediate input price (2010=100). The price of capital is obtained by dividing the residual capital costs by the stock of capital following Friedlaender and Wang Chiang (1983) where residual costs are total expenditure minus labor and intermediate inputs costs. The capital stock variable for each industry is measured using the perpetual inventory method. Output (y) is in real terms (deflated using 2010 prices) and it enters the specification as another independent variable. All variables are in logarithms. The variables of interest are import penetration and export intensity. The former is essentially the share of imports on each industry's total output. An increase in the share of imports and exports on domestic output implies stiffer competition which, at least in theory, forces firms to eliminate waste and avoid an overuse of resources through, for instance, shedding-off excess workers. The latter is the share of exports on total output.

Results and Discussion

Hypothesis 1: Trade and technical efficiency

Table 1a reports results from the diagnostic tests conducted. The null hypothesis $\beta_3 = \beta_4 = \beta_5 = \beta_7 = \beta_8 = 0$ is strongly rejected suggesting that the Translog specification is preferred over the Cobb-Douglas. Secondly, the interactions between the trend variable and the input factors, labour and capital, are significantly different from zero at 1% level indicating the presence of Hicks non-neutral technical changes. Results also show that the joint effect of the linear trend effect and the squared trend component is statistically significant at 1% level indicating non-monotonic technical changes over time. On the other hand, the LR test statistic is 140.7 and since it is larger than the 5% critical value (2.706), we can reject the null hypothesis of no technical inefficiency. In other words, the diagnostic tests provide support for an estimation of a stochastic frontier model using a Translog specification.

Table 1a: Functional Form Tests

Null Hypothesis	P-Value	Decision
$\beta_3 = \beta_4 = \beta_5 = \beta_7 = \beta_8 = \beta_9 = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = 0$	0.0000	Translog
$\beta_7 = \beta_8 = \beta_{14} = 0$	0.0000	Hicks non-neutral TC
$\beta_6 = \beta_9 = 0$	0.0000	Non-monotonic TC
LR statistic = 140.7		Technical Inefficiencies

Note: 5% critical value for LR = 2.706

Although the Translog specification is preferred, we also report results from the Cobb Douglas specification for robustness purposes. Equally important was the Hausman specification test which aided the decision between the True-Fixed-Effects SFA and the True-Random-Effects SFA. The latter assumes that the inputs are correlated with unobserved-heterogeneity while the later assumes no correlation between unobserved-heterogeneity and the inputs. The null hypothesis of the Hausman test is of no correlation between the unobserved-heterogeneity and the inputs and it is strongly rejected which necessitated the True-Fixed-Effects SFA over the True-Random-Effects SFA.

Table 1b: Hausman Specification Test

```
  Test:  Ho:  difference in coefficients not systematic

                 chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                         =      188.72
               Prob>chi2 =      0.0000
```

Empirical findings are reported in Table 2. In all cases, convergence is achieved after 100 iterations in the maximum likelihood procedure. Starting with results from the latter which are directly interpretable as elasticities, the signs of the coefficients in the stochastic frontier model are in line with theoretical expectations. They show that both labour and capital have a positive effect on output. A percentage increase in the labour input is estimated to raise output by about 0.36 – 0.40% on impact holding the capital input constant. On the other hand, a percentage increase in capital raises output by a margin of 0.36% – 0.38% holding constant the labour input. This is in line with economic theory. The year variable is positive and statistically significant at 1% level reflecting positive technical changes during the sampling period. The result particularly suggests that output grew by 1% each year between 1970 and 2016. With respect to the Translog specification, the interaction between capital and the time trend is significantly positive while that of labour and the time trend is significantly negative. This signifies that technological progress during the sampling period was capital-using and labour-saving.

Turning to the technical inefficiency model, it is important to note that the dependent variable here is technical inefficiency so that a positive sign on a particular regressor signifies a negative effect on technical efficiency and vice versa. Evidence supports the claim that export intensity raises technical efficiency. The coefficient of export intensity is negative and statistically significant signifying that technical inefficiency decreases with export intensity. An increase in export intensity by 1 percentage point lowers technical inefficiency in the subsequent year by 0.08% – 0.11% across all the variants holding constant other regressors. This result provides empirical support to the theoretical claim that participation in export markets improves technical efficiency. On the other hand, import penetration has a negative effect on technical inefficiency which increases with government spending. This is confirmed in variants (2) and (3) in which we included the interactions between government spending and the trade variables to accommodate the role that the government plays in levelling the playing field for domestic producers. Interesting is that all the interactions turn out to be significantly negative indicating that export intensity and import penetration improve technical efficiency when accompanied by increased government spending. For imports therefore, results from interactions suggest that import penetration is only capable of improving technical efficiency of home industries when accompanied by an expansionary fiscal policy. We also experimented by interacting the trade variables with other explanatory variables but the results were not significant.

