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**Markups, Productivity, and Export Dynamics**

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**Abstract**

The primary goal of this paper is to efficiently recover consistent markups from firm-level production technology under cost minimization settings in order to document the relationship between unobserved idiosyncratic productivity shocks and endogenous markups. It further documents the relationship between a firm's export status and its markup and productivity patterns to understand the performance premia of producers. The paper uses the proxy approach combined with the generalized method of moments (GMM) to estimate various production technologies in order to expunge input elasticities and estimate markups based on flexible inputs. This investigation finds that the conventional labour input-based markup estimates suffer from high labour adjustment costs and potentially other labour market frictions during the period 1994-2007, resulting in a negative correlation with the intermediate input-based alternative. An assessment of the intermediate input-based markup shows that there is substantial variability in all but one entropy index measure of markup dispersion while productivity attains a general entropy index that approaches zero. The effect of intermediate input-based markups on unobserved productivity shocks is significantly positive when estimated using previous exports as an instrumental-variable (IV) in a Two-Stage Least Squares (TSLS) regression accompanied by the Wild Restricted Efficient (WRE) residual bootstrap. Furthermore, both markups and productivity are separately correlated with export status while producers enjoy considerable performance premia from various components of export participation. Finally, a firm's product markup and its productivity have no effect on its decision to either breakthrough into export markets or abandon export participation.

*JEL Classification*: D21, D24, L11

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**Markups, Productivity, and Export Dynamics**

## 1. Introduction

The estimation of markups has a long tradition in industrial organization, international trade and anti-trust economics due to the central role it plays in the measurement of effects of competition and trade policy on market power.[1] One robust strand of literature begins with Hall (1986, 1988) and refined by De Loecker and Warzynski (2012) (aka DLW). It posits that a firm minimizes short-run production costs by optimizing its flexible input demand function. Conventionally, capital stock is treated as a state variable with high adjustment costs while labour and intermediate inputs are assumed free of costs of adjustment. The resulting first-order conditions (FOC) for this production approach yields the shadow price which is equated to the marginal cost of production, and the markup is expressed as the ratio of price to marginal cost. Product markup pricing is then determined in equilibrium, and depends on market competition and prevailing strategic interaction among producers; see DLW (Appendix). This approach subsequently leads to defining markups in relation to the output elasticity with respect to the freely variable input cost-share of revenue. The most crucial task is to estimate consistent elasticities of the input demand function using some form of production technology.

There are recent applications of the production function approach that estimate markups to perform deeper economic analyses. A sample of leading work includes DLW and De Loecker *et al*. (2016) who find that markups are significantly higher when controlling for unobserved productivity; that exporters charge typically higher markups and that markups rise upon export entry. The failure of complete cost pass-through to prices is attributed to the presence of significant markup heterogeneity and variability across narrowly defined industry and over time. In De Loecker *et al*. (2018), a markup

[1] The *demand* approach to markup estimation includes Berry (1994) who provides theoretical underpinnings for the procedure while Berry *et al*. (1995) provide theoretical extensions and application to the automobile industry, and Nevo (2001) to the ready-to-eat cereal industry. Other applications of this approach include a whole range of studies listed in Berry and Haile (2014, footnote 2), Berry and Haile (2016, Table 1) and the survey by Dubé (2018). This strand of the large and rapidly growing literature on demand and supply has distinctly focused on discrete-choice models of product differentiation in the presence of both observed and unobserved characteristics based on McFadden (1974, 1981). A common thread in the extensive and expanding variants of Berry (1994) and Berry *et al*. (1995) is shown by Berry and Haile (2014, 2018) to involve the identification of differentiated product demand, aggregate consumer welfare, marginal costs, marginal cost functions of producers under instrumental variables, and discrimination between models of conduct by producers. The role of exogenous variation in demand shifters and cost shifters has recently been clarified by Berry and Haile (2018) in the instance of simultaneous equations of supply and demand. Berry, Gandhi and Haile (2013) further introduced the concept of 'connected substitutes' designed to satisfy invertibility requirements of the demand system thereby facilitating its identification. To produce empirical results using this approach, assumptions made about firm conduct include profit maximization and competition strategy of the Bertrand-Nash type in prices or Cournot quantity competition discussed and applied in De Loecker and Scott (2017). Typically, econometricians such as Berry, Levinsohn, and Pakes (2004) rely on the increasing availability of detailed product market-level and/or consumer-level data for the estimation of, *inter alia*, markups. The invertibility of demand systems is vital in a variety of theoretical and applied settings such as demand identification and estimation, testing of revealed preferences, and uniqueness of the Walrasian equilibrium in prices in an exchange economy, see Berry, Gandhi and Haile (2013). This approach relies on detailed market-level and/or consumer-level datasets which are not readily available to researchers.

hike is driven largely by the upper tail of the markup distribution in the U.S. dataset. That is, the upper percentiles rose sharply while the median remained time-invariant. In addition, reallocation of market share from low to high markup firms emerged mainly within-industry for all industries. Brambila and Tortarolo (2014) explore systematic differences across industries and plants and find higher markups in capital-intensive industries, and in plants that are more productive, and larger. This was considered consistent with theories that predict larger markups for more efficient firms and for higher quality products. Dai, Sun, and Liu (2018) separate out the effects of export and innovation on micro-level markup and productivity. Starting to export alone is found to negatively affect micro-level performance (i.e., markups and/or productivity) while starting to innovate alone has a significant positive impact. The negative effect of starting to export on productivity may represent a decline in price-cost markup instead of a variation in physical productivity. Finally, an interesting result is generated by De Loecker and Scott (2017) who directly compare markup estimates from the demand and production approaches, and find that both approaches provide similar and plausible markup estimates in most cases. Notably, virtually all these studies use labour as the production input free of adjustment costs.

However, there is severe paucity of such research in Sub-Saharan Africa (SSA) mainly due either to the absence of micro-level panel data or inaccessibility of this source of information because of confidentiality issues. In these countries, even in instances where access is granted; it is not uncommon to discover that the data administration function is not as vigorous and reliable as one would hope for. Issues around representativeness of annual surveys of firm-level balance sheet data become a critical source of contention. As a result, the lack of access, unavailability or poor quality of panel data constrains the type of producer-level work that can be carried out to inform policy decisions and guide industry participation concerning economic patterns in these markets. For example, conceptualizing the estimation of endogenous markups and unobserved productivity shocks in the context of adjustable labour without costs of hiring, firing or quitting falls short of reality. But then such hypotheses require inference that is backed up by rigorous and consistent analysis of sufficiently rich panel data sets.

Data issues are particularly important for Eswatini for at least three reasons. First, the central agency of the State started administering annual firm-level surveys in 1994 until 2011 and then engaged in administering a national economic census in 2012. Notably, the quality of the data is somewhat marred by administrative measurement error and incompleteness of records prior to 2003. In later years, data quality suffered an additional setback characterized by increasingly limited rigor in data collection and modest computerization. On the basis of an agreement between the central agency and a State Owned Enterprise (SOE) responsible for national taxation, the latter took ownership of the whole function of annual company surveys from 2012 onwards. This latter period is associated with high quality data. Second, labour market regulations make hiring and employer-employee separations

costly. The law places a substantial burden of proof for fair employee dismissals on the employer. That is, the high firing and hiring costs act as a deterrent to producers while quitting remains an unattractive proposition to workers due to risk aversion associated with high search costs of employment. Hence, the propensity of either firing existing or hiring new workers tends to be low; hence, the labour-based markup under FOCs *may* be characterized by significant quasi-fixity of labour. Lastly, the political dispensation in South Africa since 1994 has reconfigured the industrial structure in Eswatini through firm-level relocations to larger markets for increased economies of scale. This affected the relatively larger category of firms. This paper has access only to the 1994-2007 panel dataset of firms in Eswatini after some data digitization.

The aim of this paper is to outline the theoretical framework for determining the role of endogenous variable markups on heterogeneous productivity shocks. The identification of producer efficiency effects of markup pricing is not always clear-cut due to the likelihood of reverse causality. In theoretical models such as Eckel and Neary (2010) and Melitz and Ottaviano (2008), more productive firms are likely to exploit their efficiency advantage to charge premium prices. It is therefore necessary to isolate the component of variation in markups that is not caused by firms' efficiency in order to examine the impact of competition on productivity shocks. As a result, one needs to control for simultaneity problems in the estimation model. In the process, we use bootstrap inference methods to choose between a labour-based and intermediate input-based markup distribution for further analysis. Second, we set out to investigate the impact of firm-level export status on firm performance, the markup and productivity export premia to compare the performance of exporters and nonexporters as well as the effect of export participation of performance. Lastly, we seek to determine the role of markups and productivity on firms' decisions to enter and exit foreign markets.

This paper shares a common thread with the empirical body of work by Hall (1986, 1988, 1990) based on an underlying framework of firm behaviour, DLW and De Loecker *et al*. (2018) who use Hall's methods to consistently estimate production elasticities, productivity and markups. It departs in that, rather than just rely on labour as the flexible input, it experiments with both labour and intermediate inputs to allow the data to identify the input that reasonably approximates a situation of free adjustment costs. A data driven choice of a costlessly adjustable production input is important for Eswatini, particularly because this was a period of continuous trade liberalization by a much larger trading partner in the Customs Union, South Africa. There also exists anecdotal evidence of high labour market rigidity suggesting that quasi-fixity of labour may be a sensible proposition for Eswatini during this period.

Our empirical strategy involves the estimation of the production function as it relates output to primary and intermediate inputs due to the simplicity of the methodology and availability of producer level panel data in Eswatini. This allows us to estimate input elasticities and subsequently unobserved

productivity. The most critical source of unease in this process is the estimation of input coefficients consistently. One needs to make a choice among alternative approaches to handle simultaneity problems associated with Ordinary Least Squares (O.L.S.) methods. With elasticities in hand, we are able to estimate markups using these elasticities in combination with expenditure shares of variable inputs to revenue.

More specifically, some important econometric concerns arise when the technology used in production is responsive to output determinants that are unobserved to the econometrician but observed to the producer in a cost-minimization environment. One such issue is the endogeneity problem which obviates the use of ordinary squares (OLS) methods that generate biased coefficients on inputs. The techniques since the last quarter century have been proposed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) and Ackerberg, Caves, and Frazer (2015) (ACF) and numerous others, see survey by Ackerberg, Benkard, Berry, and Pakes (2007) (ABBP). The OP technique considers micro-investment as an increasing function of idiosyncratic productivity shocks using certain theoretical and statistical assumptions, conditional on state variables such as capital stock. This strict monotonicity is crucial in enabling one to invert the investment input demand function to control for "unobserved" productivity by conditioning on a nonparametric function of "observed" investment and capital. In the first stage, OP regresses output on labour and the nonparametric function (or low order polynomial) to estimate the labour coefficient. Similarly, the LP technique relies on OP's control function approach but note lumpiness of firm-level investments and replaces investment with intermediate inputs to estimate the same labour coefficient in the first stage.

A preview of findings indicates that estimates of the distribution of intermediate input-based markups are well-behaved relative to the commonly used labour-based option. Most of the different measures of markup variability derived from the intermediate input-based method of estimation yield significantly higher inequality than labour-based measures. This outcome is consistent with high costs of hiring and firing workers.

Looking at the relationship between the measures of firm performance, we find a significantly positive impact of intermediate input-based markups on productivity, but marginally negative effects when using the labour-based alternative. Similarly, firm-level export status has positive effects on performance in that exporters experienced significant markup and productivity premia. More interestingly; and in sharp contrast to the common findings in the literature, quitting firms exhibit superior productivity performance than both incumbents and entrants. These were 'superstar' exporters exiting foreign markets not because of business difficulties but only for reasons of relocating their businesses to the trade reforming economy and larger market. At the same time, new exporters charged (weakly) higher markups than either quitters or incumbents. Only a few firms at the productivity threshold engaged in intermittent exporting to make an opportunistic profit sale and

exiting. Finally, the role of micro performance on the decision to enter or exit export markets remained insignificant.

