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Reallocation, Firm Dynamics, and Productivity Growth: Evidence from Eswatini's Manufacturing Sector[1]

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Abstract

This article investigates the contributions of real productivity, firm-size rationalization, and net-entry effects to aggregate labour productivity (ALP) growth using a panel dataset from Eswatini's manufacturing sector. It compares these results with what obtains in world economies at different stages of development. After controlling for extreme values, it found a persistent annual average increase of 2.67% in real productivity. The sector also experienced labour reallocation gains of 0.26% from incumbents and suffered losses of 0.43% from the entry/exit margins. Thus, within-firm effects dominated the intensive and extensive forms of labour input reallocation *a fortiori*. Further, the cross-sectional distributions of up-to the fourth-order moment of labour shortages were used as sources of exogenous variation in endogenous aggregate employment growth when estimating the impact of the latter on reallocation. The first-order moment was strongly associated with changes in aggregate employment growth while higher-order moments had insignificant effects. In contrast, the reshuffling of labour among incumbents and across sectors was robustly unresponsive to variations in aggregate employment growth. However, a unit percentage point increase in aggregate employment growth from a Two Stage Least Squares (TSLS) estimator inversely varied with net-entry effects at the rate of $\hat{\beta}^{TSLS} \epsilon$(-0.976, -0.926), depending on model specification

JEL Classification: J24, L6, O47.

Keywords: Firm-Level, Productivity, Reallocation, Entry/Exit, Frictions, Panel Data, Eswatini.

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1. Introduction

This paper decomposes and quantifies aggregate labour productivity (ALP) growth using an unbalanced panel dataset from Eswatini's manufacturing sector. It also determines the impact of endogenous aggregate employment shocks on plant-level and sectoral labour reallocation. While achieving the first goal is quite straightforward, the second goal requires identification of exogenous sources of variation in aggregate employment growth to estimate its impact on granular and aggregate labour reallocation. Nonetheless, the notion of aggregate employment growth taken as a function of the difference between the desired and actual number of workers has become folklore wisdom since Caballero and Engel (1993) and Caballero et al. (1997). Faced with employment shortfalls; for instance, the firm-level response mechanism is founded on the employment adjustment-hazard function (also known as the probability of adjustment). Hence, lumpy employment gaps and the microeconomic process of closing these gaps lead to the creation of a fundamental basis for labour adjustment frictions. One outcome of this is the cross-sectional distribution of input gaps *a priori* driving changes in aggregate employment growth which, in turn, causes variation in cross-plant and sectoral labour reallocation.[2]

The renewal of interest in studies of productivity growth is premised on its character as the vital engine of economic growth and a catalyst for the social welfare of economies through increased per capita incomes (Calderón, 2021). It is important therefore to understand the mechanics behind its measurement, characterization and distribution. The contemporary folk knowledge is that the efficiency with which an economy adopts new production methods and uses its inputs, and the efficiency with which inputs are reallocated across producers, make the difference between successful and unsuccessful economies. Plants that introduce superior innovative technologies in the production of goods and that rank high in management practices and stock of intangible resources tend to grow and contribute significantly to industry productivity growth.[3] In contrast, plants that rely on obsolete production technologies and low management efficacy tend to shrink and/or exit the industry thereby relinquishing their market shares to prosperous incumbents and entrants. Although firm failure occurs at a high cost for individuals, a rapid increase in the speed of plant entry, survival, contraction and exit still defines a desirable state of business dynamism.

[2] Osotimehin and Pappadà. (2017), among others, consider the role of credit constraints in relation to the cleansing effects of recessions where unproductive plants shrink and exit while efficient ones expand and prosper. We thank a referee for this point, which we will pursue further in future.

[3] There is no distinction between the words firm, plant and establishment in the dataset. This paper interchangeably uses terms within-firm effects/real productivity as well as between-firm effects/input reallocation/rationalization effects, respectively. In all our work, we follow the ingenuity of Foster et al. (2008) who reserve technical efficiency for Total Factor Productivity (TFP) based on physical-output production technology.

Models of Darwinian reshuffling of input resources across firms view industries as an assortment of heterogeneous-productivity plants that connect micro production efficiency to micro performance and survival. The leading contributions in this genre of work are Jovanovic (1982), Hopenhyn (1992), Ericson and Pakes (1995), Melitz (2003), and Asplund and Nocke (2006). One underlying mechanism in the overall theoretical framework derives from the high degree of productivity dispersion among incumbents, and between entrants and exiting plants, that creates opportunities for the movement of market-shares of inputs from low- to high-activity uses. These models point to selection-driven ALP growth that translates to a production efficiency-survival connection as a driving force behind variability in the trajectory of industry productivity. Thus, barriers to cross-plant share-shifts of inputs promote the coexistence of efficient and inefficient producers, and potentially lead to resource misallocation and reduction of industry productivity growth.

The related empirical evidence documents selection mechanism as a robust characterization of firm dynamics in manufacturing. In the case of southern Europe; for instance, these economies experienced labour productivity slowdown since the 1990s due to capital misallocation (Gopinath et al., 2017). McMillan and Zeufack (2022) studied African countries during the period spanning 1980-2018 and found rapid increase in aggregate labour productivity among large firms in 2000-2018 due to extensive use of high capital-intensity technologies. Goldin et al. (2021) considered advanced economies and found that aggregate productivity growth slowed down post-2004. The slowdown in this case was attributed to mismeasurement, deterioration in capital intensity, sub-optimal transmission of intangible asset benefits, non-robust gains from trade, and underperformance of plants in allocative efficiency.[4]

Our empirical strategy relies on statistical accounting decomposition developed by Baily et al. (1992) (hereafter referred to as BHC) as enhanced by Foster et al. (2001) (hereafter referred to as FHK). Although the BHC approach has been criticised for its inability to produce consistent reallocation results in unbalanced panels, it is used here in order to leverage on its potent properties. For example, the equality involving the FHK-between term *minus* BHC-between term and the BHC-net entry term *minus* FHK-net entry term is a useful accounting identity. Otherwise, this paper uses the FHK method to decompose ALP growth and interpret the results. Further, the insistence of Petrin and Levinsohn (2012) that the change in the aggregation of plant-level factor input expenditure adds up to the change in aggregate final demand allows us to define FHK as such in the ALP growth decomposition.[5] That is, microeconomic details within

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[4] Byrne et al. (2016) and Syverson (2017) do not find evidence to substantiate the mismeasurement hypothesis and discount the role of mismeasurement purported by the literature to explain productivity slowdown in the US post 2004 on conceptual grounds.

[5] Much of the recent literature calculates single-factor or multifactor decompositions using the statistical accounting decompositions or any other approach but in the context of the structural framework developed by Petrin and Levinsohn (2012); see, for example, Nishida et al. (2014), Petrin et al. (2011), and Kwon et al. (2015), among others.

and across plants as well as at the extensive entry/exit margins matter for macroeconomic demand for sectoral output (Baqaee and Farhi, 2019).

A preview of findings points to an increase in the ALP growth over the 10-year period of *de facto* trade liberalization in Southern African Customs Union (SACU). The characterization of the labour market in terms of gross job flows, ALP growth, and the impact of aggregate employment growth on reallocation takes the following form. For the period under review, the gross job creation and destruction were 2.5% and 7.7%, respectively. This means only 1 in 40 jobs was created while 1 in 13 jobs was destroyed annually, on average. Put differently, for every job created, the sector destroyed 3 more jobs every year. The gross job reallocation remained at 9.2% on a year-on-year basis. Similarly, the poor performance of net employment rate recorded an annual decline of circa 5.2%. Such orders of magnitude were at variance with those that obtained in Ethiopia and South Africa in terms of the high-paced churning prowess in their respective labour markets as reported in Shiferaw (2013) and Kerr et al. (2014).

On the other hand, the annual within-plant contribution to ALP growth was circa 2.7% after controlling for outliers; *albeit*, with a significant amount of heterogeneity as measured by the standard deviation of 22.5. A closer look at the distribution of within-plant effects, a multimodal kernel distribution emerges with zero productivity growth as one of the troughs. With cross-plant reallocation of workers, productivity losses of circa -0.12% arising from labour inputs moving from productive to inefficient producers were experienced. Once extreme productivity values are controlled for, the sector experienced ALP gains of 0.26% arising from labour reallocation from unproductive to productive plants. At the extensive margins, entry/exit dynamics contributed 10.8%. This turned into a productivity growth reducing factor of circa -0.43 after controlling for extreme values. Lastly, incumbent firms' reallocation of labour remained unresponsive to aggregate employment growth while entry/exit dynamics reduced resource movement by $\hat{\beta}\epsilon(-0.976, -0.926)$, depending on model specification.

This paper makes at least three contributions to the literature. First, it generates new results on gross job flows and patterns of ALP growth across two-digit ISIC codes and isolates related growth components for a small Sub-Saharan country. In the process, it assesses the relative productivity contributions of within- and between-effects to ALP growth. It also identifies confounding effects that require careful consideration in interpreting productivity indices calculated using statistical accounting decomposition methods. Second, it compares and contrasts the new results for Eswatini with productivity growth components of like sectors in other countries at different times and stages of development. Lastly, it determines the extent to which

An attractive property of the structural decomposition lies in its definition of aggregate productivity growth as the change in aggregate final demand *minus* the change in the expenditures in primary factor inputs, Petrin and Levinsohn (2012).

microeconomic adjustment hazards matter for aggregate employment growth as well as determine the impact of the latter on granular and macroeconomic fluctuations in labour input reallocation.

The next section presents an overview of the manufacturing sector in Eswatini. Section 3 undertakes descriptive analyses of data, paying particular attention to data representativeness and gross job flows. A formal presentation of ALP growth measurement, decomposition and associated discussion are carried out in Section 4. Section 5 presents quantitative determinants of ALP growth, the confounding effects of the BHC measure of reallocation, and a comparative analysis of Eswatini results with those of other economies at different levels of development. It also isolates labour reallocation among incumbent plants as well as within the extensive margins of entry/exit to determine their responsiveness, or otherwise, to aggregate employment growth. Section 6 summarises and draws conclusions.

2. Overview of the Manufacturing Sector in Eswatini

Intrinsic linkages in the economies of Eswatini and South Africa are due to historical ties and geographical contiguity. Both countries share several memberships to regional economic blocs such as SACU and the Common Monetary Area (CMA) under South Africa's dominance since 1910 and 1974, respectively. The South African Rand continues to circulate freely at a pegged ratio of 1:1 with local currency units in the CMA territory. Given the significant structural and economic size differences between South Africa and the peripheral States, the larger trading partner transmits its domestic trade policies and external shock experiences to the rest of the sub-region through the trade channel.