Table 2: Impact of Trade on Technical Efficiency

	(1)	(2)	(3)	(4)
$\log(\mathrm{L})_{it-1}$	0.41***	0.38***	7.31***	10.30***
	(0.02)	(0.01)	(2.16)	(2.93)
$\log(\mathrm{K})_{it-1}$	0.39***	0.35***	-9.46***	-8.22***
	(0.02)	(0.01)	(1.81)	(1.14)
$\log(\mathrm{I})_{it-1}$	0.141***	0.51***	0.33***	0.41***
	(0.03)	(0.02)	(0.02)	(0.03)
$0.5\ \log(\mathrm{K})_{it-1}{}^{2}$			-0.13***	-0.11***
			(0.01)	(0.02)
$0.5\ \log(\mathrm{L})_{it-1}{}^{2}$			0.19***	0.24***
			(0.03)	(0.02)
$0.5\ \log(\mathrm{I})_{it-1}{}^{2}$	0.29***	0.31***	0.16***	0.14***
	(0.01)	(0.01)	(0.03)	(0.01)
$\log(\mathrm{K})\ \log(\mathrm{L})_{it-1}$			0.04***	0.04***
			(0.01)	(0.01)
Year_{t-1}	0.01***	0.002***	0.007	-0.021***
	(0.002)	(0.0009)	(0.005)	(0.001)
$0.5 * (\mathrm{Year})_{it-1}{}^{2}$			7.11e-07	0.00002***
			(0.0001)	(0.000001)
$\log\ (\mathrm{K})(\mathrm{Year})_{it-1}$			0.01***	0.01***
			(0.0009)	(0.0009)
$\log\ (\mathrm{L})(\mathrm{Year})_{it-1}$			-0.01***	-0.01***
			(0.001)	(0.001)
$\log\ (\mathrm{I})(\mathrm{Year})_{it-1}$			0.003	0.005
			(0.02)	(0.03)
$\log\ (\mathrm{I})(\mathrm{K})_{it-1}$			0.35***	0.53***
			(0.01)	(0.04)
$\log\ (\mathrm{I})(\mathrm{L})_{it-1}$			0.65***	0.72***
			(0.05)	(0.02)
Technical Inefficiency Model				
Exp_{it-1}	-0.34***	-0.06***	-0.06***	-0.33***
	(0.04)	(0.01)	(0.01)	(0.01)
Imp_{t-1}	0.07	0.04**	0.002	0.06
	(0.06)	(0.02)	(0.01)	(0.08)
Comp_{it-1}	-0.005		-0.05	-0.016
	(0.013)		(0.141)	(0.135)
$\mathrm{logElec}_{it-1}$	-0.08		0.76***	0.83***
	(0.14)		(0.13)	(0.33)

Gexp_{it-1}	-0.11		-1.95***	-1.33***
	(0.37)		(0.53)	(0.11)
logREER_{it-1}	0.54		0.82***	0.97***
	(0.18)		(0.13)	(0.14)
Cred_{it-1}	-0.06		-0.38***	-0.18
	(0.09)		(0.14)	(0.15)
$\text{Imp}_{it-1} * \text{Gexp}_{it-1}$		-0.07***	-0.06***	
		(0.009)	(0.009)	
$\text{Exp}_{it-1} * \text{Gexp}_{it-1}$		-0.02***	-0.03***	
		(0.007)	(0.008)	
C	0.19	0.94	3.07	2.70
	(2.03)	(11.74)	(55.72)	(58.79)
No. Obs	1204	1204	1204	1204
Prob > Chi2	0.0000	0.0000	0.0000	0.0000
Mean Technical Efficiency	0.837	0.846	0.832	0.833

Note: *, **, *** denotes p<0.1, p<0.05&p<0.01 respectively. Standard errors are in parenthesis

The inefficiency coefficients in Table 2 gauge the effect of import penetration and export intensity on the conditional technical inefficiency mean. Computation[13] of marginal effects export intensity (logexp_M) and import penetration (logimp_M) on the unconditional mean ($E(u_{it})$) is achieved through a post-estimation command – predict marginal –in STATA proposed in Belotti (2013). This command generates the marginal effects that are specific to each observation in the panel and therefore a summary of these marginal effects is reported in Table 3. We only report marginal effects from our main equation (model 3 in Table 2) and the mean marginal effect export intensity is found to be 0.219 suggesting that increasing export intensity by 1 per cent raises technical efficiency of manufacturing industries by about 0.2 percent in the subsequent year. For imports, a percentage increase in import penetration is associated with a 0.04 per cent increase in technical efficiency in the subsequent period.