Our contribution to the body of knowledge relating firm performance to foreign export market dynamics is in three forms. 1) The estimation of firm-level production technology relies on Wooldridge-Blundell-Bond GMM techniques combined with control functions. 2) Bootstrap inference methods are used to technically select an appropriate measure of markups. 3) Apart from estimating markup and productivity for comparison between exporters and nonexporters, we also implement a procedure for recovering average marginal effects on firm churning in foreign markets. To the best of our knowledge, these aspects of analysis have not yet been undertaken in this subject.

The remainder of this paper is organized as follows. Sections 2 and 3 respectively lay out the theoretical motivation and econometric framework to give context to subsequent analyses. Section 4 presents an account of the structure and measurement issues of the dataset used. In section 5, we present the results while section 6 discusses them. Section 7 concludes.

## 2. Theoretical Motivation

This section describes the theoretical foundations for recovering markups from a production function in the absence of suitable data for calculating the ratio of firm-specific price over marginal cost. In the spirit of Hall (1988), DLW develop a quantitative framework for characterising markup equations by assuming that firms' objectives involve minimization of production costs. The exposition begins with a firm-specific output index over time

$$Q_{it} = F\left(X_{it}^{1}, X_{it}^{2}, \dots, X_{it}^{V}, K_{it}, \omega_{it}\right)$$

where $X_{it}^{v}$ is static freely variable production input $v$, $K_{it}$ is the state variable (e.g. dynamic capital stock), and $\omega_{it}$ represents Hicks-neutral idiosyncratic productivity shocks for multiproduct firms. In the case of single product firms, the Hicks-neutral condition is redundant (see Goldberg *et al*. (2016). The Lagrangian function for a firm's cost-minimization programme can be specified as follows

$$\mathcal{L}\left(X_{it}^{1}, X_{it}^{2}, \dots, X_{it}^{V}, K_{it}, \lambda_{it}\right) = \sum_{v=1}^{v}\left(P_{it}^{X^{v}} X_{it}^{v} + r_{it}K_{it} + \lambda_{it}\left(Q_{it} - Q_{it}(\bullet)\right)\right)$$

where the first derivative of the Lagrangian with respect to any freely adjustable input expressed is as follows

$$\frac{\partial \mathcal{L}_{it}}{\partial X_{it}^{v}} = P_{it}^{X^{v}} - \lambda_{it}\frac{\partial Q_{it}(\bullet)}{\partial X_{it}^{v}} = 0$$

where $\frac{\partial Q_{it}(\bullet)}{\partial X_{it}^{v}}$ is firm $i's$ marginal product of input $X_{it}^{v}$ at time $t$, and the Lagrange multiplier $\frac{\partial \mathcal{L}_{it}(\bullet)}{\partial Q_{it}} = \lambda_{it}$ is the standard shadow price representing the marginal cost of production at a given firm's output level, $Q_{it}$. One uses first-order conditions (FOC) of the cost-minimization problem to rearrange the terms and multiply on both sides by $\frac{X_{it}^{v}}{Q_{it}}$ and the outcome is

$$\frac{\partial Q_{it}(.)}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X^{v}} X_{it}^{v}}{Q_{it}}$$

Supposing $X_{it}$ is firm $i's$ labour input at time $t$, then conditioning on state variables, the dynamic capital stock, the output elasticity of labour can be expressed as

$$\theta_{it}^{X^{V}} = \lambda_{it} \frac{P_{it}^{X} X_{it}}{P_{it} Q_{it}}$$

where $\theta_{it}^{X}$ is the output elasticity of variable input $X_{it}$. The firm-level markup at time $t$ is defined as $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, which can therefore be measured as

$$\mu_{it} = \frac{\theta_{it}^{X}}{\alpha_{it}^{X}}$$

where $\alpha_{it}^{X}$ is the ratio of variable input expenditure to sales revenue. Since the share of expenditure on input $X_{it}$ is not always directly observed, while $\tilde{Q}_{it} = Q_{it}\exp(\widehat{\omega}_{it})$ is directly observed[2], the $\alpha_{it}^{X}$ can be estimated as

$$\widehat{\alpha}_{it}^{X} = \frac{P_{it}^{X} X_{it}}{P_{it}\, \tilde{Q}_{it} / exp(\widehat{\omega}_{it})}$$

This correction to the estimation of $\alpha_{it}^{X}$ is crucial because it purges any changes in input expenditure shares arising from output variation. The affected output variation referred to here is that part which is uncorrelated with drivers of input demand like input prices, productivity, technology parameters, and market characteristics such as elasticities of demand and levels of income. Put differently, the correction isolates the effects on input expenditure shares coming from variation in the output uncorrelated with the function $y_{it} = \phi_t(k_{it}, l_{it}, m_{it}, \boldsymbol{z}_{it})$ derived from the production function. The function $\phi_t(\bullet)$ refers to determinants of output without noise effects, where $k_{it}$ and $l_{it}$ are the dynamic capital and static labour inputs. The variable $m_{it}$ is intermediate or material input and $\boldsymbol{z}_{it}$ is a vector of instrumental variables (IVs) for firm $i$ at time $t$. That is, labour and material are assumed freely variable. However, $m_{it}$ is assumed freely variable up to inventory management. Both assumptions rule out the fixed input proportionality characterizing Leontief gross production

[2] See DLW for an expanded discussion of these ideas.

technologies, while value added production functions are assumed to allow intermediate inputs to be used in fixed proportion to purge output from the intermediate input use.

## 3. Econometric Framework

Production functions provide a fundamental vehicle for estimating output elasticities since they relate producer-level output to primary and intermediate inputs. However, this effort has historically been faced with endogeneity problems arising from determinants of production like productivity shocks unobserved to the econometrician but observed to the producer, yet are a function of inputs. This phenomenon renders O.L.S. estimates biased. In the last decade or so, methods initiated by OP, LP, Wooldridge (2009), and ACF to handle endogeneity problems have seen extensive application in the empirical literature[3]. The principle underlying the OP/LP techniques is that it is theoretically and statistically feasible to invert an optimally chosen input to enable an econometrician "observe" productivity shocks. More specifically, the OP approach identifies conditions under which micro investment, given capital stock, is a monotonic function of an unobserved productivity shock. Such strict monotonicity suggests that it is possible to invert this investment demand function and hence control for the unobserved productivity shocks by conditioning on a nonparametric representation of that inverse function of capital stock and investment, see ACF. The LP technique, on the other hand, inverts an intermediate input demand function instead to address lumpy investment problems when controlling for unobserved productivity shocks.

Building on estimation schemes developed by OP and LP, ACF argue that the first stage estimation procedure espoused in the OP/LP environment suffers from identification problems for the labour coefficient due to functional dependence. As a remedial measure, these authors propose inversion of the input demand function conditional on the labour input and show how to estimate the labour coefficient in the second stage along with other production function parameters. Wooldridge (2009) shows how to write the LP-type moment conditions in terms of two equations with the same dependent variable, where the set of instruments differs across equations, and can be implemented in a generalized method of moments (GMM) framework. Our approach follows Rovigatti and Mollisi (2018) in estimating

$$y_{it} = \alpha + \boldsymbol{l_{it}}\beta + \boldsymbol{k_{it}}\boldsymbol{\gamma} + \omega_{it} + \xi_{it}$$

using dynamic panel instruments of the Blundell and Bond (1998)-type within the Wooldridge framework. According to the control function approach, an input demand by any firm must satisfy the scalar unobservability assumption and this function must also be monotonic in the unobserved productivity, $\omega_{it}$, to qualify as a proxy. That is, the choice of intermediate inputs is $\boldsymbol{m_t}$ for some smooth function $f$ driven by the behaviour of state variables contained in the vector $k_{it}$ and

[3] See the survey by ABBP and ACF.

unobserved productivity shocks, $\omega_t$. Hence, the intermediate input demand can be inverted such that for firm $i$ at time $t$, $\boldsymbol{m_{it}} = f_t(\boldsymbol{k_{it}}, \omega_{it}) \xRightarrow{implies} \omega_{it} = f^{-1}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})$, where $\boldsymbol{m_t}$ is a 1xM vector of proxy variables and $f^{-1}$is assumed time-invariant. It is also convenient to assume that the white noise $\xi_{it}$ is conditional mean independent of current and past values of both state and freely variable inputs so that we can have

$$\begin{aligned}\mathbb{E}(y_{it}|\boldsymbol{l_{it}}, \boldsymbol{k_{it}}, \boldsymbol{m_{it}}) &= \alpha + \boldsymbol{l_{it}}\beta + \boldsymbol{k_{it}}\boldsymbol{\gamma} + f^{-1}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}}) \\ &= \alpha + \boldsymbol{l_{it}}\beta + \boldsymbol{h}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})\end{aligned}$$

where $\boldsymbol{h}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}}) = \boldsymbol{k_{it}}\boldsymbol{\gamma} + f^{-1}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})$, and $\boldsymbol{\gamma}$ and $\alpha$ are unidentified. ACF has demonstrated that if $\boldsymbol{l_{it}}$ (i.e. the labour input) is chosen simultaneously with $\boldsymbol{m_{it}}$ (i.e. the intermediate input), then there is an identification problem associated with $\beta$. That is, $\boldsymbol{l_{it}}$ is a deterministic function of $\boldsymbol{k_{it}}, \boldsymbol{m_{it}}$ and therefore $\beta$ is nonparametrically unidentified. ACF also show that $\boldsymbol{l_{it}}$ disappears when the production technology is Cobb-Douglas. Using orthogonality conditions outlined in Wooldridge (2009), the following two equations hold

$$y_{it} = \alpha + \boldsymbol{l_{it}}\beta + \boldsymbol{k_{it}}\boldsymbol{\gamma} + f^{-1}(\boldsymbol{k_{it}}, \boldsymbol{m_{it}}) + \xi_{it}$$

or

$$y_{it} = \alpha + \boldsymbol{l_{it}}\beta + \boldsymbol{k_{it}}\boldsymbol{\gamma} + g\big(f^{-1}(\boldsymbol{k_{it-1}}, \boldsymbol{m_{it-1}})\big) + \mu_{it}$$

where $f^{-1}(\boldsymbol{k_{it-1}}, \boldsymbol{m_{it-1}}) = \lambda_0 + f^{-1}(\boldsymbol{k_{it-1}}, \boldsymbol{m_{it-1}})\lambda_1$, which implies a G-order polynomial

$$g(\omega_{it}) = \delta_0 + \delta_1[k(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})\lambda_1] + \delta_2[k(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})\lambda_1]^2 + \cdots + \delta_G[k(\boldsymbol{k_{it}}, \boldsymbol{m_{it}})\lambda_1]^G.$$

LP suggest using a third-order polynomial equation. Although the higher the order of the polynomial is, the higher is the accuracy of the estimates thereof; albeit, at the cost of sample size. We therefore choose $\delta_1 = 1$ and $G = 1$ for simplicity and sample size constraints.