Thus, a brief account of South Africa's historical operating environment that affected the Customs Union (CU) requires recasting in the context of national developments in the smaller economies, particularly its effects on industrial dynamics in Eswatini. During the period 1940-1984, an import-substitution industrialization strategy drove the South African trade policy under a minority political rule.[6] Another critical factor at that time was over-reliance of the South African economy on external capital inflows. The short-term liability involved national debt of 35% of GNP by mid-1985. Soon after the state of emergency declared by President P.W. Botha in July 1985, foreign banks responded to the political and economic uncertainty by declaring an intention not to rollover the short-term loans to South Africa. In addition, there were multilateral economic sanctions imposed on the country in 1985-1987 by powerful world nations coercing it to democratize. These foreign governments pushed their own multinationals located in South Africa to disinvest. It is during this time that Eswatini received a substantial number of more productive foreign firms.

[6] See Levy (1999) for a discussion on the black community as a majority and restrictions concerning their freedom of movement and the type of jobs they could hold.

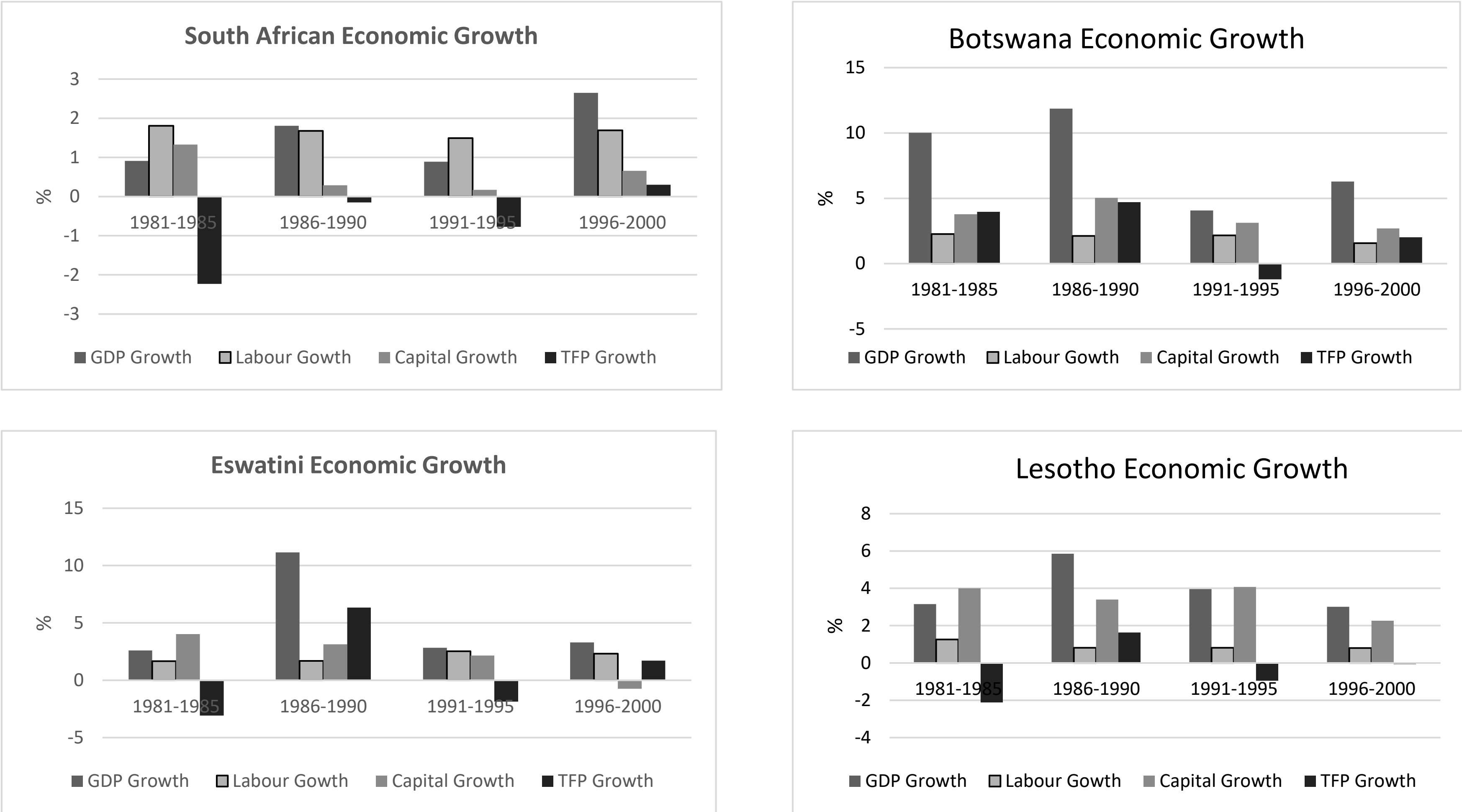
In order to return the country to normalcy after the release of President Nelson R. Mandela from prison, South Africa initiated a unilateral trade liberalization in 1990-1998 and a multilateral trade liberalization in 1995-2002. This trade policy shift meant that SACU states should now charge a Common External Tariff (CET) on imports. It also introduced import-competition with older brands and strengthened the selection mechanism driven by productivity differentials among firms in smaller CU member economies (Jonsson and Sumbranian, 2001). Domestic changes in product demand and heterogeneity in productivity led to demand-driven exit of inefficient entrants and smaller plants as well as contraction and/or exit of high-cost incumbents. As Edwards *et al.* (2013) observe; large local firms faced supply-side constraints such as regulatory restrictions in input and output markets, public policy distortions, and the high-cost of trade and transport of goods. Policy distortions that encumber high productivity firms lead plants to curtail innovation and adoption of new technologies thereby generating an endogenous productivity distribution.

Thus, an assessment of economic growth sources in the CU by Hammouda *et al.* (2010) has identified contributions of changes in production input accumulation and change in total factor productivity (TFP) to measured economic growth. This sources-of-growth identity provides a link between output growth and product quality improvement, product diversification or creative destruction through innovation thereby driving higher TFP. In a Cobb-Douglas production technology, the combination of capital as a function of foreign direct investment (FDI) and labour together with their elasticities and technical progress captured in TFP are important drivers of output growth across all industries. Figure 1 reports contributions of input and TFP to economic growth of SACU member States spanning the period 1981-2000, a subset of economies also studied in Hammouda *et al.* (2010). All economies examined here experienced negative TFP growth in the 1981-1985 and 1991-1995, except Botswana in the latter period.

The real GDP growth performance in the manufacturing sector of the core economy (South Africa) correlates with movements in TFP growth as expected. With the exception of Botswana, GDP growth patterns and component sources of growth in peripheral States vary systematically with changes in the core economy. South African developments connected to the financial and economic crisis of the latter part of the 1980s as well as the subsequent trade reforms of the 1990s largely influenced the economic performance of Eswatini and Lesotho. In the pre-1985 period, the rate of economic growth in Eswatini was 2.61% with negative TFP. FDI inflows continued; *albeit*, at a persistently declining rate. The forces that defined the South African economic trajectory led to a heightened rate of firm closure in that country in spite of their exposure to significant adjustment costs.[7] Some subsidiaries of relatively large, efficient firms landed in the local manufacturing sector mostly during the 1986-1990 period. This raised the sectoral economic growth

[7] Levy (1999) cites one observer as having said, "Many disinvesting companies simply sold their assets cheaply to local white businessmen, but maintained non-equity links such as franchises, licensing, and technology agreements that permitted them to keep operating".

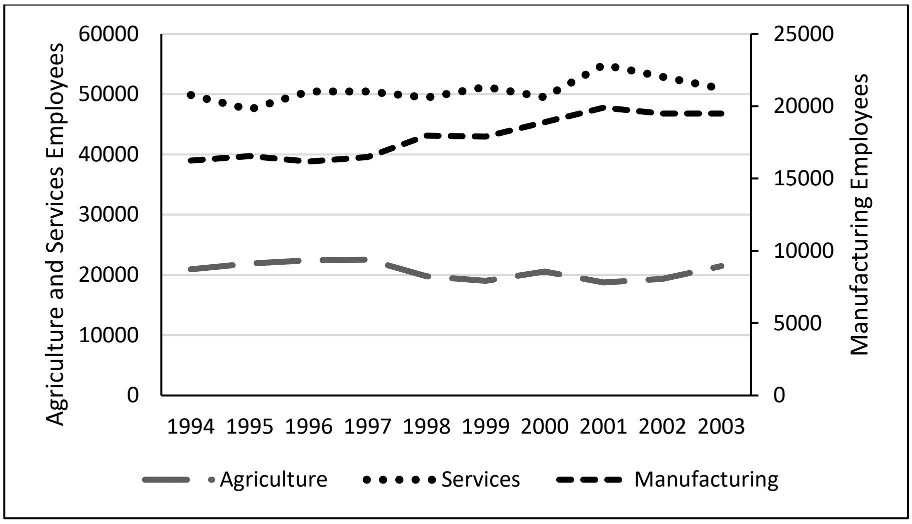
rate to 11.5% through TFP and capital contribution of 6.34% and 3.13%, respectively (Hammouda *et al.*, 2010). Surprisingly, the labour contribution to economic growth appeared to be stable the entire time with only a modest increase in the early 1990s. The local economic growth continuously weakened in the subsequent periods owing to the persistent deterioration in FDI inflows.



Source: Author Using Data from Hammouda *et al.* (2010).

Figure 1: Growth Accounting for SACU Member Countries (1991-2000)

Market economies and emerging markets face deindustrialization where the manufacturing sector is either moving towards technically intensive industries and shedding off the workforce or, possibly for developing economies, simply run out of industrialization opportunities (Rodrik, 2016). Trade liberalization had differential effects in the nations belonging to the same economic bloc in Sub-Saharan Africa. For example, although tariff cuts in Botswana had no significant effects on industrial labour attrition, instead labour expansion in the informal sector and self-employment was observed (McCaig and McMillan, 2019). The largest trading partner of Eswatini, South Africa, experienced labour contraction in both formal and informal sectors, including the manufacturing sector. This happened without any transitions from formal employment to informality; *albeit*, at the backdrop of rising unemployment (Erten et al., 2019).



Notes: Paid employees include part-time, temporary and seasonal workers. The scale for the Manufacturing sector is on the right of the diagram while Agriculture and Services are reflected on the left.

Source: IMF Country Reports 99/13, 00/113 and 06/109.

Figure 2: Paid Employees across Major Sectors

Figure 2 presents the distribution of paid workers for the Agricultural, Manufacturing and Services sectors at Eswatini spanning the *de facto* trade liberalization episode running from 1994 to 2003. Although Agriculture and Manufacturing largely co-trended in the annual size of employment, they respectively grew by 18.2% and 2.6% while the Services sector grew by 2.1%.[8] The latter two sectors had the highest employment levels in 2001, coinciding with accession to AGOA privileges. In Agriculture, farmers enjoyed

[8] The measure of sectoral labour growth is based on Davis, Haltiwanger and Schuh (1996); i.e., Growth=$\frac{X_{it}-X_{pt-1}}{0.5(X_{it}+X_{pt-1})}$, where X_{it} denotes employment level by firm i at time t.

good rainy seasons in 1996-1997 and were able to increase farm workers. However, the commencement of long spells of drought from 1998 led to perpetual labour reduction in the sector.