Table 3: Marginal Effects of Trade on $E(u_{it})$

Variable	Mean	Std. Deviation	Minimum	Maximum
logexp_M	-0.129	0.037	-0.318	-0.140
logimp _M	-0.044	0.007	-0.064	-0.028

With respect to our control variables, electricity consumption turns out with a surprisingly positive sign suggesting a negative effect on technical efficiency. A possible explanation for this puzzling result is that electricity prices have been rising in South Africa and high energy costs can have a negative impact on technical efficiency through raising variable costs. Government expenditure which captures the fiscal stance is negative and significant in two out of three cases suggesting that an expansionary fiscal policy in form of increased fiscal expenditure improves technical efficiency of manufacturing industries. This may reflect public investment by the government that encourages productivity or an increase in domestic demand that allows producers to produce more output to meet the increased demand.

[13] In some efficiency studies such as Frame and Coelli (2001), Suyanto et al., (2014) and Wang (2002) emphasis is given on the marginal effects of the inefficiency determinants. It is important to note however that our interest here is mostly on the direction of change and not on the size of the marginal effect. This is because much of the debate has been on whether trade affects efficiency positively or negatively and not on how much trade affects efficiency.

The real exchange rate enters with a positive and significant effect in two out of three cases. According to the results, a percentage appreciation of the exchange rate reduces technical efficiency by 0.54% – 0.97% in the subsequent period. This is plausible since an appreciation of the real exchange rate reduces economic competitiveness by making exports expensive on the global markets. Lastly, credit enters with a negative sign but is statistically significant only in one out of three cases. The mean technical efficiency score from the main model is 0.83 suggesting that on average, the manufacturing sector could have possibly reduced their input usage by about 17% without changing their output level. In economic theory, this happens when, for example, industries employ workers beyond, the optimum level so that an additional worker adds more to costs than output. This economic possibility is one which motivated our empirical work to determine whether competition emanating from exporting and importing can force industries to rationalize their operations by cutting wasteful expenditures and avoiding an overuse of resources.