RM use Blundell and Bond (1998) within the Wooldridge (2009) insight about the role of previous lags as instrumental variables for the GMM estimation framework, and present residual functions and instrumental variables for the following moment conditions

$$\mathbb{E}[\boldsymbol{Z'_{it}}\boldsymbol{r_{it}}(\boldsymbol{\theta})] = 0$$

where the residual function $\boldsymbol{r_{it}}(\boldsymbol{\theta})$ is defined as

$$\boldsymbol{r_i}(\boldsymbol{\theta}) = \begin{bmatrix} \mathrm{y_{i2}} - \varsigma - \mathrm{l_{i2}}\beta - \mathrm{k_{i2}}\gamma - \mathrm{c}(\mathrm{k_{i2}}, \mathrm{m_{i2}})\lambda_1 \\ \mathrm{y_{i2}} - \varsigma - \mathrm{l_{i2}}\beta - \mathrm{k_{i2}}\gamma - \mathrm{c}(\mathrm{k_{i1}}, \mathrm{m_{i1}})\lambda_1 \\ \cdots \\ \cdots \\ \mathrm{y_{iT}} - \varsigma - \mathrm{l_{iT}}\beta - \mathrm{k_{iT}}\gamma - \mathrm{c}(\mathrm{k_{iT}}, \mathrm{m_{iT}})\lambda_1 \\ \mathrm{y_{iT}} - \varsigma - \mathrm{l_{iT}}\beta - \mathrm{k_{iT}}\gamma - \mathrm{c}(\mathrm{k_{iT-1}}, \mathrm{m_{iT-1}})\lambda_1 \end{bmatrix}$$

and the vector of instrumental variable $\boldsymbol{Z}$ is given by

$$\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{Z}_2' & \boldsymbol{Z}_3' & \cdots & \boldsymbol{Z}_T' & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \bar{\boldsymbol{Z}}_3' & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \bar{\boldsymbol{Z}}_4' & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & \bar{\boldsymbol{Z}}_T' \\ 0 & 0 & \cdots & 0 & 1 & 1 & \cdots & 1 \end{bmatrix}$$

where $\bar{\boldsymbol{z}}_t$ is a 1x b vector of $\boldsymbol{z}_{t-1}, \ldots, \boldsymbol{z}_{t-b}$ as in ACF.

The discussion hitherto is based on the assumption of Leontief production technology in a flexible variable; i.e., intermediate inputs. This obviates identification of the coefficient on the perfectly adjustable input with price variation across firms and serial correlation. It simplifies estimation of relevant output elasticities under different value added specifications of production technology with the proxy function, a nonparametric low-order polynomial function and suitable orthogonality conditions between idiosyncratic shocks and various sets of instrumental variables.

In order to estimate markups based on intermediate inputs, one relaxes the assumption of fixed proportionality production technology of material inputs to output. Again, as in De Loecker *et al*. (2016), this seems sensible given the level of aggregation of the dataset at hand which allows for substitution of labour for capital while keeping output unchanged. Such a specification of functional form involves estimating a gross output production function by using multiple FOCs to simultaneously recover markups $\hat{\mu}_{it}^{l}$ and $\hat{\mu}_{it}^{m}$ through both output elasticities of labour and intermediate inputs, respectively as

$$\hat{\mu}_{it}^{m} = \hat{\beta}_m \left( \frac{P_{it}^{m} M_{it}}{P_{it} Q_{it}} \right)^{-1}$$

and

$$\hat{\mu}_{it}^{l} = \hat{\beta}_l \left( \frac{w_{it} L_{it}}{P_{it} Q_{it}} \right)^{-1}$$

where $P_{it}^{m}$ refers to the unit price of material $M_{it}$ and $w_{it}$ is the unit labour cost for firm $i$ at time $t$. The gross production function requires that material input prices vary across firms and are serially correlated over time. Furthermore, the equality $\hat{\mu}_{it}^{m} = \hat{\mu}_{it}^{l}$ is likely to hold provided there are no frictions or adjustment costs in industrial demand for labour. That is, the labour market $(L_{it})$ environment needs to be characterized by minimum regulation and as much flexibility as observed in the intermediate market, particularly the materials demand market $(M_{it})$. Lazear (1990) posits a strict

condition that requires perfect functioning of markets such that anything less remains distortionary in the goods and labour markets.

## 4. The Data and Measurement Issues

The empirical analysis of plant-level performance and export participation dynamics is based on a unique panel dataset of firms that has never been used before. The data come from the Central Statistical Office (CSO) of Eswatini and report on four-digit International Standard Industrial Classification (ISIC) sectors covering the years 1994-2007. It provides information on the value of domestic sales, value of foreign export sales, number of employees, wages, investment flows, and expenditure on material inputs. The dynamic capital stock variable, $K_{ijt}^{k}$, is calculated as $K_{ijt}^{k} = I_{ijt}^{k} + (1-\delta^{k})K_{ijt-1}^{k}$, where $I_{ijt}^{k}$ denotes the real flow of new investment of asset type k for establishment $i$ in industry $j$ and year $t$, $\delta^{k}$ represents the rate of depreciation of asset class $k$, and $K_{ijt-1}^{k}$ is the previous year's capital stock in industry $j$. The capital stock series is constructed using the Perpetual Inventory Method (PIM), see Appendix 1 for full details on variable construction.

That is, to develop an understanding of the nature of variable markup pricing abroad and at home as well as its relationship with heterogeneous productivity shocks and export entry/exit dynamics, we assembled a panel dataset of industrial producers and their balance sheet characteristics. Table 1 presents distribution of manufacturing producers by export status covering different periods, depending on whether the panel is balanced or not.

Table 1: Distribution of Firms by Export Status in the Period Spanning 1994-2007

| | UNBALANCED PANEL: 1994-2007 | | | BALANCED PANEL: 1994-2003 | | |
|---|---|---|---|---|---|---|
| **year** | **Active Firms** | **exporters** | **nonexporters** | **Active Firms** | **Exporters** | **Nonexporters** |
| **1994** | 106 | 34 | 72 | 74 | 21 | 53 |
| **1995** | 116 | 37 | 79 | 74 | 21 | 53 |
| **1996** | 127 | 46 | 81 | 74 | 27 | 47 |
| **1997** | 139 | 49 | 90 | 74 | 28 | 46 |
| **1998** | 156 | 54 | 102 | 74 | 28 | 46 |
| **1999** | 167 | 36 | 131 | 74 | 19 | 55 |
| **2000** | 312 | 36 | 276 | 74 | 20 | 54 |
| **2001** | 189 | 43 | 146 | 74 | 18 | 56 |
| **2002** | 204 | 49 | 155 | 74 | 19 | 55 |
| **2003** | 182 | 39 | 143 | 74 | 17 | 57 |
| **2004** | 145 | 14 | 131 | | | |
| **2005** | 125 | 19 | 106 | | | |
| **2006** | 115 | 22 | 93 | | | |
| **2007** | 109 | 25 | 84 | | | |

However, the sample representativeness is much harder to confirm or refute. This is because the CSO started collecting firm-level data in 1994 and stopped in 2012, when a nation-wide economic census was conducted. From 2012 onwards, the function of annual national surveys of firms was transferred to the then Swaziland Revenue Authority (SRA) through an agreement with the CSO. As a consequence of this the universe of active firms across sectors of the economy operating during 1994-

2012, for which we have the data, has 13,653 records compared to the 16,668 records for the 2012-2017 database which we were only allowed by the CSO Authorities to view on the computer screen.

The result of all this was that active firms began to show a decline in numbers from 2003, a potential indication that the vigour in data collection by officials was weakening. Looking at the logs of primary and intermediate inputs of production as well as export intensity defined as the ratio of firm exports to aggregate firm sales in Table 2, a trend that mimics the story about the pattern of producer numbers emerges.

Table 2: Evolution of Input Expenditure Shares of Revenue and Export Intensity

| **Year** | Input Expenditure Share of Revenue (in log) | | | Export Intensity |
|---|---|---|---|---|
| | Capital | Labour | Material | |
| **1994** | 13.65 | 9.76 | 14.62 | 0.3208 |
| **1995** | 13.42 | 9.82 | 14.47 | 0.3190 |
| **1996** | 13.26 | 9.80 | 14.52 | 0.3622 |
| **1997** | 13.51 | 9.83 | 14.37 | 0.3525 |
| **1998** | 13.78 | 9.93 | 14.52 | 0.3462 |
| **1999** | 14.35 | 10.03 | 14.45 | 0.2156 |
| **2000** | 14.42 | 10.00 | 14.58 | 0.1154 |
| **2001** | 14.66 | 10.28 | 14.55 | 0.2275 |
| **2002** | 14.61 | 10.39 | 14.44 | 0.2402 |
| **2003** | 14.49 | 10.37 | 14.37 | 0.2143 |
| **2004** | 14.46 | 10.32 | 14.35 | 0.0966 |
| **2005** | 14.48 | 9.97 | 14.31 | 0.1520 |
| **2006** | 14.43 | 9.89 | 14.38 | 0.1913 |
| **2007** | 14.37 | 9.83 | 14.37 | 0.2294 |

The unit of observation is the firm.[4] Although we are somewhat reticent about the representativeness of the sample, we are still confident that the dataset is fit for purpose.

## 5. Empirical Results

This section begins with investigating the unbalanced panel dataset to estimate the Wooldridge-Blundell-Bond production function, markup, and performance variability for a firm at a given point in time to understand measurement issues associated with the new dataset. It then analyses the relationship between markups and productivity, and the relationship between firm performance and its export participation.

### 5.1. Output Elasticities, Productivity and Markups

In the estimation of production technology, we follow DLW for methodological purposes and Gandhi *et al.* (2017) for robustness checks who provides elasticities for Colombia and Chile. First and foremost, the latter works as a benchmark against which our gross output and value-added estimates are compared. Furthermore, the persuasive arguments presented in Gandhi *et al*. (2017) concerning

[4] Given the structure of the dataset, firm, plant, and establishment are used interchangeably. Sometimes the unit of observation is simply referred to as the producer.

the virtues of gross output production functions in contrast to value-added production technology influenced our choice of firm-level production technology.

Table 3: Estimates of Production Function Elasticities

| | Capital | Labour | Material |
|---|---|---|---|
| **VA** under **CD** | .2052*** | .7995*** | |
| **I** = **VA** under **CD** | .1814** | .7944*** | |
| $\mathbf{I^{dfp}}$ = **VA** under **CD** | .1739*** | .7944*** | |
| **II** =Gross output | .0873* | .4481*** | .6289*** |
| Colombia | .14 | .35 | .54 |
| Chile | .16 | .38 | .55 |

**dfp** indicates that the Davidson-Fletcher-Powel optimizer was used in the LP routine.
Legend: *p<0.05; **p<0.01; ***p<0.001.

The empirical estimation of the production function relies on the proxy-GMM hybrid framework proposed by Rovigatti and Mollisi (2018) for efficient identification of parameters under value-added and gross output technologies. Conditional on its existence in the sense of Bruno (1978), the value-added function in **I** is double-deflated to estimate the output elasticity with respect to paid employees and working proprietors $\left(L_{it}^{PE}, L_{it}^{WP}\right)$ and multiply the labour elasticity by its expenditure share of revenue to produce labour-based product-level markups[5]. Second, the likelihood that the labour variable may not be adequately flexible compared to intermediate inputs leads to the use of a gross output function in **II** to estimate the material coefficient and subsequently estimate materials-based markups. In Table 4 we provide estimates of average markups and productivity by method used and compares the results with DLS who rely on the demand approach to estimate markups for the beer industry in the U.S.

Table 4: Estimates of Average Markups and Productivity by Method of Calculation

| **Method** | | $\boldsymbol{\mu_{it}}$ | $\boldsymbol{\omega_{it}}$ | $\boldsymbol{\rho(\mu_{it}, \omega_{it})}$ | $\boldsymbol{\mu_{it}}$ **from DLS** + | |
|---|---|---|---|---|---|---|
| | | | | | Demand-Based | Both Approaches |
| **I:** | $ln(\hat{\mu}_{it}^{l})$ | 1.5735 | 2.8857 | 0.0829* | | |
| **II:** | $ln(\hat{\mu}_{it}^{l})$ | 2.0110 | 2.7968 | 0.1222* | | |
| | $ln(\hat{\mu}_{it}^{m})$ | 1.2865 | 2.7968 | 0.3645* | 1.6-1.7 | 1.5-1.9 |

Notes: + denotes markups estimated for the U.S. Beer Industry by De Locker and Scott (2017).

Legend: *p<0.05; **p<0.01; ***p<0.001

First and foremost, if labour and intermediate inputs were perfectly flexible and identically amenable to costless adjustment, their correlation coefficient would asymptotically tend towards unity. However, the current dataset produces a negative correlation coefficient of -0.2. This suggests that in 20% of the time, $ln(\hat{\mu}_{it}^{l})$ and $ln(\hat{\mu}_{it}^{m})$ are moving in opposite directions, an indication of the first sign

[5] The robustness of the labour coefficient was checked against value added production technologies and found to be consistently 0.79.

that firms experienced non-negligible adjustment costs of paid labour while intermediate inputs were adjusted more regularly to meet production requirements.