These aggregate employment variations occurred in an environment of an already high and increasing informality with (min-max) = (159 000, 170 000) in 1998 and 2001, respectively.[9] This is consistent with the South African case of no labour movement from formal employment to informality, but displaced workers withdrew from the labour market to become self-employed or unemployed. A notable observation is that the unemployment rate increased from 22% in 1996 to 31.6% in 2001. Furthermore, there also exists very strong anecdotal evidence that a significant percentage of skilled labour migrated with some of the multinational firms back to the South African larger market post-1994 to benefit from economies of scale.

3. Descriptive Analysis of the Panel Dataset

3.1. Data Description and Representativeness

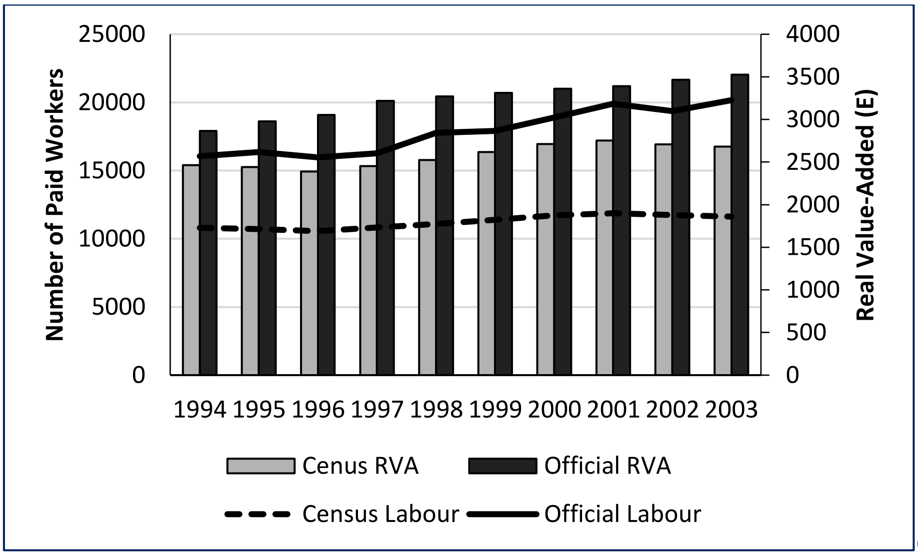
The unbalanced panel dataset used in this study spans the period 1994-2003 and is sourced from the Central Statistical Office (CSO) of Eswatini. It contains; *inter alia*, information on sales revenue, cost of material inputs, paid employees, working proprietors, unpaid family members, salaries and wages, expenditure and sales of different types of capital investments; and the cost of electricity, fuel and water.

There are two data collection instruments. One instrument focuses on firms with significant output contributions in their industry. This time-variant firm-size threshold is however not reflected in the database. The instrument itself essentially captures larger firms by design. In cases of nonresponse, the intensity of the follow-up exercise by authorities is also firm-size dependent. Hence, the probability of a firm's inclusion in the survey increasingly correlates with its scale of operation. Furthermore, a firm can appear in this type of the database at one time and disappear at another time due to output falling below the chosen threshold in a given year or due to entry/exit dynamics. Another instrument gathers information from the rest of the other firms in each industry, including those that fall below the output threshold. Thus, this latter group of plants contains plants that fall out of the large-firms' radar due to shrinking output and those that belong to the micro, small and medium enterprises (MSMEs) category. This group of plants also crosses over the output threshold to join the high output firms. Unless the apparent churning process is an outcome of entry/exit dynamics, all affected plants remain traceable in the dataset through their identity codes. A direct macroeconomic and producer-level comparative data analysis in Figure 2 shows moment distributions that are symptomatic of sample unrepresentativeness of the target universe of firms. Figure A1 in the Appendix, further presents a pattern of firm-size distribution that reflects an annual number of producers ranging from 100 to 188 in 1994 and 2002 employing 17 260 and 32 219 workers, respectively.

[9] Data scarcity prevents any direct analysis of transition by displaced workers

These patterns are also a result of data cleaning that required the purging of firms with zero sales revenue, zero employees or zero material inputs resulting in data loss of circa 0.03% of firms.

The object of this piece is to quantify ALP growth and its component drivers as well as to parametrically measure the effects of employment adjustment hazards on labour reallocation and net entry margins. It is therefore pertinent to transform the related data into a representative sample to consistently approximate the production technologies of the firm population across sectors. As observed earlier, the nonresponse rate inferred from the distribution of firms is conceptually not a feature of firms missing at random. The series terms such as inputs and output in whatever form cannot therefore yield unbiased moments of the target population of firms. This situation accords with basing the sample selection process on conditioning variables such as observable plant-level annual revenue and employment levels. For instance, Wooldridge (1999) suggests using inverse probability weighting (IPW) schemes in sampling units of analysis to recover the required population moments from selected survey samples. For example, the inverse correlation between nonresponse and firm-size distribution gives good reason for reweighting labour and real value-added by $\left(\frac{Paid\_Labour_{it}}{Paid\_Labour_t}\right)^{-1}$ and $\left(\frac{Revenue_{it}}{Revenue_t}\right)^{-1}$, respectively (Wooldridge, 2002; and Solon et al., 2015).



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Note: Data on official real value-added (RVA) and official labour come from the IMF Annual Country Reports and the World Bank Indicators. Census RVA and census labour come from the Annual Census data supplied by the CSO of Eswatini. The census labour variable constitutes Paid Employees while the census RVA is transformed using the double-deflation procedure suggested by Bruno (1978) and applied by; *inter alia*, Nishida *et al.* (2014).

Source: Author's Calculations from Inverse Probability Weighted CSO Data

Figure 3: Representativeness Determination of Firm-Level Data for the Manufacturing Sector

The dataset is supplied without information on product prices and physical quantities of product varieties. Instead, it contains sales per product distinguished according to export and/or domestic markets. In order to deflate the nominal sales revenue, it is inevitable to use the manufacturing value-added deflator

(MVADEF) taken from the World Bank Indicators (WBI). These deflators include the fixed asset deflators for capital assets, new capital investments, and the manufacturing value added (MVA) deflator for output and material inputs. Double-deflated value-added output (RVA): The value-added (va) output is measured as the sales' revenue less cost of sales. Real value-added is therefore va divided by MVADEF and multiplied by 100; i.e., $\left(\frac{va\ x\ 100}{\text{MVADEF}}\right)$. Bruno (1978) argues that this quantity yields value-added production technologies with partial derivatives that correctly measure the marginal productivities of factor inputs if each intermediate input satisfies certain conditions. One of such conditions is that the gross-output production technology must be separable in both factor and intermediate inputs.

Benchmarking the panel dataset against official information provides a platform for the assessment of data quality and integrity. Figure 3 reports official real value-added output and paid employment as well as equivalent census variables. The official real value-added output follows a marginally rising trajectory until 1997 where the speed of output increase slows down. It is not clear why the official output series is invariant to known domestic industry shocks and changes in regional policy regimes.

Looking at the comparator census real value-added output shows a rather volatile pattern that correlates with both domestic and exogenous economic shocks. First, the series begins with a large gap when measured against the related official series and narrows significantly in 1998/1999. This is likely an outcome of two factors: the fixed asset sale between two large firms in the Woods and Pulp industries as well as the effects of the 1994-1998 Unilateral Trade Liberalization and the 1995-2002 Multilateral Trade Liberalization episodes in South Africa. Second, the output rise in 2001 coincides with the country's admission into the African Growth and Opportunity Act (AGOA) for preferential market access to the US affecting the Textile sector. However, it remains hard to explain why the workforce in the panel data is always higher than official employment, which is quite dramatic in 2001-2002.

3.2. Measurement of Gross Job Flows

This subsection calculates and document measures of firm-level heterogeneity in employment variation at low frequency over a 10-year period. More specifically, these heterogeneity considerations entail gross job creation, gross job destruction, gross job reallocation, and employment growth computed using the nomenclature in Table A1 in the Appendix and reported in Table 1. For the period under review, gross job creation and destruction are 2.5% and 7.7%, respectively. This means only 1 in 40 jobs is created while 1 in circa 13 jobs is destroyed every year, on average. Put differently, for every job created, the sector destroyed 3 more jobs annually. Gross job creation comes from entrant firms and expanding incumbents whereas gross job destruction is generated through firm exit margins and contracting incumbents. Gross job reallocation, which is the sum of gross job creation and destruction, was just above 9% on a year-on-year basis. Similarly, the difference between gross job creation and destruction employment, also known as the net employment rate, fell by circa 5.2% annually.

Table 1: Gross Job Flows (1994-2003)

Year	Job Creation (JC)	Job Destruction (JD)	Job Reallocation (JR)	Net Reallocation (NR)
1995	0.012	0.139	0.151	-0.127
1996	0.019	0.025	0.044	-0.006
1997	0.015	0.071	0.086	-0.056
1998	0.013	0.014	0.027	-0.001
1999	0.024	0.127	0.151	-0.103
2000	0.013	0.047	0.060	-0.034
2001	0.012	0.024	0.036	-0.012
2002	0.014	0.103	0.117	-0.089
2003	0.031	0.142	0.173	-0.111
Mean	**0.025**	**0.077**	**0.092**	**-0.052**
Other Regions*				
Ethiopia	0.141	0.099	0.042	0.240
South Africa	0.100	0.100	0.200	0.000
OECD	0.127	0.127	0.254	0.000
Latin America	0.148	0.140	0.288	0.008
Transition Economies	0.174	0.128	0.303	0.046

Source: Author's Calculations from the CSO Data. The asterisk * refers to Shiferaw and Bedi (2013) as the source of information for other regions. The gross job flow information for South Africa comes from Kerr et al. (2014).

This pattern is in sharp contrast to what obtains in other regions of the world, given their simultaneously high-paced creation and destruction prowess in the job market. For instance, for every job that Eswatini creates, Ethiopia and South Africa create 5.64 and 4.00 jobs, respectively, while transition economies create circa 7 jobs. In terms of job destruction, the Eswatini profile mimics that of Ethiopia and South Africa. Clearly, the job creation margin of gross job flows is a potential area for public policy targeting in Eswatini.

4.0 Measurement and Decomposition of aggregate labour productivity

4.1 Definition and Measurement of ALP Growth

Among single-input productivity measures, labour productivity is the most prevalent one in the literature (Syverson, 2011). As an output-to-input ratio, it measures the amount of output produced by a single factor input. Consider two firms requiring the same inputs to produce 100 physical units of a homogeneous product each. This allows us to suppress the product quality dimension. At face value, these firms appear to have equivalent efficiency levels.

There are a few reasons why that assumption may not hold in reality. 1) Firms may individually serve geographically localized and segmented markets with market-specific pricing decisions, a reasonable supposition for most industries. A technically efficient firm with an equilibrium downward sloping demand curve can pass on the cost-savings to its customers through price reductions thereby drawing lower revenue from the relevant market (Foster et al., 2008). 2) Branding and brand loyalty without product quality adjustment may stimulate product demand and lead to new schemes of pricing decisions (Bronnenberg et al., 2011). 3) Long-term relational contracts may lead to price variation and demand shifts due to consumer-producer relationships (Foster et al., 2008). 4) The probability of downward labour adjustment by a plant that uses the excluded primary factor more intensively because of factor input price differences increases (Syverson, 2011). In general, revenue-based productivity measures such as ALP reflect differences in technical efficiency and price heterogeneity due to idiosyncratic demand factors. The precise nature of confounding factors of such productivity measures depends on whether the production technology is constant or non-constant returns to scale (Foster et al., 2008; and Foster et al., 2016). Thus, a firm with higher revenue-based productivity is not necessarily more technically efficient in the presence of supply and demand idiosyncratic frictions.