Figure 2: TFE Technical Efficiency

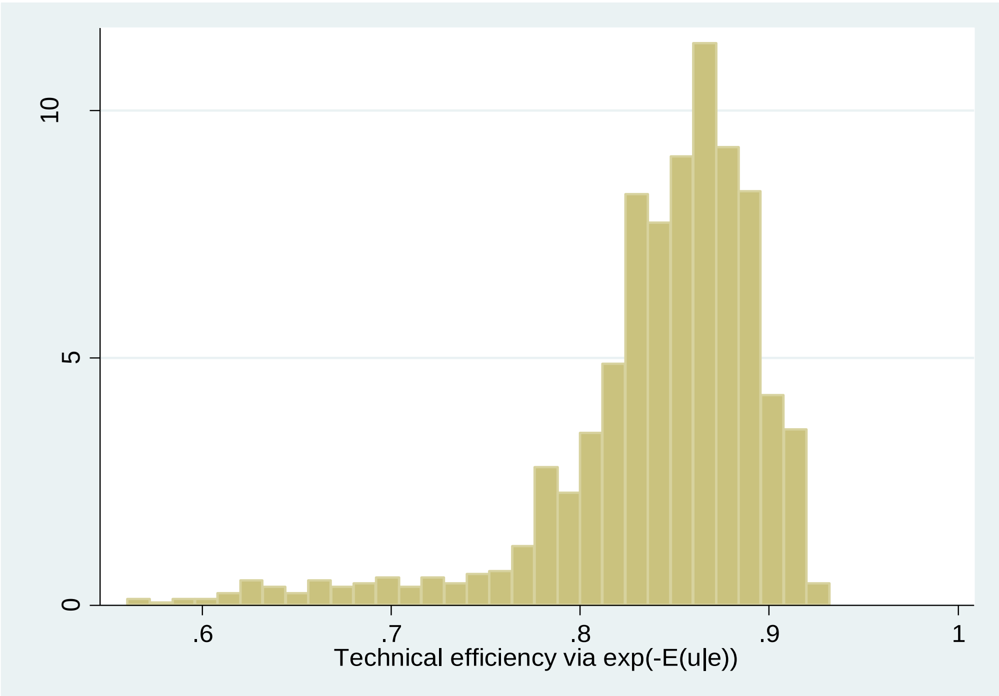


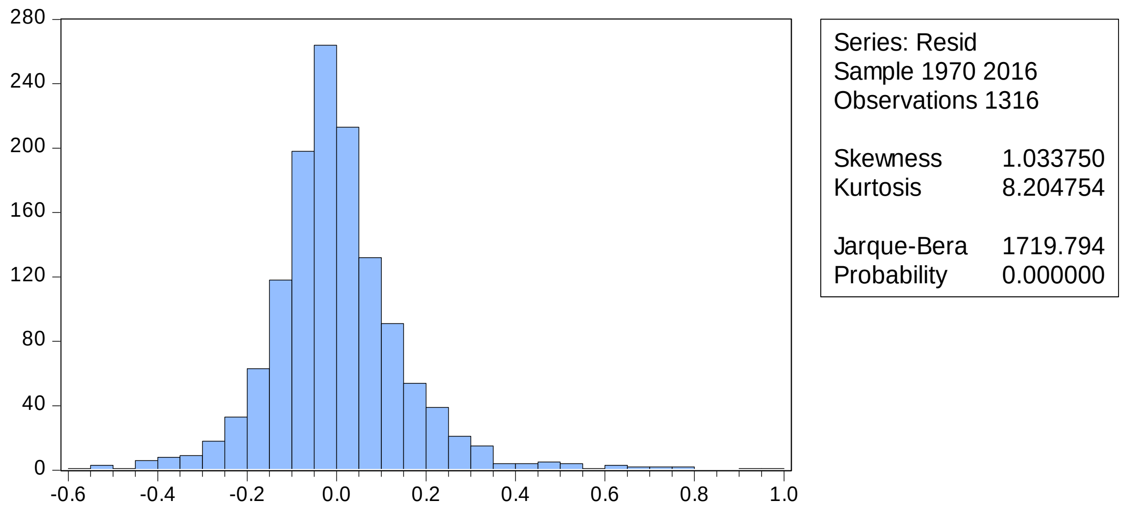
Table 4: Summary Statistics on Technical Efficiency

	Mean	Standard deviation	Minimum	Maximum
TE	0.833	0.054	0.553	0.941

Testing the Cost Efficiency Channel – Hypothesis 2

There was need for observing the skewness of residuals from a cost function estimated by the ordinary least squares method. According to Kumbhakar *et al*. (2015), the OLS residuals should be skewed towards the left for a production function and skewed towards the right for a cost function. Distribution of the residuals from a cost frontier model estimated by the ordinary least squares method (see Figure 3) were skewed towards the right which provided the greenlight to proceed with a cost frontier analysis.

Figure 3: OLS Residual Skewness



Another important preliminary test was that of an appropriate functional form between the Cobb-Douglas and the Translog specification. As Table 5 clearly indicates, the LR test statistic is larger than the 5 percent mixed chi-square critical value leading to an outright rejection of the Cobb-Douglas functional form in favour of the Translog specification. From the functional form test, it was imperative to test for cost inefficiencies. As Table 5 shows, the LR statistic is larger than the 5 percent critical value hence the null hypothesis of no cost inefficiencies was strongly rejected. This means that the estimated cost frontier model did not reduce to an ordinary least squares cost function with normal errors or rather, it was necessary and appropriate to proceed with a cost frontier analysis.

Table 5: Preliminary Diagnostic Tests Results

Test	Restrictions	Number of restrictions	5% critical value	LR-statistic
Functional form	$\alpha_{yy} = \alpha_{ll} = \alpha_{kk} = \alpha_{lk} = \alpha_{ly} = \alpha_{ky} = \alpha_{yt} = \alpha_{tt} = \alpha_{lt} = \alpha_{kt} = 0$	10	17.670	115.11***