The actual average size of $ln(\hat{\mu}_{it}^{l})$ depends crucially on the production technology used to estimate the labour elasticity. It is larger at 2.01 under the gross output specification while it remains at 1.57 under value-added production function. However, the markup based on the more flexible materials variable estimated at 1.29 compares very well with the markup estimates provided by DLW for Slovenia.[6]

Furthermore, the relationship between $ln(\hat{\mu}_{it}^{m})$ and $ln(\omega_{it})$ is high with a correlation coefficient of 0.36. In order to further enhance our understanding of the markup-productivity conundrum, there is need to present the relationship in a convex envelope of a two-dimensional set of points $(ln(\hat{\mu}_{it}^{m}), ln(\omega_{it}))$ and $(ln(\hat{\mu}_{it}^{l}), ln(\omega_{it}))$ in Euclidian space. Figure 2 presents two components of convex hulls to reveal the strength of the relationship between productivity and each measure of the markup. Clearly, $ln(\hat{\mu}_{it}^{m})$ and $ln(\omega_{it})$ on the left panel show a relatively more definitive and positive association with each other in contrast to the panel on the right which has visually no definitively discernible pattern.

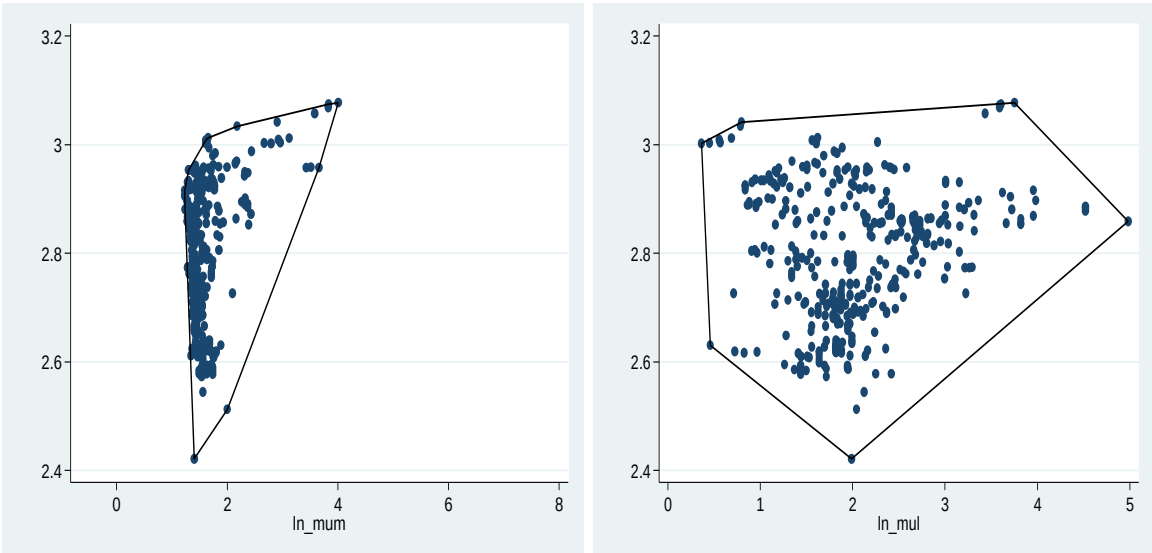


Figure 2: Convex Hulls for $\boldsymbol{ln(\hat{\omega}_{it})}$ plotted against $\boldsymbol{ln(\hat{\mu}_{it}^{m})}$ and $\boldsymbol{ln(\hat{\mu}_{it}^{l})}$

The descriptive analysis so far has focussed on cross-sectional average markups and productivity for the whole industrial sector. This masks any heterogeneity of performance indicators across similar products or volatility of these indicators over time to enable exploratory inference about cyclical

[6] An interesting piece of evidence in the South African case is the extent of industrial volatility in price-cost margins where the Rubber Products industry recorded an average markup of 0.40 in 1985-1994 and -2073.24 in the 1995-2004 period, see Fedderke, Obikili and Viegi (2018).

dynamics while providing the opportunity to identify potential events that may account for the trends. Nonetheless, it already seems clear that $ln(\hat{\mu}_{it}^{m})$ should be a preferred measure of markup over $ln(\hat{\mu}_{it}^{l})$ because of the former's stronger correlation with productivity. The labour-based markup is continuously used in subsequent sections as a cautionary endeavour to the reader when confronted with labour-based markups in publications.

We further estimate annual statistics for markups, $ln(\hat{\mu}_{it}^{m})$, and productivity to determine the distribution of firm-level profitability and production efficiency over time. An average firm in column (2) of table 5 charged a markup of circa 1.26 in 1994 and there was a general decline in profitability until 1998. A significant positive shock in markups was experienced in 1999, which coincided with a major merger in the wood industry. It is however not clear why this efficiency improvement in industrial operations of this sector did not translate into equally pronounced average productivity gains. Since productivity is measured using the Solow-residual, one potential explanation is that such improvements may have been captured in the output elasticities of primary factors of production and control variables such as industry and year fixed effects. The role of fixed effects is to determine the extent to which the drive cross-product heterogeneity or aggregate intertemporal movements in the results, see Forster, Haltiwanger and Syverson (2008). Nonetheless, the period from 2000 experienced an annual increase in markups to over 1.3. This corresponds to a period of an intensified wave of retrenchments that characterized the manufacturing sector as a whole during this period. Furthermore, a comparison between average and median markups in columns (2) and (3) shows that the latter dominates the former, an indication of negative skewness in distribution in the series. This suggests an inclination by firms to charge lower markups. Theory and evidence from the literature would have us believe that non-exporting firms charge higher markups than their exporting counterparts due to savings in fixed export costs and differences in the tightness of market competition, see Helpman, Melitz and Yeaple (2004).

Table 5: Estimates of Average and Median of Markups and Productivity from the Gross Output Production Function

| **Year** | **Markups**: $\boldsymbol{ln(\hat{\mu}_{it}^{m})}$ | | **Productivity:** $\boldsymbol{ln(\hat{\omega}_{it})}$ | |
|---|---|---|---|---|
| | Mean | Median | Mean | Median |
| 1994 | 1.2639 | 1.4082 | 2.8388 | 2.8673 |
| 1995 | 1.2870 | 1.4295 | 2.8164 | 2.8350 |
| 1996 | 1.2105 | 1.4109 | 2.8317 | 2.8566 |
| 1997 | 1.1597 | 1.3857 | 2.8003 | 2.8204 |
| 1998 | 1.2043 | 1.4116 | 2.7992 | 2.8125 |
| 1999 | 1.4041 | 1.4159 | 2.7866 | 2.7827 |
| 2000 | 1.3156 | 1.4291 | 2.7977 | 2.8041 |
| 2001 | 1.3479 | 1.4162 | 2.8033 | 2.8146 |
| 2002 | 1.3196 | 1.3881 | 2.7913 | 2.8005 |
| 2003 | 1.2233 | 1.4112 | 2.7641 | 2.7557 |
| 2004 | 1.2143 | 1.4337 | 2.7587 | 2.8273 |
| 2005 | 1.2059 | 1.4212 | 2.7698 | 2.8145 |

| | | | | |
|---|---|---|---|---|
| 2006 | 1.1934 | 1.3902 | 2.6983 | 2.7923 |
| 2007 | 1.2003 | 1.3859 | 2.6581 | 2.7884 |

Columns (4) and (5) report average and median trends in productivity. Again, the median productivity generally dominates the average counterpart for the whole period. The striking result though is the consistent marginal decline in the measure of average production efficiency. This may reflect the process of relocation of foreign firms, potentially efficient exporters, out of the country and setting up plant in the trade liberalizing larger market in South Africa.

In general, the manufacturing sector was characterized by firms exhibiting almost time-invariant production efficiency in the entire sample period. At the margin, more efficient firms exited the market to relocate in larger markets. On the other hand, the pattern of markups based on material inputs appeared to be marginally cyclical: starting off high in 1994, only to show a dip in 1997 and peaking in 1999, just to level off thereafter. Although these intertemporal movements in markups and productivity present a good indication of business cycles and reflect fluctuations in aggregate market demand, they fall short in shedding any light about the extent of dispersion.

### 5.2. Measures of Entropy for Markup and Productivity Dispersion

The measure of time series dispersion for a variable has historically been the Gini Coefficient bounded between perfect equality and perfect inequality, or $GI \in [0,1]$, due to its desirable properties such as mean independence, population size independence, symmetry, and Pigou-Dalton sensitivity transfer; see Lu and Ma (2015). However, its decomposability and statistical testability constraints have created a need for the development of an entropy index that overcomes these problems while benefitting from the GI's good characteristics. One popularly adopted measure of dispersion in the literature is the Theil Index which is expressed as

$$Theil_{it} = \frac{1}{n_{it}} \sum_{i=1}^{n_{it}} \frac{y_{ijt}}{\bar{y}_{it}} log\left(\frac{y_{ijt}}{\bar{y}_{it}}\right)$$

where $y_{ijt}$ and $\bar{y}_{it}$ denote the $ln(\hat{\mu}_{it}^{l})$, $ln(\hat{\mu}_{it}^{m})$ or $ln(\hat{\omega}_{it})$ and their industry average values for establishment $i$ located in industry $j$ at time $t$; and $n_{it}$ refers to the number of establishments in industry $j$ at time $t$. As a robustness check, 10 more entropy measures of firm-level dispersion are computed and reported in table 6.

Table 6: Entropy Measures of Firm-Level Dispersion in Markups and Productivity

| **Inequality Measures** | $\boldsymbol{ln(\hat{\mu}_{it}^{l})}$ | $\boldsymbol{ln(\hat{\mu}_{it}^{m})}$ | $\boldsymbol{ln(\hat{\omega}_{it})}$ |
|---|---|---|---|
| Relative mean deviation | 0.1385 | 0.2286 | 0.0190 |
| Coefficient of variation | 0.3701 | 0.6818 | 0.0448 |
| Standard deviation of logs | 0.3933 | 0.7520 | 0.0450 |
| Gini coefficient | 0.2015 | 0.3428 | 0.0256 |
| Mehran measure | 0.2901 | 0.5178 | 0.0388 |

| | | | |
|---|---|---|---|
| Piesch measure | 0.1572 | 0.2553 | 0.0190 |
| Kakwani measure | 0.0388 | 0.1466 | 0.0006 |
| Theil index (GE(a), a = 1) | 0.0670 | 0.1460 | 0.0010 |
| Mean Log Deviation (GE(a), a = 0) | 0.0715 | 0.1963 | 0.0010 |
| Entropy index (GE(a), a = -1) | 0.0850 | 0.0760 | 0.0010 |
| Half (Coeff.Var. squared) (GE(a), a = 2) | 0.0683 | 0.2320 | 0.0010 |

An immediate observation from these results is that labour-based markups generally deliver indices that are comparatively much lower than those produced by intermediate inputs. More specifically, the ratio of the average indices for the labour-based markups to the intermediate input-based ones is only 41.5%. Looking more closely at the Theil Index as a benchmark for all associated indices, the results show that the Theil Index for $ln(\hat{\mu}_{it}^{l})$ is only 43% of the dispersion in $ln(\hat{\mu}_{it}^{m})$. This suggests a presence of costly labour variation, and the low dispersion in $ln(\hat{\mu}_{it}^{l})$ is consistent with upward rigidity in labour demand. In a well-functioning market economy, the difference in dispersion between the two measures of markup is expected to converge to zero to produce the same distribution of $ln(\hat{\mu}_{it}^{l})$ and $ln(\hat{\mu}_{it}^{m})$ and also produce an equalized index for each product. This apparent labour market failure already provides *prima facie* evidence of significant adjustment costs in the hiring and firing of workers in the industrial sector.