The measurement of ALP in this study relies on deflated value-added (RVA_{it}) output and paid workers in each plant. That is, firm-level employment (L_{it}) for firm i at time t is defined as the total head-count of paid workers. Output per plant is constructed using double-deflation to the nominal value-added as proposed by Bruno (1978)

$$RVA_{it} = \frac{P_{it}Q_{it}}{P_t^Q} - \frac{P_{iMt}M_{it}}{P_t^M} - \frac{P_{iEt}E_{it}}{P_t^E} \qquad \text{Double Deflation} \qquad (1)$$

where Q_{it}, M_{it} and E_{it} are firm-level nominal gross output and inputs of material and energy with their respective price indices. The 'energy' variable also used in a similar manner by Petrin et al. (2011) is the total cost of fuel, electricity and water. Some studies in the literature rely only on material inputs in the determination of value-added output (e.g., Nishida et al., 2014). The double-deflation expression in Eq.1 represents relevant price indices for gross output and intermediate inputs. It is straightforward to track plant-level changes in labour productivity represented by $\phi_{it} = \frac{VA_{it}}{L_{it}}$ and aggregate those microeconomic changes to annual measures of ALP growth.

The first task to consider is how to decompose the time-path of changes in ϕ_i into its various productivity-enhancing or reducing components. A series of statistical accounting decompositions are available with varied degrees of success in getting compelling outcomes, given their inherent properties and characterizations.[10] Two of the widely used statistical decompositions are Baily, Hulten, and Campbell (1992) and Foster, Haltiwanger, and Krizan (2001).[11] The productivity growth components common to both methods are 'Within-Firm' effects and the 'Covariance' or 'Cross' term. They differ markedly in how

[10] This discussion abstracts from considering structural decomposition methods leading to the computation of multifactor productivity shocks because this article is concerned with productivity dynamics of a single primary input, labour.

[11] Baily, Hulten, and Campbell (1992) and its variants have been discounted by Nishida et al. (2014) and others arguing against the use of the output/labour ratio as a proxy for the marginal product of labour and its changes as a proxy for the micro productivity growth. The reallocation component of this method, the argument goes, is deeply confounded that it may be positively correlated, uncorrelated or negatively correlated with actual productivity growth coming from input reallocation (Nishida et al., 2014).

the extensive margins presented by firm dynamics contribute to productivity growth. Our preferred methodology for measuring ALP growth and its decomposition is Foster, Haltiwanger, and Krizan (2001), given the weaknesses identified in Baily, Hulten, and Campbell (1992).

We further implement the preferred statistical accounting decomposition in the context of the structural decomposition framework developed by Petrin and Levinsohn (2012) and Petrin et al. (2011). The appeal of the structural decomposition framework rests on its insistence that producer level variation adds up to variations in aggregate final demand, holding factor input adjustment hazards constant. Moreover; the measurement of aggregate productivity growth is independent of the method of estimation nor does it require any assumptions about the nature of market competition. Thus, the aggregated component drivers of aggregate productivity growth are readily comparable across estimation methods and across price-taking and price-setting behaviour (Foster et al., 2017).

4.2 ALP Growth Decomposition Using the BHC Method

The traditional method of $\Delta\phi_i$ decomposition adopted in this section is associated with the BHC approach in Eq.2 (or hereafter BHC_{ALP}) that tracks firms over time. Therefore, the composition of component drivers of ALP growth additively isolates the productivity gains as

$$BHC_{ALP} = \left(\overbrace{\textstyle\sum_{i\in C_t} s_{it-1}\Delta\phi_{it}}^{Within}\right) + \left(\overbrace{\textstyle\sum_{i\in C_t} \phi_{it-1}\Delta s_{it}}^{Between}\right) + \left(\overbrace{\textstyle\sum_{i\in C_t} \Delta s_{it}\Delta\phi_{it}}^{Co\,var\,iance}\right) + \left(\overbrace{\textstyle\sum_{i\in EN_t} s_{it}\phi_{it} - \sum_{i\in EX_t} s_{it-1}\phi_{it-1}}^{NetEntry}\right) \quad (2)$$

where $\Delta\phi_{it} = \phi_{it} - \phi_{it-1}$ and $\Delta s_{it} = s_{it} - s_{it-1}$. EN_t, EX_t and C_t represent entrants, exiters and incumbent firms at time *t*; respectively, while the employment share of plant *i* at time *t* is $s_{it} = \frac{L_{it}}{L_t}$. The different sources of $\Delta\phi_t$ are explained as follows

Within-Plant or Real Productivity Effects $\left(\sum_{i\in C_t} s_{it-1}\Delta\phi_{it}\right)$: This is the sum of changes in plant-level labour productivity weighted by the base-period labour-share of incumbent plants. The performance of plants depends on the value and direction of change in ϕ_{it}, given that s_{it-1} is always positive. Therefore, productivity-enhancing within-plant effects have $\Delta\phi_{it} > 0$. Otherwise, ALP growth suffers productivity losses.

Between-Plant or Rationalization Effects $\left(\sum_{i\in C_t} \phi_{it-1}\Delta s_{it}\right)$: This is the sum of changes in plant-level employment shares weighted by the base-period labour productivity for continuing plants. It measures the extent of labour share rationalization across plants where the labour input reallocation moves from less to more efficient producers. It has however been observed in the literature that after adding the entry/exit component, the balanced panel data interpretation of this term does not carry over to the unbalanced panel dataset without modification. Although the Forster *et al.* (2001) section further discusses a modified version of 'Between-Plant' effects, the Bailey et al. (1992) reallocates to high productivity uses if it attains positive values of Δs_{it}.

Covariance Effects $\left(\sum_{i \in C_t} \Delta s_{it} \Delta \phi_{it}\right)$: This is the sum of the contemporaneous product of changes in the labour market share and changes in ALP for incumbent plants. It is straightforward to interpret the product of the change in productivity and change in the labour market share for the share-shift term (Δs_{it}) and the Covariance term. When $\Delta \phi_{it} > 0$ and $\Delta s_{it} > 0$, then the characterization of plants is that they experience continuous improvement in production efficiency and human capital. That is consistent with high demand for firms' product varieties and increasing returns to scale. An alternative explanation is that producers may have pushed the production frontier outward through technological advancement in the presence of elastic demand for product varieties.

When $\Delta \phi_{it} > 0$ and $\Delta s_{it} < 0$, then firms are raising their production efficiency in lieu of labour inputs. This may obtain in the presence of effective technological innovation together with either falling demand or very inelastic demand, while labour augmenting technologies remain relevant in either outcome. In the case of $\Delta \phi_{it} < 0$ and $\Delta s_{it} < 0$, means plants' productivity and labour input behaviour are aligned with either (a) declining demand for product varieties and increasing returns to scale, or (b) negative productivity shocks in the presence of elastic demand, or (c) declining demand for product varieties and incomplete labour input adjustment. The case of $\Delta \phi_{it} < 0$ and $\Delta s_{it} > 0$ accommodates plants experiencing a productivity decline coupled with a labour input increase, a scenario consistent with a negative productivity shock and inelastic demand or increasing demand with diminishing returns. Again, an alternative explanation is that the plant-level quality of workers may have deteriorated overtime.

Net-Entry Effects $\left(\sum_{i \in EN_t} s_{it} \phi_{it} - \sum_{i \in EX_{it}} s_{it-1} \phi_{it-1}\right)$: An entrant is identified by first appearance at time *t*, and an exiting plant by its disappearance at the end of time $t + 1$. Thus, where ϕ_{it} enters the equation as raw data for firm i at time t, positive contributions to ALP growth arise from the entry of high productivity firms and exit of inefficient ones. Net-entry effects therefore refer to the difference between productivity growth contributions by entering and exiting plants.

4.3 The ALP Growth Decomposition Using the FHK Method

The decomposition of ALP using FHK (or hereafter FHK_{ALP}) is given as

$$FHK_{ALP} = \left(\overbrace{\sum_{i \in C_t} s_{it-1} \Delta\phi_{it}}^{Within}\right) + \left(\overbrace{\sum_{i \in C_t} \Delta s_{it}(\phi_{it-1} - \phi_{t-1})}^{Between}\right) + \left(\overbrace{\sum_{i \in C_t} \Delta s_{it} \Delta\phi_{it}}^{Co\,var\,iance}\right)$$

$$+ \left(\overbrace{\sum\nolimits_{EN_t} s_{it}(\phi_{it} - \phi_{t-1}) - \sum\nolimits_{i \in EX_t} s_{it-1}(\phi_{it-1} - \phi_{t-1})}^{NetEntry}\right) \quad (3)$$

where the 'Within' and 'Covariance' terms are identical to those calculated using the BHC method. The two unique ALP growth components calculated using FHK are described as follows

Between-Plant or Rationalization Effects $\left(\sum_{i \in C_t} \Delta s_{it}(\phi_{it-1} - \phi_{t-1})\right)$: This is the sum of the changing producer-level labour market-share weighted by the deviation of the base-period productivity of the continuing plant from that of the industry. An increase in a continuing plant's labour market-share makes a positive contribution to ALP growth if $\Delta s_{it} = s_{it} - s_{it-1} > 0$ and the plant's base-period productivity (ϕ_{it-1}) exceeds the base-period industry average productivity (ϕ_{t-1}); i.e., $\phi_{it-1} - \phi_{t-1} > 0$. Alternatively, the labour market-share increases the rationalization effect on ALP growth if $s_{it} < s_{it-1}$ and $\phi_{it-1} < \phi_{t-1}$. That is, the $t-1$ share of the labour market-share must be more than the current order of magnitude and the $t-1$ firm-specific productivity must also be lower than the $t-1$ industry average productivity; i.e., and product of negative values produces a positive value.

Net-Entry Effects $\left(\sum_{i \in EN_t} s_{it}\,(\phi_{it} - \phi_{t-1}) - \sum_{i \in EX_t} s_{it-1}\,(\phi_{it-1} - \phi_{t-1})\right)$: The 'Net-Entry' term reflects the difference between firm-entry and firm-exit productivity contribution. A positive net-entry contribution is obtained if a current entrant's productivity exceeds the base period productivity of an exiting firm; i.e., $\phi_{it} > \phi_{it-1}$.

5.0 Baseline ALP Growth Results

The previous sections have outlined and discussed the two traditional methods of ALP decomposition, highlighting the impact of specific firm-level patterns of resource share movements and productivity either in isolation or relative to the industry average. That enquiry does not clarify with precision how micro-factors interact to dominate in a broadly defined industry. This section is concerned with a detailed analysis of the manufacturing sector to gain insight into the patterns of productivity variation represented by cross-plant movement of resources, technical change as well as net-entry dynamics.