Cost efficiencies	$u = 0$ and $\sigma_u^2 = 0$	2	8.273	264***

Note: *** denotes p<0.01

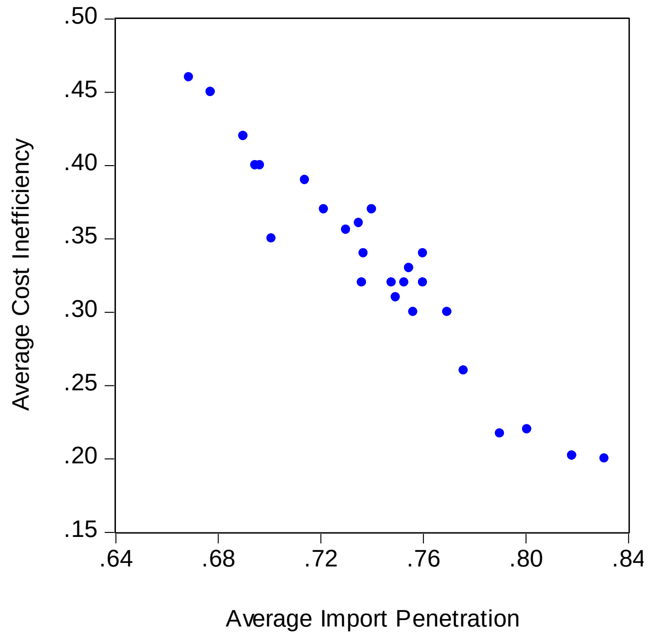
Table 6 shows the estimated results. The three cost frontier elasticities are all positive which satisfy the two assumptions that total costs are a positive function of factor prices and that marginal costs are positive (i.e. total production costs cannot decrease when output increases). Again for robustness purposes, both Cobb-Douglas and Translog results are reported. According to the results from the former specification, a percentage increase in the normalised price of labour is associated with a 0.52 percent increase in total costs holding constant the price of capital, output and technical changes. On the other hand, a percentage increase in the normalised price of capital raises total costs by a margin of 0.48 percent holding constant the price of labour, output, and technical changes. A comparison of these two elasticities shows that the price of labour has a larger effect on total costs than the price of capital. This is consistent with the fact that South Africa faces high unit labour costs. A 10 percent increase in output on the other hand is associated with a 0.10 percent increase in total costs holding constant factor prices and the trend component. The trend variable however is not statistically significant at 10 percent suggesting that technical changes might not have resulted in cost frontier shifts during the sampling period.

Turning to the results of interest, both import penetration and export intensity are significantly negative in the cost inefficiency specification suggesting that an increase in the share of imports and exports on output reduces cost inefficiency as predicted by economic theory. According to the results, a 10 percent increase in import penetration reduces cost inefficiency by 3.5 percent in the subsequent year controlling for a set of macroeconomic variables including a proxy for domestic competition. For exports, the results in Table 6 clearly indicate that raising export intensity by 10 percent translates into a 0.57 percent reduction in cost inefficiency in the subsequent year holding constant other independent variables. Put differently, a 10 percent increase in import penetration and export intensity improves cost efficiency of manufacturing industries by 3.5 percent and 0.57 percent respectively in the subsequent year ceteris paribus. These results are supportive of our hypothesis that import penetration and export intensity increase technical efficiency through an adoption of cost saving practices.

On average, the minimum possible cost was found to be 75 percent of actual costs implying that actual costs were above the minimum possible cost by about 33 percent[14] during the sampling period. Our results suggest that industries whose actual costs were significantly higher than the minimum possible cost are those that were less exposed to export intensity and import penetration. On the other hand, evidence suggests that industries whose actual costs were closer to the minimum possible cost (i.e. industries that were able to produce a given level of output with lower cost) are those that were more exposed to export intensity and import penetration. The economic reasoning underpinning this argument is that costs are low in these industries because exports and imports force them to rationalize their operations in order to stand toe to toe and keep pace with external competitors. This observation is also easy to see in form of a scatter plot (see Figure 4).

Figure 4: Cost Inefficiencies and Import Penetration

[14] This is obtained from the following calculation: $\left(\left[\frac{1}{0{,}75}\right] - 1\right) * 100 = 33.33\%$).



Note: Two atypical data points were excluded from the graph. Each data point represents the average value for each industry between 1970 and 2016.