Another interesting result pertains to measures of dispersion involving unobserved productivity shocks to production. In five out of 11 measures of productivity dispersion, the index approaches perfect equality; that is, zero. This means there is no productivity variability across establishments and products over time regardless of whether goods are homogeneous or differentiated, or whether firms participate in the exportation of goods and services. It would consequently be useful to understand the extent to which markups and productivity explain firm-level decisions to enter/exit export markets, and whether a firm's export status has an impact on its performance in markup pricing and technical efficiency. An in-depth investigation of these issues is further carried out in the sections that follow.

### 5.3. Stylized Facts

There are several emerging stylized facts associated with the behaviour of markups, depending on whether or not one is willing to assume that the labour or material input is free of adjustment costs. These include:

- The demand for intermediate inputs is more elastic than that of labour,
- The median intermediate input-based markup is higher than its mean; hence, its distribution has a left heavy tail,
- The correlation between the labour-based markup and productivity is significantly less than that which obtains between intermediate input-based markups and productivity,
- On average, measures of dispersion for $ln(\hat{\mu}_{it}^{l})$ yield less than 41.5% of the variation in $ln(\hat{\mu}_{it}^{m})$,

- Regardless of production technology used in the estimation of output elasticities, the labour-based markup is higher than the material-based one, and
- In five out of 11 measures of productivity dispersion including the Theil index, the dispersion approaches perfect equality; that is, zero.

This is a clear indication of labour rigidity induced by significant adjustment costs, and the candidature of intermediates as a free variable input in production remains unchanged.

### 5.4. Impact of Endogenous Markups on Unobserved Productivity

This section presents an econometric framework for empirical analysis of the relationship between producer efficiency and markup decisions in manufacturing. The theoretical literature provides no concrete guidance concerning the direction of causality between the two characteristics of firm performance, see Cusolito, Garcia-Marin and Faloney (2017). It is conceivable that a firm with a competitive edge and therefore some market power in a goods market over its rivals may decide to enter the market to appropriate profit maximizing opportunities like in the US, see Bernard and Jensen (1999). This suggests that causality runs from good performance, market entry to determining markups. That is, more productive firms tend to leverage on their productivity advantage by charging higher markups as in Eckel and Neary (2010) and Melitz and Ottaviano (2008). Alternatively, and adopting the Schumpeterian principle of creative destruction, Aghion and Howitt (1992) use a model of endogenous growth with vertical innovation to argue that competition has an impact on production efficiency through a firm's reconfiguration of its own incentives to invest in productivity-enhancing physical plant, machinery and equipment. The mechanism contemplated is that current research and development (R&D) crucially depends on expected future R&D in that the latter discourages the former through the threat of rent destruction arising from hastened obsolescence of current technologies. In contrast, when the prospect of future innovation is low, current R&D increases the preparedness for rent appropriation in the market.

The potential for reverse causality suggests that productivity and markup are likely endogenous. This means that modelling any one of them as an explanatory variable of the other, the presence of a relationship between the explanatory variable and the error term cannot be ruled out. Although the Aghion-Howitt thesis is adopted here allowing causality to run from markups to productivity, the econometric specification accommodates the possibility of endogeneity in markups. To do this, producer efficiency is driven by $t-1$ markups to allow the propagation mechanism enough time to realize profits for use in subsequent productivity-enhancing activities. The lagging of markups is intended to expunge contemporaneous effects from third sources on current markups and productivity; i.e., eliminates the classical simultaneity problem. As in Stock and Yogo (2005), the specification of a linear IV regression model with $n$ included endogenous regressors $\boldsymbol{y_2}$ and $K_1$ included exogenous regressors X take the form,

$$\boldsymbol{y_1} = \boldsymbol{y_2\beta} + \boldsymbol{X\Upsilon} + \boldsymbol{U}$$

$$\boldsymbol{y_2} = \boldsymbol{Z\Pi} + \boldsymbol{X\Phi} + \boldsymbol{V}$$

where $\boldsymbol{y_2}$ is the reduced-form $T\ x\ n$ matrix of included variables, $\boldsymbol{X}$ is a $T\ x\ K_1$ matrix of exogenous included variables, $\boldsymbol{Z}$ is a $T\ x\ K_2$ matrix of included exogenous instrumental, **V** in an error matrix and one assumption is that $K_2 \geq n$. The vectors $\boldsymbol{\beta}$ and $\boldsymbol{\Upsilon}$ and matrices $\boldsymbol{\Pi}$ and $\boldsymbol{\Phi}$ are parameters to be estimated. Notice that the exclusive consideration in this analysis is about the estimation of $\boldsymbol{\beta}$, which is approximated with the estimate $\widehat{\boldsymbol{\beta}}^{\boldsymbol{TSLS}}$.

Therefore, with the two-stage least squares (TSLS) framework in hand, we need to link it to the regression of unobserved productivity shocks $[\boldsymbol{y_1} = \boldsymbol{ln}(\widehat{\boldsymbol{\omega}}_{\boldsymbol{it}})]$ on endogenous markups; i.e. either $\boldsymbol{ln}(\widehat{\boldsymbol{\mu}}^{\boldsymbol{m}}_{\boldsymbol{t-1}})$, $\boldsymbol{ln}(\widehat{\boldsymbol{\mu}}^{\boldsymbol{l}}_{\boldsymbol{t-1}})$ or $\boldsymbol{ln}(\widehat{\boldsymbol{\mu}}^{\boldsymbol{m:Exp}}_{\boldsymbol{t-1}})$ separately[7]. As noted by Foster *et al*. (2008), valid instrumental variables (**Z**) are hard to find in practice. To do this, we choose experimental IVs as **Z** variables that affect different versions of markups but not productivity. Following ACF and De Loecker *et al*. (2016), we experimented with logs of export sales $[\boldsymbol{Exp_{t-1}}], [\boldsymbol{Exp_{t-2}}]$ and paid labour $[\boldsymbol{l^{PE}_{t-1}}]$ and the results are shown below. Lastly, we use a third-order polynomial of capital and labour as exogenous included variables, $\boldsymbol{X}$.

When instruments are weak, Stock *et al*. (2002) warn that the sampling distribution of IV statistics is non-normal and therefore point estimates, inference tests and confidence intervals are rendered unreliable. To test for the validity and strength of the IVs, we rely on Shea (1997) to perform an instrument relevance test and Cragg and Donald (1993) for testing for weak IVs. In the case of hypothesis testing, Djogbenou *et al*. (2018) provide alternative bootstrap methods. One particular method well-suited for this study relies on a data-generating process that is robust to heteroscedasticity of unknown form and successful in finite samples, even when IVs are weak. This has become known as the wild restricted efficient (WRE) residual bootstrap.

Table 7 shows regression results mostly under cluster-robust variance estimators (CRVE) and diagnostic tests for weak IVs. An exogeneity test of general markups and markups charged by exporting firms in foreign markets was strongly rejected at 1% level of significance. An examination of the strength of IVs using first-stage *F*-statistics proved significant; albeit, only marginally for labour and export sales combined. The *cluster 1* and 'robustified' standard errors in the first-stage column 3 present parameters of material input-based markups with one period lags of paid labour and real export sales as IVs.[8] These columns produced significantly positive and identical markup coefficients. This means a 10% increase in an industry's average markup of domestic and foreign market sales for this period will raise productivity by 0.77% next period. For example, the higher the

[7] $\boldsymbol{ln}(\widehat{\boldsymbol{\mu}}^{\boldsymbol{m:Exp}}_{\boldsymbol{t-1}})$ denotes intermediate input-based markup for exporters.
[8] The term 'robustified' standard errors was coined by Baum (2007).

elasticity of demand for a product in an industry, the higher the elasticity of demand for a production input and therefore higher markups, *ceteris paribus*. In contrast, and not surprisingly, the model in the *cluster 2* column with $t-1$ markups estimated on the basis of the product of labour demand elasticity and the labour share of revenue produced a significant but negative markup coefficient. Moreover, the labour-based markup estimation was well-behaved only if the Frisch-Waugh-Lovell (FWL) theorem was applied to partial out the exogenous variables from the other variables and excluded IVs. This helped resolve the rank-deficient estimate of the covariance matrix of orthogonality conditions, see Baum *et al*., (2007. The result of that estimation therefore requires careful interpretation. The conventional high adjustment cost of labour thwarted the potential responsiveness of firms to hire or fire workers when experiencing positive or adverse demand shocks presented largely by trade reforms. Hence, a 10% increase in the current period markup reduces productivity by 0.18% due to rigidities in labour adjustment cost. This may simply be a rejection of the labour flexibility assumption in the estimation of input elasticities in the production by the control function approach.

Table 7: Impact of Endogenous Markups on Productivity from First-Stage TSLS Results

| Variable | IV: $\boldsymbol{l_{t-1}^{PE}}$ and $\boldsymbol{ln(\text{Exports}_{it-1})}$ | | | IV: $\boldsymbol{ln(Exp_{t-2})}$ | |
|---|---|---|---|---|---|
| | Cluster 1 | First Stage | | Cluster 3 | First Stage |
| $ln(\hat{\mu}_{it-1}^{m})$ | .0773***<br>(.0091) | .0773***<br>(.0064) | | | |
| $ln(\hat{\mu}_{it-1}^{l})$ | | | -.0183*<br>(.0070) | | |
| $ln(\hat{\mu}_{it-1}^{m:\,Exp})$ | | | | .0886***<br>(.0056) | .0889***<br>(.0039) |
| Constant | -19.0247<br>(10.2947) | -19.0247<br>(10.2379) | -55.9936*<br>(39.0905) | -2.21668<br>(2.3018) | -1.9488<br>(1.9699) |
| $F$ | 6470.6562 | 326.923 | 1768.1039 | 1399.7228 | 1001.3988 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 68 | 68 | 68 | 228 | 228 |
| $R^2$ | .9742 | .9742 | .8745 | .9867 | .9869 |
| $R_a^2$ | .9691 | .9691 | .8498 | .9860 | .9858 |
| Cragg-Donald $F$-Test Statistic | 10.06 | 10.06 | 4.03 | 461.83 | 185.36 |
| Andersen-Rubin $F$-Test Statistic | 4.93* | 4.93* | - | 7.03** | 7.03** |

Legend: *p<0.05; **p<0.01; ***p<0.001

The next set of results involves replacing the general markup with the markup on real export sales to isolate the role of the latter from real domestic sales. A firm's productivity now depends on previous endogenous markups of real export sales instrumented by its own second lag. This is shown in the Cluster 3 and subsequent First-Stage columns where a 10% increase in the export markup generates productivity growth of circa 0.89 %. The impact of previous markups on current export sales is higher than the impact of markups estimated from the average of domestic and export sales. Thus, exporting firms are more productive than firms serving only the small domestic market.

However, Davidson and MacKinnon (2010) caution that it is generally difficult to make reliable inference in regression analyses based on IVs, particularly when the instruments are weak. At least two options exist for handling this difficulty: first, one can obtain reliable inference by using statistics with better underlying properties than the IV$-t$ statistic. These include the Anderson-Rubin test statistic, among others. Second, one can also implement the wild restricted efficient (WRE) residual bootstrap proposed by Davidson and MacKinnon (2010), made technically operational by Roodman *et al*. (2018) and applied by Roodman (2017). This method makes available a data-generating process (DGP) that is valid under heteroscedasticity of unknown form and has enhanced efficiency in finite samples even when IV are weak. It has been argued by its originators that the approach also delivers efficient results when used with statistics that are not heteroscedasticity-robust yet asymptotically valid under weak IV asymptotics (Davidson and MacKinnon, 2010).