First and foremost, the discussion of how the Baily *et al.* (1992) and Forster *et al.* (2001) approaches are related is best captured mechanically as

$$FHK_{Bet} - BHC_{Bet} = BHC_{Net-Entry} - FHK_{Net-Entry}$$

The left-hand side relates the $FHK_{Bet}$and BHC_{Bet} quantities for continuing plants to $BHC_{Net-Entry}$and $FHK_{Net-Entry}$ to capture the productivity effects of entry/exit dynamics. The BHC_{Bet} is just a between-firm index measuring the productivity-weighted share-shifting effects of a change in labour. These -effects can in principle either be positive due to labour growth, zero due to firm size stagnation or negative due to a producer scaling down operations.

The BHC and FHK decompositions facilitate estimation of the ALP growth and its component parts reported in Table 2. This growth decomposes into four components: (1) within, (2) between, (3) cross, and (4) net-entry terms. A few observations about the results need pointing out upfront. Column (0) produced an average ALP growth of 37.99%; indicating the impact of a giant sale of assets between two large producers. This generated a net entry productivity growth contribution for the 1998-1999 outlier years. Further, the high degree of productivity dispersion measured by the standard deviation of ALP growth suggests that the labour market may be a potential source of input misallocation. Most of this productivity growth heterogeneity derives from within-firm effects and from the extensive margins of firm entry/exit. However, if extreme values are controlled for by considering the median ALP growth instead of the mean, the sector experienced a year-on-year ALP growth of only 1.22%. Lastly, the higher moments have modest orders of magnitude with ALP growth distribution rightly skewed and only marginal excess kurtosis; i.e., fat-tailed distribution of within-firm effects with only a modicum of the granularity motivation discussed in Gabaix (2011). Which one among the determinants of ALP growth in the decomposition is driving changes in real value-added per unit of labour? The next subsections answer this question.

Table 2: Weighted ALP Growth in manufacturing (1994–2003): BHC/FHK Decomposition Using Eq. 3 and Eq. 4 in Columns 3−9.

Year	VA Growth	ALP Growth (0)	Within (1)	Between (2) BHC-Bet	Between (2) FHK-Bet	Cross (3)	Net Entry (4) BHC	Net Entry (4) FHK
1995	7.76	1.22	2.67	-12.92	-0.06	-0.31	10.85	-0.43
1996	23.09	-3.11	8.38	-7.81	0.16	-0.74	-2.37	-13.74
1997	-44.34	-32.64	-5.62	22.40	-7.48	-4.01	-5.01	-13.91
1998	265.54	78.33	13.31	-39.94	2.30	-5.94	89.95	66.33
1999	275.56	206.92	11.52	-45.03	-1.44	-5.21	70.91	49.99
2000	-16.27	-37.41	-35.71	-10.95	1.32	4.33	5.31	-6.14
2001	37.41	85.52	44.21	-11.11	0.26	-4.97	28.81	18.28
2002	-20.74	62.85	-11.42	-6.26	1.03	.811	.2539	-4.34
2003	-36.71	-19.75	-16.90	21.35	2.73	-4.56	-13.04	.921
Mean	**54.59**	**37.99**	**1.16**	**-10.03**	**-0.12**	**-2.29**	**20.63**	**10.77**
Median	**7.76**	**1.22**	**2.67**	**-10.95**	**0.26**	**-4.01**	**5.316**	**-0.43**
SD	**125.31**	**79.12**	**22.51**	**22.87**	**3.03**	**3.48**	**36.17**	**28.78**
Skewness	**1.18**	**1.04**	**0.28**	**-0.05**	**-1.69**	**0.69**	**1.06**	**1.06**
Kurtosis	**2.61**	**3.21**	**2.98**	**2.24**	**5.03**	**2.27**	**2.61**	**2.61**

Notes: Numbers in cells are percentage points. The plant-level labour productivity uses the output-to-labour ratio that vary across the 2-digit ISIC code. ALP growth represents aggregate productivity growth rate with entry and exit, and is the aggregate change in final demand *minus* aggregate change in expenditure in inputs, holding inputs constant. ALP growth decomposes into: (1) within-firm effects, and (2) between-firm effects.

Source: Author's Calculations

5.1 The Impact of Within-Firm Effects on ALP Growth

This subsection focuses only on productivity performance of incumbent plants. The overall production efficiency within this group of producers has been lethargic since the early 1990s as shown by the average labour productivity gain of only $\sum_{i \in C_t} s_{it-1} \Delta\phi_{it} =$ 1.16% reported in Column (1). Since the initial share-weight is always $s_{it-1} > 0$, then $\Delta\phi_{it} > 0$ produces the observed average productivity growth. If one purges the ALP growth distribution of those firms with outlying indices by using the median moment, then the slowdown in the ALP growth improves to 2.67%.

Again, since aggregate labour productivity growth was positive on a year-on-year basis, and the covariance contribution to growth was negative, then the sector must have experienced a decline in the labour input. The decomposition results as a whole show that annual within-firm effects produced negative indices ln four years due to; *inter alia*, implicit adverse movements in technical change. While exhibiting moderate right-skewness and a thin-tailed productivity growth distribution, the major characterization of within-firm effects lies in their significant heterogeneity in productivity growth (a standard deviation of 22.51).

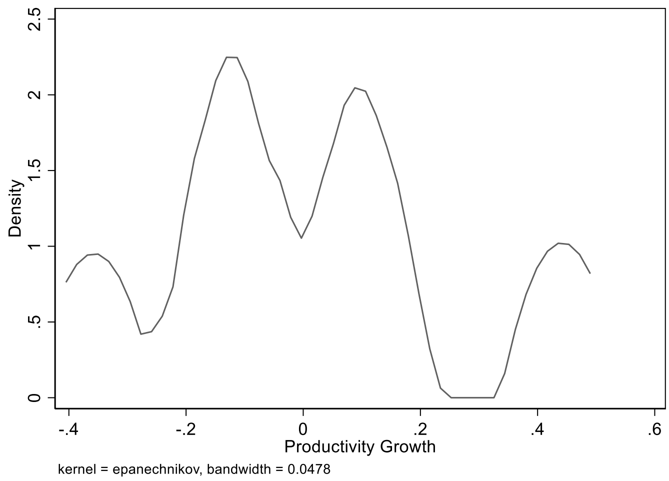


Figure 4: A Multimodal Productivity Growth Distribution

Figure 4 presents a multi-modal distribution of within-effects contribution to ALP growth: some firms' performance lingers around zero growth while others are located on either side of the y-axis with density level far apart. It is important to provide full characterization of real productivity contribution to ALP growth by relying more on its first-order moments and first-order moments of the measure of covariance, even if this is under *ceteris paribus* conditions. Since the average $(\Delta\phi_{it}) <$ median $(\Delta\phi_{it})$ and the measure of skewness is positive for real productivity, then most plants have positive productivity. The kurtosis $(\Delta\phi_{it})$ of 2.98 is an indication of thin tails in the distribution of real productivity. Further, the x-axis shows a 'missing middle' for $\Delta\phi_{it} > 0$ distribution and the distribution of $\Delta\phi_{it} < 0$ firms is a mirror image of the positive productivity growth firms. The 'missing middle' is also present at $\Delta\phi_{it} = 0$.

In view of the negative first-order moments in the covariance column, the dominant scenario was positive productivity growth $(\Delta\phi_{it} > 0)$ and downsizing of plants $(\Delta s_{it} < 0)$, notwithstanding heterogenous productivity dispersion within the sector. There are at least three explanations for this outcome. First, firms may have raised their production efficiency in the face of new competition induced by trade reforms and at the same time reduced their labour inputs. Second, a related scenario was that there could be effective technological innovation together with either falling demand or very inelastic demand causing downward labour adjustment. Third, there could be labour augmenting technologies coupled with labour rationalisation that allowed production of more output per worker.

5.2 The Impact of Between-Firm Effects and Net-Entry Margins on ALP Growth

It is important to consider the implications of Between-Firm effects in the context of the Cross term. It has already been established that the 1994-2003 period experienced a labour decline $(\Delta s_t < 0)$ and productivity growth $\left(\Delta\phi_{it} > 0\right)$; hence, the negative covariance. The manufacturing firms in Eswatini successfully downsized their operations and captured productivity gains. The negative average labour reallocation rate means that firms were on average more productive than the industry average. However, looking at the median as a first moment which is not influenced by extreme values of productivity growth, then reallocation turns positive. This productivity-enhancing component has *limited variability* in its distribution and is left-skewed with excess kurtosis. Given the firm-level heterogeneity observed in productivity growth and the almost inconsequential cross-firm reallocation with reference to overall ALP growth, it seems economic sclerosis in the sector might be a reality.

On the other hand, the productivity dynamics of firm entry and exit are reported in column (4) using the accounting decompositions of Baily *et al.* (1992) and Foster *et al.* (2001). It is again more convenient to rely on the Foster *et al.* (2001) variant for the interpretation of the results. The value of net-entry effects is positive when an entrant's productivity is larger than that of the exiting plant in the same industry. When that happens, the entrant experiences productivity gains from the market-share acquired from the firm that ceases operations.

Table 3: Effects of Firm Turnover on ALP Growth

Year	ALP Growth	Bailey et al. (1992) Entry	Bailey et al. (1992) Exit	Foster et al. (2001) Entry	Foster et al. (2001) Exit
1995	1.22	13.64	-2.79	-1.64	1.21
1996	-3.11	6.52	-8.89	-9.81	-3.93
1997	-32.64	3.49	-8.51	-14.78	0.87
1998	78.33	100.45	-10.49	71.42	-5.08
1999	206.92	71.73	-0.82	46.16	3.82
2000	-37.41	5.53	-0.21	-7.97	1.83
2001	85.52	32.53	-3.72	18.40	-0.11
2002	62.85	3.02	-2.76	-4.87	0.53
2003	-19.75	0.73	-13.77	-9.75	10.67
Mean	**37.99**	**26.41**	**-5.77**	**9.68**	**1.09**
Median	**1.22**	**6.52**	**-3.72**	**-4.87**	**0.87**
SD	**79.12**	**35.88**	**4.75**	**30.05**	**4.54**
Skewness	**1.04**	**1.25**	**-0.38**	**1.19**	**0.75**
Kurtosis	**3.21**	**3.02**	**1.77**	**2.94**	**3.49**

Source: Author's Calculations

Furthermore, net-entry effects were the largest contributing factor driven largely by a downstream-upstream sale of assets between two large firms in the Wood and Pulp industries in 1998 and 1999 as alluded to earlier.[12] This is a dominant feature of the domestic manufacturing sector that is populated by a limited number of larger firms in an industry. The consequential effect of the asset acquisition was that a small industry shake-up had magnification effects on productivity growth for the entire sector. This particular event led to an average $FHK_{Net-Entry}$ effect of 10.77%. After controlling for the M&A transaction; however, the decomposition produced a median net-entry effect of -0.43% thereby signalling the presence of entrepreneurship fragility induced by diminished start-up rates or large M&A activity. Table 3 reports the contribution of new business ventures and plant shutdowns to ALP growth. It unbundles the net-entry columns in the previous table to directly decipher the independent role of each component of firm turnover. In this sense, 1-year old firms were more efficient in production than quitters and also incumbent firms regardless of measurement method due to the 1998-1999 events and accession of Eswatini (then Swaziland) to the African Growth and Opportunity Act (AGOA) privileges in 2001.