Table 6: Impact of Trade on Cost Efficiency of Manufacturing Industries

Dep variable = $\log(\widetilde{TC})_{it}$	**Model (1)**	**Model (2)**	**Model (3)**	**Model(4)**
$\log(\widetilde{wL})_{it-1}$	0.515***	0.865***	0.876***	0.713***
	(0.035)	(0.015)	(0.034)	(0.033)
$\log(\widetilde{wK})_{it-1}$	0.475***	0.287***	0.284***	0.316***
	(0.020)	(0.034)	(0.015)	(0.017)
$\log y_{it-1}$	0.102***	0.175***	0.154***	0.0140***
	(0.019)	(0.039)	(0.039)	(0.050)
Year_{t-1}	0.001	0.001	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.002)
$0.5\log(\widetilde{wK})_{it-1}{}^{2}$	−0.229***			
	(0.048)			
$0.5\log(\widetilde{wL})_{it-1}{}^{2}$	−0.034			
	(0.047)			
$0.5\log(y)_{it-1}{}^{2}$	0.0003***			
	(0.00002)			
$0.5*(\text{Year})_{it-1}{}^{2}$	0.009*			
	(0.005)			
$\log(\widetilde{wL})\log(\widetilde{wK})_{it-1}$	0.182***			
	(0.030)			
$\log(y)\log(\widetilde{wK})_{it-1}$	0.016***			
	(0.003)			
$\log(y)\log(\widetilde{wL})_{it-1}$	0.351			
	(0.347)			
$\log(\widetilde{wK})(\text{Year})_{it-1}$	−2.786			
	(0.639)			
$\log(\widetilde{wL})(\text{Year})_{it-1}$	−0.876***			
	(0.182)			
$\log(y)(\text{Year})_{it-1}$	−0.299***			
	(0.096)			
Dep. variable = u_{it}				
$\log m_{it-1}$	−0.351***	−0.290***	−0.281***	

	(0.026)	(0.019)	(0.019)	
$\log x_{it-1}$	–0.057***	–0.019*		–0.103***
	(0.013)	(0.011)		(0.013)
$\log reer_{it-1}$	0.005***			
	(0.001)			
$\log tot_{it-1}$	0.007***			
	(0.002)			
gcons_{it-1}	0.031***			
	(0.008)			
cred_{it-1}	0.0017*			
	(0.0008)			
pcm_{it-1}	0.919***			
	(0.105)			
c	2.584	4.326	5.976	6.056
	(8.962)	(2.826)	(2.825)	(3.460)
Number of Observations	1204	1204	1204	1204
Wald Chi2	2633.63	2868.65	2945.99	2876.05
Prob>0.0000	0.0000	0.0000	0.0000	0.0000

Note: *, **, *** denote p<0.1, p<0.05 & p<0.01 respectively. Figures in parentheses are standard errors. The intercepts of the variance specifications are not reported due to space.

Similarly, cost inefficiency estimates in Table 6 imply that reducing the share of exports and imports on output for example through trade protection, suppresses foreign competition which in turn increases cost inefficiency of domestic industries. Note that the Lerner index is positive, sizeable and highly significant suggesting that an increase in the price cost margin, which signals an increase in market power or alternatively a reduction in competitive pressure, increases cost inefficiency of manufacturing industries. This result substantiates the widely accepted economic view that industries are cost inefficient when the market is less competitive.

Concluding Remarks

The evidence presented in this paper based on the true-fixed effects stochastic frontier analysis shows that South Africa's 28 3-digit level manufacturing industries exhibited technical inefficiencies between 1970 and 2016 and that trade had a relevant effect on these inefficiencies. In particular, we find evidence supporting our hypothesis that trade improves technical efficiency through reductions in cost inefficiency. Overall, our results strongly support the notion that imports and exports create a level of competition that forces domestic industries to cut back on costs in a bid to operate efficiently. This result has important policy implications. In general, pessimistic policymakers have often been fret about the obstacles and headwinds that South African industries have had to surmount in the past two decades including the perishing of infant industries given the competition stemming from the country's increasing integration into the global economy. The gist of this pre-held argument is that trade exposes South Africa's manufacturing industries to an onslaught of cheap manufacturing imports which make it difficult for domestic industries to survive on home turf. Our results are parallel to this pessimistic thinking as trade is found to have raised technical efficiency levels of manufacturing industries in South Africa through cost reductions. Based on our main result, a trade policy development that promotes exports and imports is capable of reducing cost inefficiency and raising technical efficiency levels of domestic manufacturing industries in South Africa. This policy implication is important particularly when we reconcile our results with South

Africa experience during the first wave of trade liberalization (1994 – 2000) as confirmed in the Department of Trade and Industry (DTI) 2017 report in which the manufacturing sector lost a total of 150,000 jobs against a background of harsh global competition. This is further evidence supporting our hypothesis that global competition stemming from exporting and importing forces local industries to avoid an overuse of input resources above the optimal level. At the outset, our analysis has implicitly assumed, in the cost frontier specification, allocative efficiency. Future studies might consider explicitly relaxing this assumption in a much more complex exercise. This will shed more light on how much of the cost inefficiency affected with trade is linked to technical and allocative inefficiency.