Notice that the IVs $\boldsymbol{Z} \in \left(l_{it-1}^{PE}, Exports_{it-1}\right)$ for markups in the first three columns are weak according to the Cragg and Donald (1993) test statistic which marginally exceeds 10. When the general intermediate input-based markup is replaced with export goods' markup and IVs are replaced with $\boldsymbol{Z} \in (Exports_{it-2})$, $\boldsymbol{Z}$ proves to be a strong instrument. Nonetheless; in order to conduct reliable statistical inference concerning the impact of endogenous markups on unobserved producer efficiency shocks, the WRE residual bootstrap is applied to the empirical model. The clustering of individual observations around within-industry and year groups seeks to handle serial correlation and implement heteroscedasticity-robust estimation so as aid inference. In this procedure, we perform a two-way cluster of standard errors by industry and year while relying on default runs of $B = 999$ replications. It takes draws from the Rademacher distribution and computes a symmetric two-tailed *p*-value to test if the coefficient on the endogenous markup variable is such that $\hat{\beta}^{TSLS} = 0$.

In Figure 2, we plot bootstrapped *p*-values of $ln(\hat{\mu}_{it}^{m})$ and $ln\left(\hat{\mu}_{it}^{l}\right)$. The combined instruments of previous paid workers and real export sales of material-based markups on the left panel strongly support the positive relationship between productivity and markups found in the literature. In contrast, the same instruments used on labour-based markups on the right panel marginally reject the positive relationship between markups and productivity, with the distribution of markups crossing the 5% horizontal line at the -0.057 on the left. It also crosses the same line at 0.024 and 0.196 points on the right while peaking at $ln\left(\hat{\mu}_{it}^{l}\right) < 0$.

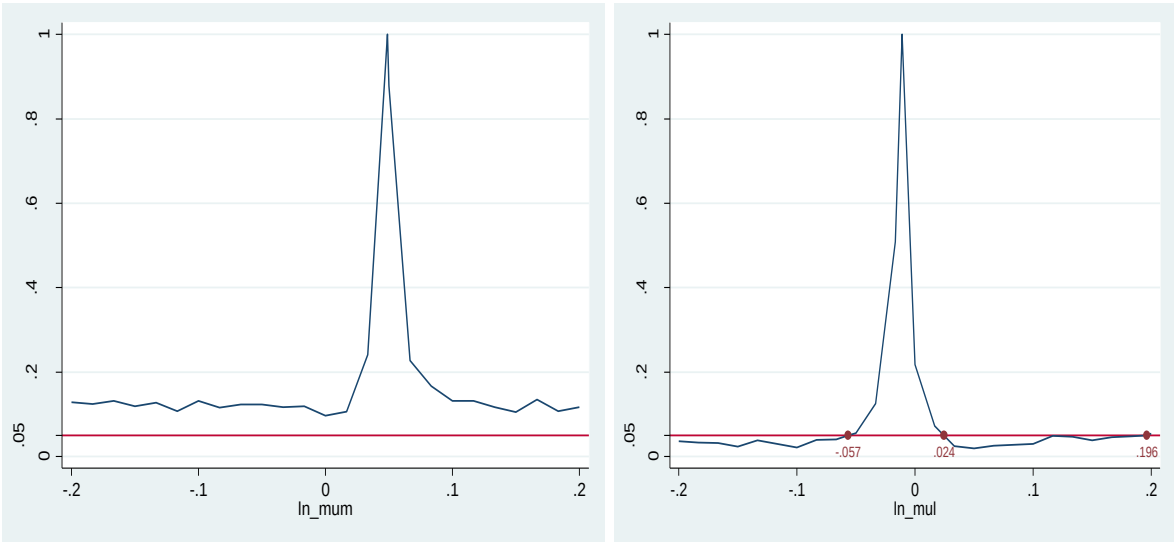


Figure 2: Distribution of bootstrapped $p$-values for various hypothesised impacts of markups on productivity based on $t$-tests of the WRE bootstrap wrapper and TSLS IV regressions.

Therefore, the results based on intermediate input expenditure shares of revenue suggest that a 10% increase in markups raises producer efficiency by a range of 0.77% - 0.89%, depending on export status. That is, export markups have a higher impact on productivity than the aggregate markups. Note that this pattern of markup pricing and its relationship with productivity involves an aggregate of diverse industries ranging from the two-digit ISIC food and food products sector (15) to furniture and other manufactures not elsewhere classified (36). A higher level of granularity, or four-digit ISIC, and level of concentration should provide more guidance in terms of specific sectors that engage in more export participation.

Henceforth, the analysis will use markups based on labour input expenditure share of revenue only for comparison purposes. The sections that follow examine the role of firm-level export status and export participation on performance measured by markups and productivity. The key idea is to try and understand the extent of exporters' heterogeneity in performance and their role of export entry/exit dynamics. It is also to determine the probability of firm entry/exit into exports when markups and productivity are controlled for.

### 5.5. Markups, Producer Efficiency and Foreign Markets

This section brings all the pieces discussed in the Introduction together to investigate whether export participation of firms has on average higher and/or raises their markups and productivity. It begins by considering cross-sectional export-performance patterns and ends with the time series dimension to determine if export entry, exit and/or continuous exporting alter a firm's markup and productivity. Notice that, in contrast to markup measures used by Fedderke *et al*. (2018) and others, the DLW method allows for measuring markups as share-weighted average markups across domestic and

foreign markets. The weight by market derives from the input's share of costs to revenue used in the production of the good sold in that market.

### 5.5.1. Productivity and markups for exporters

The ability to estimate firm-specific productivity and markups brings with it the opportunity to relate these performance outcomes to firms' export status in a regression environment. It provides for the estimation of percentage markups and productivity between exporters and nonexporters. In order to allow for comparison of results with those produced using the Hall approach, the percentages are converted to absolute differences between export participation and nonexporting. The empirical model specification taken to the data is as follows

$$ln(\hat{\mu}_{it}^{m}) = \lambda_0 + \lambda_1 Exportdummy_{it} + \boldsymbol{X}'\boldsymbol{\lambda} + \upsilon_{it}$$

and

$$ln(\widehat{\omega}_{it}) = \alpha_0 + \alpha_1 Exportdummy_{it} + \boldsymbol{X}'\boldsymbol{\alpha} + \varphi_{it}$$

where $\lambda_1$ and $\alpha_1$ represent percentage markup and productivity premia for exporting establishments.[9] The use of the natural logarithm of markups is intended to control the variability inherent in levels quantities and appeal to ordinary least squares (OLS) to minimize proportional, rather than absolute, deviations as in DLW. In order to control for firm size and factor intensity while expunging industry specific trends in both firm-level performance indicators, $\boldsymbol{X}$ collects all included control variables such as labour, fixed capital stock, and interaction of industry-year effects. Table 8 reports the correlation between export status and firm performance.

Table 8 Heterogeneity of Exporters' Productivity and Markups

| Variable | $ln(\omega_{it})$ | $ln(\omega_{it})$ | $ln(\mu_{it}^{m})$ | $ln(\mu_{it}^{m})$ | $ln(\mu_{it}^{l})$ |
|---|---|---|---|---|---|
| $\alpha_1/\lambda_1$ | .0846*** | .1024*** | .2429*** | .1915** | -.3869*** |
| $\omega_{it}$ | | | | .0216 | |
| $\mu_{it}^{m}$ | | .0014 | | | |
| $l_{it}^{pe}$ | .0995*** | .1005*** | .1033*** | .0574* | -.5106*** |
| $k_{it}$ | .0424*** | .0412*** | .0348* | .0159 | -.0274 |
| Constant | 1.260*** | 1.3246*** | 1.282*** | .9284*** | .5253 |
| $\widehat{\omega}_{EP}$ $or$ $\hat{\mu}_{EM}$ | 0.30 | 0.39 | 0.88 | 0.48 | -0.65 |
| Industry -Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 292 | 371 | 371 | 371 | 292 |
| $R^2$ | .7681 | .7771 | .2064 | .2046 | .4488 |
| $R_a^2$ | .7581 | .7690 | .1775 | .1756 | .4251 |

[9] The markup part of the equation is essentially $\frac{P_{it}}{C_{it}} = \delta_0 + \lambda_1 Exportdummy_{it} + \delta_2 \omega_{it} + \boldsymbol{X}_{it}'\sigma + v_{it}$, where $P_{it}$ is the product price for firm $i$ and $C_{it}$ is its marginal cost such that $ln(P_{it}) - ln(C_{it})$ is the markup for the firm at time $t$, controls for productivity. We now know from Katayama *et al*. (2009) and De Loecker (2011) that $\omega_{it}$ may be picking up price differences and their consequential effect is $\delta_2$ picking up additional heterogeneity in market power and/or demand conditions across producers. Also, see Foster *et al*. (2008) concerning firm selection on profitability.

Legend: *p<0.05; **p<0.01; ***p<0.001

Columns 1 and 3 in Table 6 show export participation is positively associated with a significant increase in plant-level productivity and markups. The exception is when export status is related to output elasticity with respect to labour and the inverse of the proportion of labour cost to total production expenditure. Although it is not the function of this analysis to interpret $\theta_1 \in [\lambda_1, \alpha_1]$ as causality running from export status to either markups or productivity nor to interpret any of the coefficients of the model, this setup enables us to test whether on average exporters perform better in the stipulated dimensions. With the intercept estimates $\hat{\lambda}_0$ and $\hat{\alpha}_0$ in hand, and since the constant term captures the average domestic markup or productivity, it is straightforward to compute markup and productivity level differences. More precisely, denoting export markup and export productivity levels as $\omega_{EP}$ and $\mu_{EM}$, then the estimates are $\widehat{\omega}_{EP} = \hat{\alpha}_1 exp^{\widehat{\alpha}_0}$ and $\hat{\mu}_{EM} = \hat{\lambda}_1 exp^{\hat{\lambda}_0}$, respectively; computed after estimating the relevant coefficients in either case.

This cross-sectional evidence suggests that exporters in the manufacturing sector in Eswatini charged higher markups in foreign markets and were also more productive than firms producing only for the domestic market during the period of trade liberalization in the customs union. Since $ln(\mu_{it}) = ln(P_{it}) - ln(C_{it})$, where $P_{it}$ and $C_{it}$ are respectively prices and marginal costs, and if productivity picks up the marginal cost, $ln(C_{it})$, in full as suggested by DLW, then the export effect $\lambda_1$ is a percentage measure of the price difference. Crucially, controlling for productivity in the markup equation reduces the export effect to 19.15% and still significantly explain 20% of markup variation. This directly controls for variation in marginal costs across firms, and the export status coefficient is confounded by price differences between exporters and nonexporters, see Katayama *et al*. (2009) and De Loecker (2011).

The purpose of the productivity estimate in the markup equation is to pick up additional variation involving market power and demand conditions across plants according to demand and supply models of differentiated products markets in Berry (1994) and Berry and Haile (2016). These results are consistent with literature that stresses the potential differences in the quality of both finished products and inputs of production between nonexporters and exporters. They are also consistent with international trade models such as Bernard *et al*. (2003) and de Blass and Russ (2015) where exporters are able to charge higher markups because they are more productive and therefore able to undercut prices charged by their competitors. However, this theoretical model supports this prediction only on the basis of the assumption that firms with similar productivity charge the same markup thereby making productivity seem like the only source of markup difference across establishments. In contrast, the De Loecker-Warzynski approach simply compares the average markups of nonexporters with those of exporters in the cross-section. Consequently, the export markup premium is 0.88 and it

falls considerably by 58.8% to 0.48 if productivity is controlled for.[10] That is, the markup difference between exporting producers and those supplying only to the domestic market declined significantly. This reflects the importance of controlling for productivity.

Similar results are obtained when estimating the productivity equation by controlling for markups. More importantly, the export effect strengthens marginally as it adjusts from 8.46% to 10.24% after controlling for markups which enter insignificantly in the cross-sectional dataset. As a result, the export productivity premium increases from 0.30 to 0.39 by controlling for price-cost margins. These results emphasize the need to understand the export-productivity nexus together with markup variation in an integrated framework. This is consistent with the conventional wisdom that exporters' productivity premia reflect differences in price markups. It is therefore important to study the markup and productivity trajectories each as a function of export market participation by firms.