[12] Gabaix (2011) notes that Nokia contributed 1.6% to Finland's GDP in 2000 while Microsoft paid a once-off dividend of US$24 billion that raised personal incomes from 0.6% to 3.7%. Idiosyncratic dynamics of the largest 100 firms in the US explain about 33% of the variation in output growth. Thus, any inquiry into aggregate fluctuations can be understood by studying the behavioural patterns of large establishments (Koren and Tenreyro, 2013; and Atalay, 2017. Baqaee and Farhi (2019) rely on the first- and second-order approximation of sales-to-GDP ratio, *aka* Domar weight, to determine the role of microeconomic details on macroeconomic fluctuations.

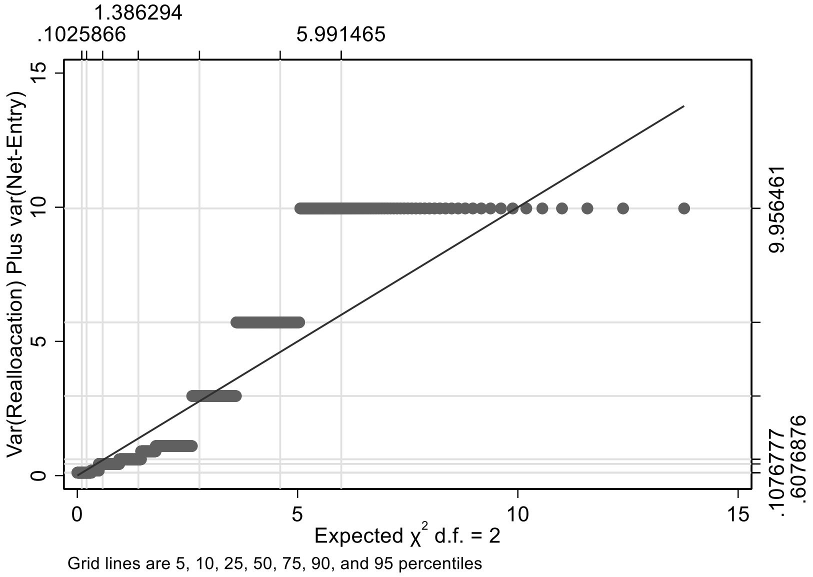


Figure 5: Quadratic Distribution of Labour Reallocation and Net-Entry Effects

Looking at both labour reallocation and net-entry effects, we note their negative correlation of -0.14. While reallocation lingers in the proximity of zero, the net-entry effects component overshoots its path in some years. Therefore; analysing the pattern of their sum of squares, standardized for their variances, may prove fruitful. Their combined variance, driven largely by net-entry effects, is depicted in Figure 5. The plot shows a quadratic distribution reflecting the fact that a variance can never be negative. This nonlinearity and potentially the nonlinearity of other higher moments matter in how aggregate reallocation and firm/exit dynamics respond to microeconomic details of the labour market. Subsection 5.5 pursues this further.

5.3 Confounding Effects of Firm Turnover on the BHC Reallocation

The reallocation metric developed by Foster et al, (2001) applies consistently to both balanced and unbalanced datasets. In contrast, in an effort to incorporate the entry/exit term, Baily et al. (1992) did not fully consider that the interpretation of the 'between-term' would not carry over to an unbalanced dataset.

The contaminated "Between-Firm" term (BHC_{Bet}) represents the labour reallocation component of -5.69 % and can be decomposed into two constituent parts: one related to reallocation and another related to the number of plants as in Nishida *et al.* (2014). Suppose there are N_t plants in manufacturing and the plant-level average share of employment is $s_t = \frac{\sum_i s_{it}}{N_t} = \frac{1}{N_t}$. Then, the relative labour-share in the i^th^ plant is defined as $\tilde{s}_{it} = s_{it} - s_t$, and the change in the relative labour-share from time $t-1$ to t is $\Delta\tilde{s}_{it} = s_{it} - \tilde{s}_t$. Therefore, the "Between-Firm" term for incumbent firms decomposes as follows:

$$BHC_{Bet} = \sum_{i \in C_t} \Delta s_{it}\, \phi_{it-1}$$

$$= \sum_{i \in C_t} [(s_{it} - s_t) - (s_{it-1} - s_{t-1})] * \phi_{it-1} + \sum_{i \in C_t} (s_t - s_{t-1}) * \sum_{i \in C_t} \phi_{it-1}$$

$$= \left(\overbrace{\textstyle\sum_{i \in C_t} \Delta \tilde{s}_{it} \phi_{it-1}}^{FirstComponent} \right) + \left(\overbrace{\left(\frac{1}{N_t} - \frac{1}{N_{t-1}}\right) \textstyle\sum_{i \in C_t} \phi_{it-1}}^{SecondComponent} \right). \tag{4}$$

The first component represents labour reallocation and the second component relates to patterns of creative destruction. An increase in the number of firms over time confounds the first component by $\left(\frac{1}{N_t} - \frac{1}{N_{t-1}}\right)$ in the negative direction, since ϕ_{it-1} can never be negative. The reverse effect obtains in the case of a persistent fall in the number of firms. The second component also gets smaller and smaller as the number of firms gets smaller and smaller, which happens if firm-exit rate is persistently higher than the entry rate. If there is no change in the number of firms in the adjacent periods, the second component falls away. That is, entry-exit dynamics have a spurious influence on labour reallocation effects. Table 7 presents a quantitative decomposition of BHC_{Bet} for the manufacturing sector.

Table 4: Decomposition of the BHC Between Term

	BHC (0):	BHC Between Term Decomposition: (0) = (1) +(2)		
Year	Between	(1) First component	(2) Second component	% Growth of firms
1995	-12.92	10.78	-23.71	11.11
1996	-7.81	14.79	-22.60	13.75
1997	22.40	21.83	0.57	-2.19
1998	-39.94	-31.17	-8.77	25.84
1999	-45.03	-19.23	-25.79	23.21
2000	-10.95	-0.43	-10.51	7.97
2001	-11.11	2.46	-13.58	10.06
2002	-6.26	4.93	-11.20	8.53
2003	21.35	-1.79	23.15	-15.16
Mean	**-10.03**	**0.24**	**-10.27**	**9.23**
Median	**-10.95**	**2.46**	**-11.20**	**10.06**
SD	**22.87**	**16.53**	**15.09**	**12.37**
Skewness	**-0.05**	**-0.70**	**1.17**	**-0.60**
Kurtosis	**2.24**	**2.62**	**3.72**	**2.92**

Notes: Percentage growth rates. The BHC 'between' term decomposes into two terms using Eq. 5 in the text.

Source: Author's calculations.

The second column is identical to the BHC_{Bet} column in Table 2. The third and fourth columns are the respective first and second components of Eq. 4, and the last column is the percentage growth of firms per year. In seven out of nine years, the manufacturing sector experienced growth in the number of firms, and in these years the confounding effect of plant expansion on the 'Between' term was negative. The comparison of the first term to the overall average of the BHC 'Between' term shows that the first term was 6.07% higher over the sample period due to the downward confounding effects of plant turnover on the worker reallocation component.

These results mimic the findings by Nishida *et al.* (2014) for Chile and Slovenia, and they cast doubt on the validity of the share-shifting effects of the BHC approach, as expected. This confirms the conclusion by Nishida *et al.* (2014) that the BHC reallocation can be negatively correlated, positively correlated or simply uncorrelated with the actual reallocation of inputs. One important question; however, is how do these results compare with those from other case studies of countries at different levels of development? The next section seeks to provide an answer to this question.

5.4 Cross-Country Comparison of Evidence on Drivers of ALP Growth

In this section, we review and compare these results with findings from other countries' statistical accounting decomposition of ALP growth. The idea is to assess the patterns of within-firm effects, labour reallocation, and the effects of entry and exit margins. One approach involves identifying those case studies that relied on the Foster *et al.* (2001) decomposition applied to datasets covering any length of period during 1994-2003 in order to pick up roughly similar exogenous global influences. Isaksson (2010) surveys sources of ALP growth in 33 advanced and developing countries as well as economies in transition. A number of these countries have undergone economic reforms to facilitate freer movement of inputs across firms in order to trigger productivity growth from resource reallocation. A consistent finding is that there has been significant ALP growth for these economies.

Table 5 presents empirical decompositions of $\Delta\varphi_t$ for the manufacturing sector covering a sample of 13 countries from the survey by Isaksson (2010), *plus* Eswatini, based on either the method developed by Foster *et al.* (2001) or by Haltiwanger (1997). This allows for the comparison of decomposition results between Eswatini and evidence from the selected country case studies. Before carrying out the assessment of these results, two features of data sources require comment. First, the dominant data source of these comparator case studies is the Regional Programme on Enterprise Development (RPED) of the World Bank, with a few exceptions that rely on panel data from national statistical agencies. Second, Germany and the Sub-Saharan (SSA) case studies do not include firm entry/exit dynamics as a determinant of ALP growth. Third, while African comparator countries define ALP using value-added, market economies and economies in transition use gross output to define it.

Table 5: Unweighted ALP Growth, $\Delta\boldsymbol{\varphi}_t$, Decomposition for the Manufacturing Sector in Industrialized Countries, Economies in Transition and in Developing Countries using Eq. 4. (percentages)

Method	Country	Period	Output/Share/ Productivity	Within	Between	Cross	Entry	Exit	Total
FHK (2001)	USA	1992 & 1997	GO/Labour/LP	109.00	-3.00	-24.00	-29.00	49.00	102.00
FHK (2001)	UK	2000-2001	GO/Labour/LP	48.00	19.00	-17.00	35.00	12.00	97.00
FHK (2001)	Germany	1993-2003	GO/Labour/LP	118.60	11.50	-30.10	-	-	100.00
FHK (2001)	Russia	1992-2004	GO/Labour/LP	-590.40	359.60	61.61	-223.70	292.93	-99.96
FHK (2001)	Slovenia	1997-2001	GO/Labour/LP	68.00	18.00	-2.00	15.00	13.00	112.00
FHK (2001)	Chile	1985-1999	GO/Labour/LP	95.00	25.00	-50.00	-35.00	65.00	100.00
FHK (2001)	Colombia	1987-1998	GO/Labour/LP	105.00	20.00	-45.00	-20.00	40.00	100.00
FHK (2001)	**Eswatini**	**1994-2003**	**VA/Labour/LP ***	**12.18**	**-1.26**	**-24.05**	**101.68**	**11.45**	**100.00**
Halti (1997)	Cameron	1990-1995	VA/Labour/LP	144.94	-25.84	-13.48	-	-	105.62
Halti (1997)	Ghana	1990-1995	VA/Labour/LP	78.97	66.15	-43.59	-	-	101.53
Halti (1997)	Kenya	1990-1995	VA/Labour/LP	445.45	282.80	-629.09	-	-	99.16
Halti (1997)	Tanzania	1990-1995	VA/Labour/LP	12.00	13.00	-36.00	-	-	99.00
Halti (1997)	Zambia	1990-1995	VA/Labour/LP	357.14	28.57	-278.57	-	-	107.14
Halti (1997)	Zimbabwe	1990-1995	VA/Labour/LP	163.33	33.33	-96.67	-	-	99.99

Notes: The text describes the methods used. LP = Labour Productivity, GO = Gross Output, VA= Value Added, and Halti (1997) = Haltiwanger (1997). Information sources include Isaksson (2010), "Structural Change and Productivity Growth: A Review with Implications for Developing Countries", *United Nations Industrial Development Organization,* Tables 1-3; Van Biesebroeck (2005), "Firm Size Matters: Growth and Productivity Growth in African Manufacturing", *Economic Development and Cultural Change*, Vol. 53(3), pp. 543-83; and the author's calculation of ALP growth components for Eswatini. The asterisk * denotes weighted drivers of ALP growth.