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Table 7: Average Import Penetration in SA's Manufacturing Sector (1970 – 2016)

Industry	Rank	Import Penetration (%)
Professional and Scientific Equipment	1	80,2
Machinery	2	65,3
TV, Radio and Communication Equipment	3	54,7
Other Transport Equipment	4	50,1
Rubber	5	33,6
Transport Equipment	6	33,3
Leather and Leather Products	7	32,3
Electrical Machinery	8	31,7
Other Chemicals	9	29,1
Basic Chemicals	10	25,8
Textiles	11	24,3
Non-Ferrous Metals	12	23,7
Clothing	13	19,0
Glass	14	18,7
Other Manufacturing	15	17,9
Footwear	16	15,8
Metal Products	17	15,8
Paper and Paper Products	18	14,7
Basic Iron and Steel	19	12,6
Furniture	20	11,0
Non-Metallic Minerals	21	10,7
Wood	22	10,2
Food	23	8,8
Plastics	24	8,1
Printing and Publishing	25	5,5
Beverages	26	4,6
Tobacco	27	2,5
Coke and Petroleum Products	28	2,3

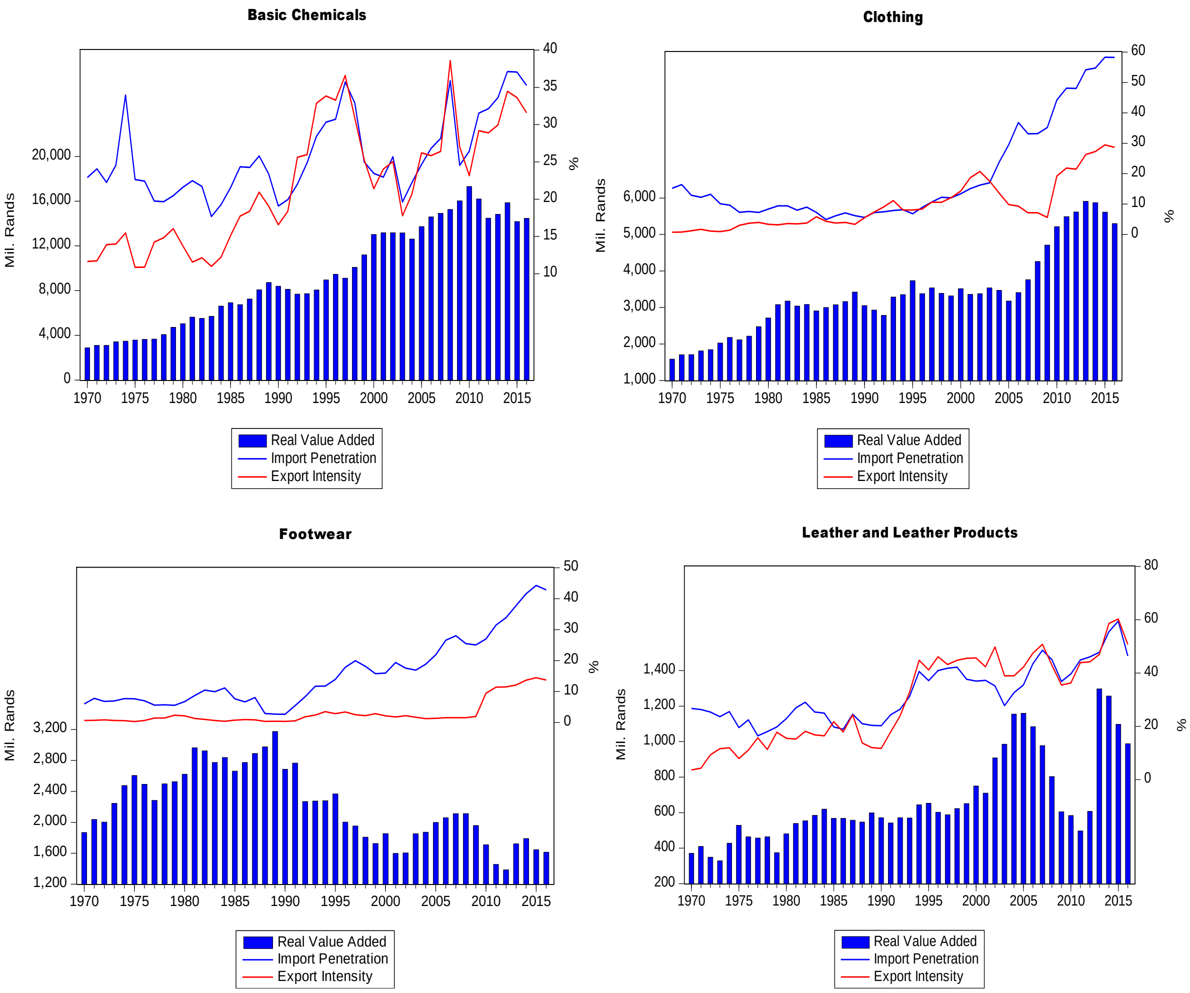
Source: own calculations using data from Quantec