### 5.5.2. Effects of Export Participation on Markups and Productivity

This section considers the impact of export participation on firm-level performance while computing the productivity and markup premia for export entry-exit dynamics. It does this by testing whether or not markups and productivity markedly differ within the exporting group of producers. In particular, it is of interest to determine if there exists a specific behavioural pattern of markups and productivity for export entrants and quitters to inform both international trade theory and trade policy. For instance, results on export entry contain information about self-selection of more productive firms that breakthrough into export markets and gain market share through the reallocation channel. Information on export quitters may contain efficiency losses due to adverse market conditions leading to increasing marginal costs induced by falling demand, information asymmetries, negative externalities, and/or higher transaction costs. The empirical model taken to the data is

$$ln(\hat{\mu}_{it}^{m}) = \lambda_0 + \lambda_1 Entry_{it} + \lambda_2 Exit_{it} + \lambda_3 Always_{it} + Controls + \upsilon_{it}$$

and

$$ln(\widehat{\omega}_{it}) = \alpha_0 + \alpha_1 Entry_{it} + \alpha_2 Exit_{it} + \alpha_3 Always_{i} + Controls + \upsilon_{it}$$

where the binary explanatory variables are $Entry_{it} = 1$ if a firm enters the export market and zero otherwise, $Exit_{it} = 1$ if a firm exits the export market and zero otherwise and $Always_{it} = 1$ if a firm is a perpetual exporter over the sample period and zero otherwise. The constant terms, $\lambda_0$ and $\alpha_0$, capture the respective average log markup and productivity for nonexporters including plants that become export entrants and firms that have stopped serving foreign markets. The parameters on the $Entry_{it}$ dummy measure firm markup and productivity percentage difference between pre- and post-entry periods. Similar effects are identified in the case of export quitters. Finally, the coefficient on

[10] The percentage change is computed as $\frac{X_2 - X_1}{\frac{1}{2}(X_2 + X_1)}$ for reasons explained in Davis and Haltiwanger (1992).

the dummy for perpetual exporters measures the markup and productivity difference for firms exporting throughout the sample period, and is expected to be positive. As before, controls include; *inter alia*, industry-year effects. We also estimate the firm performance effects from entry, exit and continuous exporting. That is, the inferred productivity and markup-level effect from export entry is $\widehat{\omega}_{it} = \alpha_1 exp^{\alpha_0}$ or $\hat{\mu}_{it}^{m} = \lambda_1 exp^{\lambda_0}$. Both the percentage differences and implied performance level effects are reported in table 9

Table 9: Impact of Export Participation on Productivity and Markups

| Dependant Variable | Export Entry Effects | | Export Exit Effects | | Continuous Export Effects | |
|---|---|---|---|---|---|---|
| | Percentage | Level | Percentage | Level | Percentage | Level |
| Productivity | .0164 | .06 | .1502** | .52 | .1005*** | .34 |
| | (.0553) | | (.0513) | | (.0184) | |
| Markups | .5589* | 1.57 | .4821* | 1.35 | .3697*** | 1.04 |
| | (.2366) | | (.2224) | | (.0901) | |

Legend: *p<0.05; **p<0.01; ***p<0.001

First, the export entry columns infer insignificant percentage difference between the productivity of nonexporters and export entrants. The table reports productivity of newly exporting firms as 1.62% with a significant percentage difference of 55.89% between average markups of nonexporters and new exporters as well as substantial export markup premium of 1.57, after controlling for productivity. These are firms almost at the point of indifference between exporting and serving only the domestic market but decide to break into foreign markets and charge high prices. Therefore, although insignificantly productive relative to producers for the domestic market, export starters still had significantly high price-cost margins in foreign export markets. This confirms the accepted regularity that export entrants are more productive than manufacturers for the domestic market. Here it may be that a few starters had their total factor productivity (TFP-GMM) distributed marginally higher than the threshold cut-off point separating exporters from nonexporters. One potential explanation for this is that export starters may have behaved ‘as if’ operated in a contestable export market. That is, it may be that industrial strategic firms in the customs union failed to offer competitive prices to consumers to prevent hit-and-run rivals induced by ‘costless’ export market churning. This would be the case even in the context of the proximity-concentration of the Brainard (1997)-type model, given the proximity of Eswatini’s industrial sector to the richest South African Gauteng Province where multinational firms are concentrated. Second, marginally productive starters may have self-selected into foreign markets as in Melitz (2003) by capturing the market share of export market quitters.

Second, effects of exiting firms in the next pair of columns similarly show a significant percentage difference of 15.02% between the TFP-GMM of producers for the local market and quitting exporters; albeit, with significant but relatively lower export markup premium than for new exporters. These are not firms that necessarily stopped exporting because their efficiency levels dropped below the

minimum cut-off point of productivity. Normally, export quitters are associated with bad performance outcomes relative to nonexporters. Such quitters naturally include firms characterized by low TFP, low labour productivity, low employment growth and more (see Bernard and Jensen, 1999). This may not be the dominant feature of our data. Instead, high productivity foreign subsidiaries in Eswatini ceased exporting because they relocated to the larger South African market with endogenous and tougher competition in order to; *inter alia*, enhance their scale economies. Endogeneity of competition in this sense arises from firm level decisions concerning the choice of products to sell, markets to serve or even endogenous product differentiation to confront import competition, see Fieler and Harrison (2018), Hoberg and Phillips (2016) and Gampfer and Geishecker (2015).

Finally, continuous exporters also experienced significant export premia with much stronger confidence level relative to the other classes of exporting. However, these firms exhibit lower magnitudes of export premia due to their production cost advantage relative to export exit margins. Just like export quitters; continuous exporters are able to charge lower prices due to their higher levels of production efficiency relative to nonexporters, holding the elasticity of demand for material input constant. These are largely long-term exporting firms that withstand negative shocks to profitability just to avoid incurring sunk costs of export market re-entry. Sunk costs arise from the need to gather new foreign market intelligence, upgrade product quality to enhance competitiveness through product differentiation, repackage products to meet buyer requirements, and establish new marketing channels. Robert and Tybout (1997) show that these costs do weigh heavily on export producer decisions and therefore generate hysteresis in foreign trade, and Das *et al*. (2007) quantify the magnitude of these sunk costs for three Colombian industries.

### 5.5.3. The Decision to Enter and Exit the Foreign Export Markets

This section delves straight into discrete choice modelling and estimation of export market entry/exit dynamics involving industrial firms to understand the effects of productivity and markups separately on firm turnover in foreign markets, if any. Our attempt is to answer questions about causality running separately from endogenous markups and idiosyncratic within-firm efficiency to the churning of firms in export markets. Does a firm's probability to export increase when either the markup price for its export product goes up or because of efficiency improvements? Does the probability of foreign market exit decline due to a fall in the markup of its export product or a deterioration in efficiency?

To respond to these issues, it is crucial to provide precise definitions of entrants and quitters to allow for the dissection of the dataset into two groups consisting of new exporters and export quitters. A firm is viewed as a foreign market entrant if its previous export sales were zero and positive

at $t$,whereas it is classified as exiting if its exports were positive at time $t-1$ and zero at $t$.[11] The decision to enter or exit foreign export markets is therefore determined by a discrete choice setting as

$$\begin{cases} X_{it}^{Entry/Exit} = 1 & if \quad X_{it}^{*} > 0 \\ 0 & \text{Otherwise} \end{cases}$$

where $X_{it}^{Entry/Exit}$ is an indicator variable that equals one if a firm enters or exits the foreign export market. $X_{it}^{*}$ is an unobserved latent variable inferred from firm churning in export market participation through either productivity or markups together with controls. The binary choice formulation of the problem given the present definitions of firm entry and exit can be estimated in a number of ways. This choice depends primarily on whether productivity and/or markups are recorded as continuous or categorical variables and/or whether the explanatory variable(s) are endogenous. For example, both variables can be assumed endogenous and it can be of interest to construct markups into a binary variable distinguishing markups as those that are greater than unity or markdowns otherwise. For purposes of this analysis; however, productivity and markups are treated as continuous variables scrutinised using probit methods of investigation and their average marginal effects on export market entry/exit changes reported in table 10.

The separate impacts of productivity and markups are statistically insignificant in the export market churning of firms. Instead, the average marginal effects with respect to sample years for export market entry/exit dynamics are significant and bounded between [-1.89, -1.53] across specifications. Actual values of these aggregate effects per model oscillated around a negative and diminishing mean over the sample period. This means these effects increased in absolute terms. Furthermore, post-estimation results generated estimates of the probability of firm entry/exit into export markets where this is expressed as the $\text{prob}\left(x_{it}^{Entry/Exit} = 1 | \widehat{\omega}_{it} \; or \; \widehat{\mu}_{it}^{m}\right)$. The probability of firms breaking into foreign export markets was 22.37%, after controlling for productivity. Otherwise, it decreases marginally to 21.57% when markups are controlled for instead. Clearly, the rate at which firms break through into export markets is in the same order of magnitude with the rate of exit from export participation. These results are robust to controlling for markups or producer efficiency.

Table 10: Firm-Level Average Marginal Effects of Export Market Entry and Exit

| | $X_{it}^{Entry} = X_{it}^{*} > 1$ | | $X_{it}^{Exit} = X_{it}^{*} > 1$ | |
|---|---|---|---|---|
| | dy/dx | dy/dx | dy/dx | dy/dx |
| $\widehat{\omega}_{it}$ | -.0162 | | -.0028 | |
| | (.0190) | | (.0189) | |
| $\hat{\mu}_{it}^{m}$ | | .0007 | | .0008 |
| | | (.0006) | | (.0007) |
| $l_{it-1}^{pe}$ | .0004 | -.0122 | -.0174 | -.0089 |

[11] This definition can be modified to capture sunk-costs as constructed by Roberts and Tybout (1997) and Bernard and Jensen (2004).

| | | | | |
|---|---|---|---|---|
| | (.0238) | (.0092) | (.0239) | (.0094) |
| $k_{it-1}$ | .0049 | -.0059 | -.0072 | -.0073 |
| | (.0133) | (.0090) | (.0132) | (.0091) |
| Year Effects | ✓ | ✓ | ✓ | ✓ |
| prob $\left(x_{it}^{Entry/Exit} = 1 \mid \widehat{\omega}_{it}\ or\ \widehat{\mu}_{it}^{m}\right)$ | .2237 | .2157 | .2263 | .2185 |
| Correctly Classified | .8221 | .8373 | .8194 | .8345 |
| McFadden's Adjusted $R^2$ | .1250 | .1600 | .1480 | .1670 |

Legend: *p<0.05; **p<0.01; *** p<0.001

Our confidence in these results derives from an assessment of the goodness-of-fit of the estimation model which cannot be rejected by the Hosmer-Lemeshow $\chi^2_{358} -$ test statistic and reports a correct classification of at least 81.94%. To complement this measure, a statistic estimating the explanatory power of the model needs to be identified. One such statistic is the popular pseudo $R^2$ for probit and logit models. It is computed as one *minus* the ratio of net full-model log-likelihood and number of $k$ predictors in the model to the intercept-only log-likelihood. In our model, the pseudo $R^2$ adjusted for predictors explains at least 12.5% of the variation in firm dynamics in export market entry after controlling for productivity; and increases to 16% when markups are controlled for instead. Again, similar results obtain in the case of export market exit. This implies that the patterns of average marginal effects of firm performance on market entry/exit dynamics can be trusted.

## 6. Discussion of Results and Potential Transmission Mechanisms

The primary goal of this study involved the consistent estimation of firm-level production functions to extract unobserved productivity and markups. This allowed us to determine 1) estimates of markups using elasticities of freely adjustable variables and their expenditure to revenue, 2) the impact of endogenous markups on productivity, 3) markup and productivity premia for exporting producers, and 4) the separate impact of markups and productivity on firms' decisions to enter or exit foreign export markets. To achieve this, one clearly relied on the production rather than the demand approach due to market and/or consumer data constraints.