All comparator case studies but Russia achieved significant ALP growth contributions from within-firm effects while Eswatini increased its own contribution by as much as 12.2 %. That is, within-firm effects from Eswatini mimic efficiency gains experienced by Tanzania, Ghana, and the U.K. In the case of labour reallocation from high- to low-productivity plants, Eswatini performed like Cameron and the U.S. The firm entry effect ranked highest while the exit contribution was only modest relative to comparator economies.

Overall, the low contribution of within-firm effects to ALP growth in the manufacturing sector is associated with technical change during *de facto* trade reforms. It reflects a producer's success or otherwise in leveraging a range of factors that raise product revenues while keeping a suitable size of labour with an optimal skill mix. However, there is a caveat to this line of thought. In the absence of physical quantities and prices of product varieties, the deflation of nominal revenue output is achieved by using a common within-industry deflator, Foster et al. (2008). The consequential effect of this is that price heterogeneity may be captured within our four-digit ISIC industry output and in ALP. If prices mirror idiosyncratic demand variation instead of product quality or productivity of labour input, then the ALP indices may not be a true reflection of technological (in)efficiency.

Finally, the movement of labour resources from high- to low-productivity plants portrayed by the reallocation of -0.12 suggests the presence of labour market frictions/wedges. One way to scrutinize this further is to rely on the economics of labour adjustment to uncover the impact of employment shortages on both the intensive and extensive margins of labour reallocation.

5.5 Labour Adjustment Hazards and Implications for Reallocation

The adjustment of employment is dependent on the ability of producers to vary their labour demand in response to uncertainty shocks. Plants can flexibly optimize the hours-of-work for their employees as a response to production efficiency shocks, Caballero et al. (1997), Eslava et al. (2004) and Trapeznikova (2017).[13] The characterization and properties of research results on labour adjustment hazards are best captured in the analyses of plant-level panel data advanced market economies (e.g., the U.S.) and markets in transition (e.g., Colombia) as a benchmark for work in other economies. In these studies, the microeconomic widening of the gap between the desired and actual employment (or employment shortages) is positively and disproportionately correlated with the size of factor input adjustment. Labour input adjustments are often spiky with long episodes of inaction, a reflection of nonconvexities in the adjustment cost technologies. These microeconomic nonlinearities amplify large aggregate shocks (Caballero et al., 1997). The goal of this subsection is to determine the first-stage effects of cross-sectional distributions labour shortages on the variation of aggregate employment. It also seeks to determine the causal-effects of aggregate employment growth on micro and aggregate labour reallocation among incumbents and within the entry/exit margins.

Under an environment of labour market sclerosis where firing and hiring costs drive the microeconomic factor-input adjustment hazards, the probability of a firm's input adjustment links to the gap between the firm's state variable and the related moving target (Caballero, and Engel, 1993; and Caballero et al. (1997). Moreover, the aggregate employment growth rate (ΔE_t) is a function of the cross-sectional M[th]-order moment distribution of the gap between the desired (e_t^*) and actual (e_t) number of workers. Since e_t^* is unobserved, Caballero et al. (1997) recommend using hours (h_{it}) and average plant-level hours $(\bar{h}_i)$ for measuring microeconomic labour shortfalls and excesses. However, the absence of information on hours worked by employees compels us to look for alternative options for estimating the "hours" covariate. To do this, we follow Eslava et al. (2004) who use total work hours per sectoral wage as $h_{sit} = \frac{Earnings_{sit}}{W_{st}}$, earnings per employee as $Earnings_{sit} = \frac{\sum_{i\epsilon s}^{S} Payroll_{sit}}{\sum_{i\epsilon s}^{S} l_{sit}^{PE}}$, gross employment hours for each firm as $h_{it} = h_{sit} l_{it}^{PE}$, and total number of paid employees as l_{it}^{PE}. That is, the relevant model specification for employment growth takes a high-dimensional sparse form as

$$\Delta e_{it} = Constant_i - \theta_i(h_{it} - \bar{h}_i) + \varepsilon_{it} \qquad [5]$$

[13] Caballero et al. (1997) rely on a plant's hours-week to construct measures of the distance between the desired and actual level of employment. Even though some micro-data sets do not contain the 'hours; variable, Eslava et al. (2004) show how to impute this from salaries and wages of current workers.

where ε_{it} is white noise. The estimation of θ_i in Eq.5 is potentially downward-biased and therefore warrants reverse estimation using the same observations with Δh_{it} as a response variable thereby introducing upward biasedness.

To address this problem, a weighted average of the coefficients from the two equations is computed to allow for the construction of time series for each plant using Eq. 6-7

$$q_{it} = \theta_i\left(h_{it} - \bar{h}_i\right) \quad [6]$$

$$q_{it}^1 = \theta_i\left(h_{it} - \bar{h}_i\right) + \Delta e_{it}. \quad [7]$$

When producers are confronted with employment shortages, they respond through a mechanism defining the employment adjustment hazard function, sometimes referred to as the probability of employment adjustment. To put it more succinctly, the general specification adopted here nests Caballero et al. (1993) and Caballero and Engel (1997) as follows

$$H(z) = \varphi_0 + \varphi_1 z + \varphi_2 z^2 + \varphi_3 z^3$$

where the employment shortfall is defined as $z = h - \bar{h}$. The specification of aggregate employment growth, ΔE_t, at time t is therefore

$$\Delta E_t = \int_{-\infty}^{\infty} z\, H(z) f_t(z) dz$$

where $f_t(z)$ is the probability density function of employment gaps. On substituting the third-order polynomial adjustment hazard-function into the aggregate employment growth expression, the left-hand side is explained by the cross-sectional distributions of the first to fourth-order moments of employment shortages in Eq. 8

$$\Delta E_t = Constant + \gamma_1 M_t^{(1)} + \gamma_2 M_t^{(2)} + \gamma_3 M_t^{(3)} + \gamma_4 M_t^{(4)} + \delta_t \quad [8]$$

where $M_t^{(r)}$ captures the r-th order moment of the cross-sectional distribution of employment shortages at time t, and $\gamma_1 \neq 0$ and $\tau\epsilon(\gamma_2, \gamma_3, \gamma_4) = 0$ means that aggregate employment growth is linearly responsive to the aggregate first-moments of the cross-sectional distribution of employment gaps. This arises when firms adjust their stock of labour only intermittently or the labour market adjusts labour stock continuously according to a quadratic model (Caballero and Engel, 2004). More realistically, when any of $\tau \neq 0$, then the higher moments become important in also explaini+.653ng aggregate employment growth. This situation occurs under lumpy labour adjustment and increasing microeconomic adjustment hazards (Caballero and Engel, 1993).[14]

Furthermore, one can define de-trended variables as $\ddot{G}_{it} = G_{it} - \frac{1}{T}\sum_{t=1}^{T} G_{it}$ in order to purge the model of fixed effects so that $\Delta\ddot{G}_{it} = \ddot{G}_{it} - \ddot{G}_{it-1}$ (Belloni et al., 2016). The identity of the reduced form equations is labour reallocation $(\mathrm{FH\ddot{K}Bet_{it}})$ and net-entrants $\ln(\mathrm{FH\ddot{K}NE_{it}})$ calculated in Table 2 explained by; *inter alia*, variation in aggregate employment growth, $\Delta ln\ddot{E}_t$. Under endogeneity conditions for structural effects, the model can be consistently estimated by Two Stage Least Squares (TSLS) using the moments in Eq.9 as exclusion restrictions suggested by the IV model

$$y_1 = y_2\beta + X\Upsilon + U$$

$$y_2 = Z\Pi + X\Phi + V \qquad [9]$$

where y_2 is the reduced-form $T\ x\ n$ matrix of included variables, X is a $T\ x\ K_1$ matrix of exogenous included variables, Z is a $T\ x\ K_2$ matrix of included exogenous instrumental, V is an error matrix and one assumption is that $K_2 \geq n$ is allowed. The vectors β and Υ and matrices Π and Φ are parameters to be estimated. Notice that the variable of interest in this analysis is endogenous y_2 and therefore estimation of $\beta,$ which is approximated with $\hat{\beta}^{TSLS}$.

Table 6: Effects of Sectoral Shocks on Aggregate Employment Growth

Moments	$q_{it} = \theta_i(h_{it} - \bar{h}_i)$	$q_{it}^1 = \theta_i(h_{it} - \bar{h}_i) + \Delta e_{it}$
	b/se	b/se
Mean	0.034*	0.406**
	(0.0145)	(0.1394)
Constant	0.510***	0.464***
	(0.0232)	(0.0120)

Notes: Estimation of parameters in this table recognizes plant-level clustering of variables; hence, cluster robust standard errors are in parenthesis. * p<0.05, ** p<0.01, *** p<0.001.

Source: Author's Calculations

Table 6 performs the first stage analysis of the effects of up to the fourth-order moment of the cross-sectional distribution of employment gaps imputed from plant-level hours. In both definitions of employment shortages, the first-order employment gap produced significant coefficients thereby preserving

[14] Caballero et al. (1997) cite the problem of omitted state variables as well as permanent and transitory shocks in the variation of employment and hours per worker. As a result, these authors and Baqaee and Farhi (2019) suggest another model specification that includes central moments as well.

its linear labour adjustment cost relationship with aggregate employment growth. This means a 1-percentage point increase in average employment shortages raises the aggregate employment growth by 0.03% or 0.41%, depending on the definition of shortages. Higher orders of aggregation of shocks produced robust zero parameters. The implied absence of second derivative approximations for aggregate employment growth is the absence of nonlinearities necessary to shape the impact of sectoral shocks (Baqaee and Farhi, 2019). That is, the typically large and infrequent episodes of factor input adjustments normally found in the empirical literature is not an accurate characterization of the current dataset.