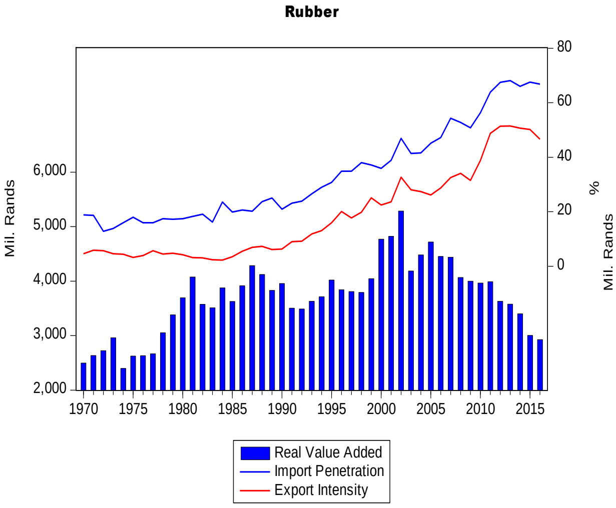
Table 8: Average Export Intensity in SA's Manufacturing Sector (1970 – 2016)

Industry	Rank	Export Intensity (%)
Non-Ferrous Metals	1	56,3
Basic Iron and Steel	2	43,7
Machinery	3	38,0
Professional and Scientific Equipment	4	36,8
Leather and Leather Products	5	29,9
Other Manufacturing	6	23,3
Other Transport Equipment	7	22,9
Basic Chemicals	8	21,9
Paper and Paper Products	9	18,8
Rubber	10	18,4
TV, Radio And Communication Equipment	11	18,4
Furniture	12	16,6
Transport Equipment	13	16,6
Other Chemicals	14	15,5
Textiles	15	14,0
Metal Products	16	13,3
Wood	17	12,9
Food	18	12,7
Glass	19	11,2
Clothing	20	9,5
Electrical Machinery	21	8,5
Tobacco	22	8,2
Non-Metallic Minerals	23	7,5
Beverages	24	7,2
Coke and Petroleum Products	25	3,5
Plastics	26	3,4
Footwear	27	3,1
Printing and Publishing	28	2,0

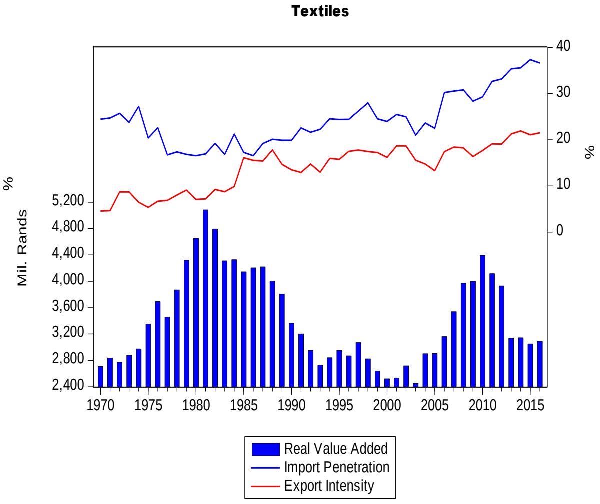
Source: own calculations using data from Quantec

Figure 3: Export Intensity, Import Penetration and Real Value Added





Rubber
Mil. Rands
%
6,000
5,000
4,000
3,000
2,000
80
60
40
20
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
Real Value Added
Import Penetration
Export Intensity



Textiles
Mil. Rands
%
5,200
4,800
4,400
4,000
3,600
3,200
2,800
2,400
40
30
20
10
0
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
Real Value Added
Import Penetration
Export Intensity