There are two main firm-level performance measures that have been quantified; namely, the markup estimated as $\hat{\mu}_{it}^{v} = \hat{\beta}_{v}\left(\frac{P_{it}^{v}M_{it}}{P_{it}Q_{it}}\right)^{-1}$ and productivity (TFP-GMM) estimated as a Solow-residual of a production function. The chosen markup is defined in terms of $v =$ intermediate inputs. Thus, this measure increased around the average of 1.3[12]. Interestingly, the average of its time series median was estimated at 1.4 and therefore higher than the cross-sectional average reported above. The meaning of this is that the distribution of markup growth is left heavy-tailed, with more firms raising their product prices at a lower rate. These increases in markups are nonetheless not synonymous with increases in

[12] This compares well with the 1.5-1.7 markup from the US beer industry measured using both the production and demand approaches, see De Loecker and Scott (2017).

market power. Market power is only one of many and varied reasons why a product's markup may increase. These include; *inter alia*, a decline in the marginal cost of the product, a surge in its demand or increase in its elasticity, a shift from competition towards a monopolistic market structure, firms taking advantage of their high productivity to charge higher prices, a favourable foreign trade agreement involving the product, and robust changes in spatial and vertical product differentiation[13]. Any of these forces may be dominant in one industry and weak or non-existent in another.

For ease of analysis and market segmentation for these industries, two types of markets are identified: the regulated and free world markets. It is conceivable that a product may enjoy foreign market access in different market segments and implement pricing-to-market strategies according to the Atkeson and Burstein's (2008) model, except in this case the pricing formula is agreed upon in advance. As a way of illustrating the point through performing some back-of-the envelope calculations, we consider of the most dominant foreign exchange earning manufacture, the ISIC D1542: sugar product. The sugar industry has the typical characteristics of a commodity traded in controlled markets and in the more volatile world market. Sugar exports to the Europe Union, the US, and SACU markets enjoys different but high prices based on trade agreements that are conditioned on product quality. However, these producer benefits may be eroded by adverse exchange rate movements. Table 11 reports an example of a 12-month pricing regime abroad for Swazi sugar from 2000-2001. In this period, the sugar product captured 9.1% market share under the sugar protocol compared to other African, Caribbean and Pacific (ACP) producers.

Table 11: Prices in Different Sugar Markets in Emalangeni: February 2000 to February 2001

| Market | February 2000 | | February 2001 | |
|---|---|---|---|---|
| | Price/Ton (E) | Index (W=100) | Price/Ton (E) | Index (W=100) |
| EU-SP | 3 073 | 541 | 3 600 | 246 |
| EU-SPS | 2 572 | 453 | 3 011 | 206 |
| US-TRQ | 2 211 | 389 | 3 426 | 234 |
| SACU | 2 001 | 352 | 2 169 | 148 |
| World | 5 68 | 100 | 1 463 | 100 |

*Note*: EU-SP denotes the European Union-Sugar Protocol, EU-SPS is the European Union-Special Preferential Sugar, US-TRQ means the United States-Tariff Rate Quota, and SACU refers to the Southern African Customs Union.
*Source*: Matsebula (2001), A Report on '*Markets for Swazi Sugar: Patterns, Challenges and Strategic Considerations*'.

Since the manufacturing production technology uses product revenue divided by industry deflator, then for the EU-SP in 2000, the revenue is E3 073 x 117 844.5 tonnes sold divided by the industry deflator. This would then be consistently regressed on inputs specifically dedicated to the production

[13] The evidence of spatial product differentiation is found in Foster *et al*. (2008) who study a homogeneous set of manufactured products, and Bronnenberg *et al*. (2006) and Bronnenberg and Dubé (2017) provide a survey on geographic distribution of consumer goods' shares and market structure in the US. Both studies note the presence of a strong and persistent supplier-buyer relationship capital that acts as an entry deterrent to new producers and the latter papers also document significant concentration, size and persistence of brand product market shares.

of this revenue and allow us to estimate the associated productivity. Thus, within-industry price heterogeneity will be embodied in producer revenues and TFP-GMM productivity shocks. Therefore, the markup for sugar will increase if its demand elasticity increases, the price of the freely variable input declines, and both the Euro and US$ exchange rate movements are favourable.

The residual sugar that cannot be absorbed by either the domestic or regulated foreign markets is shipped to the more volatile world market. Again, the estimation of the production function and markup estimation follows the same process. This low-priced market can offer prices lower than the marginal cost for some producers. To capture this market and remain profitable, vertical product differentiation is emphasised for sugar seeing that world-market buyers show a willingness to pay for higher quality, see Matsebula (2001, former CEO of the Swaziland Sugar Association). Similarly, although not directly investigated, there is also anecdotal evidence of structural state dependence in consumer choice induced by long-term first mover advantage and characterized by a high-order Markov process in sugar, see Dubé *et al*. (2010) for similar arguments on consumer packaged products. This degree of inertia in brand choice by buyers is potentially prevalent in the sugar industry.

The significant impact of markups on TFP-GMM when material input is free of adjustment costs is consistent with theoretical models of heterogeneous productivity and variable markups such as Eckel and Neary (2010) and Melitz and Ottaviano (2008). In these models, more productive firms do leverage on their high productivity performance to charge high markups. This is more pronounced when one looks at the impact of export product markups which are even higher than those of a typical product. That is, export producers used their superior productivity to capture higher markup premia in foreign markets. Under conditions of quality constraints for exporters, Hallak and Sivadasan (2009) also find US, Indian, Chilean and Colombian data that exporters sell products with high quality appeal and therefore charge high prices using data from.

However, a persuasive argument is presented by Katayama *et al*. (2009) and Foster *et al*. (2008) concerning the measurement of the dependent variable in the empirical model. For example, a firm with a high revenue-based measure of productivity (e.g. our TFP-GMM) and/or high quality product as the sugar industry may face a fairly low demand elasticity due to its larger market share. Such a scenario is probable in Cournot competition involving homogeneous products as in Foster *et al*. (2008) or under Bertrand competition based on product differentiation or even under a constant elasticity of supply (CES) demand system of the Stiglitz-Dixit type, see Katayama *et al*. (2009). This firm is likely to charge a higher markup and remain perceived as productive just like in the case when the dependent variable is measured using physical output. The literature is awash with this property, see Bernard *et al*. (2003) who link producer quality with markups in a contestable market environment, and Berry (1994) for his characterization of market equilibrium.

We now take the analysis a step further from the causality study between the performance indices of firms to determine export productivity and markup premia derived from using cross-sectional and time series data. More specifically, it seeks to find out if exporting is associated with high performance and if performance changes with export participation, holding measurement issues in relation to productivity constant.

Regression equations of markups and productivity on an export dummy are run separately using the cross-sectional data. This is not intended to establish causality but rather the degree of association between the variables of interest. The export dummy has a significant relationship with both markups and productivity. In the case of the markup, the method controls for productivity since prices are embodied in TFP-GMM. Although the price effect is insignificant in the control variable, it does marginally reduce the magnitude of the export dummy coefficient without altering its significance level. A similar outcome is obtained when regressing productivity on the export dummy and controlling for markups. However, the export dummy parameter adjusts upward without affecting its significance level. This accords with findings in the vast literature that exporters are more productive and charge higher markups, see Bernard and Jensen (2004) for empirical results on US data and Bernard *et al*. (2003) for a theoretical rendition.

Looking at export participation in relation to firm performance in markup and productivity dimensions explains the separate roles of export entry, exit and continuity. Put differently, given the level of data disaggregation, it is feasible to determine export premia enjoyed by firms from markup pricing and high productivity. As shown in the analysis sections, this study documents significant premium performance in markups and productivity for both the export entry/exit dynamic and continuous exporting.

To explain this result; it is useful to observe the presence of market constraints associated with the size of the domestic economy, its land-locked nature, and its high degree of openness to commodity-based trade. Under progressive trade liberalization in the Southern African Customs Union (SACU) since 1994, local producers had to contend with import competition while maintaining their presence in other market segments. It became necessary to increase imports of high quality intermediate inputs in order to produce high quality products and make *competitive* sales in the region. As demonstrated in models by Bastos *et al*. (2018) and Kugler and Verhoogen (2012), this vertical differentiation provides firms with the competitive edge required in a trading environment consistent with Bertrand competition with limit pricing and/or market contestability. That is, new multinationals in SACU could not fully exploit their ‘monopoly’ power for fear of new entrants who would either under-cut their prices or engage in a hit-and-run activity given the relatively free entry and exit. Additionally, as in Peters (2018), Schumpeterian principles of creative destruction present the likelihood that firms may desire to acquire market power by investing in productivity to raise markups. However, while

some of these firms may get stochastically displaced by the more efficient producers; others may be unable to accrue the kind of market power that generates supernormal profits since a faster rate of churning allows firms only a limited time to do so. The effect of all this is markup variability that responds to export dynamics. The relationship between firm performance and export participation is not confined to the SACU market. It also carries over to both non-reciprocal guaranteed and open markets for Eswatini's export products. This might suggest that firm-level performance actually drives the decision to enter/exit export markets for these products. However, a deeper analysis indicates otherwise.

A probability analysis of extensive export margins after controlling for firm performance produces results showing that the decision to export or exit is not influenced by the level of productivity or perceptions about product prices in foreign markets. Instead, firms may have entered the export market because the alternative of becoming a domestic producer had no premium of any kind. Similarly, the probability of quitting shows no relationship with firms' own performance. A significant and continuously strengthening negative impact of *time* on the decision to either export or exit was evident. This reflects the growing uncertainty about the potential impact of trade liberalization and the difficulty of incurring new sunk costs of foreign market entry as indicated by Edwards *et al*. (2013).

## 7. Conclusion

This paper sought to estimate markup pricing patterns and their impact on measured producer efficiency in manufacturing. A supplementary aim was to determine the relationship between a firm's performance in markups and productivity, and export market participation. It has used the production in lieu of demand approach to estimate micro-level markups and productivity. To do this, it relied on proxy methods combined with the Blundell-Bond GMM approach to estimate consistent elasticities of the production technology and performance indices. Given the conventional alternative uses of labour and intermediate inputs in the Olley-Pakes/Levinsohn-Petrin control functions, a data-driven choice between the two inputs for inference was rigorously pursued. Finally, the study focussed on the investigating the presence of export premia and whether or not the probability of foreign market entry and exit was influenced by product markups and productivity at the firm.

The findings of the analysis are that, first and foremost, markups estimated using the production approach bear similarities with those computed from demand data in the literature. These indices are also are characterized by significant patterns of variability as shown in several measures of entropy. The high cost of labour adjustment and potentially other labour market frictions appear to have removed the normally assumed its static nature as a variable input such that labour-based markups have -0.2 correlation with material-based ones instead of approaching equality. Bootstrap methods conclusively demonstrated that the labour-based coefficient on the markup is negative. However, this

significance is only marginal; hence, our choice of using the normally behaved material-based markups. We find that the impact of material-based markup on productivity is significantly positive while material-based export markups have magnification effects induced by export premia.

Although firm-level performance in markups and productivity have no effects on the firm's decision to break into or exit from foreign export markets, individual components of export participation produce significant export premia for firms. Export entry effects on productivity are insignificant but only slightly significant on markups, yet large in absolute value. That is, new exporters are located at the threshold productivity for breaking into exports. Quitting exporters are dominated by the most productive firms with a modest markup premium. These are firms that emigrated to the trade liberalizing economy within SACU to enjoy economies of scale. Similarly, continuing exporters are productive and have access to significant export premia.

This study focussed on firm performance and the dynamics of export participation in the manufacturing sector, which precludes a more complete aggregation of micro-effects to economy-wide results. The next area of research involves market power and profitability across all sectors of the economy to derive macroeconomic outcomes. The second area of interest combines the demand and production approaches to separate out price, scale, and productivity effects.

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