The reduced form of the model relates plant-level and aggregate variation in labour reallocation in Table 10 to aggregate employment growth. The structural parameter of interest is therefore α_0 in Eq. 7. As a result, the table reports the impact of "aggregate employment growth" on "labour reallocation" and "net entry" at micro and sectoral levels in the first row of Panel A. The row with the FULLER entry presents a robustness check calculated using a limited information maximum likelihood (LIML) estimator.

Table 7: Aggregate Employment Growth Shocks on Labour Reallocation and Net-Entry Effects

Panel A	**Employment Gap:** $q_{it} = \theta_i(h_{it} - \bar{h}_i)$			
	Firm-Level Response		**Aggregate Response**	
Variable ΔlnE_t	Reallocation b/se	Net-Entry b/se	Reallocation b/se	Net-Entry b/se
$\Delta ln\ddot{E}_t$	0.007	-0.951***	0.008	-0.962***
	(0.0066)	(0.1744)	(0.0076)	(0.1726)
$\Delta ln\ddot{E}_t$: FULLER	0.007	-0.970***	0.008	-0.976***
	(0.0065)	(0.1851)	(0.0073)	(0.1805)
Constant	0.003	0.639***	0.002	0.656***
	(0.0033)	(0.0902)	(0.0037)	(0.0927)
First-Stage F-Statistic	13.327	13.327	10.873	13.368
	(0.0381)	(0.0381)	(0.0280)	(0.0376)
Panel B	**Employment Gap:** $q^1_{it} = \theta_i(h_{it} - \bar{h}_i) + \Delta e_{it}$			
Variable	Reallocation b/se	Net-Entry b/se	Reallocation b/se	Net-Entry b/se
$\Delta ln\ddot{E}_t$	0.008	-0.926***	0.008	-0.933***
	(0.0049)	(0.1211)	(0.0047)	(0.1160)
$\Delta ln\ddot{E}_t$: FULLER	0.008	-0.935***	0.008	-0.933***
	(0.0048)	(0.1248)	(0.0046)	(0.1160)
Constant	0.002	0.631***	0.002	0.635***
	(0.0024)	(0.0644)	(0.0023)	(0.0594)
First-Stage F-Statistic	23.148	23.148	24.841	24.841
	(0.001)	(0.0016)	(0.0008)	(0.0008)

Notes: TSLS regression results are weighted and cluster robust standard errors are in brackets. Inference on FULLER coefficients is based on FULLER $(\alpha = 1)$. The first-stage results consistently report an F>10 statistic for model specification and pass the required endogeneity tests. *** p<0.001.

Source: Author's Calculations

The reshuffling of labour inputs among incumbent firms and across sectors was robustly unresponsive to movements in aggregate employment growth, regardless whether q_{it} or q^1_{it} was used as definition for employment shortfalls. A significant impact mostly occurred between aggregate employment growth and the net-entry margin of resource shifts. In Panel A, a 10% increase in de-trended employment growth reduced the micro movement of labour from shutdowns to entrant firms by 9.51% and by 9.62% at the aggregate level. The FULLER coefficients and standard errors are slightly amplified but broadly similar to the preferred specification. In Panel B, the parameters are slightly attenuated at $\hat{\beta}^{TSLS} \epsilon$(-0.933, -0.926) with systematically attenuated standard errors. Again, the FULLER alternative merely affirms the baseline model parameters. In general, the overall results suggest that a unit percentage point increase in de-trended aggregate employment growth inversely varies with net-entry effects at the rare of $\hat{\beta}^{TSLS} \epsilon$(-0.976, -0.926) percent.

6.0 Summary and Conclusion

This article has explored the patterns of gross job flows and the statistical accounting decomposition of ALP growth to understand supply-side producer dynamics using panel data from the manufacturing sector in a period of *de facto* trade liberalization. Results from the ALP growth decomposition were compared with what obtains in other world economies at different levels of development. It finally studied the causal effects of endogenous aggregate employment growth on labour reallocation and net-entry margins relying on the cross-sectional distribution of up to fourth-order moments of employment shortages.

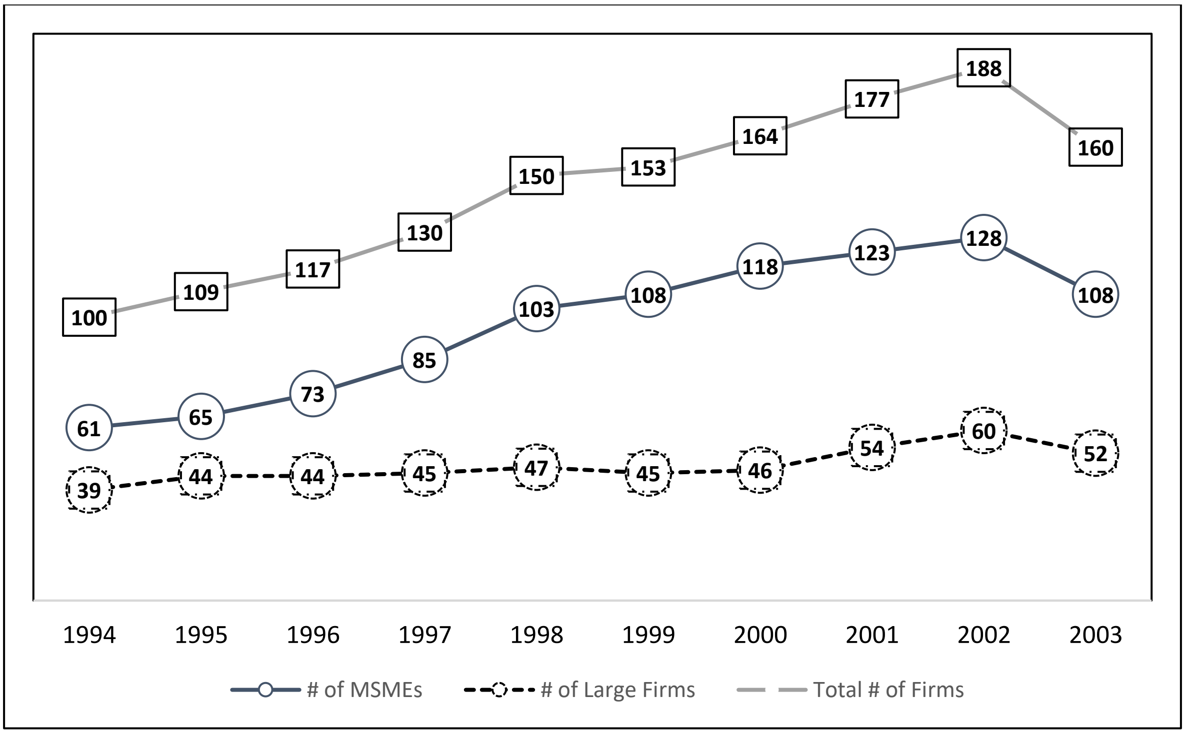
The paper found that the gross job creation and destruction were 2.5% and 7.7% during the period under review, respectively. That is, only 1 in 40 jobs was on average created at time t while 1 in circa 13 jobs was destroyed. Put differently, for every job created, the sector destroyed an annual average of 3 more jobs. Gross job reallocation was 9.4% on a year-on-year basis. Similarly, the difference between gross job creation and destruction, also known as the net employment rate, fell by circa 5.9% annually

It also found a persistent annual average increase of 1.16% in real productivity from incumbents. The sector further experienced labour reallocation losses of 0.12% across incumbents and gains of 10.77% from the entry/exit margins. The dominant contributor to ALP growth on average was the entry dimension. This margin was also dominant in relation to comparator countries. However, controlling for extreme values generated gains of 2.67% from within-firm effects, 0.26% from reallocation and losses of -0.43% from net-entry effects. Thus, within-firm effects dominated the intensive and extensive forms of labour input reallocation, *ceteris paribus*.

Further analysis involved studying the impact of endogenous aggregate employment growth on granular and aggregate labour reallocation among incumbents as well as between one-year old firms and their exiting counterparts. The cross-sectional distribution of up to the fourth-order moment of the difference between the desired and actual employment were modelled as sources of exogenous variation in endogenous aggregate employment growth. The first-order moment was strongly associated with aggregate employment growth while higher-order moments had insignificant effects, conditional on other controls in the IV regression. However, the first key finding was that labour reallocation at both granular and aggregate levels remained unresponsive to aggregate employment growth. More importantly, the second key finding was that for every job that moved from business closures to entrants, aggregate employment growth reduced granular and aggregate reallocation by a factor of $\hat{\beta}^{TSLS} \epsilon$(-0.976, -0.926), depending on model specification.

Future work will estimate TFP, quantify the structural decomposition of $\Delta lnTFP$ under monopolistic competition with heterogeneous markups, and determine drivers of factor input distortions.

Appendix



Notes: MSMEs include micro establishments employing 1-3 workers, small firms with 4-10 workers and medium plants with 11-49 workers. Large firms are employers of 50 workers or more.

Source: Author using CSO Data

Figure A.1: Distribution of Firms by Size of Employment

Table A.1: Measurement of Gross Job Flows

INDEX	DEFINITION	EQUATION
Firm-Level Growth Rate	$g_{it} = (N_{it} - N_{it-1})/(1/2)(N_{it} + N_{it-1})$	(1)
Firm-Level Weight	$\omega_{it} = (N_{it} + N_{it-1})/\Sigma_{i\in\varepsilon_{jt}}(N_{it} + N_{it-1})$	(2)
Entry	$N_{it-1} = 0,\ N_{it} > 0$, and $g_{it} = 2$	(3)
Exit	$N_{it-1} > 0, N_{it} = 0$, and $g_{it} = -2.$	(4)
Continuing and Expanding Plants	$N_{it} > N_{it-1} > 0$; hence, $g_{it} > 0$	(5)
Continuing and Contracting Plants	$N_{it} < N_{it-1}$; hence, $g_{it} < 0$	(6)
Gross Job Creation (JC_t):		
	$JC_{\mathrm{Expanding}_t} = \sum_i \omega_{it} \max\{g_{it}, 0\}$;	(7)
	$JC_{\mathrm{Entry}\ t} = \sum_i \omega_{it} \max\{g_{it}, 0\}\boldsymbol{I}\{g_{it} = 2\}$,	(8)
	$JC_t = JC_{\mathrm{Expanding}_t} + JC_{Entry_t}$	(9)
Gross Job Destruction (JD_t):		
	$JD_{\mathrm{Contracting}_t} = \sum_i \omega_{it} \min\{-g_{it}, 0\}$	(10)
	$JD_{\mathrm{Exit}_t} = \sum_i \omega_{it} \min\{-g_{it}, 0\}\boldsymbol{I}\{g_{it} = -2\}$	(11)
	$JD_t = JD_{\mathrm{Contracting}_t} + JD_{\mathrm{Exit}\ t}$	(12)
Net Job Reallocation (NR_t)	$NR_t = JC_t - JD_t$	(13)
Gross Reallocation Rate (JR_t)	$JR_t = JC_t + JD_t$	(14)
Excess Reallocation Rate (XR_t)	$XR_t = JR_t - \lvert NR_t \rvert$	(15)

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